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Contents

CHAPTER 1

How Competitive and Stable is the Commercial Banking Industry in China after Bank Reforms?

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Abstract

The Chinese banking system has come a long way, from a mono bank system before Deung Xiao Ping's 1978 economic reform to creation of four state-owned commercial banks and policy banks as well as second tier (or joint-equity) banks in the 1980s and then establishment of city commercial banks by local governments in the 1990s. The financial liberalization in the 1990s prior to its entry to World Trade Organization focused on bank reforms which include market-based interest rate reform as well as equal treatment of foreign banks. With entry of more banks, the Chinese commercial banking industry experienced continually decreasing market concentration.

This paper examines market concentration and its effect on competition in the Chinese commercial banking market for the period of 1992-2008. This study also investigates how changes in competition have affected financial stability of the Chinese commercial banks. To test the competitive conditions, we obtained the H statistic of the Panza-Rosse model from the revenue function equation, where three major input costs, labor expenses, capital costs and funding costs are used to estimate the revenue. Both total revenue and interest revenue are alternatively used. The financial stability is estimated by the Z-score formula.

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The Chinese banking industry has become increasingly less concentrated market with an increase in the number of banks, which can be attributable to financial liberalization and deregulation, creation of joint equity commercial banks and establishment of city banks by local governments. This study finds that along with decreased market concentration, competition in the Chinese banking industry has improved moderately. However, its market structure is far from a competitive market, as evidenced by small H statistic values. The Chinese banking industry is still highly concentrated and its level of competition is closer to oligopoly. It seems that bank reforms have a small effect on competitiveness of Chinese commercial banking. This study also finds that while the higher degree of market concentration may have negative effect on financial stability of the entire banking system, an individual bank's ability to earn higher markup or charge higher net interest margin contributes to financial soundness of the individual bank.

JEL classification: G21, L10
Keywords: bank competition, bank stability, Chinese banks

How Competitive and Stable is the Commercial Banking Industry in China after Bank Reforms?

1. Introduction

The last three decades witnessed a surge of bank mergers. Even though firm mergers have occurred for a long time, the mergers that occurred in the past twenty years, the so-called the "fifth merger wave" has been the most remarkable. The banking industry was not an exception from the merger wave. The banking industries all over the world have experienced a fundamental change in its market structure through rapid consolidation. Financial deregulation and financial globalization triggered fierce competition among banks and necessitated consolidation to reduce risk through business diversification and to take advantage of scale economies.

The Chinese banking system underwent a different path of structural change, from a mono bank system to a "several tier' banking system in the last 30 plus years. Several measures of financial liberalization and restructuring have been in place to improve competitiveness in the commercial banking industry since the 1990s. There have been many bank foreclosures, takeovers and mergers in China like many other countries. However, the number of new bank entered into the Chinese banking market far exceeded the number of banks disappeared.

Until 1978, there was one single bank, People's Bank of China, and then along with its economic reform, the Chinese government authorized four state-owned commercial banks between 1979 and 1984 with limited competition among them. Since then the Chinese government allowed many joint equity banks and private banks in order to mobilize needed financial resources for economic development. Furthermore, it authorized several policy banks and local (or city) banks as well as joint-equity banks in

the 1990s as a measure of financial liberalization in preparation for the entry to the World Trade Organization. All these have contributed to a continuous decrease in market concentration of the Chinese banking industry. It may be is worthwhile to examine whether and how much decreased market concentration in the Chinese banking industry has improved banking competitive conditions in China.

The purpose of this paper is to empirically investigate whether changes in bank concentration affected the degree of competition and stability in the Chinese commercial banking market for the period of 1992-2008. The degree of competition is estimated by the H statistic of the Panzar-Rosse model while the financial stability is estimated by the Z score formula. This paper is organized as follows. The next section describes developments in the Chinese commercial banking market and analyzes the trend of market concentration in the Chinese banking industry. This is followed by a section reviewing the related literature on bank competition and financial stability. Section 4 discusses the methodology used to test for the degree of competition in empirical analysis. Section 5 describes the data and interprets the estimates of the model. Section 6 investigates the relationship between competition and financial stability. The last section provides summaries and conclusion.

2. Developments in the Chinese banking industry and Changes in Bank Concentration

Before Deng Xiao Ping's 1978 reforms, China had a mono bank, the People's Bank of China, playing both roles of central and commercial banking, in order to channel funds in accordance with the state plan. With reforms, four specialized state banks were split from the People's Bank of China between 1979 and 1984, to form a two tier banking system in China, leaving the People's Bank of China (PBC) solely functioning as China's

central bank. Four state commercial banks split from the People's Bank of China are the Bank of China (BOC), Construction Bank of China (CBC), the Industrial and Commerce Bank of China (ICBC) and the Agricultural Bank of China (ABC). These specialized banks were to provide banking services to a designated sector of the economy. For example, BOC is to specialize in foreign-exchange transactions and trade finance, CBC is to specialize in medium to long-term credit for long term infrastructure projects and urban housing development, ICBC acts as the major supplier of funds to China's urban areas and manufacturing sector, and ABC is to specialize in providing financing to China's agricultural sector and offers wholesale and retail banking services to farmers.

Even though restrictions of these specialized banks to do business in only their designated territories were removed in 1985, competition among them was very limited until the mid-1990s. There was a boost to competition when the Chinese government authorized establishment of three policy banks. Three policy banks are the China Development Bank (CDB), the Export Import Bank of China (EIBC) and the Agricultural and Development Bank of China (ADBC). CDB is chartered to provide long-term lending to finance construction projects for infrastructure and pillar industries. EIBC is established to provide loans for exports and imports of capital goods. ADBC is to provide agricultural lending.

To enhance competition in the Chinese commercial banking market, the Chinese government launched the second bank reforms in the 1990s. A variety of new bank types were created, including joint-equity banks, local (or city) banks, and foreign banks. 14 joint-equity banks were established, where shares were held by the government, cooperatives and private sector. These banks are the Bank of Communication, China

Merchants Bank, Shenzhen Development Bank, Guangdong Development Bank, Pudong Development Bank, China Everbright Bank, China Minsheng Banking Corporation, Hua Xia Bank, Fuijin Industrial Bank, Hainan Development Bank, China Investment Bank, Yantai Housing Saving Bank and Bengbu Housing Saving Bank. During the mid-1990s, the central government allowed local governments to establish local (or city) banks. The number of banks continuously increases year by year. Four state-owned Chinese commercial banks became some of the top 10 banks of the world since 2012, as a consequence of the market value reduction for the U.S. and Western banks due to the global financial crisis of 2007-2008.

Among the bank reforms, the most noteworthy reform is the joint-equity reform of the four big state-owned banks because of its impact on the overall economy. A special treasury bond amounted to US$32.61 billion was issued in 1998 to strengthen the capital requirement of the four banks by raising their equity ratio to 8%. Four asset management corporations were established to purchase the non-performing loans from the four banks, resulting in a reduction of their non-performing loan ratio by 10%. These four banks took measures to improve their operational efficiency by reducing more than 55,000 branches and laying-off about 363,000 employees. Over 2003 – 2005, BOC, CCB and ICBC received capital injection from the Chinese government in the amount of $62 billion.

Along with bank reforms, the Chinese government gradually introduced market determined interest rates guided by the central bank rate, and the central bank implemented liberalization of interest rates. The gradual liberalization of interest rates took place in sequence; liberalizing the foreign currency interest rate prior to the domestic currency interest rate, liberalizing the lending rate prior to the deposit rate, and

liberalizing the large and long-term fund rates prior to the small and short-term fund rates. This kind of the gradual interest rate deregulation provided incentives for banks to strengthen their assets and liability management and to make higher profits. A nationwide unified inter-bank market had been created by the end of the 1990s, and both the inter-bank lending rate and the inter-bank bond market rate had been liberalized, which led financial institutions to have more incentives to adjust the composition of their assets by reducing their excess reserves while increasing their assets in bonds. Banks have been given more autonomy to improve their competitiveness through trading in stock markets and foreign equity investment.

China's joining the WTO had major impacts on operation of foreign banks in China as well as their involvement in ownership and management of domestic banks. According to China's commitments to the WTO, all restrictions imposed on ownership and operation of foreign banks, including restriction on licenses and the number of branches had to be removed by 2006. Furthermore, foreign banks are entitled to equal treatment as Chinese domestic banks, and the Chinese government allowed foreign banks to own up to 25% of domestic banks. By 2008, foreign banks had equity investment in three state-owned commercial banks, nine joint-equity banks and many local (or city) banks

There are a number of ways to measure market concentration. The most widely used index is HHI which is applied by the US Department of Justice in implementing its antitrust policy. Another straightforward method is to calculate what share of the industry's output or assets is owned by a few dominant firms. This top k-firm concentration ratio (CR_k) is used by some governments to determine the degree of anti-

competition of a proposed merger. Figure 1 presents HHI and CR_4 of total assets for China. We obtained HHI and CR_4 of three variables, that is, total assets, total loans and total deposits, and we found that the correlation coefficients of the HHI or CR_k among the three variables are higher than 0.99. So, only HHI and CR_4 of total assets are shown in Figure 1.

The higher the CR_4 and HHI, the more concentrated the market is. Both the CR_4 and HHI show a moderately decreasing trend over time; CR_4 decreased from 94% in 1992 to 61% in 2008 while the HHI decreased from 2743 in 1992 to 1642 in 2008. This clearly indicates that the Chinese banking market has experienced continually decreasing market concentration for the period of 1992-2008. This change is mostly attributable to a change in the Chinese government policy on banking, which allowed establishment of more banks and promoted competition among them. In spite of some mergers of banks occurred in recent years, the number of new banks created far exceeded the number of banks foreclosed and merged. The Chinese banking industry, even with gradual decrease in market concentration, is still a highly concentrated market compared to other countries. Figure 2 shows the HHI of domestic deposits among a few selected countries. China is not included in this sample. But China would be at the high end of the range along with Russia and Canada, while Germany and the US are at the low end of the range.

3. Survey of the Literature

In this section, the theoretical models and empirical findings on bank competition are briefly reviewed. Although many studies have been done to investigate the effect of bank consolidation on competition, there is little consensus on appropriate theoretical framework, and empirical findings are inconclusive. See Gilbert (1984) for a

comprehensive survey of the earlier studies and Berger and Humphrey (1992) for later studies. A concern about effect of consolidation on competition arises from the structure-conduct-performance (SCP) paradigm, which dates back to Mason (1939). The SCP model suggests that increasing market concentration leads to less competitive conduct in terms of higher prices and less output and results in higher profits at the expense of lower consumer welfare. This paradigm is the basis of the so-called "collusion" hypothesis.

Although there is a theoretical basis for these linkages, other equilibrium conditions can lead to different relationship between market concentration and conduct. As long as there are no sunk costs and hit-and-run entry is possible, then market contestability can yield competitive pricing regardless of the number of firms (Baumol, et al., 1982). The efficient structure hypothesis advances that efficient banks obtain higher profitability and greater market share because of their efficiency, which will lead to a more concentrated market. Therefore, the association between structure and performance might be spurious unless efficiency is controlled in the model (Smirlock, 1985). Adverse borrower selection may result in spurious empirical SCP linkages too (Shaffer, 2002).

Empirical results on the SCP paradigm are mixed. According to Gilbert (1984), many studies presented a mixed set of results in aggregate and tended to suffer from various methodological flaws. Weiss (1989) reported that only 21 out of 47 studies support the SCP model. More recent studies find bank profitability is unrelated or even inversely related to concentration when efficiency and market share are controlled for (Berger, 1995). Conversely, collusive actions can be found even in non-concentrated markets (Calem & Carlino, 1991; Shaffer, 1999).

Two empirical methods have been developed to remedy shortcomings of the SCP model by testing the conduct directly, without regard to industry structure. One method is the Bresnahan and Lau model (B-L model) which estimates the markup of price over marginal cost as a measure of market power. Thus, this method is also called the markup test. This model is based on two structural equations, an inverse demand equation and a supply equation derived from the first order condition of profit maximization. The following studies apply the B-L model empirically. Shaffer (1989) rejects the collusive conduct hypothesis with a sample of US banks, and Shaffer (1993) finds that the Canadian banks were competitive for the period 1965-1989 even with a relatively concentrated market. Berg and Kim (1994) show that Cournot behavior is rejected in the Norwegian banking system. Fuentes and Satre (1998) find that bank consolidation in Spain did not weaken the competition level. Gruben and McComb (2003) find regarding Mexican banks before 1995 that marginal prices were set below marginal costs and conclude that the Mexican market is super-competitive.

Another method to overcome shortcomings of the SCP model is the Panzar and Rosse model (P-R model). This model measures the extent to which a change in a vector of input prices is reflected in gross revenue. Thus, this method is also called the revenue test. If the market is perfectly competitive, then the change will be fully reflected in revenue. Shaffer (2004) contrasts both methods in detail and discusses their advantages and disadvantages. Numerous studies apply the P-R model empirically, beginning with Shaffer (1982) who finds monopolistic competition behaviors with a sample of New York banks in 1979. Nathan and Neave (1989) reject the hypothesis of monopoly power of Canadian banks. Country-specific empirical studies include Vesala (1995) for Finland,

Molyneux, at al. (1996) for Japan, Coccorese (1998) for Italy, Hondroyiannis (1999) for Greece, and Hempell (2002) for Germany. Molyneux, et al. (1994) and Bikker and Groeneveld (2000) find monopolistic competition in several European countries. On the other hand, De Bandt and Davis (2000) find monopolistic competition for large banks and monopoly for small banks in Germany and France. Bikker and Haaf (2002) find that the banking industries in 23 OECD countries for the period 1998-1999 are generally characterized by monopolistic competition with the exception of Australia and Greece. Gelos and Roldos (2002) compare eight European and Latin American countries and find that the bank consolidation process in its early stage has not lowered competition.

Uchida and Tsutsui (2005), from long-term Japanese panel data from 1974 to 2000, conclude that market competition improved during the 1970s and 1980s, but worsen since 1997. Lee and Nagano (2008) report that market concentration brought about the bank mergers does not necessarily result in low competition in Japan and Korea. Park (2009) concludes that the Korean banking industry is monopolistically competitive except for the Asian financial crisis period from the panel data of 1992-2004. Studies on bank competition in China are scanty and mostly descriptive rather than analytical. Wong and Wong (2001) describe the trend of bank concentration ratios during the 90s and Yuan (2006) examine the state of Chinese banking competition for 1996-2000. This study applies the P-R model to the data of the Chinese banks.

In regard to the relationship between competition and financial stability, there are two opposing schools of thoughts. The competition-fragility school argues that competition drives banks to undertake more risk while larger banks in concentrated banking systems can reduce financial fragility by providing higher capital buffers (Allen

and Gale, 2004, and Boyd, et al., 2006). The opposing school believing in the competition-stability linkage argues that competition leads to more stability. More credit rationing, more competitive lower loan rates and less managerial inefficiency in less concentrated banking systems reduce risk-taking behavior and decrease the probability of bank failures while banks with more powers may lead to more risk-taking behaviors (Boyd and DeNicolo, 2005, Beck, et al., 2010, and Turk- Ariss, 2010). This study will test these opposing models with the Chinese bank data.

4. Model

The P-R model is used to assess the competitive nature of the Chinese banking industry because this model is robust to the extent that market and bank level data are available. Let a bank's revenue function be $R = R(x, y_1)$ where x = a vector of products and y_1 = a vector of exogenous variables shifting the revenue function and let a bank's cost function be $C = C(x, w, y_2)$ where w is a vector of input prices and y_2 = a vector of exogenous variables shifting the cost function. y_1 and y_2 may have common variables.

Profit maximization by the bank requires that marginal revenue equal marginal cost as $R'(x, y_1) = C'(x, w, y_2)$. Panzar and Rosse (1987) calculate the sum of the elasticities of the revenue with respect to input prices from the reduced-form revenue equation and define it as the H-statistics.

$$H = \Sigma (\partial R/\partial w_i)(w_i/R) \qquad (1)$$

where w_i is i^{th} input price. Panzar and Rosse show from the profit maximization condition that the H-statistic is equal to unity (H =1) in a perfectly competitive market, and less than or equal to zero ($H \leq 0$) under monopoly. Although the Panzar-Rosse article also shows that $0<H<1$ could be consistent with oligopolistic behavior, it is common to regard

$0<H<1$ as the condition of Camberlinian monopolistic competition. This interpretation is valid under the assumption that the observations are in the long-run equilibrium (Nathan & Neave, 1989).

Following Park (2009) we specify the reduced-form revenue equation of a bank as follows.

$$\ln(R_{it}) = \alpha + \beta_1 \ln(w_{1,it}) + \beta_2 \ln(w_{2,it}) + \beta_3 \ln(w_{3,it}) + \gamma_k \Sigma z_k + \varepsilon_{it} \quad (2)$$

where R_{it} is bank i's revenue at time t, w_1 is the input price of labor, w_2 is the input price of capital, w_3 is the input price of funds, and z_k is a vector of control variables affecting the bank's revenue function. The H-statistic is the sum of β_1, β_2 and β_3. In order to eliminate manual calculation of $\beta_1 + \beta_2 + \beta_3$ and its standard error, equation (2) can be rearranged as follows.

$$\ln(R_{it}) = \alpha + \beta_1 [\ln(w_{1,it}) - \ln(w_{3,it})] + \beta_2 [\ln(w_{2,it}) - \ln(w_{3,it})] + (\beta_1 + \beta_2 + \beta_3) \ln(w_{3,it}) + \gamma_k \Sigma z_k + \varepsilon_{it} \quad (3)$$

The H-statistics is estimated by the coefficient of $\ln(w_{3,it})$ and its standard error is used to test the significance of this estimate.

The P-R model is constructed under the assumption that the market is in equilibrium. So, following Shaffer (1989), Molyneux, et al. (1996), Claessens and Laeven (2004), and Park (2009), equation (4) is used to test the equilibrium conditions.

$$\ln(ROA_{it}) = \alpha + \beta_1 \ln(w_{1,it}) + \beta_2 \ln(w_{2,it}) + \beta_3 \ln(w_{3,it}) + \gamma_k \Sigma z_k + \varepsilon_{it} \quad (4)$$

In equilibrium, rates of return on assets should not be statistically correlated with factor prices ($H=0$). On the other hand, if the market is in disequilibrium, an increase in factor prices would result in a temporary decline in the rates of return ($H<0$).

5. Empirical Analysis

The revenue (R_{it}) is typically measured by interest revenue or its ratio to total assets, presuming that the main function of banks is financial intermediation. However, with weakening of financial intermediation in recent years and diversification of bank assets, total revenue or its ratio to total assets is used in some studies. We use both interest revenue (IR) and total revenue (TR) in this study. ROA is the ratio of net after-tax income to total assets in percentage. The unit labor cost ($w_{1,it}$) is measured by the ratio of personnel expenses to the number of employees, the unit capital cost ($w_{2,it}$) is measured by the ratio of depreciation allowance and other maintenance costs to total fixed assets, and the unit funding cost ($w_{3,it}$) is measured by the ratio of interest expenses to the sum of total deposits and borrowings. Unavailability of personnel expenses in further breakdown does not make it possible to allow differing levels of human capital.

Several control variables are included in the model. Total assets (ASSET) are included to see the size effect while the number of branches (BRANCH) is included to account for the effect of bank networks. The ratio of non-performing loans to total loans (NPL) is included to control for the credit risk effect. The BIS risk-adjusted capital ratio (BIS) is alternatively used as a control variable for credit market and operational risk. The ratio of non-interest revenue to total revenue (NINT) is included to reflect the effect of changing financial intermediation or diversification. The variable BRANCH, representing bank network, was eventually deleted from the regression estimation because of its high correlation with ASSET. Bikker et al. (2006) state that inclusion of a scale explanatory variable such as ASSET in the Panzar-Rosse model may cause overestimation of the level of competition and may distort the tests on monopoly and perfect competition. So, we estimate competitive conditions in both ways, with and

without the scale explanatory variable, ASSET. However, The H values, regardless of inclusion or exclusion of ASSET in the model, show similar test results with no indication that inclusion of a scale explanatory variable causes overestimation of the level of competition. Thus, in the sections below we only report the estimation results with inclusion of ASSET in the model. We use both fixed and random effects models for comparison purpose.

Data used for China are from Bank Scope, the Almanac of Chinese Banking and Finance, and China Financial Yearbooks. Even though China has many banks, only 15 major banks are included in the sample because data availability is limited. However, these 15 banks account for most of the total bank deposits in China. Fifteen Chinese banks include the Bank of China, the China Construction Bank, the Industrial and Commercial Bank of China, the Agricultural Bank of China, the Agricultural Development Bank of China (ADBC), China Development Bank (CDB), the Bank of Communications, China CITIC Bank, China Everbright Bank, China Minsheng Bank, Guangdong Development Bank, Shenzhen Development Bank, China Merchants Bank, Shanghai Pudong Development Bank and Industrial Bank.

5.1 Competition Condition Test

Table 1 presents the estimation results of equation (2) with the dependent variables of lnIR and lnTR along with the H-statistic, which is sum of β_1, β_2 and β_3. According to the Wald test which is a test for competition condition, the hypothesis of a monopolistic market structure (H=0) and the hypothesis of a perfectly competitive market structure (H=1) are rejected at the 1% level. However, when we re-estimate equation (2) for the first half of the sample period (1992-2000), the hypothesis of H=1 is rejected, but

the hypothesis of H=0 cannot be rejected. This result indicates that there was a dramatic change in the competition level of the Chinese banking industry over the time.

The values of the H statistic for the Chinese banking industry are very small regardless of which revenue (lnIR or lnTR) is used as a dependent variable. This result indicates that the Chinese banking market is still far from being a competitive market. Relatively high adjusted R^2 values indicate the goodness of fit for all the regressions in Tables 1. All coefficients of the input costs, that is, the unit labor cost ($w_{1,it}$), the unit capital cost ($w_{2,it}$) and the unit funding cost ($w_{3,it}$), have the positive sign as expected. However, their coefficient size is of small value and some coefficients are not statistically significant. It can be inferred from the empirical results that the Chinese banking market is far from a competitive market, rather closer to monopoly or oligopoly.

The significant and positive sign of ASSET indicates the strong presence of the size effect. NINT (the ratio of non-interest revenue to total revenue) has no significant effect on both interest revenue and total revenue. The dominant source of Chinese banks' revenue is still interest revenue. Only recently some Chinese banks have expanded their business into non-loan-related activities. While NPL has a significant negative effect on lnIR or lnTR as expected, equity ratio does not have a significant positive effect on them. According to the signal theory (Berger, 1995), banks that expect to have better performance in terms of profitability credibly transmit this information through a higher equity ratio. There seems to be no stronger signaling effect of the equity ratio on profitability in China.

5.2 Equilibrium Condition Test

Table 2 gives the estimation results of equation (4) with the dependent variable, lnROA. Because the rate of return on assets of some banks was of negative value, the dependent variable is actually computed as ln (1+ROA) where ROA is the ratio of net after-tax income to total assets. Adding 1 to ROA before taking the logarithm is arbitrary, but is a common method used to handle non-positive numbers in the logarithmic transformation. Bos and Koetter (2006) point out that adding 1 affects composition of total error, but it does not affect coefficient estimates, which are our main concern. Several troubled Chinese state and joint-equity banks in their earlier years had negative rates of return on assets. The hypothesis that the market is in equilibrium, that is H = 0, is rejected at the 2% level of significance. Continuous influx of banks over time and rapid changes in the structure of the Chinese banking industry might result in disequilibrium conditions.

5.3 Trend of H value over time

To see how the values of the H static changed over time, this statistic is estimated for moving three-year time periods, that is, 1992-1994, 1993-1995, 1994-1996 and so on. The estimation results of the H statistic are reported together with HHI in Table 3.

Market concentration measured by HHI has continuously declined from 2743 in 1992 to 1642 in 2008. The H statistic with both lnIR and lnTR has gradually increased over the same time period, from less than .15 in earlier period to more than .4 in later period. So, these two variables exhibit a high negative correlation. The correlation coefficient between HHI and the H statistic with lnIR is -0.974 while correlation coefficient between HHI and the H statistic with lnTR is -0.976. Decreased market concentration in the Chinese banking sector definitely contributed to improvement in

banking competition level in China, even though the effect may be mild.

5.4 Comparison between Korea and China

Contrary to the increasing trend of market concentration in the Korean banking industry, the Chinese banking system has experienced continually decreasing market concentration. According to Park (2009), the Korean banking industry experienced an increase in the HHI of assets from 876 in 1992 to 1325 in 2004. This study finds that the HHI of assets in China decreased from 2743 in 1994 to 1642 in 2008. Bank merger activities and creation of a few mega banks in Korea contributed to the increasing trend of banking market concentration. On the other hand, financial liberalization policy of the Chinese government has increased creation of new banks year after year, contributing to the decreasing trend of banking marker concentration.

The H-statistic sheds a light on the difference in market structure in Korea and China. Park (2009) in his study of Korean banking reports that the H-statistic value for either interest revenue or total revenue ranges from .511 to .659 during the stable period, which excludes the Asian financial crisis period. This indicates that the Korean banking market is monopolistically competitive. On the other hand, this study finds that the H-statistic value for either interest revenue or total revenue ranges from .213 to .245, implying an oligopolistic market structure in the Chines commercial banking market.

6. Effect on Financial Stability

In this section, we investigate how bank competition affects financial stability of Chinese banks. While competition among banks affects bank stability, bank competition may also be influenced by the state of financial stability as banks may take different competition strategy depending on the stability condition, causing the endogeneity

problem of competition variables. Following Boyd, et al. (2006) and Beck, at al. (2013), we deployed lagged variables of the explanatory variables in the following estimation equation to address this endogeneity problem.

$$Z_{it} = \alpha + \beta k \Sigma C_{k,i\ t-1} + \gamma k \Sigma X_{k,i\ t-1} + \delta k \Sigma Y_{k,t-1} + \varepsilon_{it} \quad (5)$$

where Z_{it} = the Z score of bank i at time t, $C_{k,i\ t-1}$ = variables indicating competitiveness of bank i at time t-1, such as the net interest margin and the Lerner index,. $X_{k,i\ t-1}$ = bank specific variables of bank i at time t-1, such as equity ratio, the share of non- performing loans and number of branches, and $Y_{k,t-1}$ = macroeconomic variables such as economic growth rate, inflation rate at time t-1 and a dummy variable for the crisis period. The Z score is calculated as bank's return on assets plus the capital-to-assets ratio divided by the standard deviation of asset returns. The higher is the Z score, the less probability of bank failures.

We use three variables, the Lerner index, HHI and net interest margin as our measure of bank competition. The Lerner index which measures the mark-up of price over marginal costs indicates the degree of market power. It is calculated as:

$$L_{it} = (P_{it} - MC_{it}) / P_{it}$$

where P_{it} is the price of total assets of bank i at time t, measured by the ratio of total revenues to total assets, MC_{it} is the marginal cost of bank i at time t. Following Turk-Ariss (2010), the marginal cost of bank i at time t is calculated as follows.

$$MC = TC/Q\ [\alpha + \beta \ln Q + \sum \varphi k \ln W_k + \delta T] \quad (6)$$

where TC= total expenses, Q = total assets, W_k represents three input prices of labor, fixed capital and funding. T (Trend) is used to capture technical changes in the cost function over time. The equation (6) is scaled by the unit labor cost (ln W3) for

correction of heteroscedasticity.

Table 4 reports the estimation results of equation (5) for the Chinese commercial banks. The Lerner index and the net interest margin are highly correlated so that they enter the regression model separately in model 1 and model 2. HHI is negatively related to financial soundness while both the Lerner index and net interest margin have positive and significant effects on the Z score. Our interpretation of the results is that while the higher degree of market concentration may have negative effect on financial stability of the entire banking system, an individual bank's ability to earn higher markup or charge higher net interest margin contributes to financial soundness of the individual bank.

Among the bank specific variables, EQUITY is positively related to the Z score at the 5% significance level. On the other hand, the loans to assets ratio has a negative effect on the Z-score whereas larger banks or banks with more branches tend to be financially more stable than smaller banks. Non-performing loans (NPLs) is negatively and significantly linked to the financial stability. All the macroeconomic variables are not statistically significant. GDP growth rate has a positive effect, while inflation rate has a negative effect on the Z score, though both of them are not statistically significant. The dummy variable, CRISIS, has a negative, but insignificant effect on the Z-score, which indicates that the Chines banks were not as much affected by the Asian financial crisis of 1997-1998 as in other Asian countries.

7. Summary and Conclusions

Worldwide financial liberalization and financial globalization caused fierce competition among banks all over the world. This necessitated bank mergers and consolidation within a country and cross countries to achieve scale efficiency, to take

advantage of diversification or just to survive. The bank mergers wave began in the U.S.A. and spread to Europe, Japan and Korea. However, this wave has not yet hit the Chinese banking market because of its restricted financial openness and government regulation on banking. Bank mergers in China were typically government-initiated rather than market-originated.

In this study we examined the effect of market concentration on bank competition in China. The competitive conditions of the Chinese banking industry have definitely improved over time. The Chinese banking system progressed from one bank system to 4 state banks system in the 1980s to more than 20 banks including joint-equity commercial banks in the 1990s to more than 300 banks at the present time. This study finds that in spite of a drastic decrease in market concentration of the Chinese banking industry, its competition conditions are far from a competitive market, as evidenced by small H statistic values. It seems that bank reforms have a small effect on competitiveness of Chinese commercial banking. The sheer number of banks does not guarantee a competitive market. Lowering entry barriers for private banks and foreign banks would further facilitate competition. Institutional changes and lifting government regulation on banking are also necessary to speed up competitive behaviors in the market.

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Table 1 Test of Competition Condition: Estimation Results of Equation (2)

	Fixed Effects Model		Random Effects Model	
	lnIR	lnTR	lnIR	lnTR
Constant			-0.595* (-1.712)	-0.654 (-1.585)
$\ln W_1$	0.116** (2.394)	0.131** (2.607)	0.161*** (3.697)	0.171*** (3.491)
$\ln W_2$	-0.063 (-1.431)	0.035 (0.459)	-0.035* (-1.885)	0.041 (1.026)
$\ln W_3$	0.018** (2.645)	0.081** (2.170)	0.093** (9.251)	0.047** (10.462)
lnASSET	1.066*** (22.417)	1.009*** (21.383)	0.962*** (25.014)	0.932*** (28.936)
NINT	-0.270 (-1.462)	0.942 (1.271)	-0.347 (-1.545)	0.819 (1.231)
NPL SHARE	0.004*** (4.167)	0.006*** (4.427)	0.004*** (5.426)	0.005*** (4.857)
BIS	0.013 (1.480)	0.014 (1.610)	0.014 (1.607)	0.016 (1.433)
ADJ. R^2	0.592	0.623	0.724	0.768
H statistic	0.213*** (9.046)	0.245*** (10.277)	0.243*** (12.752)	0.268*** (11.744)
Wald test: H=0 (ρ-value)	23.92*** (0.000)	29.32*** (0.000)	28.34*** (0.000)	20.29*** (0.000)
Wald test: H=1 (ρ-value)	512.93*** (0.000)	575.62*** (0.000)	714.22*** (0.000)	790.43*** (0.000)

1. lnIR is the natural logarithm of interest revenue while lnTR is the natural logarithm of total revenue.
2. The coefficients of the constant under the fixed effects model are not reported here because there are as many as the number of banks.
3. t values are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.
4. H statistic is the sum of $\ln W_1$, $\ln W_2$ and $\ln W_3$, and its t value is obtained by estimating Equation 3.

Table 2 Test of Equilibrium Condition: Estimation Results of Equation (4)

Variable	$\ln W_1$	$\ln W_2$	$\ln W_3$	lnASSET	NINT	NPL	BIS	Adj. R^2
Coefficient	-0.009 (-0.944)	0.007 (0.655)	-0.058** (-2.175)	0.022* (1.984)	0.004 (0.145)	-0.012** (-2.158)	0.002 (1.343)	0.478

Variable	H statistic	Wald test: H=0 (ρ-value)
Coefficient	-0.059*** (-2.372)	5.712** (0.017)

1. Estimation results of the fixed effects model. The coefficients of the constant under the fixed effects model are not reported here.
2. t values are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

Table 3 Market Concentration and Competition Level Over Time

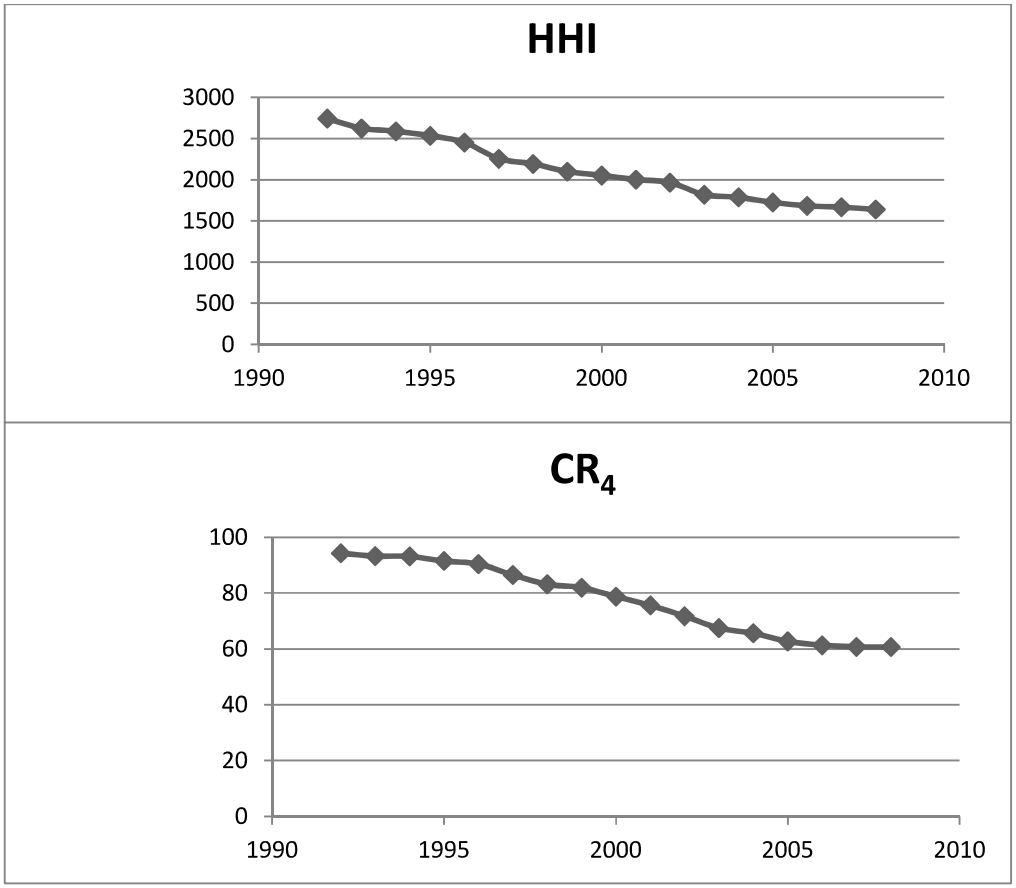
Year	HHI - Total Assets	H-statistic with lnIR	H-statistic with lnTR
1992-1994	2652	0.136	0.149
1993-1995	2583	0.164	0.174
1994-1996	2525	0.182	0.192
1995-1997	2415	0.207	0.228
1996-1998	2301	0.215	0.247
1997-1999	2184	0.233	0.269
1998-2000	2116	0.259	0.278
1999-2001	2053	0.271	0.299
2000-2002	2008	0.298	0.321
2001-2003	1931	0.302	0.343
2002-2004	1859	0.342	0.338
2003-2005	1779	0.365	0.376
2004-2006	1734	0.389	0.402
2005-2007	1694	0.405	0.427
2006-2008	1666	0.426	0.449

Table 4 Estimation Results of Equation (5), Dependent Variable: ln Z Score

Category	Variable	Model 1	Model 2
Competition Variables	Ln Lerner Index	1.024** (0.001)	
	Net Interest Margin		0.118** (0.003)
	HHI (Assets)	-0.225* (0.048)	-0.294 (0.053)
Bank Specific Variables	EQUITY	0.024 (0.096)	0.018 (0.087)
	Loans/ Assets	-0.137* (0.041)	-0.155* (0.049)
	Ln Branch	0.294* (0.039)	0.332* (0.026)
	NPL	-0.064** (0.007)	-0.057** (0.009)
Macroeconomic Variables	GDP Growth Rate	0.072 (0.198)	0.104 (0.153)
	Inflation Rate	-0.131 (0.208)	-0.097 (0.167)
	CRISIS	-0.042 (0.115)	-0.058 (0.182)
Adj. R^2		0.826	0.794

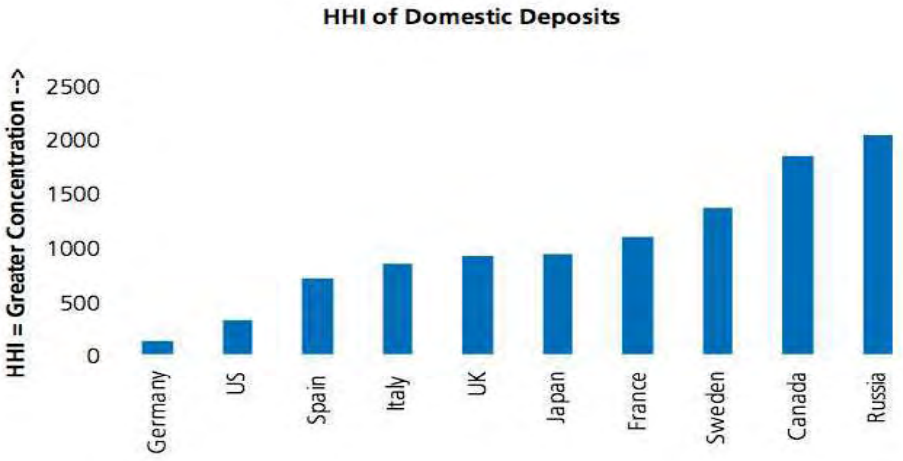
1. Estimation results of fixed effects model. The coefficients of the constant under the fixed effects model are not reported here.
2. ρ values are shown in parentheses. * and ** indicate significance at the 5% and 1% levels respectively.

Figure I



1. HHI is the Herfindahl-Hirschman index and CR_4 is the concentration ratio measured by the market share of the largest four banks.
2. Total assets are used to calculate CR_4 and HHI. Total assets include assets in both banking accounts and trust accounts.

Figure II



Source: Celent analysis, annual reports, central banks

CHAPTER 2

Credit Cycle and Balancing Capital Gap: Evidence from Korea

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Abstract

This paper studies balancing capital gap due to credit cycles using data from nationwide and regional banks in Korea. Specifically, banks' target capital ratios (TCRs) are estimated and compared with the data to identify capital gaps, and the responses to the gaps are then analyzed using a panel model. The empirical results show that, in the long-run, the capital ratio rises as the credit to gross domestic product (Credit/GDP) gap increases, and the expansion of the Credit/GDP gap impairs banks' asset management capabilities by reducing the capital gap with a higher capital target ratio. Additionally, the changes in the capital gap impact banks' asset compositions and management behaviors. A decrease in the capital gap lowers the growth rate of the total assets, risk-weighted assets (RWA), and loan obligations, but increases the growth rate of core capital relative to risky assets. These results indicate that the growth in RWA is highly sensitive to changes in capital gap compared to other balance sheet variables. Similar results are shown in various cases that use non-core liabilities to synthesize predictor variables for credit cycles.

JEL classification: G1, G2
Keywords: Target Capital Ratio, Counter-Cyclical Capital Buffer, Capital Gap

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1. Introduction

Banks have long been subject to regulations for their roles in credit provision and the payment system. Regulations on core capital remain a core regulatory objective to determine a banks' capacity to survive and recover from unexpected losses. However, from the banks' perspective, core capital serves as a potential source of profits, and the regulation of core capital in pursuit of financial stability may have detrimental effects on profitability and, hence, the financial soundness of the bank. To compromise the conflicting microeconomic and macroeconomic interests that arise from regulations on core capital, the Bank for International Settlements (BIS) international business standard Basel II accepts the banks' internal models on risk-weighted assets (RWA) and approves quasi-capital as regulatory capital along with common shares. However, continued support for the financial liberalization of major banks and developments in financial instruments that bypass regulations have vitiated the intensity of regulations. Macroeconomic policies based on credit, which emphasized the impossibility of the substitution of bank loans on macroeconomic performance, had a conciliatory stance toward regulations on core capital and developed the perception of the fundamental role of core capital on financial stability. This elevated the level of instability of financial markets by allowing excessive risk-taking fueled by financial innovations.[1]

The bankruptcy of Lehman Brothers in September 2008 and the subsequent global financial crisis served as an important lesson on the importance of understanding systemic risk[2] and macro-prudential supervision. Discussions on establishing sound financial systems and strengthening the banking sector became widespread. One of the main topics was how to structure regulations on core capital. International discussions on recovering from and preventing another financial crisis

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1 Adrian and Shin (2008) state that, historically, banks retain core capital that matches their desired level of leverage, and they adjust their capital adequacy ratio (CAR) by reducing loans in cases of external shocks that negatively affect core capital.

2 BIS, IMF, FSB for G20 (2009) define systemic risk as "a risk of disruption to financial services that is caused by an impairment of all or parts of financial system and has the potential to have serious negative consequences for the real economy." Cochrane simply defines systemic risk as risk-prone contracts with externalities.

unanimously emphasized the prevention and supervision of systemic risk and the development of macro-prudential policies to suppress its spread. Consequently, revisions to the regulations of the financial institutions' pro-cyclical management behavior and their contributions to credit cycles were discussed among the G-20 nations. The Financial Stability Board (FSB) and the Basel Committee on Banking Supervision (BCBS) led the project and created the initial draft of the financial reformation in December 2009. The draft was approved in November 2010 at the G-20 Seoul Summit, and one month later the "Basel III: Rule Text on Capital and Liquidity Regulation Standards" was announced. Basel III introduced new regulations on leverage ratio[3] and liquidity[4], and incorporated a countercyclical capital buffer to manage the stability of financial institutions due to credit cycles.[5]

Literature discusses the impacts of stricter capital regulations on bank capital channels and their subsequent effect on the economy. Contrary to Modigliani and Miller's predictions, changes in capital regulations can affect the financial behavior of banks and impact various factors, such as asset composition and the size of outstanding loans. This process ultimately affects macroeconomic variables, such as the aggregate output, inflation, and unemployment rates. Bernanke's (1983) credit

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[3]Regulations on leverage ratio seeks to protect the financial system from rapid de-leveraging by making the banks maintain a certain level of assets (total exposure to risky assets) relative to core capital.

[4]Two types of regulations on liquidity are the liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR). The former is used as a short-term indicator whereas the latter is used for medium-to-long-term analysis. The LCR is calculated as high liquid asset-to-net cash outflows for the next 30 days and NSFR is computed as the ratio between stable funding and necessary funding requirements.

[5]To amend the shortfall of Basel II that failed to detect on- and off-balance sheet risks and the uncontrolled exposure to derivatives that trading contributed to the financial crisis, Basel III acknowledges the credit risks underlying over-the-counter derivatives, strengthens the counterparty credit risk, and reduces reliance on third party credit ratings by enhancing the transparency of rating agencies by making public announcements mandatory.

view is in line with this explanation.[6] To explain the relationship between the bank capital and the real economy, the sensitivity of banks' capital and changes in their balance sheets in response to changes in capital regulations must be analyzed.

Some researchers describe that capital regulations may not be significant since the actual capital adequacy ratio (CAR) pursued by banks is higher than as required by Basel III. Berger and Udell (1994) suggest that the incorporation of capital regulations did not significantly impact the United States' credit crunch in 1990-1991. Wagster (1999) states that reductions in loans by banks are affected more by factors other than capital regulations by analyzing Germany, Japan, and the United States. Bajaras et al. (2005) show similar results from Latin American countries and conclude that capital regulations have less impact on credit supply. Countering these results, Jackson et al. (1999) state that these researchers only observed banks that had CARs that were already converged to the level defined by the regulatory capital, and did not separate this impact from regulations and market reactions.

The research claims that capital regulation has a significant impact on banks' capital and lending practices focuses on the relative effect of capital regulation on banks' capital and lending. Jackson et al. (1999) conjecture that banks respond to stricter capital regulations by reducing lending in the short-run despite the lack of empirical evidence. Furfine (2001) claims that capital regulations in addition to strict financial supervising have had major effects on the composition of banks' balance sheets, and attributes the decline in bank lending in the early 1990s to the capital regulations. VanHoose (2008) states that banks respond to capital regulations by reducing lending in the short-run and expanding the bank capital in the long-run. Francis and Osborne (2009) define banks' target capital and claim that capital regulations are crucial in deriving the target capital ratio (TCR) as a 1% difference between the actual capital and the target capital to increase the total assets and RWA by 0.06%p, and 0.1%p respectively. Finally, Osborne (2009) emphasizes the importance of capital regulation in the process of the bank capital channel.

This paper uses the model suggested in Francis and Osborne (2009) to investigate if the bank

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[6]Bernanke (1983) focuses on the operations of bank lending channels in response to policy rate changes.

capital channel works in Korea by observing data from Korean banks. One important deviation from the Francis and Osborne model is made as their model examines the effects of changes in capital regulation on a bank's internal capital ratio sensitivity and balance sheet. Rather, this paper examines the impact that the credit to gross domestic product (Credit/GDP) gap has on banks' internal target capital ratios, lending, and asset allocations.

The remainder of this paper is organized as follows. Section 2 provides the econometric models used to analyze the bank capital channel. Section 3 discusses the data used in the estimation procedure. Section 4 describes the empirical results. Section 5 exhibits the robustness of the results by introducing various proxies to identify credit cycles. Finally, Chapter 6 summarizes the results and provides a conclusion.

2. The Model

1) A Model for Target Capital Ratio

To assess the balance sheet adjustment to capital gap, we construct the TCR level. Hence, the estimation procedure consists of two stages. In the first stage, we estimate the TCR and balancing the capital gap is estimated and addressed subsequently. The first stage estimation employs the model outlined in Francis and Osborne (2009). The estimation equation based on Koyck's partial adjustment model is as follows:

$$k_{i,t} - k_{i,t-1} = \rho(k^{*}_{i,t-1} - k_{i,t-1}) + \grave{o}_{i,t} \tag{1}$$

where $k_{i,t}$ implies the actual capital ratio of bank i at time t and $k^{*}_{i,t-1}$ is the TCR recognized internally by bank i. The TCR is assumed to have the following form:

$$k^{*}_{i,t} = \sum_{j=0}^{2} x_{it-j}\theta_j + \eta_i \tag{2}$$

where $x_{i,t-j}$ denotes a set of explanatory variables at time $t-j$ and η_i indicates bank i's fixed effect. Plugging Equation 2 into Equation 1 yields the following:

$$k_{it} = (1-\rho)k_{it-1} + \rho\sum_{j=0}^{2} x_{it-j}\theta_j + (\rho\eta_i + \grave{o}_{it}) . \tag{3}$$

As we have $k_{i,t-1}$ on the right-hand side of the equation, the standard differencing method to eliminate the fixed effects will lead to biases due to the AR (1) error term. In this case, the typical remedy is the system-generalized-method-of-moments (GMM) estimator proposed by Arellano-Bond. However, as discussed by Arellano-Bond, the system-GMM is adequate for cases of large N and small T. They argue that over-fitting is more problematic when a system-GMM is applied to the date with a small N and large T, and they recommend a standard panel estimation in this case. In this paper, we tackle the problem associated with lagged dependent variables by reorganizing the estimation equation to remove the lagged dependent variables from the right-hand side equation. This yields the following equation:

$$\Delta k_{it} = \rho(\Delta x_{it}\theta_0 - \Delta x_{it-1}\theta_2) - \rho[k_{it-1} - x_{it-1}(\theta_0 + \theta_2 + \theta_2)] + (\rho\eta_i + \grave{o}_{it}) . \tag{4}$$

To estimate the parameters, the following reduced-form equation is used:

$$\Delta k = \Delta x\pi_1 + \Delta x_{-1}\pi_2 + \pi_3 k_{-1} + x_{-1}\pi_4 + (\rho\eta_i + \grave{o}) \tag{5}$$

where

$$\rho = -\pi_3$$

$$\theta_0 = \frac{\pi_1}{-\pi_3}$$

$$\theta_1 = \frac{\pi_4 - \pi_1 + \pi_2}{-\pi_3}$$

$$\theta_2 = \frac{\pi_2}{\pi_3} \quad .$$

After each estimation, delta methods are applied to recover the structural parameters from the estimated reduced-form coefficients. A set of firm-specific financial variables are used to control for systematic differences in the banks' abilities and incentives to adjust capital, which have been found useful in the literature on the determinants of bank capital ratios.

The return on equity (ROE) is used as an explanatory variable that represents the opportunity cost of capital. Although the use of ROE is subject to debate as it represents macroeconomic

conditions and market competition, a higher ROE indicates a loss of profit opportunity for banks and causes the expectation that the ROE be negatively correlated with the target CAR.[7]

Although the CAR has risk-weighted assets in its denominator, the RWA over the total assets (denoted as RISK) is included as an explanatory variable to consider a nonlinear relationship between risk and capital, e.g., riskier banks hold less capital against a risky asset due to better systems and controls or risk preferences. Riskier banks are expected to accumulate lower capital relative to identically risky assets. Higher RISK ratios indicate that banks are investing more in risky assets, and this implies lower levels of target capital compared to banks with identical RISK ratios.

Loss provision or allowance (denoted as ALLOW) is the amount accumulated based on a bank's internal evaluation of expected losses. ALLOW reflects the management's assessment of the losses embedded in the bank's asset portfolio. Higher expected losses tend to imply greater unexpected losses, and the loss provision-to-asset and capital ratios will have a positive (+) relationship. However, if banks attempt to recoup the expected losses through aggressive investments, the two ratios may have a negative (-) relationship.

We control for the degree to which a bank is exposed to market discipline by including the ratio of subordinated term debt to total liabilities (denoted as SUBDEBT), since there is evidence that subordinated debtholders may be effective in imposing discipline on bank behaviors (Covitz et al., 2004)

The liability-to-asset ratio (denoted as DEBT/ASSET) identifies the banks' level of leverage. Higher leverage may indicate the need for additional capital accumulation by banks as it indicates greater risk. However, higher leverage is the result, not the cause, of the TCR. Hence, this variable can be either positive or negative. Additionally, we add the bank's assets (denoted as ASSET) as a proxy variable to control for its effect on the CAR.

The Credit/GDP, or the credit size relative to the GDP, is used to observe the change in the capital ratio in response to credit cycles. This variable is related to the Counter-Cyclical Capital

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[7] Stolz and Wedow (2005) and Jokipil and Milne (2008) used ROE and after-tax earnings-to-book value as the opportunity cost of capital.

Buffer indicator suggested in Basel III. Thus, this paper uses the Credit/GDP as an explanatory variable to investigate the effect of credit cycles on CAR.

2) A Model for Capital Gap Adjustment

After correcting the TCR in the first stage estimation, we study the balance sheet adjustment for capital gap, defined as the difference between the AR and the TCR. To investigate how a bank responds to the gap between the AR and TCR, we establish the following panel regression:

$$Y_{it} = \beta KGAP_{it} + \sum_{k=1}^{K}\sum_{j=0}^{2} X_{ikt-j}\delta_{kt-j} + \sum_{s=1}^{4} Q_s d_s + \eta_i + \grave{o}_{it} \tag{6}$$

where Y_{it} indicates the set of total assets, RWA, bank loans, and core capital, and $KGAP_{it}$ is the capital gap defined as the difference between the AR and TCR relative to the RWA. The variable X_{ikt} denotes the macroeconomic or bank-specific characteristic variables, and Q_s is the quarterly dummy variable. Lastly, η_i is the bank's fixed effect and ε_{it} is the error term. In the estimation, X_{ikt} includes the GDP growth rate, overall lending attitude index of domestic banks[8], policy rate represented by the overnight call rate, and the consumer price index (CPI) inflation up to two preceding quarters to control for macroeconomic conditions.

3. Data

We use a set of quarterly bank data from the FAIRS dataset operated by the Bank of Korea, the central monetary authority in Korea, between 2000:Q1 and 2014:Q1. The bank data includes eight nationwide banks and six regional banks.[9] The summary statistics are provided in Table 1.

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[8] The lending attitude index is calculated based on face-to-face, mail, or telephone interviews with domestic financial intermediaries. The Bank of Korea surveys the index on a quarterly basis and utilizes the index as it is believed to contain information on overall lending attitudes, credit risks, and demand for loans of domestic banks, mutual savings banks, and credit card companies.

[9] Of the 16 nationwide and regional banks, 14 are included in the analysis. The nationwide banks included are Shinhan, Woori, Standard Chartered, Foreign Exchange, Kookmin, Citi, Hana, and IBC. The regional banks are Daegu, Busan, Gwangju, Jeju, Jeonbuk, and Gyungnam. Only two

Most financial variables between the nationwide and regional banks exhibit statistically significant differences, with the exception of the current asset-to-total asset and debt-to-total asset ratios. It is well-understood that there should be a level difference between nationwide and regional banks; however, the existence of ratio differences indicates that these types of banks have different modes of capital funding and conducting business. For our dataset, the ROE for regional and nationwide banks stands at 9.01% and 6.70%, respectively. The difference can be explained by the higher financial regulations placed on nationwide banks and the lower profitability of capital due to the scale and composition of the assets under management. Regional banks' share of RWA in total assets stands at 63.98% compared to 66.15% for nationwide banks. Lower risk and higher ROE in regional banks can be attributed to their investments in retail loans, especially collateralized house loans, which have greater return-to-risk ratios. For the liabilities/asset ratio, however, both nationwide and regional banks exhibit identical figures. Thus, the lending behaviors of banks appear to differ in the type rather than the scale of lending.

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government-sponsored nationwide banks, KDB and NH, are not included since the FAIRS has not compiled the data.

Table 1. Summary Statistics

(In Billion Won, %)

Variables	All banks[1)]			Nationwide Banks(8)			Regional Banks(6)			t-test
	Obs.	Mean	Std. Dev	Obs.	Mean	Std. Dev	Obs.	Mean	Std. Dev	
Asset	798	71,087	72,373	342	113,500	69,944	456	14,570	10,412	0.0000
Liabilities	798	66,425	67,203	342	106,000	64,676	456	13,691	9,648	0.0000
Total Capital	798	4,661	5,310	342	7,498	5,486	456	879	784	0.0000
Core Capital	798	4,310	4,788	342	6,889	4,912	456	870	797	0.0000
Loans	798	49,503	54,094	342	79,440	54,673	456	9,586	7,369	0.0000
Loss Provision	798	893	1,031	342	1,455	1,056	456	143	97	0.0000
Subordinate Debts	791	1,402	1,743	276	2193	1958	368	363	318	0.0000
RWA	798	48,560	52,080	342	77,910	51,940	449	9,420	7,066	0.0000
Current Asset	798	22,790	21,470	342	36,430	19,140	456	4,611	2,885	0.0000
RWA/Asset	798	65.22	7.71	342	66.15	7.73	456	63.98	7.51	0.0001
Provision/Asset	798	1.25	0.73	342	1.35	0.80	456	1.11	0.60	0.0000
ROE	644	7.69	7.42	342	6.70	7.14	456	9.01	7.59	0.0001
Subordinate/Liabilities	791	2.17	1.14	342	1.81	0.87	456	2.64	1.28	0.0000
Core/Total Capital[2)]	798	95.61	10.41	342	93.75	9.48	449	98.09	11.06	0.0000
Current/Asset	798	35.05	10.22	342	35.60	11.64	456	34.31	7.91	0.0783
Liabilities/Asset	798	0.94	0.02	342	0.94	0.02	456	0.94	0.01	0.2396
Capital Adequacy Ratio	798	12.28	2.05	342	12.36	1.98	456	12.18	2.14	0.0000

Note: Figures are based on the eight nationwide and six regional banks balance sheet data from the FAIRS database.

Examining the CARs of the banks can shed light on the adequacy of the estimated results. Table 2 depicts the CARs of the nationwide and regional banks in Korea. Since 2004, the CARs for

both types of banks have been higher than 11%. The CARs of the banks increased during the sample period and have remained around 13 to 14% since 2010 as the financial supervisory authorities enforced stricter capital requirements to fend off the risk of financial distress. Even though the historical trend is limited in explaining the optimal or target level of the CARs, it does provide an estimation of the current situation. One interesting finding is that banks have higher capital ratios than the 8% recommended by the BIS. This, however, does not render the BIS's capital regulation unnecessary. Alfron et al. (2004) state that it is rational for banks to maintain a capital cushion above the regulatory level to compensate for any losses and expenditures incurred during management operations.

Table 2. CAR of Korean Banks

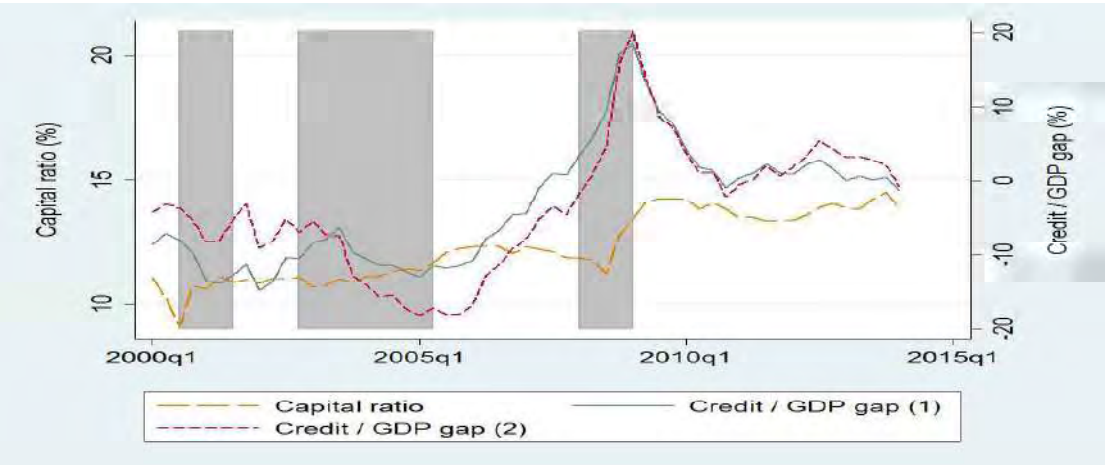
(%)

	Nationwide Banks	Regional Banks	All Banks
2000	11.06	9.23	10.28
2001	11.17	10.52	10.89
2002	10.93	11.07	10.99
2003	10.73	10.98	10.83
2004	11.36	11.11	11.25
2005	12.32	11.16	11.82
2006	12.78	11.53	12.24
2007	12.52	11.58	12.12
2008	11.81	12.04	11.90
2009	13.60	14.57	14.01
2010	13.51	14.63	13.99
2011	13.01	13.95	13.41
2012	13.54	13.96	13.72
2013	14.19	13.98	14.1
2014	14.26	13.3	13.85

Lastly, we depict the movement of the CAR and credit cycles measured by the Credit/GDP gap in Figure 1. The Credit/GDP gap is suggested by the BIS as a Counter-Cyclical Capital Buffer indicator. The significance of the indicator is confirmed in Borio and Lowe (2004) for evaluating excessive credit supply within the economy. As it is difficult to determine what to include in credit,

we provide two credit measures. Credit 1 is defined as the total outstanding loans of depository banks and nonbank financial intermediaries. Credit 2 includes both credit 1 and any direct funding through capital markets, such as corporate bonds and commercial papers. The Credit/GDP gap analyzes the deviation from the long-term trend by removing the trend through a Hodrick-Prescott (HP) filter.[10] The trends of the CAR and Credit/GDP gap indicate that the CAR moves in a retrograde manner to economic fluctuations whereas the Credit/GDP gap moves with the business cycles. Historical trends show that the Credit/GDP gap increases during economic booms and enters a correction phase during recessions. However, in the most recent recession (9th cycle), the Credit/GDP gap spiked most likely due to the expansionary credit policies pursued by governments and monetary authorities to fend off the deflationary pressures from the global financial crisis.

Figure 1. CAR and Credit/GDP gap



Note: Korea has experienced three business cycles (7th, 8th, and 9th) since 2000. The 7th cycle is from 2000:M8 to 2001:M7, the 8th cycle is from 2002:M12 to 2005:M4, and the 9th cycle is from

[10] The smoother parameter of the HP filter, λ, used to compute Credit/GDP gap is set at 400,000 as recommended by BIS. The total credit relative to GDP was calculated with quarterly data, and was annualized to match date frequencies. Ravn and Uhlig (2002) suggest that the smoothing parameter should be adjusted by the 4th power of the data frequency. Data frequency of BIS recommendation based on Ravn and Uhlig yields 3.98 days. This implies that the BIS consider the data collection periods for credit-related data should be less than a week.

2008:M1 to 2009:M2

4. Estimation Results

The first stage estimation results of both the reduced-form and structural parameters are presented in Table 3. The standard errors are provided to the right of each coefficient and *, **, and *** indicate a statistical significance of 10%, 5%, and 1%, respectively. Additionally, to investigate the long-run effects of the covariates, all lagged terms are summed and included in the table.

The summary of the results based on the long-run effect is as follows. The ROE as a measure for the opportunity cost has a negative (-) sign, consistent with our expectations, however it is statistically insignificant. Higher RISK and ALLOW levels yield lesser CARs, although only the RISK is statistically significant. This can be interpreted that banks with higher risk appetites conceive low levels of target capital. Further, as these banks are more likely to take risks, they can operate without setting a high level for target capital. ASSET is positively and DEBT/ASSET is negatively correlated with TCR, and both are statistically significant. As ASSET is included in both variables with opposing effects, the opposite signs are expected. We interpret that this result shows that the target capital increases in line with the size of the assets, but when the share of debt increases relative to the assets, the target level of capital decreases as higher debt reduces the actual level of the capital ratio. Hence, the long-run level of the capital ratio, which is what the TCR tracks, will be negatively impacted. Finally, the Credit/GDP gap is positively correlated with the TCR, and a credit boom is accompanied by a higher TCR.

Table 3. Estimation Results: TCR

Reduced-Form	π		Structural	θ	
	Coef.	S.E.		Coef.	S.E.
ΔROE	-0.008***	(0.003)	ROE	-0.045**	(0.017)
ΔRISK	-0.148***	(0.009)	RISK	-0.841***	(0.125)
ΔALLOW	0.534***	(0.149)	ALLOW	3.039***	(0.933)
ΔSUBDEBT	0.735***	(0.060)	SUBDEBT	4.177***	(0.678)
ΔASSET	0.002***	(0.000)	ASSET	0.012***	(0.003)
ΔDEBT/ASSET	-0.809***	(0.061)	DEBT/ASSET	-4.598***	(0.661)
ΔCREDIT/GDP	0.029***	(0.011)	CREDIT/GDP	0.164**	(0.067)
ΔROE(-1)	-0.002	(0.003)	ROE(-1)	0.018	(0.017)
ΔRISK(-1)	0.012	(0.009)	RISK(-1)	0.751***	(0.136)
ΔALLOW(-1)	0.351**	(0.142)	ALLOW(-1)	-1.262	(1.085)
ΔSUBDEBT (-1)	-0.006	(0.061)	SUBDEBT (-1)	-3.663***	(0.728)
ΔASSET(-1)	-0.000	(0.000)	ASSET(-1)	-0.011**	(0.004)
ΔDEBT/ASSET(-1)	-0.052	(0.061)	DEBT/ASSET(-1)	3.402***	(0.718)
ΔCREDIT/GDP(-1)	0.009	(0.010)	CREDIT/GDP(-1)	0.005	(0.094)
ROE(-1)	-0.002	(0.004)	ROE(-2)	0.014	(0.016)
RISK(-1)	-0.028***	(0.006)	RISK(-2)	-0.068	(0.054)
ALLOW(-1)	-0.038	(0.092)	ALLOW(-2)	-1.994**	(0.844)
SUBDEBT (-1)	0.096***	(0.033)	SUBDEBT (-2)	0.032	(0.348)
ASSET(-1)	0.000***	(0.000)	ASSET(-2)	0.001	(0.003)
DEBT/ASSET(-1)	-0.159***	(0.032)	DEBT/ASSET(-2)	0.294	(0.347)
CREDIT/GDP(-1)	0.021***	(0.004)	CREDIT/GDP(-2)	-0.050	(0.060)
			ΣROE	-0.013	(0.024)
			ΣRISK	-0.158***	(0.031)
			ΣALLOW	-0.216	(0.531)
			ΣSUBDEBT	0.547***	(0.187)
			ΣASSET	0.002***	(0.000)
			ΣDEBT/ASSET	-0.902***	(0.117)
			ΣCREDIT/GDP	0.120***	(0.021)
K(-1)	-0.176***	(0.023)	ρ	0.176***	(0.023)
CONSTANT	0.191***	(0.034)	CONSTANT	1.087***	(0.112)
Obs.	616				
R^2	0.563				

Note: Lags are indicated inside the parenthesis at the end of the variables. The sum of all current and lagged terms is denoted as Σ to estimate the long-run effect of the variables. The markings *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Figure 2 displays the TCRs and ARs of the individual banks based on the data in Table 3. The ARs reach their lowest level during 2008, and similar patterns are observed for the TCRs as well. All banks except the Chunbuk bank show that the discrepancy between ARs and TCRs tends to be narrow and the ARs are higher than their TCR counterparts.

The gaps between the ARs and TCRs for individual banks are provided in Appendix A. For comparison, we denote the lagged capital gap ratio (KGAP) as KGAP1 for the difference between the AR and the TCR and KGAP2 as the difference between the AR and the 8% BIS regulatory capital ratio. As demonstrated, the KGAP2 is always higher than the KGAP1, implying that the BIS ratio is not a tight boundary for the minimum capital level. However, the BIS ratio should not be considered an ineffective measure to regulate a bank's capital level. We argue that even though the actual capital level of a bank is greater than recommended by the BIS, the capital level is not much more than what is considered adequate based on the banks' internal target.[11]

[11] As the movements of KGAP1 and KGAP2 are similar, the empirical results only for KGAP1 are presented in this paper. We conduct the same empirical investigation with KGAP2 and find similar results as can be reasonably conjectured from <Figure 1>.

Figure 2 AR vs. TCR (k^*)

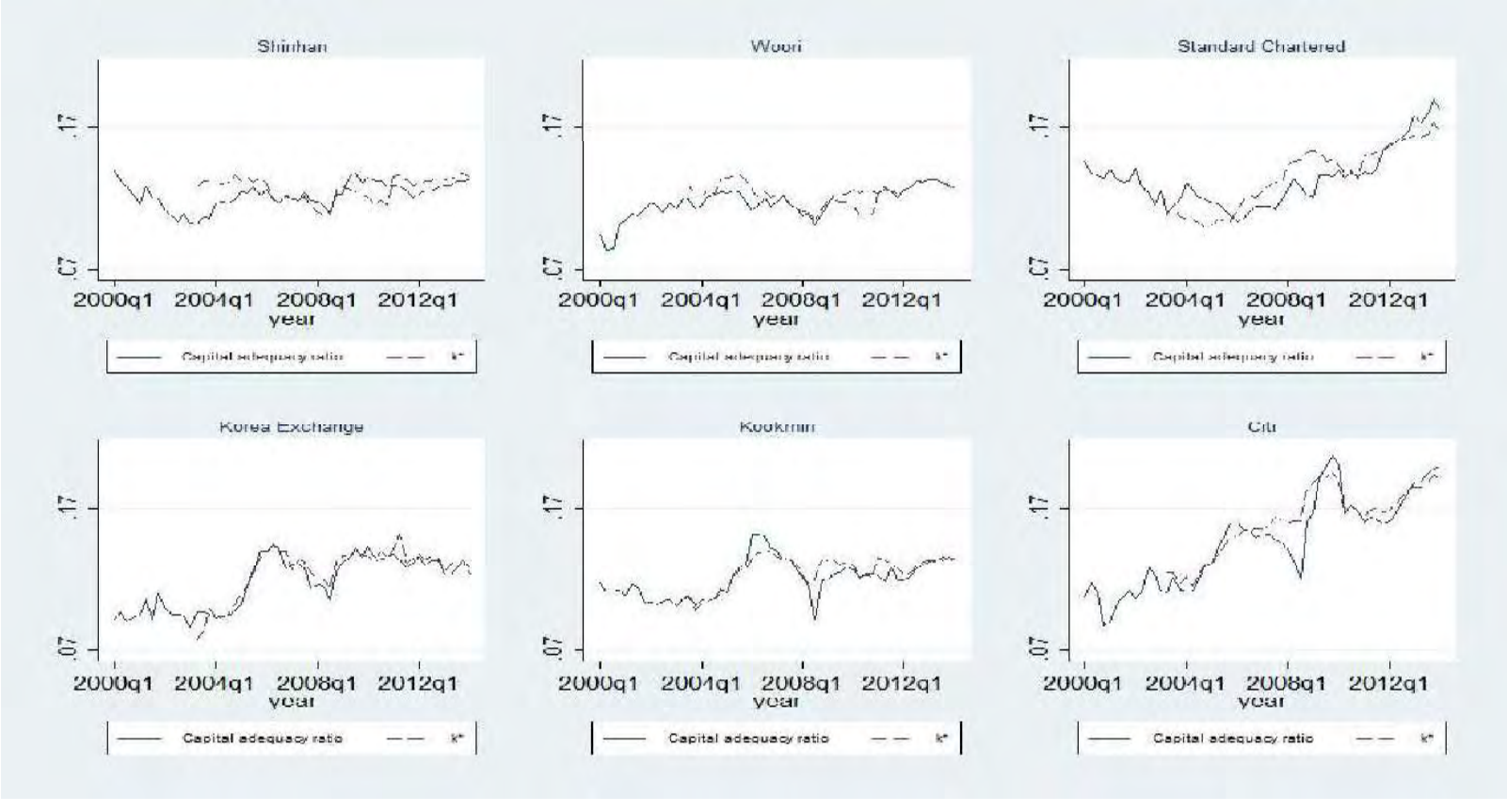


Figure 2 Actual vs. Target (k^*) Capital Ratio (Cont'd)

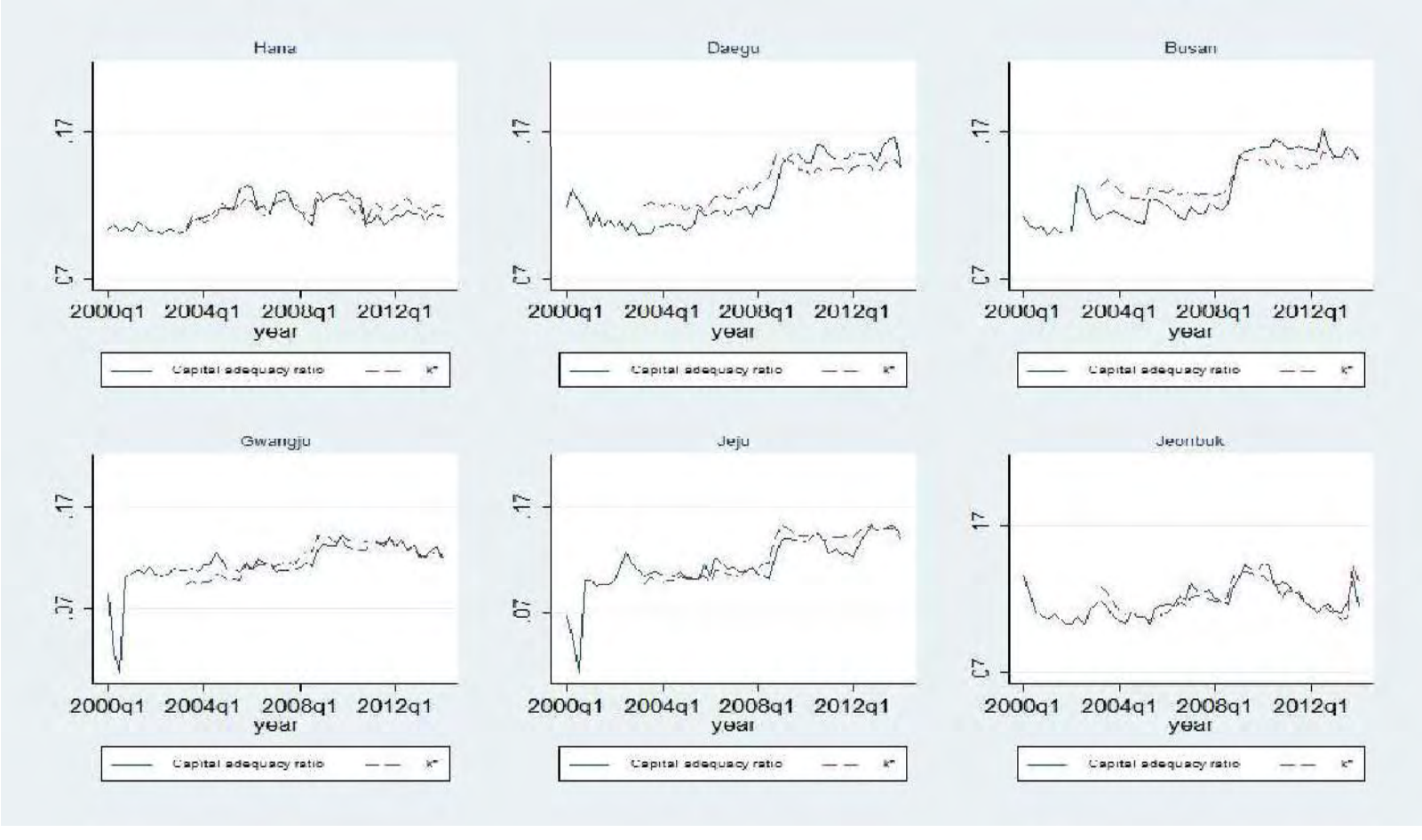
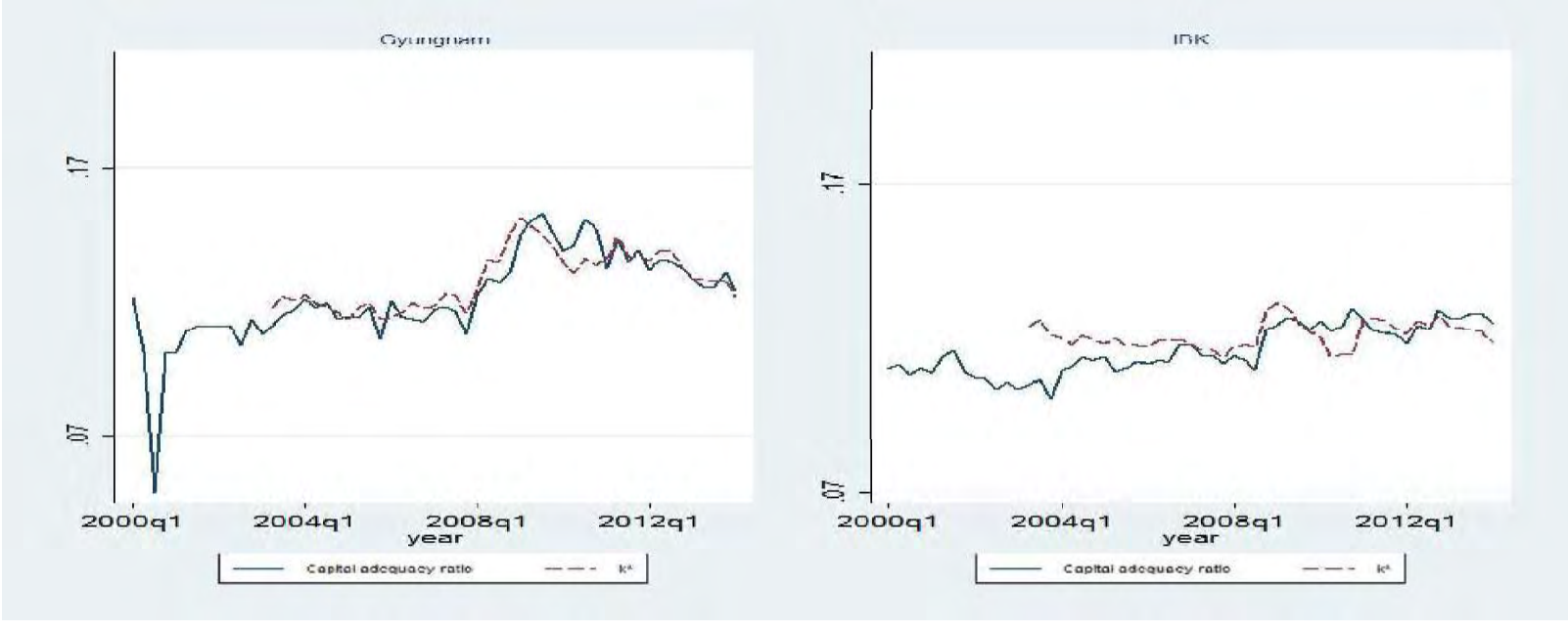
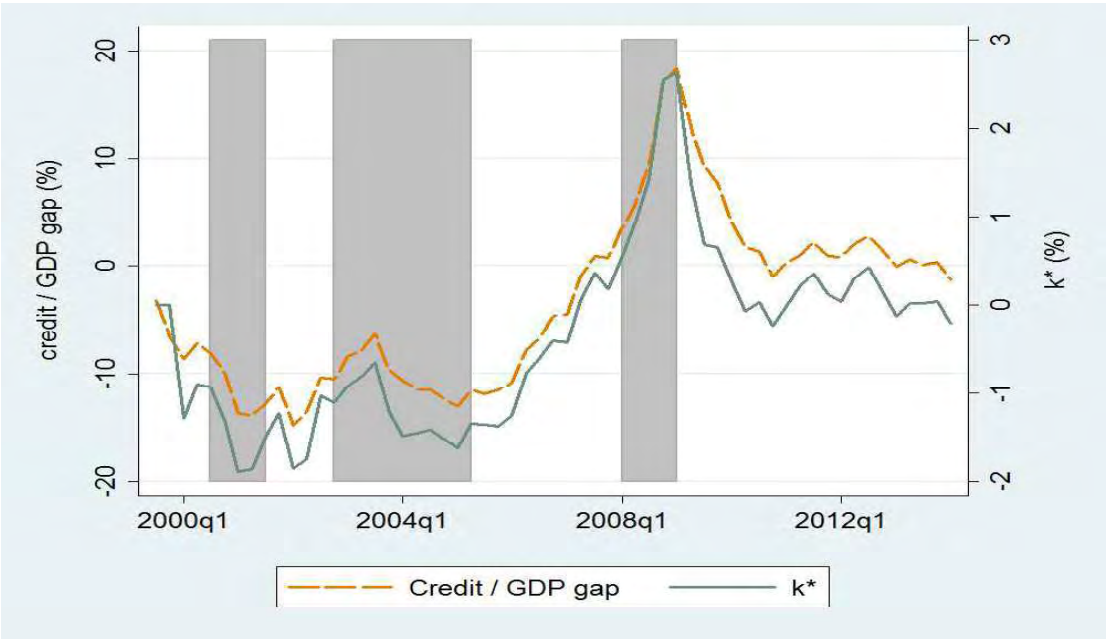


Figure 2: Actual vs. Target (k^*) Capital Ratio (Cont'd)



To examine the effect of the changes in the Credit/GDP gap on the TCR, we conduct a historical simulation. In particular, we feed the past series of the Credit/GDP gap data into the regression equation while eliminating the rest of the regressors from the equation to observe the Credit/CDP gap contribution to the TCR. As a result, we find that the contribution of the Credit/GDP gap to the TCR was maximized at 2.62% in the first quarter of 2009, which is similar in magnitude to the maximum level of the Counter-Cyclical Capital Buffer proposed by Basel III, as is illustrated in Figure 3. As the historical maximum target ratio is in line with the maximum Counter-Cyclical Capital Buffer provision, the impact of the Basel's new regulations to counter credit cycles are considered as expected for Korean banks.

Figure 3: Credit/GDP Gap and TCR: A Historical Simulation



Given the above results, we investigate how banks adjust the capital gap using the second stage estimation based on Equation 6. The estimation results are provided in Table 4.

From Table 4, we can infer that a bank will increase their assets and loans 0.485% and 0.404%, respectively, to increase the capital ratio gap by 1%, which can be interpreted as the elasticity of assets and loans to the capital gap. The growth in RWA in response to capital ratio gap

is higher than the overall asset growth. Hence, banks more aggressively take risks when there is excess capital. Interestingly, the Core Capital/RWA decreases at a similar rate as the KGAP that is statistically significant at -0.1031%.

Table 4. Balance Sheet Adjustment: Panel Regression

	ΔAssets	ΔRWA	ΔLoans	Core Capital/RWA
ΔAssets		0.611***	0.633***	0.0488***
ΔAssets(-1)	-0.129***	0.131***	0.092***	0.0103***
ΔGDP(-1)	0.595*	0.442	0.035	0.0143
Lending Attitude(-1)	0.001***	-0.000	-0.000	-0.0001**
Lending Attitude(-2)	-0.000	0.001*	0.000	0.0001*
Policy Rate(-1)	0.001	0.005	0.004	-0.0010
Policy Rate(-2)	0.018**	0.001	-0.002	0.0011
CPI Inflation(-1)	1.051*	-1.884***	-0.551*	-0.1931***
CPI Inflation(-2)	0.190	1.171*	0.151	0.1271**
Loss Provision(-1)	1.673	-1.087	-1.351	-0.0248
Loss Provision(-2)	-1.833	0.685	1.106	0.2156
KGAP1(-1)	0.485**	0.746***	0.404***	-0.1031***
Constant	-0.075***	-0.010	0.007	-0.0028
Quarterly Dummy	Yes	yes	Yes	Yes
# Obs	615	615	615	615
R^2	0.140	0.332	0.656	0.351

Note: Lags are indicated inside the parenthesis at the end of variables and Δ denotes log growth. The markings *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Based on these results, we can derive several interesting findings. First, the RWA is more sensitive than other assets to changes in the capital gap. If the actual capital is 1% higher than the internally-conceived target ratio from the previous quarter, the RWA will increase 0.746% compared to a 0.486% increase in total assets. Given that total assets can be decomposed between RWAs and non-RWAs (NRWA), the growth of total assets can be formulated as follows:

$$\frac{dA}{A} = w_{RWA}\frac{d(RWA)}{RWA} + (1 - w_{RWA})\frac{d(NRWA)}{NRWA}.$$

Letting g denote the growth rate, the above equation can be rewritten as:

$$g_A = w_{RWA} g_{RWA} + (1 - w_{RWA}) g_{NRWA}.$$

From Table 1, w_{RWA} is approximately 0.65 based on the data for all banks. Given that g_A =0.485, the value of $w_{RWA}g_{RWA}$ will yield 0.65 x 0.746 = 0.4849 using data from Table 3. This implies that the contribution from non-RWAs on asset growth, $(1-w_{RWA})g_{NRWA}$, is almost negligible and almost all the asset responses to changes in capital gap emanate from RWAs.

Second, changes in the KGAP are almost instantly countervailed by the Core Capital/RWA ratio. Changes in the Core Capital/RWA can be expressed as follows:

$$d\left(\frac{CC}{RWA}\right)=\frac{CC}{RWA}\left(g_{CC}-g_{RWA}\right).$$

From Table 3, the left hand side of this equation is known to be -0.1031. After arranging the terms, we determine g_{CC} to be -0.415.[12] Two additional features are observed from this simple computation. First, the core capital responds to changes in capital gap. As core capital consists mainly of common equity (i.e., common shares and retained earnings), it is more relevant to consider which component of common equity is more sensitive to changes in the capital gap. As the current bank data does not distinguish common shares from retained earnings, we cannot investigate this, which provides an opportunity for future research. Second, RWA is more sensitive to changes in the capital gap than the core capital. This finding suggests that balance sheet adjustments due to the adoption of a Counter-Cyclical Capital Buffer will be more active in risky assets rather than capital.

5. Robustness

In the previous section, we use the Credit/GDP gap calibrated by a HP-filter with the smoothing parameter (λ) of 400,000 to remove the effect of the credit cycle on the target capital level. Here, we check the robustness of our results by using a number of variables that can be substituted for the baseline Credit/GDP gap to strengthen the reliability of the empirical results.

The ultimate goal of this section is to examine the relationship between the proxies to predict credit cycles and the TCR. In other words, we strive to observe whether the choice of proxies has

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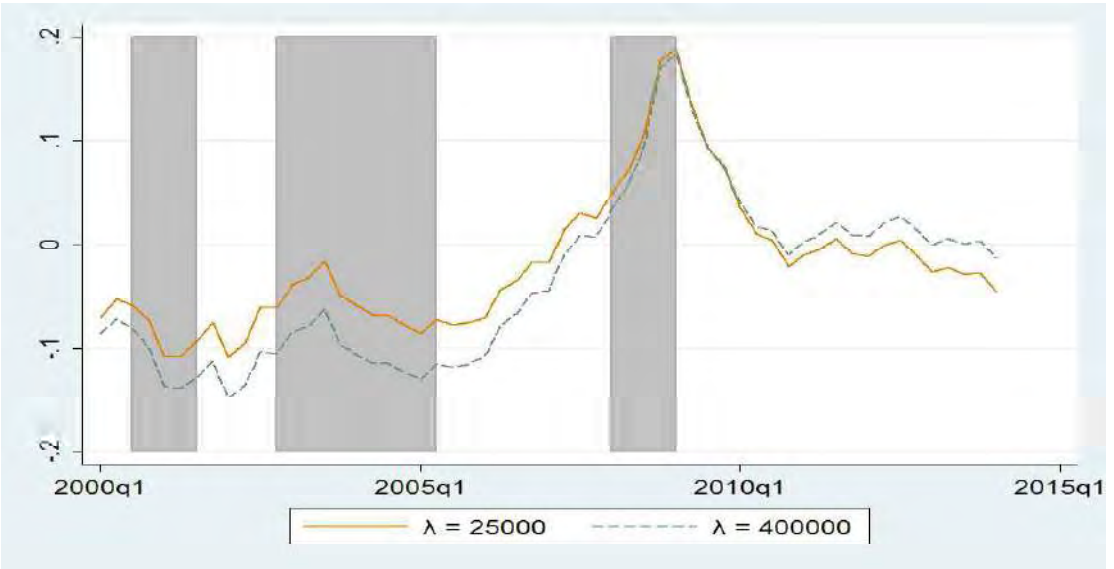
[12] The mean values of the core capital and RWA of all banks are used to compute the Core Capital/RWA ratio.

differing implications for the long-run effect of the capital gap on the balance-sheet variables. The most widely-quoted variables for predicting credit cycle are the Credit/GDP and the non-core liabilities ratios due to the seminal work by Borio and Shin, among others (Borio and Lowe, 2004; Shin and Shin, 2010; BCBS, 2010; Hahm, Shin, and Shin, 2013). Thus, this section explores the relationship between the candidate variables for predicting credit cycles and TCRs and balance-sheet adjustments to fill the capital gap. Specifically, the list of candidate variables is: (1) Credit/GDP gap with the HP filter smoothing parameter proposed by Cho, Shim, and Lee (2013), (2) Non-Core Liabilities/Total Assets, (3) Non-Core Liabilities/Core Liabilities, and, (4) Non-Core Liabilities/M2. For space considerations, and unless there are significant modifications compared to the baseline, we only present and briefly explain the estimation results.

1) Credit/GDP Gap (HP smoothing parameter λ =25,000)

Cho, Shim, and Lee (2013) discuss the validity of the smoothing parameter proposed by the Basel and conclude that the relevant parameter to extract the Korean credit cycle is 25,000. Based on their suggestions, we derive the Credit/GDP ratio using λ=25,000 and compare it with the base-line Credit/GDP ratio using λ=400,000. Overall, the trends of the two cycles are similar with a slight difference in level. One interesting observation is that the Credit/GDP gap using λ=25,000 is higher than that of λ=400,000 before the most recent economic downturn. However, this relationship has since reversed and the gap is widening, as shown in Figure 4.

Figure 4. Credit/GDP Gap using two HP filters



To study the influence of the smoothing parameter on the TCR, we re-estimate the target capital equation, and the results are presented in Tables 5 and 6. We observe that the long-run effect of the Credit/GDP gap on the TCR increases by 9% or 0.013%p from the baseline, leaving most other coefficients intact. Hence, we conjecture that the effect of using different smoothing parameters will not change the baseline findings significantly.

Table 5. TCR: Credit/GDP Gap (λ=25,000)

Reduced-Form	π		Structural	θ	
	Coef.	S.E.		Coef.	S.E.
ΔROE	-0.008***	(0.003)	ROE	-0.046**	(0.017)
ΔRISK	-0.148***	(0.009)	RISK	-0.864***	(0.129)
ΔALLOW	0.518***	(0.150)	ALLOW	3.021***	(0.954)
ΔSUBDEBT	0.748***	(0.060)	SUBDEBT	4.361***	(0.705)
ΔASSET	0.002***	(0.000)	ASSET	0.012***	(0.003)
ΔDEBT/ASSET	-0.815***	(0.061)	DEBT/ASSET	-4.750***	(0.683)
ΔCREDIT/GDP	0.029***	(0.011)	CREDIT/GDP	0.171**	(0.070)
ΔROE(-1)	-0.002	(0.003)	ROE(-1)	0.018	(0.017)
ΔRISK(-1)	0.011	(0.009)	RISK(-1)	0.773***	(0.141)
ΔALLOW(-1)	0.349**	(0.142)	ALLOW(-1)	-1.296	(1.113)
ΔSUBDEBT (-1)	-0.006	(0.061)	SUBDEBT (-1)	-3.756***	(0.750)
ΔASSET(-1)	-0.000	(0.000)	ASSET(-1)	-0.012**	(0.004)
ΔDEBT/ASSET(-1)	-0.040	(0.061)	DEBT/ASSET(-1)	3.480***	(0.739)
ΔCREDIT/GDP(-1)	0.007	(0.010)	CREDIT/GDP(-1)	0.002	(0.097)
ROE(-1)	-0.003	(0.004)	ROE(-2)	0.014	(0.017)
RISK(-1)	-0.026***	(0.006)	RISK(-2)	-0.064	(0.055)
ALLOW(-1)	-0.053	(0.092)	ALLOW(-2)	-2.033**	(0.864)
SUBDEBT (-1)	0.110***	(0.034)	SUBDEBT (-2)	0.037	(0.356)
ASSET(-1)	0.000***	(0.000)	ASSET(-2)	0.001	(0.003)
DEBT/ASSET(-1)	-0.178***	(0.033)	DEBT/ASSET(-2)	0.231	(0.356)
CREDIT/GDP(-1)	0.023***	(0.004)	CREDIT/GDP(-2)	-0.040	(0.062)
			ΣROE	-0.015	(0.024)
			ΣRISK	-0.154***	(0.031)
			ΣALLOW	-0.307	(0.547)
			ΣSUBDEBT	0.641***	(0.195)
			ΣASSET	0.002***	(0.000)
			ΣDEBT/ASSET	-1.039***	(0.117)
			ΣCREDIT/GDP	0.133***	(0.024)
K(-1)	-0.172***	(0.023)	ρ	0.172***	(0.023)
CONSTANT	0.207***	(0.034)	CONSTANT	1.208***	(0.115)
Obs.	616				
R^2	0.564				

Note: Lags are indicated inside the parenthesis at the end of variables. The sum of all the current and lagged terms is denoted as Σ to estimate the long-run effect of the variables. The markings *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Given the estimates, we conduct a balance-sheet variable adjustment of the capital gap and present the results in Table 6. Compared to the baseline, we find that the sensitivity of total assets increases while the sensitivity of RWA and loans decrease. However, the order of the elasticity is preserved. The elasticity of the core capital to capital gap is even higher than that of the baseline. However, the general pattern in the baseline is almost the same. Hence, we conclude that changes in the smoothing parameter in the HP filters do not cause a significant change, unlike the findings in Cho, Shim, and Lee (2013).

Table 6. Balance Sheet Adjustment: Credit/GDP Gap (λ=25,000)

	ΔAssets	ΔRWA	ΔLoans	Core Capital/RWA
ΔAssets		0.611***	0.633***	0.0492***
ΔAssets(-1)	-0.130***	0.131***	0.092***	0.0106***
ΔGDP(-1)	0.607*	0.466	0.048	0.0114
Lending Attitude(-1)	0.001***	-0.000	-0.000	-0.0001**
Lending Attitude(-2)	-0.000	0.001*	0.000	0.0001*
Policy Rate(-1)	0.000	0.005	0.004	-0.0009
Policy Rate(-2)	0.019**	0.002	-0.001	0.0009
CPI Inflation(-1)	1.055*	-1.892***	-0.554*	-0.1947***
CPI Inflation(-2)	0.222	1.148*	0.141	0.1196**
Loss Provision(-1)	1.593	-1.036	-1.332	-0.0073
Loss Provision(-2)	-1.788	0.684	1.109	0.2062
KGAP1(-1)	0.526**	0.647***	0.358***	-0.1131***
Constant	-0.077***	-0.011	0.006	-0.0024
Quarterly Dummy	yes	Yes	Yes	Yes
# Obs	615	615	615	615
R^2	0.142	0.329	0.654	0.359

Note: Lags are indicated inside the parenthesis at the end of variables and Δ denotes log growth. The markings *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

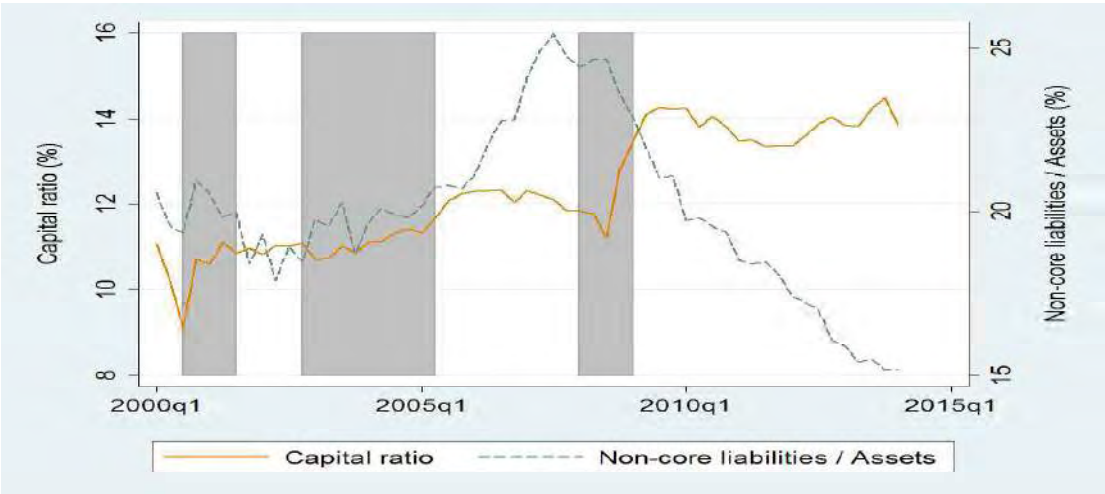
2) Non-Core Liabilities-to-Total Asset (NCL/TA)

Following Hahm, Shin, and Shin (2013), we also employ non-core liabilities (NCL) to detect credit cycles. The NCL of banks include currency and foreign currency debt, offshore foreign currency borrowings, call money, RP, inter-bank CDs, and offshore interbank foreign currency

deposits, while core liabilities include the means of traditional bank funding, such as currency deposits from customers, and individual and corporate CDs.

Figure 5 illustrates the trend of the NCL/TA ratio. The ratio increases until 2008 and then declines steadily. The inverse relationship between the capital ratio and the NCL/TA is not conspicuous before 2008, but then becomes clear.

Figure 5. CAR and NCL/TA



Using the NCL/TA ratio, we re-estimate the TCR and find that a 1% increase results in a 0.206%p increase in the TCR, as shown in Table 7. This implies the banks acknowledge the need to increase their capital ratios in response to credit booms. Additionally, a higher elasticity relative to the baseline implies that a bank is more sensitive to the development of the NCL/TA ratio than the HP-based credit cycles.

A summary of the effects of balance sheet adjustments on the capital gap is provided in Table 8. Namely, the elasticity of the total assets increases while the elasticity of the RWA and loans decreases. However, the order of the coefficients is preserved. The sensitivity of the Core Capital/RWA to the capital gap is even higher than the sensitivity of the baseline and the smoothing parameter of 25,000.

Table 7. TCL: NCL/TA

Reduced-Form	π		Structural	θ	
	Coef.	S.E.		Coef.	S.E.
ΔROE	-0.006**	(0.003)	ROE	-0.038*	(0.019)
ΔRISK	-0.154***	(0.009)	RISK	-0.957***	(0.142)
ΔALLOW	0.570***	(0.152)	ALLOW	3.530***	(1.023)
ΔSUBDEBT	0.781***	(0.062)	SUBDEBT	4.839***	(0.786)
ΔASSET	0.002***	(0.000)	ASSET	0.013***	(0.003)
ΔDEBT/ASSET	-0.874***	(0.062)	DEBT/ASSET	-5.416***	(0.768)
ΔNCL/ASSET	0.025	(0.036)	NCL/ASSET	0.154	(0.228)
ΔROE(-1)	-0.001	(0.003)	ROE(-1)	0.006	(0.019)
ΔRISK(-1)	0.010	(0.010)	RISK(-1)	0.888***	(0.157)
ΔALLOW(-1)	0.521***	(0.143)	ALLOW(-1)	-0.840	(1.205)
ΔSUBDEBT (-1)	0.013	(0.061)	SUBDEBT (-1)	-4.146***	(0.818)
ΔASSET(-1)	-0.000	(0.000)	ASSET(-1)	-0.014***	(0.005)
ΔDEBT/ASSET(-1)	-0.028	(0.062)	DEBT/ASSET(-1)	4.203***	(0.838)
ΔNCL/ASSET(-1)	-0.113***	(0.034)	NCL/ASSET(-1)	-0.554*	(0.300)
ROE(-1)	-0.004	(0.005)	ROE(-2)	0.007	(0.018)
RISK(-1)	-0.021***	(0.006)	RISK(-2)	-0.063	(0.061)
ALLOW(-1)	-0.087	(0.092)	ALLOW(-2)	-3.227***	(0.960)
SUBDEBT (-1)	0.099***	(0.035)	SUBDEBT (-2)	-0.081	(0.380)
ASSET(-1)	0.000***	(0.000)	ASSET(-2)	0.002	(0.003)
DEBT/ASSET(-1)	-0.168***	(0.033)	DEBT/ASSET(-2)	0.174	(0.382)
NCL/ASSET(-1)	0.049***	(0.014)	NCL/ASSET(-2)	0.701***	(0.217)
			ΣROE	-0.024	(0.029)
			ΣRISK	-0.132***	(0.033)
			ΣALLOW	-0.537	(0.594)
			ΣSUBDEBT	0.612***	(0.213)
			ΣASSET	0.001***	(0.000)
			ΣDEBT/ASSET	-1.039***	(0.132)
			ΣNCL/ASSET	0.301***	(0.089)
K(-1)	-0.161***	(0.022)	ρ	0.161***	(0.022)
CONSTANT	0.192***	(0.035)	CONSTANT	1.191***	(0.130)
Obs.	616				
R^2	0.549				

Note: Lags are indicated inside the parenthesis at the end of variables. The sum of all the current and lagged terms is denoted by Σ to estimate the long-run effect of the variables. The markings *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Table 8. Balance Sheet Adjustment: NCL/TA

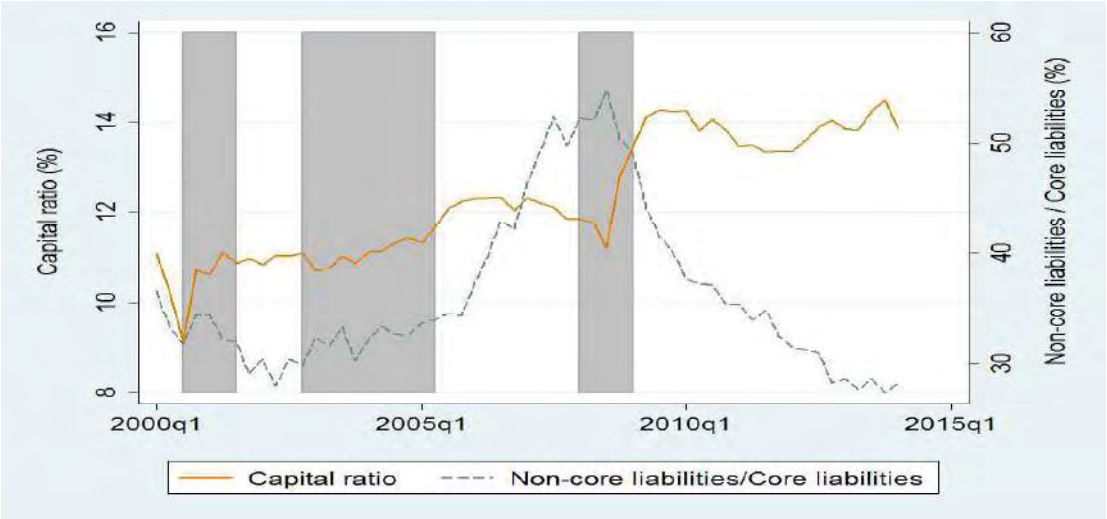
	ΔAssets	ΔRWA	ΔLoans	Core Capital/RWA
ΔAssets		0.615***	0.635***	0.0494***
ΔAssets(-1)	-0.129***	0.135***	0.094***	0.0104***
ΔGDP(-1)	0.676**	0.523	0.080	-0.0043
Lending Attitude(-1)	0.001***	-0.000	-0.000	-0.0001***
Lending Attitude (-2)	-0.000	0.001**	0.000	0.0000
Policy Rate(-1)	0.004	0.009	0.006	-0.0017**
Policy Rate(-2)	0.018**	-0.001	-0.003	0.0012
CPI Inflation(-1)	0.912	-2.025***	-0.631*	-0.1627***
CPI Inflation(-2)	0.038	0.904	0.002	0.1583***
Loss Provision(-1)	1.624	-0.735	-1.187	-0.0063
Loss Provision(-2)	-1.626	0.688	1.130	0.1658
KGAP1(-1)	0.543**	0.403*	0.239**	-0.1252***
Constant	-0.087***	-0.017	0.003	0.0000
Quarterly Dummy	yes	Yes	yes	Yes
# Obs	615	615	615	615
R^2	0.142	0.323	0.651	0.365

Note: Lags are indicated inside the parenthesis at the end of variables and Δ denotes log growth. The markings *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

3) Non-Core Liabilities/Core Liabilities (NCL/CL)

In this experiment, we change the denominator from total assets to core liabilities as an index for predicting credit cycle. The ratio between non-core and core liabilities provides timely information for the funding condition of banks, while the NCL/TA ratio provides information on banks non-traditional funding capacity and the market appreciation of the profitability of the bank. Compared to the NCL/TA ratio, the peak of the NCL/CL ratio is delayed. This implies that under financial stresses, banks rely on non-traditional sources of funding to bolster their balance sheet, while the market starts to discount the asset value of the bank to accommodate the impact of a credit bust.

Figure 6. CAR and NCL/CL



We find similar results for the TCR and balance sheet adjustments to the capital gap as illustrated in Tables 9 and 10. The TCRs increase during a credit boom and decrease during a credit bust. When the capital gap increases, the total assets, RWAs, and loans also increase but at lesser degrees. However, this does not imply that the capital adequacy ratio improves as the capital gap increases. To determine the impact of the CAR, we examine how the capital moves when the gap widens. According to our findings, the Core Capital/RWA ratio decreases at a higher rate compared to the capital gap. Combining these findings, we conclude that the capital ratio will deteriorate in times of positive capital gap as the core capital decreases and the RWA increases.

Table 9. TCR: NCL/CL

Reduced-Form	π		Structural	θ	
	Coef.	S.E.		Coef.	S.E.
ΔROE	-0.008***	(0.003)	ROE	-0.045**	(0.018)
ΔRISK	-0.151***	(0.009)	RISK	-0.878***	(0.126)
ΔALLOW	0.578***	(0.151)	ALLOW	3.355***	(0.954)
ΔSUBDEBT	0.775***	(0.062)	SUBDEBT	4.502***	(0.707)
ΔASSET	0.002***	(0.000)	ASSET	0.011***	(0.003)
ΔDEBT/ASSET	-0.852***	(0.063)	DEBT/ASSET	-4.946***	(0.682)
ΔCREDIT/GDP	-0.011	(0.011)	CREDIT/GDP	-0.063	(0.066)
ΔROE(-1)	-0.002	(0.003)	ROE(-1)	0.001	(0.018)
ΔRISK(-1)	0.011	(0.010)	RISK(-1)	0.809***	(0.140)
ΔALLOW(-1)	0.467***	(0.143)	ALLOW(-1)	-1.216	(1.124)
ΔSUBDEBT (-1)	0.005	(0.061)	SUBDEBT (-1)	-3.851***	(0.741)
ΔASSET(-1)	-0.001	(0.000)	ASSET(-1)	-0.013***	(0.004)
ΔDEBT/ASSET(-1)	-0.016	(0.062)	DEBT/ASSET(-1)	3.804***	(0.754)
ΔCREDIT/GDP(-1)	-0.031***	(0.011)	CREDIT/GDP(-1)	-0.024	(0.085)
ROE(-1)	-0.006	(0.005)	ROE(-2)	0.011	(0.017)
RISK(-1)	-0.023***	(0.006)	RISK(-2)	-0.066	(0.056)
ALLOW(-1)	-0.099	(0.093)	ALLOW(-2)	-2.711***	(0.880)
SUBDEBT (-1)	0.107***	(0.035)	SUBDEBT (-2)	-0.031	(0.357)
ASSET(-1)	0.000***	(0.000)	ASSET(-2)	0.003	(0.003)
DEBT/ASSET(-1)	-0.180***	(0.033)	DEBT/ASSET(-2)	0.096	(0.360)
CREDIT/GDP(-1)	0.016***	(0.004)	CREDIT/GDP(-2)	0.178**	(0.063)
			ΣROE	-0.033	(0.027)
			ΣRISK	-0.135***	(0.031)
			ΣALLOW	-0.573	(0.559)
			ΣSUBDEBT	0.620***	(0.199)
			ΣASSET	0.001***	(0.000)
			ΣDEBT/ASSET	-1.046***	(0.122)
			ΣCREDIT/GDP	0.091***	(0.025)
K(-1)	-0.172***	(0.022)	ρ	0.172***	(0.022)
CONSTANT	0.207***	(0.035)	CONSTANT	1.200***	(0.121)
Obs.	616				
R^2	0.550				

Note: Lags are indicated inside the parenthesis at the end of variables. The sum of all the current and lagged terms is denoted as Σ to estimate the long-run effect of the variables. The markings *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Table 10. Balance Sheet Adjustment: NCL/CL

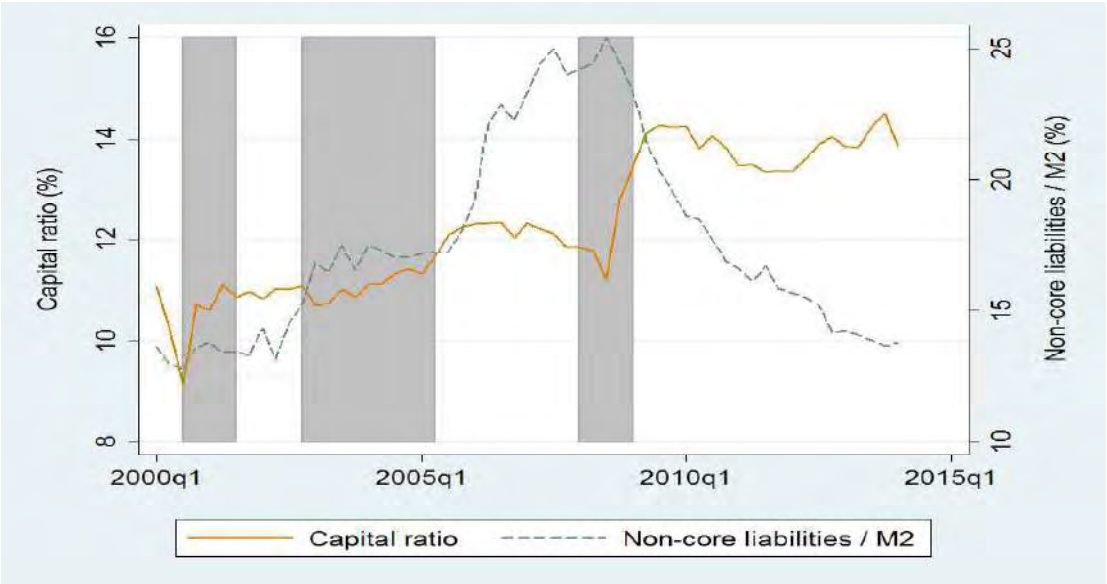
	ΔAssets	ΔRWA	ΔLoans	Core Capital/RWA
ΔAssets		0.615***	0.634***	0.0494***
ΔAssets(-1)	-0.129***	0.134***	0.093***	0.0106***
ΔGDP(-1)	0.661**	0.514	0.076	-0.0008
Lending Attitude(-1)	0.001***	-0.000	-0.000	-0.0001***
Lending Attitude (-2)	-0.000	0.001**	0.000	0.0000
Policy Rate(-1)	0.004	0.009	0.006	-0.0017**
Policy Rate(-2)	0.018*	-0.001	-0.003	0.0012
CPI Inflation(-1)	0.962	-1.990***	-0.612*	-0.1741***
CPI Inflation(-2)	0.028	0.898	0.001	0.1606***
Loss Provision(-1)	1.576	-0.804	-1.245	0.0056
Loss Provision(-2)	-1.665	0.679	1.135	0.1743
KGAP1(-1)	0.537**	0.429*	0.272**	-0.1244***
Constant	-0.086***	-0.017	0.002	-0.0003
Quarterly Dummy	yes	Yes	Yes	Yes
# Obs	615	615	615	615
R^2	0.142	0.324	0.651	0.365

Note: Lags are indicated inside the parenthesis at the end of variables and Δ denotes log growth. The markings *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

4) Non-Core Liabilities/M2 (NCL/M2)

Finally, we use the NCL/M2 as a credit cycle variable as suggested in Hahm, Shin, and Shin (2013) and, perform the same analysis. The trend of the NCL/M2 appears similar to the NCL/CL, although the level is a bit moderated.

Figure 7. CAR and NCL/M2



As shown in Tables 11 and 12, NCL/M2 has a positive long-run effect on the TCR, and balance sheet responses to the capital gap have the same signs, order, and similar magnitudes as those found when NCL/CL is employed in the previous analysis.

Hence, we conclude that the various measures of credit cycle reveal qualitatively the same results, and the quantitative features of the results are not vastly different from what we find using the baseline model. Therefore, the selection of predictors for credit cycle is rather irrelevant overall.

Table 2. TCR: NCL/M2

Reduced-form	π		Structural	θ	
	Coef.	S.E.		Coef.	S.E.
ΔROE	-0.007**	(0.003)	ROE	-0.046**	(0.019)
ΔRISK	-0.153***	(0.009)	RISK	-0.943***	(0.141)
ΔALLOW	0.589***	(0.152)	ALLOW	3.620***	(1.024)
ΔSUBDEBT	0.791***	(0.062)	SUBDEBT	4.865***	(0.786)
ΔASSET	0.002***	(0.000)	ASSET	0.012***	(0.004)
ΔDEBT/ASSET	-0.865***	(0.062)	DEBT/ASSET	-5.318***	(0.759)
ΔNCL/M2	0.000	(0.029)	NCL/M2	0.002	(0.179)
ΔROE(-1)	-0.002	(0.003)	ROE(-1)	0.005	(0.019)
ΔRISK(-1)	0.009	(0.010)	RISK(-1)	0.866***	(0.155)
ΔALLOW(-1)	0.461***	(0.145)	ALLOW(-1)	-1.322	(1.202)
ΔSUBDEBT (-1)	0.017	(0.062)	SUBDEBT (-1)	-4.132***	(0.812)
ΔASSET(-1)	-0.001	(0.000)	ASSET(-1)	-0.014***	(0.005)
ΔDEBT/ASSET(-1)	-0.031	(0.062)	DEBT/ASSET(-1)	4.027***	(0.818)
ΔNCL/M2(-1)	-0.060**	(0.027)	NCL/M2(-1)	-0.154	(0.254)
ROE(-1)	-0.005	(0.005)	ROE(-2)	0.010	(0.018)
RISK(-1)	-0.021***	(0.006)	RISK(-2)	-0.053	(0.060)
ALLOW(-1)	-0.088	(0.094)	ALLOW(-2)	-2.837***	(0.951)
SUBDEBT (-1)	0.102***	(0.035)	SUBDEBT (-2)	-0.105	(0.378)
ASSET(-1)	0.000**	(0.000)	ASSET(-2)	0.003	(0.003)
DEBT/ASSET(-1)	-0.179***	(0.034)	DEBT/ASSET(-2)	0.189	(0.380)
NCL/M2(-1)	0.035***	(0.010)	NCL/M2(-2)	0.369**	(0.165)
			ΣROE	-0.031	(0.028)
			ΣRISK	-0.130***	(0.033)
			ΣALLOW	-0.539	(0.597)
			ΣSUBDEBT	0.627***	(0.213)
			ΣASSET	0.001**	(0.000)
			ΣDEBT/ASSET	-1.103***	(0.134)
			ΣNCL/M2	0.217***	(0.065)
K(-1)	-0.163***	(0.022)	RHO	0.163***	(0.022)
CONSTANT	0.203***	(0.036)	CONSTANT	1.247***	(0.133)
Obs.	616				
R^2	0.546				

Note: Lags are indicated inside the parenthesis at the end of variables. The sum of all the current and lagged terms is denoted as Σ to estimate the long-run effect of the variables. The markings *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Table 3. Bank Capital Channel Panel Regression: NCL/M2

	ΔAssets	ΔRWA	ΔLoans	Core Capital/RWA
ΔAssets		0.616***	0.635***	0.0494***
ΔAssets(-1)	-0.129***	0.135***	0.094***	0.0105***
ΔGDP(-1)	0.661**	0.512	0.073	-0.0013
Lending Attitude(-1)	0.001***	-0.000	-0.000	-0.0001***
Lending Attitude (-2)	-0.000	0.001**	0.000	0.0000
Policy Rate(-1)	0.004	0.009	0.006	-0.0018**
Policy Rate(-2)	0.018*	-0.001	-0.003	0.0012
CPI Inflation(-1)	0.902	-2.034***	-0.635*	-0.1593***
CPI Inflation(-2)	-0.007	0.869	-0.018	0.1685***
Loss Provision(-1)	1.595	-0.763	-1.192	0.0063
Loss Provision(-2)	-1.677	0.655	1.103	0.1740
KGAP1(-1)	0.531**	0.399*	0.226**	-0.1281***
Constant	-0.086***	-0.016	0.004	-0.0002
Quarterly Dummy	yes	yes	Yes	yes
# Obs	615	615	615	615
R^2	0.142	0.323	0.650	0.366

Note: Lags are indicated inside the parenthesis at the end of variables and Δ denotes log growth. The markings *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

6. Conclusion

This paper addresses the determinants of the TCR and investigates balance sheet adjustments of the capital ratio gap based on Korean bank data. The implementation of Basel III has garnered attention for banks' reactions, asset compositions, and operations. Specifically, the Countercyclical Capital Buffer suggested in Basel III is expected to dampen the duration and volatility of the credit cycle by preventing pro-cyclical lending.

This paper provides an empirical analysis of banks' capital and asset composition behavior in accordance with credit cycles prior to the implementation of the Counter-Cyclical Capital Buffer in Korea. The effect of credit cycle on banks' target capital adequacy ratio is first observed using the

Credit/GDP gap as a variable to predict the credit cycle. The empirical results indicate that the TCR increases as the Credit/GDP gap widens in the long-run. The TCR represents the capital that banks should accumulate in the long run relative to the RWA. Widening the Credit/GDP gap increases the TCR and contracts the capital ratio gap. This lowers the asset management ability of banks. Further, changes in the capital gap will affect the bank assets, balance sheet compositions, and operational behaviors. For example, a decrease in the capital gap lowers the growth rate of total assets, especially risk-weighted assets and loans, and increases the core capital growth rate.

Significant hurdles surround predicting credit cycles, and various variables exist to aide forecasts. To increase the significance of our analysis, we also use the variables recommended by the BIS, such as the Credit/GDP gap, and other popular predictors, such as NCL. The results are similar to the baseline model. The RWA growth in response to changes in the capital gap is more sensitive than other balance sheet variables. This demonstrates that Korean banks tend to adjust RWAs relative to capital and loans in response to changes in the capital gap. The effect of changes in the capital gap on non-RWAs is almost negligible. The results imply that if a gap exists between the actual and target capital, domestic banks will more likely adjust their risky assets rather than their capital. This indicates that the adoption of the Counter-Cyclical Capital Buffer will change the balance sheet composition of Korean banks. However, based on a historical simulation assessing the impact of the new capital regulations on the TCR, the new capital regulation on the credit cycle alone would not be a major hurdle for Korean banks.

<Appendix A>

Figure A. Capital Gap

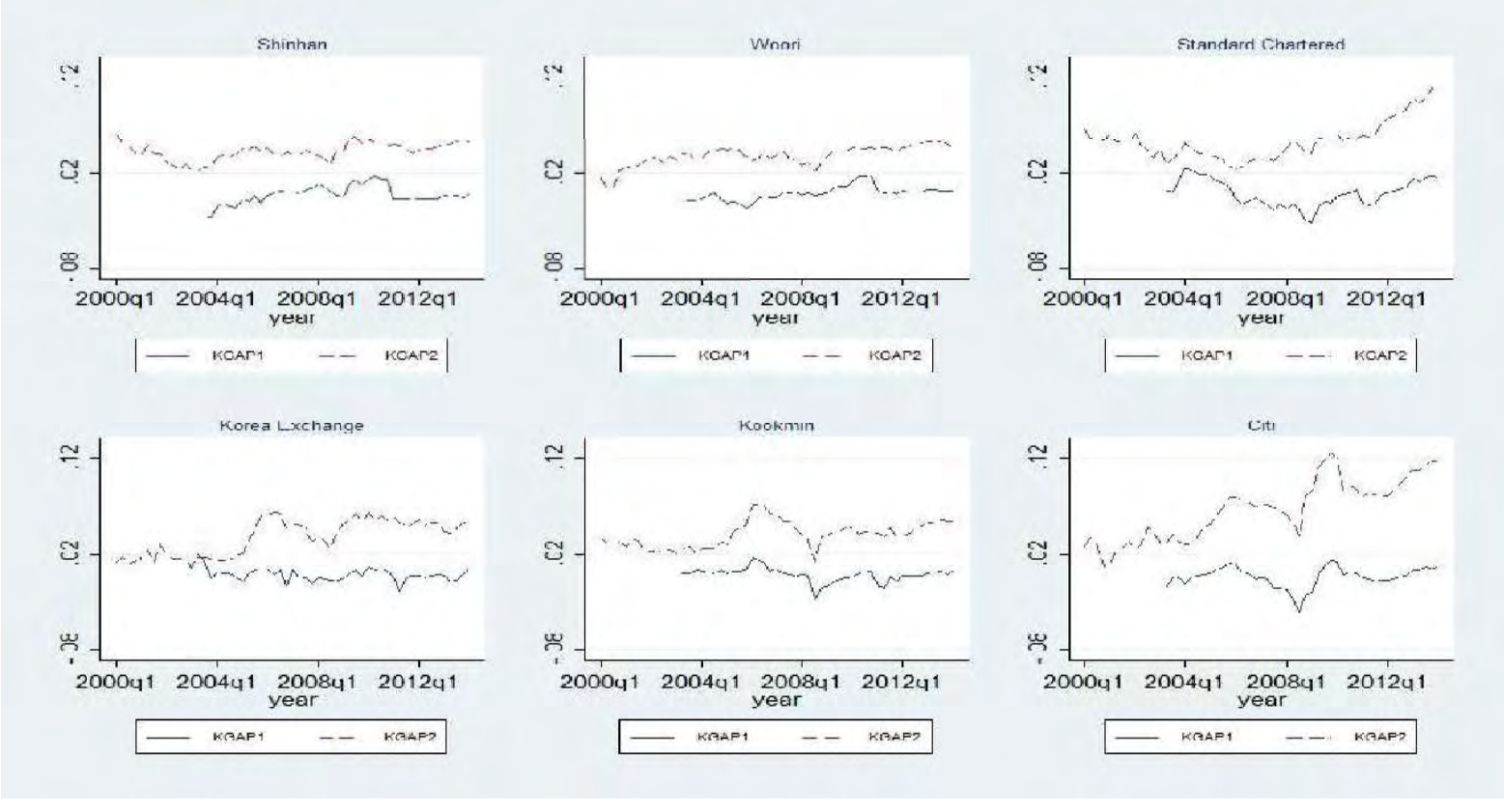


Figure A. Capital Gap (Cont'd)

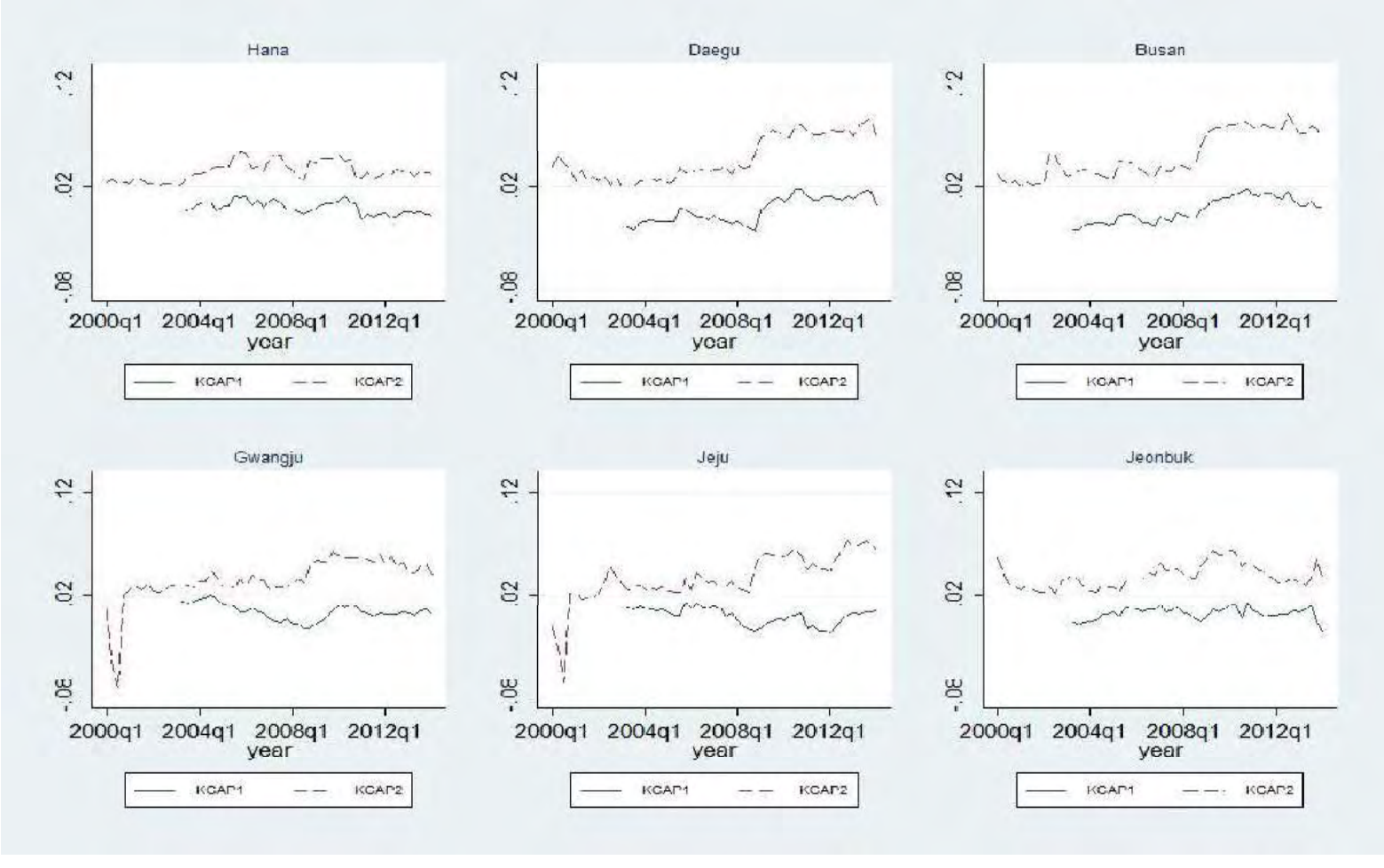
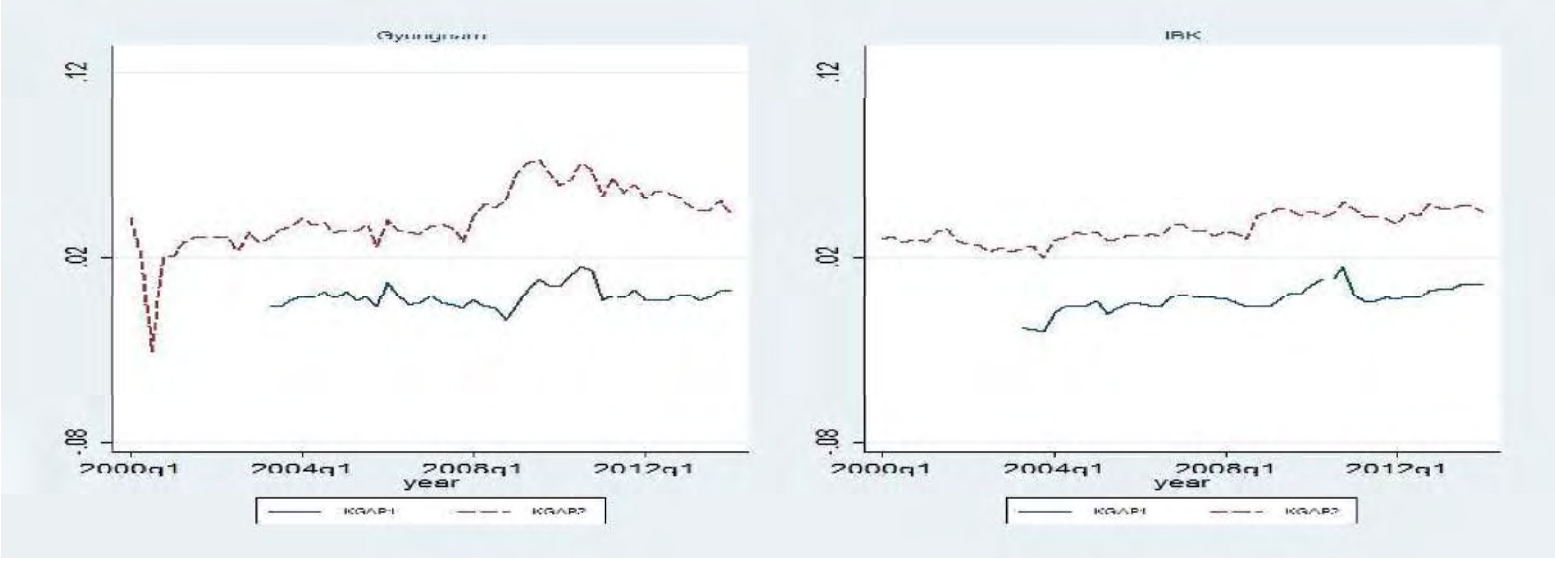


Figure A. Capital Gap (Cont'd)



<Appendix B>

Table B. Summary Statistics for Macro Variables

Variables	Mean	Std. Dev	Min	Max	Median
Real GDP Growth	4.220	2.729	-4.040	12.226	4.194
Non-Core Liabilities Growth	9.260	14.494	-12.754	43.223	7.256
NCL/ M2	17.593	3.780	12.746	25.410	16.854
NCL/Asset	20.041	2.591	15.173	25.448	19.797
Credit/GDP GAP(1)(λ =400,000)	-3.380	8.110	-14.800	18.400	-4.470
Credit/GDP GAP(2)(λ =400,000)	-3.690	8.610	-18.200	20.200	-3.760
Credit/GDP GAP(1)(λ =25,000)	-1.860	6.623	-10.864	18.816	-2.705
Credit/GDP GAP(2)(λ =25,000)	-2.149	7.244	-13.325	21.977	-2.278
Lending Attitude	0.857	11.898	-30.000	22.000	4.000
CPI Inflation	0.007	0.006	-0.003	0.021	0.007
Policy rate (O/N Call rate)	3.645	1.008	2.000	5.250	3.750

Note: The sample period is 2000:Q1 to 2014:Q1.

Source: Bank of Korea

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CHAPTER 3

Government Spending Shocks and Private Activity: The Role of Sentiments

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Abstract

This paper studies the dynamic effects of the fiscal policy shock on private activity using an array of vector autoregressive models for the post-war US data. We are particularly interested in the role of consumer sentiment in the transmission of the government spending shock. Our major findings are as follows. Private consumption and investment fail to rise persistently in response to positive spending shocks especially when shocks are anticipated, while they exhibit persistent and significant increases when the sentiment shock occurs. Employment and real wages in the private sector also respond significantly positively only to the sentiment shock. Consumer sentiment responds negatively to a positive fiscal shock, resulting in subsequent decreases in private activity. That is, our empirical findings imply that the government spending shock generates consumer pessimism, which then weakens the effectiveness of the fiscal policy.

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Keywords: Government Spending; Consumer Sentiment; Private Activity; Sentiment Channel; Vector Autoregressive; Expectational VAR; Survey of Professional Forecasters; Threshold VAR

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1 Introduction

Observing the sluggish recovery from the recent Great Recession, the economics profession has revived the debate on the effectiveness of the fiscal policy in stimulating economic activity. Can increases in government spending help promote private sector activity? And if so, will key variables of interest such as consumption, investment, employment, and real wages respond persistently positively to expansionary fiscal policy?

There is a large literature on this issue. One group of researchers reports positive responses of consumption, real wages, and output to expansionary fiscal shocks, which are consistent with the New Keynesian macroeconomic model in general. See, among others, Rotemberg and Woodford (1992), Devereux, Head, and Laphan (1996), Fatas and Mihov (2001), Blanchard and Perotti (2002), Perotti (2005), Galí, López-Salido, and Vallés (2007).

On the contrary, many other research works provide strong evidence of negative responses of consumption and real wages to fiscal spending shocks. See, for example, Aiyagari, Chirstiano, and Eichenbaum (1992), Hall (1986), Ramey and Shapiro (1998), Edelberg, Eichenbaum, and Fisher (1999), Burnside, Eichenbaum, and Fisher (2004), Cavallo (2005), Mountford and Uhlig (2009), Ramey (2013), and Owyang, Ramey, and Zubairy (2013). As Ramey (2011) explains, these negative responses to an expansionary government spending shock are consistent with a negative wealth effect that often appears in the neoclassical macroeconomic model such as Aiyagari, Christiano, and Eichenbaum(1992) and Baxter and King (1993).[1]

One related literature focuses on the output multiplier of government spending. Empirical evidence is again mixed. For instance, Ramey and Shapiro (1998), Hall (2009), Barro and Redlick (2011), and Ramey (2011) obtained fairly low, say less than one, government spending multiplier estimates, while Hall (2009) and Christiano, Eichenbaum, and Rebelo (2009) show that fiscal multipliers can be high when the nominal interest rate is bounded at zero. Overall, the range of fiscal multiplier estimates in the literature is very wide (Ramey, 2011). Also, fiscal multiplier estimates seem to vary greatly across countries depending on key country characteristics such as the exchange rate regime and public indebtedness. See Corsetti, Meier, and Müller (2012)

[1]Increases in government spending may result in a negative wealth effect because government deficits may have to be financed by tax hikes in the future. Rational consumers reduce consumption and increase labor supply in response to spending shocks, resulting in a decrease in the real wage. Note that such responses would occur even when government raises revenues by non-distortionary lump-sum tax.

and Ilzetxki, Mendoza, and Vegh (2013) for details.

Another interesting question is whether the government spending shock is more powerful during times of slack. Again, empirical evidence is mixed. For example, Auerbach and Gorodnichenko (2012), Mittnik and Semmler (2012) and Fazzari, Morley, and Panovska (2013) report much higher fiscal multipliers in a regime of a low economic activity than those in a high regime activity, whereas Owyang, Ramey, and Zubairy (2013) and Ramey and Zubairy (2014) find no such evidence.

Observing such mixed empirical evidence on the effectiveness of fiscal stimulus, we study how the government spending shock influences private activity in the US. Finding negligibly weak or even negative responses of private activity to the fiscal spending shock, we introduce and highlight the role of consumer *sentiment* in the propagation of expansionary fiscal shocks to promote economic activity.

We are not the first who discussed the interaction between consumer sentiment and economic activity. Hall (1993) and Blanchard (1993), for example, underline the causal effects of *animal spirit* on economic activity in their explanation of the 1990-1991 recession. On the other hand, Cochrane (1994) points out that close relationship between innovations in consumer confidence and subsequent changes in economic activity appear because consumer confidence shocks reflect *news* about future economic productivity. Beaudry and Portier (2004, 2006) also propose a similar model. Barsky and Sims (2012) evaluate empirical relevance of these factors in explaining innovations in consumer confidence. They showed that confidence innovations are better characterized by the latter, even though animal spirit also has non-negligible contribution. Using a nonlinear VAR framework, Bachman and Sims (2012) report high fiscal multiplier estimates during periods of economic slack. They put an emphasis on the role of confidence, which embodies information of future productivity improvements in response to fiscal spending shocks during recessions. By the same token, Bachman and Sims (2012) argue that consumers might become more optimistic in response to the fiscal shock during times of economic slack, which sharply contrasts with our work that reports solid negative responses of consumer sentiment to the fiscal shock in all phases of business cycle.

We are particularly interested in the role of consumer sentiment in propagation mechanism of the government spending shock to private activity such as consumption and investment, excluding the government sector component from the total GDP. For this purpose, we employ an array of identification methods for the fiscal shock that in-

cludes conventional recursively identified structural VAR models and the expectational VAR (EVAR) models of Ramey (2011) for the post war US data.[2] We employ the two EVAR models, one with her news (*NEWS*) variable and the other one with the survey of professional forecasters (*SPF*) data. Our major empirical findings are as follows.

First, government spending shocks are not effective in stimulating private activity. For example, consumption responds positively for a very short period of time, then becomes negative in longer-term. When we assume that changes in fiscal spending are anticipated by utilizing Ramey's (2011) expectational VAR, fiscal policy shocks become completely ineffective as we observe virtually no positive responses since the impact. Similarly, we were unable to find any persistently positive responses of investment to fiscal spending shocks. On the other hand, we observe solid positive responses of consumption and investment to the sentiment shock from all models we consider in the present paper.

Second, we observe that consumer sentiment rapidly deteriorate to a negative region since the impact of the fiscal spending shock, leading to subsequent decreases in consumption and investment. That is, unexpected increases in the government spending generate consumer pessimism, which may weaken the fiscal policy effect on the private sector GDP. We show that our empirical findings are consistent with a view that consumer sentiment leads private activity rather than it passively reflects the current state of the economy.

Lastly, the fiscal shock seems to be ineffective in improving the labor market condition either, while the real wage and private sector jobs show solid positive increases when sentiment shocks occur.

The remainder of this paper is organized as follows. Section 2 discusses our VAR models with alternative identification methods. We also discuss econometric features of our models as to the robustness of our empirical findings to alternative Wold orderings. In Section 3, we present a data description and our major empirical findings. We also discuss the role of a sentiment channel in the propagation mechanism of the fiscal spending shock. Section 4 provides an array of robustness check and additional VAR analyses. Section 5 concludes.

[2] Perotti (2011) named these models of Ramey's (2011) the expectational VAR model.

2 The Econometric Model

Abstracting from deterministic terms, we employ the following vector autoregressive (VAR) model.

$$\mathbf{x}_t = \sum_{j=1}^{p} \mathbf{A}_j \mathbf{x}_{t-j} + \varepsilon_t, \tag{1}$$

where

$$\mathbf{x}_t = [\mathbf{g}_t \;\; \mathbf{y}_t \;\; sent_t \;\; \mathbf{z}_t]'$$

$\mathbf{g}_t$ denotes a vector of (or a scalar) government spending variables, $\mathbf{y}_t$ is a vector (or a scalar) of private activity variables such as consumption ($conm_t$) and investment ($invt_t$), $sent_t$ is a scalar sentiment variable, and $\mathbf{z}_t$ is a vector of control variables that includes tax rate (tr_t), the interest rate (i_t), and the monetary aggregate (m_t). All variables are demeaned and detrended, up to quadratic trend, prior to estimations. We limit out attention to a closed economy VAR model to make the model as simple as possible.[3]

Motivated by Ramey's (2013) work, we employ an array of VAR models based on alternative identification methods for the government spending shock. Our first model, *TGOV*, resembles conventional VAR models with the government spending ordered first. Put it differently, we identify the government spending shock by unexpected increases in the total government spending ($tgov_t$), that is, $\mathbf{g}_t = tgov_t$. For similar models, see, among others, Blanchard and Perotti (2002), Perotti (2005, 2008), and Galí, López-Salido, and Vallés (2007).

We also employ VAR models which is dubbed the *EVAR* (expectational VAR) approach by utilizing her "news" variable as well as the survey of professional forecasters data. That is, $\mathbf{g}_t = news_t$ (*NEWS*) and $\mathbf{g}_t = spf_t$ (*SPF*), respectively. Ramey (2011) points out that government spending shocks, when identified with standard Choleski decomposition (recursively identified) VAR models, might not be appropriate because planned changes in fiscal variables such as military spending are likely to be anticipated by market participants before the government actually implements it. In order to deal with this timing issue, she constructed a "news" variable by estimating changes in the expected present value of government spending, utilizing information from Business Week and several other mass media sources. She also constructed an alternative news

[3] That is, we do not pay much attention to the fiscal policy effect on the net exports. For an open economy model, additional variables such as the exchange rate, foreign incomes, and the domestic and foreign prices should be added to the system.

variable via the one-quarter ahead forecast error of fiscal spending growth rates, using the Survey of Professional Forecasters from the Philadelphia Fed.

Perotti (2011), however, argues that Ramey's *EVAR* is equivalent to a model with $\mathbf{g}_t = [fgov_t,\ tgov_t]'$, where $fgov_t$ denotes the federal government (or military) spending. We also employ such a model and denote it *FGOV* model. Following Perotti (2011) and Ramey (2013), we also put $tgov_t$ next to $news_t$ for the *EVAR* models. Our empirical models are summarized as follows.[4]

$$\begin{aligned} TGOV &: \mathbf{x}_t = [tgov_t \ \ invt_t \ \ conm_t \ \ sent_t \ \ tr_t \ \ i_t \ \ m_t]' \\ FGOV &: \mathbf{x}_t = [fgov_t \ \ tgov_t \ \ invt_t \ \ conm_t \ \ sent_t \ \ tr_t \ \ i_t \ \ m_t]' \\ NEWS &: \mathbf{x}_t = [news_t \ \ tgov_t \ \ invt_t \ \ conm_t \ \ sent_t \ \ tr_t \ \ i_t \ \ m_t]' \\ SPF &: \mathbf{x}_t = [spf_t \ \ tgov_t \ \ invt_t \ \ conm_t \ \ sent_t \ \ tr_t \ \ i_t \ \ m_t]' \end{aligned} \tag{2}$$

For visual inspection of the data, we plot estimated fiscal spending shocks (residuals) as well as original spending variables from these alternative VAR models in Figure 1. Ramey's (2011) (raw) news and SPF variables look quite different from other two variables that are trending upward. However, residuals of these variables, that is, the estimated government spending shock identified from each model, look similar each other. That is, all these four measures of fiscal shocks seem fairly consistent with each other.

Figure 1 around here

It is well-known that econometric inferences from recursively identified VAR models might not be robust to alternative VAR orderings. Fiscal spending effects under our framework do not suffer from this ordering problem. For example, consider a VAR with $\mathbf{x}_t = [\mathbf{x}_{1,t},\ \mathbf{x}_{2,t}]$, where $\mathbf{x}_{1,t}$ is a vector of variables with a known ordering, while the ordering of $\mathbf{x}_{2,t}$ is completely unknown. Kim, Kim, and Stern (2015) demonstrate that all impulse-response functions of the entire variables in $\mathbf{x}_t$ to the shock to one of the variables in $\mathbf{x}_{1,t}$ are unaffected by arbitrary reshuffling of the $\mathbf{x}_{2,t}$ variables.

Note that $\mathbf{g}_t$ is ordered first in all models with an assumption that these spending variables are not contemporaneously influenced by innovations in other variables within

[4] We also implemented estimations without the total government spending for *FGOV*, *NEWS*, and *SPF* models. We obtained qualitatively very similar results. See non-for-publication appendix for all results, which is available from authors upon request.

one quarter.[5] Therefore, the impulse-response functions to the government spending shock under the present framework are invariant to all alternative orderings of the remaining variables in the system. That is, *all* response functions to the fiscal spending shock are "identical" even if we randomly shuffle the variables next to $\mathbf{g}_t$ in the system as long as $\mathbf{g}_t$ is ordered first.

However, response functions to the sentiment shock are *not* invariant to the ordering of the VAR, because s_t is ordered in the middle of the system. We implemented an array of robustness check analyses putting the sentiment variables in different locations from the first to the last. We obtained qualitatively very similar results, thus we maintain the ordering described in (1) throughout the paper.

3 Empirical Findings

3.1 Data Descriptions

We use quarterly frequency data from 1960:I to 2013:II. We obtained most of our data from the FRED with a few exceptions. The news series ($news_t$) is obtained from Valerie Ramey's website.[6] We obtained the consumer sentiment index ($sent_t$) data from the University of Michigan's Survey of Consumers database. The consumer sentiment index comes with two sub-indices, the current economic conditions index (ICC) and the index of consumer expectations (ICE). That is, $sent_t$ is a combination of consumers' perception on the current economic conditions as well as economic conditions in the near future. As can be seen in Figure 2, they are highly correlated each other, thus we report empirical findings mostly with the consumer sentiment index.

We use "total" government expenditures for government spending variables that include transfer payments and interest payments as well as capital transfer payments.[7] All public and private spending variables ($tgov_t, fgov_t, conm_t, invt_t$) are divided by the GDP deflator and population, then log-transformed. $sent_t$ is expressed in natural

[5] Unlike the monetary policy, fiscal policy actions may not be implemented immediately, because in most cases, congress and the goverment work together to determine the government budget prior to the fiscal year.

[6] For detailed explanations on how to construct her news variable, see the following webpage. http://econweb.ucsd.edu/~vramey/research.html#data

[7] Total government expenditures is a broader measure than "government consumption expenditures and gross investment," which is a government component of the total GDP. It is even greater than "government current expenditures" because it includes items that affect government activities in the future such as capital transfer payments and net purchases of nonproduced assets.

logarithm. tr_t denotes the government tax receipts divided by the total GDP. As to the money market control variables, i_t denotes the three month Treasury Bills yield and m_t is the nominal M2, expressed in natural logarithm.

Figure 2 around here

The Survey of Professional Forecasters data were obtained from the Philadelphia Fed. Starting from 1968:IV, forecasters were asked to predict *nominal* defense spending until 1981:II, whereas they were asked to predict *real* federal spending since then. We used the forecasts of the GDP deflator to convert the nominal defense spending data to real spending data.[8] We also noticed 9 changes of base year in the national income and product account (NIPA) during our full sample period. Since the SPF forecast does not reflect such changes, we rescaled all relevant forecast data with 2009 as the common base year.[9] Following Ramey (2011), we use the actual government spending growth minus the forecast of it made one quarter earlier, that is, $g_t - E(g_t|\Omega_{t-1})$ where Ω_{t-1} is the forecasters' information set at time $t-1$, as the fiscal spending shock.

One caveat is that, following Ramey (2011), we combine forecast errors of defense spending growth with those of federal spending growth rates in order to get the data with reasonably long sample period. As she discussed, however, this news variable explains substantial portion of changes in the federal spending growth. Further, we use forecast errors instead of forecasts, which will minimize the cost of combining those two data series. More detailed information on data is provided in Table 1.

Table 1 around here

3.2 Fiscal Spending Shocks and Private activity

As a preliminary exercise, we estimated fiscal spending effects on the private GDP that excludes the government spending component from the total GDP. Figure 3 reports the

[8] Nominal defense spending data from 1968:IV to 1981:II are obtained from Tom Stark at the Philadelphia Fed.

[9] Ramey (2011) and Forni and Gambetti (2014) used growth rates of government spending forecasts without adjusting for changes in base year. This is not ideal because their estimations can be influenced by suddent big changes in their fiscal spending variable up to 9 times.

response function estimates of the private GDP to the fiscal spending shock and to the sentiment shock using 4 alternative identification methods discussed in the previous section. We also report the 95% confidence bands obtained from 500 nonparametric bootstrap simulations.

It should be noted that the fiscal shock has negligible or even negative effects on the private GDP in all models we consider, which is consistent with the findings reported by Ramey (2013). This implies that any evidence of positive responses of the total GDP to the fiscal shock might be mainly due to an expansion of the public sector. Contrary to the fiscal shock, the sentiment shock yields a persistently positive effect on the private GDP over 2 years, which is significant at the 5%. We note that this finding is consistent with the work by Hall (1993), Blanchard (1993), Cochrane (1994), and Bachman and Sims (2012), for example, in the sense that we also find close relationship between consumer sentiment and economic activity. However, our findings contrast sharply with those of Bachman and Sims (2012) qualitatively, because they argue that the government spending shock has a positive effect on consumer confidence during times of slack.[10] In what follows, we show that the government spending shock generates consumer *pessimism* rather than optimism, which then weakens private activity.

Figure 3 around here

Next, we report impulse-response function estimates of private consumption and investment to the fiscal spending shock in Figure 4.[11] Consumption responds significantly positively only in the short-run (less than a year) under *TGOV* and *FGOV* identification schemes, while no meaningful or even significantly negative responses are observed when the *EVAR* models are employed. Investment responses to the fiscal shock turn out to be mostly negligible and insignificant with an exception of those from *SPF* model, where we obtained a significantly negative harmful effect of the fiscal shock on investment. These responses of consumption and investment would be consistent with negligible responses of the private GDP to the fiscal shock reported earlier.

Figure 4 around here

[10] It should be noted, however, that our models do not allow such nonlinearity in the impulse-response function estimations.

[11] Complete response function estimates are reported in the non-for-publication appendix.

One of our major objectives is to identify propagation channels through which fiscal spending shocks possibly affect private activity. We view the consumer sentiment as a potential candidate. For this purpose, we report the impulse-response functions of $sent_t$ to the fiscal spending shock in Figure 5. Note that under the *TGOV*, *FGOV*, ana *SPF* schemes, consumer sentiment rapidly falls below zero immediately after the impact of the fiscal spending shock, which might play a key role in explaining why initially positive responses of consumption quickly deteriorate to negative ones. That is, positive fiscal spending shocks may be interpreted as a sign of weak economy, which might make consumers more pessimistic, resulting in decreases in private spending. Naturally, such changes in consumer sentiment may weaken the effectiveness of the expansionary fiscal policy as consumption and investment fall in response to the fiscal shock. Under the *NEWS* VAR, we observe no meaningful responses of the sentiment, which is consistent with virtually zero-responses of consumption to the fiscal shock under the same model.

In what follows, we also show that "total" consumption responses shown in Figure 4 are more closely related with those of nondurable goods and services consumption rather than durable goods consumption. That is, consumption responses to the fiscal shock seem to be mainly driven by temporary changes in nondurable goods consumption. One way to interpret Figures 4 and 5 together would be the following. When fiscal shocks are anticipated as assumed in the EVAR models, fiscal shocks tend to generate consumer pessimism, resulting in decreases or no meaningful changes in consumption. When fiscal shocks are actually materialized, that is, when identified fiscal shocks are the same as the actual increases in fiscal spending as in *TGOV* and *FGOV* models, consumers respond to it by increasing nondurable goods consumption because they view increases in income as windfall. In other words, they may do so because they believe fiscal shocks are not going to permanently change the direction of the economy towards booms.

Overall, fiscal policy effects on private activity seem to be weak and short-lived if any. Further, the fiscal spending shock seems to fail to improve, even decrease, consumer sentiment, which may cause decreases in consumption and investment. To investigate such possibility, we report and discuss our impulse-response function estimates of private activity to the sentiment shock in next section.

Figure 5 around here

3.3 Consumer Sentiment Shocks and Private activity

Responses of private activity to the sentiment shock sharply contrast with those to the fiscal shock. As can be seen in Figure 6, both investment and consumption respond positively for a prolonged period of time in response to the sentiment shock in all four models. That is, we obtained robust evidence of persistently positive effects of the sentiment shock on private activity. Especially, consumption responses are highly significant at the 5% level for over three years. Even though investment responses are not significant at the 5% level, its point estimates are substantially skewed to the positive area.

Responses of the government spending to the sentiment shock are overall negative, reported in not-for-publication appendix, though either insignificant or marginally significant. This is not surprising because fiscal spending tends to be counter-cyclical. That is, government spending normally falls below the trend when the private GDP (consumption and investment) rises during economic booms.

In contrast to the responses to the fiscal shock, the impulse-response function estimates to the sentiment shock are not invariant to alternative orderings since $sent_t$ is put after the fiscal variable and private spending variables. For robustness check, we implemented the same analysis with the sentiment variable ordered next to $\mathbf{g}_t$. We also experimented with the sentiment variable ordered last. All results were qualitatively very similar. That is, our findings on the sentiment effect are quite robust to alternative orderings.[12]

Figure 6 around here

3.4 Fiscal Shock and the Role of a Sentiment Channel

We observe that all four models including the two EVAR models imply solid positive effects of the sentiment shock on private spending. We note that these findings may provide some useful insights on the ineffectiveness of the fiscal policy in promoting private activity as reported in the previous section. That is, the fiscal spending shock may not be able to stimulate consumption and investment if it fails to generate consumer

[12] All results are available upon request.

(or entrepreneur) optimism as can be seen in Figure 5. In other words, the effectiveness of the fiscal spending shock may critically hinge upon a sentiment channel.

Observing sudden increases in the government deficit, consumers may revise down their economic growth forecasts in the future, interpreting such policy actions as a clear sign of serious economic downturns, which may persist for a while. In this sense, our conjecture is consistent with the "news" effect discussed in Cochrane (1994) and Bachman and Sims (2012), even though Bachman and Sims (2012) are more optimistic on the role of the expansionary fiscal policy.

One may argue against this conjecture by the following logic. Consumption and investment may fall after the spending shock occurs for some unknown reason, and the sentiment passively reflect such decreases in private GDP. We are skeptical to such a possibility for the following reasons.

As we can see in Figure 4, consumption tends to rise for a short period of time in response to the fiscal shock when $TGOV$ and the $FGOV$ models are employed, whereas consumer sentiment falls almost immediately after the impact under these models. These responses are inconsistent with a view that consumer sentiment passively reflects changes in the current private GDP. If that is the case, the sentiment response should have resembled initially positive responses of consumption for about a year since the impact of the fiscal shock. Furthermore, it should be noted that the consumer sentiment is constructed to measure consumers' perception on the future economic conditions as well as the current conditions. Therefore, immediate declines of the sentiment which contrast to short-run increases in consumption imply that consumer sentiment does not passively reflect changes in private activity. Put it differently, our response function estimates overall imply the existence of a sentiment channel where the sentiment plays a leading role in determining private activity.

4 Additional VAR Analyses

4.1 Effects on Durable and Nondurable Goods Consumption

This subsection estimates the effects of the fiscal and the sentiment shocks on two sub-components of private consumption: consumption of durable goods ($cond_t$) and consumption of non-durable goods and services ($conn_t$). One motivation of this exercise is that consumers tend to adjust consumption pattern for durable goods such as automobiles and houses when they expect persistent changes in economic conditions,

while non-durable goods consumption might be also influenced by temporary changes in incomes. For this purpose, we replace $conm_t$ with $cond_t$ or $conn_t$ in (2), then re-estimate the VAR models. Impulse-response function estimates are reported in Figures 7 and 8.

Overall, durable good consumption does not respond significantly to the fiscal shock with an exception of *SPF* model which shows significantly *negative* responses. Non-durable good consumption exhibit significantly positive responses for a short period of time under the *TGOV* and *FGOV* schemes. We note that nondurable good consumption shows significantly positive responses for a while under the *SPF* identification scheme. Note also that durable good consumption responses under the same scheme exhibit much stronger decreases that dominate the positive responses of nondurable good consumption, which is consistent with decreases in the total consumption reported earlier.

Response function estimates of total consumption to the fiscal shock shown in Figure 4 resemble those of nondurable goods consumption in Figure 8 more than durable goods consumption responses in Figure 7. Put it differently, fiscal shock effects on total consumption are overall driven by responses of $conn_t$ instead of those of $cond_t$. Since consumers tend to buy more durable goods such as automobiles and home appliances when they are confident that the economy would continue to expand, these findings imply fiscal shocks fail to generate consumer optimism on economic conditions in the near future, which seems consistent with insignificant and negligible responses of durable goods consumption to the fiscal shock.

In contrast, total consumption responses to the sentiment shock are somewhat in between those of durables and nondurables consumption responses. That is, in response to a positive sentiment shock, durable goods consumption also rises significantly and persistently no matter what identification methods are employed.

Figures 7 and 8 around here

4.2 Effects on Private Employment

As Ramey (2013) points out, fiscal spending effects on private jobs may differ depending on the nature of government spending. If fiscal spending occurs mainly through government purchases of private sector goods and services, the fiscal spending shock

may increase private employment. On the contrary, increases in government value added that include mainly compensation of public employees may decrease private sector jobs as the public sector employment rises given the labor force, eroding the private sector jobs.

We estimate and report private sector labor market effects of the fiscal shock as well as those of the sentiment shock. For this purpose, we replace $invt_t$ and $conm_t$ in (2) with private jobs ($pjob_t$). Results are reported in Figure 9. We observe that fiscal shocks again fail to increase private employment when *TGOV*, *FGOV*, and *SPF* models are employed, while it temporarily increases private jobs in the short-run when *NEWS* model is used. Overall, responses of the private sector jobs are either insignificant or even negative. On the contrary, the sentiment shock has a solid positive effect on private employment that lasts several years since the shock occurs no matter what identification methods are employed.

In a nutshell, private labor market effects of the fiscal spending shock are weak and mostly insignificant, which contrast sharply with the sentiment effect that results in persistently positive increases in private sector jobs. These findings might explain why recent increases in fiscal spending fail to reduce unemployment for a prolonged period of time after the Great Recession. That is, falling private spending may weaken job creation effects of the government spending shock as it creates consumer pessimism in the economy, which in turn reduces private spending.

Figure 9 around here

4.3 Effects on Private Wages

Private wages may rise in response to the fiscal shock in either cases of government purchases of private sector goods or increases in government value added. On the other hand, private sector wages may fall if rational consumers, expecting a tax hike in the near future, increase the labor supply sufficiently. If fiscal shocks result in decreases in private activity, as implied by our estimation results, there will be negative effects on private wages due to decreases in consumption and investment.

We empirically appraise the effects of the fiscal shock on private wages by replacing $invt_t$ and $conm_t$ in (2) with private wages ($pwag_t$). As can be seen in Figure 10, we

observe slightly positive effects of the fiscal shock on private wages that are mostly insignificant from three VAR specifications with an exception of *SPF* model. That is, potentially positive effects of fiscal spending shocks are likely to be muted by negative responses of private spending, which result in decreases in demand for private sector goods and services. On the contrary, private wages respond persistently and positively to the sentiment shock for over three years that are significant at the 5% levels. Solid increases in private wages seem to be caused by increases in the demand for labor, because sentiment shocks promote private activity persistently.

Figure 10 around here

4.4 Current or Forward Looking Sentiment?

We further experiment our analyses with two sub-indices of the consumer sentiment index: the index of current economic conditions (ICC) and the index of consumer expectations (ICE). For example, Bachman and Sims (2012) use ICE instead of the combined sentiment index used in the present paper. Even though their approach has some merits, the forward-looking sentiment data (ICE), behaves very similarly to the current economic conditions index (ICC) as we saw in Figure 2.

Nonetheless, we estimate VAR models after replacing the consumer sentiment index ($sent_t$) with these two sub-indices. Results are reported in Figures 11 and 12. We obtain very similar impulse-response functions as the ones reported in Figure 4. We also estimate and report the responses of these sentiment sub-indices to the fiscal shock in Figure 13, which again resemble those in Figure 5 with the combined sentiment data. Therefore, our results are robust to the choice of alternative sentiment variables.

Figures 11, 12, and 13 around here

4.5 Sub-Sample Analysis

We also investigate the consequences of combining forecast errors for the real defense spending growth rate with those for the real federal spending growth rate via the SPF data. Following Ramey (2011), we combined these two series in order to obtain long-horizon data. Key results from a shorter sample period from 1981:III to 2013:II, the period with the real federal spending growth rate forecast errors, are reported in Figure 14.[13]

In a nutshell, we obtain very similar impulse-response functions as the ones reported previously. Consumption and investment respond significantly negatively to the fiscal shock, while they rise persistently when the sentiment shock occurs.

Figure 14 around here

4.6 Nonlinear Model Estimates

Lastly, we study the possibility of nonlinear responses of the sentiment to the fiscal shock. For this purpose, we employ the following two-regime threshold VAR (TVAR) model. Abstracting from deterministic terms, we use,

$$\mathbf{x}_t = \left(\sum_{j=1}^{p} \mathbf{A}_j^R \mathbf{x}_{t-j} \right) I(\tau_{t-d} < \tau^*) + \left(\sum_{j=1}^{p} \mathbf{A}_j^B \mathbf{x}_{t-j} \right) I(\tau_{t-d} > \tau^*) + \varepsilon_t, \tag{3}$$

where I is the indicator function and τ_{t-d} is a d-period lagged threshold variable that represents the present state of the economy. We use the (total) GDP growth rate for this threshold variable in order to investigate nonlinear responses of the sentiment to the fiscal shock during different phases of the business cycle. $\mathbf{A}_j^R(L)$ and $\mathbf{A}_j^B(L)$ are lag polynomial matrices during economic recessions ($\tau_{t-d} < \tau^*$) and booms ($\tau_{t-d} > \tau^*$), respectively. We use a one-dimensional grid search method to identify τ^* by minimizing $\ln \left\| \hat{\Sigma} \right\|$, where $\hat{\Sigma}$ is the variance-covariance matrix given a fine grid point $\tau_{t-d} \in \{\tau_{0.15}, ..., \tau_{0.85}\}$. We trimmed 15% of the data from each side to make sure we use enough number of observations in each regime. Conventional delay parameter $d = 1$ was employed.

[13] All results are reported in the not-for-publication appendix and are available from authors.

It should be noted that we need to reduce the dimension of our VAR system substantially for proper estimations of this type of TVAR models. For example, our $FGOV$ model with three lags requires estimations of $8^2 \times 3$ reduced-form coefficients for each regime, which may not be feasible with a small grid point such as $\tau_{0.15}$, because not enough number of observations may be used to estimate coefficients with such specifications. Since we are mainly interested in nonlinear responses of the sentiment to the fiscal spending shock, we employ a simple trivariate TVAR model with $\mathbf{x}_t = [g_t \;\; priy_t \;\; sent_t]'$, where $g_t = tgov_t, \; fgov_t, \; ramy_t, \; spf_t$. Regime-specific impulse-response function estimates of the sentiment to the fiscal shock are reported in Figure 15.[14]

From all 4 VAR models, we obtain solid negative responses of the sentiment to the fiscal shock in both regimes, which sharply contrasts to the work of Bachman and Sims (2012). Instead of finding positive (optimism) responses, we observed that the fiscal spending shock during recessions generates consumer pessimism as in our previous results from the linear model. We also obtain solid negative responses of $sent_t$ to the fiscal shock during economic booms as well. Put it differently, our evidence of consumer pessimism in response to the fiscal shock seems to be robust to different states of the economy, which is consistent with the work of Owyang, Ramey, and Zubairy (2013) and Ramey and Zubairy (2014). We also note that consumer sentiment shows improvement for a while since the occurence of the fiscal shock during economic booms especially in SPF model. However, $sent_t$ rapidly falls and enters a negative region, showing no persistent improvement in the sentiment.

Figure 15 around here

5 Conclusion

The recent Great Recession accompanied by the slow recovery triggered an active debate on the effectiveness of the fiscal policy in stimulating economic growth. Empirical evidence is at best mixed and the economics profession has failed to reach a consensus.

[14] We report regime-specific impulse-response function estimates based on the point estimates, since the main objective of this exercise is to see whether there's evidence of quaitatively different responses of $sent_t$ in different phases of business cycle. For more rigorous analysis, we need to estimate the generalized impulse-response functions for nonlinear models (Koop, Pesaran, and Potter, 1996).

This paper takes a different road and attempts to understand what influences the effects of the fiscal policy on the private sector economy. For this purpose, we introduce the role of consumer sentiment in a propagation mechanism for government spending shocks towards economic activity in the private sector. As Ramey (2011) points out, statistical inferences may be influenced by alternative identification methods for the spending shock. Thus, we employ an array of recursively identified VAR models as well as the two types of the expectational VAR model. We obtain solid evidence of the existence of a consumer sentiment channel that is robust to alternative identification methods.

Our major findings are as follows. First, our empirical results imply a very weak, even negative effect of the government spending shock on private sector spending such as consumption and investment, which confirms the conclusion by Ramey (2013). On the contrary, innovations in the consumer sentiment generate solid positive responses of consumption and investment for a prolonged period of time. Third, consumer sentiment negatively responds to the government spending shock since the impact, while under the conventional VAR schemes, consumption shows positive responses, mainly from nondurable good consumption, for a brief period of time, then quickly deteriorates to a negative region. This implies that the fiscal policy may become ineffective in stimulating economic activity because it generates consumer pessimism that results in subsequent decreases in consumption and investment. That is, consumer sentiment channel may be a key in understanding the propagation mechanism of fiscal policy shocks. Similar evidence are also obtained from private sector labor market variables. Employment and real wages in the private sector respond significantly positively only to the sentiment shock.

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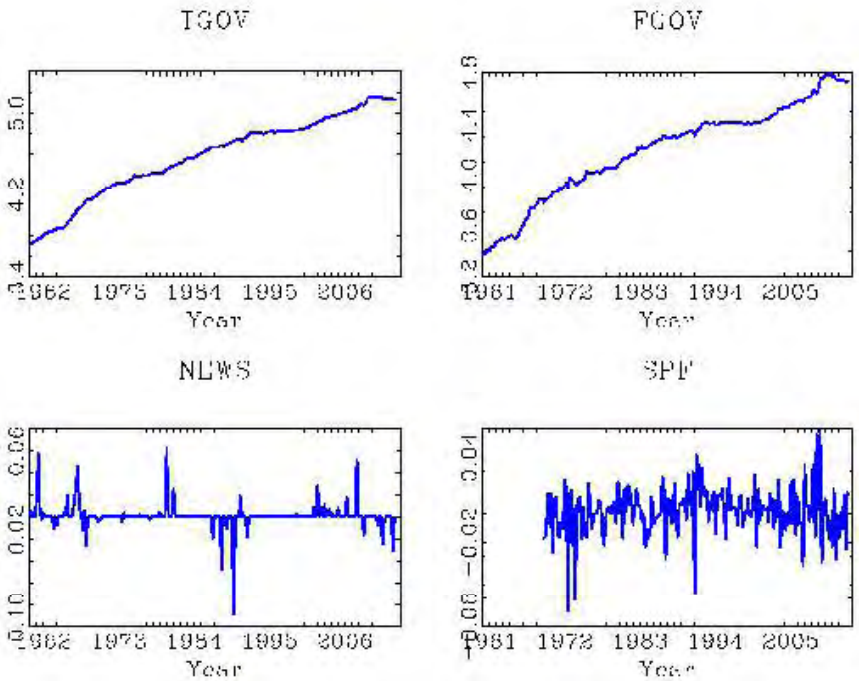
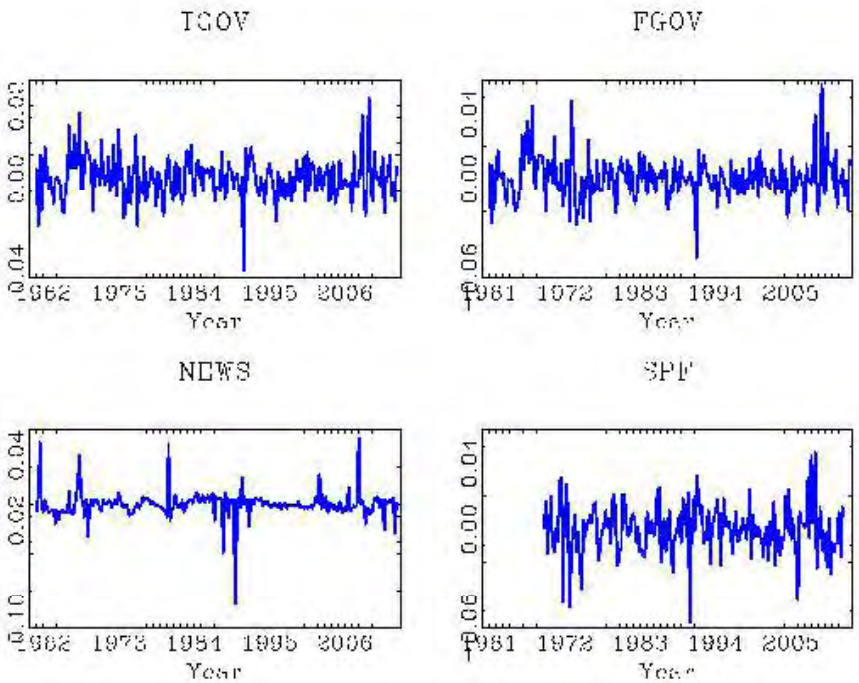
Figure 1. Government Spending Data

Level Variables

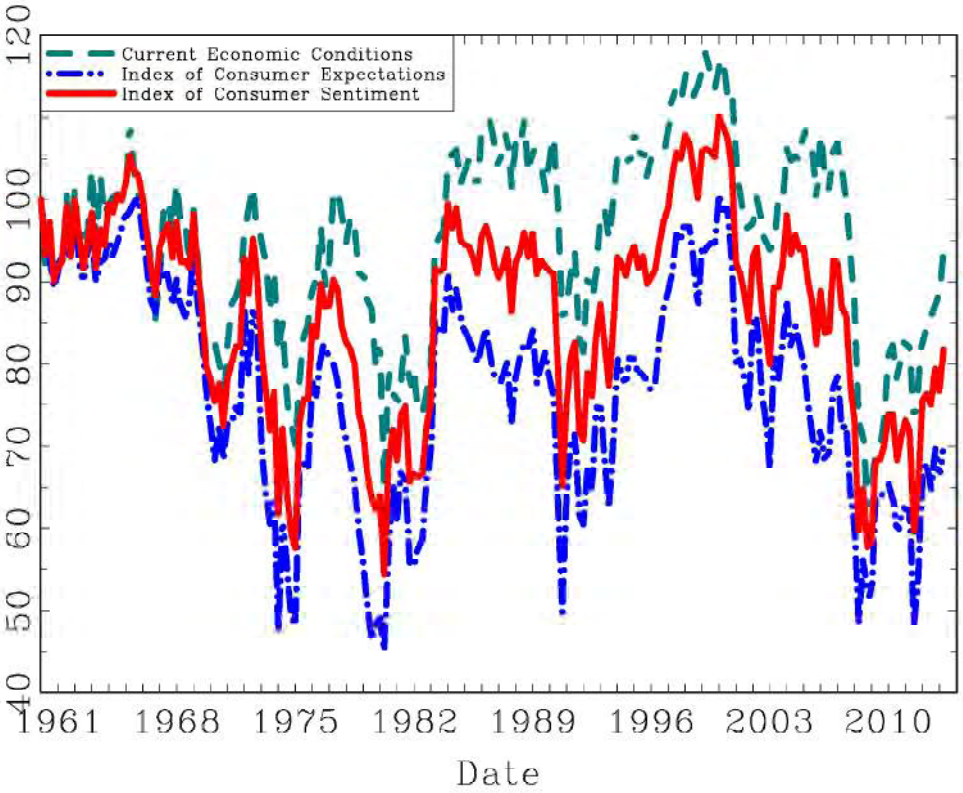


Residuals



Note: TGOV, FGOV, NEWS, and SPF denote the total government spending, federal government spending, news variable (Ramey, 2011), and SPF variable (Ramey, 2011). Residuals are obtained from VAR regressions.

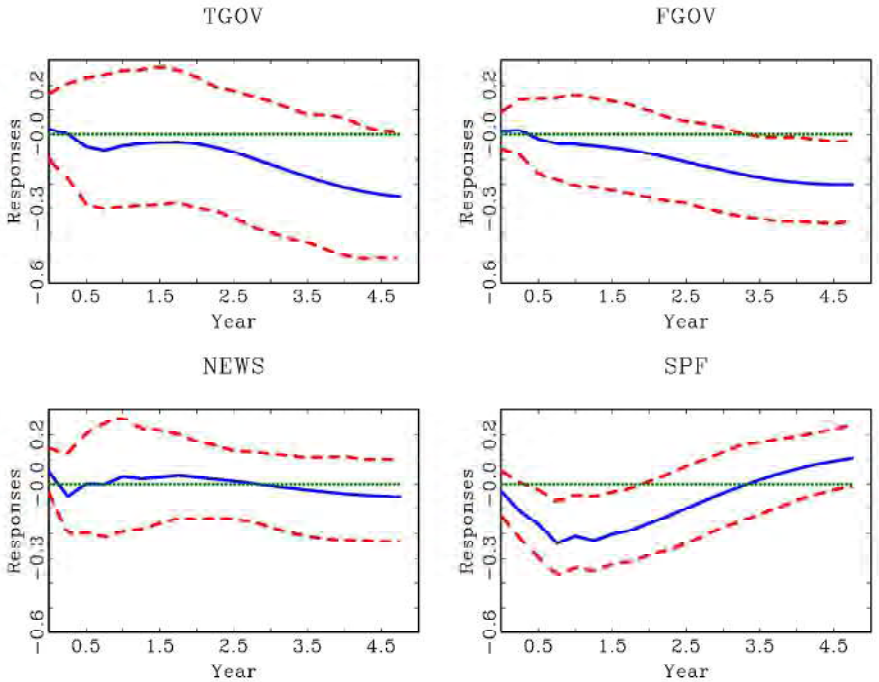
Figure 2. Consumer Sentiment Index Data



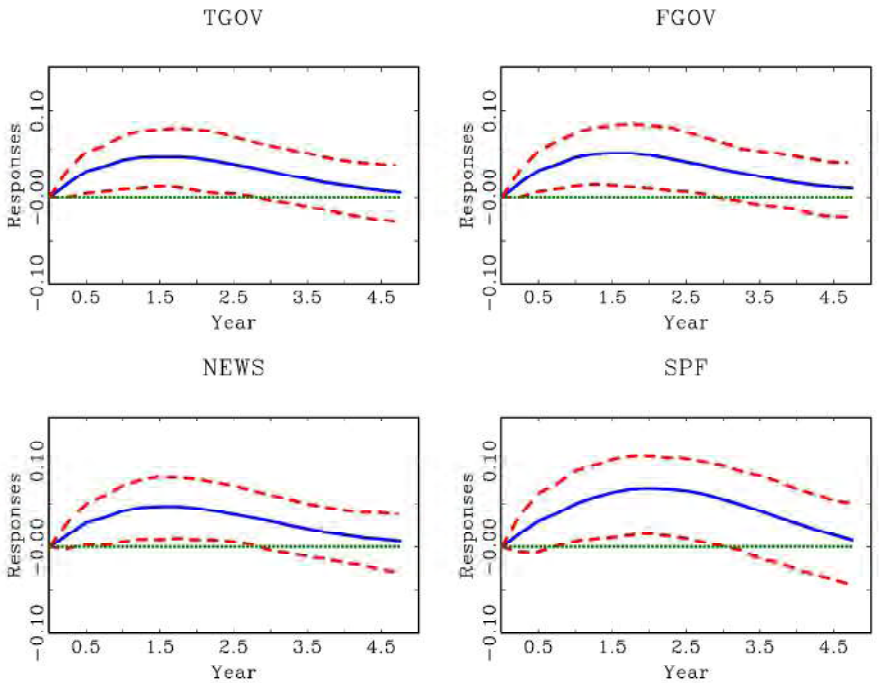
Note: We obtained the data from Surveys of Consumers website at the University of Michigan. All indices are normalized to be 100 in 1960Q1 by authors.

Figure 3. Private GDP Responses

Fiscal Shock



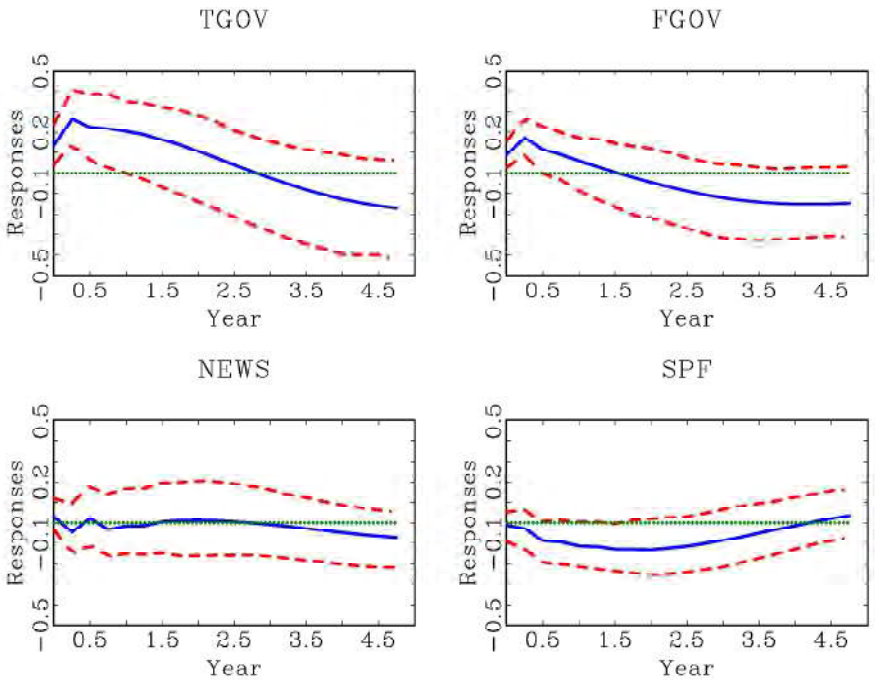
Sentiment Shock



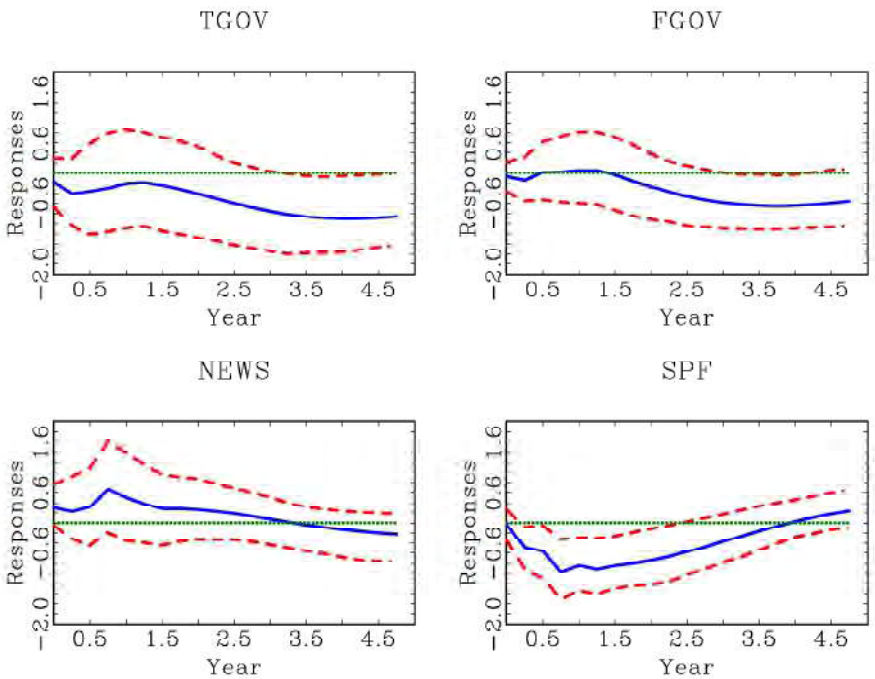
Note: Private GDP is obtained by substracting the government spending from the total GDP. We report responses of the private GDP to the fiscal spending shock from each model. Dashed lines are the 95% confidence band of the response function from 500 nonparametric bootstrap simulations.

Figure 4. Private Activity Responses to the Fiscal Shock

Consumption Responses

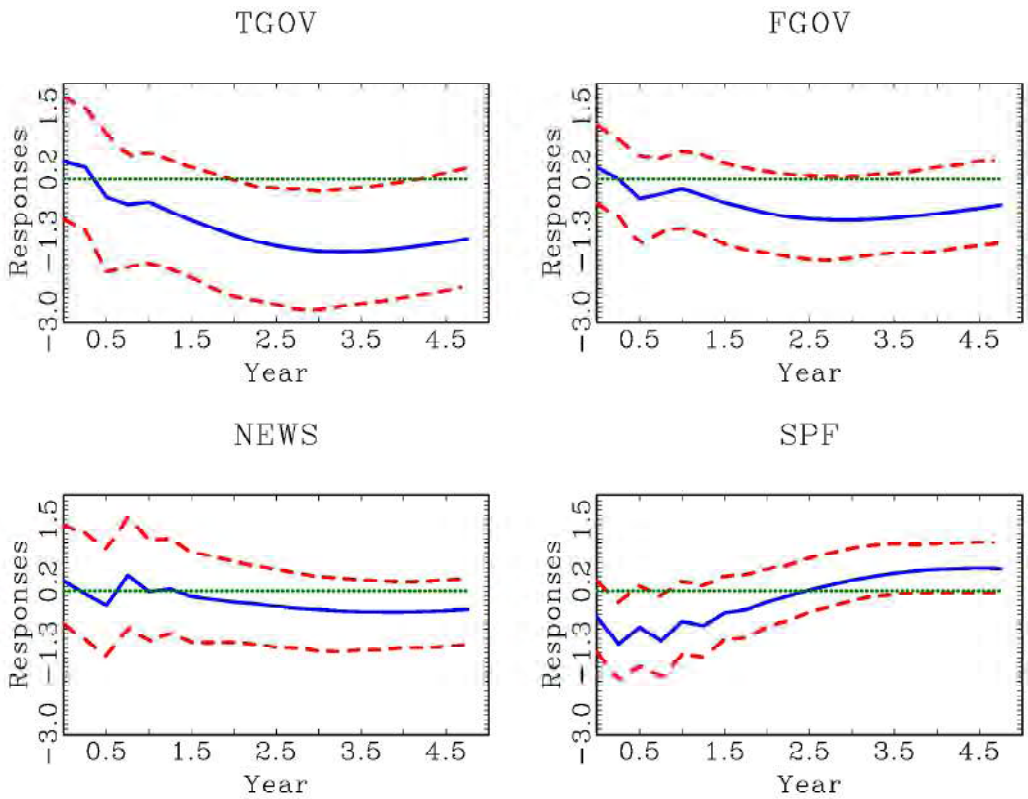


Investment Responses



Note: Dashed lines are the 95% confidence band of the response function from 500 nonparametric bootstrap simulations.

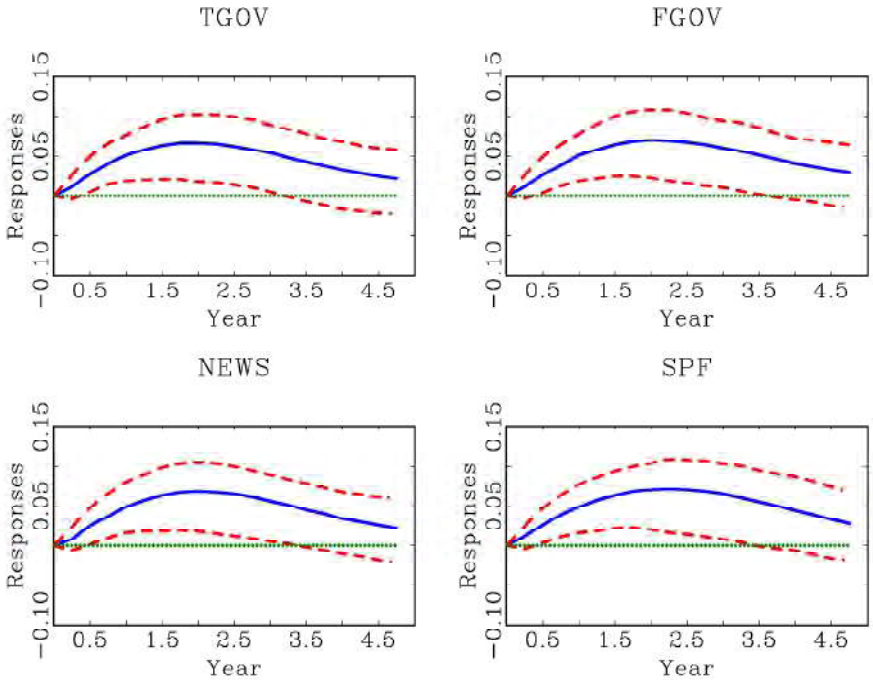
Figure 5. Sentiment Responses to the Fiscal Shock



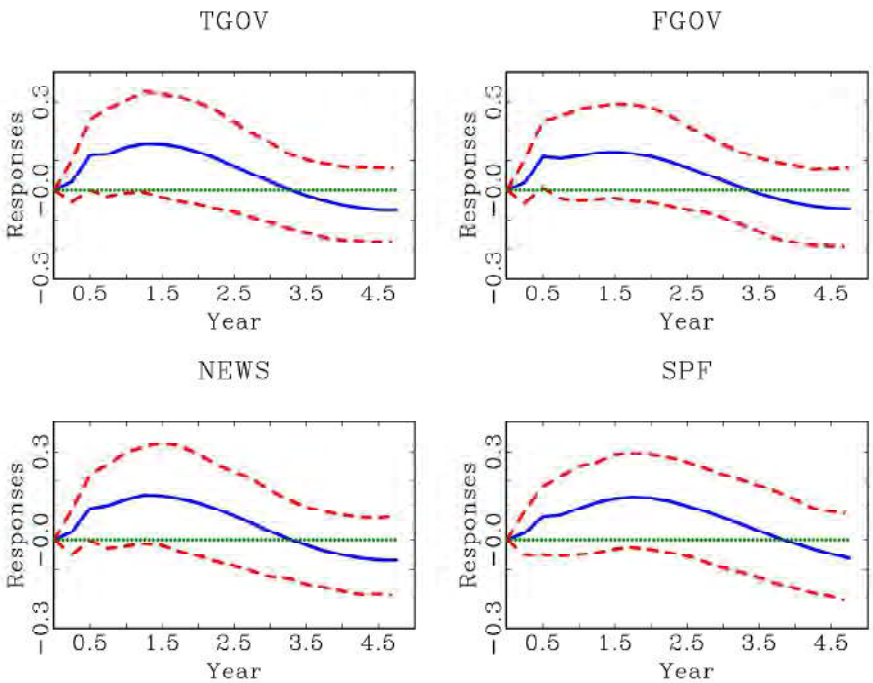
Note: Dashed lines are the 95% confidence band of the response function from 500 nonparametric bootstrap simulations.

Figure 6. Private Activity Responses to the Sentiment Shock

Consumption Responses

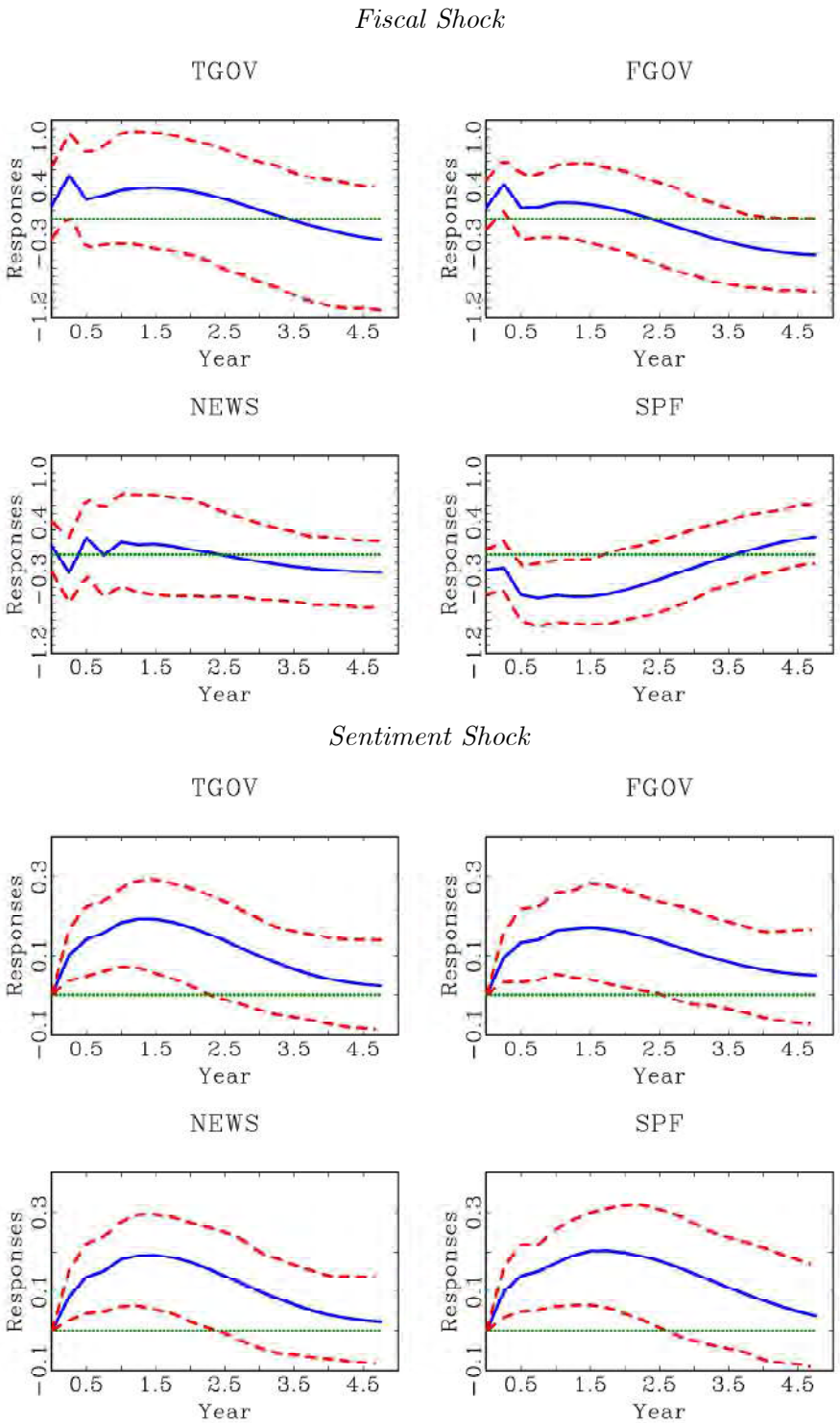


Investment Responses



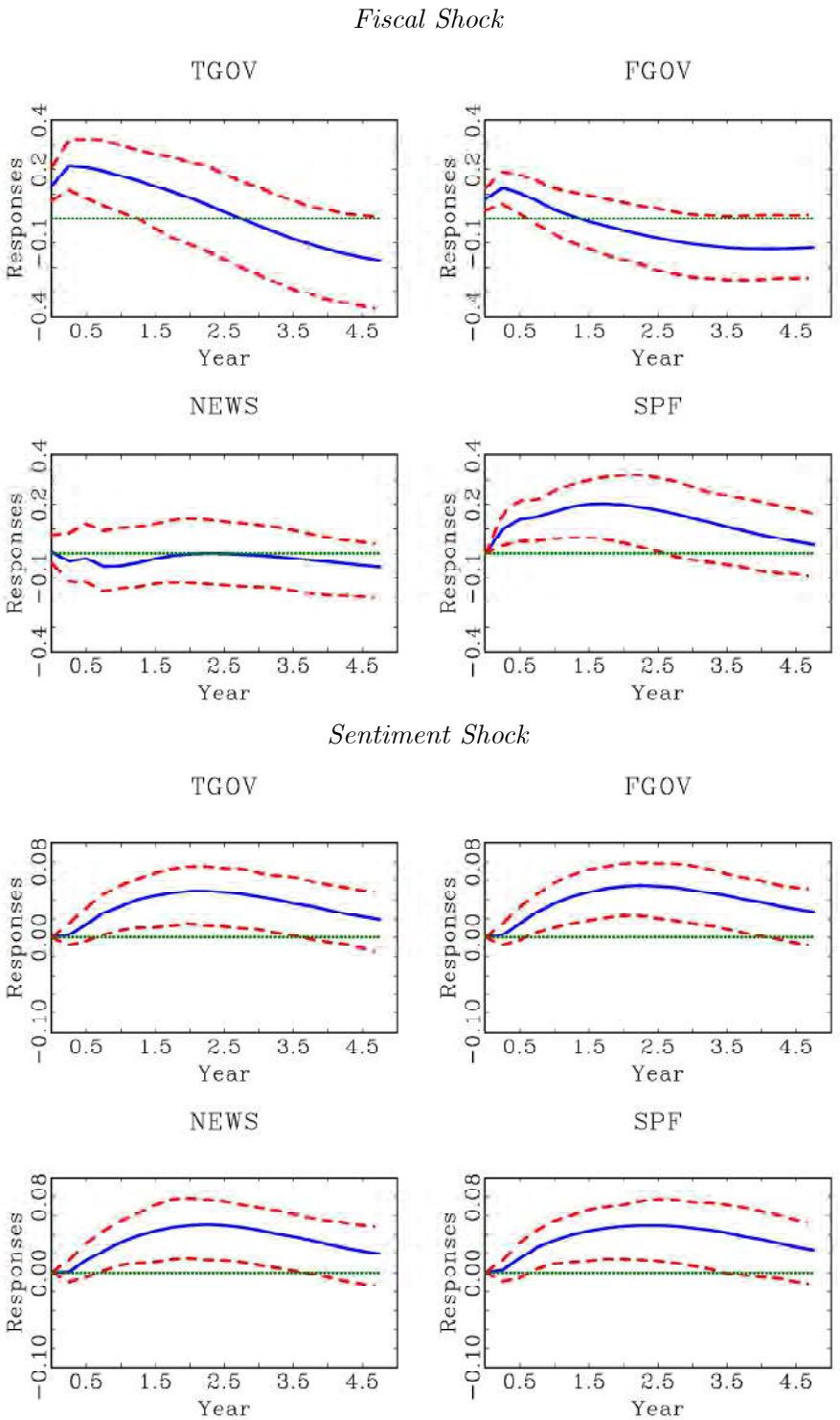
Note: Dashed lines are the 95% confidence band of the response function from 500 nonparametric bootstrap simulations.

Figure 7. Responses of Durable Goods Consumption to the Fiscal Shock



Note: Dashed lines are the 95% confidence band of the response function from 500 nonparametric bootstrap simulations.

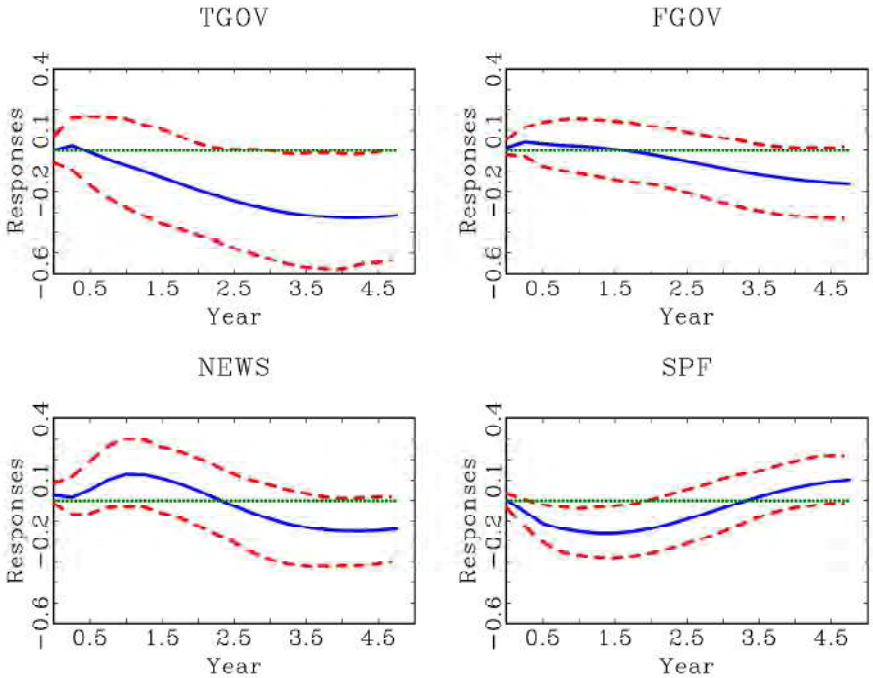
Figure 8. Responses of Nondurables Good and Services Consumption



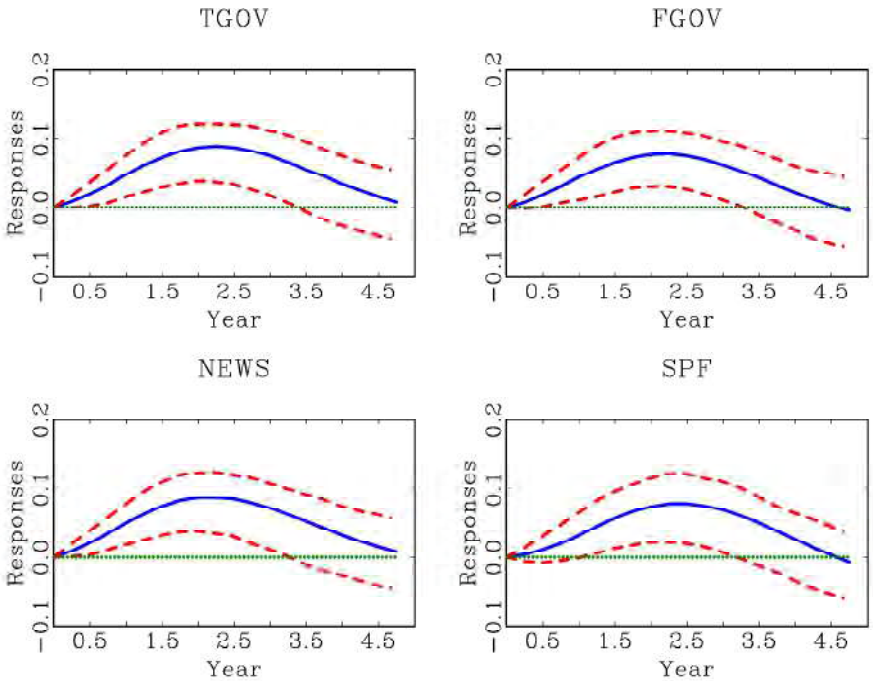
Note: Dashed lines are the 95% confidence band of the response function from 500 nonparametric bootstrap simulations.

Figure 9. Responses of Private Job

Fiscal Shock



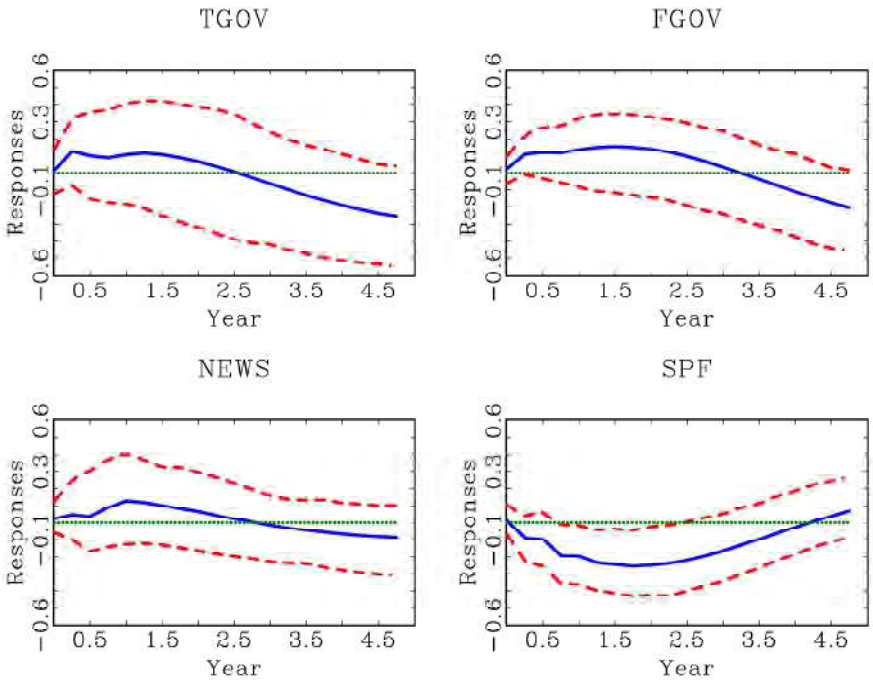
Sentiment Shock



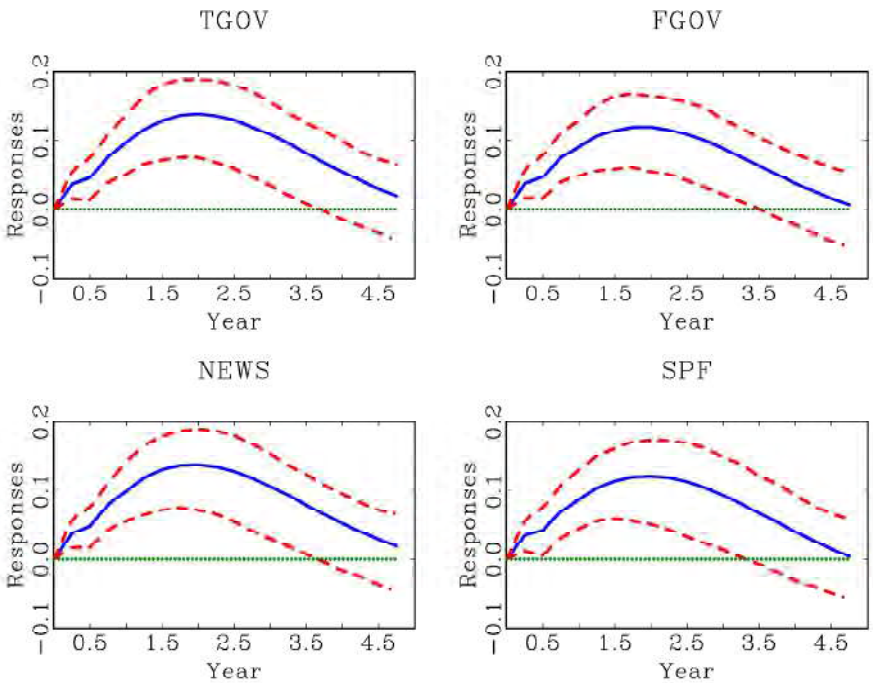
Note: Dashed lines are the 95% confidence band of the response function from 500 nonparametric bootstrap simulations.

Figure 10. Responses of Private Wage

Fiscal Shock



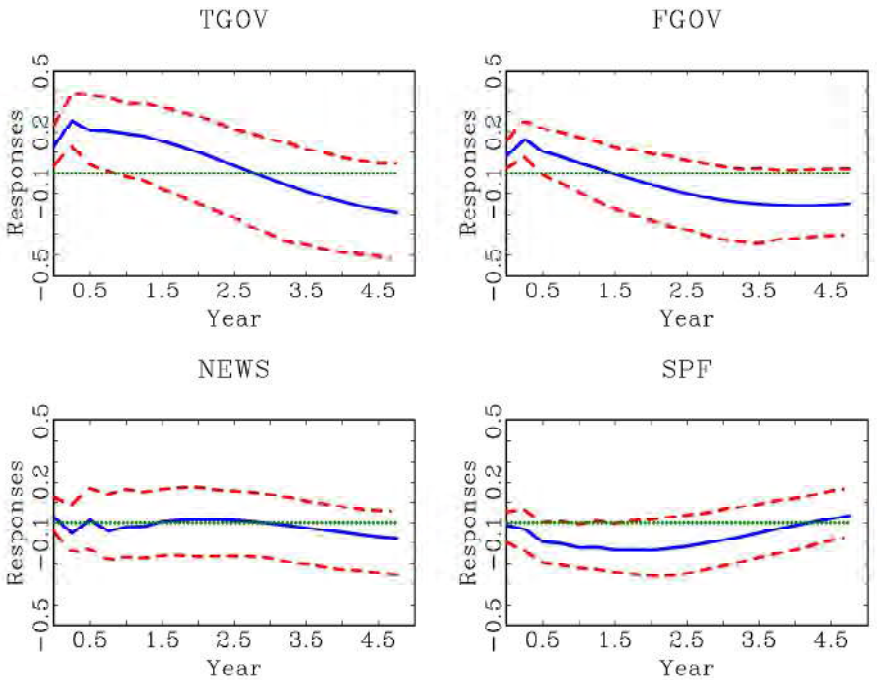
Sentiment Shock



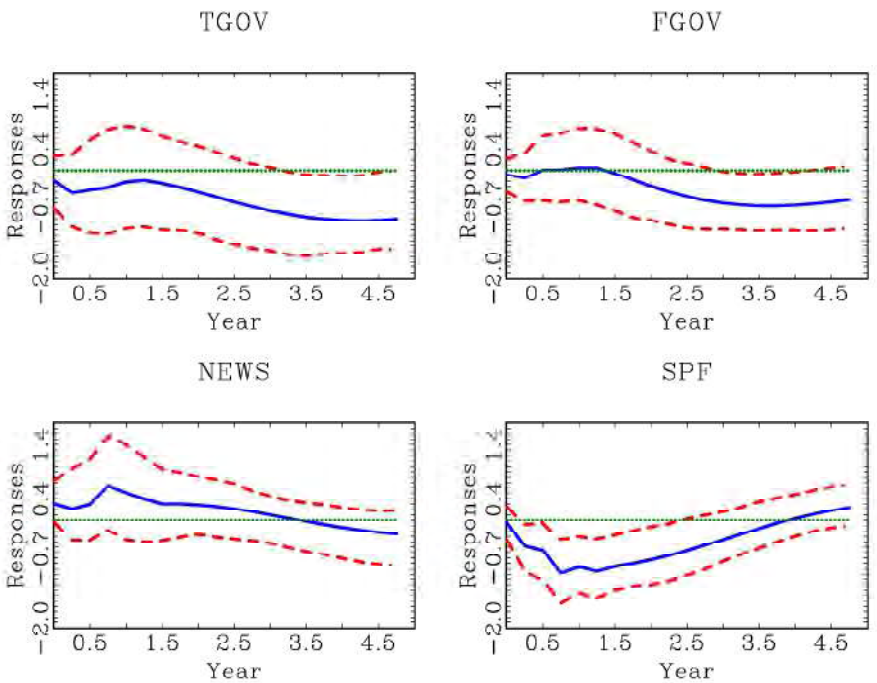
Note: Dashed lines are the 95% confidence band of the response function from 500 nonparametric bootstrap simulations.

Figure 11. Responses to the Fiscal Shock with ICE

Consumption Responses



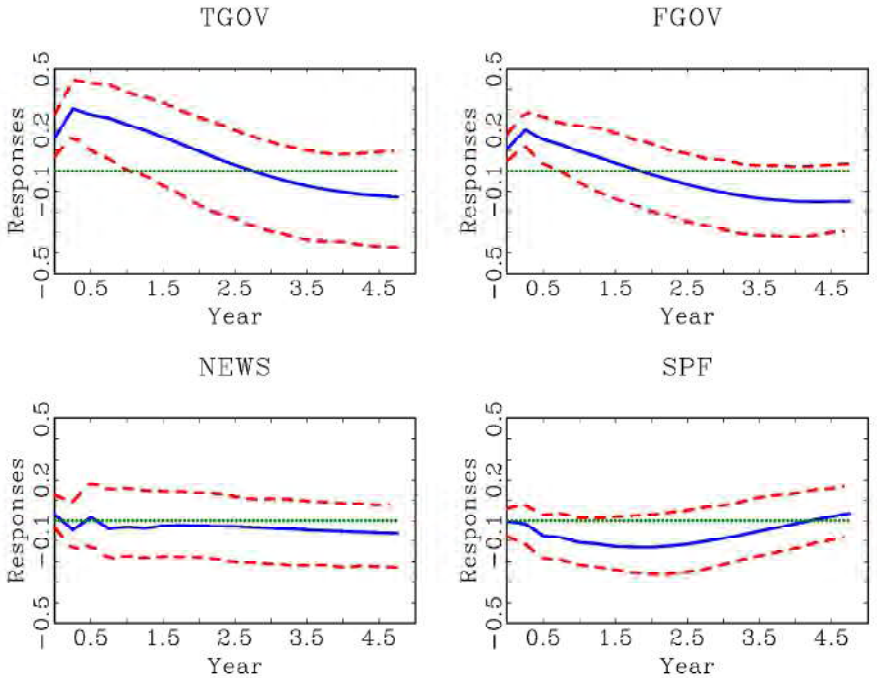
Investment Responses



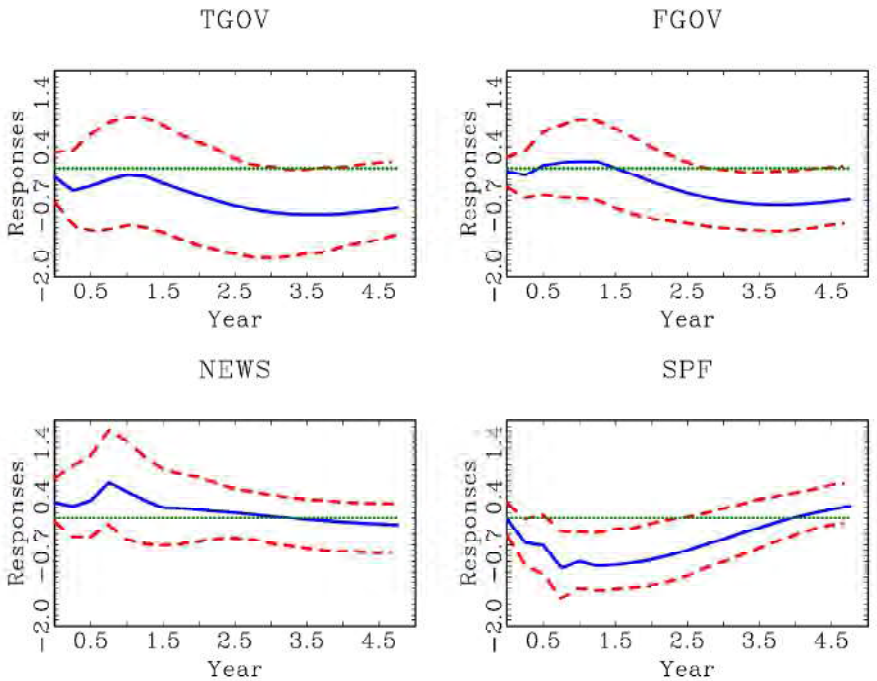
Notes: ICE denotes the index of consumer expectations.

Figure 12. Responses to the Fiscal Shock with ICC

Consumption Responses

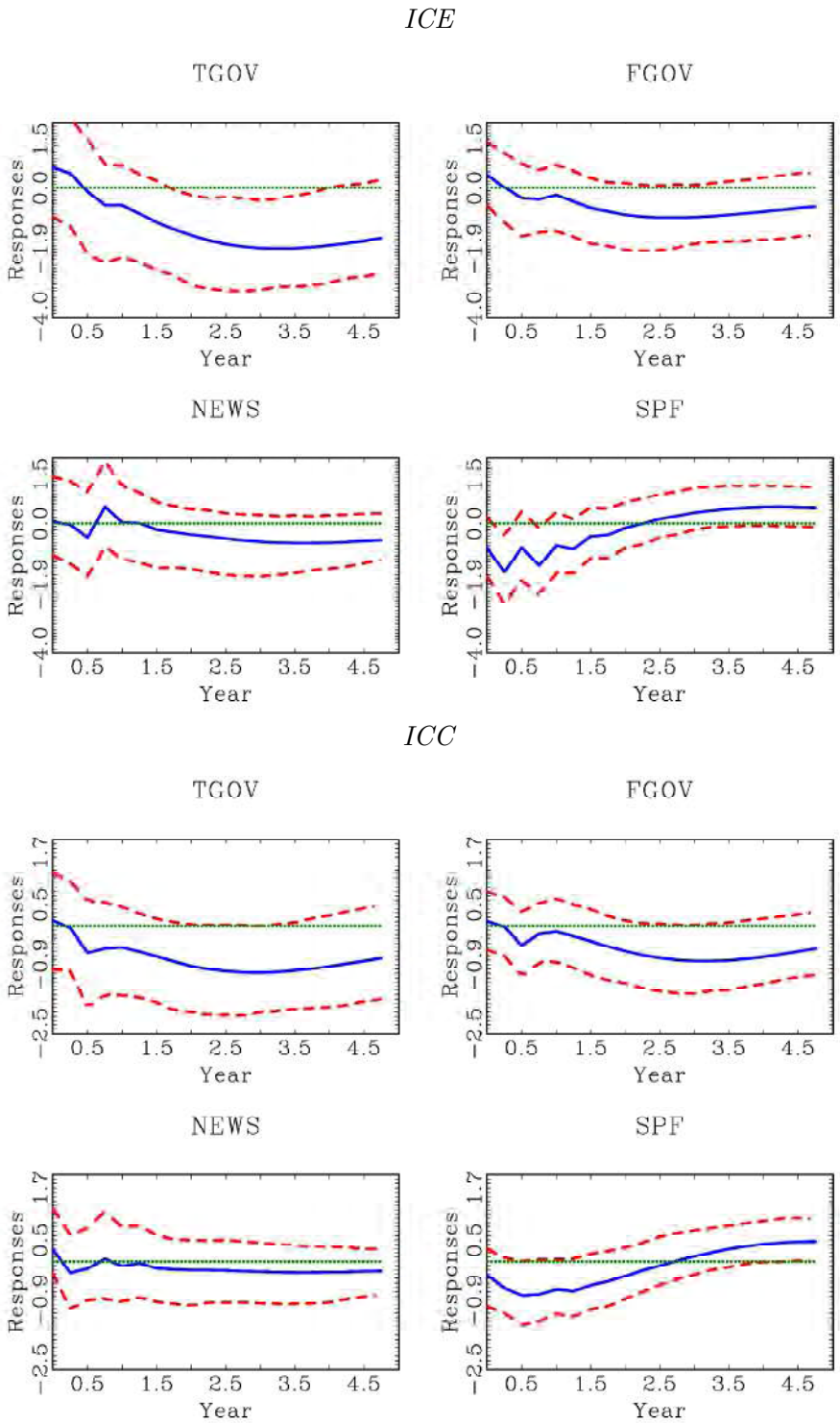


Investment Responses



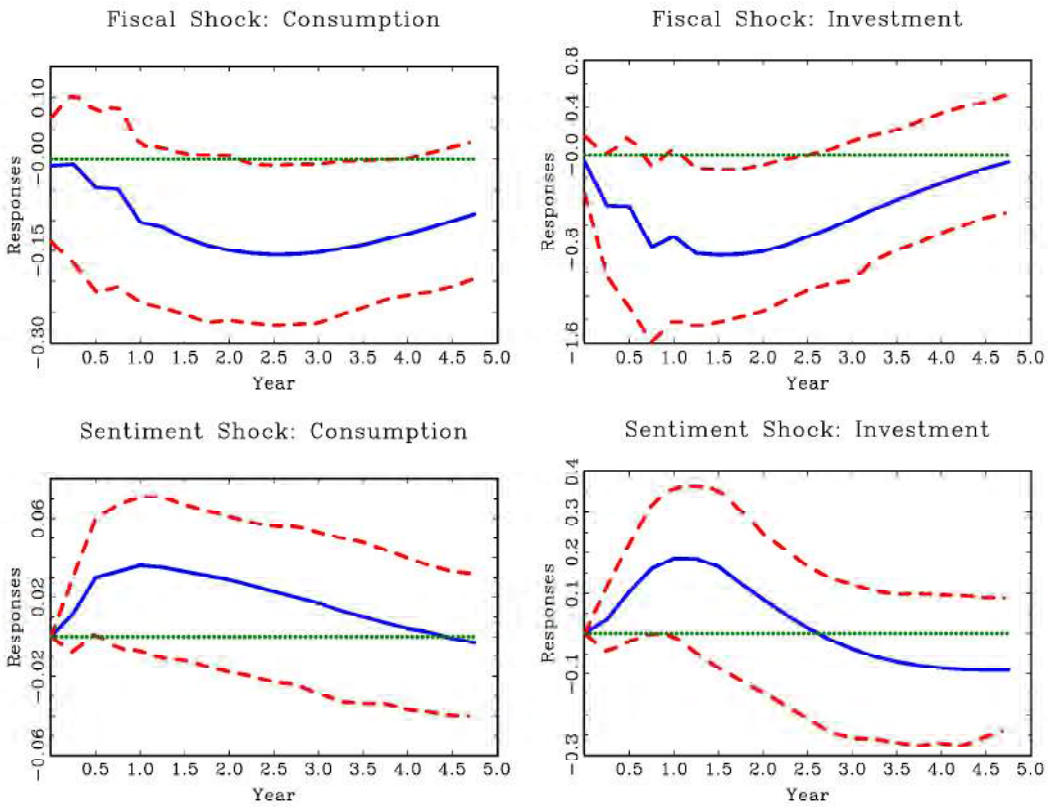
Notes: ICC denotes the index of current economic conditions.

Figure 13. Sentiment Responses to the Fiscal Shock: Sub-Indices



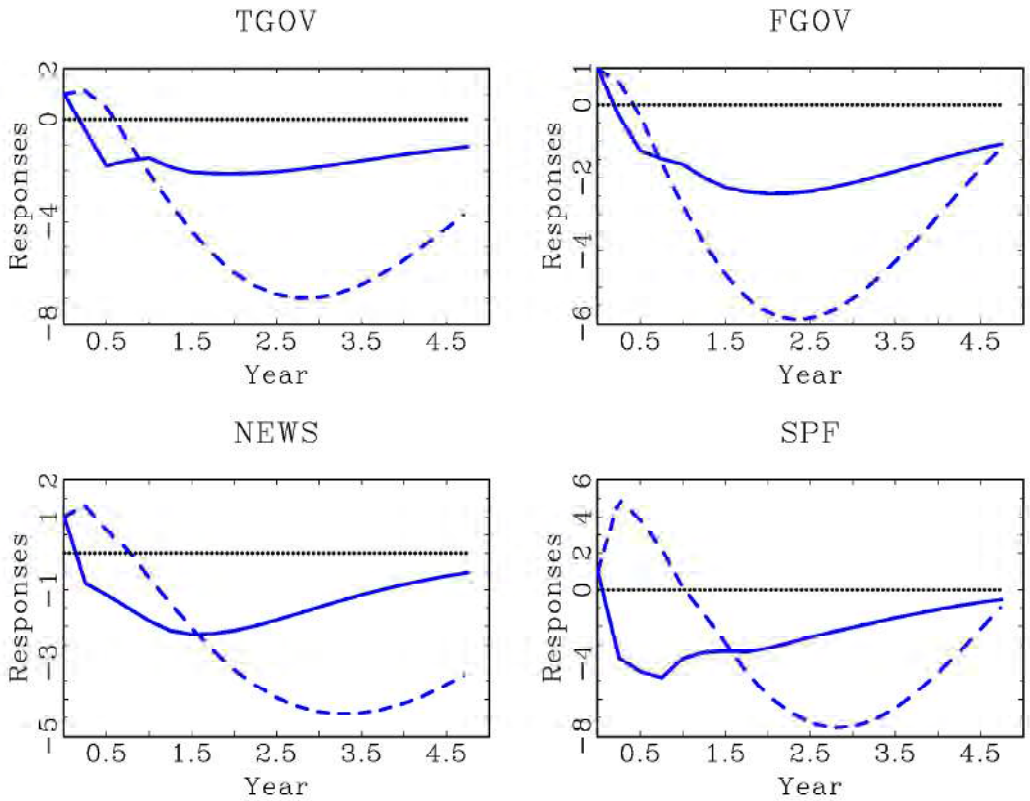
Notes: ICE and ICC denote the index of consumer expectations and the index of current economic conditions, respectively.

Figure 14. Sub-Sample Analysis: 1981:III - 2013:II



Notes: Response function estimates are from *SPF* model with the *SPF* forecast error of the federal spending growth rate excluding the forecast error of the defense spending growth rate.

Figure 15. Sentiment Responses to the Fiscal Shock: Threshold VAR



Notes: Sentiment responses to the fiscal shock are reported. The threshold variable (τ_{t-1}) is one-period lagged log differenced real (total) GDP. Solid lines are responses during recessions ($\tau_{t-1} < \tau^*$), while dashed lines are those in booms ($\tau_{t-1} > \tau^*$). The estimates are from tri-variate VAR models with the fiscal variable, the private GDP, and the sentiment variable.

Table 1. Data Descriptions

Data ID	Description
GDP	Gross Domestic Product
PCE	Personal Consumption Expenditures
PCEDG	Personal Consumption Expenditures: Durable Goods
PCEND	Personal Consumption Expenditures: Nondurable Goods
PCES	Personal Consumption Expenditures: Services
GPDI	Gross Private Domestic Investment
W068RCQ027SBEA	Government total expenditures
W019RCQ027SBEA	Federal government total expenditures
GDPDEF	Gross Domestic Product: Implicit Price Deflator, Index 2009 =100
W006RC1Q027SBEA	Federal government current tax receipts
POP	Total Population: All Ages including Armed Forces Overseas
TB3MS	3-Month Treasury Bill: Secondary Market Rate
M2	M2 Money Stock
USPRIV	All Employees: Total Private Industries
A132RC1Q027SBEA	Compensation of employees: Wages and salaries, Private industries
UMCSENT	Consumer Sentiment Index: Survey of University of Michigan
SPF	Survey of Professional Forecasters from Philadelphia Fed.

Note: We obtained most data from the Fred. UMCSENT is from the Surveys of Consumers website at the University of Michigan. "News" variable is from Valerie Ramey's website. "SPF" denotes the mean responses of the real federal government spending data from the Survey of Professional Forecasters database obtained from the Philadelphia Fed website. The data prior to 1981 (government military spending data) is obtained from Tom Stark at the Philadelphia Fed.

Figure A1. Private GDP VAR

$\mathbf{x}_t = [fgov_t \;\; priy_t \;\; sent_t \;\; tr_t \;\; i_t \;\; m_t]'$

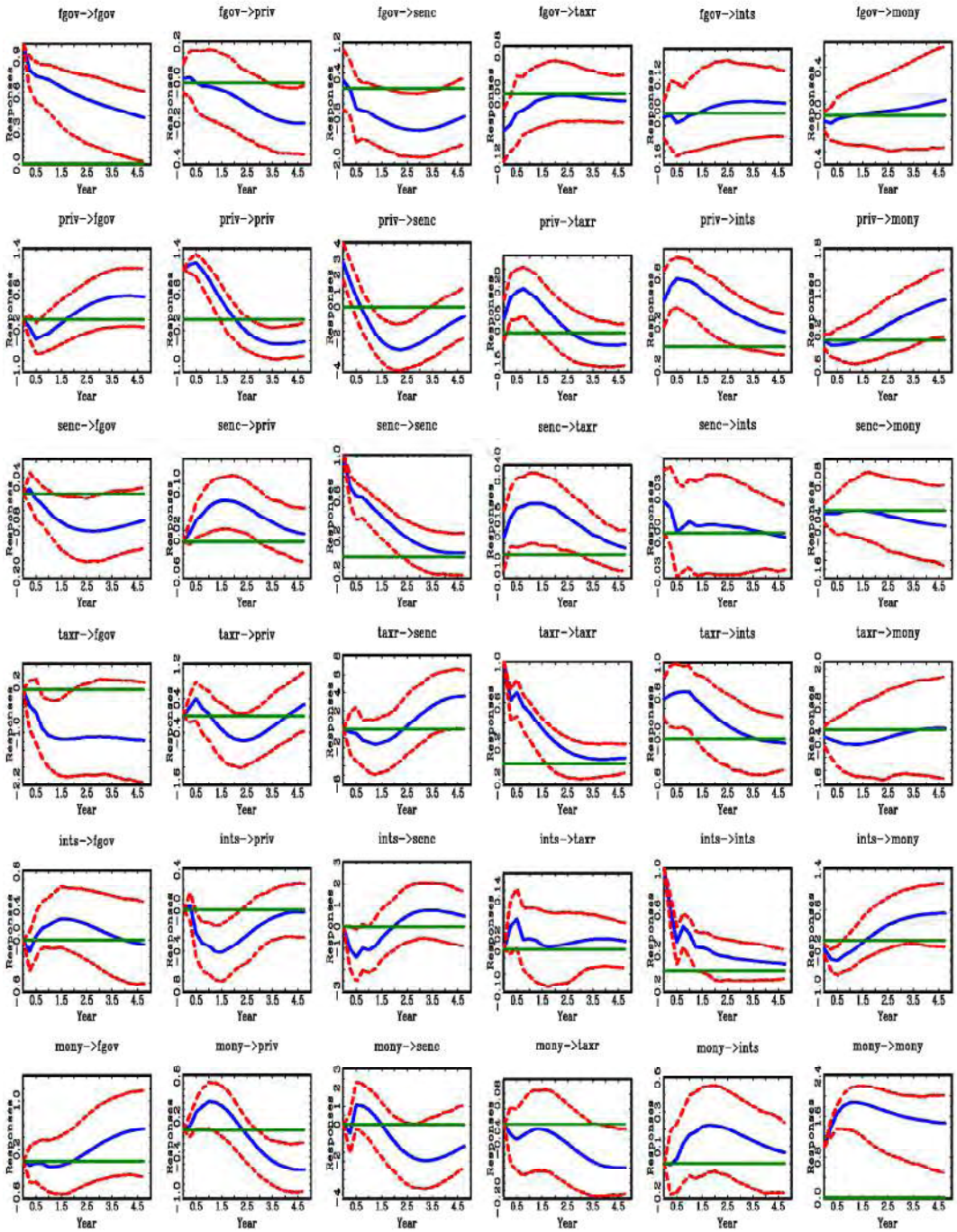


Figure A2. TG VAR

$$\mathbf{x}_t = [tgov_t \;\; invt_t \;\; conm_t \;\; sent_t \;\; tr_t \;\; i_t \;\; m_t]'$$

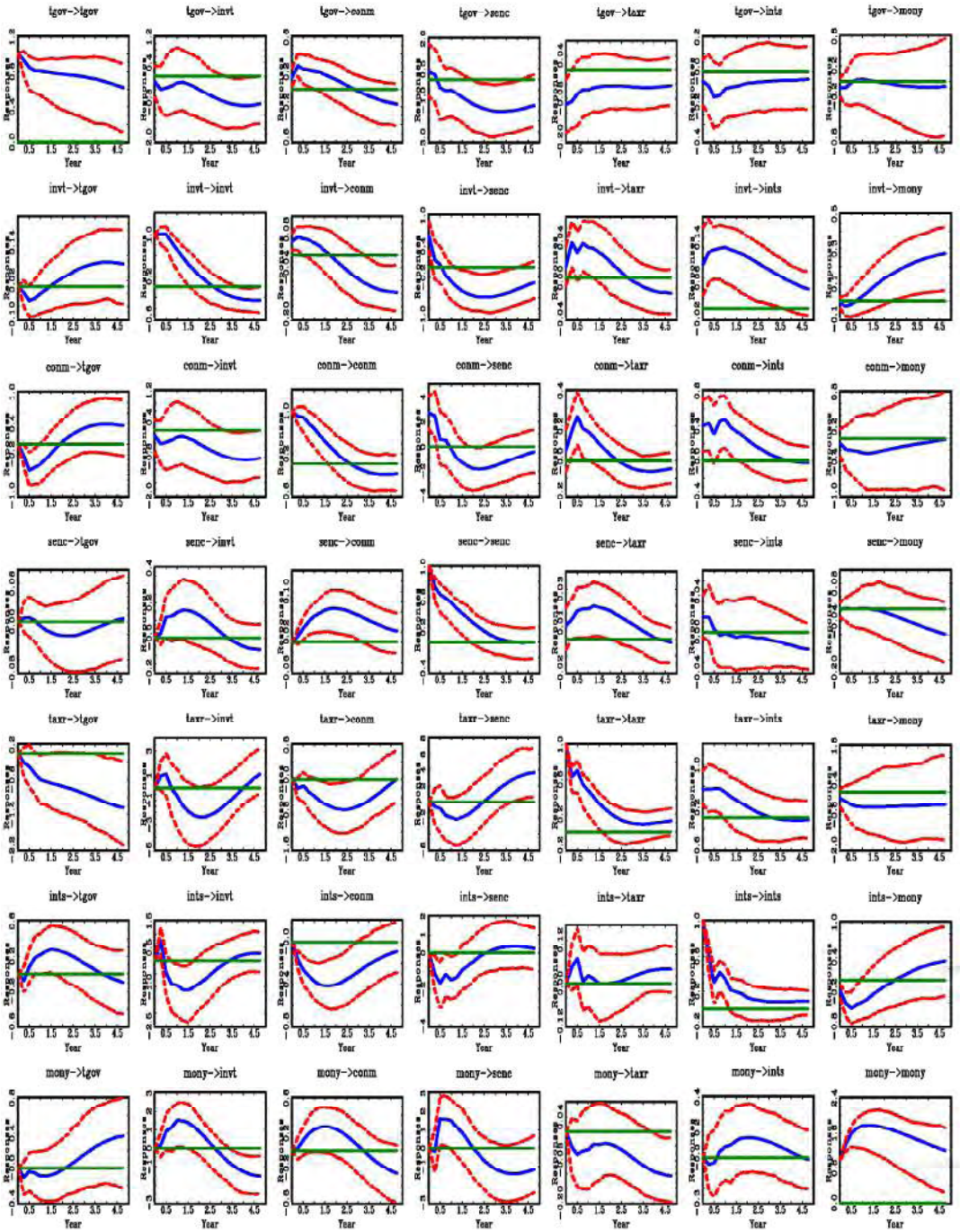


Figure A3. NEWS VAR I

$$\mathbf{x}_t = [news_t \; invt_t \;\; conm_t \;\; sent_t \;\; tr_t \;\; i_t \;\; m_t]'$$

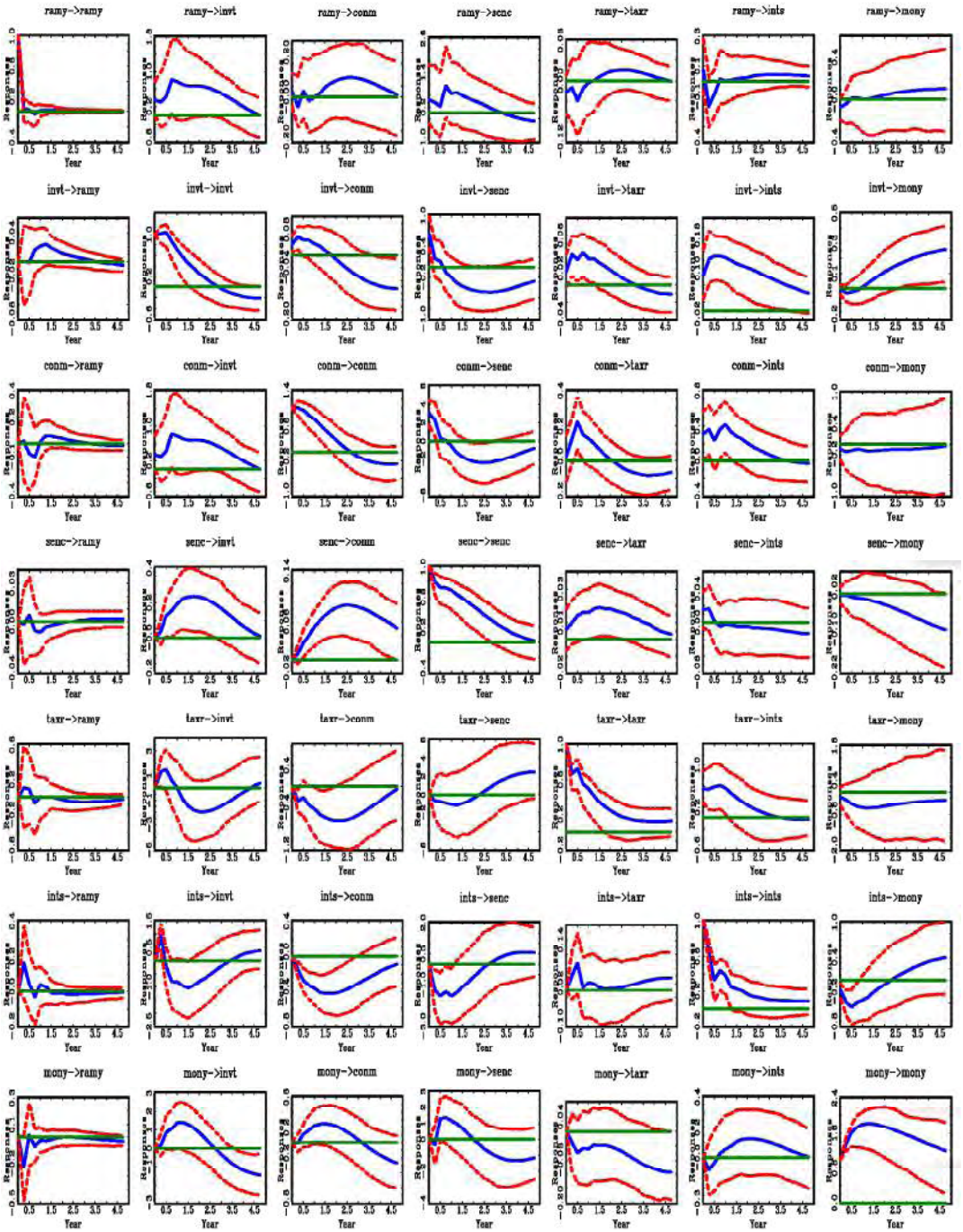


Figure A4. SPF VAR I

$\mathbf{x}_t = [spf_t \;\; invt_t \;\; conm_t \;\; sent_t \;\; tr_t \;\; i_t \;\; m_t]'$

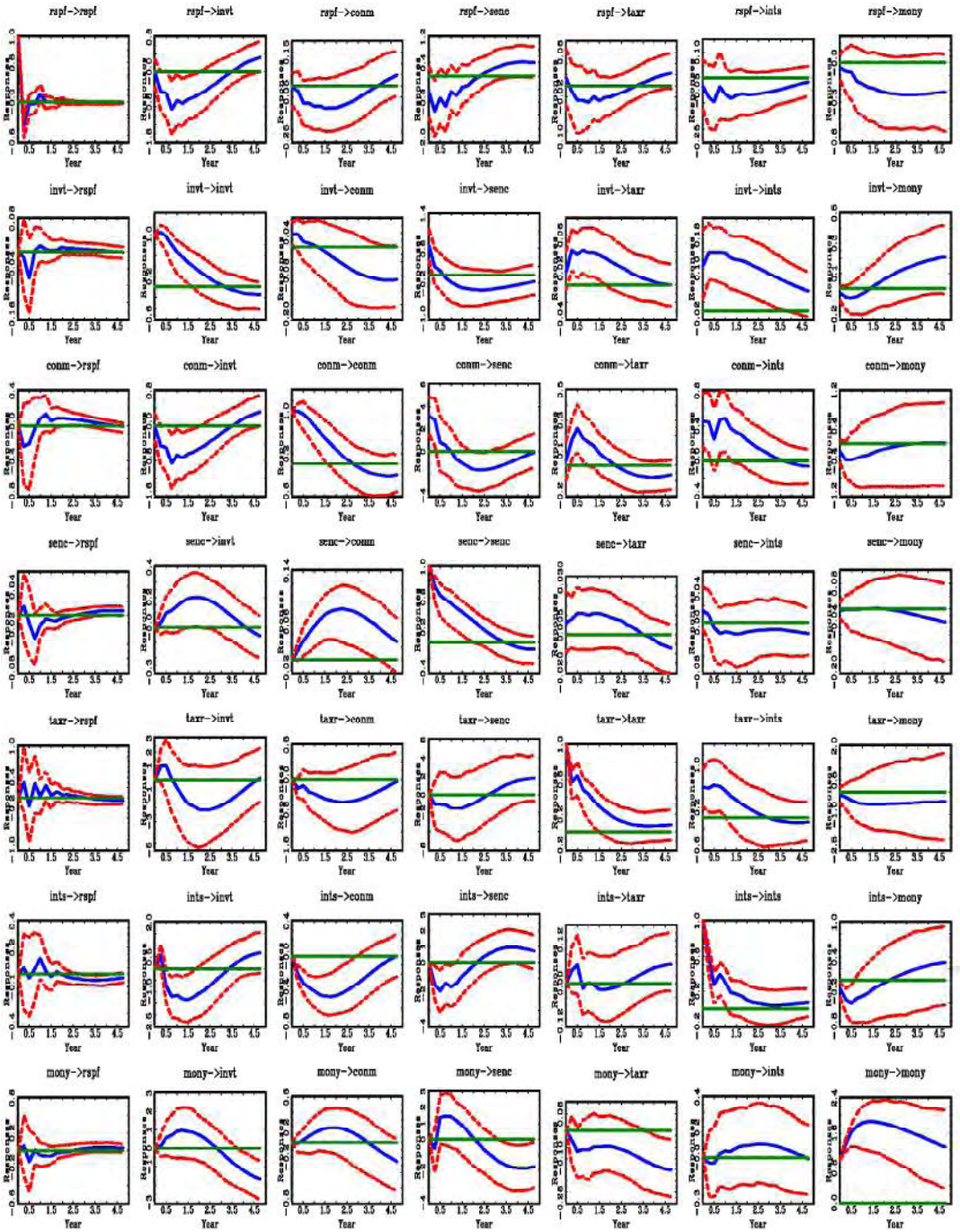


Figure A5. FG VAR

$$\mathbf{x}_t = [fgov_t \;\; tgov_t \;\; invt_t \;\; conm_t \;\; sent_t \;\; tr_t \;\; i_t \;\; m_t]'$$

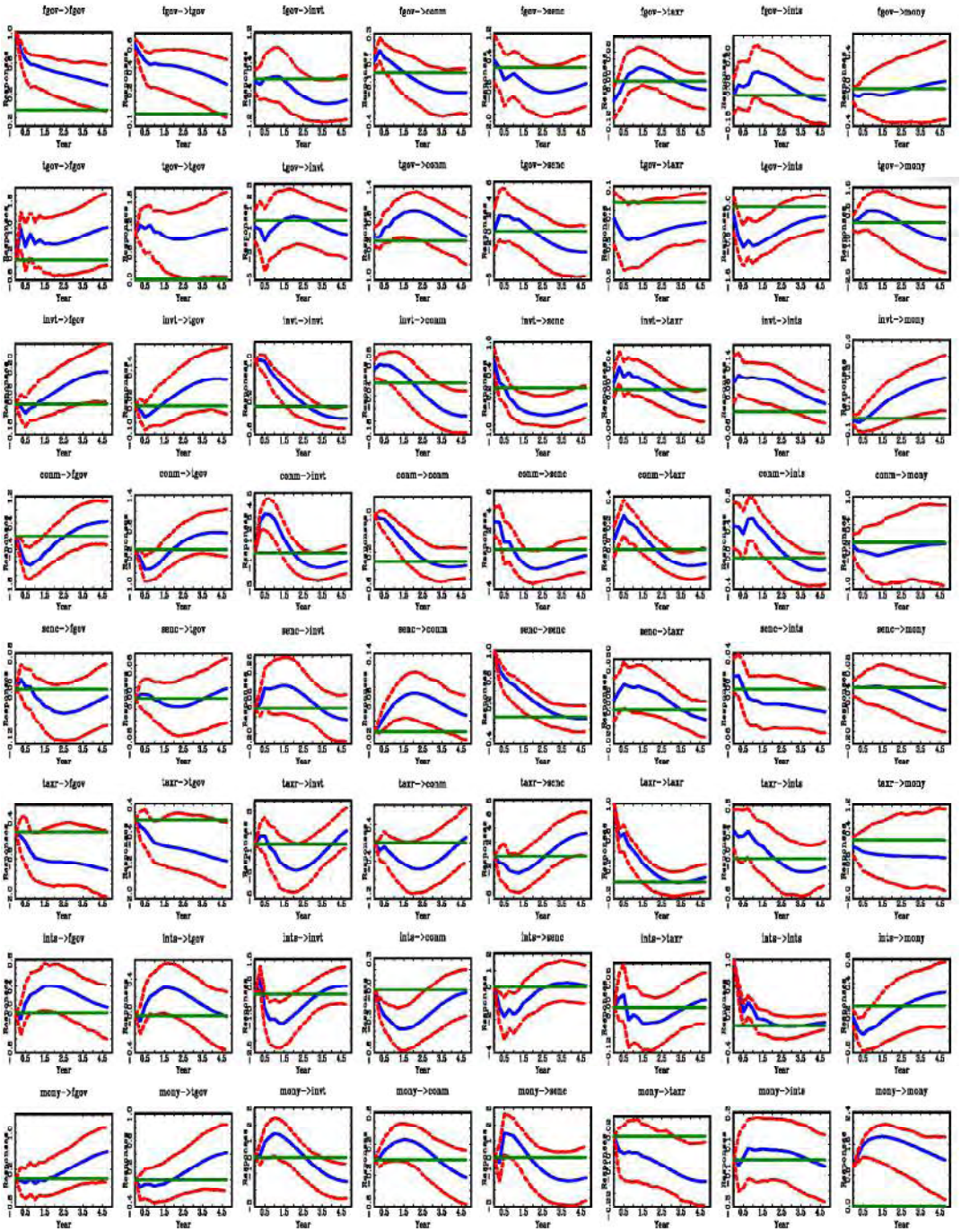


Figure A6. NEWS VAR II

$$\mathbf{x}_t = [news_t \;\; tgov_t \;\; invt_t \;\; conm_t \;\; sent_t \;\; tr_t \;\; i_t \;\; m_t]'$$

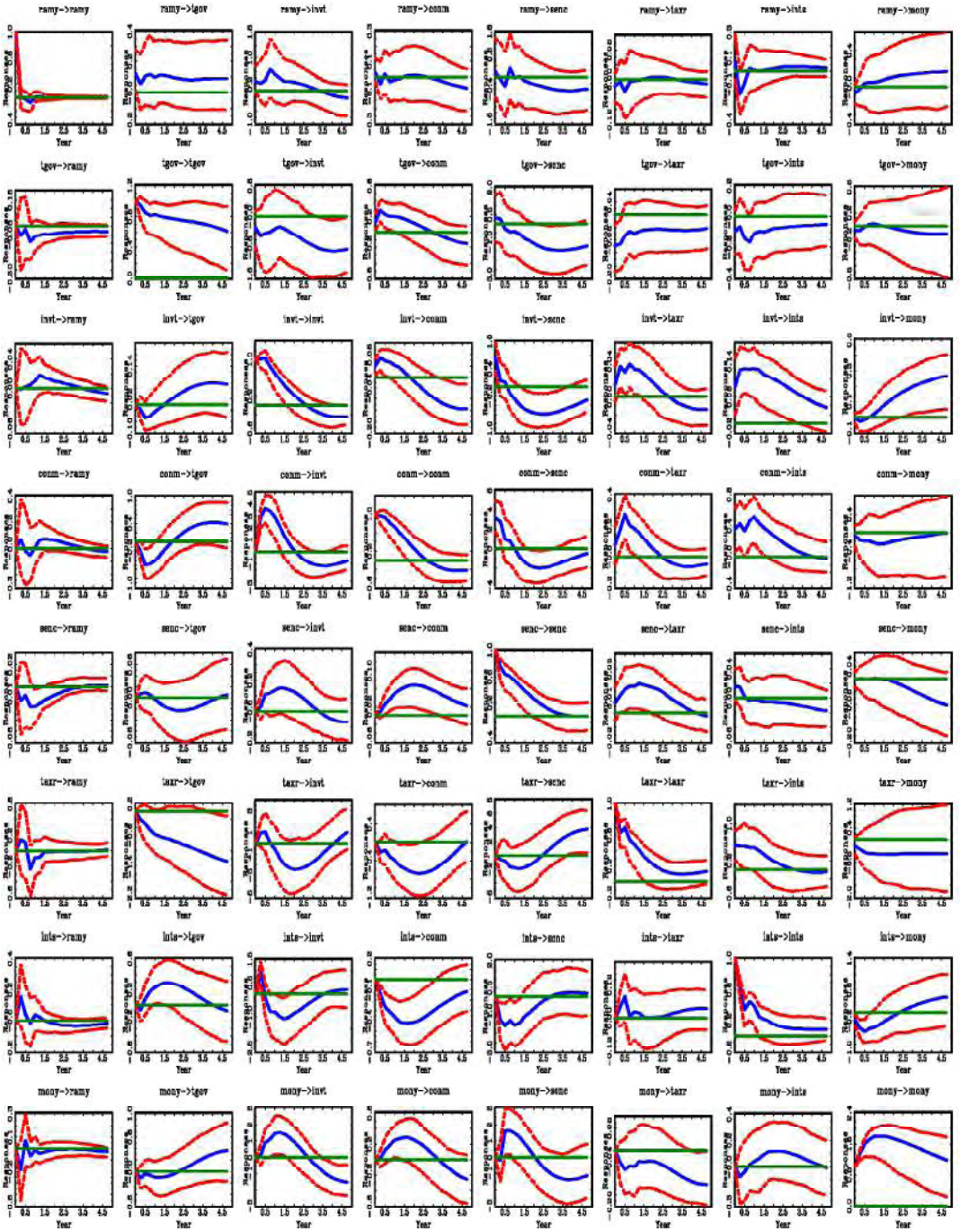


Figure A7. SPF VAR II

$$\mathbf{x}_t = [spf_t \;\; tgov_t \;\; invt_t \;\; conm_t \;\; sent_t \;\; tr_t \;\; i_t \;\; m_t]'$$

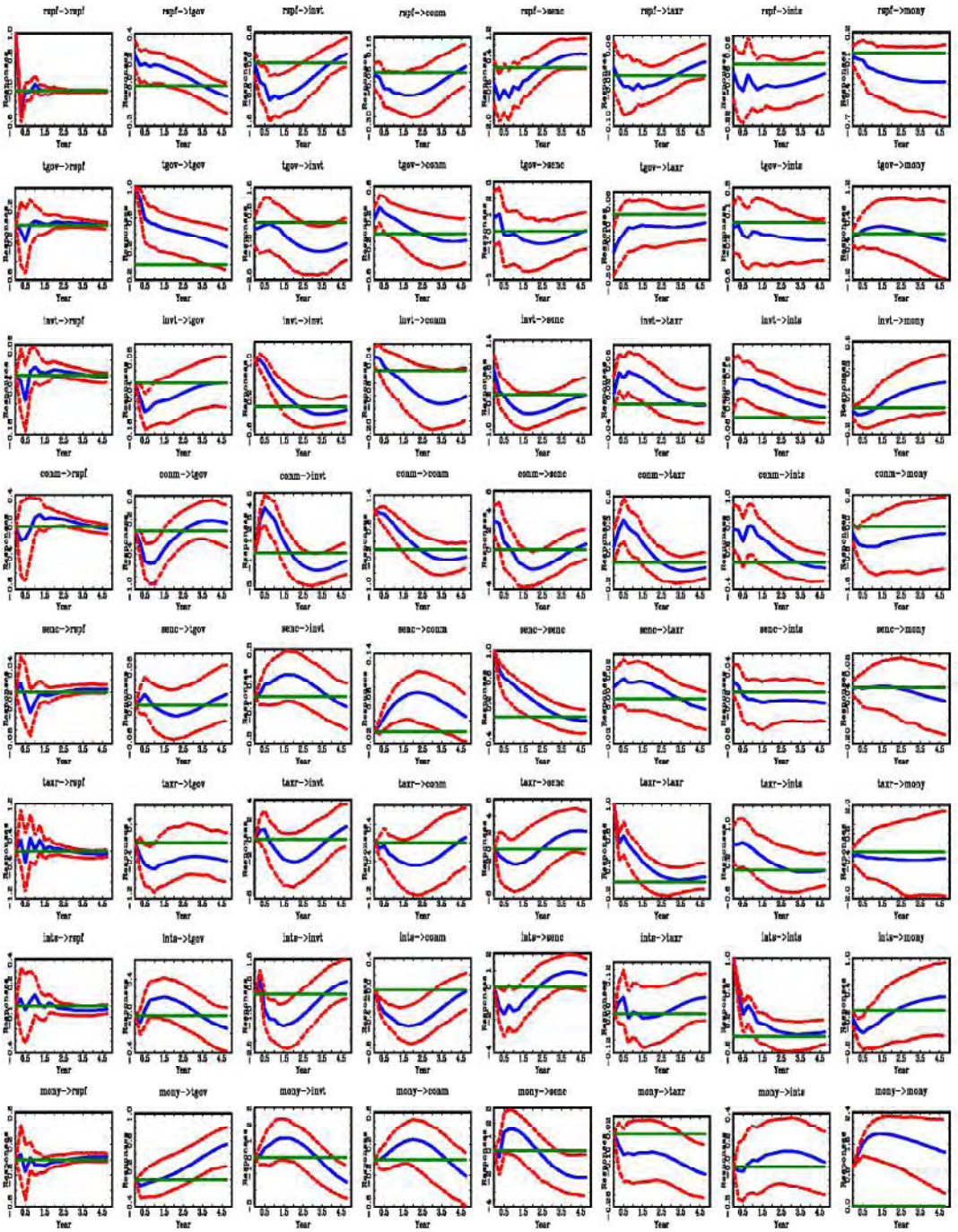


Figure A7. SPF VAR I: 1981:III - 2013:II

$\mathbf{x}_t = [spf_t \;\; invt_t \;\; conm_t \;\; sent_t \;\; tr_t \;\; i_t \;\; m_t]'$

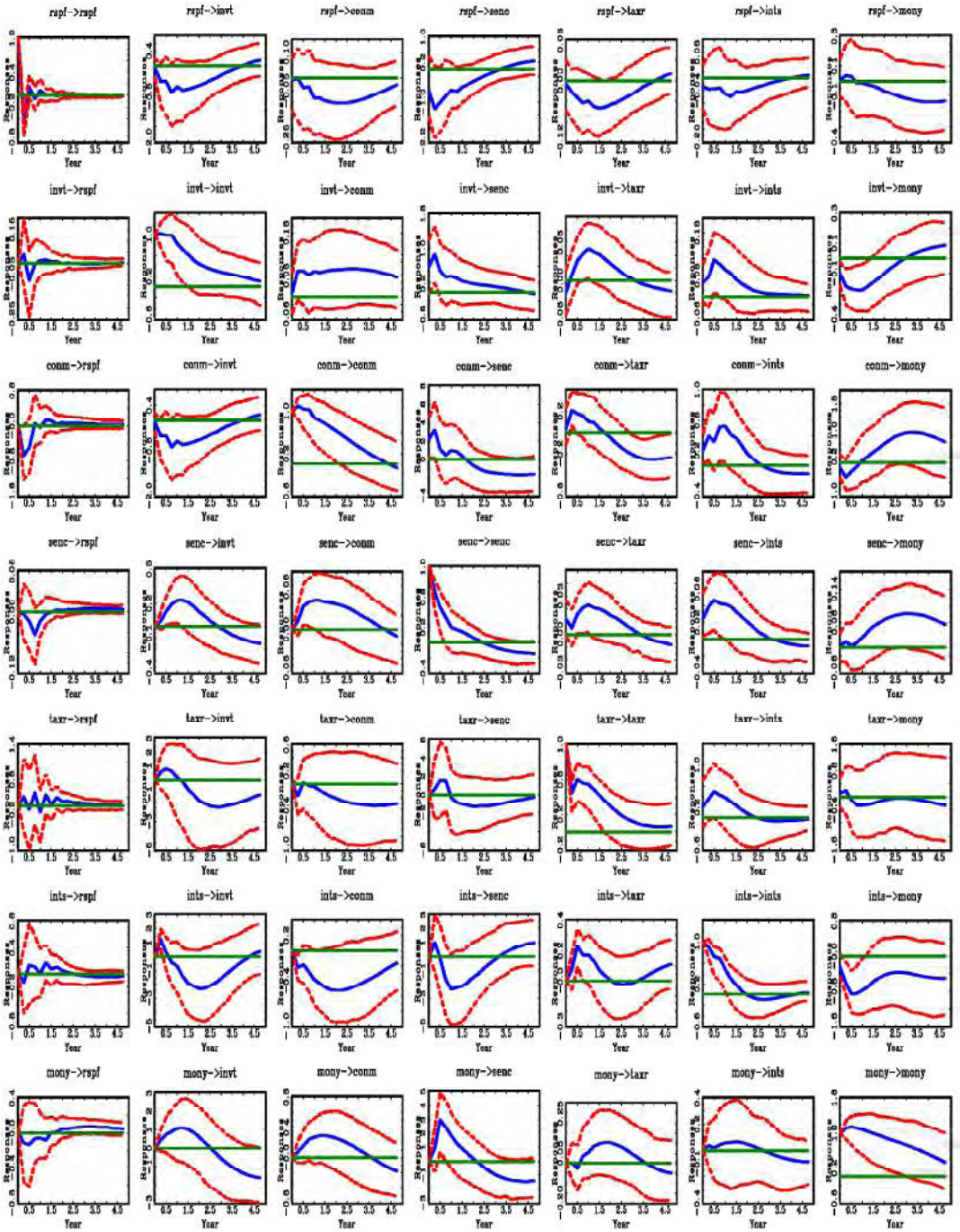
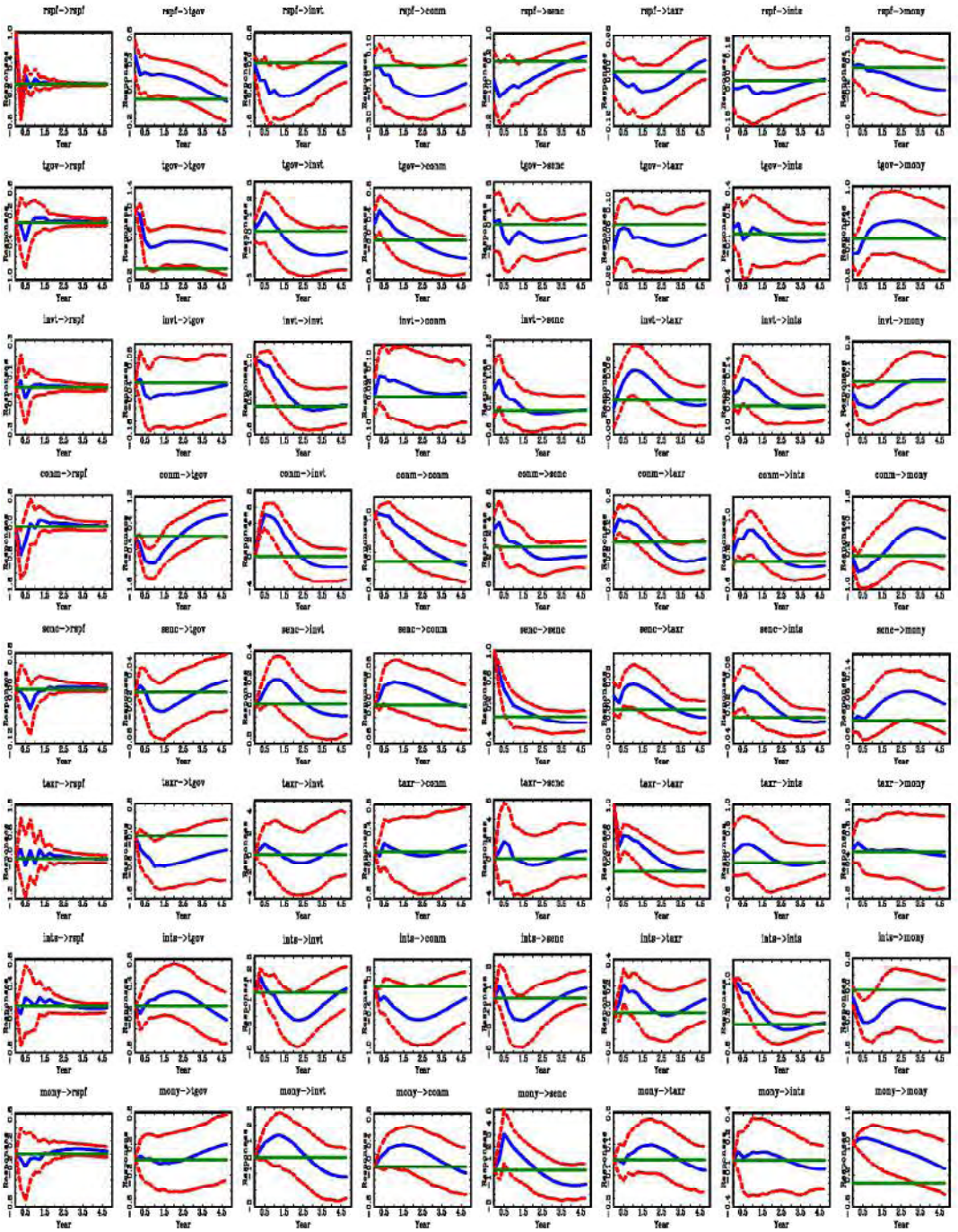


Figure A8. SPF VAR II: 1981:III - 2013:II

$\mathbf{x}_t = [spf_t \;\; tgov_t \;\; invt_t \;\; conm_t \;\; sent_t \;\; tr_t \;\; i_t \;\; m_t]'$



CHAPTER 4

Analysis of the Structural Change in Household Debt Distribution by Age of Householder in Korea and the US

By
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Abstract

This paper analyzes how and why household debt distribution by householder's age has changed over the past decade both in Korea and the US. Data shows that the proportion of household debt held by younger households has decreased, while that held by older households has increased. Empirical analysis shows that the change in householder's demographic distribution is the main driving force that has shifted household debt distribution. Since demographic aging is an inevitable trend, the proportion of household debt held by senior households is also expected to increase. Therefore, the Korean government must preemptively prepare for the household debt problem especially that held by older households by strengthening macro-prudential policies, preventing asset price deflation, restructuring household debt contract structures, and reforming labor market inflexibility.

JEL clodes: C14, D31, G28, J11
Keywords: Household debt distribution, Demographic distribution, Household income, Household asset

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1. Introduction

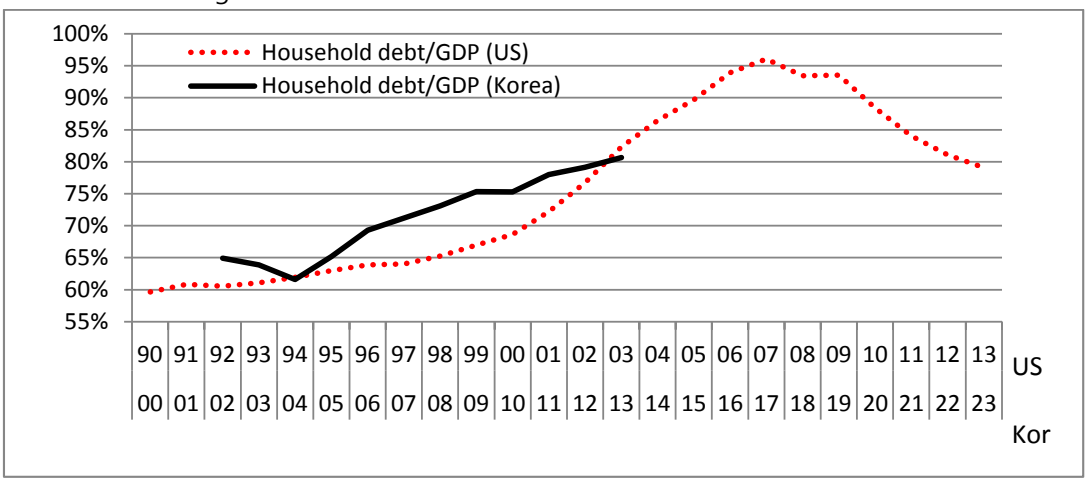
Household debt in Korea has steadily increased since the early 2000s, with the growth rate accelerating since 2012. Accordingly, policy makers and researchers in Korea have been seriously concerned about the consistent increase in household debt. Those who claim that the current level of household debt is too high argue that large amounts of household debt could lead to a deterioration in economic growth (Cecchetti et al. (2011), IMF (2012), Bornhorst and Arranze (2013), etc.). On the other hand, some argue that the general quality of household debt in Korea is moderate, since the majority of household debt is held by high income and high asset households (Hahm et al (2010), Kim and Byun (2012), Kim and Yoo (2013), etc.).

In this paper, I analyze the household debt problem from a population aging perspective. More specifically, I examine how and why household debt distribution by householder age group has changed over the past decade. It is well known that the senior population has increased in Korea. Here, I analyze how the change in demographic composition affects household debt distribution by householder's age. Moreover, I examine the effect of changes in household income and asset distribution on the change in household debt distribution.

Initially, I compare Korea's household debt distribution by householder's age to that of the US within and across time. The main motivation in comparing those two countries is that Korea's household debt-to-GDP ratio in 2013 is almost the same as that of the US in 2003 and 2013 (please see Figure 1). The US ratio went up to almost 95% and later deleveraged after being hit by the global financial crisis. Korea's household debt-to-GDP ratio, on the other hand, has not experienced any large adjustments even after the global financial crisis. It is well known that US households took out lots of loans, especially mortgages, before the financial crisis. Low-income and low-credit (or subprime-level) households could easily take out large amounts of loans before the economic crash (Mian and Sufi (2009), Keys et al. (2013), and so on). By comparing the US 2004 household debt, when loans were carelessly issued, to Korea's recent household debt distribution, I can examine the risk level of the current Korean household debt problem especially by age group.[2] (Note that the aggregate levels of household debt to GDP ratios in both countries in these two years are almost same.) In addition, I examine household income, assets, debt-to-income ratio, and debt-to-asset ratio distributions by householder's age. By comprehensively analyzing household's financial characteristics and comparing Korea to the US, I can evaluate the potential risks to Korean households.

[2] Since the US data used in this paper is not surveyed annually, the data wave of 2004 is selected. Please see the next section for more details about data sources.

Figure 1 Household Debt to GDP Ratio of Korea and the US



Note: Data from the OECD and Bank of Korea. Household debt data in the flow of fund table is used.

Next, I analyze how household debt distribution by householder's age group has changed over the last 10 years (in case of the US I can examine the change over the last 20 years).[3] Data shows that the proportion of household debt held by (relatively) younger households has decreased, while that of older households has increased over the last 10 years. Specifically, household debt distribution by householder's age group has shifted to the right. Moreover, household's income, asset, and demographic distribution by householder's age have all simultaneously shifted right. The shift in income distribution is mainly driven by the change in the demographic factor. That is, as the proportion of older households increases, the proportion of income held by older households has also increased. However, this explanation does not apply to household debt and asset distribution. Even after controlling the demographic factor, the proportion of household debt and assets held by young households has decreased, while that held by older households has increased. We can also observe such patterns in the US.

This motivates me to examine which factors mainly drive the change in household debt distribution. More specifically, I consider household debt distribution by householder's age group in 2004 and 2012,[4] and analyze which household-specific characteristics affect the change in distribution. Applying DiNardo et al. (1996), I consider a counter-factual 2004 household debt distribution where only the householder's age distribution follows the distribution of 2012, and other household-specific characteristics remain in line with 2004 distribution. By analyzing this

[3] In the case of Korea, the sample period of available micro-data is insufficient. Please see section 2 for more details.

[4] I used the most recently released KLIPS data (2012) and the 2004 wave of the KLIPS. In the case of the US, I choose 2004 and 2013 survey years. Please see data section for more details.

exercise, I can examine the effect of the change in householder's demographic distribution over the last 10 years on household debt distribution. Similarly, I simulate a counter-factual scenario where only the household income (asset) distribution follows the distribution of 2012, and other household characteristics remain in line with 2004 distribution. Accordingly, the change in householder's demographic composition is the main driver of the change in household debt distribution by householder's age. The demographic factor can explain the shift in household debt distribution almost by half. On the other hand, changes in either income or asset distribution does not fully explain the change in household debt distribution. I can also draw similar conclusions for the US, though the explanatory power of the change in demographic composition is smaller than Korea.

Since demographic aging is an inevitable trend in Korea, as well as in the US, the proportion of household debt held by older households is also expected to increase. Hence, the Korean government needs to preemptively prepare for the household debt problem especially those held by older households before the problem exacerbates. Here, I propose policy directions that the Korean government should consider. First, the government should speed up reforming the labor market inflexibility to prevent a sudden drop in household income after the retirement age. Second, policy makers should monitor the possibility of asset price deflation more carefully. Third, household debt contracts in Korea should be restructured from short-run bullet type to long-run amortization loans. Lastly, macro-prudential policies, such as a DTI regulation, must be strengthened to share risk from unexpected adverse shocks.

There are many papers that analyze the potential risk of household debt in Korea. However, to the best of my knowledge, there are no papers that analyze the structural risk of household debt originated from population aging. Kim and Byun (2012) analyzed individual-level debt distribution by income, credit score, occupation, financial intermediary type, age, and regional groups. Hahm et al (2010) and Kim and Yoo (2013) also implemented a similar empirical exercise. Generally, those papers conclude that the current level of Korean household debt is not big enough to threaten financial stability. However, some types of households, such as low-income, non-banking debtors, are potentially vulnerable in negative stress scenarios. These papers commonly analyze household debt distribution by diverse debtor-specific characteristics at a certain time. Unlike those papers, I examine household debt distribution from a long-term perspective, and analyze how and why household debt distribution has structurally changed.

Some other papers examine how household debt responds to unexpected exogenous shocks. Jeong and Kang (2013) analyzed household debt responses from unexpected changes in productivity (TFP), interest rates, or house prices. Justiniano et al. (2015) assert that the leverage and deleverage in US household debt is mainly driven by household's taste for housing services.

These papers commonly used a DSGE-style model and introduced some exogenous shocks. My analysis regarding changes in household debt is more driven by a structural factor: changes in demographic composition. In addition, this paper, unlike other papers, analyzes household debt distribution, rather than aggregate amounts (or level) of household debt.

The remainder of this paper is organized as follows. Section 2 introduces micro-data used in this paper. Section 3 compares Korea and US household debt distribution in a certain survey year (static comparison or cross-section analysis). Section 4 examines how household debt distribution both in Korea and the US has changed over the last decade (dynamic comparison or time-series analysis). Section 5 analyzes which factor(s) have mainly driven the change in household debt distribution over the past 10 years. Finally, section 6 concludes with policy implications.

2. Data Description

I used two household level micro data to analyze Korean household debt distribution: Korean Labor and Income Panel Study (KLIPS) and Survey of Household Finances and Living Conditions (SHFLC). KLIPS is a panel dataset initiated from 1999. The most recently released survey was in 2012. SHFLC started from 2010, and the most recently updated survey was in 2014. SHFLC is a panel structure between 2010 and 2011. Afterward, SHFLC re-sampled interviewees in 2012, hence, becoming panel structure for the period from 2012 to 2014. SHFLC contains more finely categorized household asset and debt information than KLIPS. Unfortunately, since the initial survey year of SHFLC is 2010, I used the KLIPS and SHFLC simultaneously to analyze the structural change in household debt distribution over the decade.

For the US case, I used the Survey of Consumer Finances (SCF) released from the Federal Reserve Board. SCF is similar to SHFLC, though the number of questionnaires is much larger than that of SHFLC. SCF is released every three years, from 1983, and is not a panel dataset. Since this paper analyzes the cross-sectional distribution of household debt over different years, the panel structure is not necessarily needed. [5]

Each dataset contains different household debt and asset categories. Hence, we need to clarify how to calculate the aggregate household-level debt and assets. For the KLIPS, household debt is the sum of financial debt (including secured and unsecured debt), non-financial debt, personal debt, chonsei deposits owed to renters, lodge money debt, and other loans. Similarly, aggregate

[5] Since each survey asks the exact amount of remaining household debt, I can calculate and compare household debt-related moments by using these different data sources.

household-level debt in SHFLC is defined by summing up the following components: financial debt, which includes both secured and unsecured debt, lodge money debt, and credit card related debt, chonsei deposits owed to renters. For the SCF, total household debt is the sum of the following debt categories: mortgage/land contract, investment real estate and vacation properties debt, business debt, vehicle loans, land contract and notes (debt), credit card debt, home equity line of credit, line of credit not secured by residential property, education loans, other loans, loan for home improvement, other debt, margin loans, loans backed by insurance, loans backed by pensions.

Similar to household debt, each dataset also defines household-level asset differently. For the KLIPS, sum of housing value, chonsei deposit, and financial asset[6] is defined as household total asset.[7] For the SHFLC, household asset is the sum of financial asset, which includes all types of saving and financial investment, chosei deposit, and real asset, which includes real estate and non-real estate real asset. Household asset in the SCF is defined by summing up following components: value of primary residence, investment real estate and vacation properties, business equity, vehicle, financial asset,[8] other asset, land contract and notes.

Household debt distribution can be analyzed in diverse dimension. I mainly focus on household debt distribution by householder's age. It is well known that Korean society is aging, and the speed of this trend is faster than any other OECD member countries. The general trend is the same in the US, though the speed of population aging is much slower. I sampled households in which the householder's age is between 20 and 79, which covers almost every household that carries on economic activities. It is known that the SCF data also surveys very rich households. Hence, I dropped extremely rich or highly indebted US households when calculating statistical moments. (Specific explanations are in the footnotes of each figure and table in the next section.)

3. Static Analysis of Household Debt Distribution

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[6] Financial asset is the sum of the following components: saving, stock, bond, mutual fund, insurance, lodge money, uncollected loan.

[7] KLIPS also contains some non-real estate real asset categories, such as vehicle, jewelry, artwork, and golf/condominium memberships. However, these asset categories are only included in limited waves of the survey. To make a consistent asset measure within KLIPS, I excluded those categories.

[8] Financial asset is the sum of the following components: checking account, IRA/Keogh, certificate deposit, saving/MMF, mutual fund/hedge fund, saving bond, any other bonds, stocks, brokerage account, annuity/any trust/managed investment account, life insurance

In this section, I compare the 2014 Korean household debt distribution by householder's age to the 2004 US household debt distribution. As shown in Figure 1, the recent household debt to GDP ratio in Korea is similar to the 2003 and 2013 ratio in the US. Before the global financial crisis, the US household debt monotonically increased. And then, the US households deleveraged their debt through government driven loan modification programs, foreclosure, bankruptcy, and so on (Gerardi and Li (2010) and Robinson(2009)). Since 2014 Korea and 2004 US are similar in terms of household debt-to-GDP ratio levels and their increasing trends, I initially choose those two years and compare household debt distribution of two countries.

I define two measures which I mainly use in this paper to analyze household debt distribution by householder's age. First, I calculate what portions of debt are held by a certain age group. Let m_i be the amount of debt held by household i, and w_i be the sample weight. Then, the proportion of debt held by a certain age group can be calculated as follows

$$Q_{\text{Age group}} = \frac{\sum_{i \in \text{Age group}} w_i m_i}{\sum_{i \in \text{All population}} w_i m_i}$$

Under this measure, the debt holding ratio by a certain age group might increase when the number of people in the age group is large enough. In order to control the age-specific population effect, I define the second measure.

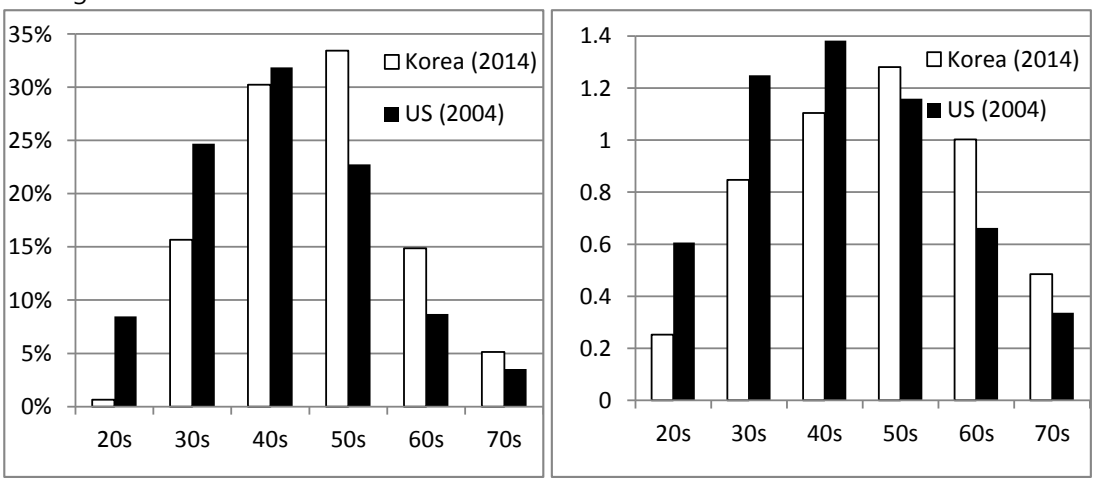
$$P_{\text{Age group}} = \frac{\sum_{i \in \text{Age group}} w_i m_i \,/\, \sum_{i \in \text{Age group}} w_i}{\sum_{i \in \text{All population}} w_i m_i \,/\, \sum_{i \in \text{All population}} w_i}$$

This is a ratio of average debt held by a certain age group to average debt held by the whole population. Hence, this ratio measures relative amounts of debt held by a certain age group, controlling the demographic effects.

Figure 2 compares 2014 Korea to 2004 US household debt distribution by householder's age group. The left figure is the debt holding ratio by householder's age ($Q_{\text{Age group}}$), and the right figure is the ratio of average amount of debt held by a certain age to average of all households ($P_{\text{Age group}}$). The older population in Korea hold bigger portions of debt, than those in the US, particularly those in their 50s. The debt of Korean households with householders in their 50s accounts for approximately 33% of the entire household debt, while it is 23% in the US, even lower than the debt held by those in their 40s. When I control the demographic difference between Korea and the US, Korean household debt is comparatively more concentrated in the older-aged groups, particularly those in their 50s. Korean households with householders in their 50s are carrying 28% more debt than that held by the average household of the entire economy, which is higher by about 16% compared to the US. Due to the high proportion of the population

in their 50s, along with a large amount of average debt, in Korea, the absolute proportion of their debts is much higher than that of the US.

Figure 2 (Left) Household Debt Ratio by Householder's Age (Right) Ratio of Per-Household Debt to Average of All Households

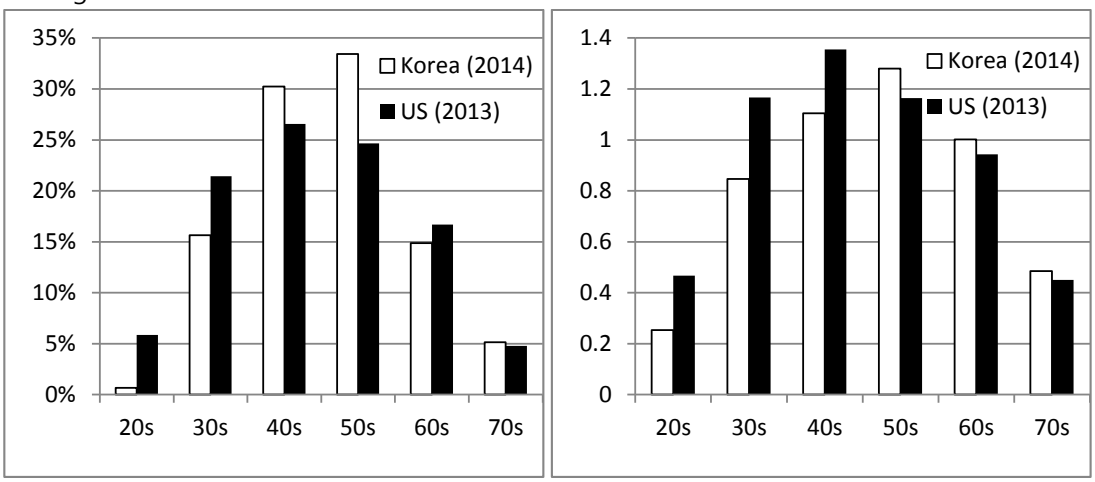


Note: US Households with debts in the top 1% are dropped. Data: (Korea) 2014 SHFLC; (US) 2004 SCF

In Figure 3, I compare the household debt distribution in Korea and the US by using the most recently released dataset. One noticeable change in the US household debt distribution is an increase in debt held by households in their 60s, and a decrease in debt by those in their 40s. When I control the demographic effect, the average amount of debt held by those in their 40s in 2013 in the US is almost same as that in 2004. Hence, a decrease in household debt held by those in their 40s is mainly driven by a decrease in their population. The proportion of debt held by those in their 60s can be explained by two forces: an increase in population and an increase in average debt.[9] (Further examination is presented in the next section.) When I compare Korean household debt to the recent US household debt distribution, rather than 2004, the portion and average amount of debt held by those in their 50s in Korea is much higher than that in the US recently.

[9] The reason why average household debt held by those in their 60s has increased in the US needs further examination. One possible story is as follows. Before the global financial crisis, households in their 50s tended to take out loans backed by their housing equity. After the financial crisis, those households become be 60s along with debt not fully repaid.

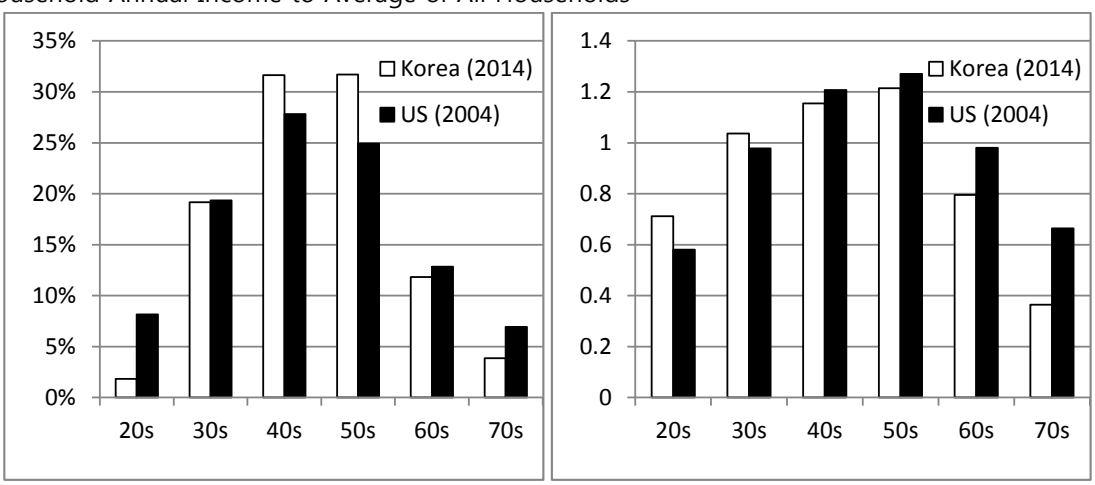
Figure 3 (Left) Household Debt Ratio by Householder's Age (Right) Ratio of Per-Household Debt to Average of All Households



Note: US Households with debts in the top 1% are dropped. Data: (Korea) 2014 SHFLC; (US) 2013 SCF

Having large amounts of household debt might not be a serious problem if households have high enough income or asset simultaneously. In Figure 4, I present household's income distribution by householder's age group. I similarly consider two measures: proportion of household income held by a certain age group, and the ratio of average income of a certain age group to the average of all households. The Figure shows that Koreans experience a sharp decline in their income after their retirement age, implying that old-aged people are more likely to face repayment and liquidity problems. The proportion of income earned by population in their 50s in Korea is higher than that in the US, which is mainly attributed by the number of population.

Figure 4 (Left) Household Annual Income Ratio by Householder's Age (Right) Ratio of Per-Household Annual Income to Average of All Households

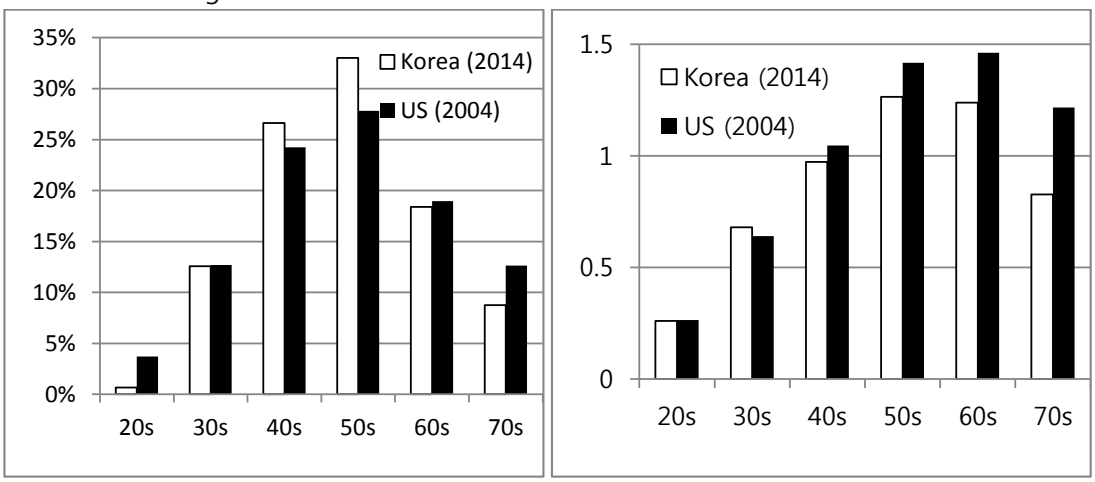


Note: US Households with income in the top 1% are dropped. Data: (Korea) 2014 SHFLC; (US)

2004 SCF

Figure 5 reports the asset distribution by householder's age. Seniors in Korea owns comparatively lesser proportions of assets than those in the US. The average amounts of assets held by the senior group, especially 60s, is higher than that held by younger people both in Korea and the US. However, average assets held by the older population in Korea is relatively lower than that in the US.

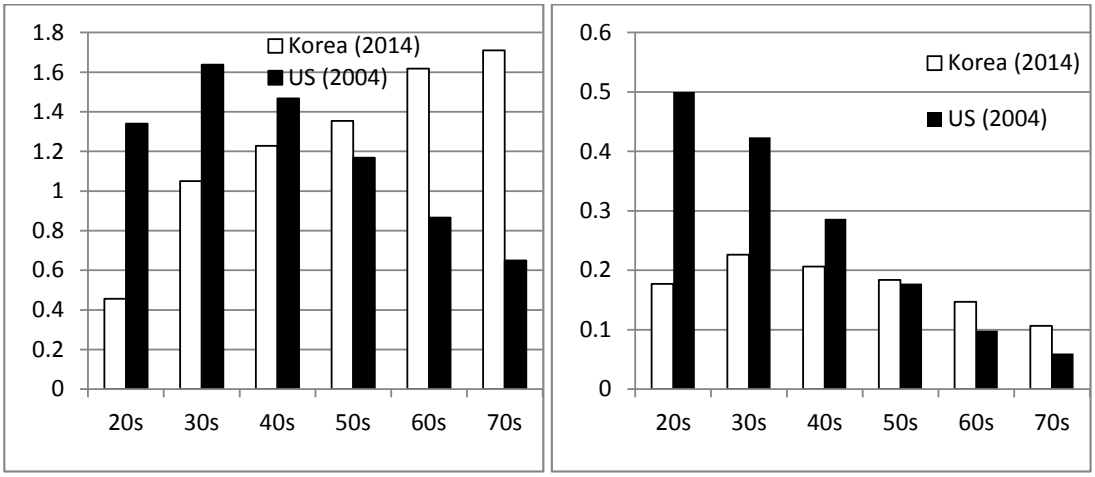
Figure 5 (Left) Household Total Asset Ratio by Householder's Age (Right) Ratio of Per-Household Total Asset to Average of All Households



Note: US Households with asset in the top 1% are dropped. Data: (Korea) 2014 SHFLC; (US) 2004 SCF

In sum, Korea's debt-to-income ratio increases as householders become older, unlike the US, and Korea's debt-to-asset ratio does not decrease as fast as that of the US. The US debt-to-income ratio decreases as householders become older, since US people tend to borrow early in their life and repay the debt throughout their entire life, such as mortgages or education loans. This pattern also holds in the US in 2013 (not presented in this paper). On the other hand, the ratio in Korea is much higher than those in the US especially after the retirement age. Unlike the US, Korean households tend to take out loans without repaying principal over their life cycle. Instead, they simply refinance loans every 2-5 years, and roll-over their debt again until their retirement age. In addition, a sudden drop in income after the retirement age might be the other factor which increases the debt burden of Korea's seniors. Similar interpretation can be applied to the debt-to-asset ratio. Since older Koreans have large amounts of debt even after their retirement age, along with having lower assets than the US, the debt burden of old-aged, evaluated by their assets, is relatively bigger in Korea.

Figure 6 (Left) Household Debt to Income Ratio by Householder's Age (Right) Household Debt to Asset Ratio by Householder's Age



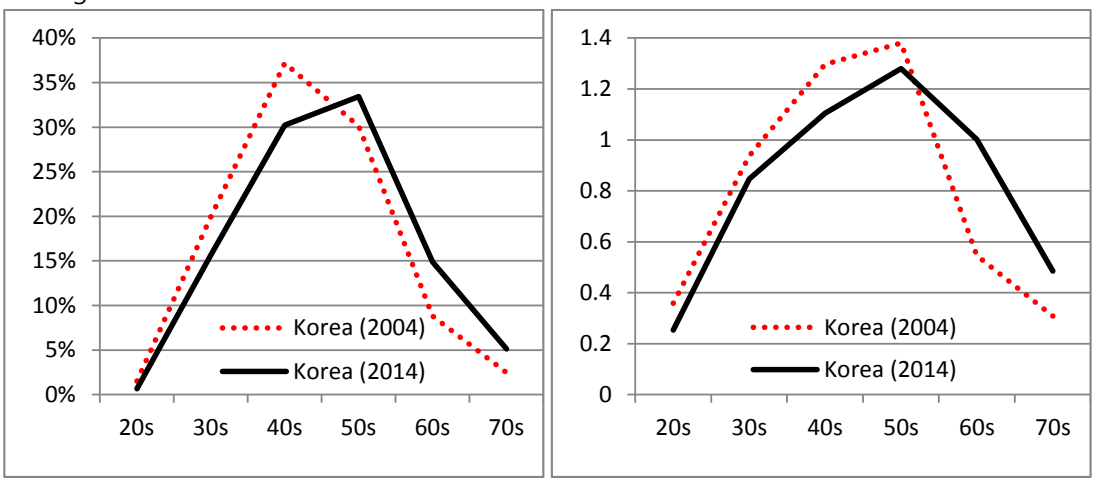
Note: US Households with either income or asset in the top 1% are dropped. Data: (Korea) 2014 SHFLC; (US) 2004 SCF

4. Dynamic Analysis of Household Debt Distribution

In the previous section, I examined household debt distribution at a certain survey year. In this section, I compare how household debt distribution has changed over the last 10 years (20 years in case of the US). Then, I can analyze whether the household debt problem is a static (or time-invariant) or dynamic problem. If it turns out that household debt distribution changes over time, we can guess the potential change of household debt distribution in future and preemptively prepare policy measures to resolve the problem.

Figure 7 presents Korean household debt distribution by householder's age in 2004 and 2014. The proportion of debts held by old-aged households has gradually increased over the last 10 years, while debt held by households whose age is less than 40s have decreased. When I control the effect of demographic changes, the average debt held by those in their 60-70s has increased, while that of the other age group has decreased. Hence, Korean household debt distribution by householder's age has shifted to the right over the last 10 years.

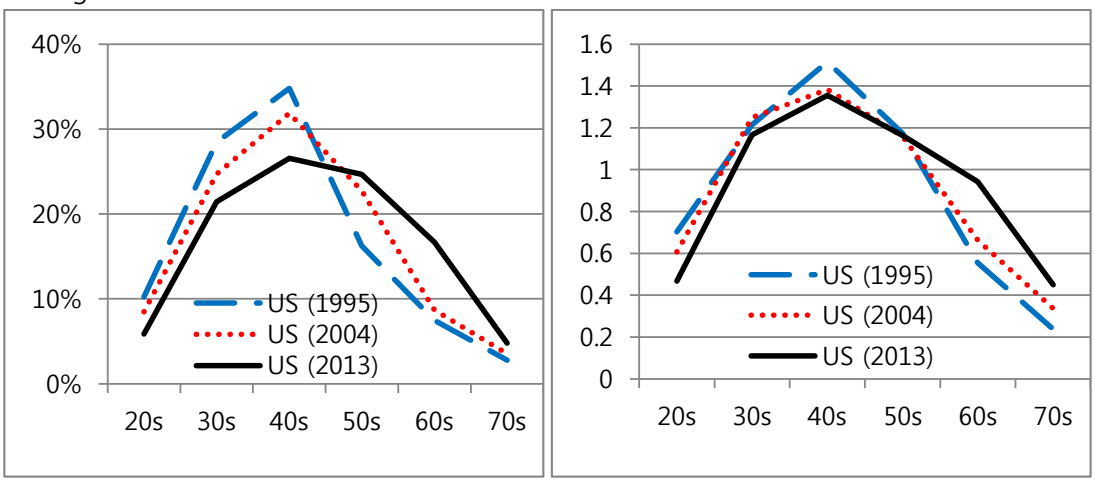
Figure 7 (Left) Household Debt Ratio by Householder's Age (Right) Ratio of Per-Household Debt to Average of All Households



Data: 2004 KLIPS and 2014 SHFLC

The household debt distribution in the US also has shifted to the right over the last 20 years. The proportion of debt held by young households has decreased, while that held by older households has increased. When I control the demographic change, the average household debt held by those in their 60-70s has increased, especially after the recent financial crisis.

Figure 8 (Left) Household Debt Ratio by Householder's Age (Right) Ratio of Per-Household Debt to Average of All Households

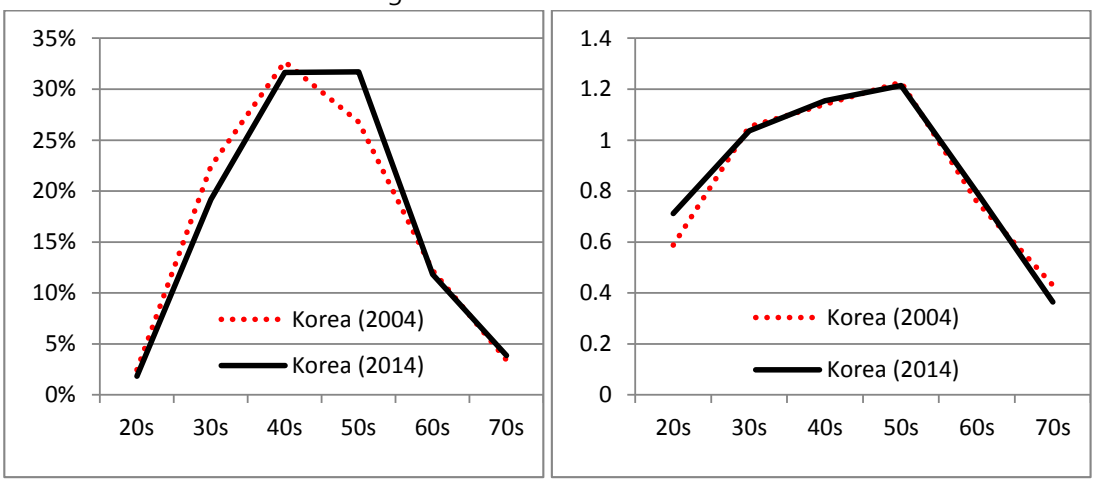


Note: US Households with debt in the top 1% are dropped. Data: 1995, 2004, and 2013 SCF

I also examine the change in household income distribution by householder's age, as in household debt distribution. Korean household income distribution similarly has shifted to the right for 10 years. That is, the proportion of household income held by those in their 50s has increased, while that held by those in their 30-40s has decreased for 10 years. The change in

household income distribution is mainly driven by a change in demographic compositions. As the number of older households increase, the portion of total income held by seniors also increases.

Figure 9 (Left) Household Annual Income Ratio by Householder's Age (Right) Ratio of Per-Household Annual Income to Average of All Households

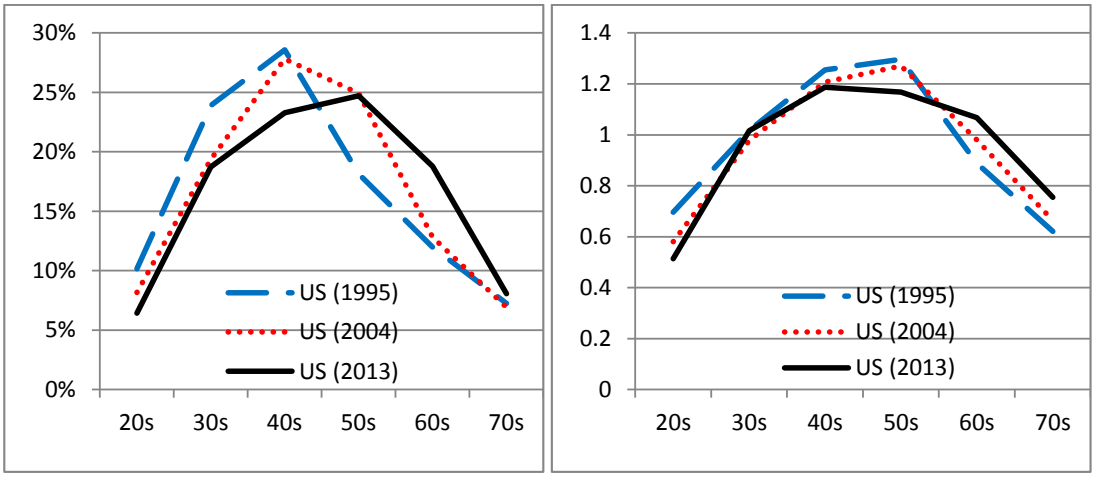


Data: 2004 KLIPS and 2014 SHFLC

We can also observe similar patterns of changes in household income distribution in the US. The proportion of total household income held by young households has decreased, while that held by older households has increased. When I control the demographic effect, the average household income (normalized by the average of all households) is almost the same especially between 1995 and 2004.

The proportion of household income held by older Korean households is much lower than that held by the counterpart group in the US. In addition, the average amount of income for Korea's older households is much lower than that of the US. This pattern holds even around 10 years ago. Hence, the fact that Korean households, on average, tend to experience a steep decline in their income once they retire in their jobs is a persistent problem, which is not recently showed up.

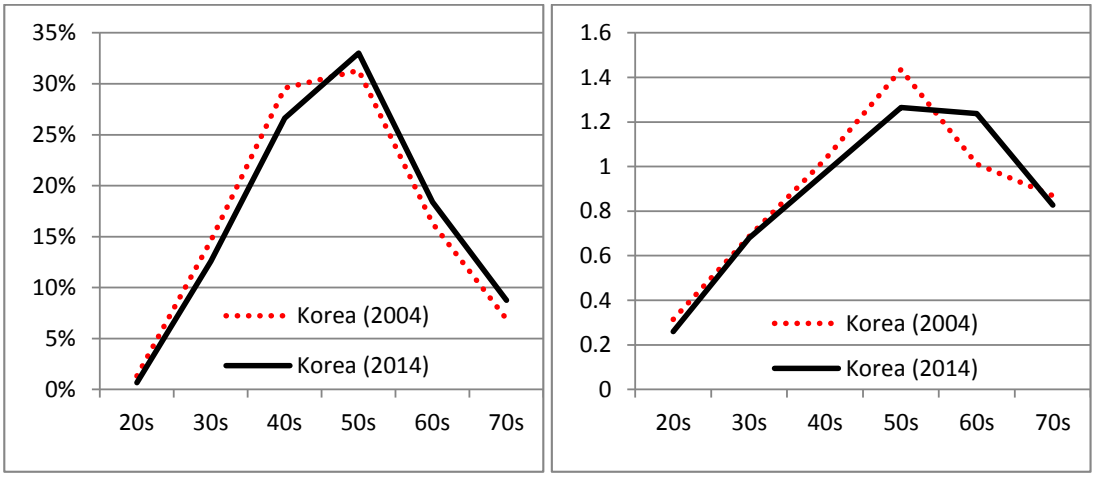
Figure 10 (Left) Household Annual Income Ratio by Householder's Age (Right) Ratio of Per-Household Annual Income to Average of All Households



Note: US Households with income in the top 1% are dropped. Data: 1995, 2004, and 2013 SCF

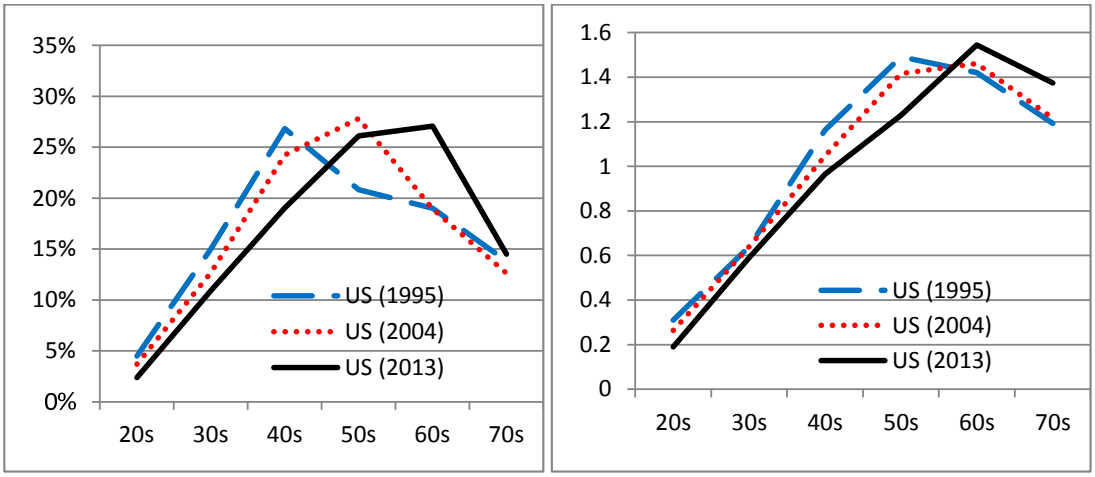
Household asset held by older Korean households has slightly increased over time. However, the proportion of asset held by older Korean households is much lower than that of the US. At the same time, the average amount of asset is lower in Korea than the US.

Figure 11 (Left) Household Total Asset Ratio by Householder's Age (Right) Ratio of Per-Household Total Asset to Average of All Households



Data: 2004 KLIPS and 2014 SHFLC

Figure 12 (Left) Household Total Asset Ratio by Householder's Age (Right) Ratio of Per-Household Total Asset to Average of All Households



Note: US Households with asset in the top 1% are dropped. Data: 1995, 2004, and 2013 SCF

In sum, the proportion of household debt held by each age group has shifted over the last 10 years. At the same time, the distribution for household income and asset also has shifted to the right. Therefore, when we prepare for policy measures to resolve the household debt problem we need to understand the nature of household debt distribution which is not time-invariant. In the following section, I analyze why household debt distribution has shifted both in Korea and the US. In turn, I examine expected changes in household debt distribution in the near future and draw policy implications.

5. Analyzing Driving Forces of the Change in Household Debt Distribution

In the previous section, I examined that household debt, income, and asset distribution by householder's age group have shifted over the past 10 years. In this section, I analyze the main driving force that has shifted the household debt distribution. More specifically, I analyze whether changes in the demographic (or age), income, or asset distribution have shifted household debt distribution, and how much each component has contributed to the shift. The analysis is based on DiNardo, Fortin, and Lemieux (1996) and its application.

5.1. Analysis Methodology

Let (m_i, z_i, t) be a household i-specific observation, where m is the amount of household debt, z is the household-specific characteristics, and t is a (survey) year which takes only two values to examine the change in distribution from the initial to terminal year of the analysis. Let $f_t(m)$ be household debt density function (pdf) at time t. Then, the unconditional household debt density

function can be re-written by

$$f_t(m) = \int f(m|z, t_m = t)dF(z|t_z = t) = f(m; t_m = t, t_z = t)$$

That is, the unconditional density, $f_t(m)$, is the integral of conditional density of household debt at time t_m, over the distribution of household characteristics density function $dF(z|t_z = t)$ at time t_z.

Suppose that household's characteristics z is composed of four components: householder age (z_1), income (z_2), asset (z_3), and other characteristics (z_4). That is, $z = (z_1, z_2, z_3, z_4)$. Then, we can re-write the above density function as follows:

$$\begin{aligned} &f\left(m; t_m = t, t_{z_1|z_2,z_3,z_4} = t, t_{z_2,z_3,z_4} = t\right) \\ &\qquad = \int f(m|z_1, z_2, z_3, z_4, t_m = t)dF\left(z_1\middle|z_2, z_3, z_4, t_{z_1|z_2,z_3,z_4} = t\right)dF(z_2, z_3, z_4|t_{z_2,z_3,z_4} = t) \end{aligned}$$

Following the notation of DiNardo et al. (1996), let's consider a counter-factual time t household debt density where household characteristics, except for z_1, remain at their t-year and the z_1 distribution is switched to their t'-year where $t \neq t'$. For example, we can imagine a hypothetical 2004 (t) household debt distribution where only the householder's age distribution follows in their 2012 (t') and all other household characteristics distributions remain in their 2004 (t). Such a counter-factual density can be written by

$$\begin{aligned} &f\left(m; t_m = t, t_{z_1|z_2,z_3,z_4} = t', t_{z_2,z_3,z_4} = t\right) \\ &= \int f(m|z_1, z_2, z_3, z_4, t_m = t)dF\left(z_1\middle|z_2, z_3, z_4, t_{z_1|z_2,z_3,z_4} = t'\right)dF(z_2, z_3, z_4|t_{z_2,z_3,z_4} = t) \\ &= \int f(m|z_1, z_2, z_3, z_4, t_m = t)\Psi_{z_1|z_2.z_3.z_4}(z_1, z_2, z_3, z_4)dF\left(z_1\middle|z_2, z_3, z_4, t_{z_1|z_2,z_3,z_4} = t\right)dF(z_2, z_3, z_4|t_{z_2,z_3,z_4} = t) \end{aligned}$$

where $\Psi_{z_1|z_2.z_3.z_4}(z_1, z_2, z_3, z_4)$ is a weighting function defined by

$$\Psi_{z_1|z_2.z_3.z_4}(z_1, z_2, z_3, z_4) = \frac{dF\left(z_1\middle|z_2, z_3, z_4, t_{z_1|z_2,z_3,z_4} = t'\right)}{dF\left(z_1\middle|z_2, z_3, z_4, t_{z_1|z_2,z_3,z_4} = t\right)}$$

The only difference between the original household debt density function and the counter-factual density function is the weight function, $\Psi_{z_1|z_2.z_3.z_4}(z_1, z_2, z_3, z_4)$. The weighting function can be re-organized by using the Bayes' rule as follows:

$$\Psi_{z_1|z_2.z_3.z_4}(z_1, z_2, z_3, z_4) = \frac{dF\left(z_1\middle|z_2, z_3, z_4, t_{z_1|z_2,z_3,z_4} = t'\right)}{dF\left(z_1\middle|z_2, z_3, z_4, t_{z_1|z_2,z_3,z_4} = t\right)} = \frac{\dfrac{\Pr\left(t_{z_1|z_2,z_3,z_4} = t'|z_1, z_2, z_3, z_4\right)}{\Pr(t_{z_1|z_2,z_3,z_4} = t'|z_2, z_3, z_4)}}{\dfrac{\Pr(t_{z_1|z_2,z_3,z_4} = t|z_1, z_2, z_3, z_4)}{\Pr(t_{z_1|z_2,z_3,z_4} = t|z_2, z_3, z_4)}}$$

In the actual computation, I used the probit model to solve the last term of the above equation. That is, generate a dummy variables which is 1 if data year is t' and 0 otherwise. Similarly, generate the other dummy variable which is 1 if data year is t and 0 otherwise. Then, for example, the weighting function can be calculated by

$$\Pr\left(t_{z_1|z_2,z_3,z_4} = t' \middle| z_1, z_2, z_3, z_4\right) = \Phi(\beta z)$$

In the actual implementation, I used the head of household age, square of their age, log real asset, log real income, education dummy (1 if less than high school degree, 0 otherwise), homeownership status, and the number of household members.

Since I mainly analyze how household debt distribution by householder's age changes over time, we need to manipulate the unconditional density function to get household debt distribution by householder's age group. The portion of household debt held by each age group can be re-written as follows:

$$\frac{\sum_{i\in \text{Age group}} w_i m_i}{\sum_{i\in \text{All population}} w_i m_i} \approx \frac{\int_{\text{Age group}} mf\left(m; t_m = t, t_{z_1|z_2,z_3,z_4} = t, t_{z_2,z_3,z_4} = t\right) dm}{\int_{\text{All population}} mf\left(m; t_m = t, t_{z_1|z_2,z_3,z_4} = t, t_{z_2,z_3,z_4} = t\right) dm}$$

Similarly, let's consider the counter-factual time-t household debt distribution by householder's age where only the z_1 distribution changes to their time-t' and other household characteristics remain in their time-t.

$$\frac{\int_{\text{Age group}} mf\left(m; t_m = t, t_{z_1|z_2,z_3,z_4} = t', t_{z_2,z_3,z_4} = t\right) dm}{\int_{\text{All population}} mf\left(m; t_m = t, t_{z_1|z_2,z_3,z_4} = t', t_{z_2,z_3,z_4} = t\right) dm}$$
$$= \frac{\int_{\text{Age}} m \int f(m|z_1, z_2, z_3, z_4, t_m = t) \Psi_{z_1|z_2.z_3.z_4}(z_1, z_2, z_3, z_4) dF\left(z_1 \middle| z_2, z_3, z_4, t_{z_1|z_2,z_3,z_4} = t\right) dF(z_2, z_3, z_4 | t_{z_2,z_3,z_4} = t)\, dm}{\int_{\text{Pop}} m \int f(m|z_1, z_2, z_3, z_4, t_m = t) \Psi_{z_1|z_2.z_3.z_4}(z_1, z_2, z_3, z_4) dF\left(z_1 \middle| z_2, z_3, z_4, t_{z_1|z_2,z_3,z_4} = t\right) dF(z_2, z_3, z_4 | t_{z_2,z_3,z_4} = t)\, dm}$$
$$\approx \frac{\sum_{i\in \text{Age group}} m_i \sum_{\forall j|m_i} \Psi_{z_1|z_2.z_3.z_4}(z_1, z_2, z_3, z_4)_{ij} w_{ij}}{\sum_{i\in \text{All population}} m_i \sum_{\forall j|m_i} \Psi_{z_1|z_2.z_3.z_4}(z_1, z_2, z_3, z_4)_{ij} w_{ij}} = \frac{\sum_{i\in \text{Age group}} m_i \Psi_{z_1|z_2.z_3.z_4}(z_1, z_2, z_3, z_4)_i w_i}{\sum_{i\in \text{All population}} m_i \Psi_{z_1|z_2.z_3.z_4}(z_1, z_2, z_3, z_4)_i w_i}$$

Therefore, the counter-factual household debt distribution by householder's age can be calculated by using the newly defined weighting function, $\Psi_{z_1|z_2.z_3.z_4}(z_1, z_2, z_3, z_4)w$.

Here, I only consider the case where only the distribution of z_1 changes to the year of t'. We can also extend the household debt density function where the distribution of z_1 and z_2 both change to the year of t', and the other characteristics remain at time t. Then, the counter-factual unconditional density function can be written as follows:

$$f(m; t_m = t, t_{z_1|z_2,z_3,z_4} = t', t_{z_2|z_3,z_4} = t', t_{z_3,z_4} = t)$$
$$= \int f(m|z_1, z_2, z_3, z_4, t_m = t) dF(z_1|z_2, z_3, z_4, t_{z_1|z_2,z_3,z_4} = t') dF(z_2|z_3, z_4, t_{z_2|z_3,z_4} = t') dF(z_3, z_4|t_{z_3,z_4} = t)$$
$$= \int f(m|z_1, z_2, z_3, z_4, t_m = t) \Psi_{z_1|z_2.z_3.z_4}(z_1, z_2, z_3, z_4) dF(z_1|z_2, z_3, z_4, t_{z_1|z_2,z_3,z_4} = t) \Psi_{z_2|z_3.z_4}(z_2, z_3, z_4) dF(z_2|z_3, z_4, t_{z_2|z_3,z_4}$$
$$= t) dF(z_3, z_4|t_{z_3,z_4} = t)$$

where the additional weighting function can be defined by

$$\Psi_{z_2|z_3.z_4}(z_2, z_3, z_4) = \frac{dF(z_2|z_3, z_4, t_{z_2|z_3,z_4} = t')}{dF(z_2|z_3, z_4, t_{z_2|z_3,z_4} = t)}$$

Other procedures are same as before. The only difference is that the new weighting function when calculating the household debt distribution by householder's age is $\Psi_{z_1|z_2.z_3.z_4}(z_1, z_2, z_3, z_4)\Psi_{z_2|z_3.z_4}(z_2, z_3, z_4)w$, rather than $\Psi_{z_1|z_2.z_3.z_4}(z_1, z_2, z_3, z_4)w$.

5.2. Results

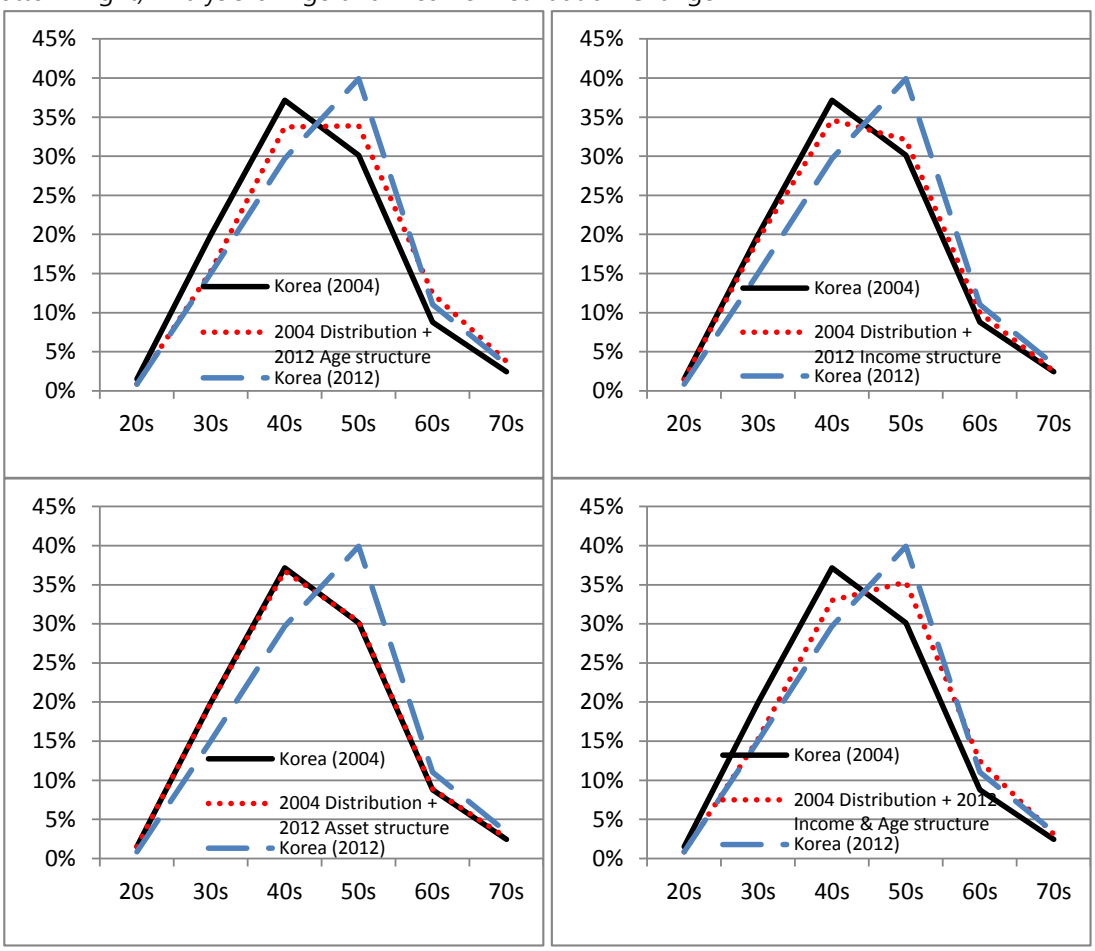
In this subsection, I analyze how changes in distribution of household-specific characteristics affect the household debt distribution by householder's age group. As I presented in the previous section, household debt distribution has shifted to the right over the past 10 years. At the same time, household's demographic, income, and asset distribution have also changed. Among those changes, I examine which factors mainly affect the change in household debt distribution, based on the methodology suggested in the previous subsection.

I choose two survey years, 2004 and 2012, by using the KLIPS data.[10] First, I consider a counter-factual scenario that only household demographic (or age) distribution changes to that of 2012, and other household characteristics remain at 2004. By analyzing such a counter-factual scenario, I could analyze how changes in demographic distribution contribute to the change in household debt distribution. The top left figure in Figure 13 shows that changes in demographic distribution from 2004 to 2012 contribute to the change in household debt distribution almost by half (please see red dotted line). A change in household income distribution also slightly affects the change in household debt distribution (please see top right figure). However, the effect of the change in income distribution is smaller than that from the change in demographic distribution. A change in asset distribution has almost no effects in household debt distribution (please see bottom left

[10] By choosing 2004 and 2012 survey years from KLIPS, I could eliminate potential inconsistence originated from different dataset. I also implemented similar exercise by using 2004 KLIPS and 2014 SHFLC. Qualitative results are almost same. Please see Appendix.

figure). Simultaneous changes in household income and demographic distribution from 2004 to 2012 make the 2004 household debt distribution nearly converge to the 2012 distribution. Therefore, a change in demographic distribution, partly along with the change in income distribution, is the main driving force which has shifted the Korean household debt distribution over the last 10 years. However, there still exists gap between counter-factual distribution and actual 2012 distribution (please see bottom right figure). I suspect that changes in financial market environment or household-specific idiosyncratic shocks might lead to differences in household debt distribution.

Figure 13 Changes in Household Debt Distribution Between 2004 and 2012 Driven by Either Age, Income, or Asset Distribution Changes. (Top Left) Analysis of Age Distribution Change (Top Right) Analysis of Income Distribution Change (Bottom Left) Analysis of Asset Distribution Change (Bottom Right) Analysis of Age and Income Distribution Change

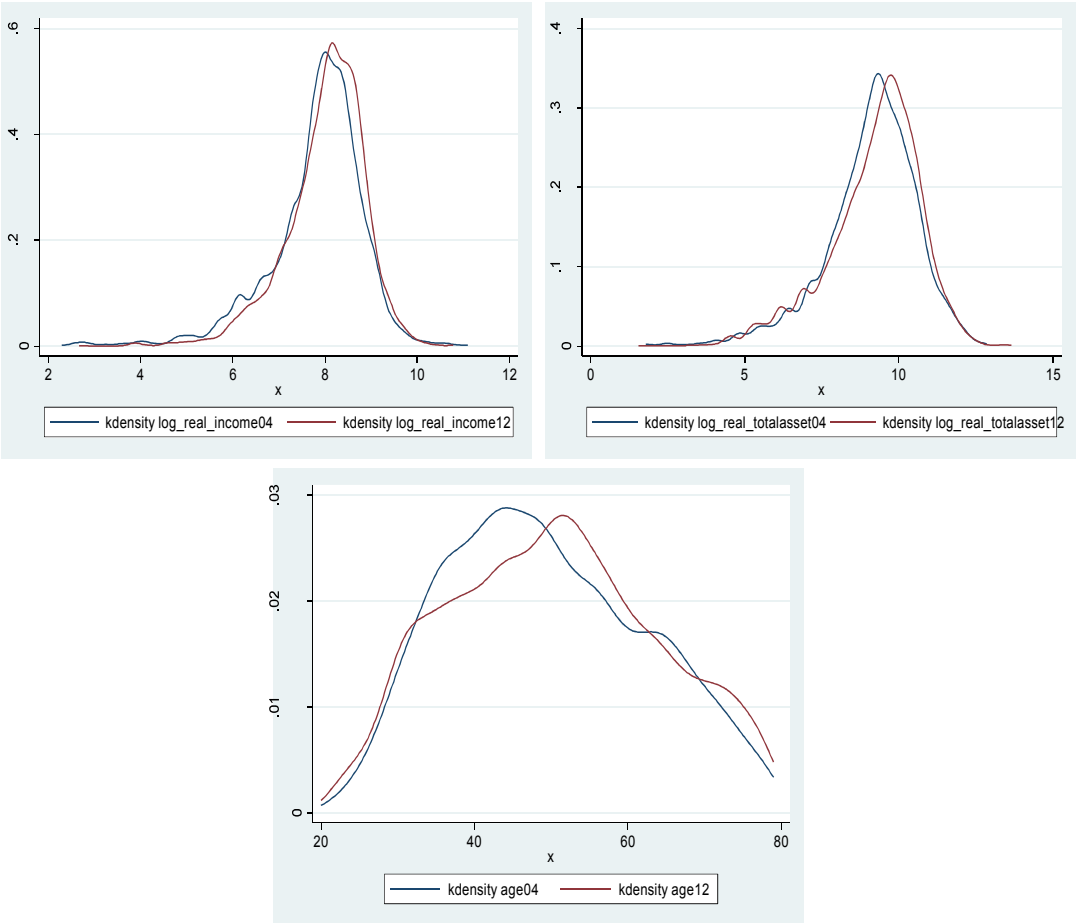


Data: 2004 and 2012 KLIPS

Then, how much have household income, asset, and demographic distribution changed over the last 10 years? Figure 14 presents the kernel density of log real household income, log real asset,

and age distribution. Household income and asset distribution have slightly shifted to the right, which partly reflect (real) growth in Korean economy. Unsurprisingly, the householder's age distribution has shifted to the right visibly. Though household asset, income, and age distribution have all shifted over the last 10 years, the change in household debt distribution is mainly explained by the change in age distribution.

Figure 14 Kernel Density of (Top Left) Log Real Income, (Top Right) Log Real Asset, and (Bottom) Age in 2004 and 2012.

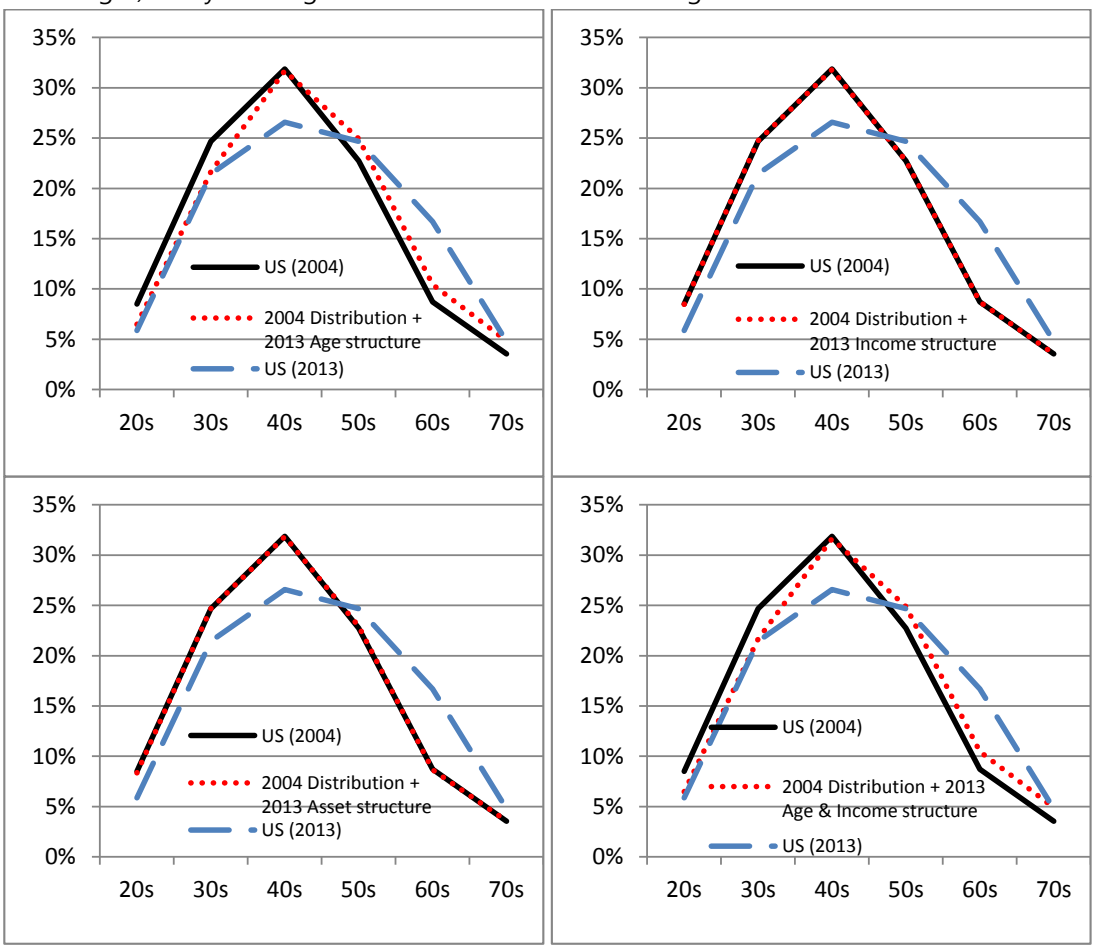


Note: Gaussian kernel function is used. Data: 2004 and 2012 KLIPS

I can draw similar results for the US. As shown in Figure 15, the change in demographic distribution partly affects the change in household debt distribution by householder's age. However, changes in household income and asset distribution have almost no effect on changes in household debt distribution. Between 2004 and 2013, the US economy experienced an unprecedented boom and bust especially in the housing market. More specifically, the US financial intermediaries lent money to households with (relatively) lax screening efforts, which contributed to the boost in the housing market (Keys et al. (2013)). As a result, many subprime loans were

issued, which triggered and exacerbated the financial crisis starting from 2007. After the crisis, the US government implemented many government-driven mortgage modification programs, which partly reduced household financial burden. Since the US economy experienced lots of events over the last 10 years, explaining the change in household debt distribution simply by using household-specific characteristics might not be successful.

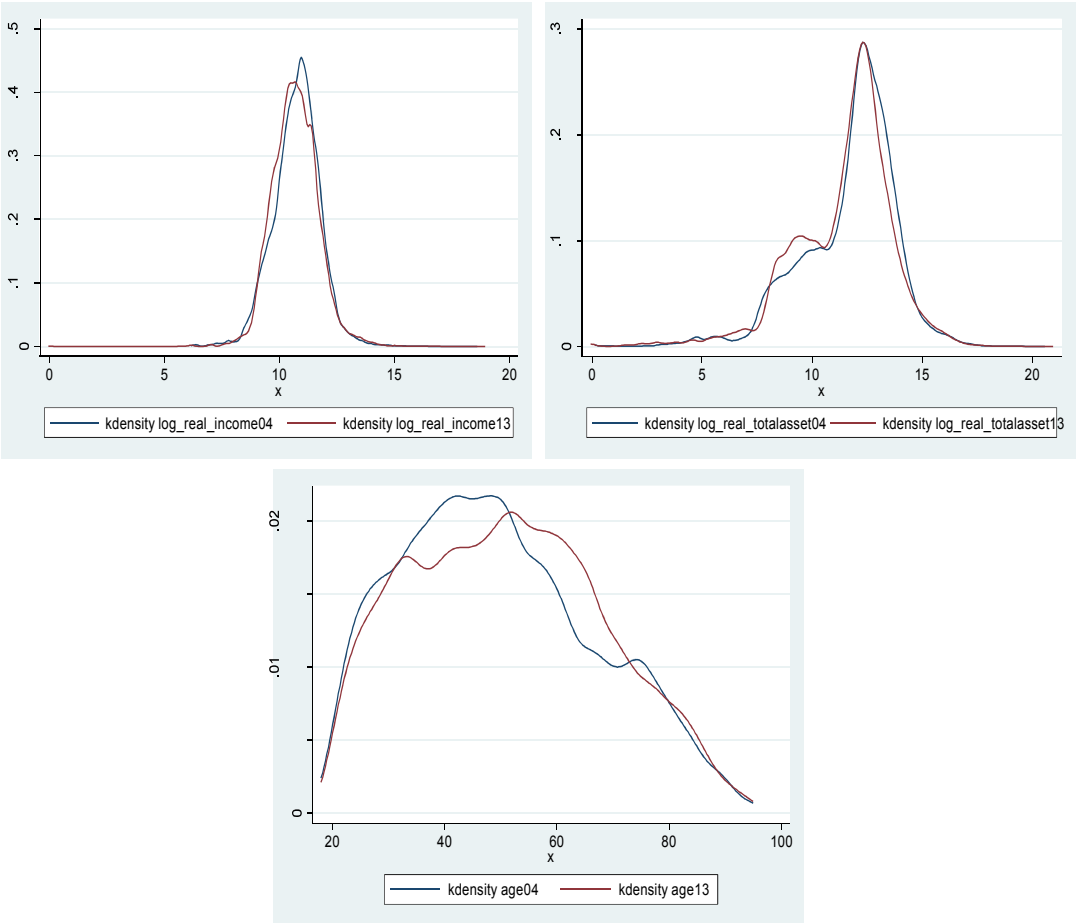
Figure 15 Changes in Household Debt Distribution Between 2004 and 2013 Driven by Either Age, Income, or Asset Distribution Changes. (Top Left) Analysis of Age Distribution Change (Top Right) Analysis of Income Distribution Change (Bottom Left) Analysis of Asset Distribution Change (Bottom Right) Analysis of Age and Income Distribution Change



Data: 2004 and 2013 SCF

Kernel densities of log real income, real asset, and age distribution are presented in Figure 16. Income and asset distribution have not changed significantly over the last 10 years. However, we can observe that the US population is also aging. Although it is not a dominant force, the change in household demographic distribution is also an important factor which explains the shift in household debt distribution in the US, as does in Korea.

Figure 16 Kernel Density of (Top Left) Log Real Income, (Top Right) Log Real Asset, and (Bottom) Age in 2004 and 2013.



Note: Gaussian kernel function is used. Data: 2004 and 2013 SCF

6. Concluding Remarks

In this paper, I analyze how household debt distribution in Korea and the US has changed over the last 10 years. Household debt distribution by householder's age in both countries has shifted to the right. My analysis shows that the shift in household debt distribution is mainly driven by a change in householder's demographic distribution, especially for Korea. Changes in either household income or asset distribution cannot successfully explain the shift in household debt distribution. For the US, the change in demographic distribution can partly, though not enough, explain the change in household debt distribution.

One possible reason why the demographic factor has a strong power in explaining the shift in

household debt distribution in Korea is the Korean-specific debt contract structure. Most mortgage and non-mortgage debt contracts in Korea are short-term and bullet-type loans. That is, households tend to take out loans with a 2-5 year contract period. And then, they repay nothing or pay only interests while in their contract duration. When it comes to the contract expiration date, households refinance loans again, with contract periods of 2-5 years. Hence, the loan principal does not decrease as time goes on and is rolled over repeatedly, with simply paying back the interest. This allows us to observe the cohort effect in debt distribution over the long-time.

On the contrary, the debt contract structure in the US is quite different. Households tend to take out loans, especially mortgages, with a long-term horizon. And then, they pay back both interests and principal over their life cycle. In turn, household's net equity increases as householders become older. That is why the demographic effect in explaining the change in household debt distribution is not as strong as in the Korean case. In addition, the US economy has experienced housing/asset boom and bust over the last 10 years. Hence, it is hard to explain the full shift in household debt distribution merely by the change in demographic or household-specific characteristics distribution.

We can draw the following policy implications for the Korean economy from this analysis. First, as Korean people become older, the proportion of household debt held by older households is expected to increase more in the near future. If older households have large amounts of asset and income, the household debt problem will not be serious. However, as presented in the main text, householder's income in their 60-70s suddenly decreases. In turn, it is highly probable that older householders might experience severer liquidity problems as they become older, along with their debt principal burden. Therefore, policy makers need to consider diverse measures to improve old-aged income. One possible way might be a structural change in the labor market which extends the retirement age of workers through an implementation of the wage peak system. In a similar vein, due to the seniority-based wage system in the current Korean labor market, older employees are unable to avoid early retirement and become self-employed, which in general leads to a sudden decrease in income.

Second, Korean policy makers need to monitor the possibility of asset price deflation more carefully. Many researchers said that Korean household debt problems will not transfer toward the systematic risk because Korean households have enough asset which is a safe buffer for the debt problem. If Korean asset prices are deflated for some exogenous reasons, financial intermediaries might force households to pay back their debt, since their collateral value also decreases. Then, it is possible that households start selling their assets in market to pay back their remaining debt burden, which in turn leads to a decrease in asset price again. The worst scenario might be a

collapse in asset values, along with a sudden increase in household defaults. In order to avoid such a sudden drop in asset value, with preserving a certain level of income for the senior citizens, policy makers can consider an extension of asset-backed security markets or reverse mortgage programs. Those programs can possibly reduce the likelihood of a sudden drop in asset prices with preventing an abrupt decrease in income of the senior households.

Third, policy efforts should be strengthened to make a transition in the debt contract structure from short-term bullet-type to long-term amortized loans. As aforementioned, Korean households tend to roll over their debt without reducing their principal. This phenomenon is possible because of the prevalence in short-term bullet-type loans. Under an economy where asset (or housing) value consistently increases, this type of loan contract structure is sustainable. That is, households have capital gain opportunities with a constant (nominal) value of debt. Hence, even when householders retire, experiencing a steep decrease in their income, they have already accumulated high enough net assets while young. However, as Korean economy has become more developed, the chance of capital gain has been narrowed. Under this environment, households that take out loans without reducing their debt have little chances to have capital gain (or increased net asset holding) when they retire. Since retired households tend to experience a serious decrease in their income, those households can possibly face both liquidity and net asset shocks. This motivates why Korean policy makers should seriously consider the change in debt contract structure. By inducing Korean households to pay back their debt over their life cycle, as do the US households, older Korean households can retire from their jobs without concerning about their remaining debt, even when their income after retirement suddenly decreases.

In sum, the household debt problem in Korea is partly a structural problem originated from the change in demographic composition. It is hard to avoid or reverse the change in demographic trend. However, Korean government can avoid the potential system risk by strengthening macro-prudential policies, labor market restructuring, asset market monitoring, changing debt contract structures, and so on. It is well known that Korea's speed of population aging is the fastest among OECD member countries. I recommend the Korean government to take action as soon as possible before exacerbating the problem.

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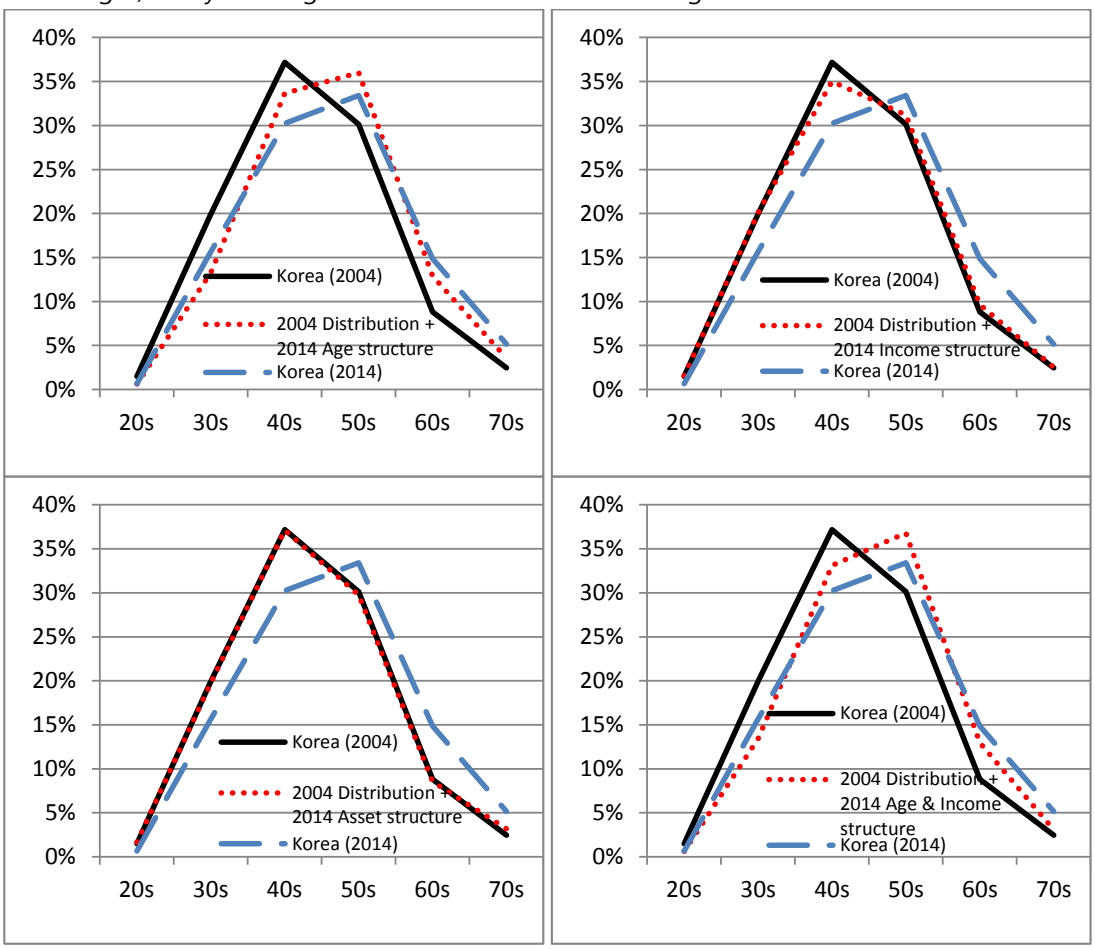
Appendix

In this Appendix, I analyze which household-specific factors drive household debt distribution by householder's age group to move by using 2004 KLIPS and 2014 SHFLC dataset. In the main text of this paper, I examined the same exercise by using 2004 and 2012 KLIPS. Since different dataset might define and survey household-specific characteristics in different ways, I used the single data source (or KLIPS) in the main exercise. As a robustness check, I implement the same exercise by using the most recently released data, 2014 SHFLC, along with the 2004 KLIPS.

Qualitative results are the same as those presented in the main text. The exercise shows that a change in householder's age distribution is the main driving force that shifts the household debt distribution between 2004 and 2014. Unlike the result in the main text, the change in demographic distribution explains almost every change in debt distribution over the last 10 years (please see the red dotted line in Figure A1). However, the counter-factual distribution over-estimates the debt holding ratio for householders whose ages are in the 40-50s. Changes in either household income or asset distribution negligibly explain the shift in the household debt distribution, which is consistent with results in the main text. Therefore, the result that a change household debt distribution is mainly driven by a change in householder's age distribution is a robust result.

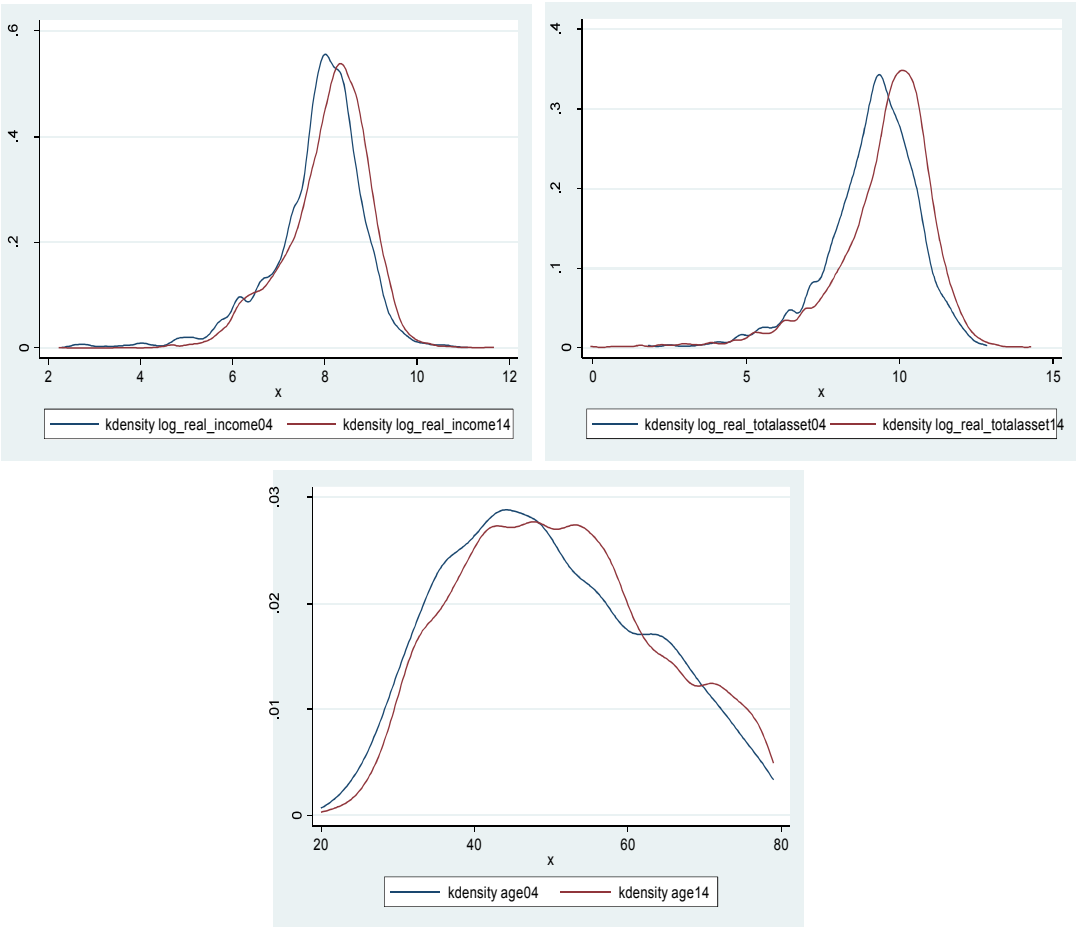
Figure A1 Changes in Household Debt Distribution Between 2004 and 2014 Driven by Either Age, Income, or Asset Distribution Changes. (Top Left) Analysis of Age Distribution Change (Top Right) Analysis of Income Distribution Change (Bottom Left) Analysis of Asset Distribution Change (Bottom Right) Analysis of Age and Income Distribution Change



Data: 2004 KLIPS and 2014 SHFLC

In Figure A2, I present the kernel density of log real income, log real asset, and householder's age by using the 2004 KLIPS and 2014 SHFLC. Though real asset and income distribution have shifted to the right over the last 10 years, those movements have little explanatory power in explaining the change in household debt distribution. Unsurprisingly, the density of householder's age also has shifted to the right for 10 years.

Figure A2 Kernel Density of (Top Left) Log Real Income, (Top Right) Log Real Asset, and (Bottom)Age in 2004 and 2014.



Note: Gaussian kernel function is used. Data: 2004 KLIPS and 2014 SHFLC

CHAPTER 5

Labor Share Decline and the Capitalization of Intellectual Property Products*

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Abstract

We study the behavior of the US labor share over the past 65 years using new data from the post-2013 revision of the national income and product accounts and the fixed assets tables capitalizing intellectual property products (IPP). We find that IPP capital entirely explains the observed decline of the US labor share, which otherwise is secularly constant over the past 65 years for structures and equipment capital. The labor share decline simply reflects the fact that the US economy is undergoing a transition toward a larger IPP sector.

JEL classification: E01, E22, E25
Keywords: Labor Share, Intellectual Property Products, 2013-BEA Revision

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1 Introduction

The constancy of the labor share (LS), one of the great fantasies of contemporary macroeconomics, is finally gone: The LS declines. Using the most recent national income and product accounts (NIPA) data after the 2013 Bureau Economic Analysis (BEA) comprehensive revision, we find that, the US aggregate LS decreases from 0.68 in 1947 to 0.60 in 2013 (Figure 1). Compared with the LS implied by the pre-revision data (Elsby et al. (2013), Piketty and Zucman (2014) and Karabarbounis and Neiman (2014a)), the decline of the updated LS starts much earlier in (at least) the late 1940s and still continues. These findings shatter the alleged constancy of the LS (Kaldor (1957), Prescott (1986)), which is nothing short of "a bit of a miracle" in Keynes' colorful language.

After carefully analyzing the national income and fixed assets data from the 2013 BEA revision that capitalizes intellectual property products (IPP), we show that the prolonged secular decline of the LS is driven predominantly by IPP capital. In particular, the capitalization of IPP accelerates the measured capital formation and depreciation, barely affecting the time series of relative prices of investment. Removing the effects from IPP capitalization on aggregate capital accumulation, depreciation and the price of investment in a parsimonious framework, we recover a LS that is trendless from 1947 to the present. That is, the shift in the speed at which aggregate capital accumulates and depreciates produced by the increasing importance of IPP capital in the US economy over time drives the observed decline in LS.

While IPP is (and has always been) part of the US economy, it is only after the change in the BEA accounting rules and the expansion of the definition of capital used in national income that the effects of IPP capital on the LS emerge from hideout. On July 31, 2013, the BEA released the 14th comprehensive revision of the NIPA. The major feature of this revision is the capitalization of a larger set of IPP.[1] That is, the BEA now treats expenditures by business, government and nonprofit institutions serving households (NPISH) for R&D and expenditures by private enterprises for the creation of entertainment, literary and artistic originals (henceforth, artistic originals) as investments in various forms of durable capital and no longer, as previously done, as expenditures in intermediate nondurable goods (for the private sector) or as final consumption (for the government sector).[2] These two new forms of investment (R&D and artistic originals),

[1] Other components of the US Economic Accounts, such as the fixed assets tables (FAT) and the industry accounts, are also revised to recognize the newly capitalized IPP. We use the revised data in FAT and the industry accounts in this paper.

[2] This revision also uses an accrual basis to compute the cost of defined benefit pension plans, thereby also accounting for unfunded liabilities. The revision contains a number of other minor improvements: expanding the set of ownership transfer costs for residential fixed assets included as fixed investment and improving the accuracy of the relevant asset values and service lives. It also improves the measurement of financial services offered

combined with software (which has been capitalized as part of equipment since the 1999 BEA revision), form a new class of intangible assets, the so-called IPP. This re-classification of capital implies an upward revision of all previous estimates of private sector GDP and importantly also an upward revision on the consumption of fixed capital to reflect the depreciation of these new assets. Overall, it captures the increasingly important role of IPP in the US economy: The share of IPP in aggregate investment has increased from 8% in 1947 to 26% in 2013 (Figure 2); see also McGrattan and Prescott (2014).

Our analysis starts by comparing the old national income data with the new. First, we show that the main difference between pre- and post-revision data lies in the measured depreciation of fixed capital. In the new data, total depreciation has been revised upward by 26.3 percentage points by 2013, or by an absolute amount ($527 billions) similar to the revision to output. Second, a simple accounting adjustment, where IPP depreciation is removed from the post-revision aggregate depreciation and output, eliminates 55% of the LS decline in the revised data. Nevertheless, an accounting adjustment, as such, ignores the effects that the capitalization of IPP may have had on other capital income components besides depreciation. Further, software, whose effects on LS we would also like to study, is already present in the pre-revision data.

To consider such effects, we turn to a simple one-sector model as a measurement device in which the LS is a function of the net return to capital, the price of investment, the stock of capital and the depreciation rate. We construct from the revised fixed assets tables (FAT) the price of investment, the value of the investment flows, and the depreciation rate of the composite capital good, with and without IPP (i.e., software, R&D and artistic originals). We then compute two distinct measures of the capital stock, with and without IPP, by using two separate investment equations that differ in the price of investment, the investment flow, and the depreciation rate. Assuming that the net return to capital is the same with and without IPP, we construct a counterfactual LS that, within the context of the model, is net of all effects from IPP capitalization. This yields the main result of our paper.

We find that the increase in the investment in IPP and its capitalization over time explain—for any practical purpose—the entire secular decline in the LS that we document to have started in the late 1940s. The investment in IPP has significantly enhanced capital accumulation, so much so as to more than offset the direct effect of its higher depreciation rate. By 2013 the aggregate capital stock expands by more than 12%, and the capital-output ratio by more than

by commercial banks by modifying the set of assets and liabilities included in such accounting by introducing borrower defaults and refining the calculation of the reference rate. Finally, it harmonizes the treatment of wages and salaries throughout the accounts and updates to 2009 the reference year for chain-type quantity and price indexes and for chained-dollar estimates. For a detailed discussion, see McCulla et al. (2013).

8%. Furthermore, the change in the price of investment accounted for by IPP capitalization is minor, and its direct effect on the LS is negligible. While R&D capital remains the largest contributor to the LS decline, the effects of software are significant and increasing since the early 1980s. These results are robust to the definition of the LS, in particular to restricting the computation of the LS to the corporate sector which abstracts from the capital-labor partition of ambiguous income (e.g., proprietors income) and also avoids potential effects from the housing and government sectors. In this case, the LS starts declining only in the early 1980s, although at a faster rate than the aggregate LS, falling from 0.65 in 1980 to 0.56 in 2013.[3] Again, for the corporate sector the capitalization of IPP completely explains the decline in the LS.

At the industry level we find a strong negative correlation between the LS and IPP capital intensity. The service and information industry—two of the only three industries whose output is expanding relative to the rest of the economy and that account for 35% of total output in 2013—have experienced a substantial decline in LS and an increase in IPP capital intensity. In addition, the four major industries whose output share declines (i.e., manufacturing of durable and nondurable goods, retail trade and wholesale trade) also display a decline in LS and an increase in IPP capital intensity. In particular, we show that for both durable and nondurable manufacturing, which have experienced the largest declines in LS, the decline is largely due to the increase in IPP investment. That is, manufacturing would not have experienced any decline since the mid-1980s in the absence of IPP capitalization.

In light of our results, it is IPP capital that has generated the acceleration in the capital-output ratio that leads to the decline in the LS over the past 65 years. The observed decline in the LS should therefore be seen as the effect of a transition, a process of structural transformation, toward an economy with a larger IPP sector (see our discussion in Section 5). While it is beyond the scope of this paper to study the growth implications of IPP investment, it seems natural to interpret the higher IPP capital intensity that we are documenting as a source of growth and a sign of prosperity, in contrast to alternative dire assessments associated with labor share decline proposed in Piketty (2014).

The rest of the paper is organized as follows. We introduce our definition of LS and discuss its behavior in the post- and pre-revision data in Section 2. In Section 3, we investigate the implications of IPP capitalization on the aggregate LS through its effects on investment, its price, and the depreciation rate, in the context of a one-sector model. Further, we study the separate role of the private and government sectors and explore the corporate labor share. In Section 5, we provide a two-sector model interpretation of our results where the declining LS reflects a process

[3]These values coincide with the updated data made available online by Karabarbounis and Neiman (2014a).

of structural transformation toward a larger IPP sector. We conclude in Section 6.

2 The US Labor Share: Pre- versus Post-2013 BEA Revision Data

In this section, we construct the US LS and discuss its behavior. The LS is defined as one minus the ratio of capital income to output. The difference in alternative definitions of LS hinges on the way ambiguous income is treated – that is, income that cannot be unambiguously allocated to capital or labor (mainly, proprietors' income).[4]

2.1 Benchmark Labor Share

As our benchmark, we use the standard definition of LS in growth and business cycle modeling from Cooley and Prescott (1995). To deal with the entries of income for which the attribution to either capital or labor is ambiguous, we attribute to capital income the same proportion of the ambiguous income as the proportion of unambiguous capital income to unambiguous income. More precisely, we define[5]

1. Unambiguous Capital Income (UCI) = Rental Income + Corporate Profits + Net Interest + Current Surplus Government Enterprises
2. Unambiguous Income (UI) = UCI + Depreciation (DEP) + Compensation of Employees (CE)[6]
3. Proportion of Unambiguous Capital Income To Unambiguous Income: $\theta = \frac{\text{UCI}+\text{DEP}}{\text{UI}}$.
4. Ambiguous Income (AI) = Proprietors' Income + Taxes on Production − Subsidies + Business Current Transfers Payments + Statistical Discrepancy

[4]See Gollin (2002) for a comprehensive discussion of this issue, which is well known and needs no further belaboring on our part.

[5]As in Ríos-Rull and Santaeulàlia-Llopis (2010), the definition of LS that we use does not include land, which we regard as inaccurately measured. Further, the flow of funds accounts, the original source for land capital and its rents, no longer publish the series, as also noted by Gomme and Rupert (2007). We can, however, add consumer durable goods to the computation of the LS, under assumptions on the rate of return of the consumption of durables. The results of our exercise do not change with this addition.

[6]While aggregate depreciation shows up as the consumption of fixed capital (CFC) in NIPA, our subsequent analysis is based on the depreciation of fixed assets (DEP) from FAT. We choose to do so, since FAT allow us to disaggregate depreciation by types of capital (i.e., structures, equipment, and IPP), which is important for the subsequent analysis. We have verified that the CFC from NIPA and DEP from FAT are almost identical. Moreover, an additional advantage of FAT data over NIPA is that the FAT provide industry-level series under the North American Industry Classification System (NAICS) throughout the entire sample period, whereas NIPA data split into the Standard Industrial Classification (SIC) and NAICS within the sample period. We return to this point in Section 4.

5. Ambiguous Capital Income (ACI) $= \theta \times$ AI.

Then, capital income, Y_K, is computed as

$$Y_K = \text{UCI} + \text{DEP} + \text{ACI},$$

which we use to construct our benchmark LS as

$$\text{Labor Share} = 1 - \text{Capital Share} = 1 - \frac{Y_K}{Y},$$

where aggregate output, Y, is the gross national product (GNP), that is, the sum of total unambiguous and ambiguous income, i.e., $Y = \text{UCI} + \text{DEP} + \text{CE} + \text{AI} \equiv \text{GNP}$.

2.2 The Behavior of Labor Share 1947-2013: Pre- and Post-Revision

Figure 1 shows the time series of the LS constructed from the post-revision data. Clearly, it exhibits a relentless secular decline starting in the late 1940s. The LS begins at 0.678 in 1947 and reaches a historical low at 0.604 in 2013, implying a decline of 11 percentage points over the past 67 years.[7] Fitting a linear time trend yields a decline from 0.678 to 0.629 during the same period, or a secular decline of 7.2 percentage points.

To visualize the effect of the revision, we plot the benchmark LS constructed from both pre-revision and post-revision data for the entire sample in panel (a) of Figure 3.[8] The pre-revision LS shows a decline over time as well but is not as steep as in the post-revision data. The decline starts at 0.685 in 1947 and ends at 0.637 in 2012, implying a decline of 7 percentage points over the same time period. The magnitude of the decline in the pre-revision LS arguably starts around early 1980s and is similar to that reported by Elsby et al. (2013) under their alternative measures. In all, in the post-revision data the LS declines 60% more than that in the pre-revision data.[9]

Since the LS is constructed by combining components of the GNP in the manner specified in Section 2.1, a natural question is "Which components of GNP are affected by the revision?" We investigate each of these components separately. To facilitate our discussion, we group the components of the GNP into three groups: net capital income and depreciation, labor income, and ambiguous factor income. We plot the differences between the post- and pre-revision measures

[7] That is, (0.678 - 0.604)/0.678 = 11%.

[8] We use tables from NIPA and FAT on the BEA's website retrieved shortly before and after the release of the 2013 comprehensive revision. The details of data sources and construction are described in the online Appendix A.

[9] We postpone our discussion of LS behavior in the corporate sector (as in Karabarbounis and Neiman (2014a)) to Section 3.6.

of each component of GNP in panels (b), (c) and (d) of Figure 3. To assess the magnitude of these differences, we also plot the post-revision to pre-revision difference of GNP in each graph.

Panel (b) of Figure 3 shows that, among components unambiguously attributed to capital income (i.e., UCI and DEP), depreciation accounts for the lion's share of the differences. In the new data, aggregate depreciation is revised upward every year and by almost as much as the GNP. The revision reaches $10 billion by 1959 and grows continuously to over $531 billion in 2012, or about 3.2% of the GNP.[10] Minor changes are instead made to net interest, rental income, and corporate profits. Net interest is revised upward for 1973-2001 and downward for 2002-2012. The revisions to rental income are small until 2002 (with the largest revision of $27 billion downward for 2000). For 2003-2012, the revisions are upward with a peak in 2012 (over $78 billion). Corporate profits are revised upward for 1972-1986, downward for 1987-2001, and upward again for 2002-2012. The changes are driven largely by two competing forces: capitalization of IPP, which tends to increase corporate profits, and adoption of accrual-based accounting for defined benefit pensions, which tends to decrease corporate profits. The movements in net interest, rental income, and corporate profit are in opposite directions, so the total effect on UCI from their revisions (i.e., excluding DEP) is relatively small and never exceeds $100 billion.

The total compensation of employees, or the unambiguous labor income, is revised by a small amount relative to the revision to GNP (see panel (c) of Figure 3). The largest upward revision occurs in 2000 (over $68 billion), while the largest downward revision is in 1984 (over $28 billion). The downward revision for 1972-1988 and the upward revision for 1989-2002 largely reflect the new treatment of defined benefit pension plans. The revision after 2002 is the result of a mixture of statistical revisions to wages, salaries, and pensions[11] and the introduction of accrual accounting for defined benefit pension plans.

Finally, as to the ambiguous income, the proprietors' income is the only component that shows traces of revision (see panel (d) of Figure 3). For 1985-2011, revisions are downward,

[10] The upward revisions to the business CFC exceed $300 billion and those to the government CFC exceed $130 billion. In both cases, the revisions are primarily due to the capitalization of IPP. For households and institutions, the upward revisions total $101 billion for 2012 and are due to the revisions on ownership transfer costs for residential fixed assets as well as the capitalization of IPP. See McCulla et al. (2013), pp.24-25.

[11] These statistical revisions on wages and salaries include "updated measures of misreporting based on data from the IRS [Internal Revenue Service], revised data on wages and salaries paid to and received from the rest of the world from the ITAs [International Transactions Accounts], improved measures of wages paid by Indian tribal governments, revised estimates of wages from cafeteria plans and the incorporation of new and revised data from the Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages." The statistical revision to pensions in the later years is due to "the new pensions data from the Department of Labor and new medical expenditures panel survey data from the Department of Health and Human Services." (Quotations are from McCulla et al. (2013), pp.23-24.)

with the largest occurring for 2007 (over $111 billion).[12] For 2012, the proprietors' income is revised upward by almost $20 billion, driven largely by the farm proprietors' income after the incorporation of revised source data from the US Department of Agriculture. This downward revision tends to cancel out the upward revision on the UCI, discussed earlier, having little effect on the total of the non-DEP components of the GNP.

The fact that the revision to GNP is driven mostly by the revision to aggregate depreciation suggests a simple counterfactual exercise, feasible thanks to the disaggregated depreciation series from FAT – namely, to remove from the aggregate depreciation series the part of depreciation that comes from the IPP and recompute the LS, a task we turn to next.

2.3 The Effects of IPP Depreciation on Labor Share

We have seen in the last section that aggregate depreciation is the component of GNP that has been notably revised. In this section, we remove the part of depreciation derived from the capitalization of IPP to gauge the effect from IPP capitalization on the LS. Before going into details, two clarifications are in order. First, the post-revision aggregate depreciation net of IPP depreciation is not identical to the pre-revision aggregate depreciation. This is because software, a component of IPP, was already capitalized and therefore reflected in the aggregate depreciation in the pre-revision data. Second, as explained in Section 2.2, IPP capitalization does affect components of GNP other than depreciation, even though the effects appear to be largely offsetting. Therefore, such a counterfactual exercise is incomplete in the sense that it ignores the effects of IPP capitalization on other components of GNP. However, it is instructive to let the data speak for themselves to the extent they can. In Section 3, we allow IPP capitalization to affect the LS through the price of investment, the depreciation rate, and capital stock in a one-sector model.

The FAT have disaggregated depreciation data by types of capital. In particular, they have the depreciation of the IPP, which includes software, R&D, and artistic originals.[13] We subtract from the post-revision aggregate depreciation the depreciation from IPP recorded in the FAT, while keeping all other components of GNP as they are in the post-revision data. We also revise the GNP downward by the amount of the IPP depreciation. Then we compute the benchmark LS that arises from this accounting exercise. Panel (a) in Figure 4 shows the result in the orange line labeled "Without IPP Depreciation." The magnitude of decline in the LS is greatly reduced.

[12] These downward revisions reflect a variety of changes from the capitalization of IPP, the expanded set of ownership transfer costs for residential fixed assets, and the improved measures of the capital gains and losses attributable to corporate partners. See McCulla et al. (2013), p.26.

[13] See Table 2.4 in FAT for private fixed assets and Table 7.3 for government fixed assets.

More specifically, the LS without IPP depreciation declines linearly by 2.1 percentage points from 1947 to 2010. In contrast, the post-revision LS (blue line) shows a linear decline of 6.0 percentage points for that period – a decline almost 3 times as large. This implies that IPP depreciation alone explains 65% of the LS decline up to 2010. Including the post-2010 years implies a linear decline of 3.3 percentage points without IPP depreciation versus a decline of 7.3 percentage points with the post-revision data, or a 55% reduction over the entire sample period.[14]

Further, to put the pre-revision data into perspective, we add the LS constructed by removing depreciation from the non-software components of IPP. The result of this exercise is plotted as the magenta line labeled "Without Non-Software IPP Dep." in panel (b) of Figure 4. This LS, which factors in the effect from the depreciation of only the software component of IPP, behaves in a manner similar to the pre-revision LS.[15] We find that by removing the non-software IPP depreciation from aggregate depreciation the decline in LS is reduced by about one-half. Precisely, the shift from the post-revision LS (in blue) to the LS excluding non-software IPP depreciation (in magenta) explains 22% of LS decline. Further removing software depreciation (i.e., entirely excluding IPP depreciation) combines to explain 55% of the LS decline, as described above.

In panel (c) of Figure 4, we present three different measures of the LS normalized to 1 in 1980: the post-revision measure, the one without IPP depreciation, and the one computed by Piketty and Zucman (2014) and Piketty (2014) for their sample period, 1975-2010. Our major finding is that the LS without IPP depreciation is virtually trendless, while both the post-revision LS and the one constructed by Piketty and Zucman (2014) show large secular declines. Despite the difference in levels, most likely due to the difference in the data sources, the two declining trends are quite similar.[16] The relevant takeaway from our results is that for the period from 1975 to 2010 chosen by Piketty and Zucman (2014) IPP depreciation entirely explains the US LS decline.

3 The Effects of IPP Capitalization on the Labor Share

While IPP depreciation alone goes a long way in explaining the LS decline, there are further effects

[14] In the online Appendix C, we conduct this counterfactual exercise on each of the components of the GNP and verify that the revision made to depreciation alone explains the change in the behavior of the LS after revision (see panels (a) through (l) of Figure C-1).

[15] From 1975 to 2013, the LS without non-software IPP depreciation declines by 4.85 percentage points, while the pre-revision LS declines by 5.05 percentage points.

[16] Piketty and Zucman (2014) compute an LS that starts at the level of 0.80 in 1974 and decreases to 0.71 in 2010—that is, a decline of 11.25 percentage points compared with our 11-percentage-point decline reported in Section 2.2.

of IPP capitalization that may come through net capital income. To study this, we introduce a simple one-sector model and decompose the total effect of IPP capitalization on the LS into several channels: the price of investment, the depreciation rate, and the investment flows. Our key assumption is that the net return to capital is identical across capital types. We are able to separately identify the effect of IPP capitalization on these variables thanks to the investment, depreciation, and capital stock data by types of capital available from the FAT.

3.1 Labor Share in a One-Sector Model

Consider an environment with one sector and one good produced with an aggregate production function, f, with two inputs, capital k_t and labor l_t. The national income accounting identity states

$$c_t + i_t + g_t + n_t = y_t = f(k_t, l_t; \Omega_t), \tag{1}$$

where c_t is consumption, i_t is investment, g_t is government expenditures, and n_t are net exports. The production function is assumed to be constant returns to scale (CRS) with an elasticity of substitution different from 1 to allow for LS dynamics. Note that Ω_t captures possibly time-varying parameters. If the production function is constant elasticity of substitution (CES), then only technical progress varies with time.[17] The investment i_t, measured in consumption good units, can be converted via a linear technology into a capital good x_t usable in production,

$$x_t = v_t i_t, \tag{2}$$

where the investment-specific technical change (ISTC) – that is, v_t – is the inverse of the relative price of investment, $p_t = \frac{1}{v_t}$.[18] Both i_t and v_t capture changes in the composition of structures, equipment, and IPP investment. The law of motion of capital, in efficiency units k_t^x, is then

$$k_{t+1}^x = x_t + (1 - \delta_t) k_t^x, \tag{3}$$

where δ_t is the depreciation rate of k_t^x for the composite of structures, equipment, and IPP

[17] For our purpose, a CES production suffices. In the CES production, Ω_t captures constant relative input share parameters, a constant elasticity of substitution, and growing technical progress.

[18] As in Greenwood et al. (1997) and Fisher (2006), we identify ISTC as the inverse of the relative price of investment. Under competitive markets, the relative price of investment in terms of consumption is $\frac{1}{v_t}$; that is, the price reflects quality. Under noncompetitive markets, however, the price will reflect both quality and sources of inefficiency such as markups or barriers to technology (or, more generally, investment wedges); see Restuccia and Urrutia (2001), Hsieh and Klenow (2007) and McGrattan and Prescott (2010). Even though here we do not distinguish ISTC from investment wedges, if the effects of IPP capitalization on LS via the relative price of investment are minor, as we find is the case, so will be the effects via ISTC and investment wedges.

capital. Aggregate capital, k_t^x, therefore, depends on the investment flow, i_t, its relative price, $\frac{1}{v_t}$, and the depreciation rate, δ_t. Note that the depreciation rate is allowed to change with time because the composition of aggregate capital also changes, particularly between IPP and non-IPP capital, as we will show.

Let the net return to capital, or the interest rate, be denoted as r_t and the gross return to capital, or the marginal product of capital, be denoted as R_t. The intertemporal investment decision of the firm implies that[19]

$$R_{t+1} \equiv \frac{\partial f(k_{t+1}, l_{t+1})}{\partial k} = \frac{1}{v_t}(1 + r_{t+1}) - \frac{1}{v_{t+1}}(1 - \delta_{t+1}). \tag{4}$$

Under the assumption that the net return to capital is identical across IPP and non-IPP capital goods, the effects of IPP capitalization on the gross return to capital, R_t, come through v_t and δ_t.

The effects of IPP capitalization on the LS,

$$LS_t = 1 - \frac{R_t k_t^x}{y_t}, \tag{5}$$

are due to its effects on the following:

1. The price of investment, $\frac{1}{v_t}$, that affects the LS indirectly through the accumulation of capital, k_t^x, in (3) and directly through the rate of return, R_t, in (4).
2. The depreciation rate, δ_t, that affects the LS indirectly through the accumulation of capital, k_t^x, in (3), and directly through the rate of return, R_t, in (4).
3. Investment, i_t, that affects the LS through its effects on capital accumulation, k_t^x, in (3).

Note that every change in capital income, $R_t k_t^x$, implies an identical change in output, y_t.

This model allows us to do two things. First, we can measure the full effects of IPP capitalization on the LS through its effects on v_t, δ_t, and i_t. Second, we can decompose the effects of IPP capitalization in two different ways: by exploring each of the three determinants (v_t, δ_t, and i_t) in isolation or by exploring R_t and the capital-output ratio separately.

[19] Writing the Bellman equation of the firm as $V(k) = \max_{k',l} f(k,l) - wl - \frac{k' - (1-\delta')k}{v} + \frac{1}{1+r'}V(k')$, then the first order condition (FOC) implies that $\frac{1}{v} = \frac{1}{1+r'}V'(k')$. By taking the derivative of the value function with respect to k, updating one period, and combining it with the FOC, we obtain (4).

3.2 The Effects of IPP Capitalization on Investment, Its Price, and Depreciation Rate

In this section, we describe the construction of the three determinants of the LS, v_t, δ_t. and i_t, separately with and without IPP capital.

3.2.1 The Price of Investment

First, we construct a time series for the price of aggregate capital accounting for the differences in the price of investment in structures, equipment, and IPP.

The construction of the price of investment, P_t^I, closely follows Ríos-Rull et al. (2012). P_t^I is built as a Törnqvist aggregate of the price index of structures (ST), equipment (EQ), and IPP investment with the shares of each type defined as[20]

$$s_t^j = \frac{P_t^{I,j} Inv_t^j}{\sum_j P_t^{I,j} Inv_t^j}, \text{ where } j = ST, EQ, IPP, \tag{7}$$

where our measure of aggregate investment includes private and government accounts and both residential and nonresidential investment.[21] Panel (a) of Figure 5 plots the series i_t with and without IPP investment together with their ratio. The series with IPP grows faster than the one without IPP. The two series start at similar levels in the late 1940s but by the end of the sample period, the one with IPP is about 36% higher than the one without IPP.

To compute the investment price growth let $\lambda(x_t) = \frac{x_t}{x_{t-1}} - 1$. Then,

$$\lambda(P_t^I) = \left(\frac{s_t^{ST} + s_{t-1}^{ST}}{2}\right)\lambda(P_t^{I,ST}) + \left(\frac{s_t^{EQ} + s_{t-1}^{EQ}}{2}\right)\lambda(P_t^{I,EQ}) + \left(\frac{s_t^{IPP} + s_{t-1}^{IPP}}{2}\right)\lambda(P_t^{I,IPP}).$$

[20] The Törnqvist price index specifies, for a variety of components indexed by j,

$$\frac{P_t^I}{P_{t-1}^I} = \Pi_j \left(\frac{P_t^{I,j}}{P_{t-1}^{I,j}}\right)^{\frac{1}{2}\left[s_t^j + s_{t-1}^j\right]}, \tag{6}$$

where s_t^j is the share of the value of the variety j.

[21] The construction of Inv_t^j and $P_t^{I,j}$ for $j = ST, EQ, IPP$ is described in the online Appendix A.1.5 including a description of the subcategories of investment that structures, equipment and IPP incorporate. As previously discussed, the 1999 BEA revision already incorporated software into equipment capital. Indeed, under such capital taxonomy, Cummins and Violante (2002) correct the series for the price of investment provided by BEA in order to adjust for the quality of capital. Here, instead, we use the post 2013 BEA revision data that separately measures the software prices and the prices of other IPP components; see further details on data sources in the online Appendix A and description of these inputs in online Appendix B.

The level of the price index for total investment can be recovered recursively,

$$P_t^I = P_{t-1}^I[1 + \lambda(P_t^I)],$$

with P_0^I=1. Let the price index of consumption be P_t^C.[22] The relative price of investment is then defined as

$$p_t = \frac{P_t^I}{P_t^C},$$

whose inverse, $p_t = \frac{1}{v_t}$, is ISTC.

We compare the price series p_t that accounts for the three kinds of capital with the series that includes only structures and equipment. They are shown, together with their ratio, in panel (b) of Figure 5. Both series have declined since the 1950s, dropping from an initial level of 1.00 in 1947 to about 0.60 in 2013. The relative price of investment with IPP is slightly lower than the one without IPP. The ratio between the former and the latter is around 0.995 in the 1960s and between 0.97 and 0.98 since the late 1980s. Altogether, the effect of IPP capitalization on the price of investment seems rather minor compared with the effect of IPP capitalization on aggregate investment.

3.2.2 Depreciation Rate

We compute the aggregate capital depreciation rate with IPP as $\delta = s_{K_{ST}}\delta_{ST} + s_{K_{EQ}}\delta_{EQ} + s_{K_{IPP}}\delta_{IPP}$, where $\delta_j = \frac{DEP_{K_j}}{K_j}$ and $s_{K_j} = \frac{K_j}{\sum_j K_j}$. The depreciation rate without IPP is computed similarly excluding δ_{IPP}.[23] The difference between depreciation rates with and without IPP is shown in panel (c) of Figure 5. The series with IPP is uniformly higher than the series without IPP and visibly accelerates in the 1980s. The series with IPP starts at 4% in 1947 and ends at 5.2% in 2013, compared with an increase from 3.7% to 3.9% for the series without IPP.

The depreciation rate in capital structures averages 2.2% per year during our sample period. The depreciation rate of equipment is around 12% per year from 1947 to 1982 and rises slightly to 13% per year by the end of the period. The depreciation rate of IPP is much higher and grows over time. It starts at 15% per year and grows to 21.4%.[24] The high depreciation rate of IPP

[22] The construction of P_t^C is discussed in the online Appendix A.1.5. Note that to make the model consistent with the data, we set the price of structures, $P_t^{I,ST}$, to be equal to the price of consumption, P_t^C.

[23] The net capital stock by types of capital is from FAT 1.1 and the depreciation of fixed assets by types of capital is from FAT 1.3. See the online Appendix A.1.3.

[24] See panel (a) of Figure B-1 in the online appendix. Clearly, software is the IPP capital with the largest depreciation rate, starting around 0.30 in the early 1960s and reaching to an average of 0.34 in the 2000s. R&D capital depreciation is roughly around 0.17 since the 1970s. The lowest depreciation rate is for artistic originals

reflects the higher rate at which IPP capital becomes obsolete.

3.3 Effects of IPP Capitalization on Labor Share through Investment, Its Price, and Capital Depreciation

In this section, we use our one-sector model to compute the full effects of IPP capitalization on the LS. For a better understanding of these effects, we also provide decomposition exercises through v_t, δ_t, and capital accumulation.

3.3.1 Total Effects of IPP Capitalization on Labor Share

To measure the full effects of IPP capitalization on the LS we use the definition in (5) and construct a counterfactual LS without IPP capitalization from our one-sector model. First, from the post-revision data, we construct the aggregate investment, the price of investment, and the depreciation rate as detailed in Section 3.2. With this in hand, we use the law of motion of capital in (2) and (3) to build the aggregate capital series, k_t^x. Then, given the LS computed in Section 2.2 using post-revision data, we recover the gross return R_t from (5) and the net return r_t as the only unknown in (4). The net return to capital r_t is set to be the same across all types of capital, an assumption that we maintain throughout.[25] Second, we construct the IPP-free gross return by combining v_t without IPP, δ_t without IPP, and investment without IPP.[26] Then, we build the aggregate capital stock net of IPP by using the perpetual inventory method as for the one with IPP. The product of IPP-free gross return and capital is our measure of capital income without IPP. Finally, to construct the counterfactual LS without IPP capitalization, we further adjust total output by the absolute change in capital income due to IPP.

Our main result is shown in Figure 6. There we plot LS with IPP capitalization – that is, our benchmark LS from the post-revision data described in Section 2 – and the counterfactual LS without IPP capitalization computed here. In striking contrast to the post-revision LS (blue line), the LS without IPP (orange line) is basically trendless over the past 65 years; the respective linear trends plotted in Figure 6 are for the 1947-2010 period. If we fit a linear trend to the LS without IPP from 1947 to any endpoint between 2008 and 2012, the estimated trend is statistically

capital with an average around 0.14 since the 1970s; see panel (b) of Figure B-1 in the online appendix. Further, note that while R&D accounts for around 80% of total IPP investment in the early 1960s, this share declines to a steady 50% in the 2000s; see panel (a) of Figure B-3 in the online appendix. In contrast, the share of software investment in IPP increases from an average of 4% in the 1960s to a steady average of 40% since the 2000s. Artistic originals account for about 10% throughout the entire sample. That is, it is the increasing importance of software capital that causes the upward trend in IPP depreciation.

[25] Given that k_t^x, v_t, and δ_t are constructed with post-revision data and with IPP, then the computed LS from equation (5) must be, by construction, identical to the post-revision LS in Section 2.2.

[26] We use the same initial value for both aggregate composites of capital with and without IPP.

insignificant.[27] By adding the value for 2013, the year in which LS reaches its minimum, the estimated slope becomes -0.0018 with a standard error of 0.00084 in 10-year averages. This linear trend has an estimated value of 0.685 in 1947 and 0.673 in 2013, for an absolute decline of 1.2 percentage points of GNP over a period of 66 years; that is one-fourth of the 5.0-percentage-point decline computed with IPP capitalization.[28,29] In other terms, the decline in LS from 66.5% in 1948 to 60.4% in 2013 is entirely explained by the IPP capital share of income that increases from 1.1% in 1948 to 6.8% in 2013, while the share of income attributed to no-IPP capital remains steady from 32.8% in 1948 to 32.4% in 2013.

The moral of this analysis is straightforward: The secular decline in the LS that started in the late 1940s can be entirely explained by IPP capital.[30]

3.3.2 A Decomposition of Total Effects

We describe several decomposition exercises in Figure 7. The first links the one-sector model to the simple accounting exercise of Section 2.3, where we removed the IPP depreciation. Note that from (4), we can express the capital income $R_t k_t^x$ as

$$R_t k_t^x = \left(\frac{1+r_t}{v_{t-1}} - \frac{1}{v_t}\right) k_t^x + \frac{1}{v_t}\delta_t k_t^x = \left(\frac{1+r_t}{v_{t-1}} - \frac{1}{v_t}\right) k_t^x + DEP.$$

We use the post-revision data to compute $\frac{1}{v_t}\delta_t k_t^x$ without IPP. The LS constructed from such data is shown as the green line in panel (a) of Figure 7. This is the model analogy of removing the depreciation of IPP from the raw data (see panel (a) of Figure 4).

In the second experiment, we begin with the trendless LS without IPP and cumulatively add back the effects of IPP on the price of investment, the depreciation rate and the investment

[27] Precisely, a linear trend from 1947 to 2008, at the onset of the Great Recession, yields a nonsignificant slope of -0.000401; a linear trend from 1947 to 2012 yields a negative but nonsignificant slope of -0.001454.

[28] Although we acknowledge that it is perhaps too soon to decide whether this dip in the LS without IPP from 2009 to 2013 is only temporary, past evidence suggests this is probably the case. For example, we do notice the surging episodes in the LS without IPP starting in 1965 and 1984 or the episodes of LS decline starting in 1971, 1993 and 2006, all of which were of a bigger magnitude than the current dip and reverted to the trend.

[29] We further note that large and persistent cyclical fluctuations of LS, however, survive our scrutiny of IPP capitalization and call for a theory. That is, simple visual inspection of Figure 6 suggests that IPP capitalization does not change the cyclical properties of the LS. Hence, while IPP capitalization can explain the secular decline of LS, the cyclical behavior of LS does not seem much altered by it and remains unexplained.

[30] We looked further back in history and explored the LS behavior from 1929 to 2013. We redo the exercises in Sections 2.3 and 3.3 with this extended sample. We obtain results very similar to those reported here for the postwar sample. The LS in the post-revision data trends down with a slope of -0.0049 from 1929 to 2013, while removing the IPP depreciation alone predicts a trend with an insignificant slope of -0.0010. Removing the effect from IPP capitalization results in a trendless LS series from 1929 to 2013. The figures for these results are in the online Appendix D.

flow (panel (b) of Figure 7). In the construction of the IPP-free LS, if we replace the price of investment without IPP with the price of investment with IPP, the resulting LS largely overlaps with the IPP-free LS (see the purple line label "+ Inv. Price with IPP"). This suggests that the changes in the price of investment induced by the capitalization of IPP play a minor role in the phenomenon we are studying.[31] If we further replace the depreciation rate without IPP by the depreciation rate with IPP, we obtain the green line labeled "+ Dep. Rate with IPP." The effect of IPP capitalization through the depreciation rate is also quite limited. Finally, we replace the investment series without IPP by the aggregate investment with IPP. This brings us back to the LS with the full impact of IPP as computed from the post-revision data. That is, it is the increase in aggregate investment due to the incorporation of IPP that generates the LS decline.

In the theoretical derivation of Section 3.1, we identify a direct and indirect channel through which the price of investment and the depreciation rate incorporating IPP can affect the LS (panel (c) and (d) of Figure 7. Panel (c) of Figure 7 shows that the price of investment incorporating IPP has almost no effect on the LS, either directly, through the gross rate of return or, indirectly, through capital accumulation. Surprisingly, panel (d) of Figure 7 shows a small effect of the depreciation rate with IPP on the LS as well. This result masks two competing effects: (i) A higher depreciation rate increases the gross rate of return, R_t, which tends to increase capital income for a given capital stock, hence reducing the LS (see the purple line labeled "+ Dep. Rate with IPP (Through R)"). (ii) A higher depreciation rate also reduces the accumulation of capital, which decreases capital income for a given rate of return, thereby increasing the LS (see the green line labeled "+Dep. Rate with IPP (Through Cap. Accum.)"). The two effects turn out to be offsetting, leaving the LS only slightly increased, if changed at all, from the reference level.

We have shown that, overall, the increased rate of capital accumulation due to IPP investment is the dominating force behind the LS decline, while the increased rate of depreciation or the reduced price of investment plays lesser roles.[32] To highlight the contribution of IPP to aggregate capital accumulation, Figure 8 plots three ratios: the capital stock with IPP to the one without IPP,[33] the output with IPP to the one without IPP, and the capital-output ratio with IPP to the one without IPP, normalizing all ratios to 1 in 1947. Between 1947 and 2013, IPP capital raises

[31] Here, note that we focus only on the effects of IPP on the price of aggregate investment. Given the small effects that we find that IPP has on the price of aggregate investment, this implies that the large decline in that price is mostly due to the decline in the price of equipment which has an important role in explaining the cross-country differences in the decline of the LS, see Karabarbounis and Neiman (2014a).

[32] As the effects of IPP capitalization on the gross rate of return, R_t, work through the the depreciation rate and the the price of investment, we find that IPP does not change R_t in a significant manner – precisely, only a 2% increase from 1947 to 2013.

[33] This capital series are divided by v_t so that capital and output are in the same consumption good units.

the aggregate capital stock by 12% and the capital-output ratio by 8% by 2013, which explains the LS decline – that is, IPP capitalization implies an increased aggregate capital that is roughly three times larger than the implied increase in output. That is, the LS decline simply reflects the fact that the US is growing toward a larger IPP economy and the revised data take this into account. We discuss this assessment further in Section 5.

3.4 The Role of Software, R&D, and Artistic Originals Capitalization on Labor Share

Here, we further examine the components of IPP in the BEA accounts: software, R&D, and artistic originals. The investment share in IPP associated with R&D has decreased from 84% in the early 1960s to around 50% in the late 1990s, while the investment share associated with software started to increase from null in the early 1960s to 40% in the late 1990s (see panel (a) of Figure 9). Interestingly, since the late 1990s the shares of R&D and software have remained steady throughout the 2000s. The remaining 10% of IPP investment is attributed to artistic originals.

The contribution of the capitalization of each of these three categories to the LS decline is illustrated in panel (b) of Figure 9.[34] Starting from the LS without IPP (the orange line), we replace the time series of investment, its price, and depreciation rate without IPP with their counterparts including only artistic originals. This produces the purple line labeled "+ artistic originals". The inclusion of the artistic originals component has little effect on the behavior of LS. However, including R&D in a similar fashion produces a larger decline in LS (the green line in the same figure), which accounts for about two-thirds of the total decline by 2013. The gap between the green line and the post-revision blue line is accounted for by adding the software component of the IPP.

Panel (c) of Figure 9 plots the change in LS upon the inclusion of each component separately. The total decline in the LS due to IPP capitalization is depicted by a continuous downward trend that registers a drop of about 5 LS points by 2010 (see the magenta line in panel (c) of Figure 9). Of the three IPP components, the effect from the capitalization of R&D is the largest. R&D alone generates 87% of the total LS decline generated by IPP capitalization until 1965. After that year the role of software becomes increasingly important: R&D accounts for 73% of the decline in the 1970s, 71% in the 1980s, 65% in the 1990s, and 57% of the decline in the 2000s. The decreasing effect of R&D is generated by the increasing role of software that accelerated in

[34] To conduct this exercise, note that the private fixed investment by type of IPP is available from NIPA Table 5.3.5 and the government investment from NIPA Table 3.9.5. The price of investment by type of IPP is from NIPA Table 5.3.4. Net stock of capital and the depreciation of fixed assets by type of IPP are available from Table 2.1 and 2.4 for private sector and 7.1 and 7.3 for government in FAT.

the 1960s and accounts for almost 30% of the LS decline by the 2000s.

3.5 The Effects of Private and Government IPP on Labor Share

This section examines the role of the private and government sectors separately. We start by showing the importance of private and government IPP in aggregate investment in panel (a) of Figure 10. Both private and government IPP investments slowly rise from the late 1940s to the mid-1960s, although this share always remains below 10% for both sectors. However, since the mid-1980s, the private IPP investment accelerates to reach 20% of aggregate investment by 2013, while the government IPP investment remains somewhat steady around 6%.[35]

As shown in panel (b) of Figure 10, removing the IPP capitalization in the private sector (analogous to Section 3.3 for the entire economy), we find that the LS decline is largely alleviated. That is, the reduction in the LS that comes from the private sector only is given by the distance between the blue line and the green line in that panel. We present this reduction as a percentage of the total decline in the LS in panel (c) of Figure 10. The capitalization of private IPP investment accounts for an increasingly large fraction of the decline in the LS since the mid-1960s. In 2000, about 73% of the decline in LS is due to the capitalization of the private sector IPP alone.

3.6 IPP Capitalization and the Corporate Sector

There are at least two motivations for investigating the labor share in the corporate sector only.[36] Firstly, by focusing on the corporate sector, we purge ambiguous income from the computation of the LS (i.e., there is no proprietors' income), see Boldrin and Fernández-Villaverde (2005), Boldrin and Peralta-Alva (2009), and Karabarbounis and Neiman (2014a). Secondly, the corporate sector does not include either the housing sector or the government sector, where the measurement of labor share is subject to criticism by Gomme and Rupert (2004) and Gomme and Rupert (2007).[37]

The corporate LS constructed using post-revision data is described in panel (a) of Figure

[35] That is, while the private and government sector show roughly an equal share of IPP investment until the late 1960s, the share of IPP investment in the private sector is 3.3 times larger than in the government sector by 2013. However, note that within sectors IPP contributes to 25% of total private investment and 32% of total government investment. The increase in the private IPP share of aggregate investment is due to a continuous increase in private R&D and a fast increase in private software, both reaching around 9% of aggregate investment by 2013 (panel (a) of Figure B-5 in the online Appendix). Instead, the government R&D share of aggregate investment decreases from 8% in mid-1960s to 5% in the early 2010s and the government software still remains below 1.2%.

[36] The corporate sector represents 55% of GNI in 1948 and 65% in 2013. It increases to 71% in the early 1980s and decreases to 65% in the 2000s.

[37] In Appendix G, we show that our main result of the effect of IPP capitalization on the economy-wide LS is robust to the exclusion of the housing and government sectors from the analysis.

11.[38,39] This LS remains steady around a value of 0.63 from the late 1940s to the mid-1970s and, as noted by Karabarbounis and Neiman (2014a), it exhibits a decline since the mid-1970s, from 0.63 in 1975 to 0.56 in 2013.[40] Further, as in our accounting exercise of Section 2.3, we find that removing IPP depreciation also removes about 43% of the LS decline that occurred between 1975 and 2013. Note that the corporate sector fixed investment consists of private nonresidential fixed investment and assets.[41] Panel (b) of Figure 11 shows the investment share of structures, equipment, and IPP in the corporate sector. The share of investment in structures declines from around 35% in the late 1940s to a somewhat steady 20% share since the late 1990s. Equipment investment accounts for a steady 53% of total investment until the late 1990s, after which it starts to decline, reaching 46% in 2013. This change is explained by an increase in the share of IPP investment from 9% in the late 1940s to 27% in the late 1990s, reaching 33% in 2013. That is, the IPP figures are larger for the corporate sector than for the entire economy (see Figure 2), suggesting a larger IPP capital intensity in the corporate sector, although this is partly due to the fact that the corporate sector does not include residential investment.[42]

The FAT decompose the fixed assets (and their depreciation) of the corporate sector into structures, equipment, and IPP (see the online Appendix A.3). This allows us to assess the effects of IPP capitalization on corporate sector LS in a one-sector model analogous to Section 3.3. The investment prices are those for the entire economy already computed in Section 3.2. The results from the counterfactual exercise of removing IPP capitalization are shown in panel (c) of Figure 11. We find, as was the case for the entire economy, that IPP capitalization completely explains the LS decline in the corporate sector. Basically, the counterfactual LS (orange line in panel (c) of Figure 11) without IPP capitalization displays no visible trend after 1975.[43]

Finally, panel (d) of Figure 11 decomposes the effects of IPP capitalization on corporate LS

[38]We compute the corporate LS by dividing the compensation of employees (i.e., the income accruing to employees, such as wages, salaries, employers' contributions for social insurance, and other labor income) by the gross value added, which consists of the consumption of fixed capital, compensation of employees, taxes on production and imports less subsidies, and net operating surplus, and, in turn, net operating surplus consists of net interest and miscellaneous payments, business current transfer payments, and corporate profits.

[39]Here we focus on the joint LS behavior of financial and nonfinancial corporate businesses. See the online Appendix A.3 for data sources and construction. The LS behavior of the entire corporate sector and the nonfinancial corporate sector are similar because the financial corporate sector is relatively small. The gross value added of the financial corporate sector accounts for 4% of the corporate gross value added; this proportion slowly increases to 12% toward the end of the sample.

[40]Our corporate LS is identical to the updated LS data supplied by Karabarbounis and Neiman (2014a) for the subperiod 1975 to 2012 (i.e., the green line in panel (a) of Figure 11).

[41]That is, the corporate sector does not include components associated with residential investment and/or government investment. It also excludes non-corporate private investment.

[42]See Figure B-4 in the online Appendix for a decomposition of investment shares for the aggregate economy without residential investment.

[43]If at all, LS seems to slightly increase by 2 LS points from the late 1940s to the mid-1970s.

by sequentially adding to the data without IPP the investment price with IPP, the depreciation rate with IPP, and the investment flow with IPP. As for the entire economy, most of the LS decline in the corporate sector is captured by the IPP investment flow.

3.7 Labor Share from Vintage Data: A Historical View without IPP Capital

As we noted earlier, while the 2013 NIPA revision incorporates new IPP, i.e., R&D and artistic originals, as investment in national accounts, software is an (indeed, the only one) IPP investment that was already included in the 1999 NIPA revision. This suggests a simple exercise to further investigate the role of IPP in determining the LS decline: If BEA did not incorporate IPP investment at all in the data released before the 1999 revision, we can directly investigate the LS behavior using vintage data released in the year 1998 for the historical series from 1947 to 1998.

This is what we do in Figure 12 that compares four LS series: The LS computed from current BEA data after the 2013 revision, our counterfactual LS that removes the effects of IPP, the LS computed from BEA data released in 1998 (i.e., before IPP investment made it to national accounts) available at the Archives Library of the St. Louis FED, and the LS computed in Gomme and Greenwood (1995) who also implemented a definition of LS similar to our benchmark using data before software entered the national accounts as investment.[44] The results are straightforward. Our counterfactual LS that removes IPP capital from the current BEA data aligns very well with the LS series from vintage data that do not incorporate IPP capital. The three series without IPP capital suggest a trendless LS. This finding strengthens our message and points to IPP capital as the main source of LS decline in the US.

4 IPP Capitalization and Labor Share by Industry

Our main result is that the LS decline is driven by IPP capitalization. In this section, we investigate which industries are becoming more intense in IPP capital and whether the decline of LS at the industry level can be explained by industry-wide IPP capital intensity.

To start, we plot the output shares of 12 main industries from 1947 to 2013 in Figure 13.[45]

[44] We would like to thank Paul Gomme for sharing their vintage data with us.

[45] We recognize 12 main industries, 11 of which correspond to the 2-digit North American Industry Classification System (NAICS) codes: agricultural, forestry, fishing and hunting, mining, utilities, construction, durable goods manufacturing, nondurable goods manufacturing, wholesale trade, retail trade, transportation and warehousing, information, and finance, insurance, real estate, rental and leasing. We additionally construct services as the twelfth industry, which includes the following set of 2-digit NAICS code industries: professional and business services, educational services, health care and social assistance, arts, artistic originals and recreation, accommodation and food services, and other services. In Section A.2 in the online Appendix, we further describe the source and sample periods of industry data and some adjustment methods that we apply to the value added data by industry.

Of all industries, only services, information, and FIRE (finance, insurance, real estate, rental and leasing) are growing relative to other industries, so their output shares increase, see panel (a) of Figure 13. The fastest-growing industry is services which starts at 13.1% of the total output in 1947 and grows to 30%, almost a threefold factor, by 2013. FIRE also shows an important increase in output share from around 12% in 1947 to 22.6%, almost a twofold factor, in 2013. Information starts low, around 3.2% and increases by about a 1.5-fold factor reaching an output share that is still small, 5.5%, compared with the other growing industries. The output shares of industries that stagnate or decline are found in panel (b) of Figure 13. The industry with the largest decline is clearly manufacturing. The durable goods manufacturing share of output drops from nearly 18% in the early 1950s to 7.6% in 2013, and the nondurable goods manufacturing share of output drops from 14.3% in 1947 to 6.9% in 2013. In relative terms, it is also important to note the drop in the agricultural share of output from 9.3% in 1947 to 1.4% in 2013. In short, output is moving to services, FIRE and information, and the industries with stagnant or decreasing output shares by 2013 that still represent a large share of output are manufacturing (in durables and nondurables), retail trade, and wholesale trade.

Next, we use additional industry-level data of investment, price of investment, and depreciation from the FAT to construct industry LSs using equation (5) from Section 3.1.[46] We apply that formula separately to each industry under the assumption that the net return to capital is identical across NAICS industries. The main reason to use this LS construct, in addition to ensure consistent industry classification under NAICS throughout the 1947-2013 period, is that it allows us to study the effects of IPP capitalization on the LS at the industry level, in the same manner that we explored these effects at the aggregate level in Section 3.3.[47] At the same time, we construct the industry IPP capital intensity by dividing the IPP capital stock by the total capital stock in each industry. We investigate the relationship between LS and the IPP capital intensity by industry for two subsample periods, 1947-1999 and 2000-2012 in panel (a) in Figure 14.[48] This exercise explores whether industries that have grown more in IPP capital intensity have also

[46] A nice feature from the FAT is that, unlike NIPA, they consistently use NAICS codes from 1947 to 2013. The change in the industry classification in NIPA makes the construction of a consistent measure of LS over time from NIPA alone unfeasible for some industries, for lack of disaggregated subindustry data.

[47] For the subperiod 1998-2012 we also construct the NAICS industry LS computed directly from the national income components in NIPA according to Section 2.1; this is not feasible for the pre-1997 years because the NIPA industry classification for those years is based on the Standard Industrial Classification (SIC). We plot industry-level LS constructed from the FAT data against industry-level LS computed from NIPA in Figure E-4 in the online Appendix E. By and large, the two constructs of LS correspond well. Since our model is frictionless, the difference of the model-based LS and the data-based LS is an indicator of frictions beyond what is factored into the price series of investment.

[48] The point break of 2000 is motivated by the fact that, since the ealry 2000s, we find IPP investment has reached a steady structure of its components, that is, the share of software, R&D, and artistic originals in total IPP investment has remained relatively stable after year 2000; see the discussion in the online Appendix B.

experienced a decline in LS.

There are three observations to highlight. First, in terms of IPP capital intensity, we find that the industries with the highest intensity are also those that experience larger growth in IPP capital intensity in the 2000s. In addition, these industries consist of six of the seven industries with the highest output share in 2013.[49] These industries include information and services—that is, two of the three growing industries identified in Figure 13—that respectively grow by about 0.05 and 0.06 IPP capital intensity points from the first to the second subperiod, nondurables and durables manufacturing which respectively grow by 0.166 and 0.088 IPP capital intensity points, and wholesale and retail trade, which respectively grow by 0.080 and 0.030 IPP capital intensity points. Some of these industries, such as nondurables and durables manufacturing and information, have a relatively high level of IPP capital intensity above 0.10 before 2000, and others such as wholesale trade and services start from IPP capital intensity below 0.06 before 2000. Second, in terms of LS, the largest decline occurs in durables manufacturing by 0.15 LS points, in nondurables manufacturing by 0.08 LS points, in both information and retail trade by 0.07 LS points, and in wholesale trade by 0.04 LS points from the first to the second subperiod. These results represent the first direct empirical evidence of the relationship between the largest growth in IPP capital intensity and the largest declines in LS at the industry level. The largest increases in IPP capital intensity and declines in the LS occur for industries with large initial LS values. Instead, industries with relatively low LS such as agriculture, FIRE, and utilities, barely experience an increase in IPP capitalization and declines in the LS. Finally, only two of the 12 main industries exhibit a positive relationship between IPP capital intensity and LS, transportation and mining.

We also disaggregate the 12 main industries into 46 subindustries (3 and 4-digits NAICS) for the period 1947-2013.[50] For each of these subindustries, panel (b) in Figure 14 reports on the vertical axis the difference (i.e., changes in levels) in LS between the pre- and post-2000 years and on the horizontal axis the difference in IPP capital intensity between the pre- and post-2000 years. Our sample largely populates the bottom-right quadrant of that panel suggesting that most subindustries display a decline in their LS associated with an increase in their IPP capital intensity, with very few industries showing a decline in IPP capital intensity and/or an increase in LS (e.g., petroleum and coal products (Sub-24)). For example, chemical products (Sub-25) shows an increase in IPP capital intensity by .26 points and a decline in LS by .06 points and computer and electronic products (Sub-13) shows an increase in IPP capital intensity by .15 points and a decline in LS by .17 points. The results are clear. The general pattern that emerges is that

[49] Only FIRE is missing with a high output share but low IPP capital intensity.

[50] See Table E-1 in online Appendix E for industry codes and names. Our sample increases to 57 subindustries if we restrict the attention to the post-1970 years, without providing additional insights in our results.

increases in IPP capital intensity go hand in hand with decreases in LS at the subindustry level; a simple regression weighted by subindustries output shares implies that for a .100 points increase in IPP capital intensity, LS declines by .020 points. In all, even with a finer industry classification, we find a negative relationship between LS and IPP capital intensity that is consistent with our main findings for 2-digit NAICS industries described previously.

When IPP capitalization for each industry is removed in the same fashion as described in Section 3.3, we confirm that the LS of industries that invest in IPP flattens out. These results are shown in Figure 15 for the main industries that invest in IPP—that is, information, services, nondurable and durable goods manufacturing, wholesale trade and retail trade.[51] The effects of IPP on LS are largest for the manufacturing sector. Using the post-revision data, the LS of nondurable goods manufacturing and that of durable goods manufacturing declines by, respectively, 0.20 and 0.25 LS points from 1947 to 2013, representing the two largest LS declines in all industries. Further, at the same time, these two industries have also invested heavily in IPP, especially in the post-2000 period, suggesting a potential relationship between IPP capitalization and LS. Removing the effects from IPP capitalization largely mitigates the decline in LS. For nondurables manufacturing, the LS without IPP decreases by 15 percentage points from 1947 to 1984, but it actually increases by 5 percentage points from 1985 to 2013, netting a 10% decline over the entire sample. For durable goods manufacturing, LS without IPP declines by 10 percentage points from 1947 to 1983 and thereafter remains constant until the end of our sample. In sum, IPP capital drives the LS of the manufacturing industries down.

Finally, the effects of IPP capitalization on the LS in information industry are also large: With IPP capitalization, the LS in information declines from 0.68 in 1947 to 0.50 in 2013, a drop of 0.18 LS points. After removing IPP capitalization, the LS drop in information reduces to 0.06 LS points from 0.71 in 1947 to 0.65 in 2013, and LS displays an increase from 0.60 in the mid-1980s to 0.65 in 2013. For the services industry the LS starts at 0.86 in 1947. With IPP capitalization, the LS in services falls to 0.82; without IPP capitalization, LS remains essentially flat and ends at the same 0.86 in 2013. We find similar effects of IPP capitalization on the LS in wholesale trade and retail trade.

5 What Does IPP Capitalization Imply For the US?

Omitting IPP investment implies ignoring 10% and 32% of nonresidential aggregate investment by respectively 1950 and 2013. Such a large change in the composition of investment in the US economy translates into a shift of the economy's technological structure to much higher IPP

[51] For industries that do not invest in IPP the effects of removing IPP capitalization are, obviously, negligible.

output. And the shift toward IPP is still continuing.[52] This suggests that a fruitful approach to understanding the US economy is one that recognizes the increasing importance of the IPP sector, and hence, one that recognizes LS decline.

5.1 An Interpretation with A Two-Sector Model

To explore this point, we adopt a two-sector model with one final good sector and one IPP investment good sector, a framework that mimics that in McGrattan and Prescott (2010, 2012).[53] The sole difference is that we allow the LS to differ across the two sectors.

The final good sector produces a consumption good, the numéraire, using labor, $l_{1,t}$, traditional capital (i.e., structures and equipment), $k_{1,t}$, and IPP capital, d_t:

$$y_t = A_{1,t}(k_{1,t})^{\theta_1}(d_t)^{\phi_1}(l_{1,t})^{1-\theta_1-\phi_1}.$$

The IPP sector produces an IPP investment good using labor, $l_{2,t}$, traditional capital, $k_{2,t}$, and IPP capital, d_t:

$$x_t^d = A_{2,t}(k_{2,t})^{\theta_2}(d_t)^{\phi_2}(l_{2,t})^{1-\theta_2-\phi_2}.$$

Note that the traditional capital and labor are split across the two sectors: $k_t = k_{1,t} + k_{2,t}$ and $l_t = l_{1,t} + l_{2,t}$. However, IPP capital is shared across sectors.

Under competitive markets this implies that LS in the final good sector, $1 - \theta_1 - \phi_1$, and in the IPP sector, $1 - \theta_2 - \phi_2$, are constant. The aggregate labor share, LS_t, can be expressed as

[52] Investment in software and R&D, in particular, is changing the very best and largest firms in the US, even more so in the most recent years. The increase in aggregate IPP investment is created, in a large part, by firms such as Amazon, Microsoft, Intel, Merck & Co., Johnson & Johnson, General Motos, Google and Cisco that lead the innovative process. Take Amazon, for example. The level of logistic efficiency in Amazon's fulfillment centers is unimaginable without its investment in infrastructure software. New products and technologies created by Amazon—such as the electronic visual display that underlies Kindle and the unmanned aerial vehicle (or "drone")—usually take years of development in the in-house R&D labs before commercialization. Indeed, in a recent interview with Charlie Rose, Jeff Bezos, the founder and CEO of Amazon, estimates their drones can deliver 86% of total Amazon purchases (i.e. weighing up to 5 lbs.). Like Amazon, 3D Robotics, DJI, Google, and several other companies that invest in drone technology are awaiting changes in airspace regulation. The interview was released December 1, 2013, at CBS News 60 Minutes-Business: http://www.cbsnews.com/news/amazons-jeff-bezos-looks-to-the-future.

[53] See also a more recent discussion in McGrattan and Prescott (2014).

an average of the two sector-specific LSs weighted by the output shares of the two sectors[54]:

$$\text{LS}_t = (1-\theta_1-\phi_1)\frac{y_t}{y_t+\frac{1}{v_t^d}x_t^d} + (1-\theta_2-\phi_2)\frac{\frac{1}{v_t^d}x_t^d}{y_t+\frac{1}{v_t^d}x_t^d},$$

where v_t^d is the inverse of the relative price of IPP investment and captures ISTC in that sector.

Our empirical results at the industry level suggest that the LS declines with IPP capital intensity (see previous Section). Given that the IPP is often conducted in-house, industries that invest more in IPP are also likely to be those producing IPP. This suggests that the LS in the IPP sector may well be lower than that in the rest of the economy, that is, $1-\theta_2-\phi_2 < 1-\theta_1-\phi_1$, which can be achieved with $\theta_1 = \theta_2$ and $\phi_1 < \phi_2$. Such calibration is consistent with the aggregate results in Figure 6 implying that a higher IPP output (i.e., investment) share in aggregate output leads to a higher aggregate IPP capital share of output while the no-IPP capital share (i.e., structures and equipment) remains constant. This mechanism declines the aggregate LS in response to increases in the IPP output share. If, however, the ratio between IPP and non-IPP output remains constant, the aggregate LS must be constant as well. The fact that we do not observe such steady behavior in the US LS suggests, in the light of this model, that the US economy is still in transition to a larger IPP sector.

That is, a standard two-sector model featuring IPP capital along the lines of McGrattan and Prescott (2010, 2012) that further allows for differential LS across sectors is able to capture the decline in the aggregate LS. This setting recognizes LS decline as a result of a process of structural transformation of the US economy to a larger IPP sector.

5.2 Further Challenges

Two further challenges arise from current data limitations. First, BEA is likely to fall short in accounting for the entire set of IPP capital. While BEA investment accounts incorporate software, R&D, artistic originals, they leave out other recognized sources of IPP such as brand equity and organizational capital. Under the direct data approach implemented by BEA to measure IPP, there are good reasons for such choice because the capitalization of these additional IPP components requires series of investment and depreciation rates that are either not readily available or do not exist. The literature has explored alternatives to get around this limitation in the data. McGrattan and Prescott (2005, 2010) use the structure of their economic model to recover series

[54] If the factor shares are identical across sectors (as is in McGrattan and Prescott (2010)), that is, $\theta_1 = \theta_2$ and $\phi_1 = \phi_2$, then the aggregate LS will be constant. In their Technical Appendix, McGrattan and Prescott (2010) allow for differences in the output shares of non-IPP and IPP capital across sectors (i.e., $\theta_1 \neq \theta_2$ and $\phi_1 \neq \phi_2$), while keeping the LS identical across sectors (i.e., $1-\phi_1-\theta_1 = 1-\phi_2-\theta_2$).

of aggregate IPP capital (a latent variable in their setting) such that other model moments—that do not directly involve IPP—are consistent with their observable counterparts.[55] Their exercise gives us a unique opportunity to compute how much BEA currently captures of total IPP using a measure of total IPP obtained with an entirely different methodology. If we focus on the corporate sector, we find that BEA IPP capital represents 14.1% of total capital in the late 1990s, while this figure is 29.4% in McGrattan and Prescott (2005). In terms of capital income shares, we find that BEA IPP capital accounts for 4.5% of total income in the 2000s, while this figure is 7.6% in McGrattan and Prescott (2010). These comparisons confirm the notion that BEA captures a fraction, i.e., between 48% and 59%, of total IPP.

To address this issue, at least partially, we extend the BEA accounts to incorporate advertising capital, an important dimension of branch equity.[56] In an earlier setting, at a time where only software investment was part of national accounts, Corrado et al. (2009) conduct a similar exercise and implement their own methodology to incorporate a wider set of IPP components to national accounts.[57] Here, we follow Hall (2014) and use the investment series for advertising largely based on the work by Douglas Galbi.[58] We find that advertising accounts for roughly a constant 9% of aggregate investment from 1947 to 2010. The share of advertising in aggregate investment is the largest of all IPP components until the mid-1950s and still at least as large as software and slightly below R&D by 2010.[59] Assuming a depreciation rate of .5, the median in the set of estimates in Bagwell (2007), we recover advertising capital. Finally, we extend our exercise in Section 3.4 to explore the effects of advertising capitalization on the LS. We find that advertising parallelly shifts the LS down around 0.015-0.017 LS points from 1947 to 2010 but does not strengthen (or alleviate) the decline of LS.

Finally, the second limitation from the data is that, even though preliminary results from industry data in Section 4 are consistent with our interpretation of the declining LS, a direct test requires direct measures of output and factor income shares of the IPP sector, and we cannot

[55] Alternatively, Hall (2000) uses stock market data to estimate intangible capital stock with a model that incorporates such features.

[56] This exercise is described in detail in the online Appendix F. Of the set of IPP components currently omitted by BEA, advertising is perhaps the IPP component for which there are, till some extent, more available measures of investment and depreciation, see Bagwell (2007), McGrattan and Prescott (2014) and Hall (2014).

[57] A close look to the Figure 3 in Corrado et al. (2009) suggests that a LS that extends the pre-2013 BEA revision capital with a large set of IPP capital (e.g., R&D, branch equity, organizational capital, and human capital) remains fairly constant from the early 1950s to the early 1980s, and declines roughly about 5% LS points from 1980 to 2005.

[58] These series consist of aggregate advertising expenditures in newspapers, other periodicals, magazines, direct mail, farm publications, business papers, billboards, out of home yellow pages, radio, television, broadcast TV, cable and Internet. They are available at purplemotes.net, `http://www.galbithink.org/cs-ad-dataset.xls` (as of January 2014).

[59] McGrattan and Prescott (2014) also find large expenditures in advertising that are similar to those of R&D using Compustat data.

separately identify these LSs across sectors in the current data. One option is to use the Input-Output Tables in a manner similar to Valentinyi and Herrendorf (2008), classify commodities into a new IPP sector and compute the capital and labor share for each dollar of IPP output. Alternatively, the BEA has already contemplated the possibility of creating an R&D industry in the US industry accounts.[60] In preparing for the 2013 NIPA revision, the BEA has built a R&D satellite account that provides detailed statistics on the nominal and real R&D investment (i.e., R&D output), the R&D capital stock, the rate of return, and the depreciation rate of R&D capital.[61] Using the performer-based data of the National Science Foundation surveys, from which the R&D satellite account itself draws heavily, it should be possible to combine wages and compensations of R&D personnel to form the basis of a measure of labor income in the R&D sector.[62] If the BEA could expand such effort on the R&D satellite account to all components of IPP, we would be able to construct the LS for the IPP sector the same way we construct the LS at the industry level. We call for an effort from the statistical agencies to consolidate the production of IPP into an integral account that differentiates the IPP sector from the rest of the economy. The potential gain from such cleaner IPP accounting framework in understanding the current US economic model could be huge.

5.3 Links to the Labor Market: Potential Future Directions

The behavior of LS can be further related to observations in the US labor market, in particular, the effects of globalization (Autor et al. (2013)). Specifically, the observed decline in the US LS since the 1980s could also reveal cumulative effects of outsourcing US manufacturing as argued in Elsby et al. (2013). In this direction, we have found that manufacturing shows the largest increases in IPP and the largest declines in LS (see our discussion in Section 4). This way, from our perspective, it seems natural to interpret globalization as a source generating IPP investment. That is, firms outsource the routine process of their production, which allows them to focus on the innovation process. For example, Bloom et al. (2011) show Chinese import competition led to increased innovation within EU firms and reallocated employment between firms toward more technologically advanced firms.[63] Under this interpretation, one channel through which the relocation of production units to countries with low labor costs can affect the US LS is through increases in the US IPP capital intensity, particularly, in the manufacturing industry; although we

[60] See Section V of "R&D Satellite account: Preliminary Estimates" (on page 62 of Okubo et al. (2006)).

[61] For a detailed summary of the BEA's methodology of estimating the output, its price, and the depreciation of R&D, see online Appendix A.4.

[62] These expenditure data are used in the BEA's construction of an input-cost price index of R&D output, which later gave way to an alternative output price index believed to better capture the productivity increase of R&D.

[63] Petri Böckerman and Mika Maliranta (2012) find similar effects of globalization on employment that shift employment from firms with high LS toward firms with low LS in a panel of Finnish firms.

acknowledge that this argument deserves further exploration.

Finally, a large body of research that examines the increase in wage inequality suggests that capital-skill complementarity is an important dimension behind skill-biased technical change (Krusell et al. (2000)). In this scenario, if we consider IPP capital as potentially more complementary to skilled work than to unskilled work, then both "IPP capital deepening" and "skill deepening" can be concurrently in process and behind LS decline. Yet, the effects on the LS are not trivial and hinge critically on the cross-elasticities of substitution between traditional capital, IPP capital, skilled work, and unskilled work, an area of investigation that remains unexplored.

6 Conclusion

Using new insights from the post-2013 BEA revision data that capitalize IPP, we show that the decline in the labor share of national income during the past 65 years can be attributed entirely to IPP capital. Further, the somewhat weaker and more recent decline in the labor share displayed by the pre-revision data is analogously explained by the capitalization of software, which was the only IPP component capitalized before the revision. The decline of the labor share should therefore be seen as the result of a shift toward a more IPP-intensive economy, a shift induced by continuing innovation and technological change. It is such technological change and its implications on income distribution across sectors and factors of production that should be modeled.

To better inform modeling choices, we believe the BEA can make further progress on data organization. Specifically, separating firms, or units of firms that specialize in the production of IPP, to form an IPP industry will help clarify a number of issues ranging from the factor shares of income in the IPP sector to the economic relation between the IPP sector and the rest of the economy. So far, our analysis on the labor share across industries ranked by IPP capital intensity suggests that the labor share in the IPP sector is likely to be lower than that of the non-IPP sector, which is consistent with the secular labor share decline of an economy that is becoming more IPP capitalized over time.

Looking ahead, while we have focused on the secular behavior of US data and across its industries, firm-level analysis and multi-country analysis pose interesting challenges for further research. For example, exporting IPP capital to China could potentially reduce the Chinese labor share. Further, we also confirmed the presence of large and persistent cyclical fluctuations in factor shares that are not altered by IPP capitalization and that, hence, still beg for an explanation. Finally, while we have not attempted to link labor share and economic inequality (see recent discussions in Krusell and Smith (2014) and Karabarbounis and Neiman (2014b)), the fact that IPP capital is behind the US labor share decline suggests that an explanation of the joint dynamics

between the labor share and inequality can benefit from explicitly incorporating entrepreneurial agents and activities that generate IPP.

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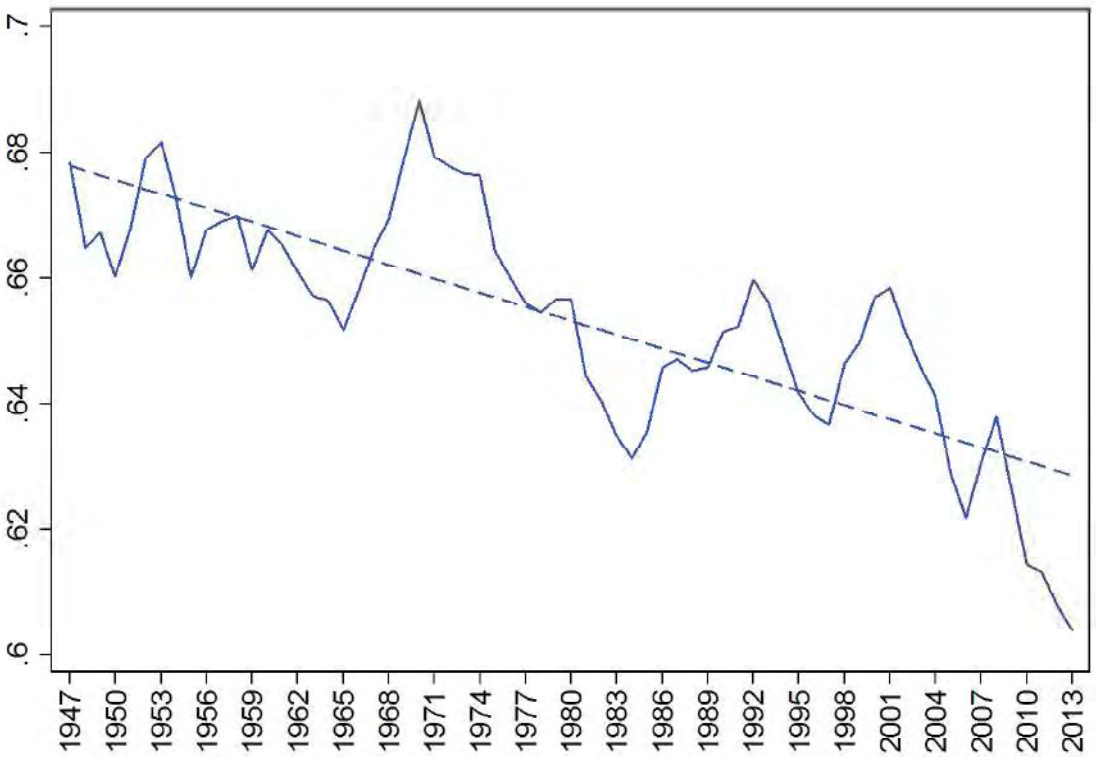
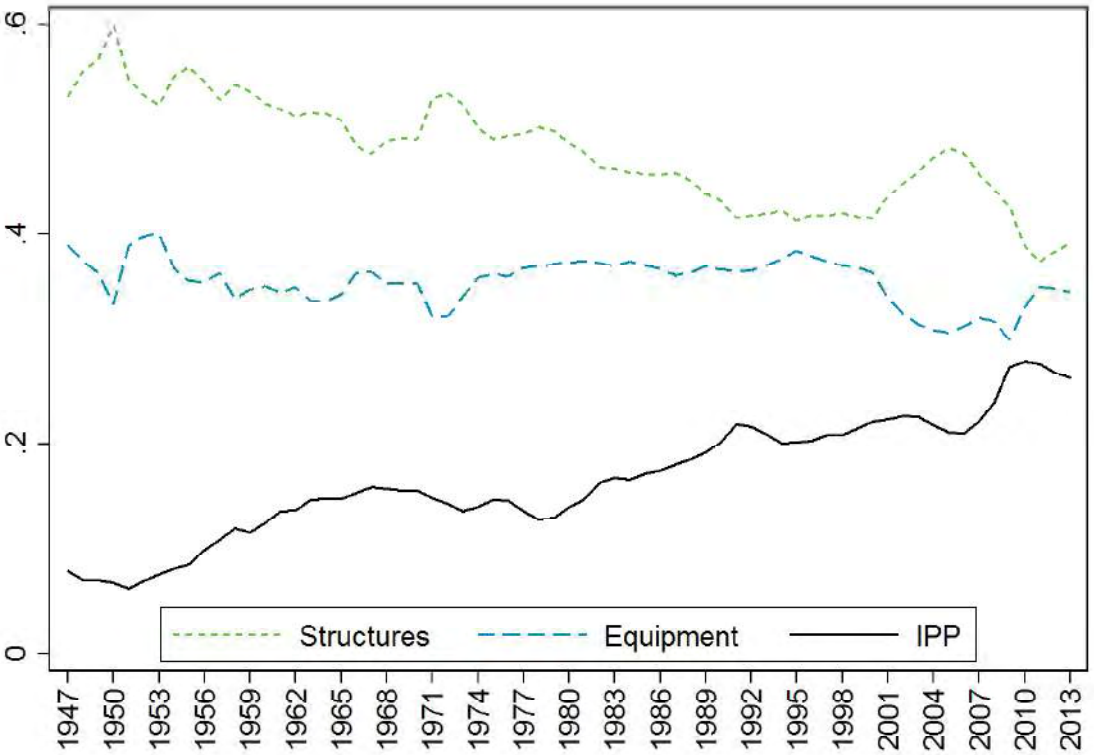
Figure 1: US Labor Share, BEA 1947-2013



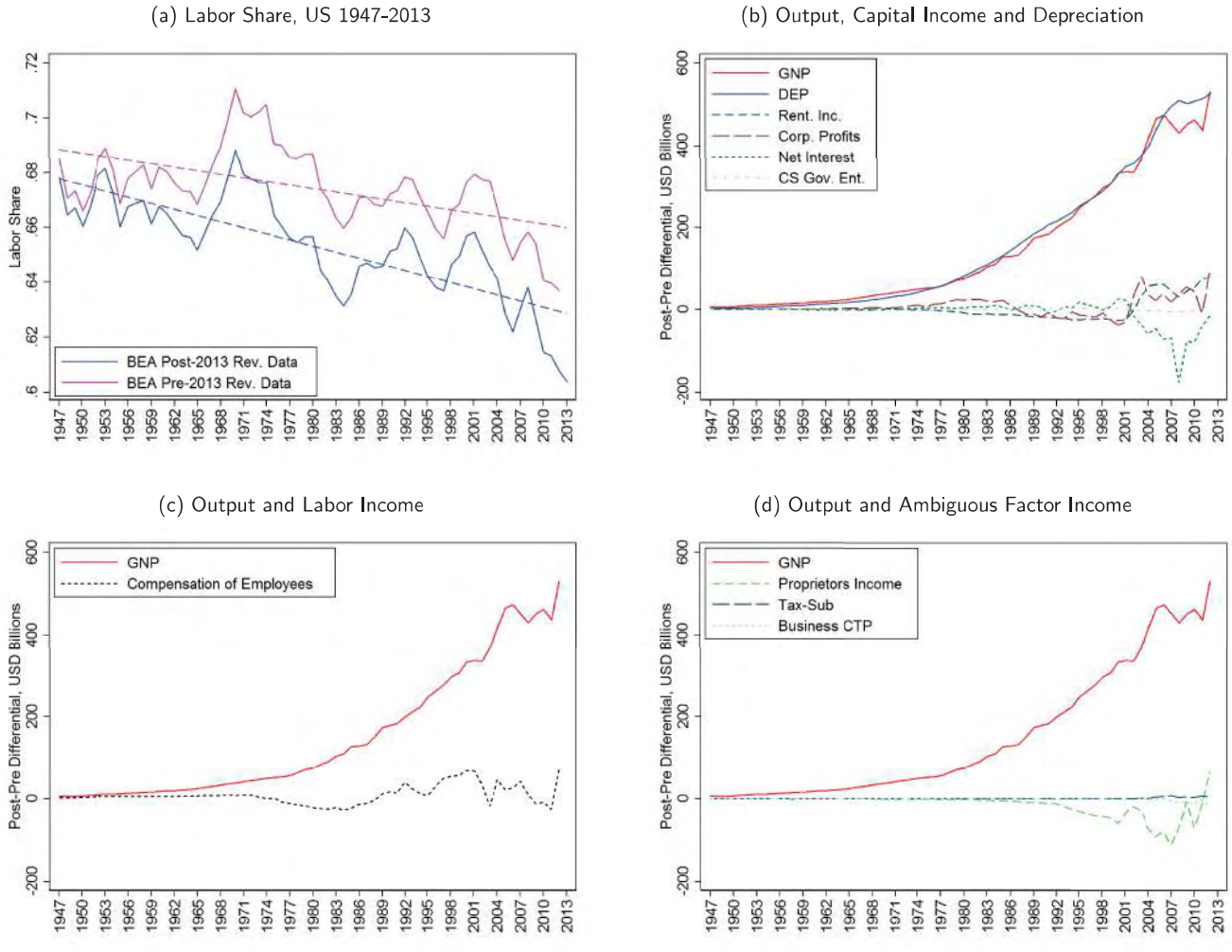
Notes: The labor share of income refers to the benchmark definition described in Section 2.1 and uses only post-2013 BEA revision data. The sample period is 1947-2013. The dashed line is a fitted linear trend with an absolute decline of 7.4% LS points, i.e., from a LS of .678 in 1947 to .603 n 2013. All variables used in computations are in nominal terms.

Figure 2: Structures, Equipment and IPP Investment Shares, BEA 1947-2013



Notes: The investment shares are in terms of aggregate investment that includes both private and government investment and both residential and nonresidential investment. See data construction details in Section 3.2.

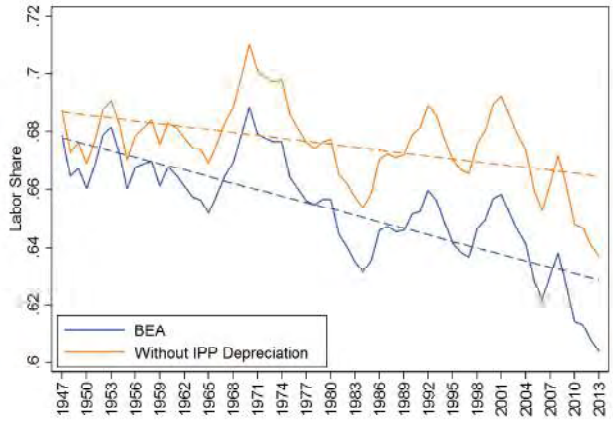
Figure 3: Pre- vs. Post-2013 BEA Revision Data: Labor Share and Its Components



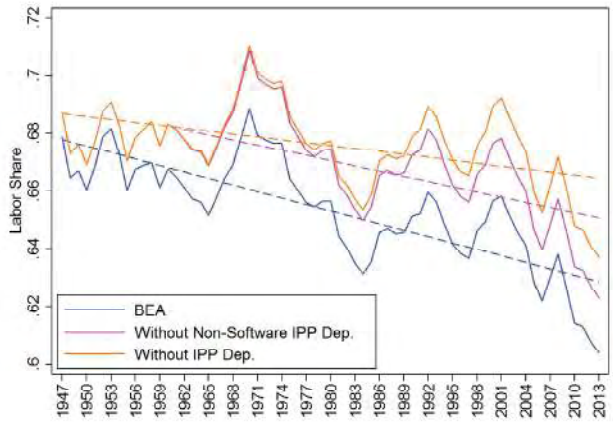
Notes: The labor share of income in panel (a) is constructed using the benchmark definition described in Section 2.1. The 'Pre-Post Differential' reported in panel (b), (c) and (d) are defined as post-2013 BEA revision data minus pre-2013 BEA revision data, in USD Billions. All variables are in nominal terms.

Figure 4: IPP Depreciation and Labor Share, BEA 1947-2013

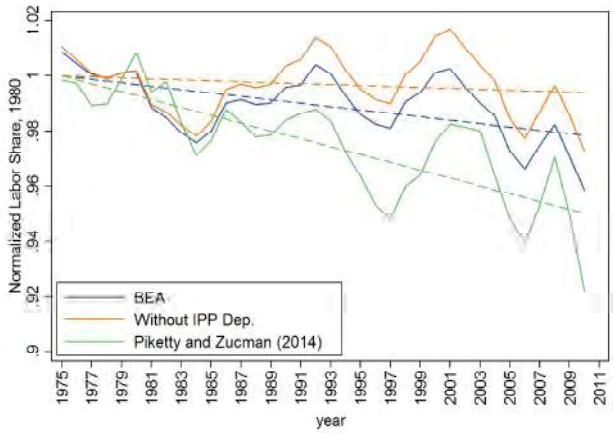
(a) Labor Share Net of IPP Depreciation



(b) Labor Share Net of Software and non-Software IPP Depreciation



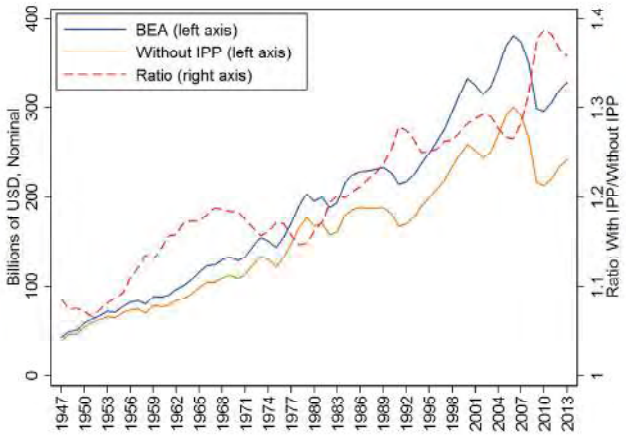
(c) IPP Depreciation vs. Piketty and Zucman (2014), 1975-2010



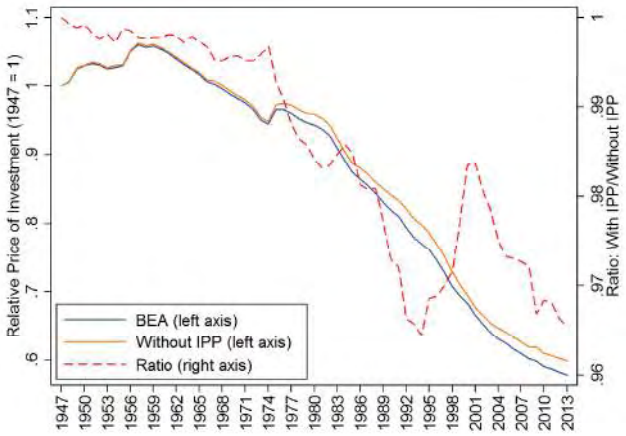
Notes: Benchmark labor share is defined in Section 2.1. In panel (a), labor share without IPP depreciation uses post-2013 revision FAT data to remove, from capital income and from GNP, the increase in depreciation solely generated by IPP, see Section 2.3. Analogously, in panel (b), for labor share without non-software IPP depreciation we solely remove non-software IPP depreciation from the computation of labor share, see Section 2.3. The labor share in Piketty and Zucman (2014) and Piketty (2014) reported in panel (c) is taken from their online appendix in '.xls' form, see more discussion in Section 2.3.

Figure 5: Effects of IPP Capitalization on Aggregate Investment, Its Price and Depreciation Rate

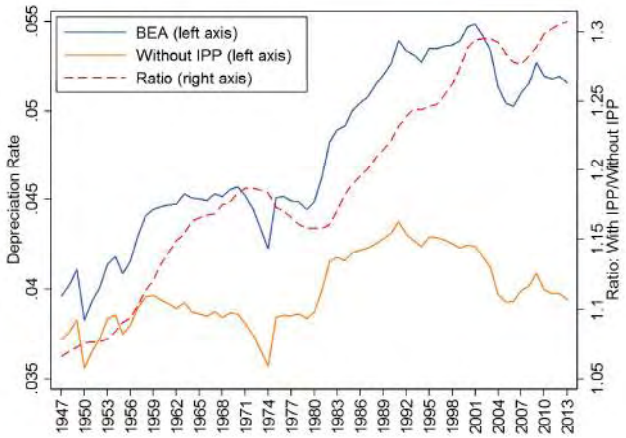
(a) Aggregate Investment With and Without IPP



(b) Relative Price of Investment With and Without IPP

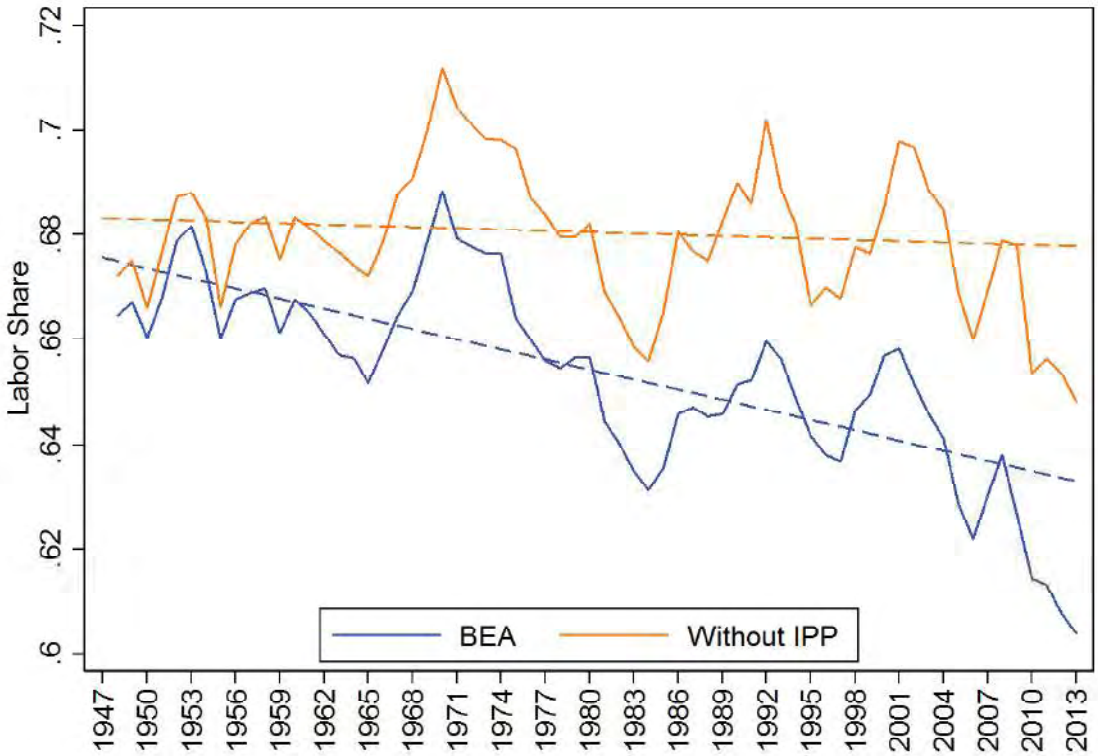


(c) Depreciation Rate With and Without IPP



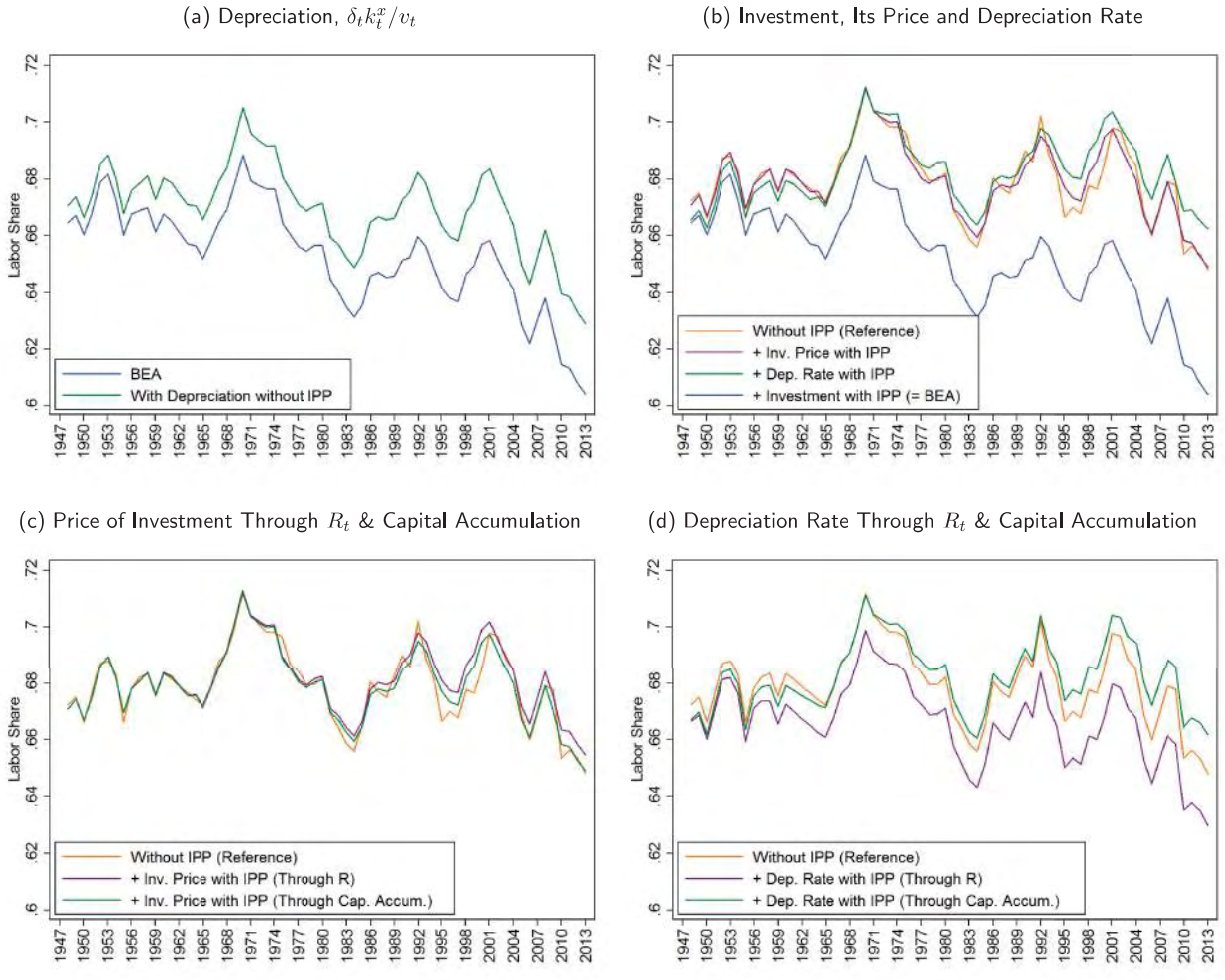
Notes: The construction of aggregate investment, investment price, and depreciation rate for, respectively, panel (a), (b) and (c), is discussed in detail in Section 3.2.

Figure 6: Effects of IPP Capitalization on Labor Share, US 1947-2013



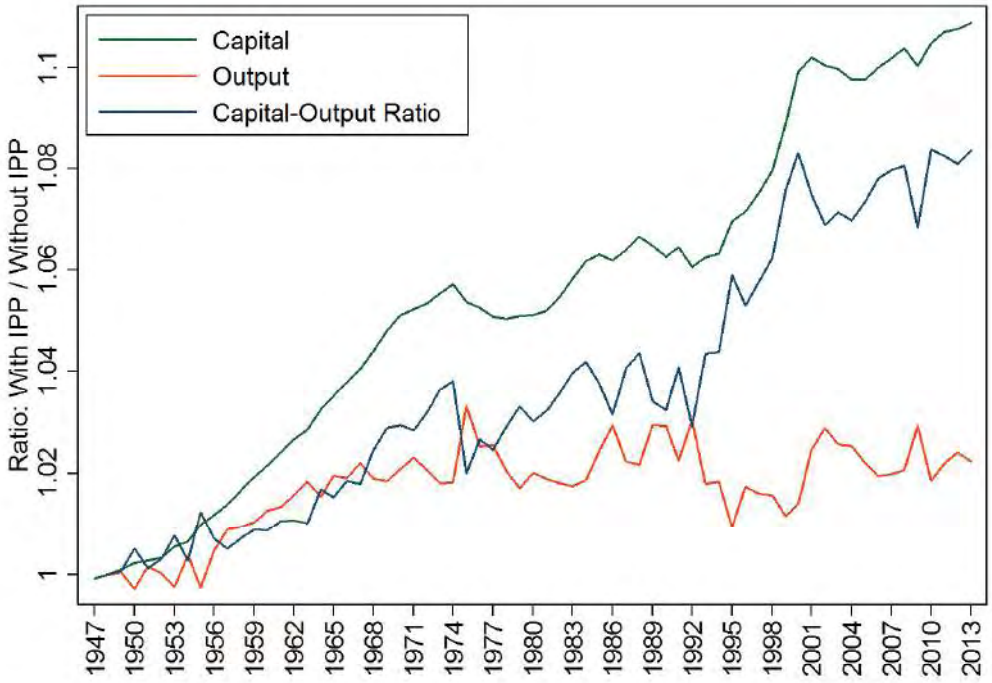
Notes: The labor share labeled as "BEA" refers to the benchmark definition described in Section 2.1 and uses only post-2013 BEA revision data (also depicted in Figure 1). The labor share without IPP refers to the counterfactual labor share that results from entirely removing IPP capitalization by setting v, δ and investment to their values without IPP in the computation of labor share, see Section 3. The underlying linear trend for labor share without IPP is not significantly different from zero from 1947 to 2012; the plotted dashed line refers to 1947-2010.

Figure 7: A Decomposition of the Effects of IPP Capitalization on Labor Share: It is All in Capital Accumulation



Notes: In panel (a) the reference scenario is the benchmark labor share with IPP and the counterfactual labor share results from imposing capital depreciation, $\delta_t k_t^x / v_t$, without IPP to the reference scenario. In panel (b) the reference scenario is benchmark labor share without IPP and the counterfactual experiment consists of sequentially adding to the reference scenario the investment price with IPP, the depreciation rate with IPP, and investment with IPP such that we end up recovering benchmark labor share with IPP. The last two panels take the benchmark labor share without IPP as reference scenario and compute the counterfactual labor shares that results from adding, respectively, the price of investment (in panel (c)) and depreciation rate (in panel (d)) with IPP to the reference scenario separately revealing their effects through R_t and through capital accumulation.

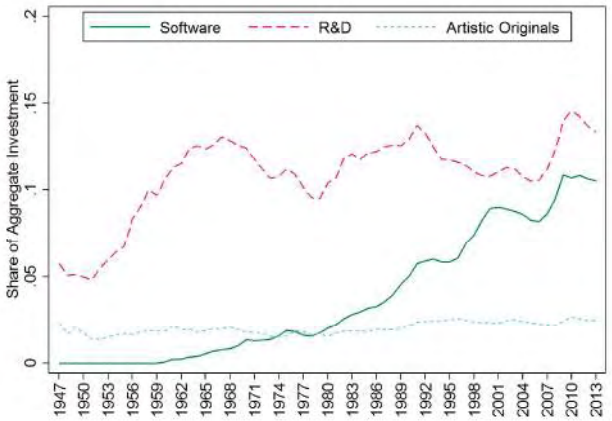
Figure 8: The Effects of IPP Capitalization on Aggregate Capital



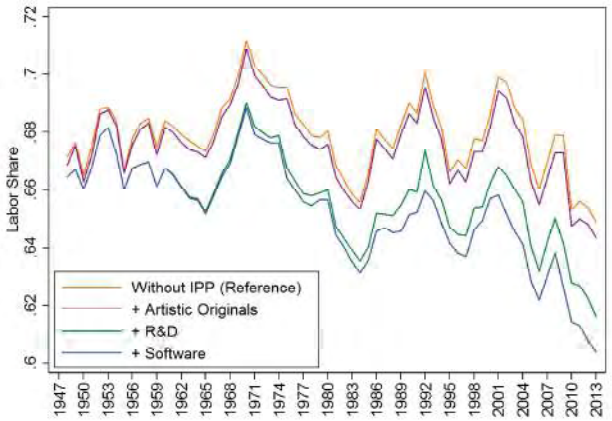
Notes: The effects of IPP capitalization on capital, output and the capital output-ratio refer to the ratio between each of these variables with IPP to without IPP.

Figure 9: Effects of Software, R&D and Artistic Originals Capitalization on Labor Share

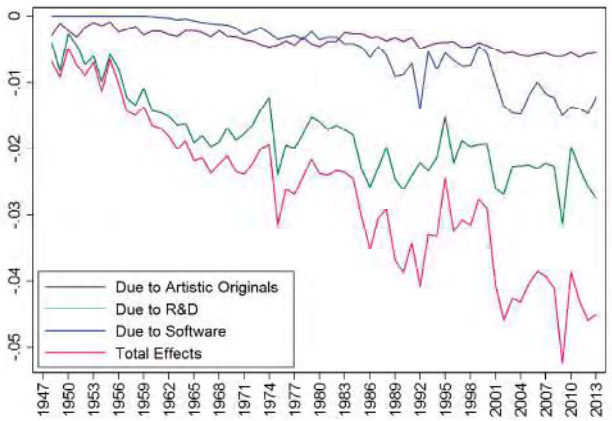
(a) Software, R&D and Artistic Originals Investment Shares, BEA



(b) Effects of IPP Capitalization on Labor Share: By Type of IPP



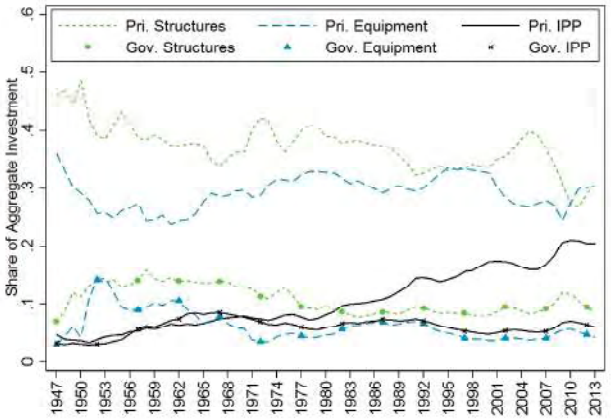
(c) Labor Share Decline Decomposition: By Type of IPP



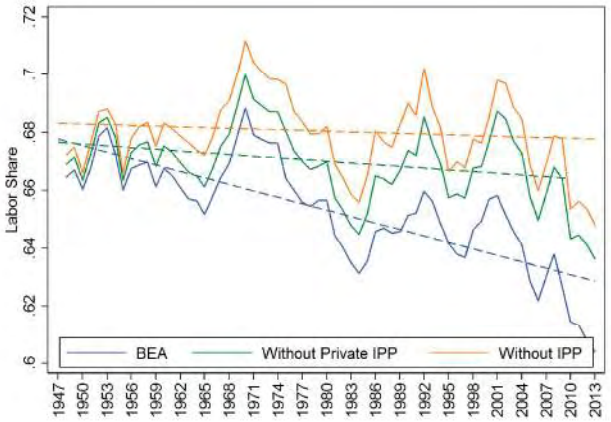
Notes: Panel (a) shows the IPP components shares of aggregate IPP investment. In panel (b) the reference scenario is benchmark labor share without IPP and the counterfactual labor share consists of sequentially adding artistic originals, R&D and sofware capitalization. Panel (c) shows the amount of labor share decline separately generated by each type of IPP capital.

Figure 10: Effects of Private and Government IPP Capitalization on Labor Share

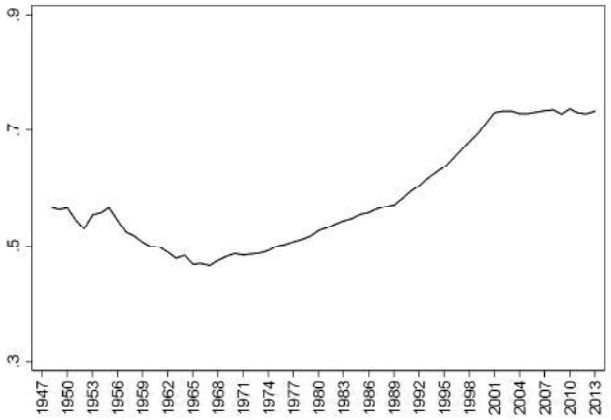
(a) Structures, Equipment and IPP Investment Shares, BEA



(b) Effects of Private and Government IPP Capitalization on LS

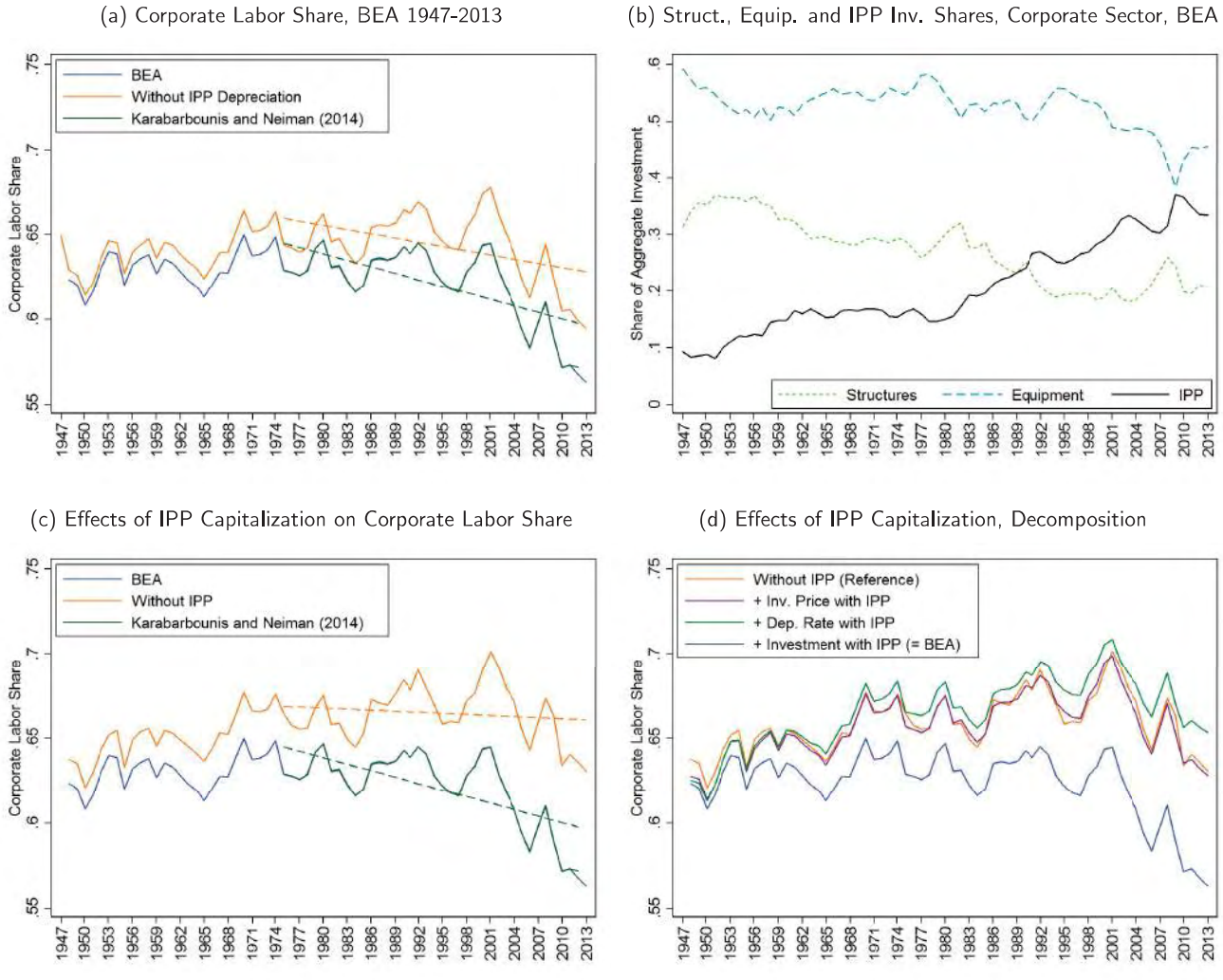


(c) Percentage of LS Decline Due to Private IPP Capitalization



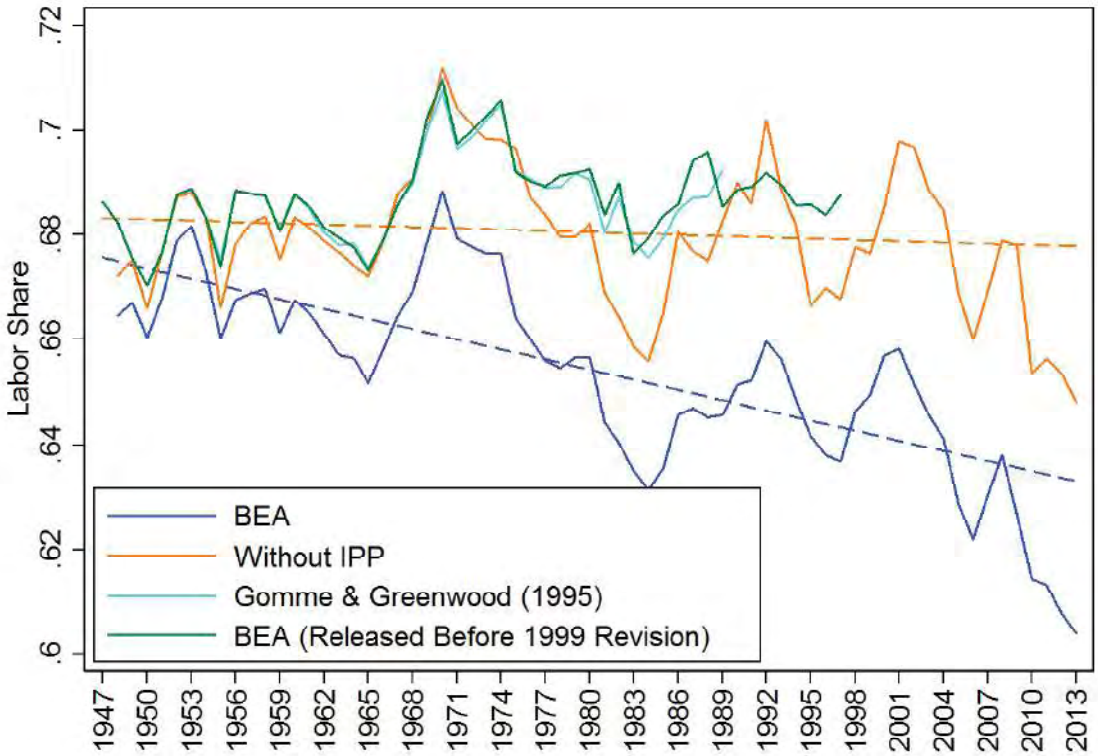
Notes: Panel (a) shows the evolution of each type (i.e., structures, equipment and IPP) of private and government investment as share of aggregate investment. Panel (b) shows the effect on the labor share from private and government IPP capitalization separately. The reference scenario is benchmark labor share with IPP capitalization. Panel (c) shows the reduction in labor share generated by the capitalization of private IPP as a percentage of the total labor share decline. See section 3.5 for a discussion.

Figure 11: Effects of IPP Capitalization on Corporate Labor Share



Notes: In panel (a) the reference scenario is the benchmark labor share for the corporate sector from the post-revision data (i.e. the blue line). This measure of labor share is identical to the updated labor share data supplied by Karabarbounis and Neiman for their 2014 QJE paper for the subperiod 1975 to 2012 (i.e. the green line). This panel shows the effects of removing IPP depreciation (i.e., the orange line). Panel (b) shows the share of nominal investment by type of assets. In panel (c), we remove the entire effect from IPP capitalization (i.e. the orange line). In panel (d), we decompose the effects of IPP capitalization by sequentially adding to the sans-IPP scenario, the effects from the price of IPP investment, the depreciation rate of IPP and the IPP investment.

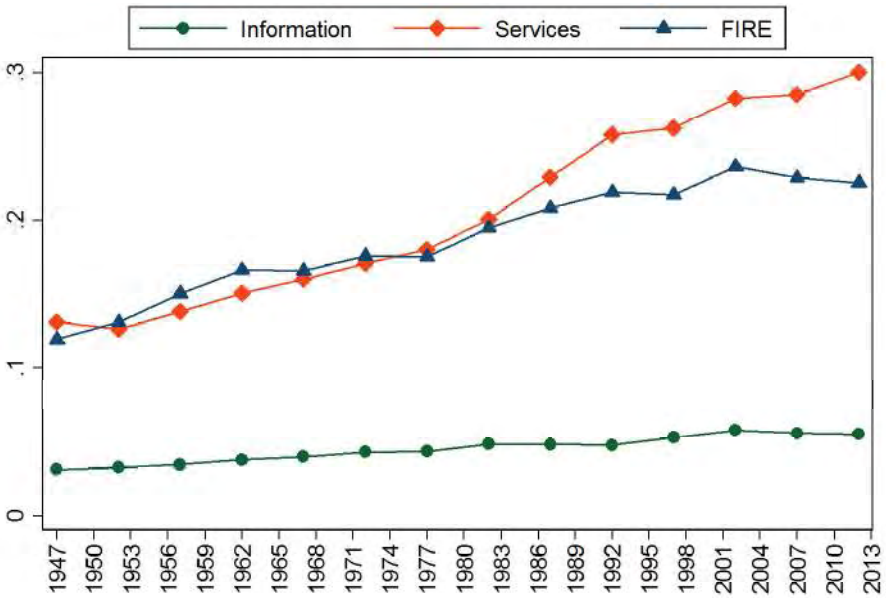
Figure 12: Labor Share from Vintage Data: A Historical View without IPP Capital



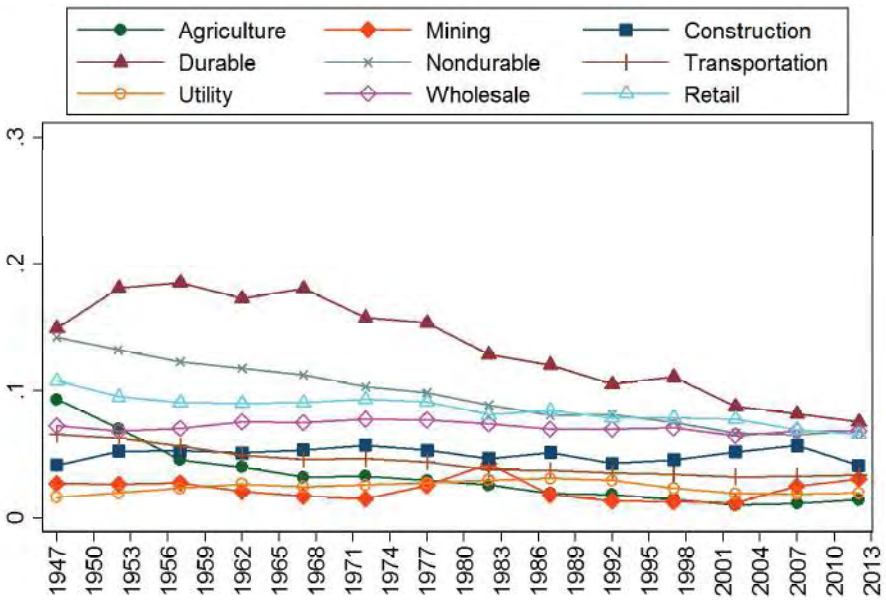
Notes: The labor share labeled as "BEA" refers to the benchmark definition described in Section 2.1 and uses only post-2013 BEA revision data (also depicted in Figure 1). The labor share labeled "Without IPP" refers to the counterfactual labor share that results from entirely removing IPP capitalization, see Section 3. The labor share labeled as "BEA Released Before 1999 Revision" is computed using data released by BEA in 1998 and available at the Archives Library of the St. Louis FED. Finally, we also report the labor share computed in Gomme and Greenwood (1995) who also implemented a definition of LS similar to our benchmark using data before software entered the national accounts as investment. To avoid differences in levels, we normalize the mean of the last two series of labor share to the mean of our counterfactual labor share. See Section 3.7 for a discussion.

Figure 13: US Output Shares by Industry, BEA 1947-2013

(a) Growing Industries



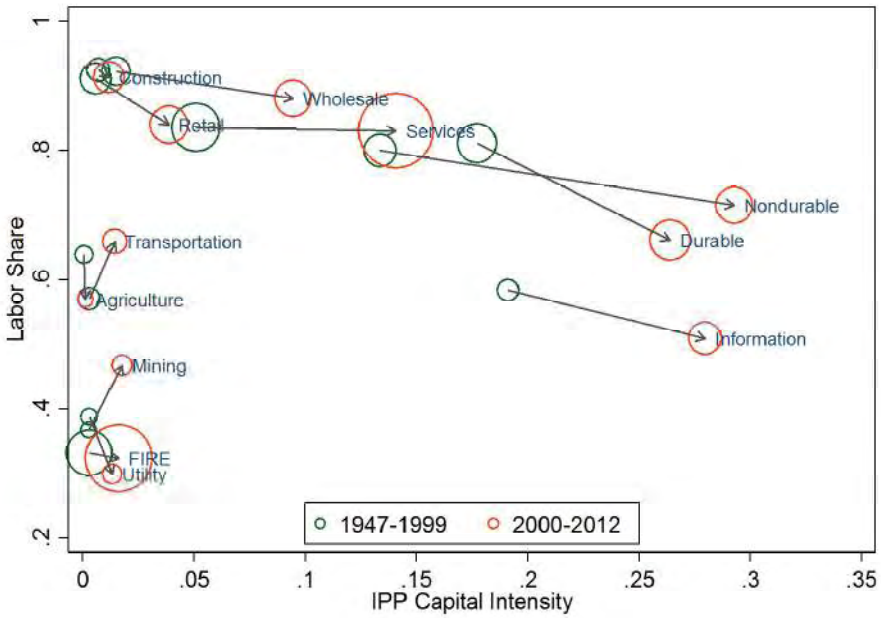
(b) Declining Industries



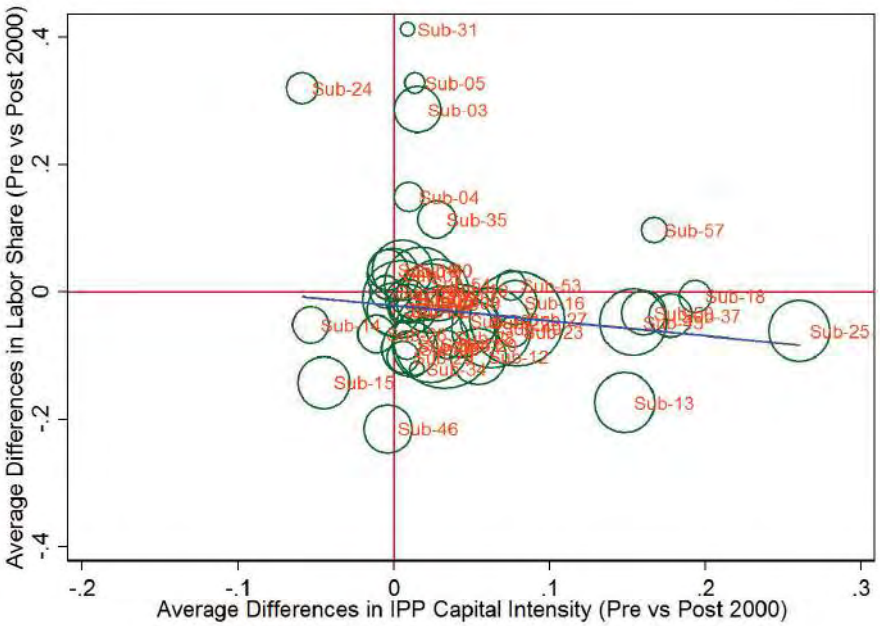
Notes: The output shares by industry are computed using NAICS classification as described in Section 4.

Figure 14: Labor Share and IPP Capital Intensity by Industry: Pre- and Post-2000s

(a) Main Industries

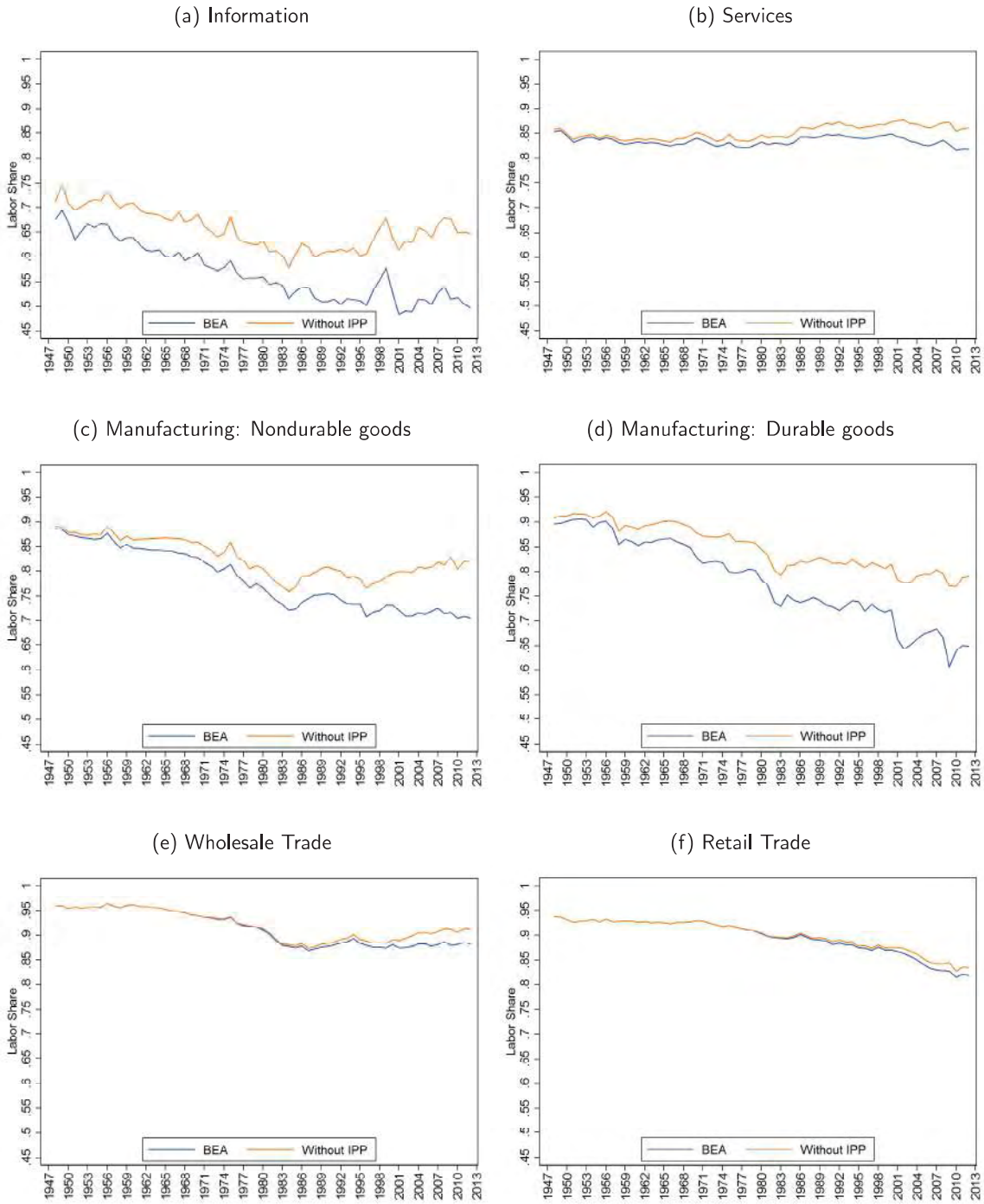


(b) Sub-Industries



Notes: Labor share is computed by industry using NAICS classification. IPP capital intensity is the share of IPP capital in total capital by industry (or subindustry). The size of the points refers to the industry-specific share of output in the aggregate economy. See a discussion in Section 4.

Figure 15: The Effects of IPP Capitalization on Labor Share By Industry



Notes: In each panel, the blue lines labeled "BEA" are the labor shares for the six industries which invest appreciably in IPP capital. The orange lines labeled "Without IPP" are the counterfactual labor share constructed by removing the full effects of IPP capitalization on the price of investment, the investment flow and the depreciation rate. See Section 4 for a discussion.

CHAPTER 6

Interindustry Wage Differentials, Technology Adoption, and Job Polarization*

By
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Hee-Seung Yang‡
(Department of Economics, Monash University)

Abstract

Using data on the U.S., we find that high-wage industries in 1980 experienced (1) more evident job polarization and (2) higher growth rate of information and communication technology (ICT) capital per worker between 1980 and 2009. These findings are consistent with the hypothesis that firms optimally respond to interindustry wage differentials, which (at least partly) arise from exogenous factors at the firm level. As the relative price of ICT capital declines, the persistent structure of interindustry wage differentials pushes high-wage industries to replace routine workers with ICT capital more intensively than low-wage industries. As a result, those industries exhibit slower employment growth of routine workers than low-wage industries, which led to heterogeneity in job polarization across industries.

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1 Introduction

The structure of the labor market in the U.S. has changed dramatically over the past 30 years. One of the most prevalent aspects of the change is job polarization: employment has become increasingly concentrated at the tails of the skill distribution, while there has been a decrease in employment in the middle of the distribution. This hollowing out of the middle has been linked to the disappearance of routine occupations that can be easily replaced by machines.[1] In the U.S., routine occupations accounted for around 60 percent of total employment in 1981, while this share fell to 44 percent in 2010.[2]

While many previous studies have examined job polarization at the "aggregate" level (see Goos, Manning, and Salomons (2009); Acemoglu and Autor (2011); Cortes (2016); and Jaimovich and Siu (2014)), the extent of job polarization differs across industries (see Autor, Levy, and Murnane (2003); Goos, Manning, and Salomons (2014); and Michaels, Natraj, and Reenen (2014)). Figure 1.1 shows changes in employment share by industry between 1980 and 2009. This figure demonstrates that job polarization is more pronounced in some industries than in others. For instance, the decrease in the employment share of routine occupations is large in manufacturing, communication, and business-related services, while the decrease is much smaller in transportation and retail trade.

[1] As emphasized by Autor (2010), Goos, Manning, and Salomons (2009), and Michaels, Natraj, and Reenen (2014), job polarization is not restricted to the U.S.; several European countries have experienced job polarization as well.

[2] Numbers are calculated from the March Current Population Survey (CPS).

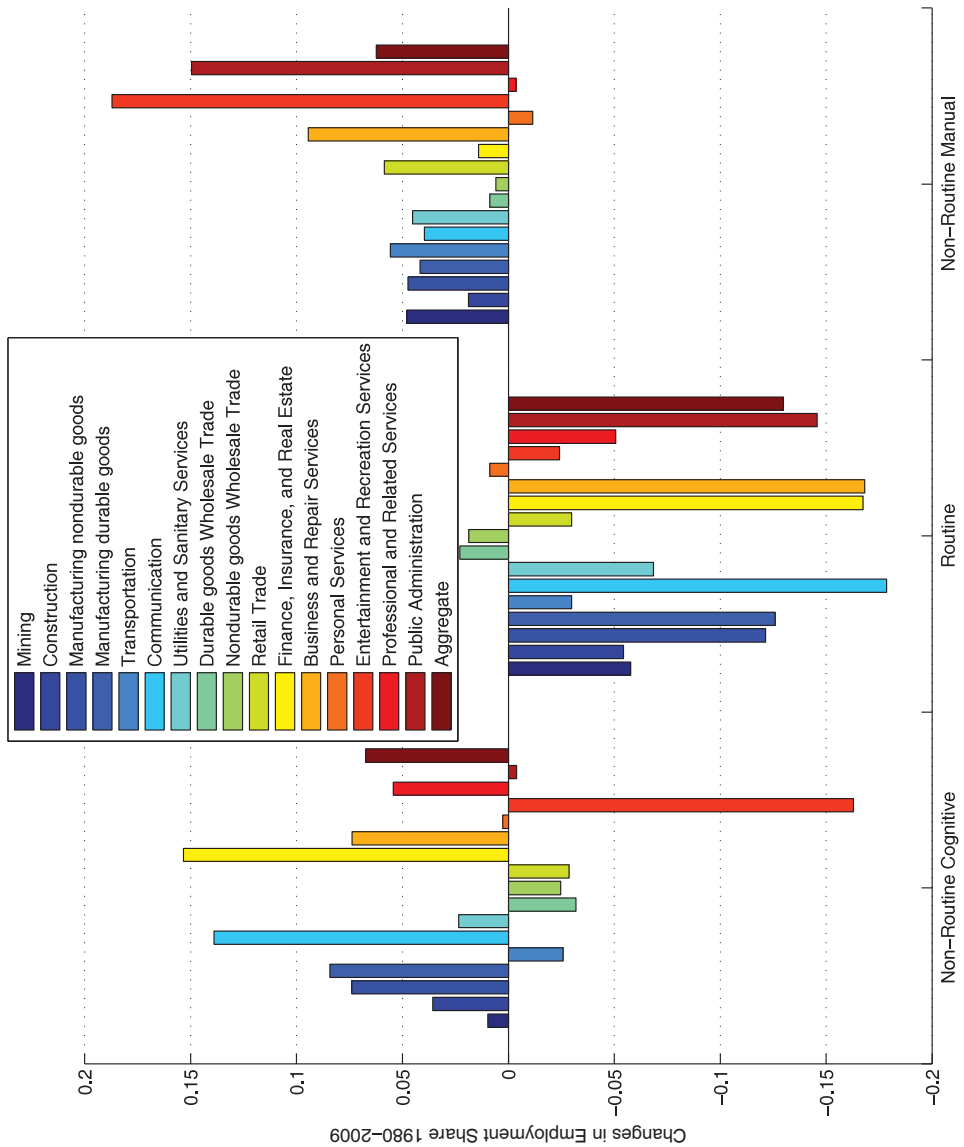

Figure 1.1: Changes in Employment Share by Industry between 1980 and 2009

Note: The horizontal axis denotes three occupational groups (each occupational group includes 16 industries and one aggregate variable) and the vertical axis denotes the change in employment share of a specific occupational group in each industry between 1980 and 2009.
Source: The U.S. Census.

This paper provides a new perspective to understand heterogeneity in job polarization across industries. In particular, we find that "interindustry wage differentials," the phenomenon that observationally equivalent workers earn differently when employed in different industries, are closely related to the heterogeneous job polarization across industries; the annualized growth rate of routine employment between 1980 and 2009 decreased by 0.42 percent when the initial industry wage premium in 1980 rose by 10 percent, which is strictly greater than the estimates for non-routine occupations in absolute terms. In other words, job polarization between 1980 and 2009 was more apparent in the high-wage industries in 1980. We further find that the annualized growth rate of information and communication technology (ICT, henceforth) capital per worker between 1980 and 2007 increased by 0.35 percent when the initial (i.e., 1980) industry wage premium increased by 10 percent. On the other hand, the annualized growth rate of non-ICT capital per worker is not associated with the initial industry wage premium.

To understand the empirical relationship between the interindustry wage differentials and the degree of job polarization, we present several hypotheses that can potentially explain our findings. In particular, we examine whether the relative price of routine to other occupations, initial share of routine workers, or capital-labor ratio can predict our results, and show that these hypotheses are not supported by data. We then introduce our theory, which is consistent with empirical evidence. In the theory, interindustry wage differentials arise from exogenous factors that are beyond firms' control. As a result, high-wage firms seek alternative ways to reduce production costs instead of lowering wages. The firm's response to the industry wage premium would thus change employment toward other production factors as in Borjas and Ramey (2000). Firm's adjustment of its employment, however, is not even across workers; routine workers are more easily replaced by ICT capital. As the price of ICT capital has substantially declined since the 1980s, firms in a high-wage industry are more likely to substitute ICT capital for routine workers than firms in a low-wage industry, which results in different degrees of job polarization across industries.

This paper has three major contributions. First, our study contributes to the existing literature on job polarization by aiding understanding of heterogeneity in job polarization across

industries. In particular, we provide the first evidence that polarized employment is connected with interindustry wage differentials. Second, our results highlight the importance of considering "exogenous factors" in explaining the industry wage premium, adding to the literature and discussion on interindustry wage differentials. Lastly, this paper provides additional evidence to the literature on firms' optimal responses to the labor market structure (Acemoglu (2002) and Caballero and Hammour (1998)).

The paper is organized as follows. Section 2 introduces two key concepts, interindustry wage differentials and job polarization, with reviews of related literature. Section 3 describes the data, and Section 4 presents main results and introduces hypotheses that can potentially justify our findings. After we show that these hypotheses are not supported by data, we introduce our theory to explain empirical findings in Section 5. Section 6 concludes.

2 Literature Review

In this section, we introduce key concepts that are important to understand our paper and discuss the related literature.

2.1 Interindustry Wage Differentials

Persistent dispersion in wages across industries (i.e., the existence of interindustry wage differentials) has been one of the most challenging subjects in labor economics. In order to understand why it is so puzzling from the perspective of the competitive labor market equilibrium theory, it is useful to consider two workers with the same observable socioeconomic characteristics (including education, age, gender, race, region, and occupation) but who work in different industries. The competitive labor market theory predicts that the wages should be (at least in the long run) the same between the two workers in equilibrium. If wages differ, a worker in a low-wage industry will attempt to find a job in a high-wage industry; in equilibrium, this increases (resp. decreases) labor supply to the high- (resp. low-) wage industry, and hence wages will be equalized in a competitive labor market. This notion of a competitive labor market, however, is not supported by data; for instance, a worker employed in the petroleum-refining industry earned about 40 percent more than a worker

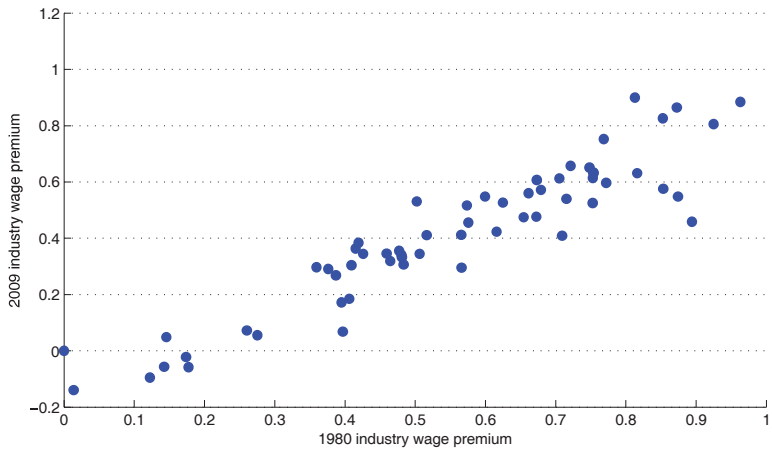

Figure 2.1: Persistency of Interindustry Wage Differentials: Comparison between 1980 and 2009

Note: We omit the industry of "hotels and lodging places," which has the lowest value of estimated coefficients in the wage regression of 1980, so that every other coefficient for industry dummies has a positive sign.
Source: The U.S. Census and American Community Survey (ACS).

in the leather-tanning and finishing industry in 1984 even after controlling for all observables (Krueger and Summers (1988)). In addition, the wage dispersion is not a transitory perturbation from the competitive equilibrium. To demonstrate this, we compute the industry wage premia in 1980 and 2009 separately using a typical wage equation, which regresses log wages over various socioeconomic characteristics and industry fixed effects, and present a scatter plot of the two sets of industry fixed effects in Figure 2.1. It shows that industries that paid relatively high wages in 1980 also paid high wages in 2009, which implies that the structure of interindustry wage differentials is highly persistent. We also find, as Dickens and Katz (1987) show, that an industry variable has been a consistently important factor in explaining wage differentials.[3]

Our paper is unique in this literature in the sense that we study how interindustry wage differentials can be associated with structural changes in the aggregate labor market such as job polarization. In this regard, Borjas and Ramey (2000) is the only paper related to our study.

[3]We run the wage regression (4.1) for different periods (1980, 1990, 2000, and 2009) and compute the explanatory power of the wage equation with and without industry dummies, following Dickens and Katz (1987). The results are reported in Table A.1. In particular, 4 to 16 percent of the wage variation is explained by industry. Interestingly, the explanatory power attributable to the industry is very stable and substantial over time, which implies that industry should be considered as an important factor in explaining wages.

Borjas and Ramey (2000) find that industries that paid relatively high wages to workers in 1960 experienced (1) lower employment growth and (2) higher capital-labor ratio growth and higher labor productivity growth between 1960 and 1990. While they focus on the "average" effect of interindustry wage differentials on workers, our findings emphasize the importance of considering heterogeneity across workers (occupations) in studies of the labor market.

2.2 Job Polarization We classify occupations into three groups as follows, to be consistent with the job polarization literature including Autor (2010), Acemoglu and Autor (2011), and Cortes (2016):

- Non-routine cognitive occupations: Managers; Professionals; and Technicians
- Routine occupations: Sales; Office and administration; Production, crafts, and repair; and Operators, fabricators, and laborers
- Non-routine manual occupations: Protective services; Food preparation and building and grounds cleaning; and Personal care and personal services

Using the March CPS between 1971 and 2010,[4,5] we plot Figure 2.2 to show job polarization graphically: while the employment share of non-routine cognitive (henceforth, cognitive) and non-routine manual (henceforth, manual) occupations has grown over time, that of routine occupations has decreased.

One intuitive reason behind job polarization is that the skill (task) content of each occupation is different. Among the three groups, routine occupations are most easily replaced by ICT capital, as demonstrated by Autor, Levy, and Murnane (2003); the tasks that routine workers perform are easier to codify than other tasks because the tasks have routine procedures. Meanwhile, cognitive and manual occupations are not easily substituted. For instance, business decisions of managers (cognitive occupations) cannot be replaced by technology; introduction of new technology, such

[4]Data were extracted from the IPUMS website: http://cps.ipums.org/cps (see King, Ruggles, Alexander, Flood, Genadek, Schroeder, Trampe, and Vick (2010)).

[5]We apply the method of "conversion factors" to obtain consistent aggregate employment series. See Shim and Yang (2015) for a detailed discussion on the method of conversion factors.

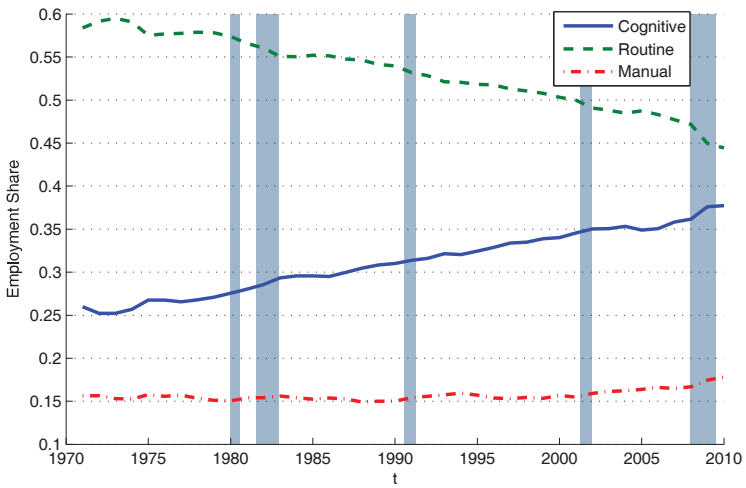

Figure 2.2: Job Polarization
Note: The shaded regions are the official NBER recession dates.
Source: The March CPS.

as advanced software, does not substitute for these managers; rather, it is a complement to their tasks. In addition, people involved in cooking or cleaning (manual occupations) cannot be directly replaced by machines; these jobs require humans to perform non-routine manual tasks. In contrast, a great portion of the tasks that a bank clerk performs are easily replaced by an ATM; deposits and withdrawals are routine tasks, and machines can perform these tasks more efficiently than humans. Hence, these jobs have disappeared over time, as the economy has experienced rapid technological progress in ICT capital.[6] Consistent with this story, Cummins and Violante (2002) show that investment-specific technological changes have mainly occurred for ICT capital rather than for other types of capital so that the relative price of ICT capital has declined more rapidly since the 1970s.[7]

[6] "Offshorability" is also higher for routine occupations than for cognitive and manual occupations. Most of the service jobs (manual occupations) are not tradable and occupations that require cognitive tasks are not easily offshored while factories can be relatively easily relocated to foreign countries.

[7] The period in which the growth rate of investment-specific technological changes increased does not perfectly match the occurrence of job polarization, which is usually said to be after 1980. Consistently with this timing problem, we find that job polarization also occurred before 1980, while the magnitude was smaller than the one after 1980.

A few papers have studied the possibility of heterogeneous job polarization across industries.[8] Acemoglu and Autor (2011) show that changes in industrial composition do not play an important role in job polarization. Jaimovich and Siu (2014) and Foote and Ryan (2014) note that job polarization may be more pronounced in the construction and manufacturing industries. While Autor, Levy, and Murnane (2003), Goos, Manning, and Salomons (2014), and Michaels, Natraj, and Reenen (2014) also consider possible differences in job polarization across industries, they do not connect interindustry wage differentials and heterogeneity in job polarization; however, our findings indicate that they are closely related.

3 Data

There are two main sources of data for this paper: (1) the decennial Census and ACS data,[9] and (2) the EU KLEMS data. Following Acemoglu and Autor (2011), we use the 1960, 1970, 1980, 1990, and 2000 Census and the 2006, 2007, and 2009 ACS. As Acemoglu and Autor (2011) note, the relatively large sample size of the Census data makes fine-grained analysis within detailed demographic groups possible.[10] We drop farmers (and related industries) and the armed forces. Age is restricted to 16−64 years and we only consider persons employed in wage-and-salary sectors. Table B.1 in Supplementary Online Appendix B describes the industry classification used in the analysis.[11]

The second data set, EU KLEMS, has information on value added, labor, and capital for various industries in many developed countries, including the U.S. The EU KLEMS is useful since it provides detailed information on capital: in the data, capital is divided into two parts, ICT capital and non-ICT capital, so we can analyze the roles of different types of capital in a firm's behavior. We use U.S. data between 1980 and 2007, where industries are defined according to the

[8] Some recent papers, including Mazzolari and Ragusa (2013), Autor, Dorn, and Hanson (2013a), and Autor, Dorn, and Hanson (2013b), analyze job polarization at the local labor market level.

[9] Data were extracted from the Integrated Public Use Microdata Series (henceforth, IPUMS) website: https://usa.ipums.org/usa (Ruggles, Alexander, Genadek, Goeken, Schroeder, and Sobek (2010)).

[10] In determining the size of the sample, we follow Acemoglu and Autor (2011): 1 percent of the U.S. population in 1960 and 1970 and 5 percent of the population in 1980, 1990, and 2000.

[11] We follow Dorn (2009) to overcome the inconsistency problem of occupation codes due to the frequent changes in occupation coding in the Census and to construct a consistent occupation series.

North American Industry Classification System of the United States (henceforth, NAICS). Since the industry classification of EU KLEMS is different from the Census data, we reclassify industries to be consistent between the Census and the EU KLEMS data. Table B.2 in Supplementary Online Appendix B describes the industry classification of EU KLEMS used in the analysis.

4 Empirical Analysis

This section presents our main empirical findings. We first estimate industry wage premia as follows.

$$\log w_{hit} = X_{hit}\beta_t + \omega_{it} + \varepsilon_{hit} \tag{4.1}$$

where w_{hit} is the wage rate of worker h in industry i in Census year t; X_{hit}, a vector of socio-economic characteristics, includes the worker's age (five age groups: 16−24, 25−34, 35−44, 45−54, or 55−64 years), educational attainment (five educational groups: less than 9 years, 9 to 11 years, 12 years, 13 to 15 years, or at least 16 years of schooling), race (indicating if the worker is African-American), gender, and region of residence (indicating in which of the nine Census regions the worker lives). Our findings are not sensitive to controlling for state dummies and various interaction terms of age, gender, race, and education in the wage regression. We also control for three occupation dummies (cognitive, routine, or manual occupations). ω_{it}, an industry fixed effect, measures the industry wage premia.

The result of equation (4.1) in 1980 is reported in Table A.2.[12] After we obtain the estimated coefficients for 60 industry fixed effects, $\hat{\omega}_{it}$, from equation (4.1), we estimate the second-stage regression as follows:

$$\Delta y_{ijt,t+k} = \theta_j \hat{\omega}_{it} + \eta_{ijt} \tag{4.2}$$

where y_{ijt} is the variable of interest such as employment of occupation group j in industry

[12]The estimated coefficients are consistent with the usual intuition: (1) wages are strictly increasing in education, (2) wages also rise in ages until workers reach their prime age, and then decrease slightly, and (3) African-American earns less.

i. $\Delta y_{ijt,t+k}$ is the annualized (average) growth rate of y_{ijt} between periods t and $t+k$, and $j \in \{cognitive, routine, manual\}$.[13] We estimate equation (4.2) separately for cognitive, routine, and manual occupations.

Note that we use the estimated value, $\hat{\omega}_{it}$, as a regressor in the second-stage regression, which raises a concern about the generated regressor problem. In particular, it is possible that the error term in equation (4.2) is heteroscedastic. In order to address this issue, we weigh the regression by the initial (i.e., 1980) employment of each industry. In addition, the large sample size of the Census data weakens the generated regressor problem; there are at least $1,000$ observations in each cell of occupation j in industry i in Census year t.[14] Furthermore, in order to address the potential endogeneity of the wage premium, we use the previous decade's estimated industry wage premium as an instrumental variable (IV).

4.1 Job Polarization and Initial Industry Wage Premia

In this section, we empirically test if interindustry wage differentials are related to different degrees of job polarization across industries. If there is no link between industry wage dispersion and job polarization, the coefficients on $\hat{\omega}_{it}$ in equation (4.2) would not differ across occupations; that is, the subsequent employment growth of each occupational group does not react differently to industry wage premia. If they are related, however, we should observe $\theta_r < \theta_c$, θ_m, where r, c, and m indicate routine, cognitive, and manual occupations, respectively.

Figures 4.1 to 4.3 show graphically how initial industry wage premia are related to the subsequent employment growth of each occupational group. The horizontal axis is the industry wage premia in 1980, which is estimated using equation (4.1). The vertical axis denotes the average employment growth rate of each occupational group by industry between 1980 and 2009. We can observe that the slope of the fitted line is negative and the steepest in the case of routine occupations (Figure 4.2), which supports the hypothesis that firms facing high wages reduce their demand for routine workers more. Interestingly, Figure 4.3 shows that there is a weaker (positive) relationship between initial industry wage premia and subsequent employment growth

[13] That is, $\Delta y_{ijt,t+k} = (\log(y_{ij,t+k}) - \log(y_{ijt}))/k$.

[14] For a more detailed discussion on the generated regressor problem, see Wooldridge (2001).

in manual occupations. We will return to this issue later in Section 4.3.1.

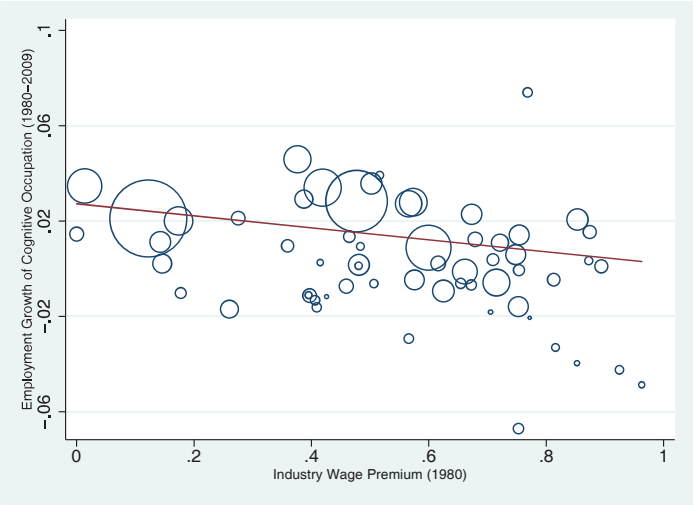

Figure 4.1: Dynamic Responses of Firms to Interindustry Wage Differentials–Cognitive Occupations

Note: The size of a circle denotes the employment level of each industry in 1980.
Source: The U.S. Census and ACS.

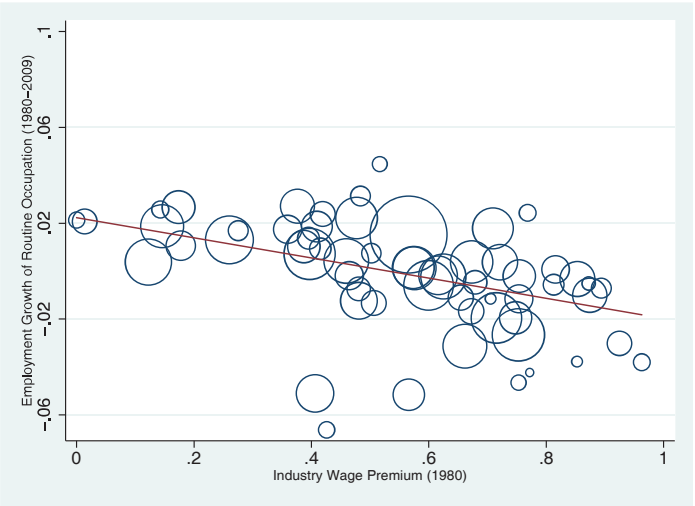

Figure 4.2: Dynamic Responses of Firms to Interindustry Wage Differentials–Routine Occupations

Note: The size of a circle denotes the employment level of each industry in 1980.
Source: The U.S. Census and ACS.

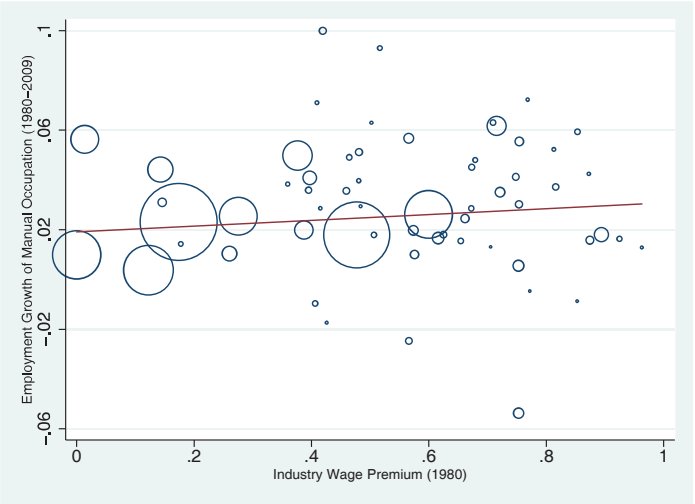

Figure 4.3: Dynamic Responses of Firms to Interindustry Wage Differentials–Manual Occupations

Note: The size of a circle denotes the employment level of each industry in 1980.
Source: The U.S. Census and ACS.

The main empirical finding based on equation (4.2) is reported in Table 4.1. The dependent variable in the first row is the annualized growth rate of aggregate employment for industry i. The estimate confirms the robustness of the main result of Borjas and Ramey (2000) in the sense that their finding is also observed for a later period; they use Census data between 1960 and 1990.

In the remaining rows, we report the estimates of equation (4.2), where the dependent variable is the average growth rate of employment for occupation j in industry i between 1980 and 2009. When estimating equation (4.2) for each occupation, the initial industry wage premium ($\hat{\omega}_{i,1980}$) does not depend on occupation. In this sense, the results in Table 4.1 reveal how "average" industry wage premia affect different occupational groups in a distinct manner.

The estimated coefficients reported in the second to fourth rows in Table 4.1 are consistent with Figures 4.1 to 4.3. The average growth rate of routine employment between 1980 and 2009 decreased by 0.42 percent when the initial industry wage premium in 1980 increased by 10 percent, while that of cognitive employment decreased by 0.25 percent. The initial industry wage premium has a positive relationship with the subsequent employment growth rate of the manual

Table 4.1: Estimates of Employment Growth by Occupation Groups (1980−2009)

	OLS		IV	
Occupation Groups	Coefficient	R-Squared	Coefficient	R-Squared
Total	$-0.0381^{***}(0.0073)$	0.24	$-0.0331^{***}(0.0069)$	0.24
Cognitive Occupations	$-0.0252^{***}(0.0071)$	0.14	$-0.0197^{***}(0.0066)$	0.13
Routine Occupations	$-0.0421^{***}(0.0090)$	0.21	$-0.0412^{***}(0.0086)$	0.21
Manual Occupation	0.0117(0.0137)	0.03	$0.0206^{*}(0.0114)$	0.13

Note: 1. The regressions are weighted by each industry's initial (i.e., 1980) employment.
2. The instrument is the previous decade's (i.e., 1970) industry wage premium.
3. The sample size is 60.
4. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

occupation group and the OLS estimate is not significant.[15] In summary, employment growth of routine occupations between 1980 and 2009 is negatively correlated with industry wage premium in 1980.[16] The IV estimates are also reported in Table 4.1. Both the OLS and IV regressions yield similar coefficients, which implies that measurement errors in the estimated $\hat{\omega}_{it}$ and the generated regressor problem are not severe.

One might raise a concern that the results might be exaggerated by the great recession that occurred at the end of 2007, which disproportionately affected the employment of routine occupations (Jaimovich and Siu (2014)). In order to address this issue, we estimate the same regression with a sample period between 1980 and 2007, which is reported in Table 4.2. The results are similar to those reported in Table 4.1: the subsequent employment growth of routine occupations between 1980 and 2007 still decreases in the initial industry wage premium and its coefficient is the greatest in absolute terms.[17] In addition, one might argue that the heterogeneity in job polarization might be driven by part-time workers as they are more likely to be affected by firms' responses to wage pressure and more likely to have routine occupations. In Table A.3, we conduct the same exercise with a sample of full-time workers only and the results are largely

[15]We test if these coefficients are significantly different from each other; at the 5 percent significance level, θ_r is not equal to either θ_c or θ_m, and hence, the firm's response to the initial industry wage premium is not uniform across different occupations.

[16]Interindustry wage differentials had been observed even prior to 1980; for instance, the estimation of Borjas and Ramey (2000) is based on the industry wage premium in 1960. The magnitude of the responsiveness is, however, much lower than that of the latter period and the explanatory power drops by half. This suggests that the heterogeneous aspect of job polarization across industries became more pronounced after 1980.

[17]Estimates with a sample period between 1980 and 2006 are also similar to the main results.

unaffected.

Table 4.2: Estimates of Employment Growth by Occupation Groups (1980−2007)

	OLS		IV	
Occupation Groups	Coefficient	R-Squared	Coefficient	R-Squared
Total	$-0.0431^{***}(0.01)$	0.23	$-0.0369^{***}(0.0093)$	0.22
Cognitive Occupations	$-0.0259^{***}(0.0083)$	0.12	$-0.0195^{***}(0.0076)$	0.11
Routine Occupations	$-0.0412^{***}(0.0097)$	0.18	$-0.0387^{***}(0.0095)$	0.18
Manual Occupations	$-0.0005(0.0154)$	0.00	$0.0105(0.0136)$	0.00

Note: 1. The regressions are weighted by each industry's initial (i.e., 1980) employment.
2. The instrument is the previous decade's (i.e., 1970) industry wage premium.
3. The sample size is 60.
4. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Another possible concern about our estimates obtained from equation (4.2) is that there might be other industry-specific factors that could affect the subsequent employment growth of each occupation group. We test the robustness of our results to the inclusion of various industry-specific factors: share of routine workers in industry i in 1980, capital per worker and ICT capital per worker in industry i in 1980[18], and union membership rate in industry i in 1983.[19] The estimation results are reported in Table 4.3.[20]

Table 4.3: OLS Estimates of Employment Growth by Occupation Groups (1980−2009): Including Industry-Specific Variables

	Cognitive	Routine	Manual
Industry wage premium	-0.0010	-0.0339^{**}	0.0068
Routine share	-0.0393^{***}	-0.0085	0.0269^{*}
Capital per worker	0.0000^{**}	0.0000^{**}	0.0000
ICT capital per worker	0.0005^{***}	0.0003^{**}	0.0011^{**}
Union membership (1983)	-0.0418^{***}	-0.0192	-0.0564^{***}
R^2	0.52	0.26	0.29

Note: 1. The regressions are weighted by each industry's initial (i.e., 1980) employment.
2. The sample size is 60.
3. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[18] Information on capital is only available for 29 industries in EU KLEMS data; thus, we assigned the information for those industries to the 60 Census industries by matching industry codes.

[19] Union data at industry level are available only from 1983. See Hirsch and Macpherson (2003) for details.

[20] We discuss in detail why the first two variables are included in the regression in Section 4.3.

We find that the inclusion of the various industrial factors does not alter our results in Table 4.1. In fact, it increases the differences between the coefficients of routine workers and non-routine workers. Hence, our main results are robust to the addition of other industry-specific factors. The results also show that union membership seems to affect employment growth of non-routine occupations only, even though the higher union membership rate might put more pressure on firms. This might be because routine workers were mostly covered by unions until the 1990s and unions might prevent firms from replacing them with capital.

As the last robustness check, we estimate the same second-stage regression with a different dependent variable–the changes in employment share of occupation groups between 1980 and 2009. As shown in Table 4.1, the employment growth of routine occupations has been lower than that of cognitive and manual occupations for the last 30 years. As a result, the employment share of routine occupations has declined, while the share of at least one of either cognitive or manual occupations has increased. Thus, we should observe that (1) the change in employment share of routine occupations is negatively related to the initial industry wage premium and (2) the change in employment share of cognitive or manual occupations is (weakly) positively related to the initial industry wage premium. In estimating equation (4.2), we set $\Delta y_{ijt,t+k} = es_{ij,t+k} - es_{ijt}$, where es_{ijt} is the employment share of occupation j in industry i at Census year t. Table 4.4 summarizes the results of the alternative estimation.

Table 4.4: Estimates of Employment Share by Occupation Groups (1980−2009)

	OLS		IV	
Occupation Groups	Coefficient	R-Squared	Coefficient	R-Squared
Cognitive Occupations	0.0076(0.0802)	0.00	0.0119(0.0808)	0.00
Routine Occupations	−0.1833***(0.0572)	0.19	−0.2421***(0.0599)	0.16
Manual Occupations	0.1306(0.0960)	0.13	0.1813**(0.0797)	0.11

Note: 1. The regressions are weighted by each industry's initial (i.e., 1980) employment.
2. The instrument is the previous decade's (i.e., 1970) industry wage premium.
3. The sample size is 60.
4. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

First, the employment share of routine occupations decreases more in industries with a high initial wage premium, which is consistent with the previous results in Table 4.1. Second, the

coefficient for manual occupations is much greater than zero in both the OLS and IV regressions, while the coefficient for cognitive occupations is estimated to be almost zero. This is because (1) the negative responsiveness of the employment growth of cognitive occupations to the initial industry wage premium is not large compared to that of routine occupations and (2) there is weak correlation between the subsequent employment growth of manual occupations and the initial industry wage premium.

4.2 ICT Capital per Worker and Initial Industry Wage Premia

We now analyze if growth rate of ICT capital per worker since 1980 is related to industry wage premia in 1980. In addition, we also test if the relationship between the growth rate of ICT capital per worker and initial industry wage premia is different from the relationship between that of non-ICT capital per worker and initial industry wage premia. If non-ICT capital is general-purpose capital, the coefficients from the regression would be lower in magnitude for non-ICT capital per worker than for ICT capital per worker. Notice that the growth rate of capital level may be negatively related to the initial industry wage premium. If the size of an industry shrinks as labor demand decreases, capital demand itself might also decrease. If the rate at which the demand for capital decreases is lower than the rate at which the demand for labor decreases, the resulting capital-labor ratio grows in the industry wage premium.

For the analysis, we use the EU KLEMS database. Since it provides information on employment and capital in 29 industries, we recompute the initial industry wage premium in 1980 by reclassifying the Census 60 industries into 29 industries.[21] Each capital series (aggregate capital, ICT capital, and non-ICT capital) is real fixed capital stock based on 1995 prices. In order to obtain capital per worker series, we divide capital by employment for each industry. We first show graphical evidence of our argument.

First, Figure 4.4 shows a positive relationship between the industry wage premium in 1980 and the subsequent annualized growth rate of ICT capital per worker between 1980 and 2007. Figure 4.5, however, suggests that changes in non-ICT capital per worker between 1980 and 2007 may not be precisely related to interindustry wage differentials.

[21] Details on the classification can be found in Supplementary Online Appendix Table B.2.

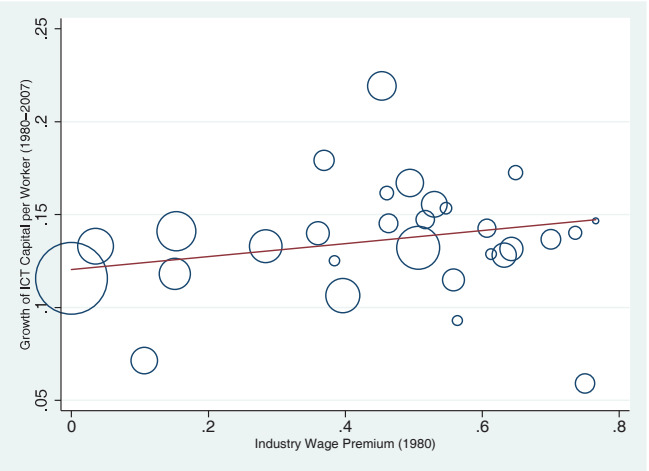

Figure 4.4: ICT Capital per Worker to Initial Industry Wage Premium (1980−2007)

Note: The size of a circle denotes the employment level of each industry in 1980.
Source: The EU KLEMS.

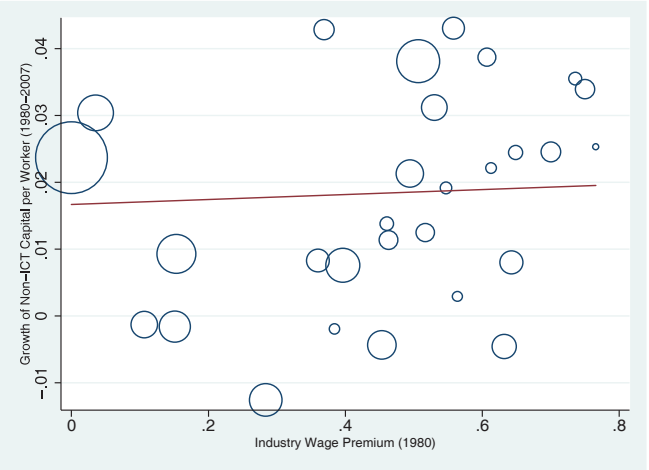

Figure 4.5: Non-ICT Capital per Worker to Initial Industry Wage Premium (1980−2007)

Note: The size of a circle denotes the employment level of each industry in 1980.
Source: The EU KLEMS.

For the complete analysis, we estimate equation (4.3).

$$\Delta y_{it,t+k} = \theta \hat{\omega}_{it} + \eta_{it} \tag{4.3}$$

where y_{it} is capital per worker, capital level, or employment in industry i at time t. The OLS and IV results, which are quite similar, are reported in Table 4.5. Before we discuss the main result, we focus on the last row, in which the dependent variable is the average employment growth rate. The estimate using the EU KLEMS data is similar to the coefficient obtained from the Census data (see Table 4.1), which confirms the robustness of our findings.

Table 4.5: Estimates of Capital, Productivity, and Employment Growth (1980−2007)

	OLS		IV	
Dependent	Coefficient	R-Squared	Coefficient	R-Squared
Capital/Worker	0.0145(0.0134)	0.05	0.0138(0.0139)	0.05
ICT Capital/Worker	0.0350*(0.0190)	0.09	0.0400***(0.0171)	0.09
Non-ICT Capital/Worker	0.0037(0.0136)	0.00	0.0030(0.0144)	0.004
Capital	−0.0201*(0.0110)	0.10	−0.0181(0.0114)	0.10
ICT Capital	0.0004(0.0217)	0.00	0.0081(0.0204)	0.000
Non-ICT Capital	−0.0308***(0.0107)	0.25	−0.0289***(0.0115)	0.25
Output	−0.0055(0.0089)	0.01	−0.0044(0.0087)	0.01
Labor Productivity	0.0290***(0.0089)	0.22	0.0275***(0.0091)	0.22
Employment	−0.0345***(0.0076)	0.27	−0.0319***(0.0072)	0.27

Note: 1. Both the EU KLEMS and the Census data are used for the estimation.
2. The regressions are weighted by each industry's initial (i.e., 1980) employment.
3. The instrument is the previous decade's (i.e., 1970) industry wage premium.
4. The sample size is 29.
5. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
6. Labor productivity is obtained by dividing output by workers in each industry.
7. Capital and output are real variables.

The relevant coefficients for different types of capital are presented in the first three rows. As the initial industry wage premium increased by 10 percent, the annualized growth rates of aggregate capital per worker, ICT capital per worker, and non-ICT capital per worker between 1980 and 2007 increased by 0.14 percent, 0.35 percent, and 0.03 percent, respectively. That is, $\theta_{ICT} > \theta_{Aggregate} > \theta_{non-ICT}$. Furthermore, only θ_{ICT} is statistically significant.

The fourth to the sixth rows in Table 4.5 are also noteworthy. First, both capital and non-ICT capital decrease in the initial industry wage premium. Together with the fact that these industries also decrease demand for labor, capital per worker and non-ICT capital per worker are not related to interindustry wage differentials. ICT capital, however, is not correlated with the

initial industry wage premium; as a result, ICT capital per worker rises more in industries with a high initial industry wage premium. Finally, we find that the growth rate of labor productivity increases in the initial wage premium, which is consistent with Borjas and Ramey (2000).

4.3 Possible Explanations

In this section, we examine three hypotheses that might explain our findings and show that none of them are consistent with empirical evidence.

4.3.1 Price Effect: Are Routine Workers Paid the Highest?

Note that the main findings in Table 4.1 offer two possible explanations. The first is the "task content" explanation: as routine jobs can be easily replaced by other production factors, demand for routine occupations is more sensitive to the initial industry wage premium. The second argument is the "relative price" explanation: if the routine occupations are paid more than other groups, firms would decrease their relative demand for the routine occupation group since this group is actually the most expensive production factor (while the property of tasks required by routine occupations may enhance the firms' dynamic responses to interindustry wage differentials, it may not be of the first order).

To check which explanation fits better, we consider an occupation-specific industry wage premium, denoted as ω_{ijt}, which is the wage premium of occupation j in industry i, in the following alternative wage equation:

$$\log w_{hit} = X_{hit}\beta_t + \underbrace{\omega_{it} \times \psi_{jt}}_{=\omega_{ijt}} + \varepsilon_{hit} \tag{4.4}$$

where ω_{it} is the industry fixed effect and ψ_{jt} is the occupation fixed effect. Thus, $\omega_{it} \times \psi_{jt}$ is the interaction of each industry dummy and each occupation dummy. We call this the "occupation-specific" industry wage premium. In this alternative wage equation, we do not include the fixed effect terms, ω_{it} and ψ_{jt}. By regressing the above equation, we obtain information about the extent to which an occupation group in a specific industry earns more than the same occupation group in other industries, and this also allows for within-industry comparisons of the wage premia.

Figure 4.6 depicts occupation-specific industry wage premia by industry. In order to see how

the average industry wage premium (ω_{it}) and the occupation-specific industry wage premium (ω_{ijt}) are related, we sort industries by the average industry wage premium in ascending order. To the left, there are low-wage industries such as hotels and lodging places, and to the right, there are high-wage industries such as mining and investment. All values are estimated in 1980. Figure 4.6 shows that the relative price explanation is not supported by the data: in any industry, we observe that $\omega_{ict} > \omega_{irt} > \omega_{imt}$, which means that the cognitive occupations are paid the most, followed by the routine and manual occupations. Hence, we can exclude the possibility of the relative price explanation.[22]

Figure 4.6 also shows that the occupation-specific industry wage premium rises almost monotonically in the average industry wage premia for cognitive and routine occupation groups, while there is much variation in the manual occupation-specific industry wage premium. This is one of the reasons that the effect of the average industry wage premium on the employment growth of the manual occupations is not negative in Table 4.1; even when firms face relatively higher average industry wage premia, firms may not pay high wages to manual workers. For example, the "security, commodity brokerage, and investment companies industry" (on the right in Figure 4.6) paid manual workers less than quite a few other industries did. As a result, the wage pressure from the manual occupation group is not as large as the pressure from other occupation groups. Therefore, firms have less incentive to decrease their labor demand for manual occupations when facing high wages.

4.3.2 Level Effect: Heterogeneity in relative importance of routine workers

We introduce another hypothesis that the initial share of routine workers is important to understand the relationship between interindustry wage differentials and job polarization. To test this hypothesis, we pay attention to the fact that the correlation between the employment share of routine workers in 1980 and the industry wage premium in 1980 is strictly positive. For instance,

[22] One interesting finding is that the slope of the line in Figure 4.6 is steeper for routine occupations than for cognitive occupations. In the end, the gap between the cognitive occupation-specific industry wage premium and routine occupation-specific industry premium becomes almost zero. This fact implies that while cognitive occupations are paid more than routine occupations, there is a tendency for high-wage industries to actually pay relatively more for the routine occupations than low-wage industries. This feature may have a "price" effect on our estimates, but given that the level of the cognitive occupation-specific industry wage premium is highest for any industry, we do not analyze this further.

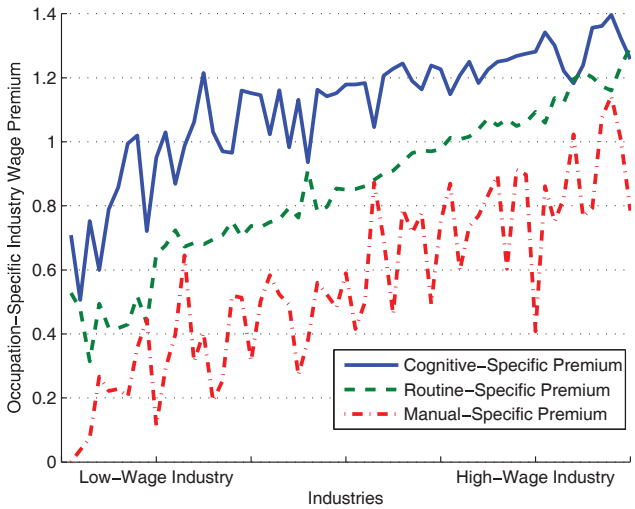

Figure 4.6: Occupation-Specific Industry Wage Premium

Note: We order industry by the industry wage premium obtained by equation (4.1).
Source: The U.S. Census and ACS.

the manufacturing industry had a higher share of routine workers than other industries in 1980 and it paid relatively higher wages to workers because it faced higher unionization rates. Therefore, as the relative price of capital has declined, the high-wage industries would have experienced more replacement of routine workers because they employed routine workers more intensively in 1980; that is, the "level effect" might be a dominant reason why the job polarization was more evident in the high-wage industries. In the sense that level effect is the product of heterogeneous production functions across industries, our analysis in this section can be interpreted as the indirect test of the hypothesis based on production functions.

We test this hypothesis by replacing the initial industry wage premium with the initial employment share of routine workers in the main equation (4.2). The result in Table 4.6 does not support the level effect: when we estimate the effect of the initial share of routine workers on the employment growth of each occupation, the coefficient for routine occupations is rather smaller in absolute value than the coefficient for cognitive occupations. Therefore, we are able to rule out the level effect of the initial share of routine workers.

Table 4.6: OLS Estimates of Employment Growth by Occupation Groups (1980−2009): Level Effect

Occupation Groups	Coefficient	R-squared
Total	$-0.0353^{***}(0.0075)$	0.30
Cognitive Occupations	$-0.0362^{***}(0.0071)$	0.33
Routine Occupations	$-0.0238^{**}(0.0116)$	0.07
Manual Occupations	$0.0236^{**}(0.0103)$	0.09

Note: The main regressor is the employment share of routine workers in 1980 instead of the initial industry wage premium.

4.3.3 Wage premium as outcome of high capital-labor ratio

Lastly, we test the hypothesis that the high wage premium was the consequence of high capital-labor ratio in 1980, which is basically based on competitive labor market theories. Capital-intensive industries might pay higher wages in 1980 because their labor productivity was high. Hence, as the price of capital declines, those industries might adopt more capital since they are more efficient in using capital by the intrinsic nature of the industries. As a result, more (routine) workers might have been replaced by (ICT) capital in capital-intensive industries.

However, this hypothesis is at odds with data in two respects. First, it is not consistent with the long-run trend of an industry wage premium. If this theory is correct, the dispersion of industry wage premium should have further increased because the (ICT) capital-labor ratio increased more in high-wage industries as in Table 4.5. However, industry wage dispersion has slightly decreased (see Borjas and Ramey (2000)). Second, we again estimate the main equation (4.2) by replacing the initial industry wage premium with the initial ICT capital-labor ratio.[23] The result in Table 4.7 shows that the last hypothesis is not consistent with the data: the effect of capital-labor ratio in 1980 is almost zero. In addition, the estimation result in Table 4.3 shows that our finding is not affected by the factors that we discussed in this section.

[23]Results do not change when we use initial (general) capital-labor ratio.

Table 4.7: OLS Estimates of Employment Growth by Occupation Groups (1980−2009): Capital-Labor Ratio

Occupation Groups	Coefficient	R-squared
Total	−0.0000537(0.0000793)	0.00
Cognitive Occupations	0.0000821(0.0000693)	0.00
Routine Occupations	−0.0000846(0.0000976)	0.00
Manual Occupations	0.0015398*(0.0008162)	0.03

Note: The main regressor is the capital-labor ratio in 1980 instead of the initial industry wage premium.

5 Theoretical Consideration: Firms' Responses to Persistent Wage Structure across Industries

In the previous section, we consider three possible hypotheses, but none of them are shown to be fully supported by the data. Then, how can interindustry wage differentials be connected to heterogeneity in job polarization? We suggest a plausible hypothesis in this section: it is the firm's optimal response to the existing interindustry wage differentials, which arise from exogenous factors that cannot be controlled by firms, that results in different degrees of job polarization across industries.

We first note that there exist two sources of interindustry wage differentials: (1) worker heterogeneity and (2) exogenous factors to firms. Exogenous factors include different union power across industries, compensating wage differentials, search friction with positive labor mobility cost, and heterogeneous detection technology for shirking workers to generate interindustry wage differentials.[24] We first show, in subsection 5.1, that a model assuming worker heterogeneity without exogenous factors does not explain our findings. Conversely, in subsection 5.2, we show that the predictions of our main model (that is, assuming exogenous factors without worker heterogeneity) are consistent with the data.

The intuition of our theory is as follows; the cost of labor to produce the same output, which is the product of wage and employment, is different across industries. As it is difficult

[24] It can be shown that the assumptions made here yield the same equilibrium outcomes. The results are available upon request.

for high-wage firms to reduce wages relative to low-wage firms, they respond to the high labor cost by adjusting employment over time. When a firm changes its labor demand, however, the effect is not uniform across workers. Since the routine workers' tasks are more easily codifiable or computerized, they are more affected by a firm's dynamic decision to substitute capital for labor.[25]

In particular, the relative price of ICT capital has decreased since the 1980s, and firms with incentives to adjust employment are more likely to reduce the relative demand for routine workers by replacing them with ICT capital. As a result, firms in a high-wage industry experience more evident job polarization as the demand for routine workers declines to a larger extent in these firms. In addition, the ICT capital-labor ratio in a high-wage industry rises by a greater amount than in a low-wage industry, since more ICT capital is introduced to substitute for routine workers.

In a simple partial-equilibrium firm model, we consider two types of tasks (workers)–"non-routine" tasks (non-routine workers) and "routine" tasks (routine workers)–in order to capture the features of job polarization.[26] As is usually assumed in the job polarization literature, capital is a relative substitute for routine workers, while it is a relative complement to non-routine workers.[27] In this sense, the capital considered in our model can be interpreted as ICT capital. In order to generate interindustry wage differentials, we assume that owing to some exogenous factors, industry 1 pays higher wages than industry 2. The theoretical results we show in section 5.2 are preserved even when we consider the general equilibrium model.[28] In particular, the supply side of labor market is introduced in Appendix B.1.1 where the supply of the labor in each sector is positive.

5.1 Model with Worker Heterogeneity

We first examine if the competitive view of the labor market generating interindustry wage differentials can explain our findings. One of the

[25] Offshoring is another possibility, as Goos, Manning, and Salomons (2014) and Oldenski (2014) show.

[26] One might further decompose non-routine workers into cognitive and manual workers; given, however, that these workers have similar roles in the production function (both workers are relative complements to capital), we choose to use only two types of workers in the model for simplicity of discussion. The same strategy is used by Beaudry, Green, and Sand (2013) and Jaimovich and Siu (2014).

[27] See Autor, Levy, and Murnane (2003), Autor and Dorn (2013), and Cortes (2016), for instance.

[28] The results are available upon request.

main arguments for industry wage dispersion is that workers' productivities are actually different (due to unobserved heterogeneity). This also nests the case where a worker is paid more because she is more productive in using capital.

Suppose that there exist the same numbers (measure 1) of workers and firms in the economy. In the labor market, each firm that produces the same consumption goods is matched to one worker. Each worker n is assumed to have different productivity, and x_n denotes the productivity of a worker where $n \in [0, 1]$. Without loss of generality, x_n is assumed to be decreasing in n. The production function of a firm is given as $y = x_n + x_k k$, where k is the amount of capital a firm buys from the international market at unit price p and x_k is the productivity (efficiency) of the capital measured by the consumption goods. For simplicity, the production function assumes perfect substitutability between labor and capital. Thus, one implicit assumption here is that the workers in this economy are routine workers.[29] Note that if there is no capital, $y = x_n$ such that the competitive labor market implies $w_n = x_n$. Hence, the wage differentials among workers are the direct result of their productivity differences.

We now introduce capital into the economy, and the firm minimizes $TC = w + pk$ subject to the production function. Suppose that a firm that initially hired worker n produces x_n unit of consumption goods. Then, the total cost of producing consumption goods is equal to x_n when the firm employs only labor, and $p\frac{x_n}{x_k}$ when it uses only capital to produce the same amount of goods. This implies the threshold condition of the firm for production: a firm chooses to use labor (resp. capital) in the production if $x_k/p < 1$ (resp. $x_k/p > 1$). Suppose that the price of capital was initially so high that $x_k/p < 1$, and hence, no firm used capital.

The price of capital decreases owing to the "routine-replacing technology changes." Then, the following proposition holds, which is a natural consequence of the model above.

Proposition 5.1 (Job Polarization when Workers are Heterogeneous)**.** *Suppose that $x_k/p < 1$; hence, no firm used capital. As p decreases, the adoption of new technology to use capital occurs at the same time in every firm. In other words, the occurrence of job polarization, that is, the*

[29] The key results are identical even when we include non-routine workers in the production function. For example, $y = \min\{x_{nr}h, x_r + x_k k\}$, where x_{nr} is the productivity of the non-routine worker, x_r is the productivity of the routine worker, and h is the number of non-routine workers that are employed by a firm.

replacement of workers with capital (other production factors), is not apparent in the high-wage firms.

Therefore, the prediction of the model that assumes only ex-ante heterogeneous workers is not consistent with our empirical findings.

5.2 Model with Exogenous Factors

In this section, we introduce our main theory to explain the link between job polarization and interindustry wage differentials.

Setup: A Firm's Problem We assume that the goods market is perfectly competitive so that a firm's profit is zero in equilibrium. Each firm produces an output by utilizing two types of workers and capital. A firm in industry i solves the following static profit maximization problem:

$$\max_{\{k_{it}, h_{it}, \tilde{h}_{it}\}} p_{it} y_{it} - w_{it} h_{it} - \tilde{w}_{it} \tilde{h}_{it} - r_t k_{it} \tag{5.1}$$

subject to

$$y_{it} = h_{it}^{\alpha} \left(\tilde{h}_{it}^{\mu} + k_{it}^{\mu} \right)^{\frac{1-\alpha}{\mu}}$$

where $\mu \in (0,1)$ and $\alpha \in (0,1)$. h_{it} (resp. $\tilde{h}_{it}$) denotes hours of non-routine (resp. routine) workers supplied to industry i and w_{it} (resp. $\tilde{w}_{it}$) is the corresponding wage rate. We assume that labor is infinitely supplied by workers as firms would like to hire and capital is rented at the competitive international market at rate r, which can possibly vary due to investment-specific technology changes.

Following Autor, Levy, and Murnane (2003), Autor, Katz, and Kearney (2006), and Autor and Dorn (2013), we assume a CES production function. Notice that the elasticity of substitution between non-routine workers and total routine inputs is 1, while the elasticity of substitution between routine workers and capital is $\frac{1}{1-\mu} > 1$, since $\mu > 0$. As a result, as in Autor and Dorn (2013), capital is a *relative substitute* for routine workers and a *relative complement* to non-routine workers. Hence, capital in our model is ICT capital.

A final remark on the firm's problem is that the implications of our model are still preserved

even when we assume heterogeneous production functions (different α and μ) across industries under some conditions on exogenous industry wage premia.[30] Hence, we will maintain the assumption that production functions are the same across industries in this paper in order to clearly show the relationship between the industry wage premium and job polarization.

In order to understand the role of changes in the price of capital, we derive the following equation in the equilibrium:

$$\frac{\tilde{w}_{it}}{r_t} = \left(\frac{k_{it}}{\tilde{h}_{it}}\right)^{1-\mu} \tag{5.2}$$

This equation implies that capital per routine worker increases as the relative rental cost over routine workers decreases because capital is a relative substitute for routine workers and firms replace routine workers with capital as the relative cost of utilizing capital becomes lower.

In order to capture the industry wage differentials observed in the data, we assume that the wage in industry 1 is higher than that in industry 2 by a factor $\lambda > 0$ so that

$$w_{1t} = (1+\lambda)w_{2t} \text{ and } \tilde{w}_{1t} = (1+\lambda)\tilde{w}_{2t} \tag{5.3}$$

λ is the parameter that is governed by exogenous factor(s) to firm; equation (5.3) can be derived with (1) labor unions with different power or (2) compensating wage differentials.[31] In this sense, we can interpret the labor market environment used in our model as a parsimonious way to generate wage differentials across industries with exogenous factors. One might worry that labor is supplied only in the high-wage sector, which is resolved under a labor market environment discussed in Appendix B.1.1.

One can further check that capital per routine worker is always higher in a high-wage firm, which arises from the fact that it can lower production costs by employing more capital than the low-wage firms. Notice that this equilibrium property is consistent with empirical facts reported by Dickens and Katz (1987) and theoretical predictions provided by Alexopoulos (2006) and

[30] For the high-wage industry to experience more pronounced job polarization, the industry wage premium should be high enough. Details of the results with heterogeneous production functions are available upon request.

[31] The results are available upon request.

Acemoglu and Shimer (2000).

Demand for goods is given by $y_t = \left[y_{1t}^{1-\nu} + y_{2t}^{1-\nu}\right]^{\frac{1}{1-\nu}}$ so that the individual inverse demand function can be derived as $p_{it} = \left(\frac{y_t}{y_{it}}\right)^{\nu}$.

Predictions In what follows, we provide predictions of the model by analyzing the comparative statics of steady-state equilibrium.

Since we are interested in how changes in the ratio of wage rates for routine workers and the rental price of capital ($\tilde{w}/r$) affect the two industries differently, we conduct the comparative statics exercise by analyzing the behavior of the steady-state economy when there is an exogenous change in r so that $\tilde{w}/r$ varies. For a clear comparison between industries, we focus on how the increase in $\tilde{w}_2/r$, the relative wage of routine workers over capital price in the low-wage industry, affects job polarization in each industry. While we only consider two industries (firms), the analysis can be extended easily to $n > 2$ industries.

The next proposition is the collection of predictions of the model when $\tilde{w}/r$ rises. An increase in $\tilde{w}/r$ is introduced to capture the fact that the relative price of (ICT) capital has declined over time; one can think of the steady-state economy as the U.S. economy in the beginning of 1980, and then there was an exogenous decline in r so that the new steady state is the U.S. economy in 2010. We first define $s_i \equiv \frac{h_i}{\bar{h}_i}$, which measures the usage of non-routine workers relative to routine workers. Then, job polarization in our model indicates the situation in which s_i increases. Next, we define $\kappa_i \equiv \frac{k_i}{\bar{h}_i}$, which is the capital-routine worker ratio.

Proposition 5.2 (Job Polarization: Connection to Interindustry Wage Differentials)**.** *Suppose that $\tilde{w}_i/r$ increases in all industries. Then, the following results hold in the steady state:*

1. *The capital-routine worker ratio increases in both industries, while it rises more in the high-wage industry. In addition, the difference between industries increases in the wage premium (λ) and substitutability between capital and routine workers (μ). Formally,*

$$\frac{d\kappa_1}{d\frac{\tilde{w}_2}{r}} = (1+\lambda)^{\frac{1}{1-\mu}} \frac{d\kappa_2}{d\frac{\tilde{w}_2}{r}} > 0 \tag{5.4}$$

2. *Job polarization occurs in both industries. Formally,*

$$\frac{ds_i}{d\frac{\tilde{w}_2}{r}} = \frac{\alpha}{\chi(1-\alpha)} \frac{d\kappa_i^{\mu}}{d\frac{\tilde{w}_2}{r}} > 0 \tag{5.5}$$

where $\chi = w_i/\tilde{w}_i$.

3. *The change in the employment share of non-routine over routine workers in industry* 1 *is greater than that in industry* 2*; that is, job polarization is more evident in the high-wage industry. In addition, the difference in the degree of job polarization across industries increases in the wage premium* (λ) *and substitutability between capital and routine workers* (μ)*. Formally,*

$$\frac{ds_1}{d\frac{\tilde{w}_2}{r}} = (1+\lambda)^{\frac{\mu}{1-\mu}} \frac{ds_2}{d\frac{\tilde{w}_2}{r}} \tag{5.6}$$

Proof. See Appendix A.1. □

First of all, it is a natural consequence of the model that firms try to use capital more than routine workers when the relative price of capital declines, because capital and routine workers are substitutes. One can show that capital per routine worker rises more as the substitutability, μ, rises. In addition, the first part of the proposition shows that firms that are constrained to pay a higher wage markup use capital more intensively in production, and hence, the capital-routine worker ratio grows more in those firms. The difference across industries increases in λ, the parameter that governs the industry wage premium; as firms should pay more to workers, their incentive to utilize capital increases, which results in more rapid growth of the capital-routine worker ratio in those firms than in firms that can pay less.

The second part of Proposition 5.2 shows that, consistent with previous models on job polarization, including Autor and Dorn (2013), Autor, Levy, and Murnane (2003), and Cortes (2016), a decline in the relative price of capital over routine workers is one of the critical factors in job polarization. The last part of the proposition is another key prediction of our model: the non-routine share of hours (employment) grows more in the high-wage industry since new technology (utilizing capital) is adopted more aggressively by the firms that face high labor costs,

as discussed in the first part of the proposition. Furthermore, the difference in the degree of job polarization across industries increases in λ, which shows the importance of the industry wage premium in explaining heterogeneous aspects of job polarization across industries.

Therefore, our model is consistent with the empirical evidence that is presented in Section 4; the positive correlation between (1) the degree of job polarization and the initial industry wage premium and (2) the subsequent growth rate of ICT capital per worker and the initial industry wage premium. The availability of capital as a substitute for routine labor leads to the demand for routine labor being more elastic than that for non-routine labor, and so the industry wage premium reduces the demand for routine labor more than it reduces the demand for non-routine labor. The other finding, $\theta_{ICT} > \theta_{Aggregate} > \theta_{non-ICT}$, from Table 4.5, is also consistent with our hypothesis; the growth rate of non-ICT capital per worker between 1980 and 2007 is not correlated with the industry wage premium in 1980, as non-ICT capital can be interpreted as general-purpose capital that complements workers.

6 Conclusion

Over the past decades, employment has become polarized in the U.S., with composition of the labor force shifting away from routine occupations toward both cognitive and manual occupations. In this paper, we show that the degree of job polarization is different across industries and identify the factor that is related to this phenomenon by demonstrating that the job polarization is connected with wide dispersion in wages across industries.

Our empirical findings can be explained as firms' dynamic responses to interindustry wage differentials: firms that paid high industry wage premia coped with the wage pressure by substituting ICT capital for routine workers. Therefore, the heterogeneous aspect of job polarization across industries can be the result of optimal responses of industries to existing industry wage differentials.

This paper aids in understanding the heterogeneity in job polarization across industries by presenting the underlying mechanism and empirical regularities that reveal the relationship between job polarization and the wage structure of industries. In addition, the paper adds to

the literature on industry wage dispersion by showing that non-competitive factors are relevant to the existence of interindustry wage differentials. Without exogenous factors such as labor unions, low-wage firms are expected to experience more evident job polarization when workers are heterogeneous in their productivities. Our findings suggest that compared to low-wage firms, high-wage firms respond more actively to the "rigid" interindustry wage structure by replacing workers with other production factors over time. This indicates that exogenous factors are also important determinants of the industry wage premium.

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A Appendix

A.1 Proof of Proposition 5.2 We first list the equilibrium conditions for the firm's problem in the steady state.

$$w_1 = (1+\lambda)w_2 \text{ and } \tilde{w}_1 = (1+\lambda)\tilde{w}_2 \tag{A.1}$$

$$y_i = h_i^{\alpha}\left(\tilde{h}_i^{\mu} + k_i^{\mu}\right)^{\frac{1-\alpha}{\mu}} \tag{A.2}$$

$$\frac{w_i}{p_i} = \alpha\frac{y_i}{h_i} \tag{A.3}$$

$$\frac{\tilde{w}_i}{p_i} = (1-\alpha)\frac{\tilde{h}_i^{\mu}}{\tilde{h}_i^{\mu} + k_i^{\mu}}\frac{y_i}{\tilde{h}_i} \tag{A.4}$$

$$\frac{r}{p_i} = (1-\alpha)\frac{k_i^{\mu}}{\tilde{h}_i^{\mu} + k_i^{\mu}}\frac{y_i}{k_i} \tag{A.5}$$

We first obtain the following equations by dividing equation (A.3) (equations (A.4) and (A.5)) for industry 1 by equation (A.3) (equations (A.4) and (A.5)) for industry 2 and apply the wage structure given in equation (A.1):

$$1+\lambda = \frac{p_1}{p_2}\frac{y_1}{y_2}\frac{h_2}{h_1} \tag{A.6}$$

$$1+\lambda = \frac{p_1}{p_2}\frac{y_1}{y_2}\frac{\tilde{h}_2^{1-\mu}}{\tilde{h}_1^{1-\mu}}\frac{\tilde{h}_2^{\mu} + k_2^{\mu}}{\tilde{h}_1^{\mu} + k_1^{\mu}} \tag{A.7}$$

$$\frac{p_1}{p_2}\frac{y_1}{y_2} = \frac{k_1^{1-\mu}}{k_2^{1-\mu}}\frac{\tilde{h}_1^{\mu} + k_1^{\mu}}{\tilde{h}_2^{\mu} + k_2^{\mu}} \tag{A.8}$$

Combining equations (A.7) and (A.8), we obtain the following relationship:

$$\frac{k_1}{\tilde{h}_1} = \phi \frac{k_2}{\tilde{h}_2} \tag{A.9}$$

where $\phi = (1+\lambda)^{\frac{1}{1-\mu}} > 1$. For simplicity of notation, we let $\kappa_i = \frac{k_i}{\tilde{h}_i}$ in what follows. Hence, the above equation is now $\kappa_1 = \phi\kappa_2$.

We then combine equations (A.4) and (A.5) to obtain the following equation:

$$\frac{\tilde{w}_i}{r} = \kappa_i^{1-\mu} \tag{A.10}$$

We first differentiate equation (A.10) with respect to $\frac{\tilde{w}_i}{r}$:

$$\frac{d\kappa_i}{d\frac{\tilde{w}_i}{r}} = \frac{\kappa_i^{\mu}}{1-\mu} > 0 \tag{A.11}$$

Hence,

$$\begin{aligned} \frac{d\kappa_1}{d\frac{\tilde{w}_1}{r}} &= \frac{\kappa_1^{\mu}}{1-\mu} = \frac{(\phi\kappa_2)^{\mu}}{1-\mu} = \phi^{\mu}\frac{d\kappa_2}{d\frac{\tilde{w}_2}{r}} \\ \Leftrightarrow \frac{d\kappa_1}{d\frac{\tilde{w}_2}{r}} &= \phi\frac{d\kappa_2}{d\frac{\tilde{w}_2}{r}} \end{aligned} \tag{A.12}$$

The last step comes from $\tilde{w}_1 = (1+\lambda)\tilde{w}_2$.

As a result, as one can expect from the substitutability between routine workers and capital, a lower relative rental cost of capital accelerates capital deepening (in terms of the capital-routine worker ratio). In addition, $\frac{d\kappa_1}{d\frac{\tilde{w}_2}{r}} = \phi\frac{d\kappa_2}{d\frac{\tilde{w}_2}{r}} > \frac{d\kappa_2}{d\frac{\tilde{w}_2}{r}} > 0$ implies that capital deepens more in the high-wage industry; the high-wage industry tries to find a way to reduce labor cost, and the reduction of the relative price of capital provides the incentive for the high-wage industry to rent more capital in order to replace routine workers more than the low-wage industry.

We define $s_i = \frac{h_i}{\tilde{h}_i}$. This measures, as discussed in the main text, the share of non-routine workers over routine workers. If s_i is increasing, it means that more non-routine workers are employed for given numbers (hours) of routine workers, and hence, it can be interpreted as

job polarization. In order to study the effect of changes in $\frac{\tilde{w}_i}{r}$ on job polarization, we combine equations (A.3) and (A.4):

$$\frac{1}{\chi} = \frac{1-\alpha}{\alpha}\frac{s_i}{1+\kappa_i^{\mu}} \tag{A.13}$$

Here, we use the fact that $\frac{\tilde{w}_i}{w_i}$ is the same across industries due to (A.1) and define $\frac{\tilde{w}_i}{w_i}$ as $1/\chi$. Notice that the left-hand side of the above equation is constant at $1/\chi$ while κ_i increases as $\frac{\tilde{w}_i}{r}$ increases. As a result, $\frac{ds_i}{d\frac{\tilde{w}_i}{r}} > 0$. Formally,

$$\frac{ds_i}{d\frac{\tilde{w}_i}{r}} = \frac{\alpha}{\chi(1-\alpha)}\mu\kappa_i^{\mu-1}\frac{d\kappa_i}{d\frac{\tilde{w}_i}{r}} = \frac{\alpha}{\chi(1-\alpha)}\frac{d\kappa_i^{\mu}}{d\frac{\tilde{w}_i}{r}} > 0 \tag{A.14}$$

Hence, as the relative rental cost of capital over routine workers decreases, job polarization occurs in both industries.

Now, we compare the degree of job polarization across industries. Notice that the degree of job polarization is apparent in the high-wage industry if $\frac{ds_1}{d\frac{\tilde{w}_1}{r}} > \frac{ds_2}{d\frac{\tilde{w}_2}{r}}$. We use equation (A.14), the relationship $\kappa_1 = \phi\kappa_2$, and $\tilde{w}_1 = (1+\lambda)\tilde{w}_2$:

$$\begin{aligned}\frac{ds_1}{d\frac{\tilde{w}_2}{r}} &= \frac{\alpha}{\chi(1-\alpha)}\mu\kappa_1^{\mu-1}\frac{d\kappa_1}{d\frac{\tilde{w}_2}{r}} \\ &= \frac{\alpha}{\chi(1-\alpha)}\mu\phi^{\mu-1}\kappa_2^{\mu-1}\phi\frac{d\kappa_2}{d\frac{\tilde{w}_2}{r}} = \phi^{\mu}\frac{ds_2}{d\frac{\tilde{w}_2}{r}}\end{aligned} \tag{A.15}$$

Hence, $\frac{ds_1}{d\frac{\tilde{w}_1}{r}} > \frac{ds_2}{d\frac{\tilde{w}_2}{r}}$ since $\phi > 1$ and $\mu > 0$.

The above equation shows clearly that the degree of job polarization becomes greater in the high-wage industry when $\frac{\tilde{w}_2}{r}$ increases. Suppose instead that $\lambda = 0$, so that there is no industry wage premium. Then, it is clear that $\frac{ds_1}{d\frac{\tilde{w}_1}{r}} = \frac{ds_2}{d\frac{\tilde{w}_2}{r}}$, and hence, job polarization is of the same magnitude across industries. As a result, the heterogeneity in the progress of job polarization across industries increases in λ, which is consistent with our intuition.

A.2 Additional Tables

Table A.1: Source of Wage Variation (R-Squared)

	1980	1990	2000	2009
Total	0.40	0.42	0.42	0.43
Industry Only	0.14	0.14	0.13	0.16
Covariates Only	0.36	0.37	0.38	0.38
Observations	4,307,598	4,940,215	5,530,409	1,202,671

Note: 1. 1980, 1990, and 2000 data are from the Census and 2009 data are from the ACS.
2. The first row is the explanatory power (R^2) of the wage regression when individual characteristics (see Section 4 for details) and 60 industries are all controlled for. The second row is the explanatory power of the wage equation when industry dummies are the only independent variables and the third row is that of the wage equation when only covariates are considered as independent variables.
3. The sum of the explanatory power reported in the second and third row is not equal to the value reported in the first row since industries and covariates are not exactly orthogonal (Dickens and Katz (1987)).

Table A.2: OLS Estimates of the Wage Regression in 1980

Variable	Coefficient	Variable	Coefficient
Female	−0.5413(0.0009)	Cognitive Occupation	0.4892(0.0030)
Age1	1.0227(0.0035)	Routine Occupation	0.2267(0.0029)
Age2	1.5225(0.0035)	Manual Occupation	0.0081(0.0031)
Age3	1.7141(0.0035)	Region1	−0.0355(0.0024)
Age4	1.7916(0.0035)	Region2	0.0329(0.0020)
Age5	1.7775(0.0036)	Region3	0.0684(0.0020)
Edu1	−0.5575(0.0020)	Region4	−0.0188(0.0023)
Edu2	−0.4799(0.0017)	Region5	−0.0045(0.0020)
Edu3	−0.2689(0.0013)	Region6	−0.0612(0.0024)
Edu4	−0.2418(0.0014)	Region7	−0.0011(0.0022)
Edu5	0 (Omitted)	Region8	0 (Omitted)
African-American	−0.0842(0.0014)	Region9	0.0665(0.0021)
R-Squared	.4045	Observations	4,307,598

Note:
1. Robust standard errors are reported in parentheses.
2. Region1 to Region9 correspond to New England Division, Middle Atlantic Division, East North Central Division, West North Central Division, South Atlantic Division, East South Central Division, West South Central Division, Mountain Division, and Pacific Division, respectively.
3. Age1 to Age5 correspond to 18−24, 25−34, 35−44, 45−54, and 55−64, respectively.
4. Edu1 to Edu5 correspond to workers with fewer than 9 years, 9 to 11 years, 12 years, 13 to 15 years, and at least 16 years of schooling, respectively.

Table A.3: OLS Estimates of Employment Growth by Occupation Groups, Full-Time Workers Only (1980−2009)

Occupation Groups	Coefficient	R-squared
Total	$-0.0427^{***}(0.0078)$	0.26
Cognitive Occupations	$-0.0272^{***}(0.0067)$	0.15
Routine Occupations	$-0.0461^{***}(0.0098)$	0.20
Manual Occupations	0.0091(0.0124)	0.02

Note: 1. The regressions are weighted by each industry's initial (i.e., 1980) employment.
2. The sample size is 60.
3. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B Supplementary Online Appendix: Additional Tables

B.1 Supply Side of Labor Market

B.1.1 Household We consider an environment in which a representative household consists of identical workers, whose total hours supplied to the labor market are denoted by n_t.[32]

There is an infinitely lived representative household in the economy that solves the following deterministic maximization problem:

$$\max_{\{c_t, k_{t+1}, x_t, n_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t \left[\log c_t + \theta(\bar{n} - n_t)\right] \tag{B.1}$$

subject to

$$(1)\ c_t + x_t = w_t n_t + r_t k_t + \pi_t$$

$$(2)\ k_{t+1} = (1-\delta)k_t + q x_t$$

where $\theta > 0$ is a constant, $k_0 > 0$ is given, $\bar{n} > 0$ is total hours with which a household is endowed, and π_t is a lump-sum transfer from the labor broker that is described below.

The period t income can be used to purchase consumption goods, c_t, or used to generate investment goods, x_t, with the technology q. Hence, higher q means that the technology to generate investment goods improves; more investment goods can be generated with the same income and consumption. We sometimes refer to $1/q$ as the relative price of capital. We normalize the price of the final good to 1. In addition, r_t and $\delta \in [0, 1]$ are the rental cost and the depreciation rate of capital, respectively. In addition, equation (2) is the law of motion for capital that a household owns and rents to firms. The household supplies labor at wage rate w_t. Detailed discussions on wage rates are provided in the next section.[33]

[32] The assumption on the representative household is made in order to avoid the distributional issue that arises from different wage rates across industries and types of workers.

[33] We assume that the utility is linear in hours worked in order to make clear predictions and to avoid the problem that the labor market may not clear when labor supply is inelastic under the existence of the industry wage premium.

The key optimality condition for the household problem is given as follows:[34]

$$\frac{c_{t+1}}{c_t} = \beta \left[q r_{t+1} + (1 - \delta) \right] \tag{B.2}$$

We focus on comparative statics in the steady state, and therefore we set $c_t = c_{t+1}$ and obtain a relationship between r and q as follows.

$$r = \frac{\frac{1}{\beta} - 1 + \delta}{q} \tag{B.3}$$

The rental cost of capital (r) is strictly decreasing in q; that is, the steady-state level of capital can be sustained with less investment when the technology, q, is more efficient. Hence, less demand for capital lowers the rental rate of capital.

B.1.2 Labor Market

The labor market is assumed to be intermediated by a labor broker that receives hours worked from the household and allocates them across industries 1 and 2 and routine and non-routine occupations.[35] Let h_{it} (resp. $\tilde{h}_{it}$) be the hours of non-routine (resp. routine) workers supplied to industry i. We further define w_{it} (resp. $\tilde{w}_{it}$) to be the wage rate of non-routine (resp. routine) workers employed in industry i.

As discussed in the main text, the industry wage differentials observed in the data are captured by assuming that the wage in industry 1 is higher than that in industry 2 by a factor $\lambda > 0$ so that

$$w_{1t} = (1 + \lambda) w_{2t} \text{ and } \tilde{w}_{1t} = (1 + \lambda) \tilde{w}_{2t} \tag{B.4}$$

As non-routine occupations[36] require more complex skills of a worker, the broker sets the following wage rule to compensate the skill differences across occupations:[37]

[34] There is another optimality condition for labor supply, $w_t = \theta c_t$, which we abstract from here since it is not relevant for our analysis.

[35] Or equivalently, one can assume rationing in the labor market so that only some fractions of workers can be employed in the high-wage industry. Households then collect total labor income as a sum of labor income from all workers, as discussed in Alder, Lagakos, and Ohanian (2013). All of these features are to obtain equilibrium in which all firms employ positive hours.

[36] Here, we focus on cognitive occupations.

[37] Or equivalently, we can assume that there are two types of workers that constitute a household and leisure is

$$w_{it} = \chi \tilde{w}_{it} \tag{B.5}$$

where $\chi > 1$ measures the compensation to the occupations that require relatively complex skills.

The broker compensates the hours supplied by the household at the lowest wage in the market that corresponds to the wage of a routine worker in industry 2.[38] It then allocates the hours according to the demand of firms in the two industries given the assumed wage differentials and wage rule. The additional wage income received by the broker on the hours supplied to industry 1 is rebated to the household as a lump-sum transfer:

$$\pi_t = \tilde{w}_{2t}(\lambda\chi h_{1t} + \chi h_{2t} + \lambda \tilde{h}_{1t}) \tag{B.6}$$

B.2 Additional Tables

Table B.1: Census Industry Classification

Number	Industry	IND1990 Code
1	Metal mining	40
2	Coal mining	41
3	Oil and gas extraction	42
4	Nonmetallic mining and quarrying, except fuels	50
5	Construction	60
6	Food and kindred products	100 – 122
7	Tobacco manufactures	130
8	Textile mill products	132 – 150
9	Apparel and other finished textile products	151 – 152
10	Paper and allied products	160 – 162
11	Printing, publishing, and allied industries	171 – 172
12	Chemicals and allied products	180 – 192
13	Petroleum and coal products	200 – 201

linear in both types of workers, which yields identical results.

[38] One can set a different wage rule without changing equilibrium properties; for example, $w_t = w_{1t}$ is also possible but then the household should pay back the remaining labor income to the broker.

14	Rubber and miscellaneous plastics products	210 – 212
15	Leather and leather products	220 – 222
16	Lumber and woods products, except furniture	230 – 241
17	Furniture and fixtures	242
18	Stone, clay, glass, and concrete products	250 – 262
19	Metal industries	270 – 301
20	Machinery and computing equipments	310 – 332
21	Electrical machinery, equipment, and supplies	340 – 350
22	Motor vehicles and motor vehicle equipment	351
23	Other transportation equipment	352 – 370
24	Professional and photographic equipment and watches	371 – 381
25	Miscellaneous manufacturing industries / Toys, amusement, and sporting goods	390 – 392
26	Railroads	400
27	Bus service and urban transit / Taxicab service	401 – 402
28	Trucking service / Warehousing and storage	410 – 411
29	U.S. postal service	412
30	Water transportation	420
31	Air transportation	421
32	Pipe lines, except natural gas / Services incidental to transportation	422 – 432
33	Communications	440 – 442
34	Utilities and sanitary services	450 – 472
35	Durable goods	500 – 532
36	Nondurable goods	540 – 571
37	Lumber and building material retailing	580
38	General merchandiser (Note 2)	581 – 600
39	Food retail	601 – 611
40	Motor vehicle and gas retail	612 – 622
41	Apparel and shoe	623 – 630
42	Furniture and appliance	631 – 640
43	Eating and drinking	641 – 650
44	Miscellaneous retail	651 – 691
45	Banking and credit	700 – 702
46	Security, commodity brokerage, and investment companies	710
47	Insurance	711

48	Real estate, including real estate-insurance offices	712
49	Business services	721 – 741
50	Automotive services	742 – 751
51	Miscellaneous repair services	752 – 760
52	Hotels and lodging places	761 – 770
53	Personal services	771 – 791
54	Entertainment and recreation services	800 – 810
55	Health care	812 – 840
56	Legal services	841
57	Education services	842 – 861
58	Miscellaneous services (Note 3)	862 – 881
59	Professional services	882 – 893
60	Public administration	900 – 932

Note: 1. Numbers 6−15 are "nondurable manufacturing goods," 16−25 are "durable manufacturing goods," 26−32 are "transportation," 35−36 are "wholesale trade," 37−44 are "retail trade," 45−49 are "finance, insurance, and real estate," 49−51 are "business and repair services," and 55−59 are "professional and related services" industries.

2. General merchandiser includes hardware stores, retail nurseries and garden stores, mobile home dealers, and department stores.

3. Miscellaneous services include child care, social services, labor unions, and religious organizations.

Table B.2: EU KLEMS Industry Classification

Number			Industry	IND1990 Code
1			Mining and quarrying	$40-50$
2			Total manufacturing	
	$2-1$		Food, beverages, and tobacco	$100-130$
	$2-2$		Textiles, textile, leather, and footwear	$132-152, 220-222$
	$2-3$		Wood and of wood and cork	$230-242$
	$2-4$		Pulp, paper, printing, and publishing	$160-172$
	$2-5$		Chemical, rubber, plastics, and fuel	
		$2-5-1$	Coke, refined petroleum, and nuclear fuel	$200-201$
		$2-5-2$	Chemicals and chemical products	$180-192$
		$2-5-3$	Rubber and plastics	$210-212$
	$2-6$		Other non-metallic mineral	262
	$2-7$		Basic metals and fabricated metal	$270-301$
	$2-8$		Machinery, NEC	$310-332$
	$2-9$		Electrical and optical equipment	$340-350$
	$2-10$		Transport equipment	$351-370$
	$2-11$		Manufacturing NEC; Recycling	$371-392$
3			Electricity, gas, and water supply	$450-472$
4			Construction	60
5			Wholesale and retail trade	
	$5-1$		Sale, maintenance and repair of motor vehicles and motorcycles; Retail sale of fuel	$500, 612-622, 672, 751$
	$5-2$		Wholesale trade and commission trade, except of motor vehicles and motorcycles	$501-571$
	$5-3$		Retail trade, except of motor vehicles and motorcycles; Repair of household goods	$580-611, 623-671, 681-691$
6			Hotels and restaurants	$762-770$
7			Transport and storage and communication	
	$7-1$		Transport and storage	$400-432$
	$7-2$		Post and telecommunications	$440-442$
8			Finance, insurance, real estate, and business services	
	$8-1$		Financial intermediation	$700-711$
	$8-2$		Real estate, renting, and business activities	$712-760$
9			Community, social, and personal services	$761-810$
10			Public administration and defence; Compulsory social security	$900-932$
11			Education	$842-861$
12			Health and social work	$812-840, 841$
13			Other community, social, and personal services	$862-893$

Table B.3: Occupation-Specific Industry Wage Premia in 1980

Industry	Average	Cognitive	Routine	Manual	Industry	Average	Cognitive	Routine	Manual
1	0.8524(.0097)	1.1828(.0181)	1.1954(.0111)	1.0234(.0660)	31	0.8938(.0060)	1.3965(.0104)	1.1606(.0071)	1.1442(.0131)
2	0.9627(.0073)	1.2585(.0173)	1.2947(.0079)	0.7852(.0838)	32	0.5164(.0090)	1.1424(.0159)	0.7964(.0105)	0.5229(.0478)
3	0.8128(.0063)	1.3019(.0094)	1.1361(.0075)	0.7512(.0539)	33	0.8531(.0049)	1.2388(.0069)	1.2174(.0056)	0.7661(.0343)
4	0.7051(.0101)	1.1480(.0250)	1.0123(.0112)	0.8694(.0600)	34	0.7212(.0049)	1.1831(.0069)	1.0390(.0056)	0.7687(.0170)
5	0.5656(.0045)	1.1518(.0065)	0.8544(.0052)	0.4819(.0194)	35	0.6248(.0048)	1.2285(.0067)	0.9098(.0055)	0.4597(.0304)
6	0.6158(.0050)	1.2072(.0080)	0.9004(.0057)	0.6949(.0155)	36	0.5755(.0049)	1.1837(.0073)	0.8610(.0056)	0.4987(.0237)
7	0.7718(.0121)	1.3420(.0231)	1.0594(.0137)	0.8614(.0673)	37	0.4835(.0071)	1.1310(.0135)	0.7634(.0080)	0.2699(.0810)
8	0.5659(.0053)	1.1789(.0108)	0.8505(.0059)	0.5900(.0231)	38	0.2603(.0048)	1.0194(.0077)	0.5185(.0056)	0.3553(.0129)
9	0.4061(.0052)	1.2145(.0127)	0.6792(.0058)	0.4035(.0305)	39	0.3969(.0050)	1.0609(.0098)	0.6838(.0056)	0.3128(.0157)
10	0.7534(.0055)	1.2674(.0098)	1.0496(.0063)	0.9124(.0270)	40	0.4593(.0050)	1.1522(.0093)	0.7371(.0057)	0.3153(.0291)
11	0.4809(.0053)	0.9827(.0079)	0.7939(.0061)	0.4910(.0312)	41	0.1773(.0062)	0.9946(.0122)	0.4295(.0070)	0.2041(.0419)
12	0.7540(.0049)	1.2752(.0065)	1.0607(.0058)	0.8968(.0180)	42	0.3595(.0063)	0.9503(.0120)	0.6492(.0071)	0.1138(.0522)
13	0.8724(.0074)	1.3563(.0116)	1.2011(.0088)	0.7933(.0530)	43	0.1737(.0045)	0.8572(.0068)	0.4181(.0067)	0.2277(.0054)
14	0.6543(.0057)	1.2446(.0097)	0.9382(.0065)	0.7914(.0289)	44	0.1457(.0055)	0.7895(.0092)	0.4188(.0063)	0.2218(.0246)
15	0.4259(.0079)	1.1603(.0254)	0.7035(.0085)	0.5134(.0522)	45	0.5735(.0046)	1.1792(.0057)	0.8521(.0055)	0.4151(.0188)
16	0.5063(.0062)	1.1625(.0143)	0.7820(.0070)	0.5604(.0337)	46	0.7683(.0079)	1.2815(.0138)	1.0938(.0092)	0.4082(.0575)
17	0.4804(.0063)	1.1613(.0142)	0.7575(.0070)	0.5229(.0458)	47	0.6730(.0048)	1.2383(.0066)	0.9704(.0055)	0.4936(.0294)
18	0.6722(.0057)	1.1642(.0109)	0.9782(.0064)	0.7780(.0346)	48	0.3871(.0058)	1.8683(.0095)	0.7241(.0072)	0.3979(.0107)
19	0.7525(.0046)	1.2502(.0065)	1.0509(.0052)	0.8954(.0150)	49	0.3762(.0051)	1.0299(.0068)	0.6757(.0066)	0.2917(.0085)
20	0.7152(.0045)	1.2500(.0059)	1.0159(.0053)	0.7358(.0184)	50	0.4092(.0063)	1.0308(.0142)	0.6946(.0069)	0.1908(.0574)
21	0.6614(.0046)	1.1896(.0060)	0.9648(.0054)	0.7154(.0199)	51	0.4151(.0083)	0.9705(.0219)	0.7090(.0090)	0.2536(.0820)
22	0.8742(.0050)	1.3618(.0079)	1.1730(.0057)	1.0748(.0178)	52	0.00(Omitted)	0.7086(.0120)	0.5276(.0102)	0.00(Omitted)
23	0.7480(.0048)	1.2259(.0061)	1.0781(.0057)	0.8322(.0241)	53	0.2753(.0061)	0.7207(.0132)	0.4343(.0093)	0.4462(.0078)
24	0.6790(.0056)	1.2268(.0075)	0.9771(.0067)	0.7521(.0330)	54	0.1425(.0063)	0.5998(.0098)	0.4938(.0104)	0.2662(.0091)
25	0.4644(.0061)	1.1455(.0109)	0.7338(.0069)	0.5019(.0339)	55	0.4770(.0043)	1.0231(.0052)	0.7489(.0056)	0.5829(.0054)
26	0.9247(.0055)	1.3237(.0100)	1.2363(.0061)	1.0065(.0281)	56	0.5021(.0069)	0.9358(.0106)	0.9103(.0080)	0.3791(.0700)
27	0.3950(.0072)	0.9870(.0161)	0.6723(.0080)	0.6458(.0297)	57	0.1223(.0044)	0.7527(.0052)	0.3141(.0058)	0.0750(.0062)
28	0.7092(.0051)	1.2070(.0107)	1.0078(.0057)	0.5972(.0350)	58	0.0137(.0053)	0.5056(.0066)	0.4788(.0078)	0.0374(.0092)
29	0.8159(.0054)	1.2214(.0120)	1.1231(.0060)	0.8248(.0256)	59	0.4192(.0052)	0.9655(.0062)	0.7514(.0076)	0.5198(.0276)
30	0.7528(.0094)	1.2554(.0170)	1.0699(.0108)	0.6032(.0541)	60	0.5995(.0043)	1.0453(.0054)	0.8814(.0054)	0.8729(.0057)

Note: 1. Industry numbers follow Table B.1. Standard errors are in parentheses.
2. Average is the industry wage premium estimated from equation (4.1) and cognitive, routine, and manual are the occupation-specific industry wage premia estimated from equation (4.4). We normalize the industry wage premium.

CHAPTER 7

Comparing Nested Predictive Regression Models with Persistent Predictors*

By

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Abstract

Inference on stock return predictability is commonly conducted by the in-sample inference on the coefficient estimator of the predictive regression, for which several problems have been identified such as the finite sample bias (when predictors are weakly stationary) and the non-pivotal and non-standard asymptotic distribution and un-correctable bias (when predictors are persistent), and various solutions to these problems have been suggested. In this paper, we adopt the out-of-sample inference of the predictive regression model by the encompassing statistic (ENC) that was studied by Clark and McCracken (2001) when predictors are weakly stationary. The contribution of this paper is to show that the ENC statistic has the asymptotic standard normal distribution even when predictors are persistent as well as when predictors are weakly stationary. This new result is important for empirical research on stock return predictability. While many technical problems arise for in-sample inference on the predictive regression due to persistence of predictors, the out-of-sample inference based on ENC is actually benefited from persistence of predictors because it makes the super-consistency and the asymptotic normality of the parameter estimation. Monte Carlo simulation shows that the asymptotic results hold in finite samples when predictors are weakly stationary and persistent. An application to the predictive regression of the equity premium reveals strong predictive ability of several persistent predictors.

JEL classification: C53, E37, E27

Keywords: inference on stock return predictability, predictive regression, local to unit root process, out-of-sample inference, encompassing test, asymptotic normality, equity premium.

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1 Introduction

When two non-nested models are compared, Diebold and Mariano (DM 1995) point out that the t-statistic of the mean squared forecast error (MSFE) loss-differential is asymptotically standard normal. However, when two nested models with weakly stationary predictors added to a bigger model are compared, Clark and McCracken (CM 2001, 2005, 2009) point out that the t-statistic of DM behaves quite differently from non-nested case, which may result in non-standard distribution. Also, Clark and West (CW 2006, 2007) point out that due to the finite sample parameter estimation error, the DM statistic tends to be negatively biased under the null hypothesis of the equal predictive ability. The bias-corrected DM statistic can be shown to be the encompassing (ENC thereafter) test of Harvey, Leybourne and Newbold (1998). Under the null hypothesis that a stationary predictor has no predictive power, CM (2001) show that ENC is asymptotically standard normal when the ratio of the number of out-of-sample (OOS) forecasts (P) over the number of in-sample observations in estimation window width (R) to goes to a finite constant ($P/R \to \pi < \infty$) and when the predictors are weakly stationary.

CM (2001) did not deal with the important two cases when $P/R \to \infty$ and when the predictors are persistent. The case when $P/R \to \infty$ is important because several authors recently derived the optimal rolling window width (R) in forecasting under unstable environment. For example, Giacomini and White (2005) suggested to fix R, namely $R = O(T^0)$, Inoue, Jin, and Rossi (2014) derived the optimal in-sample estimation window width $R = \left(T^{2/3}\right)$, and Sun, Hong, and Wang (2015) derived in-sample estimation window width $R = \left(T^{4/5}\right)$. In these cases when $R = \left(T^{\delta}\right)$ with $\delta < 1$,we have $P = T + 1 - R = O(T^1)$ and hence $P/R \to \infty$. Considering the case $P/R \to \infty$ is also important for the power of the OOS test which increases with P. The second case when the predictors are persistent has been studied by numerous papers such as Stambaugh (1999), Kothari and Shanken (1997), Campbell and Yogo (2006), Jansson and Moreira (2006), Elliott (2011), Cai and Wang (2014), Phillips and Magdalinos (2007, 2009), and Phillips and Lee (2013, 2014), among others. All of these papers are based on the in-sample infer-

ence of the coefficient of the predictor. While Hansen and Timmermann (2015) show that equivalence of the in-sample tests and out-of-sample tests under the assumption that the predictors are stationary, our paper provides an important advantage of using the OOS test over using the in-sample test when the predictors are persistent.

In this paper we show that under the null hypothesis, the ENC statistic follows the asymptotically standard normal distribution when the ratio of the out-of-sample number of forecasts (P) to the in-sample number of observations (R) goes to infinity ($P/R \to \infty$). This holds when the predictors are weakly stationary or not.

When the predictors are persistent, not all OOS test statistics provide the standard asymptotic distribution. For example the OOS conditional moment test of Chao, Coradi, and Swanson (2001) will have the non-standard asymptotic distribution because it checks for the correlation between forecast errors and the persistent predictor. The actual advantage of the ENC comes from the fact that ENC is constructed using only the forecast errors, but not using predictors directly.

CM (2001) and Clark and West (CW 2006, 2007) considered predictive mean regression with weak stationary predictor. This paper considers the predictive mean regression with a highly persistent predictor with an AR root local to unity. We compare two nested regression models using the squared-loss function. We show that DM statistic still tends to be negative under the null hypothesis of the equal predictive ability and is more severely undersized if the predictor is a highly persistent predictor. The t-statistic of encompassing test, in which a positive term is added to correct the negative bias of DM, is a robust test and has the correct size under the null hypothesis. We analytically show that the robustness arises from the super consistency property of the additional predictor from Model 2 that follows Ornstein–Uhlenbeck process, thus the convergent rate of the forecast error from Model 2 is faster than that from Model 1 and the asymptotic distribution of ENC statistic has the same asymptotic distribution as shown in CW (2006, 2007). We use Monte Carlo simulation to compare two different statistics and show that when the highly persistent estimator is added in Model 2, the ENC statistic is robust and has the

correct size, whereas DM test is seriously undersized. An application to the predictive regression of the equity premium reveals strong predictive ability of several persistent predictors (such as inflation and interest rate) by ENC, but with little or none can be seen from DM.

The paper is organized as follows. Section 2 presents the framework to test for out-of-sample Granger-causality in mean using rolling scheme. Section 3 presents the asymptotic distribution of the encompassing test with a weak stationary predictor. Section 4 presents the asymptotic distribution of encompassing test with a highly persistent estimator. Section 5 is Monte Carlo simulation to examine the finite sample behavior of the ENC statistic in comparison with DM. In Section 6 we present the empirical analysis for Goyal and Welch (2008) in comparing the two nested mean models for forecasting equity premium. Section 7 concludes.

2 Comparing out-of-sample predictive ability of nested models

To test for the out-of-sample predictive ability of x_t for y_{t+1}, we consider the following two nested models with the predictor x_t in Model 2 being local to unit root process:

$$\text{Model 1} \quad : \quad y_{t+1} = x'_{1,t}\beta_{1,t} + e^{(1)}_{t+1} = c_1 + e^{(1)}_{t+1}, \tag{1}$$

$$\text{Model 2} \quad : \quad y_{t+1} = x'_{2,t}\beta_{2,t} + e^{(2)}_{t+1} = c_2 + bx_t + e^{(2)}_{t+1}, \tag{2}$$

where c_i is the constant term for Model i, x_t is the predictor with local to unit autoregressive (AR) root process $x_{t+1} = \phi x_t + v_{t+1}$. We will consider the simple case when $x'_{1,t} = 1$ and $x'_{2,t} = (1\ x_t)'$. Under the null hypothesis, $b = 0$ and $e^{(1)}_{t+1} = e^{(2)}_{t+1}$, denoted as e_{t+1}. At each time t, both c_i and b are estimated with the rolling window of size R up to time t. Therefore

$$\begin{aligned} \hat{c}_{1,t} - c_1 &= B_1(t)\, H_1(t) \\ \left(\hat{c}_{2,t}, \hat{b}_t\right)' - (c_2, b)' &= B_2(t)\, H_2(t) \end{aligned}$$

where $x'_{1,t} = 1$, $x'_{2,t} = (1\ x_t)'$, $q_{i,t} = x'_{i,t}x_{i,t}$ for Model i at time t, and $B_i(t) = \left(R^{-1}\sum_{j=t-R}^{t-1} q_{i,j}\right)^{-1}$, $h_{i,t} = x'_{i,t}e_{t+1}$ and $H_i(t) = R^{-1}\sum_{j=t-R}^{t-1} h_{i,t}$. Let $f_{t+1}^{(1)} = \hat{c}_{1,t}$ be the forecasts for Model 1 and $f_{t+1}^{(2)} = \hat{c}_{2,t} + \hat{b}_t x_t$ be the forecast for Model 2 at time t and $\hat{e}_{t+1}^{(1)} = y_{t+1} - f_{t+1}^{(1)}$, $\hat{e}_{t+1}^{(2)} = y_{t+1} - f_{t+1}^{(2)}$ be the forecast errors with the squared forecast-error loss

$$L\left(\hat{e}_{t+1}^{(i)}\right) \equiv \left(\hat{e}_{t+1}^{(i)}\right)^2, \qquad i = 1, 2.$$

To test for equal predictive accuracy of the two models, the null hypothesis is

$$\mathbb{H}_0 : \mathbb{E}\left[L\left(\hat{e}_{t+1}^{(1)}\right) - L\left(\hat{e}_{t+1}^{(2)}\right)\right] = 0. \tag{3}$$

Under $\mathbb{H}_0$, x_t does not Granger-cause y_{t+1} in mean and thus $b = 0$. If x_t Granger-causes y_{t+1}, i.e., $b \neq 0$, thus the alternative hypothesis is

$$\mathbb{H}_1 : \mathbb{E}\left[L\left(\hat{e}_{t+1}^{(1)}\right) - L\left(\hat{e}_{t+1}^{(2)}\right)\right] > 0. \tag{4}$$

The Diebold-Mariano square loss differential is defined as

$$\hat{D}_P = P^{-1}\sum_{t=R}^{T} L\left(\hat{e}_{t+1}^{(1)}\right) - L\left(\hat{e}_{t+1}^{(2)}\right), \tag{5}$$

and the adjusted MSFE loss-differential is defined as

$$\hat{B}_P = P^{-1}\sum_{t=R}^{T} \hat{e}_{t+1}^{(1)}\left(\hat{e}_{t+1}^{(1)} - \hat{e}_{t+1}^{(2)}\right),$$

where R is the number of observations in the rolling windows for the in-sample estimation, P is the number of out-of-sample forecasts, and $R + P = T + 1$. The two statistics are standardized to form the DM statistic $DM_P \equiv \hat{S}_P^{-0.5}\sqrt{P}\hat{D}_P$, and the encompassing statistic $ENC_P \equiv \hat{Q}_P^{-0.5}\sqrt{P}\hat{B}_P$, where $\hat{S}_P$ and $\hat{Q}_P$ are the consistent estimators of $S_P = var\left(\sqrt{P}\hat{D}_P\right)$ and $Q_P = var\left(\sqrt{P}\hat{B}_P\right)$ respectively.

3 Asymptotic distribution of ENC with a stationary predictor (CM 2001)

First, we consider a stationary predictor as in CM (2001, 2005) and CW (2006, 2007).

Assumption 1a. $\{x_t\}$ is a weakly stationary process and $\mathbb{E}(q_{i,t})$ is bounded for all t and $i = 1, 2$. We define $B_i = (\mathbb{E}q_{i,t})^{-1}$ for model $i = 1, 2$.

Let $\pi = \lim_{P,R\to\infty} P/R$ and $\xi = R/T = R/(P+R)$. Note that $1/\xi - 1 \to \pi$. We consider three cases on π :

Assumption 2a. $0 < \pi < \infty$.

Assumption 2b. $\pi = 0$ (or $\xi \to 1$).

Assumption 2c. $\pi = \infty$ (or $\xi \to 0$).

Proposition 1 (CM 2001). Under Assumptions 1a and 2a,

$$ENC_P \Rightarrow \frac{\int_\xi^1 \xi^{-1}\left[W(s) - W(s-\xi)\right] \mathrm{d}W(s)}{\sqrt{\int_\xi^1 \xi^{-2}\left[W(s) - W(s-\xi)\right]^2 \mathrm{d}s}},$$

under $\mathbb{H}_0$, where $W(s)$ is a Wiener process and $s \in [0, 1]$. When Assumption 2a holds, the RHS of Equation (6) is *not* standard normal.

Proposition 2 (CM 2001). Under Assumptions 1a and 2b,

$$ENC_P \Rightarrow \lim_{\xi\to 1} \frac{\int_\xi^1 \xi^{-1}\left[W(s) - W(s-\xi)\right] \mathrm{d}W(s)}{\sqrt{\int_\xi^1 \xi^{-2}\left[W(s) - W(s-\xi)\right]^2 \mathrm{d}s}} \sim N(0, 1), \tag{6}$$

under $\mathbb{H}_0$, where $W(s)$ is a Wiener process and $s \in [0, 1]$. When Assumption 2b holds, the RHS of Equation (6) is standard normal.

Remark 1. CM (2001) shows that when Assumption 2b holds ($\xi \to 1, \pi \to 0$) then ENC_P is asymptotically standard normal. However, CM (2001) does not consider the case when Assumption 2c holds ($\xi \to 0, \pi \to \infty$). In Section **??** below, we consider this case and show that ENC_P is still asymptotically standard normal.

Remark 2: CM (2001) assumes Assumption 1a that the predictor $\{x_t\}$ is weakly stationary and shows that ENC_P is asymptotically standard normal under Assumption 2b.

4 Asymptotic distribution of ENC with a persistent predictor when $P/R \to \infty$

Suppose the predictor x_t in Model 2 follows an AR process $x_{t+1} = \phi x_t + v_{t+1}$ where $\mathbb{E}\left(v_{t+1}^2\right) = \sigma_v^2$. If $|\phi| < 1$, then

$$T^{-1}\sum_{t=1}^{T} x_t^2 \xrightarrow{p} \frac{\sigma_v^2}{1-\phi^2}, \qquad T^{-0.5}\sum_{t=1}^{T} x_t v_{t+1} \Rightarrow N\left(0, \frac{\sigma_v^2}{1-\phi^2}\right),$$

as $T \to \infty$. Many recent papers generalize the above to the case when ϕ approaches to 1 as the sample size T increases, see Bobkoski (1983), Cavanagh (1985), Chan and Wei (1987), Giraitis and Phillips (2006), Mikusheva (2007, 2015), Park (2003), Phillips (1987), Phillips and Lee (2013), and Stock (1991). Let $\phi = 1 - c/T$ for some fixed constant $c \geq 0$, $t = [Tr]$, $r \in [0\ 1]$. Let $x_{[Tr]}/\sqrt{T} \Rightarrow J_x^c(r) = \int_0^r e^{(r-s)c} dB_x(s)$ be an Onstein-Uhlenbeck process and B_x is a Brownian motion. If the AR coefficient ϕ is local to unity, then

$$T^{-2}\sum_{t=1}^{T} x_t^2 \Rightarrow \int_0^1 J_x^c(r)^2\,\mathrm{d}r, \qquad T^{-1}\sum_{t=1}^{T} x_t v_{t+1} \Rightarrow \int_0^1 J_x^c(r)\,\mathrm{d}B_x(r),$$

as $T \to \infty$. To consider the persistent predictor we take the local to unit root process in the following Assumption 1b.

Assumption 1b. $\{x_t\}$ follows an AR process with a root local to unity, $\phi = 1 - c/T$, for some fixed constant $c \geq 0$.

Let $t \equiv [Ts]$ and $\xi \equiv R/T$. Then we have $t/T \to s$ and $(t - R + 1)/T \to (s - \xi)$.

Under Assumption 1b,

$$T^{-2}\sum_{j=t-R+1}^{t} x_j^2 \Rightarrow \int_{s-\xi}^{s} J_x^c(r)^2\,\mathrm{d}r, \qquad T^{-1}\sum_{j=t-R+1}^{t} x_j v_{j+1} \Rightarrow \int_{s-\xi}^{s} J_x^c(r)\,\mathrm{d}B_x(r), \qquad t = R, \ldots, T,$$

as $T \to \infty$. Now, we state the main result, for the numerator of ENC_P, that is $\sqrt{P}\hat{B}_P$.

Proposition 3. Under Assumptions 1b and 2c, we have

$$\sum\nolimits_{t=R}^{T} \hat{e}_{t+1}^{(1)}\left(\hat{e}_{t+1}^{(1)} - \hat{e}_{t+1}^{(2)}\right) = -\sum\nolimits_{t=R}^{T} e_{t+1}\left(e_{t+1} - \hat{e}_{t+1}^{(1)}\right) + o\left(\xi^{-1}\right)$$

under $\mathbb{H}_0$.

Proof: Under the null hypothesis that $b = 0$, $e_{t+1}^{(1)} = e_{t+1}^{(2)} =: e_{t+1}$. Note that

$$\hat{e}_{t+1}^{(i)} = e_{t+1} - x_{i,t}' \left(\hat{\beta}_{i,t} - \beta_i\right)$$

for Model i. Recall $x_{1,t}' = 1$. For $\hat{B}_P$, the numerator of ENC_P, we decompose

$$\begin{aligned}
& \sum\nolimits_{t=R}^{T} \hat{e}_{t+1}^{(1)} \left(\hat{e}_{t+1}^{(1)} - \hat{e}_{t+1}^{(2)}\right) \\
= & \sum\nolimits_{t=R}^{T} \left[e_{t+1} - x_{1,t}' \left(\hat{\beta}_{1,t} - \beta_{1,t}\right)\right] \left(e_{t+1} - x_{1,t}' \left(\hat{\beta}_{1,t} - \beta_1\right) - e_{t+1} + x_{2,t}' \left(\hat{\beta}_{2,t} - \beta_2\right)\right) \\
= & \sum\nolimits_{t=R}^{T} \left[e_{t+1} - x_{1,t}' \left(\hat{\beta}_{1,t} - \beta_1\right)\right] \left(-x_{1,t}' \left(\hat{\beta}_{1,t} - \beta_1\right) + x_{2,t}' \left(\hat{\beta}_{2,t} - \beta_2\right)\right) \\
= & \sum\nolimits_{t=R}^{T} e_{t+1} \left[-x_{1,t}' \left(\hat{\beta}_{1,t} - \beta_1\right)\right] + \sum\nolimits_{t=R}^{T} e_{t+1} \left[x_{2,t}' \left(\hat{\beta}_{2,t} - \beta_2\right)\right] \\
& + \sum\nolimits_{t=R}^{T} \left(\hat{\beta}_{1,t} - \beta_1\right) x_{1,t} x_{1,t}' \left(\hat{\beta}_{1,t} - \beta_1\right) - \sum\nolimits_{t=R}^{T} \left(\hat{\beta}_{1,t} - \beta_2\right) x_{1,t} x_{2,t}' \left(\hat{\beta}_{2,t} - \beta_2\right) \\
\equiv & A_1 + A_2 + A_3 + A_4 \qquad (7)
\end{aligned}$$

Lemmas 1-3 show that $A_1 + A_2 + (A_3 + A_4) = O\left(\frac{T}{R}\right) + O\left(\frac{P}{T}\right) + o(1)$. Hence (7) is dominated by A_1 because $\frac{T}{R} \to \infty$ and $\frac{P}{T} \to 1$ under Assumption 2c.

Lemma 1. Under Assumptions 1b and 2c, $A_1 \Rightarrow -\sigma_e^2 \xi^{-1} \int_\xi^1 [W(s) - W(s-\xi)] \mathrm{d}W(s) = O\left(\xi^{-1}\right) = O\left(\frac{T}{R}\right)$ under $\mathbb{H}_0$.

Proof: Following Lemma A6 of CM (2001), we show

$$\begin{aligned}
A_1 &= \sum\nolimits_{t=R}^{T} e_{t+1} \left[-x_{1,t}' \left(\hat{\beta}_{1,t} - \beta_1\right)\right] \\
&= -\sum\nolimits_{t=R}^{T} e_{t+1} \left(e_{t+1} - \hat{e}_{t+1}^{(1)}\right) \\
&= -\sum\nolimits_{t=R}^{T} e_{t+1} \left(R^{-1} \sum\nolimits_{j=t-R+1}^{t} e_j\right) \\
&= -\sum\nolimits_{t=R}^{T} e_{t+1} \left(T^{-1} \sum\nolimits_{j=t-R+1}^{t} e_j\right) / \xi \\
&= -\sum\nolimits_{t=R}^{T} \left[\left(T^{-1/2} e_{t+1}\right) \left(T^{-1/2} \sum\nolimits_{j=1}^{t} e_{,j} - T^{-1/2} \sum\nolimits_{j=1}^{t-R} e_{,j}\right)\right] / \xi \\
&\Longrightarrow -\sigma_e^2 \xi^{-1} \int_\xi^1 [W(s) - W(s-\xi)] \, \mathrm{d}W(s).
\end{aligned}$$

Lemma 2. Under Assumptions 1b and 2c, $A_2 = \sum_{t=R}^{T} e_{t+1}\left[x_{2,t}'\left(\hat{\beta}_{2,t}-\beta_{2,t}\right)\right]$ is $O(1-\xi) = O\left(\frac{P}{T}\right)$ under $\mathbb{H}_0$.

Proof: Rewrite

$$\begin{aligned}
A_2 &= \sum_{t=R}^{T} e_{t+1}x_{2,t}'\left(\hat{\beta}_{2,t}-\beta_2\right) \\
&= \sum_{t=R}^{T} e_{t+1}x_{2,t}'\left(\sum_{j=t-R}^{t-1} x_{2,j}x_{2,j}'\right)^{-1}\left(\sum_{j=t-R}^{t-1} x_{2,j}e_{j+1}\right) \\
&= \sum_{t=R}^{T} e_{t+1}x_{2,t}'G_T^{-1}\left[G_T^{-1}\sum_{j=t-R+1}^{t} x_{2,j}x_{2,j}'G_T^{-1}/\xi\right]^{-1}\left[G_T^{-1}\sum_{j=t-R+1}^{t} x_{2,j}e_{j+1}/\xi\right],
\end{aligned}$$

where $G_T = \mathrm{diag}(T^{0.5}, T)$ as before, and for the two bracketed terms in the last line, we have

$$\begin{aligned}
G_T^{-1}\left(\sum_{j=t-R+1}^{t} x_{2,j}x_{2,j}'\right)G_T^{-1}/\xi &\Rightarrow \begin{pmatrix} \xi & \int_{s-\xi}^{s} J_x^c(r)\,\mathrm{d}r \\ \int_{s-\xi}^{s} J_x^c(r)\,\mathrm{d}r & \int_{s-\xi}^{s} \left(J_x^c(r)\right)^2\mathrm{d}r \end{pmatrix}/\xi \sim O(1), \\
G_T^{-1}\sum_{j=t-R+1}^{t} x_{2,j}e_{j+1}/\xi &\Rightarrow \begin{pmatrix} \int_{s-\xi}^{s} 1\mathrm{d}W(r) \\ \int_{s-\xi}^{s} J_x^c(r)\,\mathrm{d}W(r) \end{pmatrix}/\xi \sim O(1),
\end{aligned}$$

where $J_x^c(r)$ is an Ornstein-Uhlenbeck process, and $W(r)$ is a Wiener process. Hence

$$\begin{aligned}
A_2 &= \sum_{t=R}^{T} e_{t+1}x_{2,t}'G_T^{-1}\left[G_T^{-1}\sum_{j=t-R+1}^{t} x_{2,j}x_{2,j}'G_T^{-1}/\xi\right]^{-1}\left[G_T^{-1}\sum_{j=t-R+1}^{t} x_{2,j}e_{j+1}/\xi\right] \\
&\Rightarrow \int_{\xi}^{1}\begin{pmatrix} 1 & J_x^c(s) \end{pmatrix}\begin{pmatrix} \xi & \int_{s-\xi}^{s} J_x^c(r)\,\mathrm{d}r \\ \int_{s-\xi}^{s} J_x^c(r)\,\mathrm{d}r & \int_{s-\xi}^{s} J_x^c(r)^2\mathrm{d}r \end{pmatrix}^{-1}\begin{pmatrix} \int_{s-\xi}^{s} 1\mathrm{d}W(r) \\ \int_{s-\xi}^{s} J_x^c(r)\,\mathrm{d}W(r) \end{pmatrix}\mathrm{d}W(s) \\
&= \int_{\xi}^{1}\begin{pmatrix} 1 & J_x^c(s) \end{pmatrix}\begin{pmatrix} O(\xi) & O(\xi) \\ O(\xi) & O(\xi) \end{pmatrix}^{-1}\begin{pmatrix} O(\xi) \\ O(\xi) \end{pmatrix}\mathrm{d}W(s) \\
&= O(1-\xi)
\end{aligned}$$

Therefore $A_2 = \sum_{t=R}^{T} e_{t+1}x_{2,t}'\left(\hat{\beta}_{2,t}-\beta_{2,t}\right) = O(1-\xi)$.

Lemma 3. Under Assumptions 1b and 2c, $A_3 + A_4$ is $o(1)$ under $\mathbb{H}_0$.

Proof: Let $E_T = \text{diag}(T^0, T^{0.5})$, $F_T = \text{diag}(T^1, T^{1.5})$, $G_T = \text{diag}(T^{0.5}, T^1)$, then for any 2×2 matrix K, we have $E_T F_T = G_T G_T$ and

$$E_T \times K \times F_T = G_T \times K \times G_T,$$

because E_T, F_T, G_T are diagonal. Therefore

$$\begin{aligned} A_3 + A_4 &= \sum\nolimits_{t=R}^{T} \left(\hat{\beta}_{1,t} - \beta_{1,t}\right) x_{1,t} x_{1,t}' \left(\hat{\beta}_{1,t} - \beta_{1,t}\right) - \sum\nolimits_{t=R}^{T} \left(\hat{\beta}_{1,t} - \beta_{1,t}\right) x_{1,t} x_{2,t}' \left(\hat{\beta}_{2,t} - \beta_{2,t}\right) \\ &= \sum\nolimits_{t=R}^{T} H_1'(t) B_1(t) q_{1,t} B_1(t) H_1(t) - \sum\nolimits_{t=R}^{T} H_1'(t) B_1(t) x_{1,t} x_{2,t}' B_2(t) H_2(t), \end{aligned}$$

where the second line appears to be the same as the second bracketed right-hand side term in (A7) of Lemma A10 in CM (2001), which shows that the above is $o(1)$ under Assumption 1a. However, under Assumption 1b, x_t has an AR root local to unity. We show below that the local-to-unit root in x does not affect Lemma A10 of CM (2001). This is because terms involving x can be suitably normalized as follows

$$\begin{aligned} A_3 + A_4 &= \sum\nolimits_{t=R}^{T} H_1'(t) B_1(t) q_{1,t} B_1(t) H_1(t) \\ &\quad - \sum\nolimits_{t=R}^{T} H_1'(t) B_1(t) x_{1,t} \left(x_{2,t}' E_T^{-1}\right) \left[E_T \times R^{-1} B_2(t) \times F_T \times \xi\right] \left[F_T^{-1} \times R H_2(t) / \xi\right] \\ &\equiv \sum\nolimits_{t=R}^{T} H_1'(t) B_1(t) q_{1,t} B_1(t) H_1(t) - \sum\nolimits_{t=R}^{T} H_1'(t) B_1(t) x_{1,t} \ddot{x}_{2,t}' \ddot{B}_2(t) \ddot{H}_2(t). \end{aligned}$$

where

$$\ddot{x}_{2,t}' \equiv x_{2,t}' E_T^{-1} \Rightarrow \begin{pmatrix} 1 & J_x^c(r) \end{pmatrix} = O(1),$$

$$\begin{aligned} \ddot{B}_2(t) &\equiv E_T \times R^{-1} B_2(t) \times F_T \times \xi \\ &= G_T \left[R^{-1} B_2(t)\right] G_T \times \xi \\ &= \left[G_T^{-1} \left[R^{-1} B_2(t)\right]^{-1} G_T^{-1}\right]^{-1} \times \xi \\ &= \left[G_T^{-1} \sum\nolimits_{j=t-R+1}^{t} x_{2,j} x_{2,j}' G_T^{-1}\right]^{-1} \times \xi \\ &\Rightarrow \begin{pmatrix} \xi & \int_{s-\xi}^{s} J_x^c(r)\,\mathrm{d}r \\ \int_{s-\xi}^{s} J_x^c(r)\,\mathrm{d}r & \int_{s-\xi}^{s} \left(J_x^c(r)\right)^2 \mathrm{d}r \end{pmatrix}^{-1} \times \xi \\ &= \begin{pmatrix} O(\xi) & O(\xi) \\ O(\xi) & O(\xi) \end{pmatrix}^{-1} \times O(\xi) = O(1), \end{aligned}$$

and

$$
\begin{aligned}
\ddot{H}_2(t) &\equiv F_T^{-1} \times RH_2(t)/\xi \\
&= F_T^{-1} \sum\nolimits_{j=t-R+1}^{t} x_{2,j} e_{j+1}/\xi \\
&= \begin{pmatrix} T^{-1}/\xi \times \sum\nolimits_{j=t-R+1}^{t} e_{j+1} \\ T^{-1.5}/\xi \times \sum\nolimits_{j=t-R+1}^{t} x_j e_{j+1} \end{pmatrix} \\
&= \begin{pmatrix} T^{-0.5}/\xi \times T^{-0.5} \sum\nolimits_{j=t-R+1}^{t} e_{j+1} \\ T^{-0.5}/\xi \times T^{-1} \sum\nolimits_{j=t-R+1}^{t} x_j e_{j+1} \end{pmatrix} \\
&\Rightarrow \begin{pmatrix} T^{-0.5}/\xi \times \int_{s-\xi}^{s} 1 \mathrm{d}W(r) \\ T^{-0.5}/\xi \times \int_{s-\xi}^{s} J_x^c(r)\, \mathrm{d}W(r) \end{pmatrix} \\
&= \begin{pmatrix} O\left(T^{-0.5}/\xi\right) \times O(\xi) \\ O\left(T^{-0.5}/\xi\right) \times O(\xi) \end{pmatrix} = O\left(T^{-0.5}\right).
\end{aligned}
$$

Therefore, $\ddot{x}'_{2,t}, \ddot{B}_2(t), \ddot{H}_2(t)$ have the same orders of magnitude as $x'_{2,t}, B_2(t), H_2(t)$ in stationary case of Lemma A10 in CM (2001). Therefore $A_3 + A_4$ is $o(1)$ not only under Assumption 1a but also under Assumption 1b.

Based on Lemmas 1-3 under Assumption 1b and Assumption 2c, $\sum\nolimits_{t=R}^{T} \hat{e}_{t+1}^{(1)} \left(\hat{e}_{t+1}^{(1)} - \hat{e}_{t+1}^{(2)}\right) = -\sum\nolimits_{t=R}^{T} e_{t+1} \left(e_{t+1} - \hat{e}_{t+1}^{(1)}\right) + o(1)$. Hence, this is the encompassing test for the martingale difference model $y_{t+1} = e_{t+1}$ and the constant mean model $y_{t+1} = c + e_{t+1}^{(1)}$, as studied by CW (2006).

Proposition 4. Under Assumptions 1b and 2c, the asymptotic distribution of ENC_P is

$$
\frac{-\sigma_e^2 \xi^{-1} \int_{\xi}^{1} [W(s) - W(s-\xi)]\, \mathrm{d}W(s)}{\sqrt{\sigma_e^4 \times \xi^{-2} \int_{\xi}^{1} [W(s) - W(s-\xi)]^2\, \mathrm{d}s}}
$$

under $\mathbb{H}_0$.

Proof: From Lemma 1, $A_1 = O\left(\xi^{-1}\right)$ is the dominant term of in $\hat{B}_P$ and hence ENC_P is

$$\begin{aligned} ENC_P &= A_1/\sqrt{\operatorname{var}(A_1)} + o(1) \\ &= \frac{-\sum_{t=R}^{T} e_{t+1}\left(e_{t+1} - \hat{e}_{t+1}^{(1)}\right)}{\sqrt{\sum_{t=R}^{T}\left[-e_{t+1}\left(e_{t+1} - \hat{e}_{t+1}^{(1)}\right) - \hat{c}_P\right]^2}} + o(1) \\ &\Rightarrow \lim_{\xi\to 0} \frac{-\sigma_e^2 \xi^{-1} \int_\xi^1 [W(s) - W(s-\xi)]\,\mathrm{d}W(s)}{\sqrt{\sigma_e^4 \times \xi^{-2} \int_\xi^1 [W(s) - W(s-\xi)]^2\,\mathrm{d}s}} \end{aligned}$$

where $A_1 \Rightarrow -\sigma_e^2 \xi^{-1} \int_\xi^1 [W(s) - W(s-\xi)]\mathrm{d}W(s)$, $c_{t+1} = -e_{t+1}\left(e_{t+1} - \hat{e}_{t+1}^{(1)}\right)$ and $\hat{c}_P = P^{-1}\sum_{t=R}^{T} c_{t+1} = P^{-1}A_1$. The denominator follows from Lemma 4.

Lemma 4. Under Assumptions 1b and 2c,

$$\sum_{t=R}^{T}\left[-e_{t+1}\left(e_{t+1} - \hat{e}_{t+1}^{(1)}\right) - \hat{c}_P\right]^2 \Rightarrow \sigma_e^4 \times \xi^{-2}\int_\xi^1 [W(s) - W(s-\xi)]^2\,ds.$$

Proof: Following Lemma A11 of CM (2001), we have

$$\begin{aligned} & \sum_{t=R}^{T}\left[-e_{t+1}\left(e_{t+1} - \hat{e}_{t+1}^{(1)}\right) - \hat{c}_P\right]^2 \\ = & \sum_{t=R}^{T}\left[e_{t+1}\left(e_{t+1} - \hat{e}_{t+1}^{(1)}\right)\right]^2 - P\hat{c}_P^2 \\ = & \sum_{t=R}^{T}\left[e_{t+1}\left(R^{-1}\sum_{j=t-R+1}^{t} e_j\right)\right]^2 + O\left(P^{-1}\times\xi^{-2}\right) \\ = & \frac{T^2}{R^2}\sum_{t=R}^{T}\left[(e_{t+1})^2\left(T^{-1/2}\sum_{j=1}^{t} e_{,j} - T^{-1/2}\sum_{j=1}^{t-R} e_{,j}\right)^2\right]\frac{1}{T} + O\left(P^{-1}\times\xi^{-2}\right) \\ \Rightarrow & \xi^{-2}\int_\xi^1 \sigma_e^2\left[\sigma_e W(s) - \sigma_e W(s-\xi)\right]^2\mathrm{d}s, \end{aligned}$$

where line 3 follows from Lemma 1 for $P\hat{c}_P = A_1 = O\left(\xi^{-1}\right)$.

Next, we show that under Assumptions 1a and 2c, under $\mathbb{H}_0$,

$$\frac{-\sigma_e^2 \xi^{-1} \int_\xi^1 [W(s) - W(s-\xi)]\,\mathrm{d}W(s)}{\sqrt{\sigma_e^4 \times \xi^{-2} \int_\xi^1 [W(s) - W(s-\xi)]^2\,\mathrm{d}s}} \sim N(0,1)$$

Proposition 5.

$$\lim_{\to 0} \frac{\int^{1} \quad {}^{-1} \left[W(s) - W(s - \quad)\right] \mathrm{d}W(s)}{\sqrt{\int^{1} \quad {}^{-2} \left[W(s) - W(s - \quad)\right]^{2} \mathrm{d}s}} \sim N\left(0,1\right), \tag{8}$$

Proof: We firstly consider the numerator of equation (8) by dividing $[0,1]$ to n equal segments and let $t = [Ts]$, where $[Ts]$ is the integer part of Ts and $s \in [0,1]$. Since is sufficiently small, we can write $\equiv 1/n$. We discretise both the numerator and the denominator. Let $\{u_i\}_{i=1}^{n}$ be a mixing sequence drawn from the standard normal distribution $N\left(0,1\right)$ with $E\left(u\right) = 0$ and $\mathrm{var}(u) = 1$. Let $U_t = \sum_{i=1}^{t} u_i$ be the partial sum. Then we have $U_t = \sum_{i=1}^{t} u_i \sim N(0,t)$ and therefore

$$\frac{U_t}{\sqrt{n}} = \frac{\sum_{i=1}^{t} u_i}{\sqrt{n}} \equiv U_n\left(s\right) \Rightarrow W(s),$$

where $U_n\left(s\right)$ is a '*cadlag*' function and $W\left(s\right)$ is a Wiener process. Note that

$$\begin{aligned} n^{-1}\sum_{t=1}^{n} u_{t-1}u_t &= n^{-1}\sum_{t=1}^{n} U_{t-1}u_t - n^{-1}\sum_{t=1}^{n} U_{t-2}u_t \\ &\Rightarrow \int^{1} W(s)\mathrm{d}W(s) - \int^{1} W(s - \quad)\mathrm{d}W(s) \\ &= \int^{1} \left[W(s) - W(s - \quad)\right] \mathrm{d}W(s) \end{aligned}$$

Considering the term $\int^{1} \left[W(s) - W(s - \quad)\right]^{2}\mathrm{d}s$ in the denominator, we have

$$n^{-2}\sum_{t=1}^{n} u_{t-1}^{2} = n^{-2}\sum_{t=1}^{n} \left(U_{t-1} - U_{t-2}\right)^{2} \Rightarrow \int^{1} \left[W(s) - W(s - \quad)\right]^{2} \mathrm{d}S.$$

We construct the an AR(1) regression model, regressing $\{u_{t+1}\}$ on $\{u_t\}$:

$$u_{t+1} = \delta u_t + e_t$$

The estimator $\hat{\delta}$ equals $\left(\sum_{t=1}^{n} u_{t-1}u_t\right) / \left(\sum_{t=1}^{n} u_{t-1}^{2}\right)$ and the variance $\hat{\delta}$ equals $\left(\sum_{t=1}^{n} u_{t-1}^{2}\right)^{-1}\mathrm{var}(u) = \left(\sum_{t=1}^{n} u_{t-1}^{2}\right)^{-1}$. Therefore Equation (8) can be approximated by

$$\frac{\int^{1} \quad {}^{-1} \left[W(s) - W(s - \quad)\right] \mathrm{d}W(s)}{\sqrt{\quad {}^{-2} \int^{1} \left[W(s) - W(s - \quad)\right]^{2} \mathrm{d}s}} \Rightarrow \frac{\sum_{t=1}^{n} u_{t-1}u_t}{\sqrt{\sum_{t=1}^{n} u_{t-1}^{2}}} \sim N(0,1).$$

Remark 3: We have consider the nested models in which the null model contains a constant term need to be estimated. We now consider the nested model analogue to Clark and West (2006) in which the null model does not contain a constant term and the error term is martingale difference series

$$\text{Model 1} \quad : \quad y_{t+1} = 0 + e_{t+1}^{(1)}, \tag{9}$$

$$\text{Model 2} \quad : \quad y_{t+1} = x_{2,t}'\beta_{2,t} + e_{t+1}^{(2)} = c + bx_t + e_{t+1}^{(2)}, \tag{10}$$

hence in null model we impose 0 as predictors and the forecast error is the true error term. therefore $\hat{e}_{t+1}^{(1)} = y_{t+1} = e_{t+1}^{(1)}$, $\hat{e}_{t+1}^{(2)} = y_{t+1} - f_{t+1}^{(2)}$. We have the following result (proposition 6) when $c_1 = 0$.

Proposition 6. Under Assumptions 1b and 2c, if Model 1 does not involve any parameter estimation, then $\lim_{\xi \to 0} ENC_P \Rightarrow N(0,1)$ under $\mathbb{H}_0$.

Proof: Under the null hypothesis that $\{x_{1,t}\} \equiv 0$ Therefore Equation (7) only has A_2 term, whose limiting distribution is

$$\int_{\xi}^{1} \begin{pmatrix} 1 & J_x^c(s) \end{pmatrix} \begin{pmatrix} \xi & \int_{s-\xi}^{s} J_x^c(r)\,\mathrm{d}r \\ \int_{s-\xi}^{s} J_x^c(r)\,\mathrm{d}r & \int_{s-\xi}^{s} J_x^c(r)^2\,\mathrm{d}r \end{pmatrix}^{-1} \begin{pmatrix} \int_{s-\xi}^{s} 1\mathrm{d}W(r) \\ \int_{s-\xi}^{s} J_x^c(r)\,\mathrm{d}W(r) \end{pmatrix} \mathrm{d}W(s)$$

In the next section, Monte Carlo simulation shows that ENC test is standard normal.

5 Monte Carlo

We compare the two statistics by changing $\{x_t\}$ from stationary process to Ornstein-Uhlenbeck process and use the data generating process in Model 1 and Model 2 as follows: the additional variable x_t in Model 2 has the AR process: $x_t = \phi x_{t-1} + z_t$, where z_j is i.i.d., following $N(0,1)$, and $\mathbb{E}(z_t|x_{t-1}) = 0$, The error term $e_{t+1}^{(2)} \sim N(0, \sigma_e^2)$. We set c_2 = 1 (we also set $c_2 = 0$ for martingale difference series $\{y_t\}$ and report the result.) $b \in$

$\{0.0, 0.1, 1.0\}$, $\phi \in \{0, 0.5, 0.9, 0.95, 0.99, 1\}$, and $\sigma_e \in \{0.1, 1.0\}$. Model 1 is estimated by regressing $\{y_j\}_{j=t-R+1}^{t}$ on constant term to obtain $\hat{c}_{1,t}$, where $t = R, \ldots, T$. Model 2 is estimated by regressing $\{y_j\}_{j=t-R+1}^{t}$ on $\{1, x_{j-1}\}_{j=t-R+1}^{t}$ to obtain $\left(\hat{c}_{2,t}\ \hat{b}_t\right)$. The forecast errors from the two models are $\hat{e}_{t+1}^{(1)} = y_{t+1} - \hat{c}_{1,t}$ and $\hat{e}_{t+1}^{(2)} = y_{t+1} - \hat{c}_{2,t} - \hat{b}_t x_t$ over the forecast evaluation period at $t = R, \ldots, T$. The number of observations for the rolling windows for estimation are chosen from $R \in \{60, 120, 240\}$. Let $P = T - R + 1 \in \{48, 240, 1200\}$. From these, we compute the two statistics DM_P and ENC_P. All above tests are repeated 2000 times to find out the Monte Carlo distributions of DM_P and ENC_P, and to compute their size and power. Also we consider the test statistics when $\rho \equiv Corr\,(v_t, e_{t+1}) = -0.95$, $R_T = 0.8$.

The Table 1 shows the size of test with additional covariate from stationary process to local to Ornstein-Uhlenbeck process using rolling scheme when $c_1 \neq 0$. We see that DM statistics are undersized for large P/R ratio. ENC test is robust, having correct size for all ϕ ranging from 0 to 0.99. Table 2 and 3 show the power of test using rolling scheme when $c_1 \neq 0$. We see that as ϕ increases, the powers approach to 1 dramatically since higher ϕ implies higher singal-to-noise ratio. Tables 4-6 are similar to table 1-3, showing the statistics of DM and ENC test when there is no constant term in Model 1, we see that ENC test also has a good performance since the test is asymptotically standard normal under null hypothesis. Figures 1-12 show the Monte Carlo distributions of DM_P and ENC_P using rolling scheme when $c_1 \neq 0$. Under $\mathbb{H}_0$, we can see that for size of test, ENC has the correct size regardless of ϕ. Figures 13-24 show the Monte Carlo distributions of DM_P and ENC_P using rolling scheme when $c_1 = 0$.

Tables 1-6 About Here

Figures 1-24 About Here

6 Application

We apply the two statistics (DM, ENC) to the Goyal and Welch study (2008) and construct nested models to test if a predictor such as dividend-yield ratio (DY), dividend-price

ratio (DP), long term rate of yield (LTY) and inflation (INFL) Granger-causes the equity premium in the conditional mean. The dividend-yield ratio at time t is defined as the most recent dividend at t divided by stock price at time t, the dividend-price ratio at time t is defined as the most recent dividend at $t-1$ divided by stock price at time t. The explanation of other variables are available from the homepage of A. Goyal. The two nested models are as shown in (11) and (12) below

$$\text{Model 1} \quad : \quad y_{t+1} = c_1 + e_{t+1}^{(1)}, \tag{11}$$

$$\text{Model 2} \quad : \quad y_{t+1} = c_2 + bx_t + e_{t+1}^{(2)}, \tag{12}$$

where y_{t+1} is the equity premium and x_t is the covariate. We use monthly data ranging from 1926 to 2011, containing 1032 observation for all four models. In Model 1, we only have a constant term, therefore at time t, we predict the future equity premium by solely using the historical average of previous R observations of the equity premium from time $t-R+1$ to t. In Model 2, we use the 1-lag covariate to forecast the equity premium in the next month. See Goyal and Welch (2008) for more on data descriptions. We intend to check if two nested models have the same predictive accuracy. We use the rolling window scheme of the window size R starting from the 15% of the total observations is $T = 1032$ to the 85% of T. The in-sample observation R ranges from $R = 155$ ($R/P = 155/877$) to $R = 877$ ($R/P = 877/155$). The red line represents DM_P under different allocation of R and P. The blue line represents ENC_P.

We find: (i) The ENC statistics always have higher statistics than DM test. (ii) DP and DY figures show that ENC test is significant with small R/P ratio. Intuitively, for R/P, we are unable to account for the y_{t+1} by solely using the previous y up to time t since there is not sufficient information available, therefore we need to exploit the property of additional variable x. In this way, x has predictive power for ENC test; however when R/P is large, we can predict y_{t+1} using previous information of y up to time t, which weakens the predictive power of x. (iii) LTY figure shows that long-term yield has predictive power for equity premium for all R ranging from 150 to 877 using ENC test, which can not directly been observed from DM statistic. (iv) INFL figure shows that for ENC test,

the inflation rate has predictive power when the number of in-sample observations is below 600.

Figure 25 About Here

7 Conclusions

This paper extends the work of CM (2001), CW (2006, 2007) from nested mean model with weak stationary predictor to nested mean model with a highly persistent predictor. CM (2001) and CW (2006, 2007) found that the DM statistic tends to be negative under the null hypothesis of the equal predictive ability because of parameter estimation error. We find that the DM is even more severely undersized when the predictor is highly persistent with the AR root closer to unity. We find that the ENC test is robust as it remains the correct size under the null hypothesis of the equal predictive ability, also it has high power under alternative. We show that the highly persistent predictor following the Ornstein-Uhlenbeck process implies the convergent rate of the estimator from Model 2 faster than that from a model with stationary predictor and the ENC test can shown to be asymptotically standard normal when the ratio of out-of-sample to in-sample observation is infinite. By using Monte-Carlo simulation, we see that ENC test is robust and has the correct size under null hypothesis whereas DM is severely under-sized. An application to the predictive regression of the equity premium reveals strong predictive ability of several persistent predictors.

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Table 1: Rejection frequency at 5% level, $b = 0$ (With intercept Model 1)

		$P = 48$		$P = 240$		$P = 1200$	
$Repeat = 2000$		DM_P	ENC_P	DM_P	ENC_P	DM_P	ENC_P
	$R = 60$	0.010	0.039	0.000	0.037	0.000	0.043
$\rho = 0,\ \sigma_e = 0.1$	$R = 120$	0.009	0.030	0.001	0.029	0.000	0.042
	$R = 240$	0.025	0.040	0.006	0.034	0.000	0.032
	$R = 60$	0.005	0.027	0.000	0.026	0.000	0.030
$\rho = 0,\ \sigma_e = 1$	$R = 120$	0.016	0.037	0.000	0.029	0.000	0.038
	$R = 240$	0.029	0.046	0.006	0.025	0.000	0.031
	$R = 60$	0.012	0.049	0.000	0.037	0.000	0.040
$\rho = 0.1,\ \sigma_e = 0.1$	$R = 120$	0.018	0.040	0.000	0.029	0.000	0.031
	$R = 240$	0.018	0.033	0.006	0.030	0.000	0.029
	$R = 60$	0.008	0.036	0.000	0.037	0.000	0.040
$\rho = 0.1,\ \sigma_e = 1$	$R = 120$	0.018	0.038	0.002	0.034	0.000	0.034
	$R = 240$	0.025	0.037	0.003	0.029	0.000	0.031
	$R = 60$	0.005	0.033	0.000	0.028	0.000	0.038
$\rho = 0.5,\ \sigma_e = 0.1$	$R = 120$	0.015	0.036	0.001	0.026	0.000	0.036
	$R = 240$	0.018	0.032	0.004	0.028	0.000	0.032
	$R = 60$	0.010	0.038	0.001	0.036	0.000	0.044
$\rho = 0.5,\ \sigma_e = 1$	$R = 120$	0.019	0.036	0.000	0.028	0.000	0.039
	$R = 240$	0.023	0.039	0.004	0.029	0.000	0.035
	$R = 60$	0.007	0.035	0.000	0.033	0.000	0.043
$\rho = 0.9,\ \sigma_e = 0.1$	$R = 120$	0.011	0.034	0.001	0.026	0.000	0.044
	$R = 240$	0.023	0.044	0.004	0.024	0.000	0.033
	$R = 60$	0.007	0.035	0.000	0.034	0.000	0.048
$\rho = 0.9,\ \sigma_e = 1$	$R = 120$	0.016	0.035	0.000	0.027	0.000	0.037
	$R = 240$	0.023	0.040	0.003	0.032	0.000	0.036
	$R = 60$	0.002	0.024	0.000	0.028	0.000	0.047
$\rho = 0.95,\ \sigma_e = 0.1$	$R = 120$	0.012	0.036	0.001	0.036	0.000	0.039
	$R = 240$	0.023	0.038	0.005	0.032	0.000	0.036
	$R = 60$	0.005	0.028	0.000	0.037	0.000	0.040
$\rho = 0.95,\ \sigma_e = 1$	$R = 120$	0.013	0.033	0.001	0.027	0.000	0.047
	$R = 240$	0.017	0.031	0.003	0.017	0.000	0.034
	$R = 60$	0.008	0.034	0.000	0.031	0.000	0.037
$\rho = 0.99,\ \sigma_e = 0.1$	$R = 120$	0.012	0.036	0.001	0.034	0.000	0.043
	$R = 240$	0.026	0.049	0.001	0.019	0.000	0.040
	$R = 60$	0.003	0.033	0.000	0.032	0.000	0.045
$\rho = 0.99,\ \sigma_e = 1$	$R = 120$	0.010	0.032	0.000	0.031	0.000	0.040
	$R = 240$	0.021	0.036	0.003	0.030	0.000	0.035

Table 2: Rejection frequency at 5% level, $b = 0.1$ (With intercept on Model 1)

		$P = 48$		$P = 240$		$P = 1200$	
$Repeat = 2000$		DM_P	ENC_P	DM_P	ENC_P	DM_P	ENC_P
	$R = 60$	0.954	1.000	1.000	1.000	1.000	1.000
$\rho = 0,\ \sigma_e = 0.1$	$R = 120$	0.948	1.000	1.000	1.000	1.000	1.000
	$R = 240$	0.943	1.000	1.000	1.000	1.000	1.000
	$R = 60$	0.023	0.107	0.004	0.233	0.001	0.601
$\rho = 0,\ \sigma_e = 1$	$R = 120$	0.049	0.124	0.015	0.247	0.021	0.728
	$R = 240$	0.070	0.142	0.060	0.325	0.129	0.823
	$R = 60$	0.949	1.000	1.000	1.000	1.000	1.000
$\rho = 0.1,\ \sigma_e = 0.1$	$R = 120$	0.943	1.000	1.000	1.000	1.000	1.000
	$R = 240$	0.945	1.000	1.000	1.000	1.000	1.000
	$R = 60$	0.020	0.097	0.006	0.214	0.000	0.614
$\rho = 0.1,\ \sigma_e = 1$	$R = 120$	0.040	0.108	0.016	0.255	0.032	0.731
	$R = 240$	0.069	0.149	0.055	0.331	0.110	0.829
	$R = 60$	0.983	1.000	1.000	1.000	1.000	1.000
$\rho = 0.5,\ \sigma_e = 0.1$	$R = 120$	0.977	1.000	1.000	1.000	1.000	1.000
	$R = 240$	0.975	1.000	1.000	1.000	1.000	1.000
	$R = 60$	0.032	0.122	0.006	0.284	0.002	0.751
$\rho = 0.5,\ \sigma_e = 1$	$R = 120$	0.057	0.159	0.031	0.347	0.064	0.848
	$R = 240$	0.081	0.164	0.079	0.404	0.238	0.923
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.9,\ \sigma_e = 0.1$	$R = 120$	0.999	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	0.078	0.311	0.128	0.771	0.511	1.000
$\rho = 0.9,\ \sigma_e = 1$	$R = 120$	0.133	0.390	0.301	0.865	0.936	1.000
	$R = 240$	0.170	0.445	0.435	0.933	0.993	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.95,\ \sigma_e = 0.1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	0.110	0.441	0.317	0.927	0.926	1.000
$\rho = 0.95,\ \sigma_e = 1$	$R = 120$	0.220	0.571	0.619	0.976	1.000	1.000
	$R = 240$	0.255	0.586	0.709	0.990	1.000	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.99,\ \sigma_e = 0.1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	0.252	0.623	0.676	0.986	1.000	1.000
$\rho = 0.99,\ \sigma_e = 1$	$R = 120$	0.434	0.770	0.928	1.000	1.000	1.000
	$R = 240$	0.519	0.824	0.970	1.000	1.000	1.000

Table 3: Rejection frequency at 5% level, $b = 1$ (With intercept on Model 1)

		$P = 48$		$P = 240$		$P = 1200$	
$Repeat = 2000$		DM_P	ENC_P	DM_P	ENC_P	DM_P	ENC_P
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0,\ \sigma_e = 0.1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	0.964	1.000	1.000	1.000	1.000	1.000
$\rho = 0,\ \sigma_e = 1$	$R = 120$	0.950	1.000	1.000	1.000	1.000	1.000
	$R = 240$	0.953	1.000	1.000	1.000	1.000	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.1,\ \sigma_e = 0.1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	0.953	1.000	1.000	1.000	1.000	1.000
$\rho = 0.1,\ \sigma_e = 1$	$R = 120$	0.956	1.000	1.000	1.000	1.000	1.000
	$R = 240$	0.939	1.000	1.000	1.000	1.000	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.5,\ \sigma_e = 0.1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	0.979	1.000	1.000	1.000	1.000	1.000
$\rho = 0.5,\ \sigma_e = 1$	$R = 120$	0.980	1.000	1.000	1.000	1.000	1.000
	$R = 240$	0.970	1.000	1.000	1.000	1.000	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.9,\ \sigma_e = 0.1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.9,\ \sigma_e = 1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.95,\ \sigma_e = 0.1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.95,\ \sigma_e = 1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.99,\ \sigma_e = 0.1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.99,\ \sigma_e = 1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000

Table 4: Rejection frequency at 5% level, $b = 0$ (Without intercept on Model 1)

		$P = 48$		$P = 240$		$P = 1200$	
$Repeat = 2000$		DM_P	ENC_P	DM_P	ENC_P	DM_P	ENC_P
	$R = 60$	0.006	0.042	0.000	0.045	0.000	0.047
$\rho = 0,\ \sigma_e = 0.1$	$R = 120$	0.016	0.040	0.000	0.033	0.000	0.047
	$R = 240$	0.019	0.042	0.002	0.035	0.000	0.032
	$R = 60$	0.004	0.032	0.000	0.035	0.000	0.048
$\rho = 0,\ \sigma_e = 1$	$R = 120$	0.014	0.043	0.001	0.032	0.000	0.038
	$R = 240$	0.020	0.051	0.003	0.039	0.000	0.032
	$R = 60$	0.003	0.033	0.000	0.035	0.000	0.038
$\rho = 0.1,\ \sigma_e = 0.1$	$R = 120$	0.013	0.046	0.001	0.026	0.000	0.045
	$R = 240$	0.019	0.038	0.002	0.034	0.000	0.042
	$R = 60$	0.006	0.042	0.000	0.031	0.000	0.042
$\rho = 0.1,\ \sigma_e = 1$	$R = 120$	0.013	0.046	0.001	0.029	0.000	0.041
	$R = 240$	0.023	0.052	0.003	0.030	0.000	0.040
	$R = 60$	0.006	0.038	0.000	0.035	0.000	0.041
$\rho = 0.5,\ \sigma_e = 0.1$	$R = 120$	0.010	0.039	0.000	0.025	0.000	0.036
	$R = 240$	0.018	0.041	0.001	0.033	0.000	0.034
	$R = 60$	0.006	0.039	0.000	0.038	0.000	0.036
$\rho = 0.5,\ \sigma_e = 1$	$R = 120$	0.009	0.034	0.000	0.031	0.000	0.040
	$R = 240$	0.017	0.036	0.002	0.029	0.000	0.034
	$R = 60$	0.003	0.039	0.000	0.040	0.000	0.047
$\rho = 0.9,\ \sigma_e = 0.1$	$R = 120$	0.008	0.037	0.000	0.038	0.000	0.036
	$R = 240$	0.023	0.043	0.002	0.032	0.000	0.038
	$R = 60$	0.003	0.032	0.000	0.044	0.000	0.045
$\rho = 0.9,\ \sigma_e = 1$	$R = 120$	0.008	0.040	0.000	0.029	0.000	0.036
	$R = 240$	0.018	0.040	0.002	0.028	0.000	0.035
	$R = 60$	0.003	0.031	0.000	0.036	0.000	0.052
$\rho = 0.95,\ \sigma_e = 0.1$	$R = 120$	0.005	0.030	0.000	0.034	0.000	0.042
	$R = 240$	0.018	0.038	0.002	0.031	0.000	0.037
	$R = 60$	0.003	0.038	0.000	0.040	0.000	0.055
$\rho = 0.95,\ \sigma_e = 1$	$R = 120$	0.012	0.042	0.000	0.028	0.000	0.037
	$R = 240$	0.011	0.032	0.002	0.032	0.000	0.031
	$R = 60$	0.003	0.028	0.000	0.035	0.000	0.049
$\rho = 0.99,\ \sigma_e = 0.1$	$R = 120$	0.008	0.039	0.000	0.035	0.000	0.040
	$R = 240$	0.014	0.035	0.002	0.031	0.000	0.036
	$R = 60$	0.002	0.027	0.000	0.036	0.000	0.045
$\rho = 0.99,\ \sigma_e = 1$	$R = 120$	0.005	0.030	0.000	0.028	0.000	0.045
	$R = 240$	0.015	0.037	0.002	0.023	0.000	0.030

Table 5: Rejection frequency at 5% level, $b = 0.1$. (Without intercept on Model 1)

		$P = 48$		$P = 240$		$P = 1200$	
$Repeat = 2000$		DM_P	ENC_P	DM_P	ENC_P	DM_P	ENC_P
	$R = 60$	0.937	1.000	1.000	1.000	1.000	1.000
$\rho = 0$, $\sigma_e = 0.1$	$R = 120$	0.948	1.000	1.000	1.000	1.000	1.000
	$R = 240$	0.943	1.000	1.000	1.000	1.000	1.000
	$R = 60$	0.013	0.078	0.001	0.157	0.000	0.463
$\rho = 0$, $\sigma_e = 1$	$R = 120$	0.037	0.103	0.006	0.225	0.001	0.595
	$R = 240$	0.050	0.131	0.026	0.268	0.031	0.758
	$R = 60$	0.932	1.000	1.000	1.000	1.000	1.000
$\rho = 0.1$, $\sigma_e = 0.1$	$R = 120$	0.940	1.000	1.000	1.000	1.000	1.000
	$R = 240$	0.935	1.000	1.000	1.000	1.000	1.000
	$R = 60$	0.014	0.073	0.002	0.182	0.000	0.484
$\rho = 0.1$, $\sigma_e = 1$	$R = 120$	0.031	0.112	0.007	0.214	0.001	0.624
	$R = 240$	0.051	0.124	0.035	0.263	0.027	0.731
	$R = 60$	0.973	1.000	1.000	1.000	1.000	1.000
$\rho = 0.5$, $\sigma_e = 0.1$	$R = 120$	0.974	1.000	1.000	1.000	1.000	1.000
	$R = 240$	0.973	1.000	1.000	1.000	1.000	1.000
	$R = 60$	0.010	0.102	0.001	0.230	0.000	0.616
$\rho = 0.5$, $\sigma_e = 1$	$R = 120$	0.038	0.129	0.012	0.296	0.007	0.753
	$R = 240$	0.062	0.150	0.051	0.366	0.075	0.873
	$R = 60$	0.998	1.000	1.000	1.000	1.000	1.000
$\rho = 0.9$, $\sigma_e = 0.1$	$R = 120$	0.999	1.000	1.000	1.000	1.000	1.000
	$R = 240$	0.998	1.000	1.000	1.000	1.000	1.000
	$R = 60$	0.052	0.298	0.050	0.753	0.119	1.000
$\rho = 0.9$, $\sigma_e = 1$	$R = 120$	0.099	0.356	0.191	0.838	0.726	1.000
	$R = 240$	0.144	0.401	0.369	0.902	0.967	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.95$, $\sigma_e = 0.1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	0.114	0.468	0.264	0.941	0.818	1.000
$\rho = 0.95$, $\sigma_e = 1$	$R = 120$	0.194	0.552	0.521	0.972	0.995	1.000
	$R = 240$	0.228	0.577	0.678	0.989	1.000	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.99$, $\sigma_e = 0.1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	0.473	0.795	0.875	0.998	1.000	1.000
$\rho = 0.99$, $\sigma_e = 1$	$R = 120$	0.544	0.831	0.953	0.999	1.000	1.000
	$R = 240$	0.547	0.827	0.968	1.000	1.000	1.000

Table 6: Rejection frequency at 5% level, $b = 1$. (Without intercept on Model 1)

		$P = 48$		$P = 240$		$P = 1200$	
$Repeat = 2000$		DM_P	ENC_P	DM_P	ENC_P	DM_P	ENC_P
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0$, $\sigma_e = 0.1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	0.939	1.000	1.000	1.000	1.000	1.000
$\rho = 0$, $\sigma_e = 1$	$R = 120$	0.940	1.000	1.000	1.000	1.000	1.000
	$R = 240$	0.939	1.000	1.000	1.000	1.000	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.1$, $\sigma_e = 0.1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	0.934	1.000	1.000	1.000	1.000	1.000
$\rho = 0.1$, $\sigma_e = 1$	$R = 120$	0.939	1.000	1.000	1.000	1.000	1.000
	$R = 240$	0.940	1.000	1.000	1.000	1.000	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.5$, $\sigma_e = 0.1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	0.975	1.000	1.000	1.000	1.000	1.000
$\rho = 0.5$, $\sigma_e = 1$	$R = 120$	0.976	1.000	1.000	1.000	1.000	1.000
	$R = 240$	0.970	1.000	1.000	1.000	1.000	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.9$, $\sigma_e = 0.1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.9$, $\sigma_e = 1$	$R = 120$	0.999	1.000	1.000	1.000	1.000	1.000
	$R = 240$	0.999	1.000	1.000	1.000	1.000	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.95$, $\sigma_e = 0.1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.95$, $\sigma_e = 1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.99$, $\sigma_e = 0.1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 60$	1.000	1.000	1.000	1.000	1.000	1.000
$\rho = 0.99$, $\sigma_e = 1$	$R = 120$	1.000	1.000	1.000	1.000	1.000	1.000
	$R = 240$	1.000	1.000	1.000	1.000	1.000	1.000

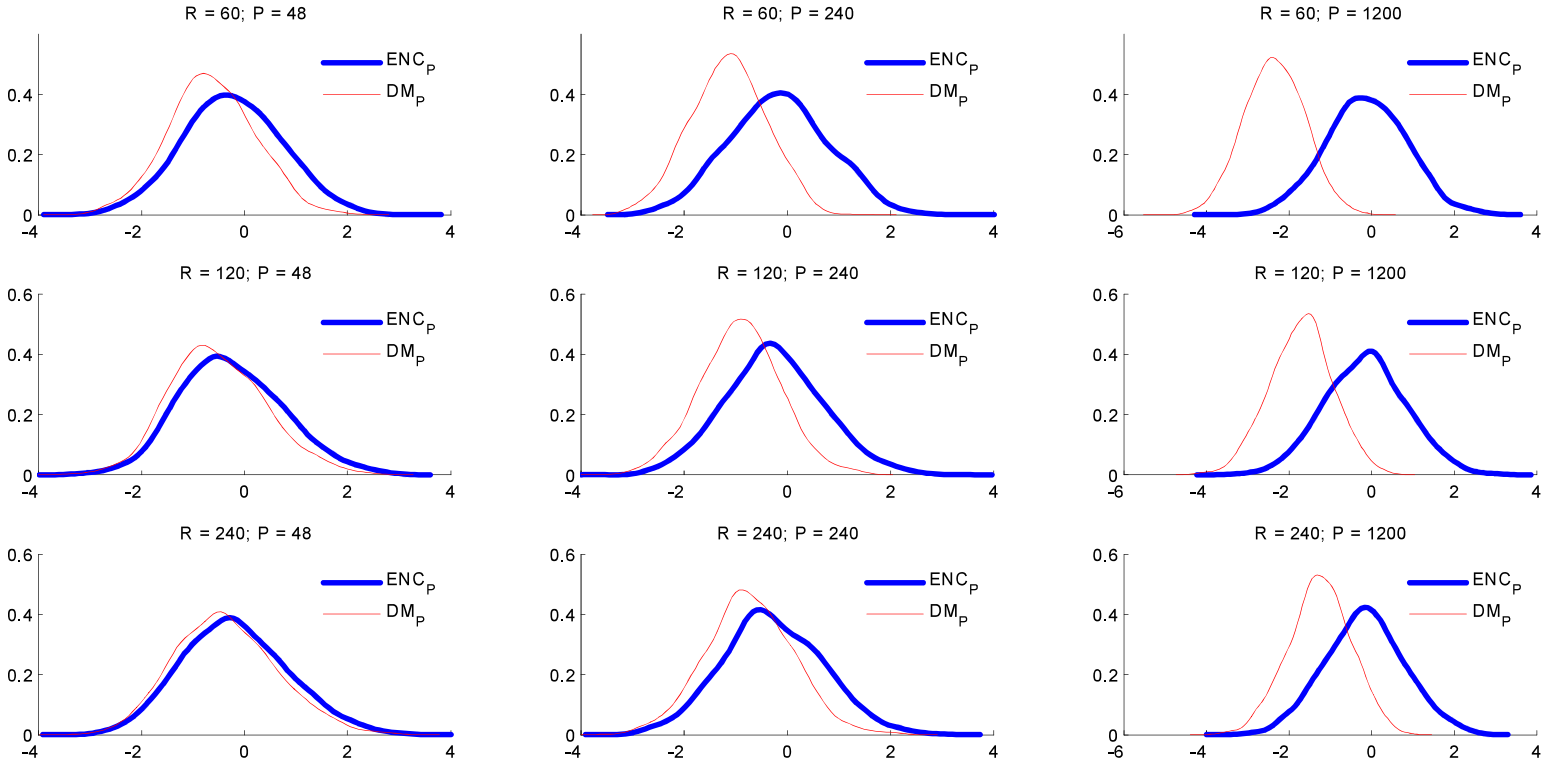

Figure 1: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_0$, $\phi = 0$, $b = 0$, $\sigma_e = 1$, with intercept on Model 1, 2000 Repeats.

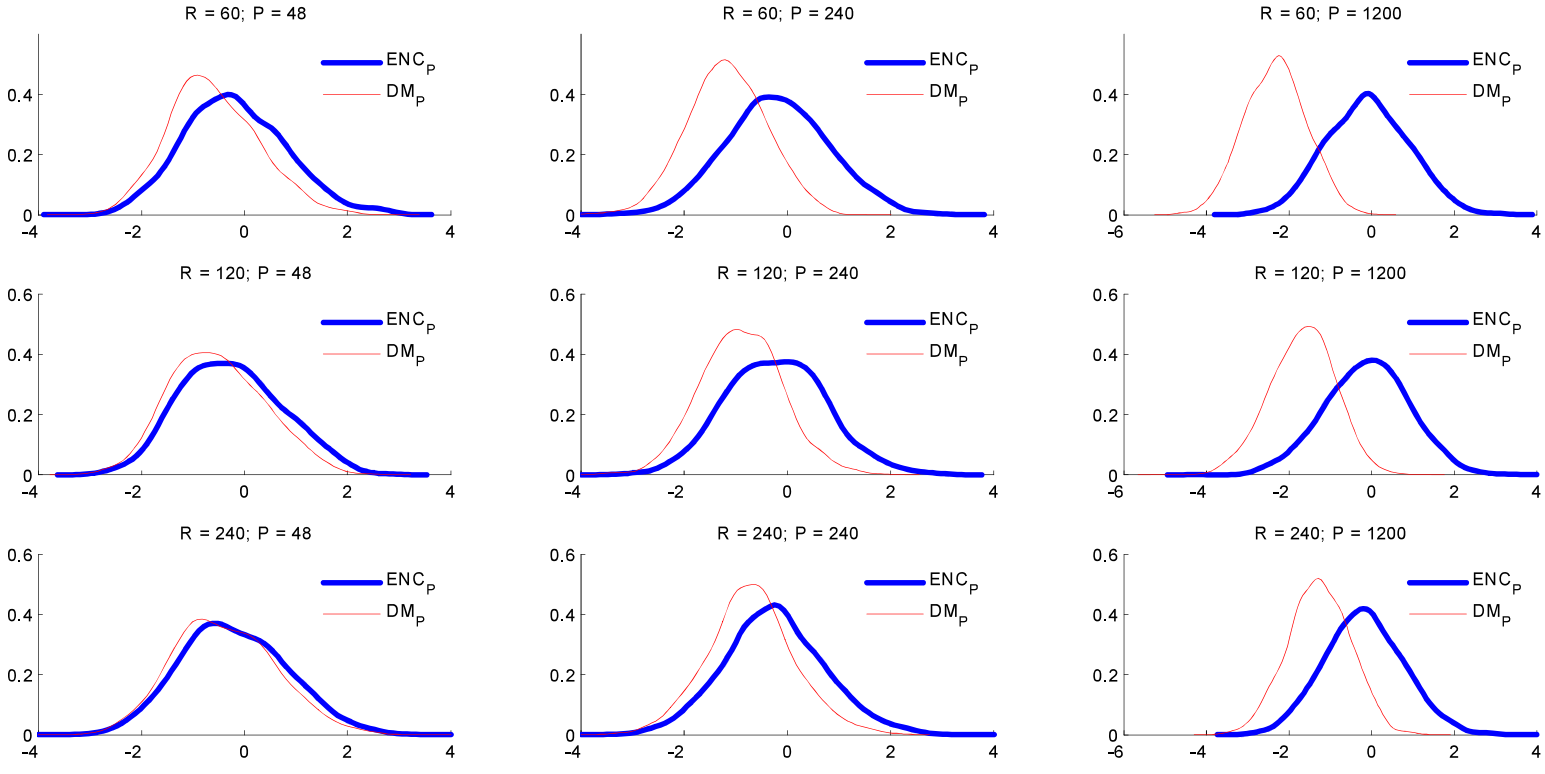

Figure 2: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_0$, $\phi = 0$, $b = 0$, $\sigma_e = 0.1$, with intercept on Model 1, 2000 Repeats.

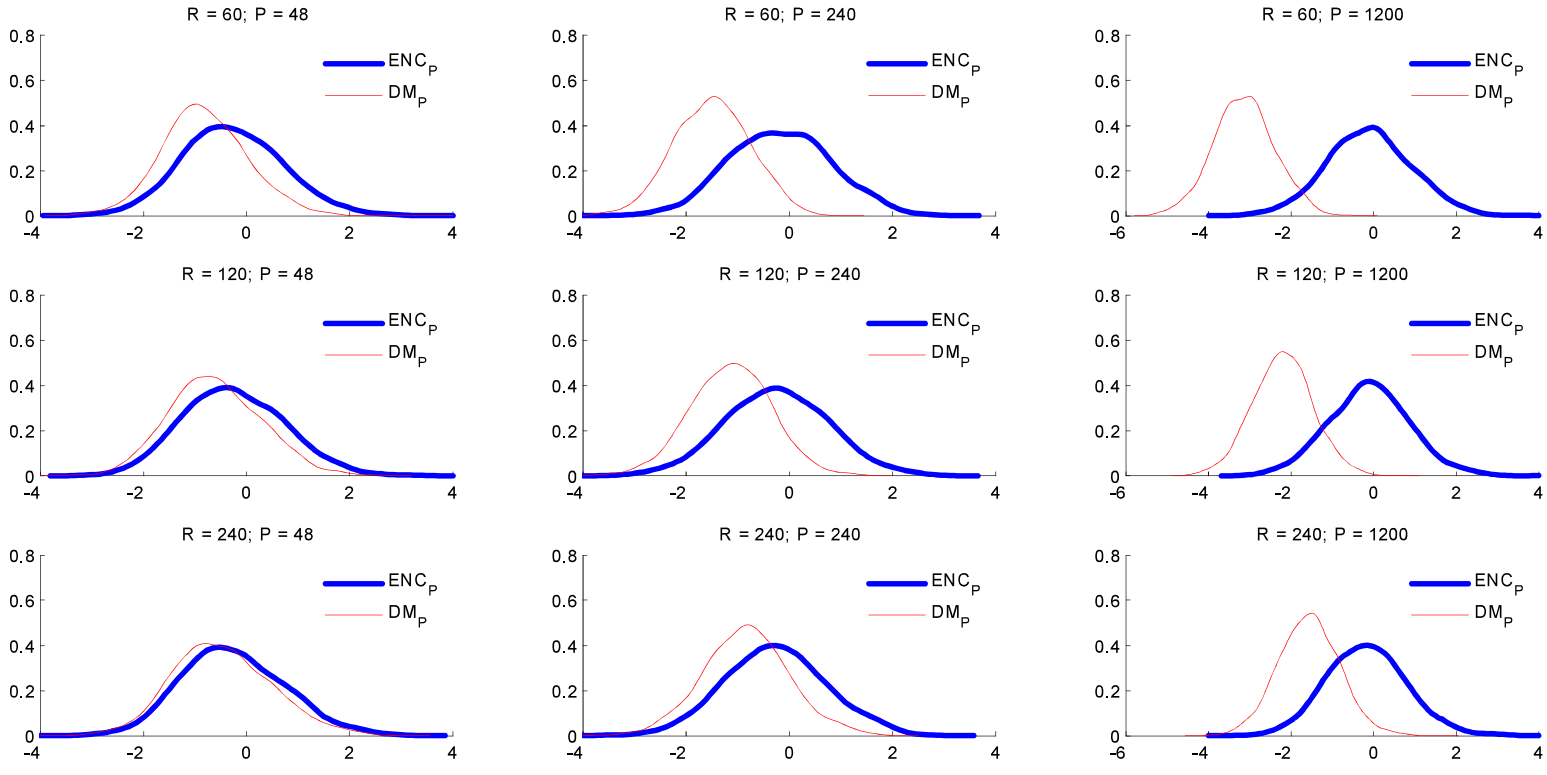

Figure 3: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_0$, $\phi = 0.99$, $b = 0$, $\sigma_e = 1$, with intercept on Model 1, 2000 Repeats.

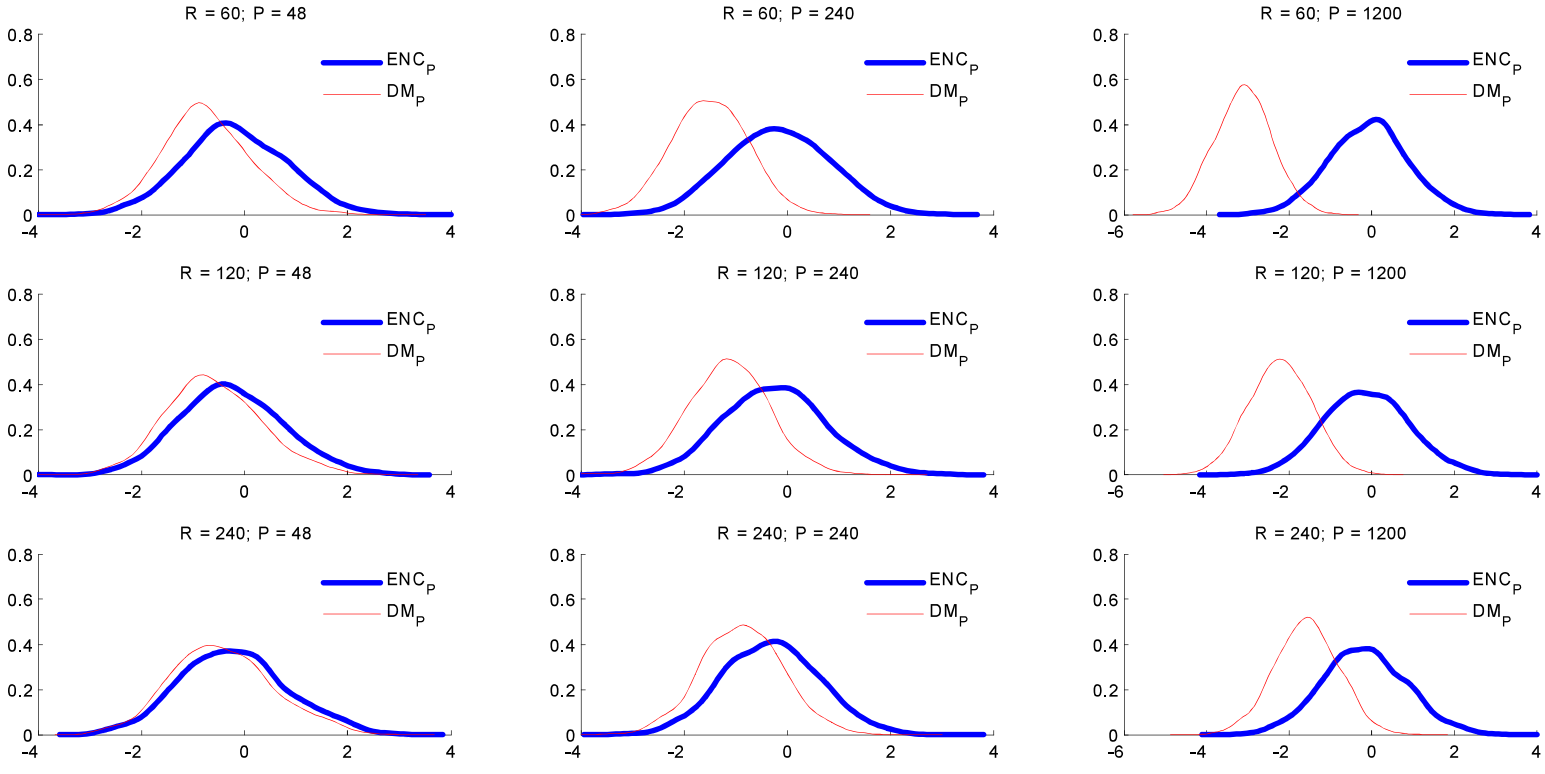

Figure 4: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_0$, $\phi = 0.99$, $b = 0$, $\sigma_e = 0.1$, with intercept on Model 1, 2000 Repeats.

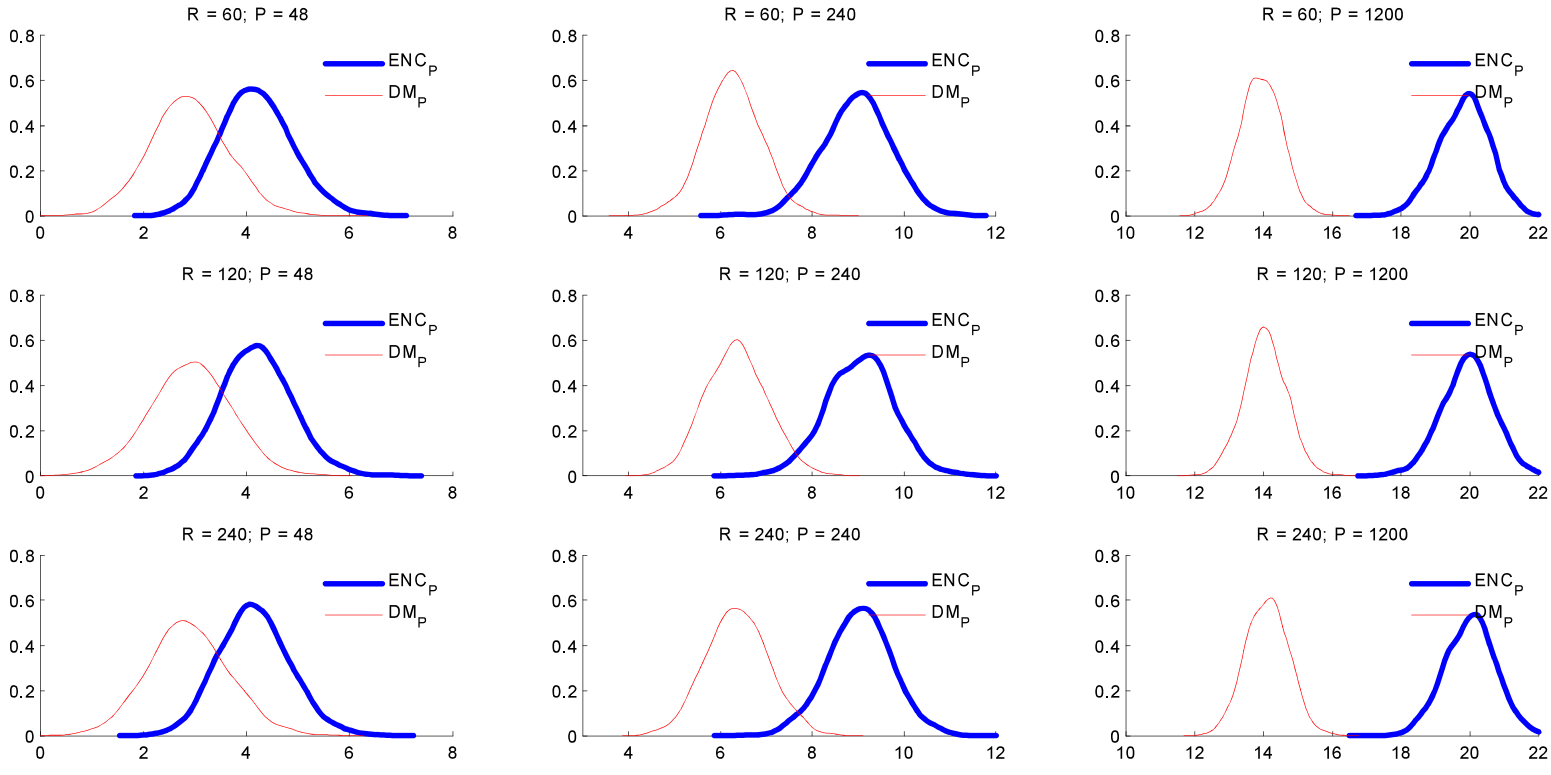

Figure 5: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_1$, $\phi = 0$, $b = 0.1$, $\sigma_e = 0.1$, with intercept on Model 1, 2000 Repeats.

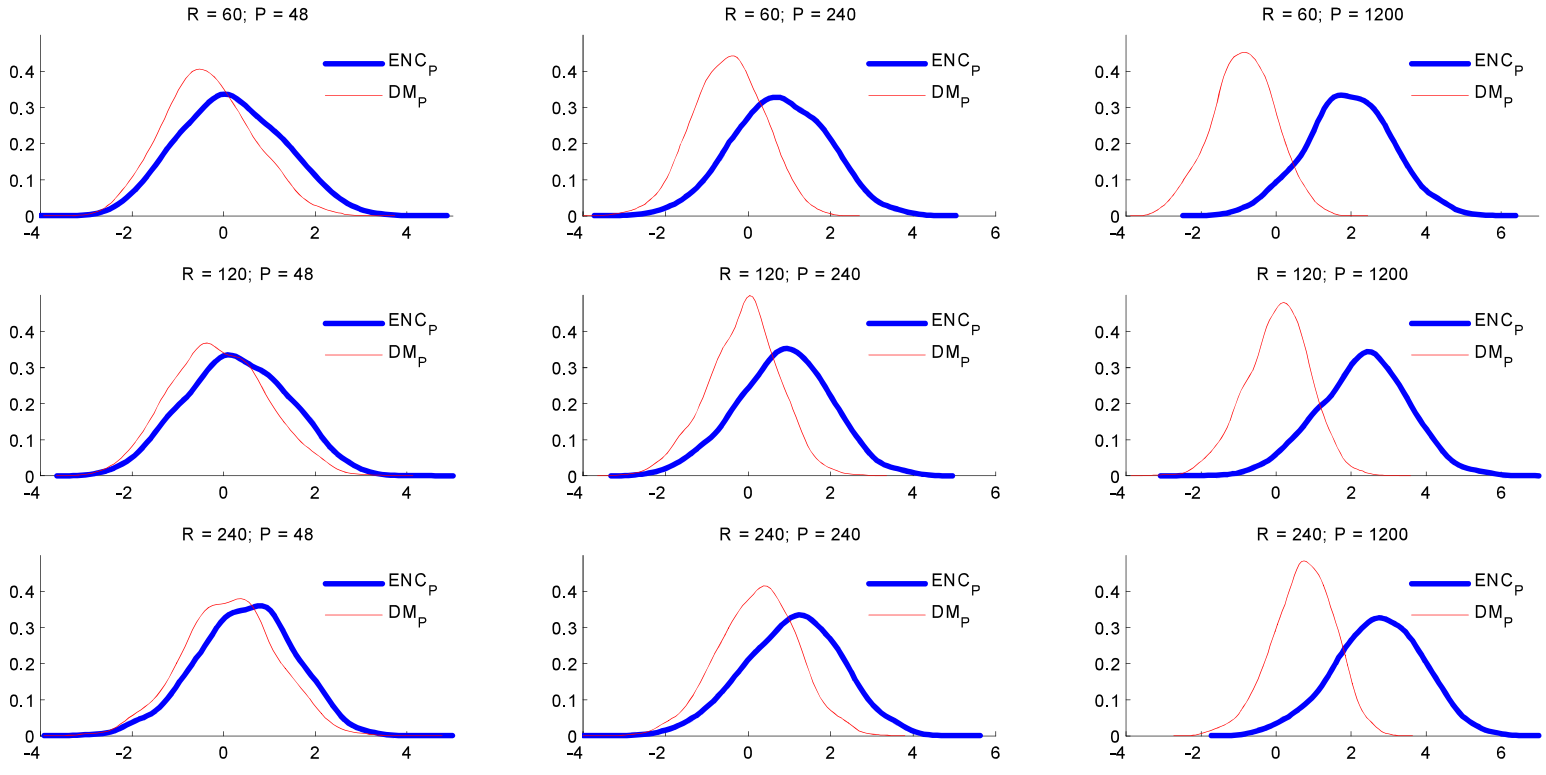

Figure 6: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_1$, $\phi = 0$, $b = 0.1$, $\sigma_e = 1$, with intercept on Model 1, 2000 Repeats.

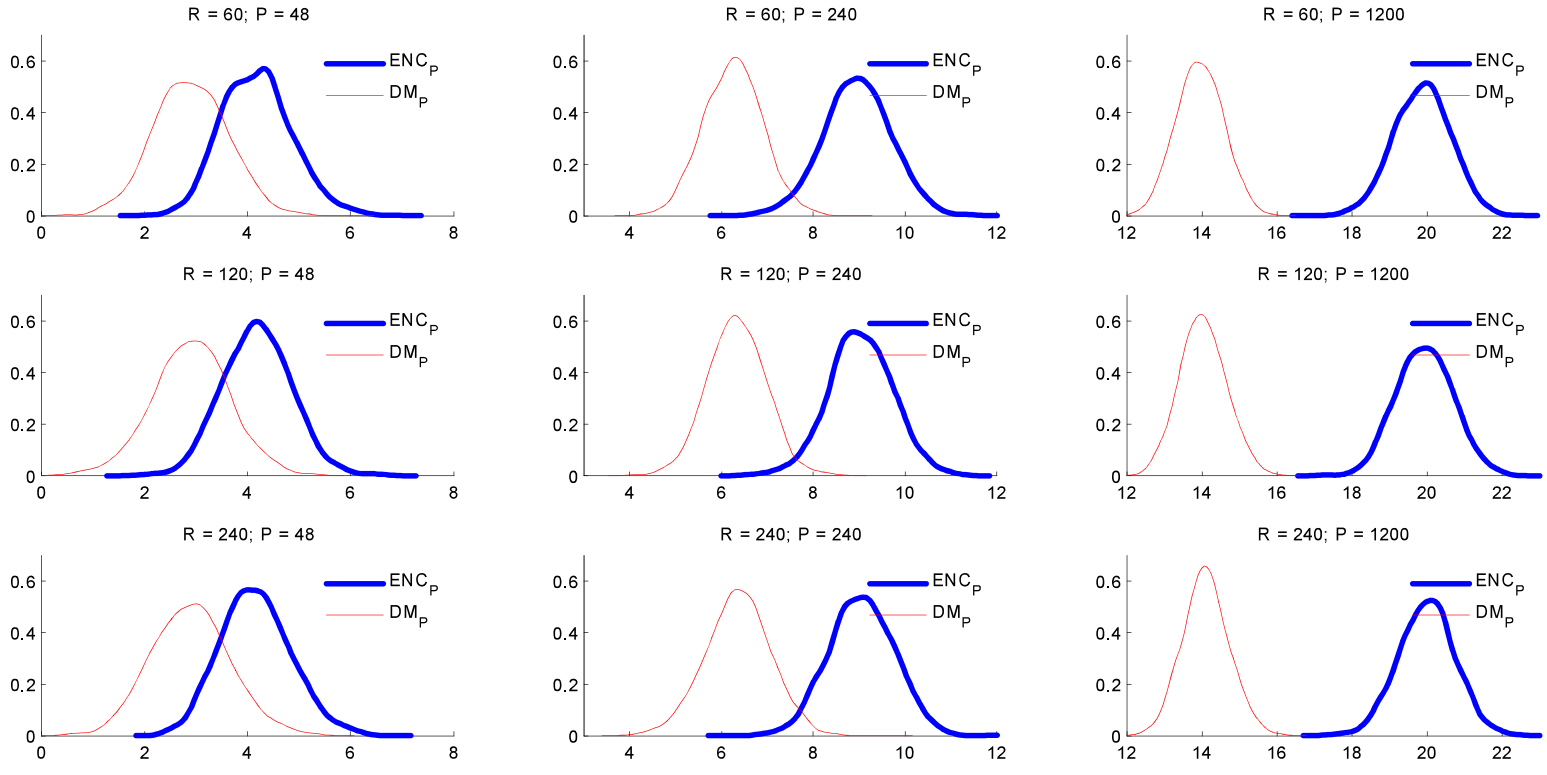

Figure 7: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_1$, $\phi = 0$, $b = 1$, $\sigma_e = 1$, with intercept on Model 1, 2000 Repeats.

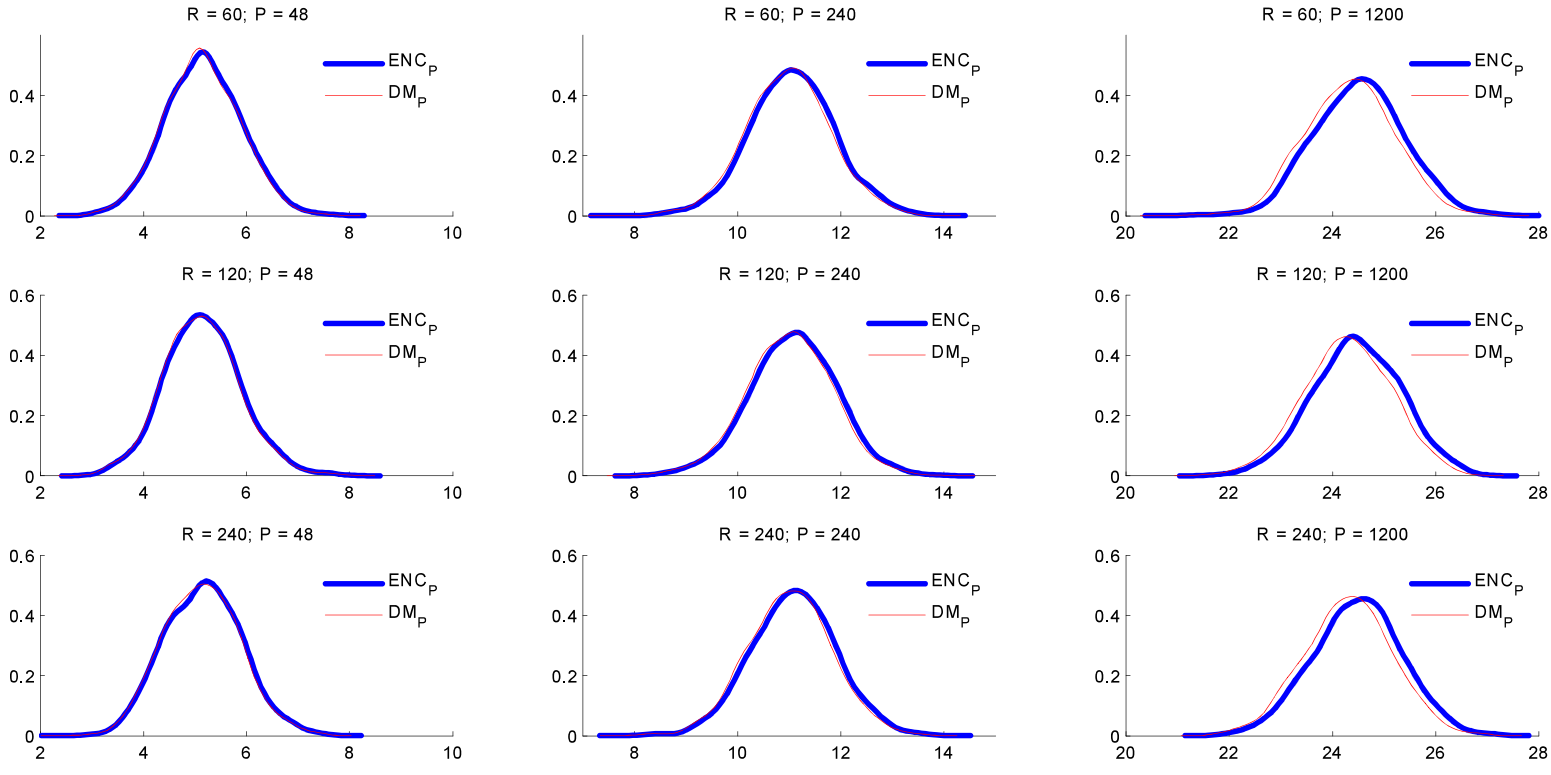

Figure 8: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_1$, $\phi = 0$, $b = 1$, $\sigma_e = 0.1$, with intercept on Model 1, 2000 Repeats.

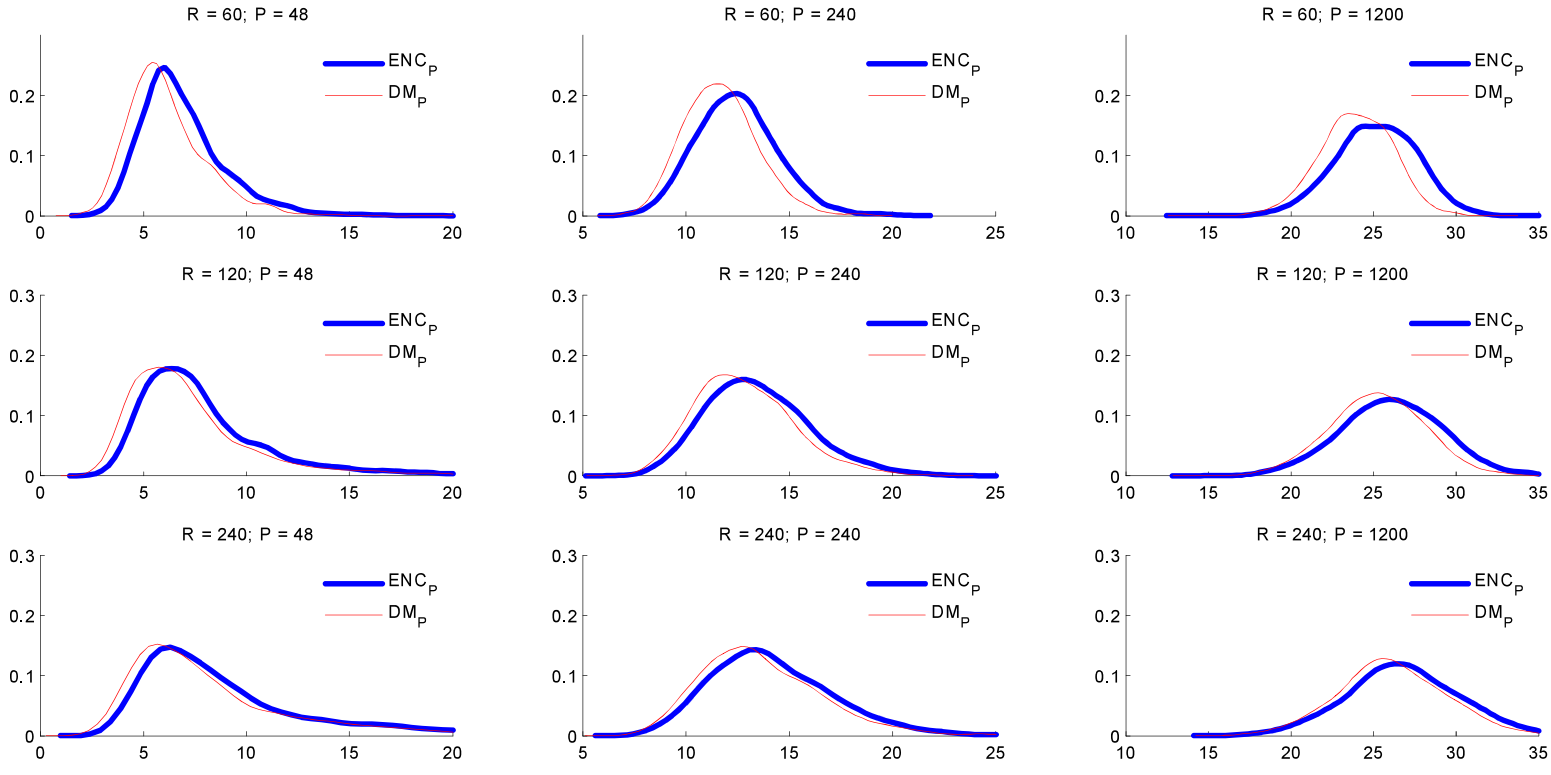

Figure 9: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_1$, $\phi = 0.99$, $b = 0.1$, $\sigma_e = 0.1$, with intercept on Model 1, 2000 Repeats.

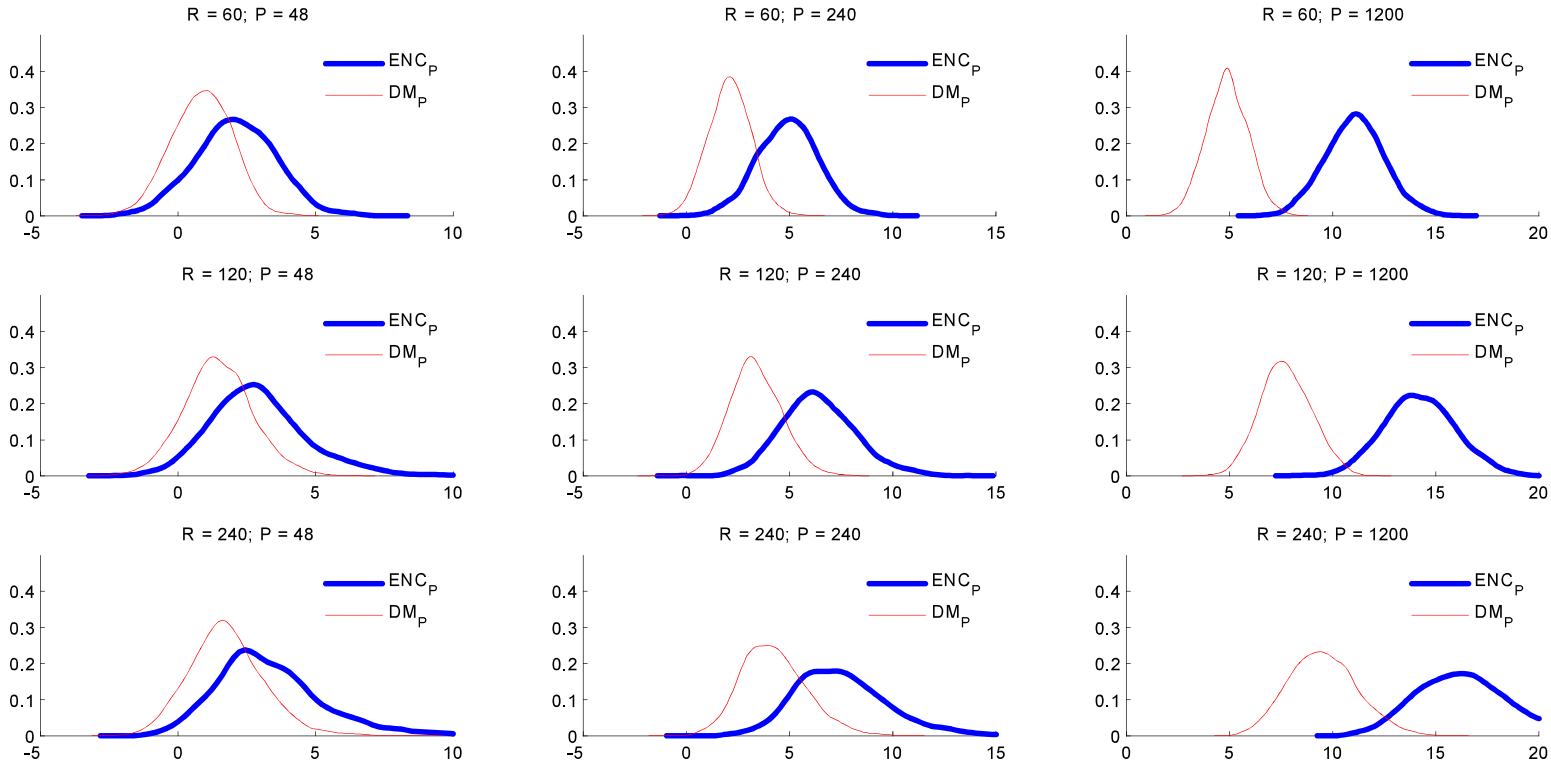

Figure 10: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_1$, $\phi = 0.99$, $b = 0.1$, $\sigma_e = 1$, with intercept on Model 1, 2000 Repeats.

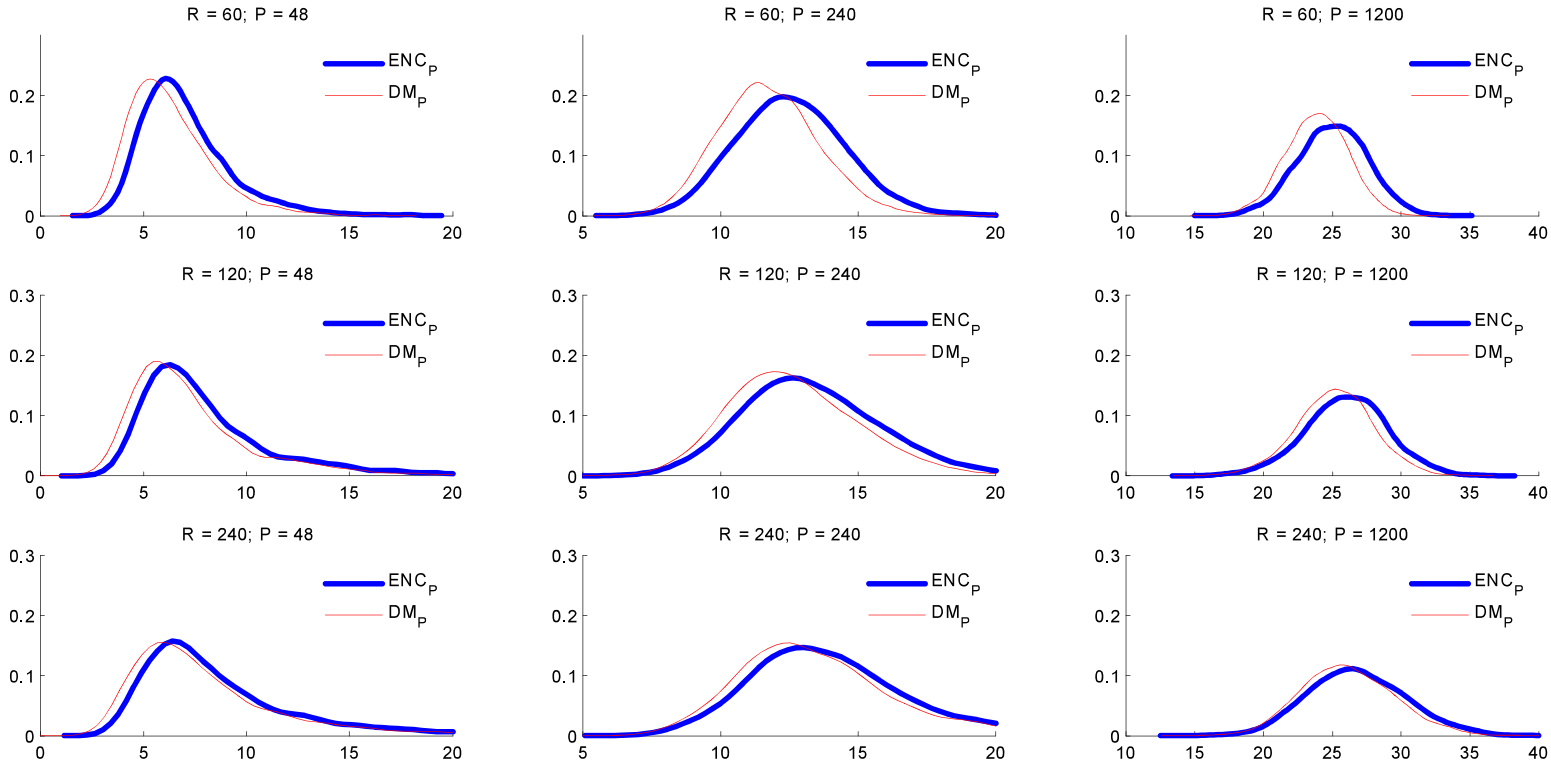

Figure 11: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_1$, $\phi = 0.99$, $b = 1$, $\sigma_e = 1$, with intercept on Model 1, 2000 Repeats.

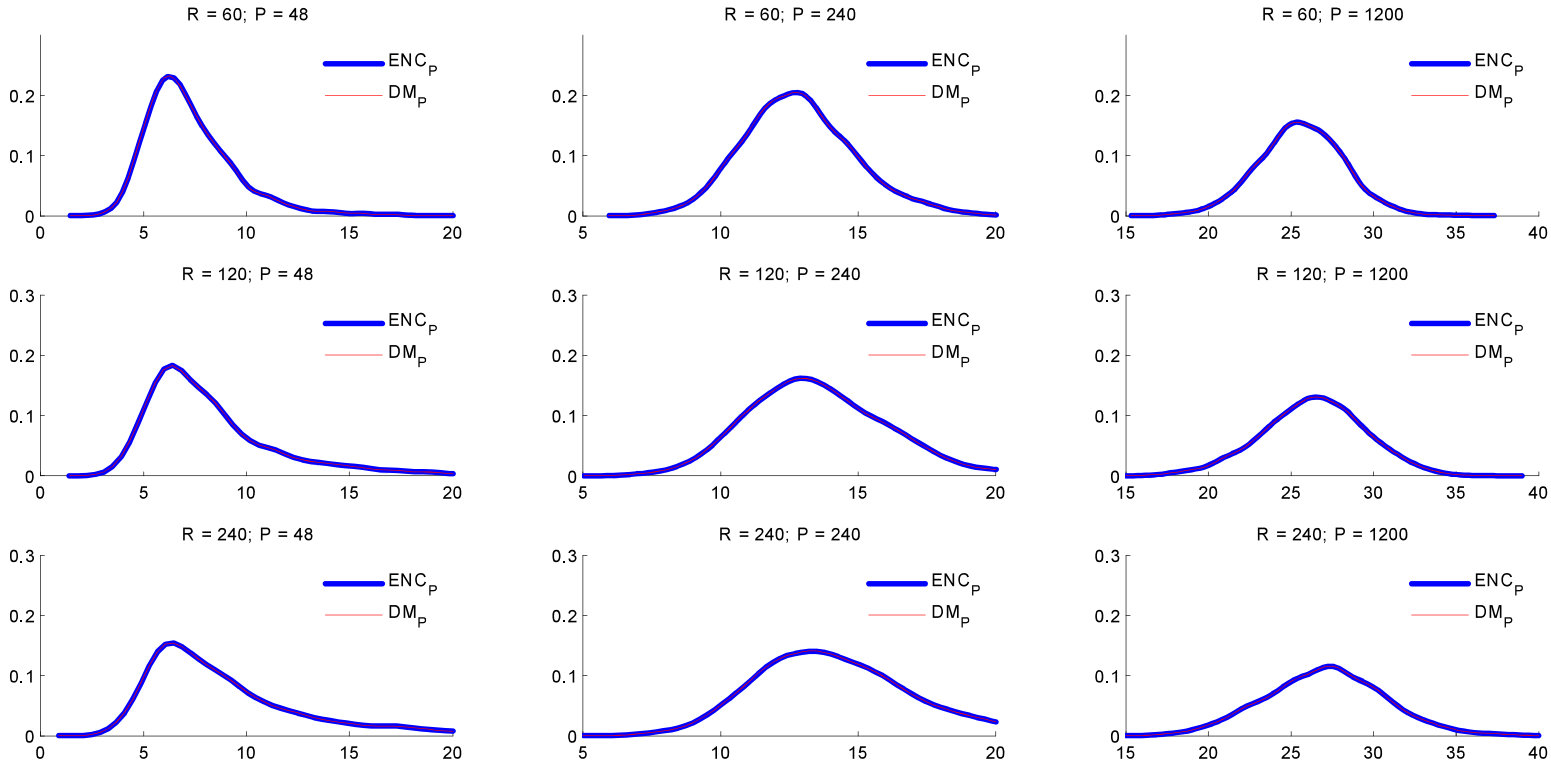

Figure 12: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_1$, $\phi = 0.99$, $b = 1$, $\sigma_e = 0.1$, with intercept on Model 1, 2000 Repeats.

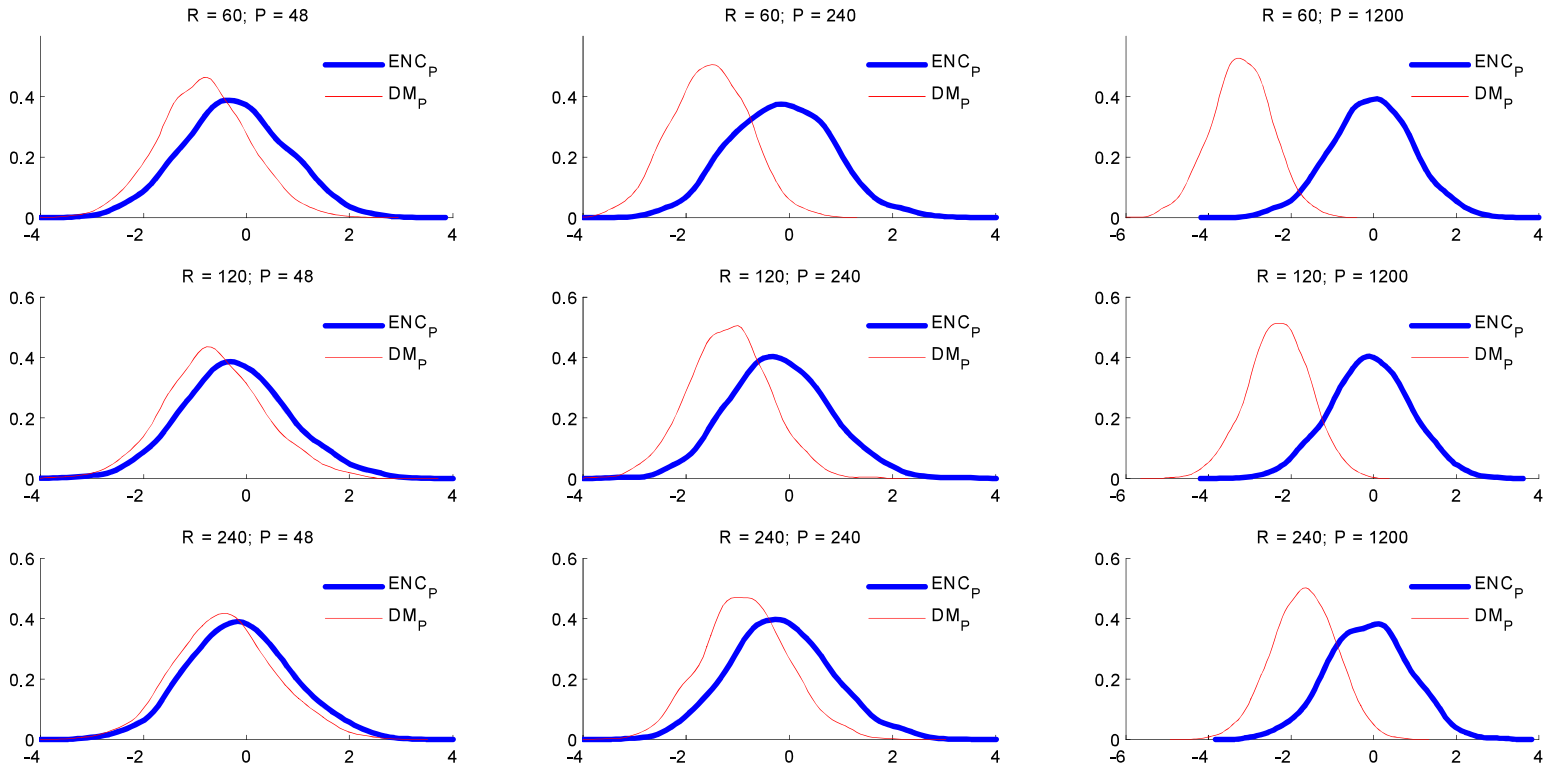

Figure 13: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_0$, $\phi = 0$, $b = 0$, $\sigma_e = 1$, without intercept on Model 1, 2000 Repeats.

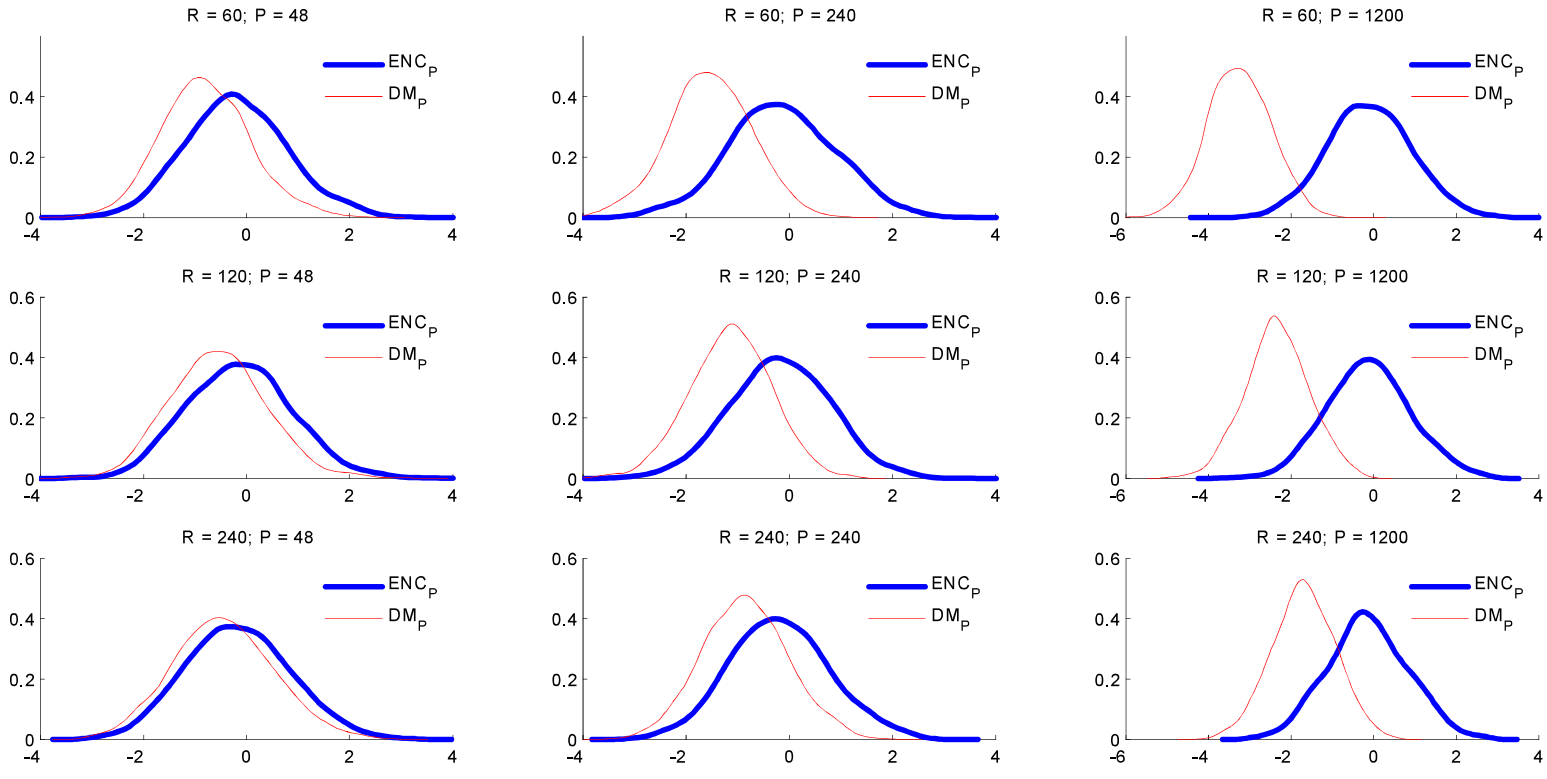

Figure 14: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_0$, $\phi = 0$, $b = 0$, $\sigma_e = 0.1$, without intercept on Model 1, 2000 Repeats.

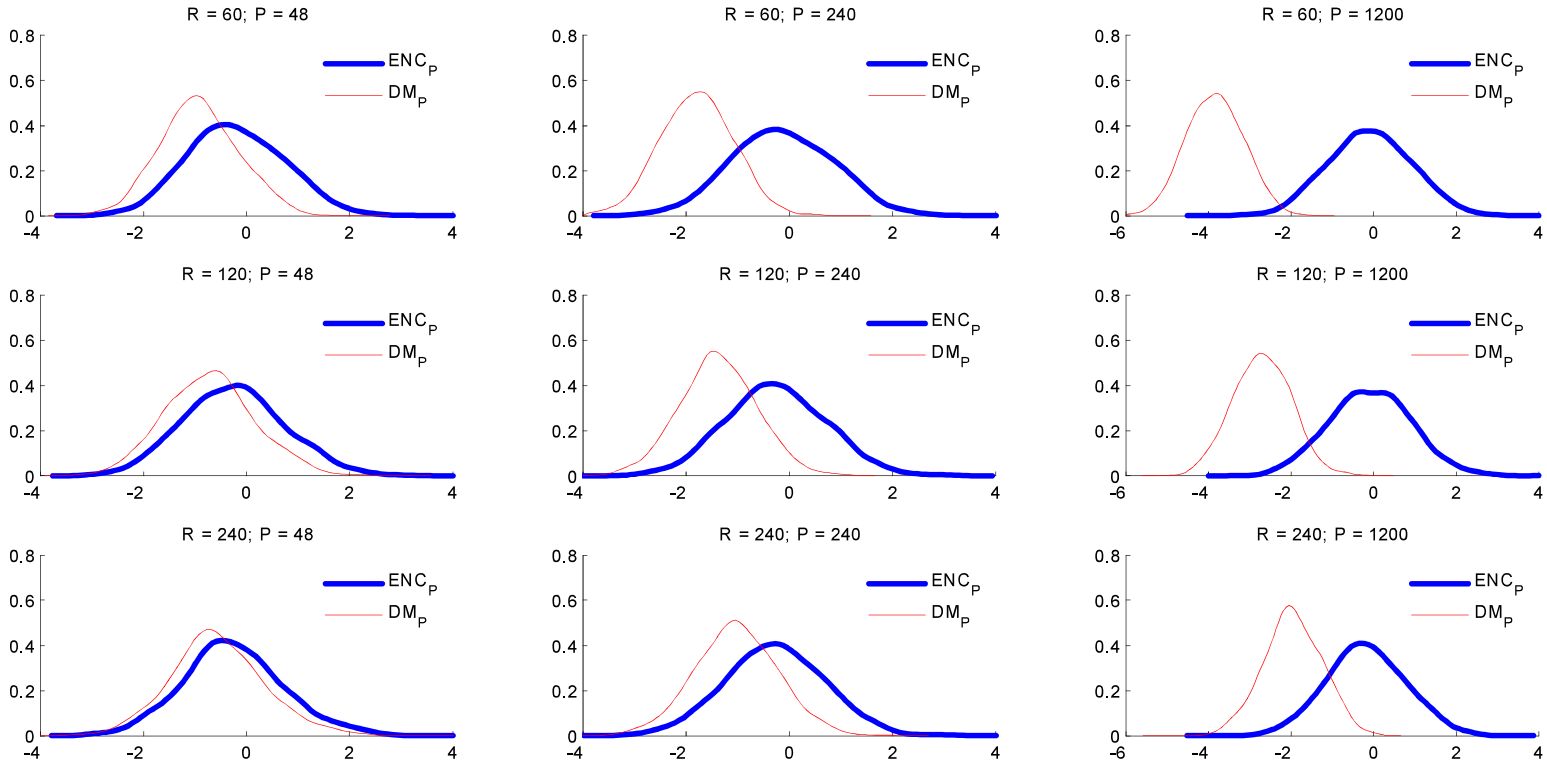

Figure 15: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_0$, $\phi = 0.99$, $b = 0$, $\sigma_e = 1$, without intercept on Model 1, 2000 Repeats.

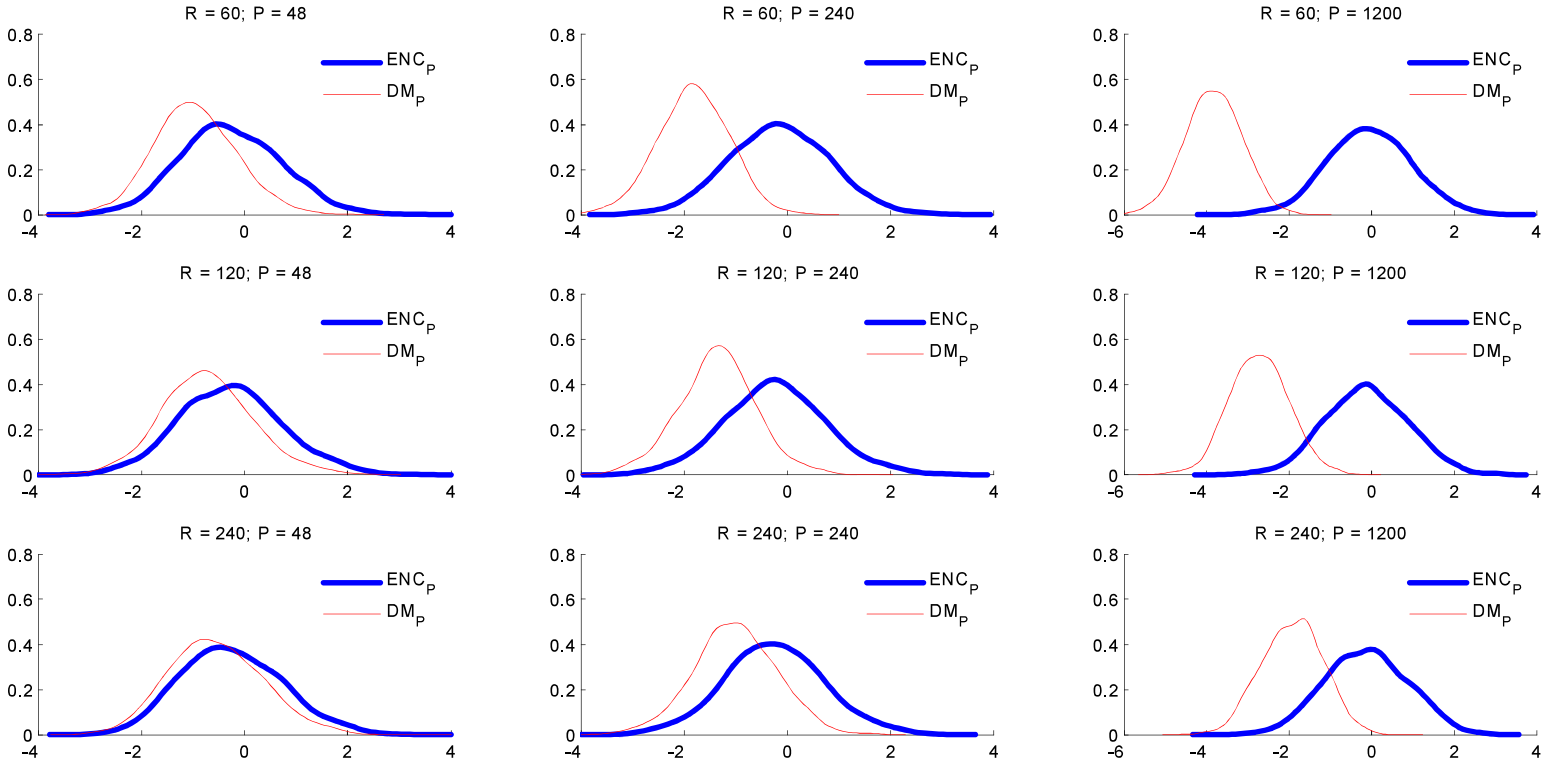

Figure 16: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_0$, $\phi = 0.99$, $b = 0$, $\sigma_e = 0.1$, without intercept on Model 1, 2000 Repeats.

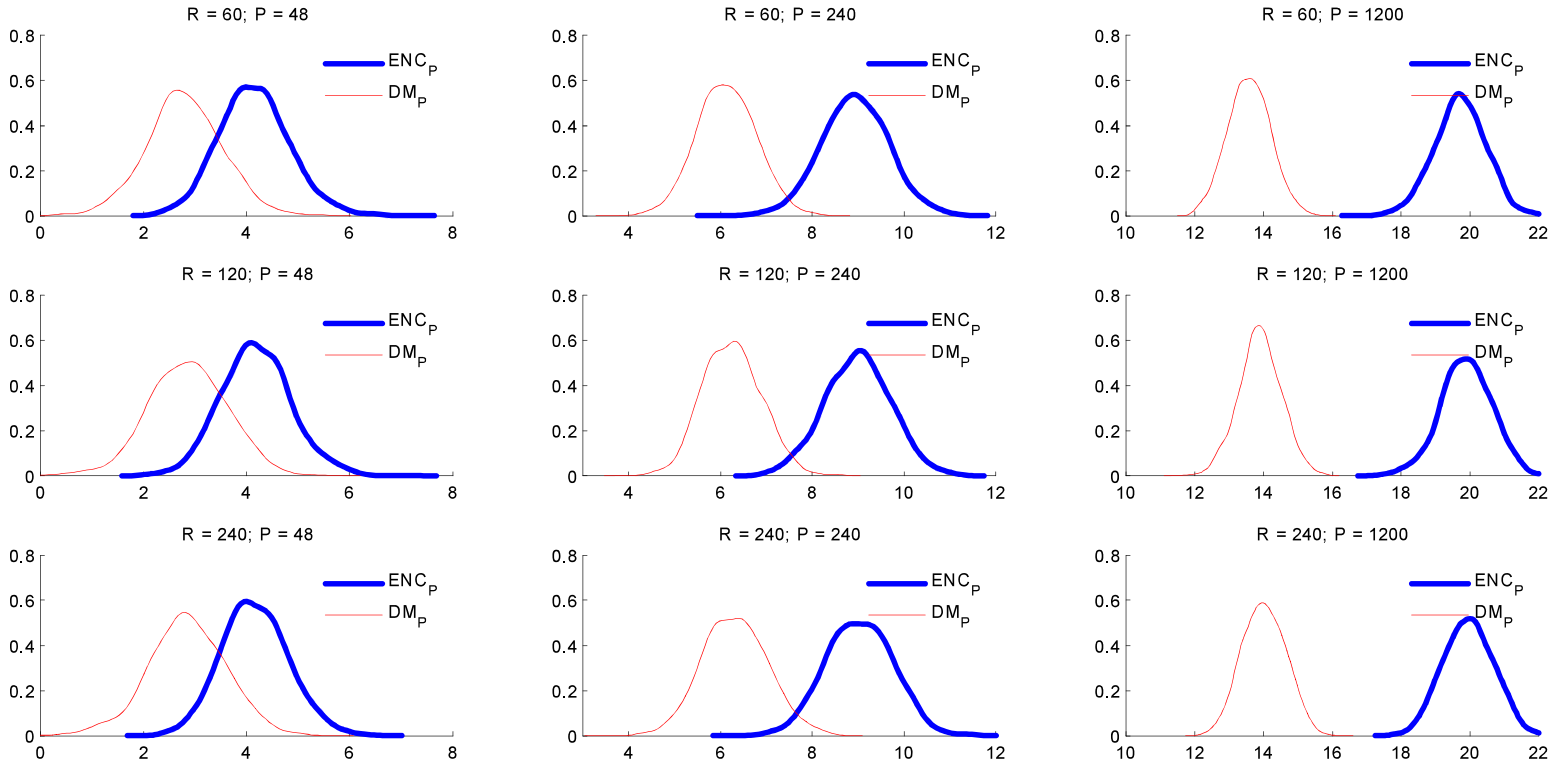

Figure 17: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_1$, $\phi = 0$, $b = 0.1$, $\sigma_e = 0.1$, without intercept on Model 1, 2000 Repeats.

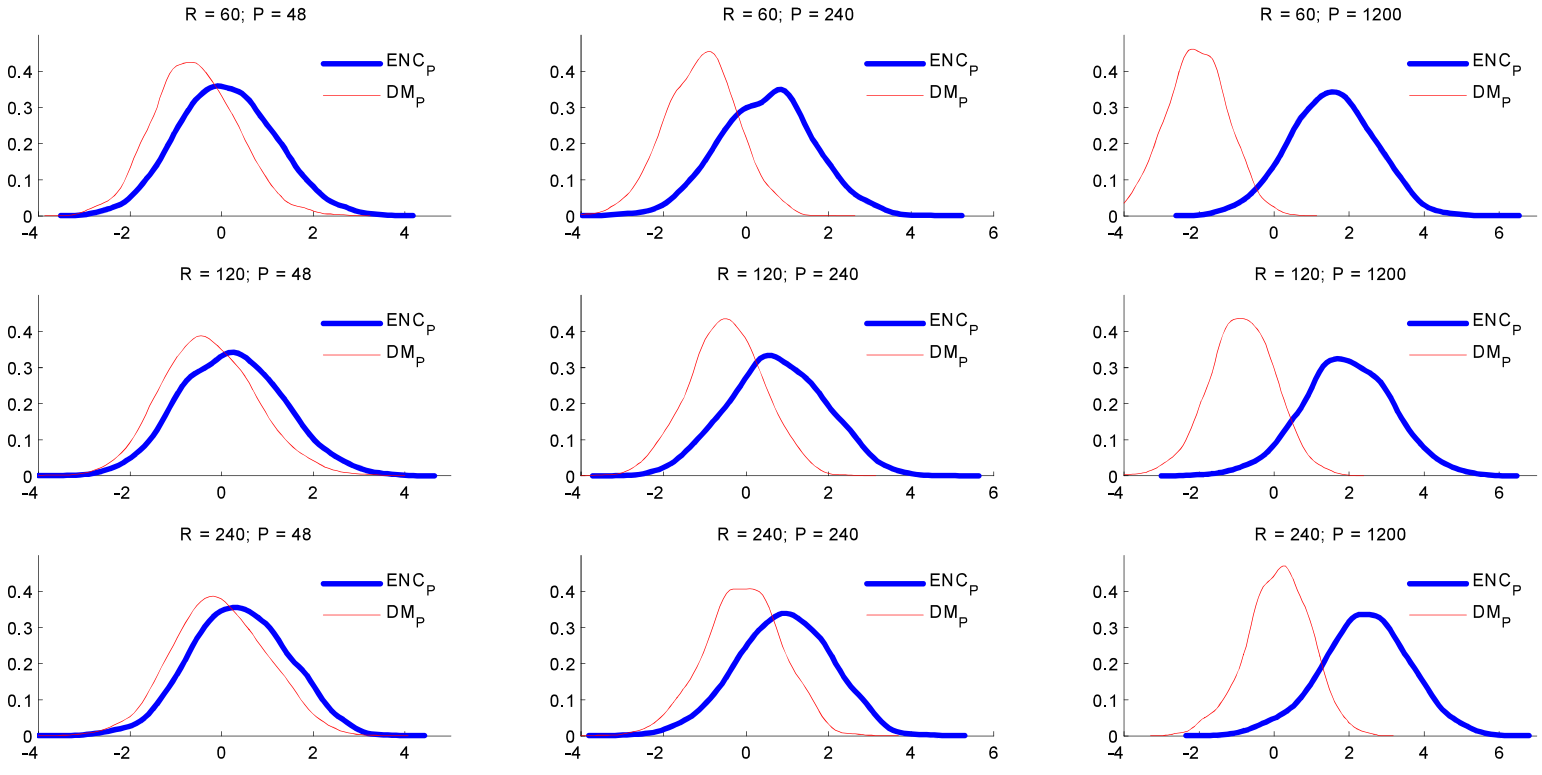

Figure 18: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_1$, $\phi = 0$, $b = 0.1$, $\sigma_e = 1$, without intercept on Model 1, 2000 Repeats.

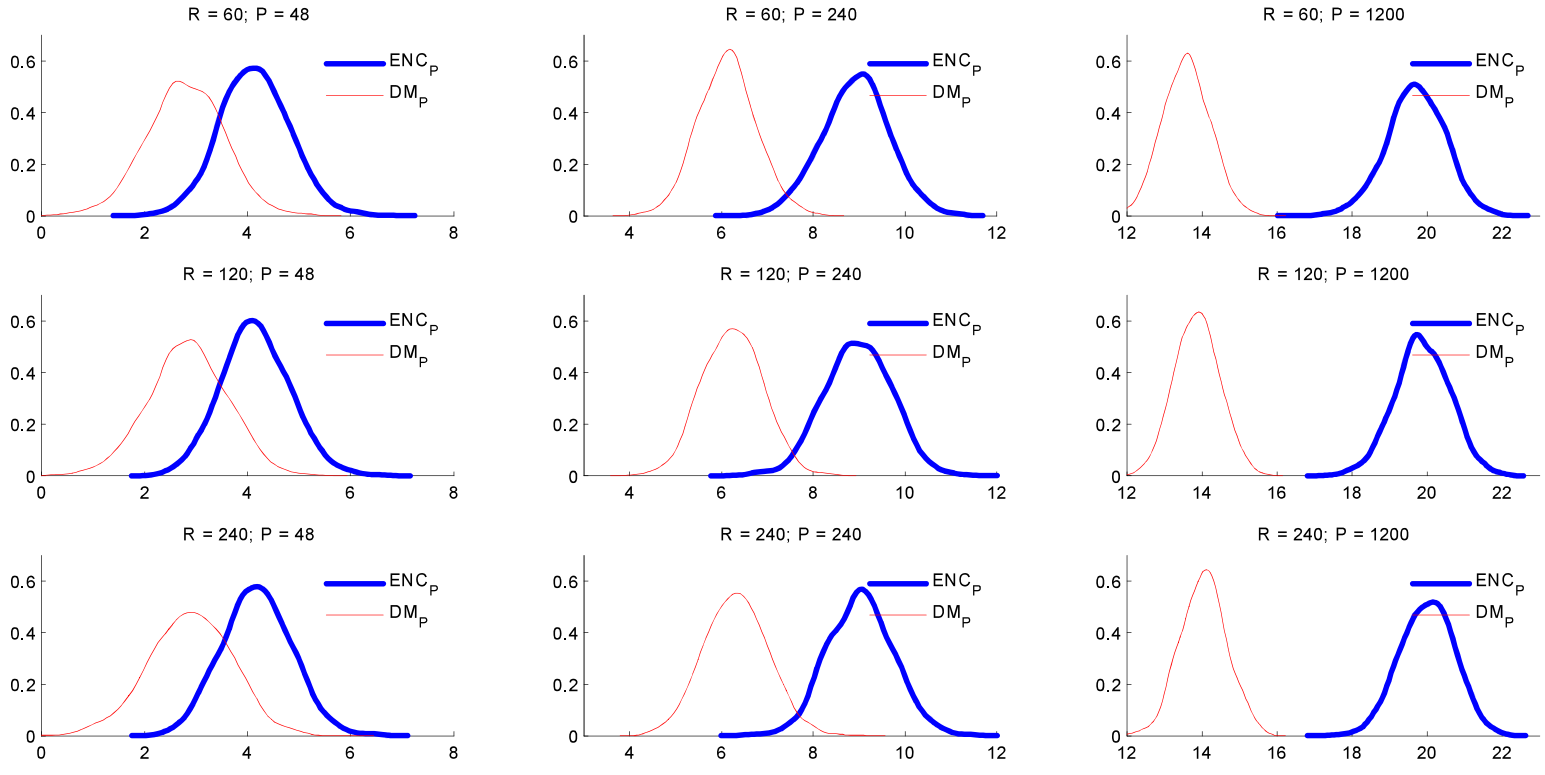

Figure 19: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_1$, $\phi = 0$, $b = 1$, $\sigma_e = 1$, without intercept on Model 1, 2000 Repeats.

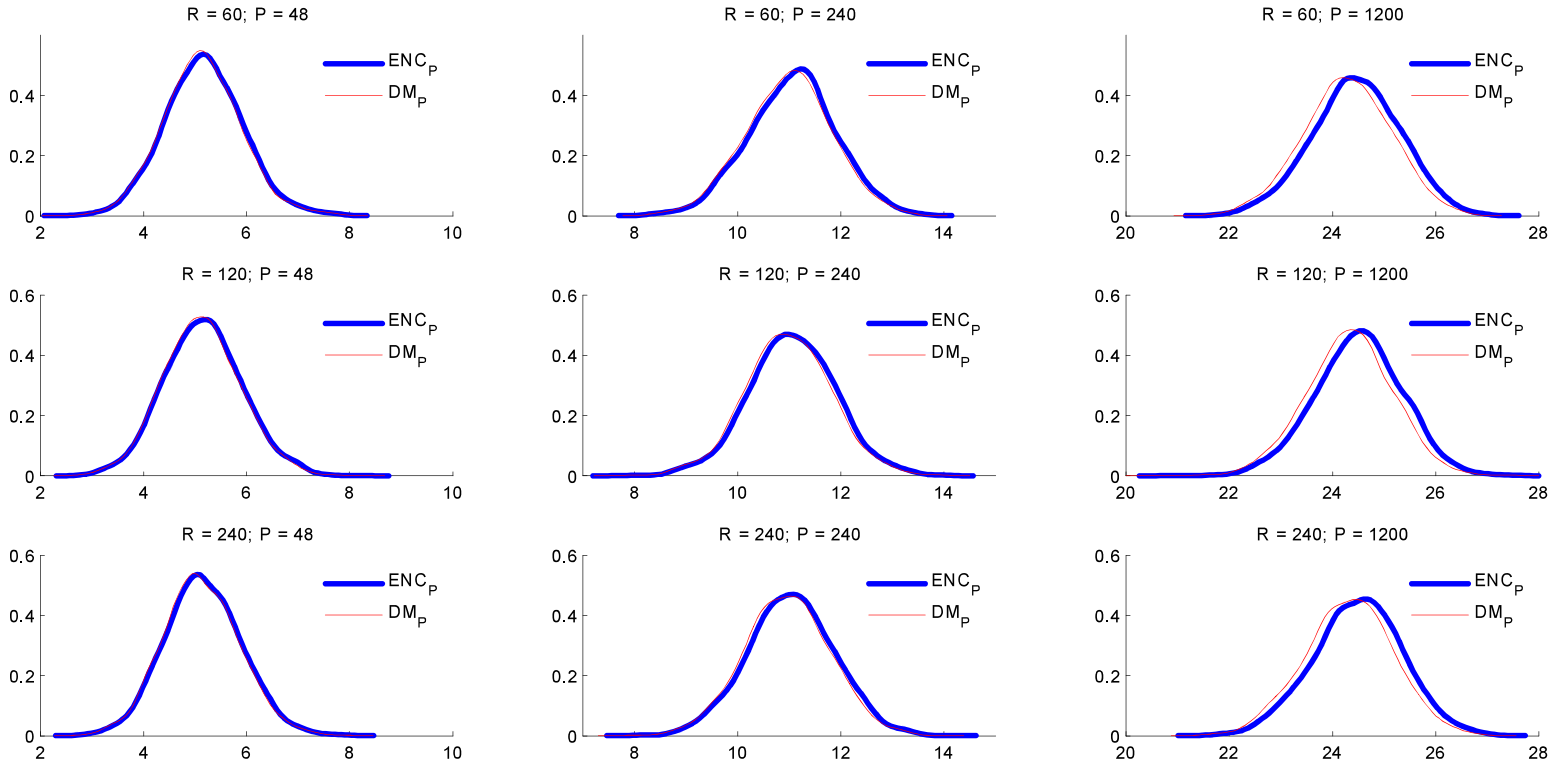

Figure 20: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_1$, $\phi = 0$, $b = 1$, $\sigma_e = 0.1$, without intercept on Model 1, 2000 Repeats.

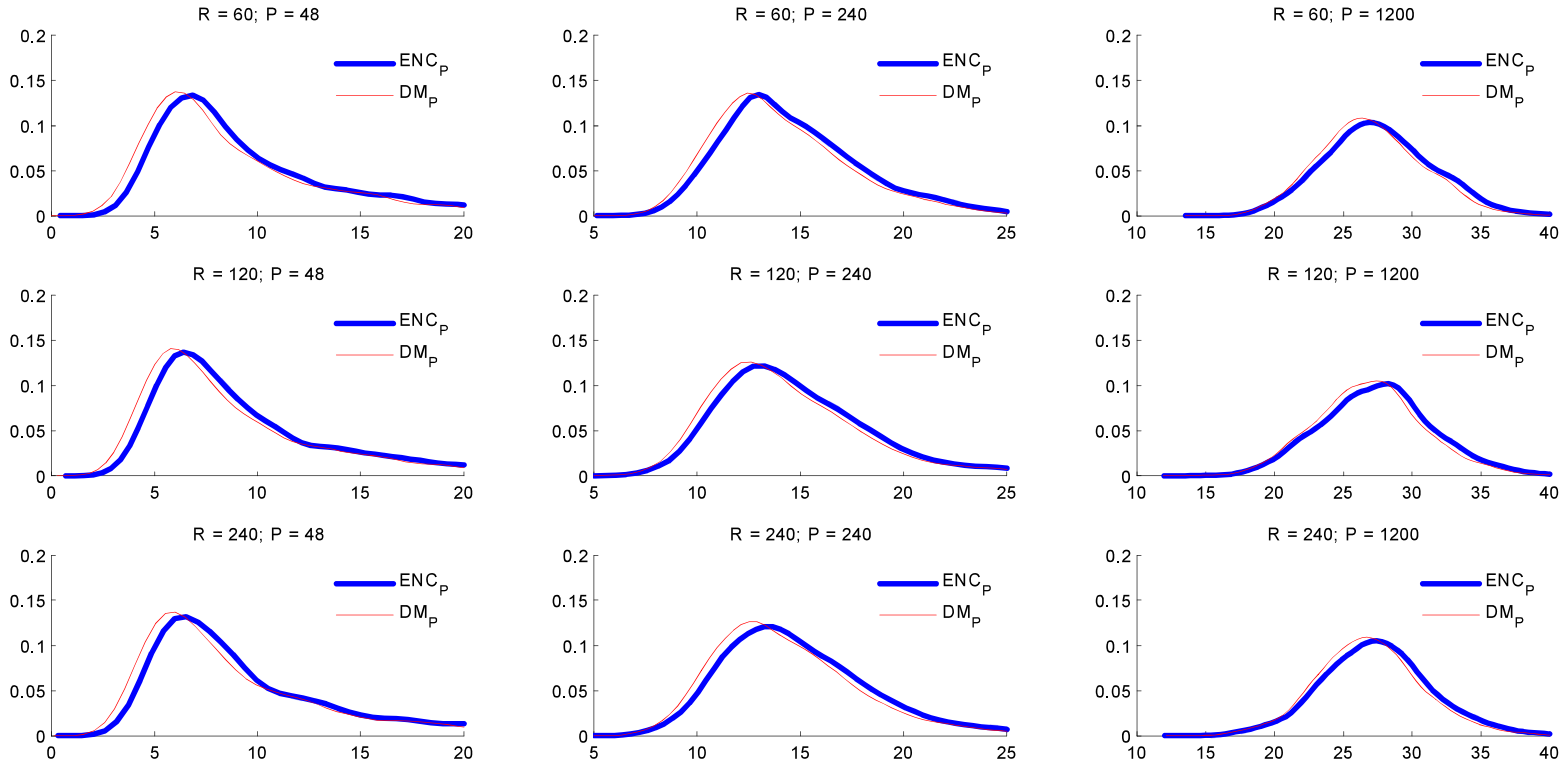

Figure 21: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_1$, $\phi = 0.99$, $b = 0.1$, $\sigma_e = 0.1$, without intercept on small model, 2000 Repeats.

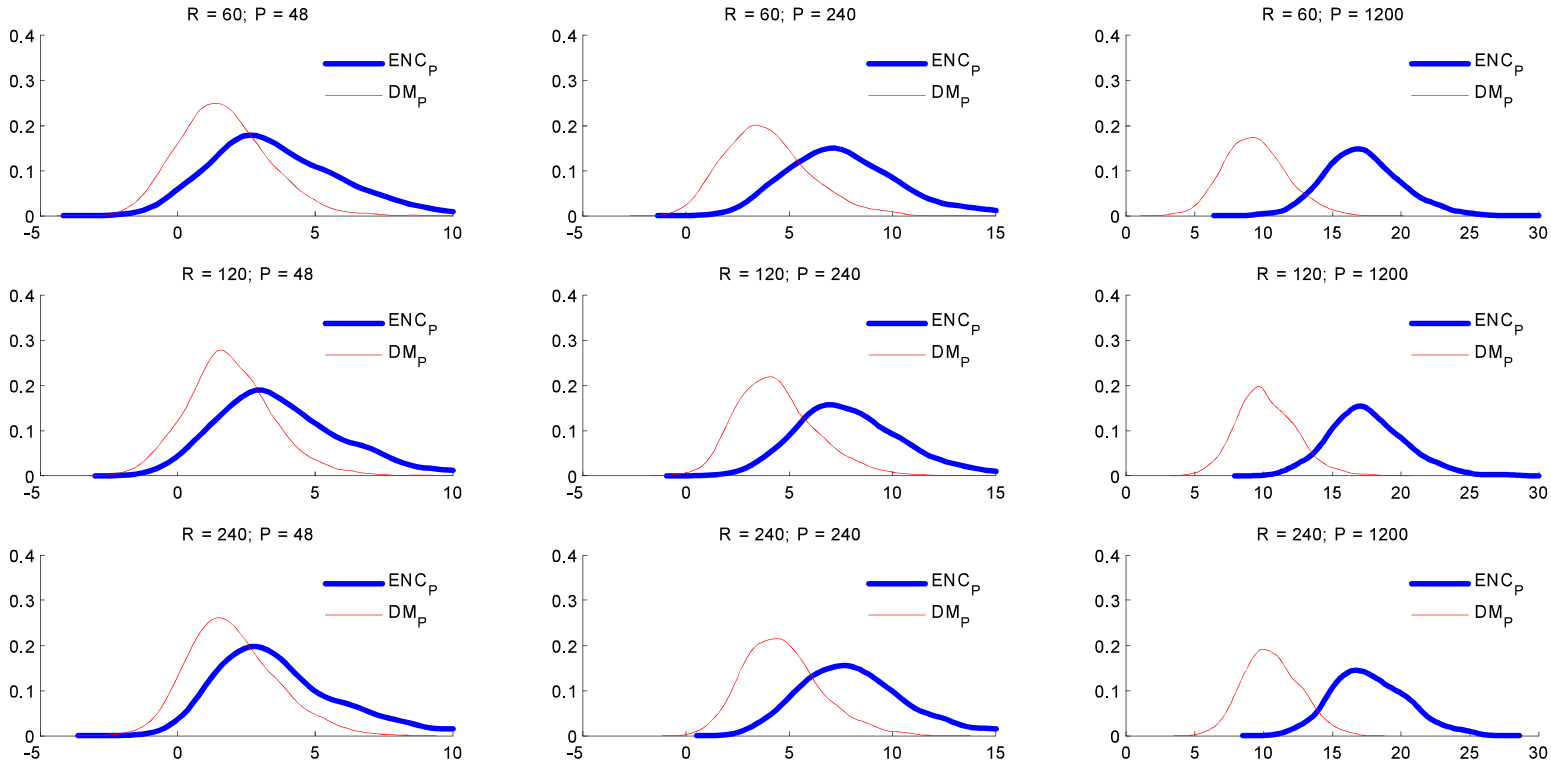

Figure 22: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_1$, $\phi = 0.99$, $b = 0.1$, $\sigma_e = 1$, without intercept on Model 1, 2000 Repeats.

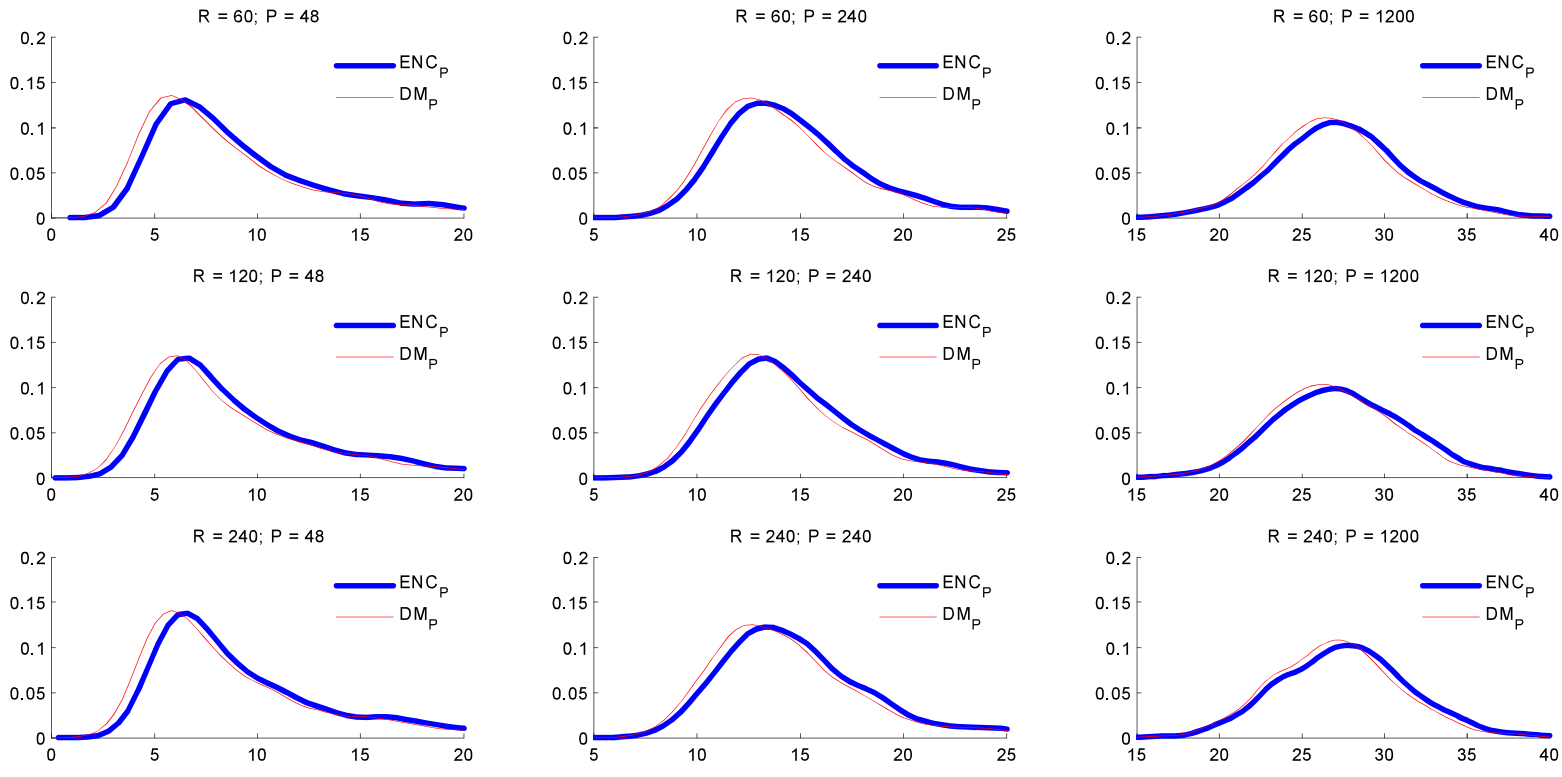

Figure 23: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_1$, $\phi = 0.99$, $b = 1$, $\sigma_e = 1$, without intercept on Model 1, 2000 Repeats.

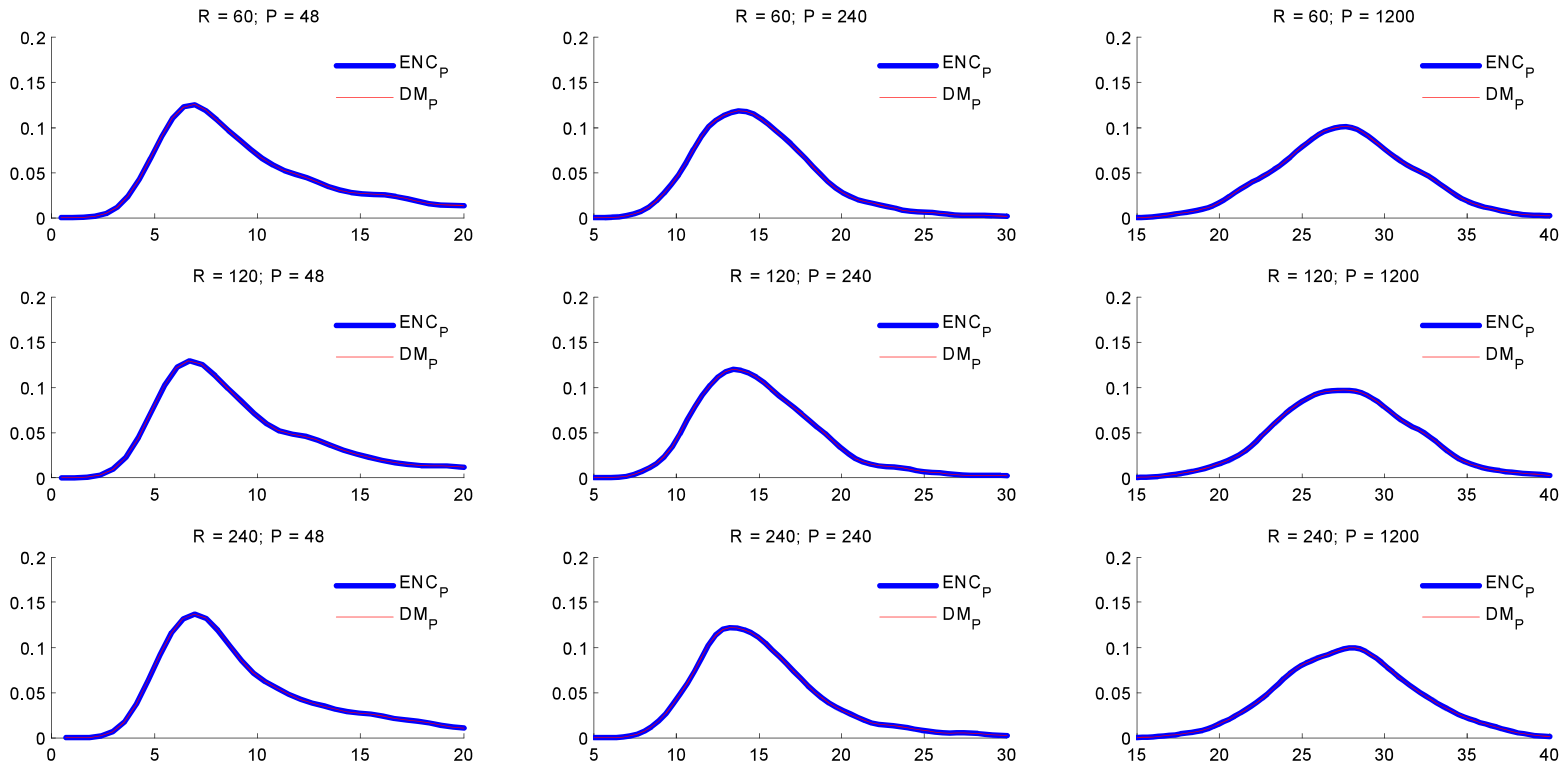

Figure 24: Monte Carlo distribution of ENC (blue line), and DM (red line) under $\mathbb{H}_1$, $\phi = 0.99$, $b = 1$, $\sigma_e = 0.1$, without intercept on Model 1, 2000 Repeats.

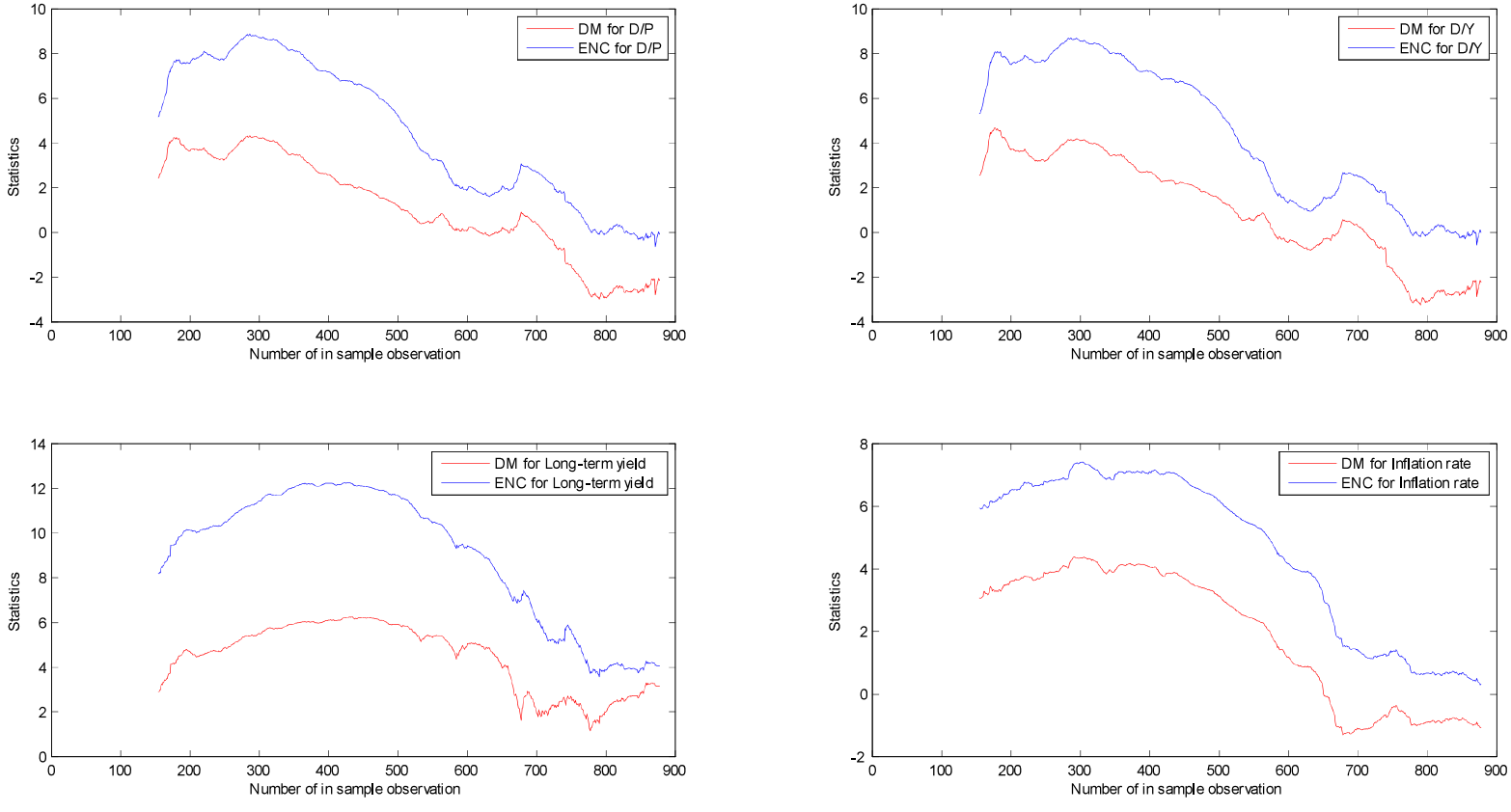

Figure 25: Testing for predictive ability of persistent predictors for equity premium using rolling scheme (with intercept in Model 1)

CHAPTER 8

Have Mismatches Lowered the Korean Young Men's Employment Rate?

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Abstract

Young men's employment is at its lowest low level in Korea now. The ratio of employment to civilian population among men aged between 25 and 29 years stands at 69.4 percent as of 2014, which is below the level in most advanced countries and down by 10 percent points from its level in 2000. The most commonly acclaimed explanation for the low employment is the 'mismatch' hypothesis, though the terminology is used somewhat differently from that in the standard economics literature. The hypothesis maintains that the cause lies in the supply side: Over-education and the widened discrepancy between young men's job expectation and their opportunities have made them to search for jobs for a longer period. This paper investigates whether the common belief is supported by empirical evidences and obtains a negative result. First, mass higher education did not enlarge the size of mismatches commensurately as the over-educated, who are college graduates at high school jobs, still enjoyed some college education premium. Secondly, there exists no systematic relationship between mismatches and durations of the search period for the first job no matter how the mismatches are defined. As a conclusion, this paper suggests that the cause lies on the demand side and not on the supply side.

JEL code: J21, J24, J64
Keywords: Mismatch, over-education, youth unemployment, Skill Surplus, Hazard Models

"Everybody's gettin' so goddam educated in this country there'll be nobody to take away the garbage…You stand on the street today and spit, you're gonna hit a college man," Keller in Arthur Miller's play, "All My Sons", written in 1946.

I. Introduction

Throughout the 2000s, the Korean youth labor market continued to deteriorate. The market had been hit very hard by the Asian financial crisis at the end of 1997. Although the economy successfully moved out of the crisis in a few years, the downward trend for the youth labor market did not halt and the trend is still on-going.

The employment rate, which is the ratio of employment to civilian population, of the Korean young men is now at its lowest low level. Of the young men with age between 25 and 29 years, just 69 percent are employed as of 2014. The ratio is down by nearly 10 percent points from its level in 2000, in which year it stood at 78 percent.[1] Before, Korea was known for its disciplined youth and it touted one of the highest youth employment rates in the whole world, though women's labor market status was significantly behind. High youth unemployment was a problem for Europe. Now youth unemployment became one of the biggest problems of the Korean economy. The level of its young men's employment rate is now lower than those in most European countries.

In Korea, the most commonly known theory for the cause of high youth unemployment is the 'mismatch' hypothesis. The theory explains as follows: The Korean youth are over-educated and there are too many college graduates; they compete for a limited number of 'college' job positions while many high school jobs are left unfilled; and thus, too many young people are outside the labor market, just piling up their 'specs' (qualifications) for slim opportunities.[2] Hence the youth labor market is in a 'mismatch' situation. This explanation is basically a supply-side theory.

[1] All the employment rates for Korea in this article are the rates in urban areas where 95% of the total population reside. To eliminate the bias caused by declining population share of rural areas, where employment rates are typically high, in a time series comparison, I disregard rural area observations in labor force survey data.

[2] 'Spec' is short for 'specifications.' Specifically, the 'specs' are job qualification scores that are referenced in job recruiting, such as TOEIC scores, foreign language skills, experiences abroad, et cetera.

Youth unemployment has been a serious social problem at different times at different places, but a 'mismatch' has seldom been put forth at as its cause. For example, when youth unemployment rate soared in France in the 1970s, Malinbaud (1984) pointed to 'disequilibrium' and state dependence as its cause, by which he meant insufficient aggregate demand and persistent nature of unemployment. State dependence means that the longer a person stays in the unemployment state, the lower is his chance to exit from the state. Hence his recipe was a combination of expansionary macro policy combined with government intervention in labor market. In the 1980s, the mainstream viewed the high unemployment in Europe as structural unemployment. European system's rigidity both in the commodity and labor markets was diagnosed to have lowered job creation and blocked the youth from entering the labor market. Logical solutions were reforms for flexibility in both markets. The OECD Jobs Strategy (1994) persuasively put forth this view. However, labor reform attempts hereto achieved only partial successes and increased temporary workers.3 Consequently, the OECD 'revisited' the issue and now emphasizes quality jobs and higher skills.4 In the U.S., education and training have been stressed traditionally under a flexible labor market system. In the late 1970s to the early 1980s the over-education issue was raised but the objective was to warn against government R&D expenditure cut and not to curb over-investment in education.

But in Korea, universal college education and the youth's overblown aspiration is frequently mentioned as the cause for youth unemployment. A high-ranking government official remarks, 'The real problem is not that there are not enough jobs, but that college educated young people are not willing to work at the positions.'5 But unless the Korean youth are far different from their partners abroad, the mismatch hypothesis does not seem to be a proper explanation that leads to a right solution.

Furthermore, the hypothesis has some theoretical weaknesses. First, it is not logical to assume that an informed college graduate continues to anticipate that he can get a college job knowing that 40 percent in his cohort have bachelor's degrees. Secondly, ever since

[3] OECD Employment Outlook, 2005.

[4] OECD, Off to a Good Start? Jobs for Youth, 2010, p.19.

[5] Dae-ki Kim, The Korean Economy in the Trap, Kimyoung-sa, 2013, p.89.

Gary Becker's Human Capital Theory, economists do not traditionally support the notion that more education harms a person although it may bring little benefits. Moreover, labor demand has shifted a lot towards the skilled since his theory. An explanation that a person remains jobless because he is educated is hard to grasp. Third, Korea is not a very exceptional country in terms of the incidence of over-education, while its youth employment rate drop is unparalleled.6 Under the mismatch hypothesis, facts do not fit together very well.

This paper derives testable implications of the mismatch hypothesis and see if they are supported by empirical evidences. Among them are that the job search duration are longer among those who are mismatched, that the youth employment rate drop are contributed disproportionately by college graduates, and that college graduates experience longer job search duration as their share grew, etc. The target for this paper is the labor market of young men aged between 25 and 29. Young women's labor market is not considered, not because their labor market is different but because the employment rate drop is not very clear among them as it is counter-balanced by a long-term trend of female labor supply increase. College graduates increased among young women as well, and it can be inferred that their labor market is affected by the same factors as young men's labor market.

This paper is organized as follows: Section 2 briefly summarizes the trend in Korea. Section 3 reviews the mismatch hypothesis in the literature. The section contains a review for existing research in the field in Korea. Originally, a mismatch means a skill surplus match where a worker is over-educated. And the consequence is measured in terms of wages. Section 4 deals with the wage effect of mismatches. To investigate if over-education has led an employment rate drop, Section 5 and 6 analyzes how job search duration is related to quality of job matches or the trend of increasing higher education. Section 5 reviews match quality and job search spells and Section 6 does a hazard model analysis. Section 7 summaries and concludes.

[6] See for example, Hartog, 2000.

II. Employment Rate Drop among the Young Korean Men

Until the 1990s, the Korean young men's employment rate was among the highest in OECD countries. In 1990, the rate stood at 87.4% among men between 25 and 29 years old. And between 30 and 34 years old, it stood at 95.1%, which is the second highest next to Japan. (See Table 1.) The level of employment rate between 25 and 29 is not among the highest but it is very high if the military service duty is taken into account. Even the economic crisis of 1997 did not pull down young men's employment rate much. But a real drop occurred in the 2000s. As of 2012, Korean young men's employment rate in the 25-29 group is below 70 percent, lower by 10 percent points than those in France, Germany, and the U.S. In the past, high youth unemployment was a European phenomenon, but now Korea has an even lower youth employment rate. In the 30-34 group, the employment rate fell much less, but Korea is not any higher than European countries. Korea's youth employment rate fall was not accompanied by any significant change in unemployment benefits or in labor market institutions. In fact, the labor market itself became more fluid. Hence widened college education is first looked at as a candidate for the cause.

< Table 1 here >

Table 2 is the change across time in the composition of economic activity status among young men from 1995 to the recent in urban areas.[7] The trend shows that the increase in the share of education and training falls short of the drop in employment rate. Between 2000 and 2013, the employment rate fell by 8.8 percentage points, from 78.1 to 69.3, in the 25-29 age group. Out of the drop, just 2.1 percentage points can be attributed to the growth of the proportion of education or training. Unemployment contributed just 1.0% point. By far the largest part, 5.7 percentage points, is contributed by the growth of the NEET (Not in Education, Employment, and Training). In the 30-34 age group, the employment rate dropped by 2.8 percentage points, education increased by 0.2 percent

[7] Employment rates are typically higher in rural areas and the rural area population share drop makes the overall employment rate lower. To eliminate the composition effect, only the urban area employment rates are compared.

points, unemployment fell by 0.4 percentage points, and the NEET increased by 3.0 percentage points. The sub-intervals within the period show similar trends. College education growth does not fully account for the drop in young men's employment rate, and the growth of the NEET is as important a factor. Contribution of unemployment has been minor.

< Table 2 here >

As job matching is a dynamic process, let us stop and think what such a fall in employment rates means for job search durations. Employment rates can fall either when non-employment spells become longer or become more frequent. But given data conditions, we cannot confirm the non-employment duration changes. To simplify, let us assume that every young man experience spells of education, non-employment, and employment only once. Then the proportion of employment spell within a year is equal to the employment rate. According to Table 2, a typical young men between age 25 and 29 spent 12.1 percent of the year as non-employed in 2000 and 18.8 percent in 2013. The figures mean a 55 percent growth of non-employment duration from 2000 to 2013, and 30 percent growth from 2005 and 2013. This calculation is crude but gives a sense of how much the youth labor market has deteriorated. I come back to this point in Section 4.

III. The Mismatch Hypothesis

In the human capital literature, the term 'mismatch' is used to describe the quality of match between a worker and a job. A mismatch usually means a skill surplus match, where skills are not fully utilized and the workers are not properly compensated for their skills.8 But the Korean literature uses the term more often to describe a discrepancy between aggregate supply and demand.9 If college labor supply is greater than college labor demand, it is said that there exists an excess supply of college labor and hence a

[8] Find the article.***

[9] See KEIS (2012) or Oh (2012), as examples of how the term 'mismatch' used.

‘mismatch’ exists.10 Therefore while under the former definition a mismatch can only be determined after a match has been observed, under the latter definition, a mismatch can exist a priori. The latter mismatch is not match-specific. Even under a mismatch situation, a graduate can end up with a proper match, or a skill surplus match, or no match at all. This notion of mismatch similar to the ones used in manpower planning literature. In manpower planning, a mismatch means over- or under-supply of specific trades. For example, if the number of hairdresser training exceeds the number demanded, hairdressers are mismatched and so one. The problem with this conceptualization is that skills acquired from college education are much more general in nature than trades. The notion ignores adaptability of skills and wide heterogeneity among college graduates.11

The existing Korean researches on the causes for youth unemployment can be grouped into four categories. The first group points to the macro-economic condition. Lee (2004) and Chung (2004)12 argued that the primary cause lies in the weak job creation due to sluggish economic growth. Economic growth rates nearly halved after the economic crisis of 1997. The average growth rate in real terms between 1993 and 1997 stood at 7.2%, but it fell to 4.8% between 2000 and 2004. The growth slowdown had a disproportionate effect on the youth as firms froze new hiring to adjust their workforce. Further, quality jobs disappeared even faster. According to the Employment Insurance System (EIS) database, between 1997 and 2002 jobs at the 30 largest business groups, public enterprises, and financial institutions combined decreased by 20 percent, and their new hiring reduced by 25 percent.[13] However, while economic growth continued at the lower level, the youth employment rate dropped further throughout the 2000s. The low economic growth explains why youth employment rate fell from its pre-crisis level, but it does not explain its continued decline. According to Chang et al. (2011) at BOK, the proportion of quality jobs in total employment dropped from 25.9 percent in 1995 to 20.9 percent in 2000, but this ratio slowly rebounded and reached 24.4 percent in 2010 (Figure

[10] Typically, ‘mismatch’ is used to describe the current situation where many college graduates are without jobs and small and medium sized firms claim ‘labor shortages’ by which they mean cheap labor is hard to get by.

[11] See Hanuchek (2015) for improperness of years of educations as a measure for skills.

[12] 정봉근

[13] Both Chung (2004, p.11) and Yoon (2004, p.35) cite this statistic.

24, p.13).[14] The loss of quality jobs between 1997 and 2002 was exceptionally large, but the loss was recovered later though the pace was slow and gradual. In contrast, youth employment rate continued to fall.

The second group points to the changes in firms' recruiting practice particularly unfavorable to the youth. Having experienced difficulties in labor adjustments, firms preferred workers with experience to untested fresh graduates. The Employment Insurance System database shows that in 1997, workers with experience accounted for 41 percent of total hiring but this share rose to 82 percent in 2002 in the 30 largest business groups, public enterprises, and financial institutions taken together (Yoon 2004; Chung 2004). Companies definitely became less aggressive after experiencing the crisis and hired workers to fill vacancies than for expansion and new investments. Yoon (2004) pointed out that two factors aggravated the youth job problem: the first is increase of temporary positions, and the second is the change in firms' hiring practice that preferred skilled and experienced workers to new market entrants. Both can be results of labor demand shifts towards the skilled away from the young. Kim, D. (2004) looked at the proportion of lifetime first jobs among the newly hired workers between age 25 and 29. He claimed that this proportion from 50 percent at the beginning of 1998 to near 10 percent by the end of 2002 (pp.439-441).15 He found that in industries where wages grew fast, the proportion of workers with experience in new hiring is high (p.445).16 From the results he inferred that skill demand shift was unfavorable towards the youth. The second group considers that the skill demand shift had a larger effect than economic growth slowdown. Both the first and second group view weak labor demand for the youth as the main cause.

The third and fourth groups look at the supply side and argue that excess supply of college graduates is the main cause. The mismatch view usually refers to these studies.

[14] They define quality jobs as follows: i) all occupations at establishments with 300+ workers; ii) managers, professionals, and clerks at establishments with 30 to 299 workers plus agricultural occupations at 100-299 worker establishments; iii) managers and professionals at 10-29 worker establishments, iv) managers and at 1-9 worker establishments. The criteria used was average wage level by occupations and by establishment sizes (p.30)

[15] The change is drastic is because he compared monthly high with monthly low in the period between Jan 1998 to Dec 2002. The long-term trend is much more modest than this but it does decline.

[16] The result can be interpreted as the effect of skill demand shift on youth jobs, since high wage growth is likely to be a result of changing worker composition towards highly skilled.

The third group observes that mismatches are prevalent among college graduates. Several studies suggest convincing evidences of over-education matches (Won et al., 2005; Kim, J. 2005; Oh 2005; Lee et al, 2005; Park and Ban, 2007). For example, Oh (2005) adopts a job analysis method. For each job, he takes its required education level in the GED (General Educational Development) scale from the 2003 Korea Dictionary of Occupations published by the KIES.17 If a worker's actual education in the 2005 GOMS data is beyond the required level, the worker is construed as over-educated. According to his estimation, incidence of over-education is 18.8 percent for college graduates and 10.1 percent for junior college graduates. When he takes self-assessment method and determines over-education according to worker assessment, incidences are 20.7 and 18.8 percent, respectively. Kim J. (2005) estimated incidence of over-education as 22.8 percent using a self-assessment method from the 3rd wave (2003) of Youth Panel data of the KIES. Park and Ban (2007) used the same method and estimated over-education as 24.0 percent among 4-year college graduates from GOMS data of 2002 to 2005. Kim, Y. (2008) shows that the proportion of college graduates at each industry-occupation cell has steadily increased from 1994 to 2007 on average (Figure 2-4, p.17). This mismatch view has now become popular. The KIES officially takes the view and published their annual labor market projection report under the title, 'Manpower Mismatch Analysis and Projections: 2011-2020' in 2012.

The relationship between over-education and unemployment or employment rate is investigated by the fourth group. An implicit assumption held by the mismatch view is that the job search spell is longer for those who ended up with an over-education match than for those who were properly matched. But the evidence does not fully support this hypothesis. Oh (2005) finds that those at over-education jobs have had more job interviews but found jobs more quickly. Among college graduates, the over-educated had 3.3 interviews on average, whereas the properly educated had 3.0 and the under-educated

[17] KIES stands for the Korea Employment Information Service (한국고용정보원), a government agency under the Ministry of Employment and Labor in charge of production and delivery of job information with an aim to promote employment and career development. The GOMS (Graduates Occupational Mobility Survey, 대졸자직업이동경로조사) is a survey conducted by the KIES to gather information about school to labor market transition. The survey collects job and worker information for a sample composed of about 20,000 new graduates from colleges and junior colleges, and conducts a follow-up survey after two years. The survey supplements the 'Graduate Job Status Survey' by the ministry of education, which is surveyed two months after graduation, thus lacks the full labor market transition information.

had 2.7 interviews. It took 4.0 months on average for an over-educated to find a job, whereas a properly educated needed 4.4 months and an under-educated needed 5.3 months (Table 3, p.16). But the differences are not statistically significant. The standard deviation is approximately 5 interviews and 7 months of job searches. Incidence of over-education is not related to the number of interviews or the length of the first job search spell in a statistically significant way.

Results from hazard model estimation are similar. Park, S-J (2008) estimates the relationship between the length of the first job search spell after final stage education and personal characteristics using the KIES GOMS data sets. He finds that i) the first job search spell of college graduates are longer than those of junior college graduates, and ii) the higher the wage of the first job, the longer is the job search spell. The two findings are consistent with each other since wages are higher for college graduates. He argues that the high wage group has a high reservation wage, and hence the high target wage caused mass unemployment among the youth (ibid, p.34, p .40). But that a high wage job is associated with a longer job search spell is a direct implication of a job search model. A high wage job is least likely be an over-education match, and his results do not support the hypothesis that mismatches involves longer job search spells. Lancaster and Chesher (1983) showed that setting a reservation wage is an optimal policy for a job seeker faced with a distribution of wage offers, and its level is determined by expectation on the distribution. According to them, a high reservation wage and a long search spell is a consequence of optimal job search strategy and has nothing to do with personal preferences. Thus the evidences do not support his claim that wrong information and attitudes lie behind the high unemployment. Woo (2011) applied a proportional hazard model to the college graduate sample of the 2006 GOMS data. He takes Flinn and Heckman (1982) estimation method and the reservation wage is set as the minimum of wage offers. From the estimation, he finds no evidence that high reservation wage is the cause for employment rate drop. In his model, a hazard rate is virtually determined by job offer arrival rates and an employment rate drop can only be caused by the less frequent offer rates (Table 6-2 and 6-3, pp.124, 126).

Several other studies have tried to see if the high reservation wage is the underlying cause for high unemployment. But a convincing evidence has not yet been put forth partly because of the deficiency in survey data. Oh et al. (2012) conducted a survey on 1,236 juniors and seniors in four-year colleges and asked average wage levels the students thought they would receive after college and the minimum of offered wages they would accept. College students had fairly accurate ideas on actual wages but the minimum or 'reservation' wages were way above the average wages.18 From the survey result, they inferred that college students set their 'reservation' wages too high and college education has in effect pushed up unemployment by fueling their aspirations too far.19 But the conclusion is subject to two criticism: One is that what they surveyed are not genuine reservation wages but their wished levels and hence not relevant.[20] In reality, a job seeker adjusts his reservation wage as he learns about his chances. The students have not yet even started a job search when they were surveyed. They have matched the survey results with the GOMS data and analyzed how the surveyed reservation wages were related to actual wages they received. They found a positive relationship between the two (Table 4-11, p.162). But they do not report whether the high reservation wages the job seekers had when they were students had actually caused longer unemployment spells. There are other earlier studies that analyzed reservation wages (Rhyu and Ryoo 2002; Lee et al. 2002). But the studies used single cross sections of reservation wages and investigated the relationship between the reservation wage levels and personal characteristics with little implication for employment. Nam (2006) analyzes inflow and outflow of unemployment among the youth. He finds that the youth have as high job entry rates as other age groups but they experience higher unemployment rates as they are more frequently separated from jobs (Figure 2 and 3, p.26). He finds the weak labor

[18] The average wage level was 2,565 thousand won per month, and the 'reservation' wage was 2669 thousand won for men. (Oh et al. 2012, Table 2-17, p.64.)

[19] In GOMS data for the class of 2007 graduates, worker mobility from small to medium firms to large companies was very limited. Just 6.6% of those who were employed at small to medium firms right after graduation land in large companies after 20 months, while 6.2% of those who did not find a job immediately after graduation got hired at large companies.

[20] In a Ministry of Labor (2009)'s report, the wage is called the students' 'hoped' wage level. (pp.32-44)

demand and the youth's precarious labor market status as the major cause for high youth unemployment.

IV. Wage Effects of Mismatches

Consequences of skill mismatches are more often discussed in terms of their effects on wages and not on employment. Skill surplus means that the skills are not fully utilized, and the concern is on wasted skills. To see whether skills are properly utilized and compensated, wage effects are measured. Over-education is frequently used interchangeably with skill surplus. But technically over-education means that acquired years of schooling is beyond the required level for the job. As skill requirements are set by occupations, skill mismatch is operationally occupational mismatch. How well skill levels can be measure by years of schooling is in fact dubious.[21] (Halaby, 1994; Hanushek 2015) But since Becker's Human Capital Theory, years of schooling is taken as a standard measure for skill levels.

Incidence of skill surplus is measured in three alternative ways: from job analysis (JA), from worker self-assessment (WA), or from realized matches (RA).[22] In job analysis a required level for a job is determined by a professional job analyst. If a worker's acquired years of schooling is beyond this level, the match is considered as a skill surplus match. Hartog (2000, Table 1, p.134) applied this method and reported that over-education in the Netherlands grew from 14% in 1971 to 24% in 1995. Duncan and Hoffman (1981) applied this method to the 1976 PSID data and estimated incidence of over-education as 42%. The reason for such a high incidence rate for the U.S. is that the U.S. labor market had a much higher share of jobs that require virtually no schooling (0-5 years of schooling) than the Netherlands. The share was 21.9% in 1976 compared with just 3.8% in the Netherlands in 1982. (Hartog and Oosterbeek, 1988, p.192) The share of over-education is high in the U.S. at the laborer jobs and the difference in distribution of jobs explains the difference in over-education incidence. In the Korean literature, Oh

[21] Halaby notes that the connections between nominal overeducation and the concept of 'skill mismatch' are so weak and inconsistent as to cast doubt on the validity of this popular conceptualization. (Halaby, 1994, p.48)

[22] See Hartog (2000) p.132 for detailed explanations on the methods.

(2005) estimated the share as 18.8% among college graduates and Park and Ban (2007) claimed 24.0% of them are over-educated at their jobs in the early 2000s as surveyed in Section 2. When worker self-assessment is used Oh (2005) reports that 21% of college graduates and 19% of junior college graduates said that they are over-skilled at their jobs.

However, it is very hard to determine whether Korea is more or less over-educated from the numbers since measurement errors are large (Leuven and Oosterbeek 2011). Since job analyst's assessment on required level of skills is based on the distribution of workers at the occupation on the assessment point, the shorter the time lag between job assessment and measurement of over-education, the less the estimated size of over-education tends to be. The reason that the size of over-education is estimated smaller in Korea than in the U.S. or Europe is because in both Oh (2005) and Park and Ban (2007) the time lag is very short. In both studies, the job assessment has been made just two years earlier than estimation of over-education incidence. According to Leuven and Oosterbeek's survey, the mean of published over-education incidence ratio estimates is 30% and that of under-education is 26% (Table 1, p.16). And the estimates do not show any trend across decades.

In the realized matches (RA) method, required education is derived from workers. Hence if the share of college graduates increase incidence of over-education at jobs naturally increase.[23] Hecker (1992) categorized 'high school type jobs' as those one-digit occupations for which employers did not traditionally required a college degree, and demonstrated that the proportion of college and post-college graduates in 'high school type jobs' in the U.S. rose from 10.0% in 1970 to 17.9% in 1990.[24] Verdugo and Verdugo (1998) used the same method and estimated the share of over-education among white males as 11%. A similar estimation result is obtained if the method is applied to the Korean data sets. I choose the Wage Survey of Ministry of Employment and Labor data for years 2002 and 2008 for which occupational classifications are consistent. For each two- or one-digit occupation, the mean and variance of actual years of schooling of

[23] See the graph in in Kim (2008), Figure 2-4, p.17.

[24] Specifically, occupations within retail sales; administrative support; service; precision production, craft, and repair; operator, fabricator, and laborer; and farm jobs, except those noted above. (Hecker, 1992, p.4)

workers calculated from the 2002 data set.[25] From the 2008 data set, workers with years of schooling above (or below) 0.25 standard deviation away from the mean are classified as over-educated (or under-educated). The overall incidence of over-education obtained in this way is 21.6%, and under-education, 10.1%. The choice of one-quarter of standard deviation as the borderline between over- and proper education is purely arbitrary. Verdugo and Verdugo (1989) used one standard deviation, and if this number is applied I obtain an estimate of approximately 8% for incidence of over-education.

As such, the size of the incidence of over-education is not so meaningful in a practical sense. It depends upon how job requirements are assessed, how workers evaluate their own jobs, and it involve a lot of measurement errors. Hence, evaluation of wage impacts of over-education is more useful practically.

The wage impact of over-education can be embed in a set of existing wage determination theory. In the competition theory of Thurow (1975), the marginal productivity is taken as a fixed characteristic of a job, independent of a worker. Earnings are related to jobs rather than to the worker in this theory, and education just raises a worker's chance to get a high wage job. This yields a log wage as a function of the required years of schooling for the job, r. That is, wages are:

$$\ln w = \beta_0 + \beta_1 r \tag{1}$$

On the other hand, the human capital theory of Becker (1964) is fundamentally a supply side theory and claims that a workers' human capital determines his marginal productivity. Human capital is a function of a worker's attained years of schooling, s.

$$\ln w = \alpha_0 + \alpha_1 s \tag{2}$$

The job allocation theory of Tinbergen (1956) viewed wages as instrumental in allocating the society's skill endowments to skill demands. Log wages are not only a function of jobs characteristics (r) but also a function of a worker's skills (s).

$$ln\, w = \gamma_0 + \gamma_1 r + \gamma_2 s^0 + \gamma_3 s^u \tag{3}$$

where $s^0 = s - r$, if $s > r$, and $= 0$, otherwise

$s^1 = r - s$, if $s < r$, and $= 0$, otherwise

[25] The Wage Survey data sets contain up to three digit classification codes for clerks, craft, assemblers and operators, and laborers, and two digit codes for other occupations.

The equation (3) embeds equation (1) and (2) as special cases. In equation (3), $s^0 = 0$ if the match is proper. By comparing the return to r, which is the return to education in a proper match and s^0, which is the amount of over-education, we can estimate the wage impact of over-education. Table 1 is the estimation result by Duncan and Hoffman (1976) along with the results for the Netherlands given in Hartog and Osterbeek (1988). The sample is the 1976 PSID while male age 18-64 for Duncan and Hoffman (1976) and Hartog and Osterbeek (1988) used a corresponding sample for the Netherlands according to their exposition.[26] Variables used along with years of education are experience and its square, city size, and a dummy for residence in South. In both studies, over-education is determined by job assessment method. For Korea, I used a realized match method using the 2002 and 2008 wage data. The sample is men with age 18 to 64 and regression is run with age and age squared variables.

TABLE 1. COMPARISON OF INCIDENCE AND WAGE EFFECTS OF OVER-EDUCATION: US, NETHERLANDS AND KOREA

	Incidence (%)			**Wage Effects**		
	US (1976)	Netherlands (1982)	Korea (2008)	US (1976)	Netherlands (1982)	Korea (2008)
Proper match $(r = s)$	46.1	62.2	69.6	.063	.071	.136
Over-education $(r < s)$	42.0	16.0	21.7	.029	.057	.049
Under-education $(r > s)$	11.9	21.8	10.1	-.042	-.025	-.053

Notes: US and Netherlands are from Hartog and Oosterbeek (1988), Table 5, p.192.

Korea is among young men with age between 30 and 34 and figures are from Choi (2014).

The estimation results are very comparable. Korea in 2008 shows much steeper returns to years of schooling, but in all cases an over-educated worker gains significantly from additional years of schooling. A college graduate at a high school job typically earns 20 percent (=0.49 x 4 years) higher than a high school graduate at the job. If he were at a college job, he would have received 35 percent (= (0.139-0.049) x 4 years) higher. College education yields a large return, even if the worker cannot find a college job.

[26] Specifically the NPAO-Mobility Survey. For data description, see footnote 8, page 193 in Hartog and Oosterbeek (1988).

If a worker is matched with an over-educated job, his wage is less than from a properly matched job, but his actually loss is likely to be smaller than the estimates because he may be less qualified. Pryor and Schaffer (1997) show that when supplementary measures other than years of schooling are used and worker skills are properly accounted for, the actual size of mismatch is smaller than what appears in the data. They claim that it is primarily those university students lacking university-level literacy skills who are taking the high school jobs (p.3). As the workers have chosen their jobs knowing their own skill qualities, actual mismatches form them may not be very large. Oh (2005) reports a similar finding. He matched each observation in the GOMS data with the average College Scholastic Ability Test (CSAT) score, which is Korea's SAT, of the class. He found that low test scores are associated with high probability of over-education incidence in both college and junior college samples. (Table 5 and 6, pp.21-22). As test scores are positively correlated with wages, inclusion of the CSAT scores reduces the estimated size of wage loss in an over-education match.

V. Mismatch and the Length of the First Job Search Spell

In this section, I use the Youth Supplementary Survey data compiled by the Statistics Korea since 2002 to see if evidences support the view that mismatches have contributed to the fall of young men's employment rate. The hypothesis subject to test is that i) mismatches are associated with longer search periods prior to the matches, and ii) as mismatches become more frequent, the youth employment rate fell.

The Statistics Korea began compiling the Youth Supplementary Survey as a part of its monthly EAPS (Economically Active Population Survey) since 2002 as youth unemployment became serious after the crisis of 1997. In May interview for the EAPS each year, the Statistics Korea asks an extended list of questions to a young respondent with age under 30. The supplementary survey asks a young respondent whether he or she has finished or permanently quitted the final stage of education. If the answer is a 'yes,' the survey asks the date and whether the respondent has ever worked since, and the starting date of the first job. Hence the survey records the beginning and ending date of the first job search spells, and I analyze these spell.

An employment rate is an indicator of the static distribution of activity status in a labor market and not directly related to the distribution of job search spells. But without assuming a positive relationship between the lengths of the first job search spells and the aggregate employment rate, no testable relationship between mismatches and employment rates can be obtained from the data set. The advantage of using the Youth Supplementary Survey is that a full series of youth labor markets between 2002 and 2014 can be analyzed if these data sets are used. Oh (2005) found no statistically significant relationship between mismatches and the first job search spells in a single cross section of the 2005 GOMS data. But the study cannot address the time-series trend of employment rate drop because a single cross-section is analyzed. Whether mismatches are related to lower employment rates can only be addressed when a multiple of cross sections are analyzed.

Table 3 is the distribution of men in age 25-29 by their job experience. Column (1) is the share of those who are still in education. They may be going to school or temporarily out of school, but all of them answered they have not completed their education yet. The

share rose steadily until 2010 and then largely flattened out.[27] The shares of 'never had a job' in column (2) consistently increased. They are the proportions of those who finished education but never had a job experience after graduation until the survey date. Column (3) is the share of those who finished education and have a job experience. Column (1) to (3) are exclusive grouping by the person's job market experience. The share of those who experience jobs after completion of education in this age group fell because the share of in education (column 1) and the share of no job experience after education (column 3) grew. The share of job experience group is not equal to the employment because some of those in school are employed and not all of the job experience group are currently employed. To see an exact relationship with the trend of employment rate fall in column (5), we need to know how much of those 'in school' and 'job experience' are currently employed, and Table A1 in Appendix shows this. Approximately, half of those 'in school' are currently employed and 90 percent of the 'job experience' group are employed. The ratios have been stable throughout the period.

< Table 3 here>

Between 2003 and 2014, the employment rate of this age group fell by 7.8% points from 77.1 to 69.3 percent. In the meantime the share of 'in school' grew by 8.6 % points.[28] But the effect of this growth in lowering the employment rate is just 3.1% points because the employment rate is 50% within the 'in school' group and 80% among those not 'in school.' In other words, if the employment rates within the 'in school' and out the group remained unchanged from the 2003 level, the growth of the size of the 'in school' group lowered the employment rate by 3.1% points. The remaining 4.7% point drop is made by the increase of the 'never had a job' group. Its share rose by 4.6% points and lowered the employment rate as much. The employment rate of the 'job experience' group dropped by 1.3% points from 88.2% to 86.9%. And the group lowered the

[27] The high ratio in 2010 seems to be an outlier. In education statistics, high school graduates' advancement rate to tertiary education peaked in 2008 at 84 percent and declined since.

[28] I take the period from 2003 to 2014 for analysis because there has been a major revision of questionnaires in 2003. For example, the starting date of the first job is not included. The survey month was June in 2002 and May from 2003.

employment rate by just 0.2% points. Thus the largest contribution to the employment rate drop is made by the growth of 'never had a job' group, followed by the growth of 'in school' group.

The 'never had a job' group are consisted of graduates who have not found jobs until the survey date. Hence, their job search spells are incomplete and generally longer than those of job experience group. The median is 15 months, which means that a median person out of school in February did not find a job until May in the next year, while the median among complete spells are 3 months. The interval distribution change little throughout the period from 2003 to 2014.

The structure of search spells has changed little in the period. As the median of completed search spells of those who have job experience is 3 months and the share of 'never had a job' grew, the average search spells of those who finished education have increased.

Both quintiles and cumulative distributions are used to describe spell distribution, but I use cumulative distribution in Table 4 to characterize distribution of completed spells because there are many non-positive spells in the 'job experience' group. If the first job began in the same month as the gradation, the spell length is zero month and if it began before, the length is negative. Column one shows this share slightly declined. At other interval points such as six or twelve months from graduation, the proportions varied very across years.

A. Job Search Spells by Education

This subsection reviews the distribution of job search spells, before investigating the relationship between mismatches and job search durations in the following subsection. The spells of the 'job experience' group are consisted of predominantly short spells. Those spells that end in self-employment jobs are excluded in this review, because the spells are very short and the shares decreased. They are less than 5 percent of total spells. Among the completed spell, 25 to 30 percent have zero or negative durations, which

means that the workers are hired before or in the same month as graduation.[29] The regular recruiting in Korea is from October to December for the next year's graduates and it is common for companies to hire their new recruits before graduation ceremonies and begin training. This share has modestly decreased from over 30% in 2004, 2005, and 2007 to under 25% recently in 2014, 2010, and 2011. Corresponding to this decrease, the proportion of very short spells increased and shares at other interval points largely remained unchanged (Table A2 in Appendix). The positions of the median and the third quintile remained at near 3 and 15 months throughout the period (Table 4). Even within educational groups, just the median of high school graduates' spells jumped in 2009, and no major shift is observed in other groups in Table 4.30 The 'never had a job' between 25 and 29 is a very small group among high school educated men and the shift can be viewed as coming from a small sample problem. Within the 'job experience' group, the distribution of the first job search spells largely did not change and contributed little to the employment rate drop.

<Table 4 here>

A major contribution to the employment rate drop is made by the growth of the share of 'never had a job' group. The share of 'never had a job' jumped from 4.0% in 2003 to 8.6% in 2014 (Column (4), Table 3). Table 5 shows the share of this status group by education along with the composition of graduates by education. The 'never had a job' group was just 11.1% of college graduates in 2003 but the share grew to 17.8% by 2014. Among high school graduates, the share jumped from 1.2% to 7.1%. Among those from junior colleges, the majority of which are vocational colleges, the share changed little.

< Table 5 here >

[29] In fact, there is some impreciseness in measuring the interval due to ambiguity in the survey question. If the person is employed at the date of graduation, the reported starting date is the first month of the job regardless of whether the job is a full-time job or part-time. When the person experienced multiple jobs after finishing education, the starting date of the first job is recorded, but it is not clear if the job is the first one after completion of education.

[30] The 3rd quintile of high school graduates' spells are exceptionally long and greater than 27 months. This is because the graduates carries out their military service duties for almost two years after graduation before working at companies.

It is sometimes argued that with the expansion of college education, low quality high school graduates have advanced to college education and relabeling of them as college graduates have lowered employment rates among college graduates. High school teachers say that those who advance to colleges are not necessarily the best students and that often better ones choose to advance to junior colleges than colleges. The Panel B of Table 5 shows composition of graduates by education. College graduates' share increased from 31% to 49%, while high school graduates share fell from 43% to 21%. It is true that the employment rate of college graduates fell while their share among all graduates increased during the 2000s. However, the employment rate did not rise among high school graduates as their share fell. On the contrary, the share of the 'never had a job' jumped recently. And among college graduates the rise of the share of the 'never had a job' group did not rise steadily as their share among graduates increase and the shares fluctuated. It peaked in 2009 and 2014, responding to demand conditions. Further the hazard rate estimates by education in the next section show that college graduates performed better in finding jobs than high school graduates. And their advantage did not weakened over time.

< Table 6 here. >

The time series trend of the 1st quintiles, medians, and the 3rd quintiles of the incomplete spells are shown in Table 6. Among all graduates, except for the year 2003, the observed spell distribution did not shift a lot.31 Recession years are 2003, 2009, 2013, and 2014. And the bad market conditions affected long-term unemployed at the tail disproportionately. If we compare with the completed spell distribution in Table 4, completed spell distribution is not affected by recession. The effects of recessions are conspicuous among long spells in Table 6. Those disadvantaged in the labor market, who experience long spells, are particularly susceptible to market condition deterioration at bad times. Thus, a trend of growing non-employment durations as the youth employment

[31] The search spells of high school graduates who have no job experience until age 25-29 are consisted of very long spells. In 2003, 11% in the 'never had a job' group are high school graduates where as their shares are 8% in 2004 and 6% in 2005. The high proportion of high school graduates made the Q3 in 2003 particularly high.

rates fall is not observed the distribution of completed spells and the distribution of incomplete spells need to be taken into account in a hazard analysis for youth employment rate drop.

B. Incidence of Mismatches and Completed Search Spells

The Youth Supplementary Survey records workers' self-assessment on the quality of the match. Specifically the assessment is a response to the question, 'How is your job considering your major at your final education?' The answer is recorded in four categories: 1. Bad, 2.Poor, 3.Fair, and 4.Good. The result is shown in Table 8. Since the question is asked to graduates who have a job experience, and its share in the age group has decreased, I report the distribution of answers as a ratio to total graduates in the age group in Table 8.[32]

Column (1) is the proportion of people who 'never had a job' and thus they have never been matched with a job. Column (2) is the proportion of people who answered that their matches with their jobs are bad. As the youth employment rates continued to fall, and mismatches are conceived as the cause, it might be guessed that the ratio has risen overtime. On the contrary, the share of bad matches have declined. Even when I add the shares of 'poor' matches to them, the shares of 'bad' and 'poor' matches have fallen. Supporters of the mismatch hypothesis may claim that the 'never had a job' group represents even worse matches than 'bad' matches since they did not even take job offers. But this claim is tautological. And the sum of the shares of the 'never had a job' and bad matches did not rise in the period. The sum is nearly constant from 2004 to 2012 at approximately 40% and rose a little in 2013 and 2014.

< Table 7 here >

< Table 8 here >

[32] The share of school graduates in the age group also has decreased over time (See Table 3). But the pace of its decline is modest compared with the decline in the share of the 'job experience' group.

By education, high school graduates tend to report bad or poor matches, and college graduates report fair and good matches. Junior college graduates are in between. Table 8 reports the distribution by intervals, for brevity. This pattern leads one to suspect that in fact respondents have reported how much they are satisfied at their jobs rather than how well fitted their skills are to the jobs.

To check for this possibility, in Table 9, I have regrouped the answers by occupations. The majority of high school graduates are assigned to production jobs at crafts and assembler/operator occupations. At these jobs, a job analyst would have judged the matches as proper. But the majority of them answered that their matches are 'bad.' At service and sales jobs and at elementary occupations, they were even unhappier. College graduates report 'good' matches at professional and semi-professional jobs and expresses dissatisfaction at service and sales jobs. The distribution makes us to cast doubt upon accuracy of the self-assessment. However, it is not likely that improved measurement may change the relationship. In the following, I show that self-assessed match qualities are not statistically significant as determinants of the length of search durations. Even when occupations are used instead, the relationship is not significant. As job analysis method and realized matches method uses occupations in determining quality of matches, insignificance of occupation variable means that the relationship with other definitions of mismatches is insignificant as well.

< Table 9 here >

Before moving on to the next step, let us try to answer the question 'Has a mismatch caused youth employment rate drop?' with the evidences collected so far. The main contributor to the young men's employment rate drop is the growth of the 'never had a job' group. Since match qualities are determined after the matches, the explanatory power of match qualities on employment rate drop has to be limited. Thus there is little chance the Youth Supplementary Survey which contains information on worker characteristics and match quality can enable us to identify causes of the employment rate drop. However, since the growth of long spells is the main reason for the employment

rate drop, a detailed analysis on long spells may lead us a better understanding of the youth employment problem.

C. Completed Spell Durations and Mismatches

In this subsection, I investigate if mismatches are associated with long spells. As match qualities are observed only for complete spell, I can only address their relationship with completed spells. However the Youth Supplementary Survey data set is large enough so that each year's sample has about 1,500 completed spells, which enables a meaningful statistical analysis.

Underlying the mismatch hypothesis is the presumption that a mismatched worker must have searched for a longer period than a properly matched worker as he must have been unsatisfied with initial job offers. If so, increased mismatches mean a longer average search period and an employment rate drop. Table 10, Panel A is the mean duration of complete search spells by education and match qualities. Both in the combined samples of 2003 to 2005 and 2012 to 2014, high school graduates have the longest duration of around 20 months and college graduates have the shortest duration of around 7 months. By match qualities bad matches are associated with longer completed spells in Columns (1) and (5). However, completed spells at bad matches are longer because there are more of the less educated at bad matches and they are more likely to report bad matches and not because poor matches involve longer search spells. By education groups, poor matches are associated with a little bit longer spells but the differences are very small and statistically insignificant. In Panel B are linear regression results when spell durations are run against match quality dummies with the 'bad' match as the reference point. Hence the coefficient estimates are sample mean differences as all variables are categorical. By education, just a few entries are statistically significant, and in 2012-14 combined sample, good matches have longer spells.

The mismatch hypothesis in fact claims that among the college graduates, mismatched ones, who are in service/sales or in production jobs, spend longer time as non-employed before they finally accept job offers. But in Panel B of Table 10, all estimates coefficients are statistically insignificant. A similar regression can be done with

occupation dummies in place of mismatch dummies. Again in all education sample, occupation dummies have statistically significant coefficient estimates. Specifically, professional /semi-professionals and clerks have statistically significant shorter durations when a regression is run with the craft/assemblers occupation as the reference. But this is because college graduates have shorter durations and are more likely in the occupations. By education, occupation dummies have statistically insignificant coefficients estimates except for a few. Since job analysis method and realized matches method use occupations in determining mismatches the result implies that even under other definitions, mismatches do not have statistically significant statistical relationship with search durations.

< Table 10 here>
< Table 11 here >

D. Propensity of Long Spells and Mismatches

From the regressions of mean durations against match qualities, I could not identify a statistically significant relationship in the previous subsection. The youth employment rate drop has been disproportionately contributed by the growth of the 'no job experience' group, which are consisted of long spells. As only the completed spells contains match quality information, in this subsection I investigate whether there is a relationship between long completed spells and mismatches.

The propensities of long spells are summarized in Table 12. Long spells are defined as the spells longer than 12, 24, and 36 months. In Panel D are the shares of the cells among all complete spells. The share of 'all education' is 0.94 and 0.90 and not equal to 1.0 since 'all education' does not include less than high school education and higher than college education group. Post-college education group has gained a significant share recently so that in 2012-14 the all education share fell to 0.90. The entries in Panel A, B, and C denote the probability that the duration is greater than the specified months. For example, in Panel A, 30.2% of all spells are longer than 12 months, and among high school graduates the probability is 38.2% et cetera. Similarly as in the mean regression, the propensity of long spells is higher among the less educated but within the education

group, the difference by match qualities are not very large. Table 13 shows the results of logit analysis on the propensities with match quality dummies as explanatory variables. Again as in the case of mean regression, estimated parameters are statistically insignificant and have wrong signs in some cases.

Table 14 and 15 are the propensities of long spell and share of each cell in the sample by occupation instead of match qualities. At all threshold months, when all education group is put together those who finally landed on elementary occupations have the highest probability to experience a long search spell. But this is because the lower educated group have higher probability and within an education group, the differences across occupations are small. If the mismatch hypothesis is right, as the college graduates who accept elementary or production jobs are most mismatched they have the highest risk of experiencing long search spells. But as Table 15 and the logit test results in Table 16 shows, the risk for them is not any higher than in other occupations in a statistically significant way.

VI. Hazard Model Estimates

Empirical evidences do not support the relationship between match qualities and search spell durations. However, a manpower planning version of the mismatch hypothesis fingers at the mismatch between the supply and demand of higher education as the cause, and not the match qualities. If the claim is right, the youth employment condition would have deteriorated among the college graduates and led to the overall employment rate drop. In order to see if the claim is supported by data, I estimate a hazard model for the hazard to find a job after graduation. As the contribution of incomplete spells is more important than the extension of completed spell duration in the youth employment rate drop, hazard model estimation need to be based upon open intervals as well as close ones.

To implement hazard model estimation, I construct three samples: Pooled samples consisted of observations in years from 2003 to 2005, from 2009 to 2011, and from 2012 to 2014. The reason that three samples are constructed instead of two is that the last period can be viewed as a deviation from the trends as the proportion of 'never had a job' jumped in 2013. In the sample for hazard model estimation, post-college graduates and high school dropouts are eliminated to keep homogeneity across years. The reported first job dates earlier than 12 months prior to graduation dates are dropped as the respondents may have misunderstood the first job date as the first work experience date. Each sample is consisted of around 5,000 observations. The numbers of completed and incomplete spells in the samples by education is as follows:

< Table 17 here >

A. Non-parametric Estimation

Kaplan-Meier nonparametric estimates show that later period survivor functions are located above earlier ones, confirming the trend of extending first job search durations. The differences are statistically significant in a log-rank test. By education groups, survivor functions of higher education groups are above those for lower education groups. The differences are statistically significant between the three education groups in all three period except between junior college and college education groups in the period 2012-

2014. The gap between the two education groups have been narrowing and by this period the statistical significance disappeared. Between high school and junior college or college groups, no such tendency is recognized. Within education groups and across time, nonparametrically estimated hazard functions show a rising trend.

The survivor functions have moved upwards in all education groups across time, and not just among college graduates. Thus, increasing share of college graduates is not the major reason for a growing share of young man still in the searching stage. In fact, survivor functions of higher education group stayed above those for the less education throughout the period. As college graduates increase the boundary between them and junior college graduates became blurred and by 2012-14 the difference disappeared.

However, when incomplete spells or open intervals are not taken into account, not all of these trends are confirmed. The upward shifts of survivor functions between 2003-05 and 2009-11 and between 2009-11 and 2012-14 are not statistically significant among completed spells in a log-rank test, although the shift between 2003-05 and 2012-14 is statistically significantly different. By education groups, upward shifts are confirmed between sub-intervals except for the rise between 2009-11 and 2012-14 among junior college graduates, and the gaps between junior college and college graduates are statistically significant in all periods. When open intervals are ignored in hazard model estimation, much information is lost especially on the behaviors of recent graduates and of college graduates, because the share of 'never had a job' group increased among them. (See Table 3 and 5)

B. Parametric Hazard Model Estimates

Parametric forms of hazard models allow us to characterize the shifts across time and gaps between education groups in a much simpler way. I use a Weibull distribution proportional hazard model, which nests exponential distribution as a special case. The parametric hazard model is as follows:

$$h(t) = \lambda p t^{p-1}, \qquad \lambda = \exp(x'\beta) \tag{4}$$

The p parameter is the shape parameter that determines the direction of duration dependence. When p is equal to one, the model is an exponential distribution model and the hazard is constant. When $p > 1$, the hazard rises with duration and when $p < 1$, it becomes a falling hazard model which implies the negative duration dependence. Typically unemployment spells have a negative duration. As for covariates x, only the age variable is continuous, and others are all categorical, for which education and time dummies are used. Hence, the baseline hazard shifter, λ is as follows:

$$\lambda = \exp(x'\beta) = \exp(\beta_0 + \beta_1 AGE + \beta_2 EDU_1 + \cdots + \beta_4 TIME_1 + \cdots) \qquad (5)$$

Estimation is done by a maximum likelihood method using the STATA statistical package. The results by period and by education groups are shown in Table x. In all equations, the shape parameter p is estimated around 0.75, which means that the hazard function is $h(t) = -0.75\,\lambda\, t^{-0.25}$. Written in a log form, log hazard is $\ln h(t) = \ln(-0.75\,\lambda) - 0.25 \ln t$ and the hazard function has a negative duration. That is, the longer the search period, the lower is the job seeker's probability to find a job and exit the status. Compared to a person who have been in search for 6 months, the chances of exit for a person after 12 months' duration is 16% lower ($\left(\frac{12}{6}\right)^{-0.25} = 0.84$).

In Table x, the estimates are presented in hazard ratios, which is equal to $\exp(\beta)$. Thus, estimates less than one means that the hazard declines as the value of the covariate increases. For example, in the period 2003 to 2005 the hazard ratio estimate for the 'AGE' variable is 0.98 which means that one year older person have a 2% lower chance of exiting from the search status. To see this, if the hazard function is $h(t) = \lambda p t^{p-1}$ where $\lambda = \exp(\beta_0 + \beta_1 * age)$, the relative hazard of a person with age *A+1* at time t compared to a person of age *A* at *t* is given as $h(A+1, t)/h(A, t) = \exp(\beta_1)$. Thus, with one unit increase of the covariate variable, the relative change of the hazard is equal to the hazard ratio, $\exp(\beta)$.

The estimation result in Table 18 shows that a high school graduate has a 30 to 40% lower chance of exiting from the search stage compared to a junior college graduate.

And a college graduate had a 10% higher chances of exit but this premium almost disappeared later, although the difference is statistically significant in a parametric model.

By education groups, the hazard fell in all education groups. (Table 18, Panel B.) Compared with the period 2003-05, the market deteriorated most for high school graduates and their changes to find a job and exit from a search status fell by 10 to 14%. The market for college graduates worsened almost as much. And junior college graduates suffered least and their chances fell by 2.3 to 4.5% in 2009-11 and 2012-14 compared with the period 2003-05.[33] But among them, college graduates still have an advantage in finding jobs.

When incomplete spells are omitted, estimates are less consistent. In Panel A, college dummy hazard ratio with junior college graduates as reference group, is estimated as 1.02 in 2009-11 but rises to 1.26 in 2012-14. And in Panel B, high school and college graduates' hazards drop approximately 10% and 5%, respectively, in the late 2000s compared with the period 2003-05, but junior college graduates' hazards rose by 2%.

Cox proportional hazard semiparametric estimation produces almost identical estimates and the results are not presented here.

VII. Summary and Conclusion

The popular mismatch hypothesis, that is the claim that over-education has in effect widened the gap between young workers' job aspiration and reality and resulted in youth employment rate drop is based upon casual observations of the youth labor market situation where there exist too many idle college graduates while labor shortages are found among small and medium sized firms and at medium to low waged jobs. However, this view is not supported by empirical evidences.

A college graduate at a high school job receives 20 percent higher wage than a high school graduate at a high school job, although if he could find a college job he would have been able to get 35 percent higher wage. Thus, even though college education did

[33] The differences between 2009-11 and 2012-14 are statistically significant in all education groups.

not offer him a college job, college education has been remunerative for him and he has reason to receive college education. As the share of college graduates among the youth are high, it can be guessed that the incidence of mismatches is high in Korea. But high incidences of mismatches are found in other countries as well. Further the timing does not coincide. The share of college graduates stopped increasing in the mid-2000s, on the other hand young men's employment continued to fall throughout the 2000s and even accelerated recently.

In the Youth Supplementary Survey datasets, a relationship between match qualities and job search spells is not found, regardless of whether match qualities are determined by self-assessment or by occupations. Reported mismatches are more frequent among the less educated which is again not consistent with the mismatch hypothesis, according to which mismatches should increase among college graduates. Even when a different measure is used, that is the propensity for long search spells instead of lengths of search spells, a relationship is still not confirmed. By education group, the highly educated do have an advantage in finding jobs than the less educated. That is the exit probability from the searching status is higher for the more educated. Compared to the early 2000s the exit probability fell for all education groups, which reflects the deteriorating labor market situation for them. The deterioration progressed quicker for college graduates and their advantage over junior college graduates significantly depreciated although the gap is still statistically significant.

The analytical results show that the popular 'mismatch' hypothesis is standing on very weak evidences. In other words, the supply side explanation on the youth employment rate drop is not really supported by empirical evidences. In retrospect, the mass unemployment argument of Malinvaud or the structural unemployment diagnosis sought the answers on the demand side for youth labor and not on the supply side. As in the case of Euroscelosis, the empirical results indicate that the reason may lie on the demand for young and newly educated labor. This issue will be address in a sequel to this paper.

TABLES AND FIGURES

TABLE 1. EMPLOYMENT RATES OF YOUNG MEN: 1980~2012

	Men 25 to 29				Men 30 to 34			
	1980	1990	2000	2012	1980	1990	2000	2012
France	90.2*	87.4	83.4	80.0	93.8*	91.5	88.4	85.3
Germany	84.7	79.7	81.1	80.9	94.2	88.2	89.3	88.8
Italy	87.2	79.4	69.4	64.7	95.7*	91.8	86.3	79.4
Japan	94.3	94.2	90.3	87.0	95.9	98.5	93.7	91.3
Korea	88.3	87.4	78.2	70.4	93.0	95.1	91.2	89.0
U.K.	83.4†	89.0	87.6	84.0	86.4†	89.8	89.7	88.0
U.S.	86.8	88.1	88.9	80.5	91.0	89.7	91.5	84.0

Note: * in 1983, † in 1984
Source: OECD data base (http://stats.oecd.org), extracted 22 Jan 2014.

TABLE 2. YOUNG MEN'S ECONOMIC ACTIVITY STATUS: 1995~2012

Men 25 to 29

	1995	2000	2005	2010	2013
Employment	86.6	78.1	74.8	70.0	69.3
Unemployment	3.3	5.8	6.0	6.7	6.8
Education/Training	6.8	9.8	10.7	12.1	11.9
NEET	3.3	6.3	8.5	11.3	12.0

Men 30 to 34

	1995	2000	2005	2010	2013
Employment	95.6	91.4	90.0	87.6	88.6
Unemployment	1.7	4.2	3.5	4.4	3.8
Education/Training	0.4	0.6	1.2	1.5	0.8
NEET	2.3	3.8	5.3	6.4	6.8

Notes: Urban areas. Employment / Training corresponds to activity category 6. 'in school' in 1995~2002 data sets; category 6. 'in formal education', 7. 'in exam coaching institutes,' 8. 'in job training institutions' between 2003~04; and category 7. 'in formal education', 8. 'in exam coaching institutes,' 9. 'in job training institutions' between 2005~13 data sets.

Source: Author's calculation from the Statistics Korea, the Economically Active Population Survey (EAPS) micro data sets.

TABLE 3. DISTRIBUTION OF JOB EXPERIENCE AFTER FINAL STAGE EDUCATION AMONG MEN 25-29: 2002~2014

Men 25-29	*In school*	*Never had a job (A)*	*Job experience (B)*	*A/(A+B) %*	*Employment rate, (%*
2002	20.0	4.2	75.9	5.2	77.9
2003	18.9	4.0	77.1	4.9	77.1
2004	19.1	4.3	76.6	5.3	76.2
2005	23.3	4.5	72.2	5.9	75.5
2006	25.5	5.4	69.1	7.3	73.3
2007	26.4	5.6	68.0	7.6	71.5
2008	25.5	5.9	68.6	7.9	70.8
2009	25.7	6.6	67.7	8.9	72.2
2010	29.4	5.3	65.3	7.6	72.1
2011	26.3	6.0	67.7	8.1	71.9
2012	25.4	5.9	68.8	7.9	71.1
2013	26.3	7.4	66.3	10.0	70.5
2014	27.6	8.6	63.8	11.9	69.3

*Note: * in June in 2002 and in May in other years*

Source: author's calculation from the Statistics Korea, the EAPS Youth Supplementary Survey micro data sets.

TABLE 4. DISTRIBUTION OF COMPLETED SEARCH SPELLS BY EDUCATION

	All grads			*High school grads*			*Jr college grads*			*college grads*		
year	Q1	Med	Q3	Q1	Med	Q3	Q1	Med	Q3	Q1	Med	Q3
2003	0	3	17	1	3	37	0	3	15	0	1	11
2004	0	2	14	1	3	33	0	2	13	0	1	9
2005	0	2	13	1	4	28	0	2	12	0	1	6
2006	0	3	17	1	7	41	0	2	13	0	1	8
2007	0	2	14	1	4	37	0	2	13	0	1	8
2008	0	3	15	2	7	41	0	2	12	0	2	9
2009	1	3	16	1	11	41	0	3	15	0	2	10
2010	1	3	14	1	8	37	0	2	13	0	2	8
2011	1	3	13	1	6	42	1	3	11	0	2	9
2012	0	3	12	1	4	35	0	3	9	0	2	9
2013	0	3	13	1	4	27	1	3	14	0	1	10
2014	1	3	14	1	4	43	1	3	14	0	2	10

Note: In the 'job experience' group

TABLE 5. SHARES OF 'NEVER HAD A JOB' AND COMPOSITION OF GRADUATES BY EDUCATION

	A. shares of 'never had a job' by education			*B. Distribution of education among all graduates*		
	High School	Junior College	College	High School	Junior College	College
2003	1.2	3.6	11.1	42.8	21.9	31.1
2004	1.1	2.7	11.6	38.9	25.8	31.9
2005	1.0	3.4	12.3	36.0	25.7	35.1
2006	0.4	3.5	15.4	34.1	27.0	35.4
2007	1.6	2.3	16.9	30.7	31.2	35.1
2008	1.9	4.0	15.4	28.5	30.4	38.2
2009	2.7	3.8	17.3	26.6	31.3	39.4
2010	1.4	4.0	14.3	26.9	30.5	40.4
2011	1.2	2.5	15.8	22.5	30.1	44.4
2012	2.1	4.3	13.3	23.4	30.3	43.9
2013	5.6	4.7	15.5	20.6	29.7	46.2
2014	7.1	3.5	17.8	21.0	27.0	49.4

TABLE 6. DISTRIBUTION OF INCOMPLETE SPELLS BY EDUCATION

	All education			*High school grads*			*Jr col grads*			*college grads*		
year	Q1	Med	Q3	Q1	Med	Q3	Q1	Med	Q3	Q1	Med	Q3
2003	3	15	51	87	87	111	3	15	39	3	9	33
2004	3	3	27	87	99	123	15	27	51	3	3	15
2005	3	9	27	87	111	123	3	9	15	3	3	15
2006	3	15	27	87	111	123	3	15	39	3	3	27
2007	3	15	27	87	99	99	9	27	39	3	3	15
2008	3	15	27	99	111	111	3	27	51	3	15	27
2009	3	15	33	75	111	135	15	27	75	3	3	27
2010	3	15	27	75	87	99	9	27	63	3	15	27
2011	3	9	27	75	99	99	3	21	39	3	3	15
2012	3	15	27	63	94	94	15	27	51	3	3	15
2013	3	15	39	75	87	106	15	39	63	3	15	17
2014	3	15	39	99	99	117	3	15	51	3	15	27

Note: In the 'never had a job' group

TABLE 7. DISTRIBUTION OF SELF-ASSESSED MATCH QUALITY

	never had a job	Bad	poor	fair	Good
2003	5.1	39.4	15.8	24.3	15.4
2004	5.5	36.3	16.7	25.3	16.2
2005	6.1	35.6	17.6	24.8	15.8
2006	7.5	33.1	15.5	28.4	15.5
2007	7.9	31.5	15.3	27.3	18.1
2008	8.1	33.1	15.3	24.4	19.1
2009	9.1	32.4	13.9	26.7	17.9
2010	7.9	33.0	12.1	26.3	20.8
2011	8.4	31.1	13.7	27.0	19.8
2012	8.2	32.0	15.3	24.1	20.4
2013	10.3	33.2	12.8	21.0	22.7
2014	12.3	29.7	14.0	21.2	22.8

Note: Among those with 'job experience,' self-employment first job are excluded.

TABLE 8. DISTRIBUTION OF SELF-ASSESSED MATCH QUALITY BY EDUCATION

High school	*No job*	*bad*	*poor*	*fair*	*good*
2003-07	1.1	50.0	20.9	21.8	6.1
2008-12	2.0	48.1	20.8	24.2	5.0
2013-14	6.6	49.6	18.8	17.8	7.3
Junior College	*No job*	*bad*	*poor*	*fair*	*good*
2003-07	3.2	33.9	16.1	29.9	16.9
2008-12	3.8	35.5	14.0	26.8	19.8
2013-14	4.9	38.7	12.7	19.7	24.0
College	*No job*	*bad*	*poor*	*fair*	*good*
2003-07	13.9	20.8	12.5	27.5	25.2
2008-12	15.7	20.0	10.8	25.8	27.7
2013-14	17.2	20.7	11.5	22.9	27.8

TABLE 9. DISTRIBUTION OF MATCH QUALITY BY EDUCATION AND OCCUPATIONS

	2003-2005					*2012-2014*				
	High School Grads									
	bad	Poor	Fair	Good	%occ	bad	poor	Fair	good	%occ
professional/semi	54.2	18.9	23.1	3.8	9.4	37.5	15.2	29.7	17.6	3.7
clerks	39.8	21.7	29.8	8.7	8.1	48.9	24.2	17.5	9.5	8.9
service/ sales	64.0	20.9	10.5	4.7	20.0	56.0	21.0	18.7	4.2	27.4
crafts/operators	45.8	19.4	25.1	9.7	52.4	44.0	19.9	24.9	11.1	44.7
elementary	62.4	21.0	14.0	2.5	10.1	64.6	17.4	13.7	4.3	15.3
	Junior College Grads									
professional/semi	19.2	11.9	35.9	32.9	27.5	20.1	7.5	25.1	47.3	23.4
Clerks	30.4	21.8	34.4	13.5	22.9	30.5	20.8	31.8	17.0	15.8
service / sales	48.2	16.1	23.8	11.9	16.5	38.9	18.5	26.2	16.4	20.0
crafts/operators	35.1	16.8	31.9	16.1	28.2	37.1	16.4	23.9	22.6	32.9
elementary	70.5	20.2	9.2	0.0	4.9	78.6	11.3	8.1	2.0	7.9
	College Grads									
professional/semi	11.2	15.8	28.7	44.4	46.9	14.6	7.5	25.7	52.1	42.5
Clerks	22.2	18.2	40.8	18.8	35.4	19.3	17.7	35.1	27.9	34.6
service / sales	53.3	16.9	14.2	15.5	8.6	38.9	25.1	21.2	14.8	11.5
crafts/operators	37.5	17.4	32.4	12.7	7.5	40.0	16.4	30.8	12.8	8.8
elementary	93.6	4.3	2.2	0.0	1.7	63.1	12.3	6.7	17.9	2.6

TABLE 10. REGRESSION OF MEAN DURATIONS OF COMPLETED SPELLS AGAINST MATCH QUALITIES

	2003-2005				2012-2014			
	All Educ	By education			*All Educ*	By education		
		HS	Jr Coll	College		*HS*	*Jr Coll*	*College*
A. Sample Means								
HS	19.8	-	-	-	20.6	-	-	-
Jr Coll	9.6	-	-	-	10.0	-	-	-
College	6.6	-	-	-	7.3	-	-	-
Bad	15.4	20.0	11.2	7.2	12.7	19.5	11.1	7.3
Poor	13.9	20.1	8.5	6.8	12.6	23.4	9.3	7.3
Fair	11.5	19.4	8.6	6.5	10.6	17.5	10.7	7.7
Good	8.7	16.2	9.2	6.0	9.0	29.3	8.0	7.1
B. Linear regression estimates								
Poor	3.9***	0.6	2.6***	0.7	2.1**	2.1	0.3	-0.3
Fair	2.4***	1.4	-1.0	0.3	1.9*	5.9*	-1.4	-0.4
Good	-2.8***	-3.2	0.5	-0.6	-1.6*	11.8***	-2.8**	-0.6

TABLE 11. REGRESSION OF MEAN DURATIONS OF COMPLETED SPELLS AGAINST OCCUPATIONS

	2003-2005				2012-2014			
	All Educ	By education			*All Educ*	By education		
		HS	Jr Coll	College		*HS*	*Jr Coll*	*College*
A. Means								
professional/semi	9.9	26.9	9.3	5.7	8.3	18.2	8.6	7.8
clerks	10.0	21.7	8.4	7.4	8.4	19.2	9.4	6.7
service/ sales	13.8	17.0	11.1	8.3	14.5	24.0	10.6	8.2
crafts/operators	16.0	19.5	8.2	7.2	14.8	20.7	11.7	8.6
elementary	17.7	21.7	9.3	6.3	12.4	19.0	8.2	2.9
B. Linear regression estimates								
professional/semi	-6.1***	7.5	1.0	-1.5	-6.6***	-2.5	-3.2**	-0.9
Clerks	-6.0***	2.2	0.2	0.1	-6.5***	-1.4	-2.4	-1.9
service / sales	-2.2***	-2.4	-2.9**	1.1	-0.3	3.3	-1.1	-0.4
elementary	1.7	2.2	2.2	-0.9	-2.4	-1.7	-3.6*	-5.7**

TABLE 12. PROPENSITY OF LONG SPELLS BY MATCH QUALITY AND EDUCATION

	2003-2005					2012-2014				
	A. PROPENSITY OF SPELLS >= 12									
	Bad	poor	fair	Good	all	Bad	poor	fair	good	all
All edu	34.2	31.6	28.2	22.6	30.2	31.7	27.9	26.3	23.6	27.8
HS	37.5	40.5	40.8	27.6	38.2	41.8	38.0	35.7	55.0	40.9
Jr C	33.8	24.8	25.4	29.5	28.9	28.7	30.0	28.1	23.9	27.5
College	22.4	22.5	19.9	19.4	20.8	21.4	19.7	22.4	20.9	21.2
	B. PROPENSITY OF SPELLS >= 24									
	Bad	poor	fair	Good	all	Bad	poor	fair	good	all
All edu	23.0	21.7	16.8	12.1	19.3	20.2	16.6	15.8	13.2	16.9
HS	28.8	32.3	29.8	21.7	29.2	32.5	31.1	28.8	41.0	32.4
Jr C	18.1	13.4	13.8	13.7	15.2	17.8	13.3	17.1	10.5	15.1
College	9.6	10.5	8.0	9.4	9.2	9.7	9.0	9.6	11.8	10.3
	C. PROPENSITY OF SPELLS >= 36									
	Bad	poor	fair	Good	all	Bad	poor	fair	good	all
All edu	17.8	15.5	11.1	6.6	13.8	16.9	15.6	12.3	7.3	13.7
HS	24.4	26.7	24.5	20.7	24.7	26.3	28.5	27.1	32.2	27.3
Jr C	11.8	6.4	6.4	6.8	8.3	9.8	5.2	10.0	6.8	8.6
College	4.7	3.9	3.7	2.5	3.6	4.3	3.3	3.2	3.4	3.6
	D. SHARES IN THE SAMPLE									
	Bad	poor	fair	good	all	Bad	poor	fair	good	all
All edu	0.36	0.17	0.24	0.15	0.94	0.31	0.14	0.21	0.21	0.90
HS	0.20	0.08	0.08	0.03	0.39	0.11	0.04	0.04	0.02	0.21
Jr C	0.08	0.04	0.07	0.04	0.24	0.10	0.04	0.07	0.07	0.28
College	0.07	0.05	0.09	0.08	0.29	0.10	0.06	0.10	0.13	0.39

TABLE 13. LOGIT MODEL ESTIMATES OF PROPENSITY OF LONG SPELLS

2003-05	*t=12*			*t=24*			*t=36*		
T=12	*HS*	*Jr coll*	*College*	*HS*	*Jr coll*	*College*	*HS*	*Jr coll*	*College*
bad	-	.40**	-	-	-	-	-	-	-
poor	-	-	-	-	-	-	-	-	-
good	-.58**	-	-	-.42*	-	-	.76**	-1.2***	-
2012-14	*t=12*			*t=24*			*t=36*		
T=12	*HS*	*Jr coll*	*College*	*HS*	*Jr coll*	*College*	*HS*	*Jr coll*	*College*
bad	-	-	-	-	-	-	-	.72**	-
poor	-	-	-	-	-	-	-	-	-
good	.71**	-	-	-	-.50*	-	-	-	-

TABLE 12. PROPENSITY OF LONG SPELLS BY MATCH QUALITY AND EDUCATION

	2003-2005					2012-2014				
	A. PROPENSITY OF SPELLS >= 12									
	Bad	poor	fair	Good	all	Bad	poor	fair	good	all
All edu	34.2	31.6	28.2	22.6	30.2	31.7	27.9	26.3	23.6	27.8
HS	37.5	40.5	40.8	27.6	38.2	41.8	38.0	35.7	55.0	40.9
Jr C	33.8	24.8	25.4	29.5	28.9	28.7	30.0	28.1	23.9	27.5
College	22.4	22.5	19.9	19.4	20.8	21.4	19.7	22.4	20.9	21.2
	B. PROPENSITY OF SPELLS >= 24									
	Bad	poor	fair	Good	all	Bad	poor	fair	good	all
All edu	23.0	21.7	16.8	12.1	19.3	20.2	16.6	15.8	13.2	16.9
HS	28.8	32.3	29.8	21.7	29.2	32.5	31.1	28.8	41.0	32.4
Jr C	18.1	13.4	13.8	13.7	15.2	17.8	13.3	17.1	10.5	15.1
College	9.6	10.5	8.0	9.4	9.2	9.7	9.0	9.6	11.8	10.3
	C. PROPENSITY OF SPELLS >= 36									
	Bad	poor	fair	Good	all	Bad	poor	fair	good	all
All edu	17.8	15.5	11.1	6.6	13.8	16.9	15.6	12.3	7.3	13.7
HS	24.4	26.7	24.5	20.7	24.7	26.3	28.5	27.1	32.2	27.3
Jr C	11.8	6.4	6.4	6.8	8.3	9.8	5.2	10.0	6.8	8.6
College	4.7	3.9	3.7	2.5	3.6	4.3	3.3	3.2	3.4	3.6
	D. SHARES IN THE SAMPLE									
	Bad	poor	fair	good	all	Bad	poor	fair	good	all
All edu	0.36	0.17	0.24	0.15	0.94	0.31	0.14	0.21	0.21	0.90
HS	0.20	0.08	0.08	0.03	0.39	0.11	0.04	0.04	0.02	0.21
Jr C	0.08	0.04	0.07	0.04	0.24	0.10	0.04	0.07	0.07	0.28
College	0.07	0.05	0.09	0.08	0.29	0.10	0.06	0.10	0.13	0.39

TABLE 13. LOGIT MODEL ESTIMATES OF PROPENSITY OF LONG SPELLS

2003-05	*t=12*			*t=24*			*t=36*		
T=12	*HS*	*Jr coll*	*College*	*HS*	*Jr coll*	*College*	*HS*	*Jr coll*	*College*
bad	-	.40**	-	-	-	-	-	-	-
poor	-	-	-	-	-	-	-	-	-
good	-.58**	-	-	-.42*	-	-	.76**	-1.2***	-
2012-14	*t=12*			*t=24*			*t=36*		
T=12	*HS*	*Jr coll*	*College*	*HS*	*Jr coll*	*College*	*HS*	*Jr coll*	*College*
bad	-	-	-	-	-	-	-	.72**	-
poor	-	-	-	-	-	-	-	-	-
good	.71**	-	-	-	-.50*	-	-	-	-

TABLE 17. SAMPLE STATISTICS FOR HAZARD MODEL ESTIMATION

	2003-05			*2009-11*			*2012-14*		
	closed	open	All	closed	open	All	closed	open	All
HS	2,674	33	2,707	1,662	18	1,680	1,109	33	1,142
Jr Coll.	1,415	57	1,472	1,373	63	1,436	956	48	1,004
Coll	1,662	284	1,946	1,557	336	1,893	1306	297	1,603
Total	5,751	374	6,125	4,592	417	5,009	3,371	378	3,749

TABLE 18. PARAMETRIC HAZARD MODEL COEFFICIENT ESTIMATES

PANEL A. BY PERIODS

	2003-05	*2009-11*	*2012-14*
AGE	0.982	0.989	0.996
HS DUM	0.698	0.627	0.622
COL DUM	1.114	1.016	1.012
CONS	0.315	0.226	0.190
P	0.712	0.759	0.736

PANEL B. BY EDUCATION

	HS	*JR*	*COL*
age	1.021	0.976	0.953
Dyear09-11	0.898	0.977	0.884
Dyear12-14	0.863	0.955	0.863
cons	0.082	0.329	0.719
P	0.701	0.759	0.758

Note: all coefficients are statistically significant at 1% level.

APPENDIX

TABLE A1. COMPOSITION OF EMPLOYMENT AND NON-EMPLOYMENT BY JOB EXPERIENCE

year	In school		never a job	Job experience		Employment rate
	Employed (A)	non-employment	non-employment	Employed (B)	non-employment	(=A+B)
2003	9.1	9.8	4.0	68.0	9.1	77.1
2004	9.2	9.9	4.3	67.0	9.6	76.2
2005	12.5	10.8	4.5	63.0	9.1	75.5
2006	13.1	12.4	5.4	60.2	8.9	73.3
2007	12.9	13.5	5.6	58.5	9.5	71.5
2008	12.3	13.2	5.9	58.5	10.1	70.8
2009	13.4	12.3	6.6	58.8	8.9	72.2
2010	14.6	14.7	5.3	57.4	7.9	72.1
2011	12.7	13.6	6.0	59.2	8.6	71.9
2012	11.9	13.5	5.9	59.2	9.5	71.1
2013	12.1	14.2	7.4	58.3	8.0	70.5
2014	13.9	13.7	8.6	55.4	8.4	69.3

TABLE A2. DISTRIBUTION OF DURATION OF COMPLETED JOB SEARCH SPELLS

Duration	*<= 0*	*< 6*	*< 12*	*< 24*	*< 36*	*36+*
2003	25.8	59.2	66.5	78.2	84.3	100.0
2004	30.3	61.6	70.1	81.7	86.8	100.0
2005	32.6	64.3	72.8	82.2	87.6	100.0
2006	28.3	58.7	68.4	78.9	84.2	100.0
2007	30.7	62.1	70.7	81.6	87.2	100.0
2008	25.3	59.6	69.2	80.0	86.5	100.0
2009	24.7	57.8	67.6	80.2	86.4	100.0
2010	24.5	58.6	70.3	82.1	88.4	100.0
2011	23.8	60.7	71.6	83.0	88.4	100.0
2012	27.4	64.2	74.1	84.9	90.3	100.0
2013	26.5	60.3	71.4	83.0	88.8	100.0
2014	23.7	60.7	71.0	81.5	87.6	100.0

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