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Market Access Approach to Urban Growth†

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This paper studies urban growth in Korean cities. First, I document that population growth patterns change over time and that the current population distribution supports random urban growth. I confirm two empirical laws—Zipf's law and Gibrat's law—both of which hold in the period of 1995-2015, but do not hold in the earlier period of 1975-1995. Second, I find a systematic employment growth pattern of Korean cities in spite of the random population growth. I examine market access effects on employment growth. Market access, a geographical advantage, has a significant influence on urban employment growth. The market access effect is higher in the Seoul metropolitan area than in the rest of the country. This effect is stronger on employment growth in the manufacturing industry compared to employment growth in the service industry. These results are robust with various checks (e.g., different definitions of urban areas). The results here suggest that policymakers should consider geographical characteristics when they make policy decisions with respect to regional development.

Key Word: Urban Growth, Market Access, Agglomeration Economies,
City Size Distributions
JEL Code: R11, R12, J21

I. Introduction

This study aims to analyze urban population and employment growth.[1] among the indicators of regional development. Population dispersion is a direct goal of balanced regional development, but the distribution of a population cannot be changed rapidly in the short term. Therefore, I investigate how cities have grown over the long run by analyzing changes in population distribution and growth. I document that the population patterns of Korean cities follow well-known empirical laws, implying that

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[1] As is typical in urban studies literature, urban growth refers to population or employment growth in this paper. Specifically, it refers to population growth in Chapter 2 and employment growth in the following chapters.

the historical evidence supports *random* urban growth. Although the urban growth patterns appear to be random, I find that the historical data show a *systematic* urban growth pattern with the concept of market access, a geographical advantage. With this, I argue that employment in cities with high market access has increased more rapidly than that in cities with low market access, as population and employment have changed for economic as well as geographical reasons.

Regional development policies in Korea have been implemented along with economic development policies. In order to advance, the industrial structure focused on light industry in the early stages of economic development, with heavy and chemical industries fostered in the southeastern region of the country. The government also provided various benefits to companies willing to move industrial infrastructure concentrated in the Seoul metropolitan area (SMA) to areas the outside of the SMA. These policies for regional development, dispersing industrial facilities and populations across the country, aim to lessen economic disparities across regions. The policy stance for resolving regional imbalances has become more prominent since the 2000s, and regional policies, such as the relocation of public organizations, have been implemented to achieve more balanced regional development.

For balanced regional development, many reports have made comparisons between the SMA and non-SMA regions. Figure 1 shows the population trends in the SMA, referring specifically to Seoul, Incheon, and Gyeonggi-Do, against non-SMAs. The graph shows that the population of SMA continues to increase, currently accounting for more than 50% of the total population of Korea as of the end of 2019. However, there is little research on the agglomeration in regional development, which drives the growth of regions and so the disparities across regions. The agglomeration effects of concentrated urban areas arise not only in Seoul but also in

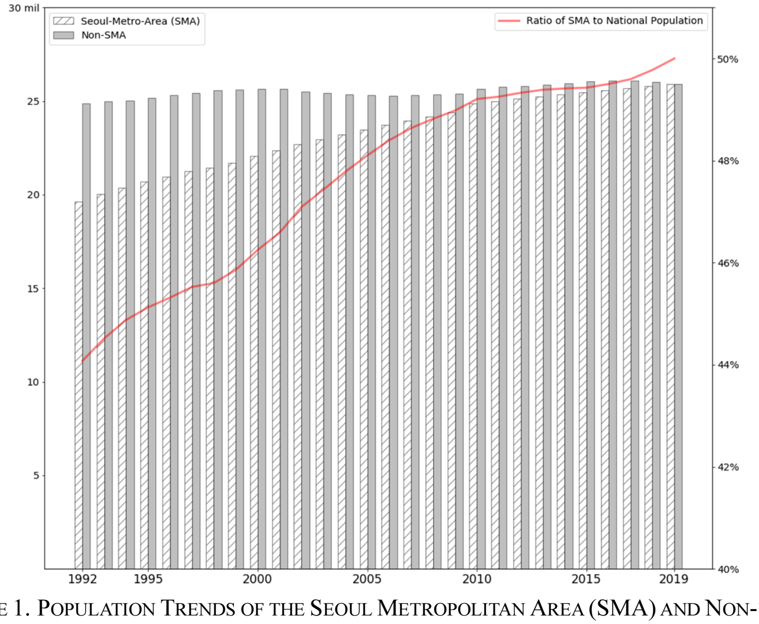

FIGURE 1. POPULATION TRENDS OF THE SEOUL METROPOLITAN AREA (SMA) AND NON-SMA

Source: Statistics of Residence Registration Population (1992~2019); Ministry of the Interior and Safety.

other large cities. In regional hub cities other than Seoul, however, the agglomeration effects appear to be reaching its limit.

Figure 2 shows the population trends of Korea's metropolitan cities, in this case Seoul and six Gwangyeok-Si (metropolitan cities). All metropolitan cities except Incheon show decreases in terms of the population of registered residents. Busan experiences a population decline in all years except 1995 and 2010. In 1992, when data began to be collected, there were more than 3.8 million people in Busan, but in 2019, its population had declined to less than 3.5 million, showing nearly a 10% decline during that span. The population of Daegu, Korea's third largest city in 1992, stagnated as it fell to the fourth largest city, behind Incheon, in 1999. Gwangju, the hub city of Jeollanam-Do, has been a smaller city than Daejeon since the late 1990s, showing a decline to less than 1.5 million. Daejeon had increased steadily, surpassing 1.5 million in 2010, but declined more recently, recording about 1.5 million inhabitants as of the end of 2019. Of the six metropolitan cities, Incheon alone sent positive news that it has recently exceeded 3 million. If the current trend remains, Incheon will become Korea's second largest city in the next few decades.

The decreasing trend in the populations of local hub cities has more important implications than a population comparison between the SMA and non-SMAs. Population is the main cause of the agglomeration effect of consumption and is closely related to employment, which is the main source of the production of agglomeration. It would be very beneficial for metropolitan areas to maximize the agglomeration effect by exchanging positive interactions within regions. The populations of local metropolitan cities are, however, decreasing, and they are less likely to show their potentials in aggregation. This means that preventing the decline

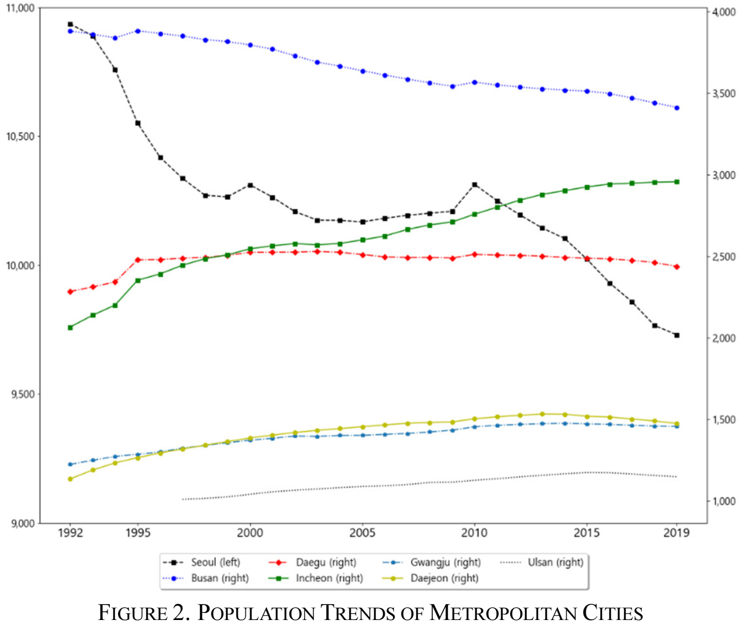

FIGURE 2. POPULATION TRENDS OF METROPOLITAN CITIES

Note: Seoul (dashed line with black dots) is on the left axis and the other cities are on the right axis. Ulsan (small dashed line) was promoted to Gwangyeok-Si status in 1997.

Source: Statistics of Residence Registration Population (1992~2019); Ministry of the Interior and Safety.

of local hub cities could be one of the most important starting points for balanced regional development, which is one of the government's main tasks. As shown in the following empirical analysis, if the populations of local hub cities continue to decrease, their agglomeration effects on the surrounding area will also lessen, which will in turn hamper regional development. It is necessary to promote the development of regional hub cities so as to disseminate the agglomeration effects to the surrounding areas.

To that end, we will examine the distributions of populations across cities and how these distributions have changed over time. Population size distributions and growth are known to follow Zipf's law and Gibrat's law. With historical population data, I will confirm these empirical laws. In addition, the effect of the population distribution on the growth of cities will be investigated through an empirical analysis. Changes in population distributions due to population growth or migration will affect economic activities in urban areas, and this effect will depend on several geographical factors. Among these, the concept of 'market access' is introduced, quantified and reflected in the empirical model. Based on this model, data from Korean cities in five-year periods will be constructed as panel data and analyzed more rigorously through a fixed-effect model.

Market access is an advantage of economic geography, first introduced in the field of international trade. However, some factors related to international trade, such as tariffs, do not apply between regions within a country. Therefore, market access is more simply applied to the movement of people and goods within a country. As discussed in more detail later, market access is associated with the size of the local market and the distances across regions. In other words, if there is a large local market nearby, the region has high market access. Assuming that the regional market is proportional to the population, it can be said that the population distribution affects market access. When there is such a populous city or large market, the surrounding areas are likely to develop. The main purpose of this study is to estimate an accurate measure of the impacts of these large markets on their surrounding areas.

This study is organized as follows. In Chapter 2, I discuss in detail the population distribution and growth of cities in Korea. Chapter 3 introduces the concept of market access and presents a model of market access and employment growth to examine the relationship between them. Chapter 4 explains the data used with the model. Chapter 5 analyzes the effect of market access on urban growth and shows that the agglomeration effect of hub cities on the growth of neighboring regions is significant. Finally, Chapter 6 concludes the study.

II. City Size Distribution and Urban Growth

This chapter examines the population distributions of Korean cities. According to Zipf's law, which is an empirical rule about population distributions, I analyze the distributions of urban populations over time and discuss the implications of population distributions. Section A discusses the characteristics of population distributions in Korean cities using Zipf's law. Second, Section B shows the relationship between changes in Korea's population distributions and urban growth according to Gibrat's law. The theory on random urban growth supports these laws according to Gabaix and Ioannides (2004) and the references therein.

In order to check whether the empirical laws hold, I define the spatial scope of the cities using the Korean words 'Si' (city) and 'Gwangyeok-Si' (metropolitan city). This is distinguished from the normal definitions of cities. For the purpose of administration, 'Si' (city), 'Gun' (county), and 'Gu' (district) are mostly used. However, this normal classification is not appropriate for the empirical laws we discuss in this chapter. Appendix A describes in detail the definitions of urban areas and why I adopt these definitions.

A. *City Size Distribution and Zipf's law*

This section discusses the characteristics of the population distributions across Korean cities using Zipf's law (Zipf, 1949). This empirical law describes the relationship between population size and the rank of cities. Based on this law, I analyze how Korea's population is distributed across regions.

Figure 3 shows the distribution of population sizes of all cities in Korea over time. Using the Statistics Korea's Population Census, 85 cities are shown for every ten years from 1975 to 2015. After all cities are listed according to their population size, the ranks are plotted on the vertical axis and the population sizes are on the horizontal axis. Both are in log scale. Seoul is the most populous city, Busan is second and Incheon third. This graph illustrates Zipf's law, an empirical law which states that such a graph is linear and its slope is one. According to Gabaix and Ioannides (2004), the graphs of most countries are largely linear, but concave. That is, very large cities and small regions in fact fall short of this type of linear trend. This characteristic also

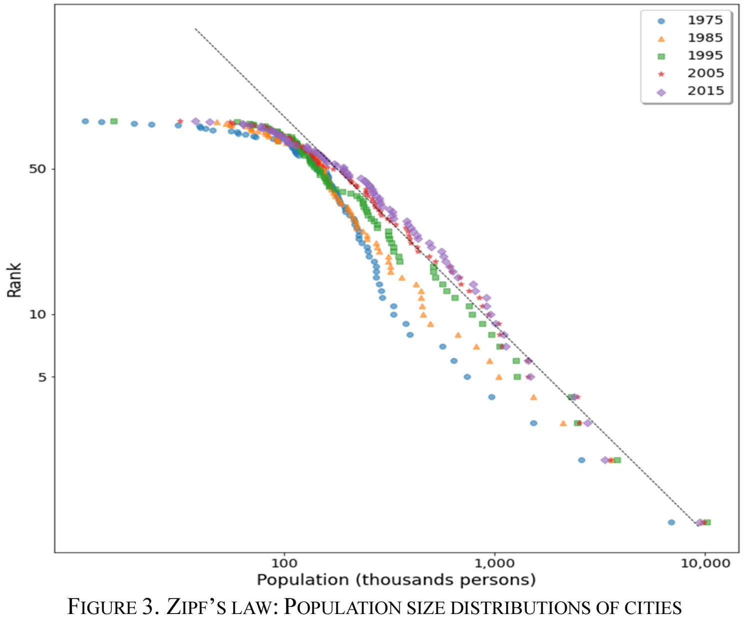

FIGURE 3. ZIPF'S LAW: POPULATION SIZE DISTRIBUTIONS OF CITIES

Note: Both axes are in log scale. The graph shows 85 cities and their ranks. The -45-degree line is also drawn.

Source: Population Census (1975~2015); Statistics Korea.

applies to Korea, where the population sizes of the second largest and the third largest cities are below the trend line. Additionally, some cities, from metropolitan cities such as the firth largest city to cities with populations of 100,000 or more, are located above the trend line.

Looking at the past population distributions through the lens of Zipf's law, we see different patterns. Since 1995, the population distribution has not changed much, appearing to follow a linear pattern, as predicted by Zipf's law. The distributions in 2005 and 2015 follow nearly the same line, with concave distributions toward the origin. Before 1995, however, the overall population distributions are shown to be out of alignment. In particular, the population distribution in 1975, as far back as the data stretches, is far from a linear line.

In conclusion, large cities showed increases in populations in the early stages of industrialization such that their population distributions deviated from a linear line. However, as medium cities have grown since the 1980s, linearity has arisen. I add a quantitative analysis of Zipf's law to the Appendix. In that analysis, the Zipf's coefficient estimates are approaching one as time goes by.

B. *Urban Growth and Gibrat's law*

This section discusses population distributions and urban growth in Korea. More specifically, I examine Gibrat's law on population growth as it applies to Korean cities. Gibrat's law was advocated by Gibrat (1931), which states that the population growth of cities is independent of their size. Technically, the expected value and variance of population growth rates in any region are independent of the size of the region, meaning that both large and small cities have the same expected growth rate. This is related to random growth because urban growth is unrelated to the size of the city. This is also linked to Zipf's law, as discussed earlier. As noted in Gabaix and Ioannides (2004), the populations of cities growing randomly follow a log-normal distribution. This log-normal distribution is not very different from a power distribution when excluding small cities and focusing on the right side. Accordingly, Zipf's law appears to hold if Gibrat's law holds. Eeckhout (2004) actually showed that US city sizes follow a lognormal distribution, and Rossi-Hansberg and Wright (2007) proved this with a theoretical model.

However, Gibrat's law, a theoretical prediction, is not always confirmed empirically. Emprical results vary by the definitions of regions. Eeckhout (2004) mentioned above examined the law with data based on the core-based statistical areas (CBSAs) of the United States, confirming that population growth in these regions is independent of their population sizes. Holmes and Lee (2010) compare population growth at all locations by dividing the United States into equally sized grids, revealing that the growth rate at all grids forms an inverted U as the population increases. Michaels *et al*. (2012) find a U shape with county-level data. As such, the growth rates of populations are likely to differ depending on the regional unit and time period.

In Korea, I find that the relationship between population size and the growth rates of the cities forms a U shape in the early time period of 1975-1995, whereas this becomes blurred in the later period of 1995-2015. Figure 4 shows the results for these two periods. The graph on the left represents the first 20 years from 1975 to

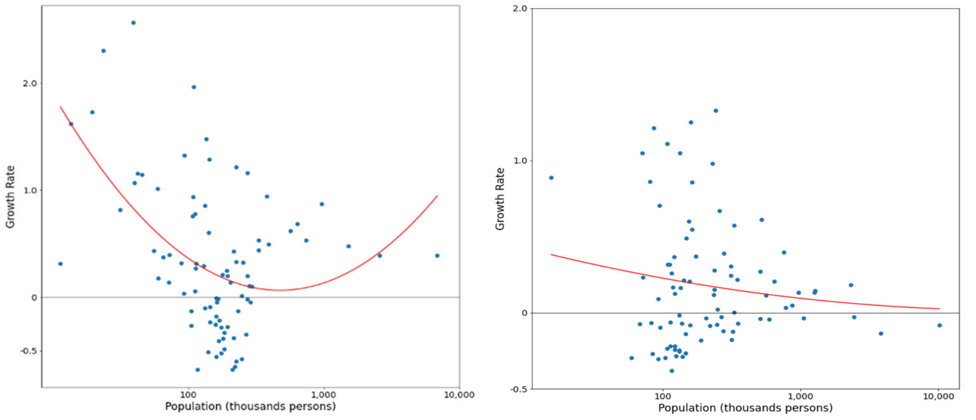

FIGURE 4. GIBRAT'S LAW: RELATIONSHIP BETWEEN POPULATION AND GROWTH RATE

Note: The x-axis denotes the population in the year 1975 for the graphs on the left, with that for 1995 on the right. They are in log scale. The y-axis is the annual growth rate over the 20-year period. The red lines are estimated in a parabola.

Source: Population Census (1975~2015); Statistics Korea.

1995, and that on the right is for the recent 20 years of 1995-2015. In these graphs, the horizontal axes indicate the population in log scale, and the vertical axes show the annual population growth rate for 20 years. If Gibrat's law holds and so urban populations grow independently of the population size, then the trend line would be horizontal with no slope. The graph on the left in Figure 4, however, shows a U-shaped pattern between 1975 and 1995. On the other hand, the trend tends to fade in the later period, suggesting that Gibrat's law holds. In the early period, the graph with the U shape implies that small and large cities showed greater increases in their populations between 1975 and 1995 compared to mid-size cities. Many medium-sized cities in fact underwent population decreases. However, there is no clear pattern between population size and population growth between 1995 and 2015. As a result, the population growth is independent of city size, which is consistent of what we have seen in the previous section. I add a quantitative analysis of Gibrat's law to the Appendix. In that statistical check, I confirm that the recent data support Gibrat's law.

III. Market Access and Urban Growth

In the previous chapter, I verify two empirical laws as well as random urban growth. In this chapter, I introduce market access to show a systematic urban growth pattern. Section A explains the concept of market access and quantifies market access as it pertains to Korean cities. Section B establishes an empirical model to clarify the relationship between market access and employment growth of Korean cities.

A. *Market Access*

In this section, we define market access, which plays an important role in the analysis. People and businesses choose locations with good accessibility in which to live or engage in economic activities. Workers demand to live in areas where many jobs are available or where good transportation allows them to commute. Firms want to produce goods and services in places with good accessibility, close to large markets and many consumers. According to Fujita and Krugman (1995) and Fujita *et al.* (1999), moreover, many companies locate in urban areas with large numbers of consumers to compete and provide more diverse products. Such accessible regions provide both consumers and producers with more opportunities, and they promote economic activities (Hanson and Xiang, 2004; Head and Ries, 2001).

The concept of accessibility was recently examined by Davis (2003) and Donaldson and Hornbeck (2016) in an effort to analyze the effects of US railroad connections on the agricultural development of the central region in the US. They also provide a theoretical background showing that market access in this case stems from the model devised by Eaton and Kortum (2002), which is well known in international trade. Market access is also used in Lin (2017) and in Blankespoor *et al*. (2018) in their analyses of transportation development effects. It is also widely applied in various studies.

Market access is expressed as follows:

$$MA_i = \sum_{r \neq i} L_r \tau_{ir}^{-\theta},$$

where MA_i denotes market access of a city i, L_r represents the consumers or population of the city r, and τ_{ir} denotes the transport cost between city i and city r. That is, the market access of a city is a function of the populations of other cities and the transport costs between them for all cities in the country. Therefore, if a large city is close to city i, the market access of city i, MA_i, will then be large. A large city has a strong influence on the market access of surrounding cities, and that influence decays with greater distances at the rate of θ.

Regarding the transport elasticity of parameter θ, I set it to 8.22 according to Donaldson and Hornbeck (2016). According to Head and Mayer (2014), who performed a meta-survey of estimations of various estimated coefficients in many studies, including that by Eaton and Kortum (2002), the average value of this coefficient estimates is 6.74. The median value is 5.03. This study sets θ to 8.22 and checks a range of values between 4 and 10. The results are robust and not sensitive to this parameter.

The market access outcomes for Korea's cities are calculated and displayed as a map in Figure 5. In this figure, I show all of the cities and counties in Korea except Jeju and Ulleung because market access in these islands is exceptionally low. Higher market access is indicated by a darker color. I also list the cities sorted by market access in Table 1. In this table, I sort the cities into SMA and non-SMA categories, as cities in the SMA have very high levels of market access. Also, Appendix C contains a list with more cities. Here, we examine the market access of non-SMA cities. The city with the highest value is Gyeryong near Daejeon. The second and the fourth cities are respectively Kimhae and Gyeongsan, adjacent to Busan. The fifth city is Gyeongsan, neighboring Daegu. The sixth is Naju, next to Gwangju.

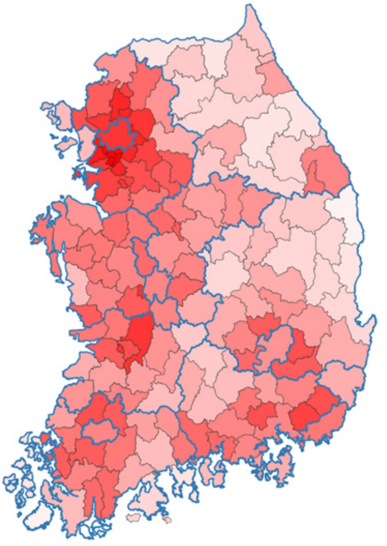

FIGURE 5. GEOGRAPHIC MAP OF MARKET ACCESS

Note: Market access levels in log scale are shaded in red. Darker red represents a higher value of market access, while lighter red areas have low market access. Jeju and Ulleung are excluded from this map because theirs are extremely low.

Source: Population Census (1975~2015); Statistics Korea.

TABLE 1— SI (CITIES) WITH THE HIGHEST MARKET ACCESS

Region	Si (Do)	Market Access	Population (rank)	Adjacent large city
Seoul Metropolitan Area (SMA)	Gunpo (Gyeonggi-Do)	0.1372	235,233 (33)	Seoul
	Uiwang (Gyeonggi-Do)	0.1287	108,788 (67)	Seoul
	Anyang (Gyeonggi-Do)	0.0878	591,106 (13)	Seoul
	Gwangmyeong (Gyeonggi-Do)	0.0571	350,914 (18)	Seoul
	Gwacheon (Gyeonggi-Do)	0.0544	68,077 (81)	Seoul
Non-SMA	Gyeryong (Chungcheongnam-Do)	0.0003285	15,495 (83)	Daejeon
	Kimhae (Gyeongsangnam-Do)	0.0000578	256,370 (28)	Busan
	Jeonju (Jeollanam-Do)	0.0000468	563,153 (14)	-
	Yangsan (Gyeongsangnam-Do)	0.0000352	163,351 (41)	Busan
	Gyeongsan (Gyeongsangbuk-Do)	0.0000255	173,746 (39)	Daegu

Source: Population Census (2015) and Census on Establishments (2015); Statistics Korea.

Note that these cities are all adjacent to a Gwangyeok-Si. Thus, I argue that metropolitan areas with many cities of many people show high market access. These are referred to as hub cities, which have much influence on the surrounding areas.

B. *Model*

This section provides a description of the model used here to illustrate the relationship between market access and urban growth. The model is simplified as much as possible to focus on the effects of market access on urban growth. The basic framework of the model stems from Glaeser *et al*. (1992), which examines the effects of industry specialization and competition on urban growth. The study by Glaeser *et al.* (1992) does not consider growth factors outside of cities. Thus, the present study attempts to expand an urban growth model to include outside factors, specifically market access, discussed in the previous section. In this model, urban growth means employment growth rather than population growth.

The environment of the model is as follows. It is assumed that a representative firm in a city produces the final goods. This representative company employs only labor to produce the goods. In addition to the input factor of labor, the total factor productivity (TFP) determines the output. I assume that the TFP[2] is affected by not only internal factors in the city, such as labor skills, but also by external factors outside of the city, i.e., market access. This means that geographical factors of a city have impacts on production in the city.

The formula is as follows. The representative firm in a city has the following production function:

$$Y = AF(L_i)$$

where L_i represents labor in city i. Consumption goods are produced using the labor force in the city. Labor is the only input factor, and A is the total factor productivity. TFP can be divided into local components A_i within the city and those components outside of the city, A_{-i}, as follows:

$$A = A_i \times A_{-i}.$$

We can convert this equation into a form of growth account, with the result being

$$\ln\left(\frac{A_{t+1}}{A_t}\right) = \ln\left(\frac{A_{i,t+1}}{A_{i,t}}\right) + \ln\left(\frac{A_{-i,t+1}}{A_{-i,t}}\right).$$

This study is distinguished from Glaeser *et al*. (1992) in that the growth rate of total factor productivity of the external factors is determined by urban geography. That is, productivity depends on where the city is located. It is also assumed that external productivity is determined by market access, which is defined as before.

Next, we express external TFP as a function of market access, as follows:

$$\ln\left(\frac{A_{-i,t+1}}{A_{-i,t}}\right) = \ln f(MA_{i,t}) = \ln MA_{i,t}^{\alpha}.$$

This equation states that the change in the external TFP over time is assumed to

[2]TFP includes any factor other than the input factors—labor in this model—that is considered as related to production technology. Therefore, all factors, including external factors—market access in this model—must not be problematic to be a part of TFP. For example, the TFP may be higher with higher market access because firms in a city with a high market access can benefit from high productivity compared to firms in nearby cities.

be a function of market access with constant elasticity. Geographical factors, represented by market access, are as important channels in production technology.

In this study, we consider situations in which demand shocks are caused by population growth and population migrations within a country. This type of shock has different effects across regions. Given a population distribution, aggregate demand shocks as a national factor spread and have different effects depending on the geographical locations of cities. Because geographic locations do not change due to the unique characteristics of cities, the population distributions of the surrounding areas are relative to the characteristics of the cities. It is assumed that higher market access, determined based on the population distribution and the location of a city, leads to a greater demand shock, affecting production in that city. This assumption is interpreted to mean, according to the theory of new economic geography (Krugman, 1980), that high demand of the surrounding area makes the city's production more efficient. This has been proved in studies such as Baum-Snow and Pavan (2013) and Combes *et al*. (2012) on city sorting as well as Baldwin and Okubo (2005) and Behrens, Duranton and Robert-Nicoud (2014) on firm sorting, demonstrating that companies with higher productivity are located in larger cities.

Next, local components, A_i, also play a role in urban productivity. To this end, A_i is assumed to be related to a city's population density, education level, industrial structure, and other related factors. Population density is a typical variable for urban agglomeration, and education levels have been found to have a significant impact on productivity. Therefore, the density of the population can confirm the effect of agglomeration on urban production, and the level of education is indicative of the quality of human resources.

As such, the representative firm in a city solves the following profit maximization problem based on the production function discussed above. The problem of maximizing the profits of representative firms in cities is expressed as follows:

$$\max_L \Pi_i = A_i F(L_i) - w_i L_i,$$

where w_i is the wage for labor in the city. To solve this problem, we obtain the following first-order condition (FOC):

$$A_i F'(L_i) = w_i.$$

In addition, it is assumed that the production function is in the Cobb-Douglas form. That is, we can replace the production function with $F(L_i) = L_i^{1-\beta}$ in the FOC. Next, taking the natural log on both sides in the FOC above and expressing it in terms of growth account gives us the following linear empirical equation:

$$\beta \ln\left(\frac{L_{i,t+1}}{L_{i,t}}\right) = \ln\left(\frac{A_{t+1}}{A_t}\right) - \ln\left(\frac{w_{i,t+1}}{w_{i,t}}\right).$$

This equation means that the rate of increase in employment in the city is proportional to the rate of increase in the TFP, which includes market access and local factors, and inversely proportional to the rate of increase in wages in the city. Moreover, we can replace TFP with the local and national factors previously assumed, and replace the national TFP with a function of market access. This results in the following equation:

$$\beta \ln\left(\frac{L_{i,t+1}}{L_{i,t}}\right) = \alpha \ln MA_{i,t} + g(X_{i,t}) - \ln\left(\frac{w_{i,t+1}}{w_{i,t}}\right).$$

where $g(X_{i,t}) = \ln(A_{i,t+1} / A_{i,t})$ is the rate of increase in the total factor productivity due to urban local factors. This will be replaced with the population density in the city, the level of education and the proportion of the service sector, which represents the industrial structure.

Finally, there may be an endogeneity problem in the wage term. Thus, we can replace the wage term with the initial level of wages, as was done with other terms. However, given that there is no available data on wages by cities, this is expressed here as a function of the education level and age according to the Mincer wage equation. According to Mincer (1974), the wage formula can be expressed as a function of years of education, and career years. In particular, the return of career years on wages is assumed to be a quadratic function of experience in the labor market:

$$\ln w = \ln w_0 + \rho School + \beta_1 x + \beta_2 x^2 + \varepsilon.$$

We then obtain the final equation for the empirical analysis. Because a balanced panel dataset is constructed, as will be discussed in the next section, a fixed-effect model will be adopted. As a result, how the employment growth rate is related to market access in cities is estimated with the following empirical model:

$$\ln\left(\frac{L_{i,t+1}}{L_{i,t}}\right) = \alpha_0 + \alpha_1 \ln MA_{i,t} + \alpha_3 School_{i,t} + \alpha_4 Age_{i,t} + \alpha_5 Age_{i,t}^2$$
$$+ \beta X_{i,t} + FE_i + FE_t + \varepsilon_{i,t}.$$

IV. Data

Based on the model discussed in the previous section, I analyze a panel dataset to estimate the effect of market access on employment growth in the city.

The dependent variable is the growth rate of employment. The total number of employees in urban areas comes from Enterprise Survey by the National Statistics' survey for business operations in the nation. I construct panel data from the survey on a five-year basis from 1995. The national Enterprise Survey has been conducted every year since 1994, but for the sake of consistency with the Census, only five-year data is used here. The Population Census in Korea is a survey also conducted on a five-year basis. I harness the Census to construct market access variables and the other variables. We also look at employment by industry. The total employment in the city can be divided into the manufacturing and service sectors to investigate different effects on the employment growth of each industry. Finally, the rate of change in the population will also be employed as a dependent variable to test the robustness of the model.

The explanatory variables include not only market access of all cities but also variables that influence urban growth among the factors within the cities. These factors control other factors that may affect dependent variables rather than market access. As such variables, population density, education level, and the service sector weight are selected. Since Ciccone and Hall (1996), who showed that there is a positive relationship between population density and productivity, population density has been a well-known variable used to estimate the urban aggregation effect. In general, the higher the population density is, the greater the agglomeration effect becomes.

Industrial structure is one of the main explanatory variables. I choose the share of the service industry as a variable by which to represent the industrial structure. The service share is the ratio of the number of employees engaged in the service sector to the total number of those employed in a city. Urban employment can largely consist of the manufacturing sector and the service industry. Because the manufacturing share is perfectly inversely related to the service share, the latter is used. This share will control for labor demand from the service sector. Wage is also an important explanatory variable. Because wage data is not available, wages are replaced by the Mincer equation, as discussed in the model specifications. In the Mincer wage model, education level and years of experience are the main variables, as derived from the Population Census. From this survey, I take the average of ages and education years the population between 15 and 65 years old to describe the labor force characteristics living in a city, after which these are inserted into the wage equation. The industry structure and the variables for wage are explanatory to isolate the effects of market access.

Furthermore, I conduct robustness checks in the Appendix with different samples of cities. There are 83 cities and 76 counties as of the end of 2018. For the first verification, the samples are classified into the Seoul metropolitan area (SMA) and non-SMAs. The SMA refers to 30 cities, including Seoul and Incheon and those in Gyeonggi-Do, and the non-SMAs consist of 53 cities outside of the SMA. We will observe the differences between these two samples. Second, the cities will be redefined as ‘Si (cities)’ as of 1995 given the endogeneity problem in the sample selection of the cities. There were 68 cities to analyze as of the end of 1995. Finally, the definitions of cities are expanded to all regions, including the 83 Si (cities) and 76 Gun (counties), totally 159 in Korea.

The time period in which to examine recent urban growth is 20 years, from 1995 to 2015. Because the main data source, the Population Census, is conducted in every five years, the data for the analysis is constructed into the format of the Census, using the five-year periods between 1995 and 2015. Basic statistics for the variables are shown in Table 2 without weights. The minimum population in 1995 is in Gyeryong-Si, at 15,495, and the maximum is the population of Seoul for every year, which declined from around 10 million in 1995 to 9.4 million in 2015. The minimum value of employment is also in Gyeryong-Si in 1995, and the maximum number of

TABLE 2— BASIC STATISTICS (UNWEIGHTED)

Variable	Year	Mean	Standard Deviation	Min	Max
Employment	1995	150,384	447,620	2,683	3,874,597
	2000	150,121	412,805	3,808	3,574,824
	2005	168,391	443,430	5,838	3,843,010
	2010	196,546	514,170	7,404	4,487,357
	2015	232,183	585,968	8,851	5,108,828
Employment growth	1995	1.46%	2.61%	-3.45%	11.12%
	2000	2.54%	2.73%	-1.67%	11.94%
	2005	3.24%	1.73%	-0.63%	8.84%
	2010	3.80%	2.68%	-1.02%	22.35%
	2015	-	-	-	-
Population	1995	481,125	1,222,665	15,495	10,231,217
	2000	502,626	1,189,460	27,122	9,895,217
	2005	521,356	1,180,106	31,699	9,820,171
	2010	538,827	1,177,133	41,528	9,794,304
	2015	535,372	1,136,265	37,690	9,394,807
Population density	1995	1,612	2,999	71	16,904
	2000	1,720	3,000	64	16,349
	2005	1,825	3,127	57	16,225
	2010	1,896	3,159	57	16,182
	2015	1,869	3,043	54	15,522
Market access	1995	0.0059	0.0238	0.0000	0.1372
	2000	0.0061	0.0246	0.0000	0.1383
	2005	0.0064	0.0260	0.0000	0.1506
	2010	0.0065	0.0261	0.0000	0.1490
	2015	0.0063	0.0253	0.0000	0.1437
Education years	1995	10.5	1.1	8.4	13.8
	2000	11.1	1.0	9.2	14.0
	2005	11.9	1.0	9.9	14.6
	2010	12.9	0.7	11.4	15.1
	2015	13.0	0.6	11.9	15.1
Age	1995	39.0	2.0	34.6	43.8
	2000	40.2	1.8	36.8	44.6
	2005	41.8	1.8	37.8	46.2
	2010	41.9	1.5	38.9	45.5
	2015	44.2	1.4	41.2	47.4
Service sector ratio	1995	65.6%	13.3%	33.1%	92.1%
	2000	70.4%	12.4%	40.4%	92.7%
	2005	71.0%	12.0%	41.8%	91.3%
	2010	70.1%	12.7%	39.6%	91.8%
	2015	70.2%	12.3%	42.6%	91.4%

Source: Population Census (1995-2015) and Census on Establishments (1995-2015); Statistics Korea.

employees is in Seoul for all years. In Seoul, employment has risen since 2000 unlike the population with the lowest being in 2000.

Although not shown in the table, the variables of population and employment are highly correlated. The correlation between the population and employment levels reaches 0.9803 over the entire period. In cities with many people, there is much employment. Additionally, the correlation coefficient of the changes in these variables between periods is 0.8304. As observed in relation to the growth rate of employment, there are many variations affecting urban population growth.

Market access in the table is reported in log scale. As explained early, this is calculated using the population and the distances between regions. Thus, the interpretation is ambiguous. We will revisit this issue in the results section. Education years and age are calculated as the averages of the populations in the regions with micro-data from the Population Census. Based on the age variable, the youngest city among the 83 cities is Ansan, Gyeonggi-Do, in 1995. The region with the highest educational level based on schooling years is Gwacheon in Gyeonggi-Do.

V. Results

This section discusses the results of the analysis based on the empirical model described in Chapter 3 with the data above. The main result is how market access affects urban employment growth. As discussed with the empirical model, employment growth, our dependent variable, is used for the analysis, with market access being one of the explanatory variables. The change in employment is the annual growth rate over five-year periods for 20 years from 1995 to 2015. It should be noted that market access is calculated in the starting year of a period, i.e., 1995 for the period from 1995 to 2000. That is, variations of market access at the beginning of the periods will lead to differences in the annual change rates of employment over the periods.

As mentioned above, I apply various samples for robustness checks. First, panel data on 83 cities constructed as the main definitions of cities are adopted. With these data, two models are compared: pooled OLS and a fixed-effect model with city effects. In these two models, the yearly time effects are also included so as to control for compounding factors which have an influence on employment in all regions. For example, macroeconomic variables such as GDP or the consumer price level are identical for all areas in each period.

The results of this empirical analysis are shown in detail in Table 3. In addition to the OLS and fixed-effect models, model types (1) and (2) are classified according to whether or not the mean age squared is included in the explanatory variables. Market access, the most interesting result, was found to increase employment growth in both the pooled OLS and fixed-effect models. In the two types of regressions, a 1% change in market access increases employment growth by 0.00219%p or 0.00227%p, which is significant at the level of 1%. In the fixed-effect model, the magnitude of this effect is much larger, reaching 0.0196%p, or as small as 0.0178%p. All of these outcomes are significant at the level of 1%. In other words, the effect of market access is largely predicted in the fixed-effect model. This confirms what was discussed earlier. Cities with higher market access tend to experience higher employment growth due to geographical advantages. Most of the cities with high market access are located around regional hub cities, confirming that the agglomeration effect from hub cities is significant.

Moreover, the F-statistics in Table 3 show that more attention should be paid to

TABLE 3— RELATIONSHIP BETWEEN EMPLOYMENT GROWTH AND MARKET ACCESS

Dependent Variable: △ln Employment	Pooled OLS		Fixed-effect model	
Explainable Variables	(1)	(2)	(1)	(2)
ln Market Access	0.00219***	0.00227***	0.0196***	0.0178***
	(0.000382)	(0.000385)	(0.00598)	(0.00565)
ln Population Density	-0.00983***	-0.0100***	-0.0595***	-0.0665***
	(0.00147)	(0.00146)	(0.0101)	(0.0115)
Education years	0.00708**	0.00665**	0.0163***	0.0200***
	(0.00313)	(0.00313)	(0.00523)	(0.00614)
Age	-0.00351***	0.0249**	0.00124	0.0369
	(0.00135)	(0.0110)	(0.00214)	(0.0248)
Age^2	-	-0.0354**	-	-0.0445
		(0.0137)		(0.0309)
Ratio of Service	0.00675	0.00511	0.117***	0.107***
	(0.0116)	(0.0116)	(0.0215)	(0.0227)
Cities	-0.0247***	-0.0232***	-0.00421	-0.00276
	(0.00803)	(0.00796)	(0.00689)	(0.00657)
Constant	0.172**	-0.390*	0.375***	-0.338
	(0.0723)	(0.223)	(0.115)	(0.504)
Year Fixed-effect	YES	YES	YES	YES
Citi Fixed-effect	NO	NO	YES	YES
F-statistics	-	-	177.51	183.65
R^2	0.601	0.605	0.722	0.726
# of Observations	332	332	332	332
# of Cites	83	83	83	83

Note: 1) The dependent variable is the average annual growth rate of employment over the 5-year period. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively, 2) The robust standard errors are in parentheses, and clustered by cities, 3) Among 85 cities, Jeju and Seoguipo are excluded.

Source: Population Census (1995~2015); Statistics Korea.

the results of the fixed-effect model. The fixed-effect models with city fixed-effect dummies control for unobservable and time-invariant factors in cities, thus reducing omitted variable bias. Any unobservable compounders that do not change over time are controlled by city fixed effects. These include time-invariant geographical conditions and environmental factors. The F-statistics of 177.51 and 183.65 reject the hypothesis that all city fixed-effect dummies are null, indicating that estimates of the pooled regression model are likely to be biased. Because the pooled OLS analysis does not reflect the unobservable individual characteristics of cities, these omitted factors cause bias. The fixed-effect model focuses on within-variation rather than between-variation factors, meaning that a 1% change in the market access of a specific city has an effect of approximately a 0.02%p change in the employment growth of that city. This does not stem from differences between cities but from the unobservable characteristics within a specific city.

Regarding the coefficients estimated, it is worth noting that the coefficient for population density is negative. As shown in the previous chapter, Gibrat's law is seen to hold in this period. That is, urban employment growth is independent of the city's population size without controlling for variables. If we assume that urban areas are unchanged, the population density is directly associated with the population size. Thus, estimates of the population density should be close to zero according to Gibrat's law. In Chapter 2, when no other variables were controlled, the corresponding estimates were statistically null in the period of 1995 to 2015. As shown in Table 3, however, the population density is inversely related to employment growth in cities. The denser the city is, the slower employment grows. Furthermore, because population density is used as a proxy variable for the agglomeration effect, it can be interpreted as meaning that the agglomeration effect in the city is generally negative. As the size of a city grows, so does the population density. This implies that large cities have less potential to create additional jobs. This is a phenomenon that usually occurs in cities where growth has slowed. This negative external effect is due to traffic congestion, rising house prices, or increasing levels of crime. The negative coefficient estimates suggests that negative externalities are stronger than positive agglomeration effects. Because this hampers urban growth, it is good to minimize these side effects for urban areas to continue to grow.

Next, we examine education effects. In both models, schooling years are positively correlated with employment growth. The level of education is used as a proxy variable for the total factor productivity of the region in the empirical model and as one of the factors of wages in the Mincer model. Therefore, the effects through these two channels can be estimated together. First, it is assumed that the higher the education level is, the higher the human capital of the urban workforce becomes, thus leading to higher productivity. Conversely, in cities with high wage levels, the demand for employment can be reduced, leading to a small increase in employment. As such, the relationship between education level and employment growth rate can be interpreted as a composite of these two channels. As a result, positive coefficient estimates show that the productivity effect is greater than the employment effect, implying that the positive externalities of high human resources in productivity are more important.

Robustness checks are also important. Accordingly, here we examine the likelihood that the results discussed above are dominated by a faction of the sample regions. In particular, metropolitan cities showed high market access in that they are close to Seoul, the largest city in Korea. Therefore, there is a marked difference in population and employment growth levels in this region as compared to the other regions. It is possible that the market access effect would be great in the Seoul metropolitan area.

However, the results in Table 4 tell us that this is not the case. The table shows the results of the fixed-effect model with two samples, the SMA and the non-SMAs. SMA here refers to Seoul, Incheon and 28 cities in Gyeonggi-Do, i.e., 30 cities in total. On the other hand, non-SMA regions consist of 53 cities in all regions outside of the SMA. In the analysis of only the SMA, coefficients are estimated to be 0.0261 ~ 0.0276 and the effect of market access in the non-SMA regions is approximately 0.017. This suggests that the effect of market access on employment growth is greater in the SMA than in the non-SMA cities.

The results also show limitations. Nearly half of Korea's population lives in the SMA, but there are only 30 cities in the Seoul metropolitan area. Moreover, most of the cities in the metropolitan area are quite large. Therefore, the growth of employment is likely to be somewhat limited. This can be seen by examining the

TABLE 4— RELATIONSHIP BETWEEN EMPLOYMENT GROWTH AND MARKET ACCESS BY REGION (SMA AND NON-SMA)

Dependent Variable: △ln Employment	Seoul Metropolitan Area (SMA)		Non-SMA	
Explainable Variables	(1)	(2)	(1)	(2)
ln Market Access	0.0261**	0.0276**	0.0169**	0.0170**
	(0.00995)	(0.0103)	(0.00705)	(0.00708)
ln Population Density	-0.0804***	-0.0792***	-0.0456***	-0.0450***
	(0.0149)	(0.0155)	(0.0114)	(0.0146)
Education years	0.0307**	0.0298**	0.00818	0.00810
	(0.0113)	(0.0121)	(0.00750)	(0.00775)
Age	0.00771**	-0.00587	-0.00462	-0.00644
	(0.00371)	(0.0494)	(0.00296)	(0.0245)
Age^2	-	0.0174	-	0.00229
		(0.0632)		(0.0323)
Ratio of Service	0.0963	0.0983	0.170***	0.171***
	(0.0647)	(0.0659)	(0.0431)	(0.0415)
Cities	-0.00643	-0.00677	0.000821	0.000744
	(0.00823)	(0.00824)	(0.0114)	(0.0114)
Constant	0.225	0.500	0.511**	0.544
	(0.191)	(1.018)	(0.211)	(0.478)
Fixed-effect	YES	YES	YES	YES
R^2	0.833	0.833	0.659	0.659
# of Observations	120	120	212	212
# of Cites	30	30	53	53

Note: 1) The dependent variable is the average annual growth rate of employment over the 5-year period. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively, 2) The robust standard errors are in parentheses, and clustered by cities, 3) Year fixed-effect and city fixed-effect are included.

Source: Population Census (1995~2015); Statistics Korea.

variable of population density. The estimate for this is about -0.08, indicating steeper negative elasticity than the estimate of about -0.045 for the non-SMA cities. The larger the population of the city is, that is, the denser the population density, the more stagnant the growth is. This may occur because larger cities are concentrated in the Seoul metropolitan area. This is likely to offset the effects of greater market access. However, the impact of market access may be greater in the SMA because it is overestimated to offset the negative density externalities. Despite this concern, the results show that market access has a positive effect on employment in both the SMA and in non-SMA regions.

Next, we look at the growth of employment by industry. This is important because the impact of market access may differ by industry. Table 5 shows the impact of market access by industry. Employment growth, which is the dependent variable, is calculated in one industry among the manufacturing or service industries. Manufacturing represents the trading sector, and service denotes the non-trade sector. Although the statistical significance is lower than in the previous results for all industries, the market access effect is greater in the manufacturing than in the service sector. In cities with high market access, employment increases more in manufacturing than in services. This result implies that over the past two decades,

TABLE 5— RELATIONSHIP BETWEEN EMPLOYMENT GROWTH AND MARKET ACCESS BY INDUSTRIES

Dependent Variable: △ln Employment	Manufacturing Sector		Service Sector	
Explainable Variables	(1)	(2)	(1)	(2)
ln Market Access	0.0295*	0.0349**	0.0175**	0.0146**
	(0.0156)	(0.0165)	(0.00772)	(0.00709)
ln Population Density	-0.0614***	-0.0479**	-0.0620***	-0.0759***
	(0.0183)	(0.0193)	(0.0152)	(0.0168)
Education years	0.0250**	0.0163	0.00815	0.0145*
	(0.0116)	(0.0108)	(0.00714)	(0.00775)
Age	-0.00140	-0.0772*	-0.000795	0.0656*
	(0.00445)	(0.0426)	(0.00241)	(0.0359)
Age^2	-	0.0948*	-	-0.0825*
		(0.0535)		(0.0441)
Ratio of Service	0.272***	0.287***	0.0102	-0.00903
	(0.0573)	(0.0562)	(0.0259)	(0.0235)
Cities	-0.00650	-0.00809	-0.00598	-0.00253
	(0.0101)	(0.0109)	(0.00798)	(0.00726)
Constant	0.370	1.921**	0.637***	-0.672
	(0.347)	(0.938)	(0.167)	(0.742)
Fixed-effect	YES	YES	YES	YES
R^2	0.407	0.412	0.437	0.453
# of Observations	332	332	332	332
# of Cites	83	83	83	83

Note: 1) The dependent variable is the average annual growth rate of employment over the 5-year period. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively, 2) The robust standard errors are in parentheses, and clustered by cities, 3) Year fixed-effect and city fixed-effect are included.

Source: Population Census (1995~2015); Statistics Korea.

large cities with large populations have more strength in services than in manufacturing, causing manufacturing facilities to move to nearby high market access cities. According to Glaeser and Gottlieb (2006) and Couture and Handbury (2017), the growth of consumption in the service industry is the main reason for the stagnant growth of US metropolitan cities in the 2000s. Similar phenomena may have occurred in Korean cities. Greater importance of consumption for services leads to more employment in the services in large cities.

Next, the definition of a city will be tested for robustness. We define ‘cities’ by Si (city) in the current administrative district as of 2018. We will examine how the results of this study differ with other definitions of cities. First, Si (city) is examined as of 1995, the first year of the analysis. There were only 68 cities with the status of “Si (city)” in the administrative districts in 1995. In contrast, I extend the sample into all cities and counties to observe how the results change. The results are reported in the Appendix.

Finally, Table 6 reports the results of analysis on the population growth. Note that the dependent variable is the average annual rate of change in the population, and the explanatory variables are identical to those used before. Overall, the explanatory power is lower than in the model of employment growth. This implies that the impact of market access on population growth is smaller than on employment changes. This

TABLE 6— RELATIONSHIP BETWEEN POPULATION GROWTH AND MARKET ACCESS

Dependent Variable: △ln Population	Pooled OLS		Fixed-effect model	
Explainable Variables	(1)	(2)	(1)	(2)
ln Market Access	0.00128***	0.00129***	0.0104**	0.00784**
	(0.000374)	(0.000373)	(0.00444)	(0.00345)
ln Population Density	-0.00907***	-0.00910***	-0.0804***	-0.0904***
	(0.00150)	(0.00151)	(0.00904)	(0.0101)
Education years	0.00803**	0.00796**	0.00328	0.00768
	(0.00341)	(0.00340)	(0.00445)	(0.00505)
Age	-0.00596***	-0.000362	-0.00215	0.0478***
	(0.00145)	(0.0159)	(0.00175)	(0.0169)
Age^2	-	-0.00692	-	-0.0622***
		(0.0192)		(0.0210)
Ratio of Service	-0.0125	-0.0130	-0.00958	-0.0249
	(0.0121)	(0.0124)	(0.0178)	(0.0183)
Cities	-0.0222***	-0.0218***	0.0208**	0.0236**
	(0.00705)	(0.00717)	(0.00962)	(0.00928)
Constant	0.259***	0.147	0.787***	-0.201
	(0.0796)	(0.334)	(0.108)	(0.335)
Year Fixed-effect	YES	YES	YES	YES
Citi Fixed-effect	NO	NO	YES	YES
F-statistics	-	-	25.66	24.29
R^2	0.461	0.461	0.548	0.566
# of Observations	332	332	332	332
# of Cites	83	83	83	83

Note: 1) The dependent variable is the average annual growth rate of employment over the 5-year period. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively, 2) The robust standard errors are in parentheses, and clustered by cities, 3) Among 85 cities, Jeju and Seoguipo are excluded.

Source: Population Census (1995~2015); Statistics Korea.

may occur because decisions by people about where to live are less responsive to market access than decisions by firms about where to produce. Although the explanatory power is low, the estimates are similar in terms of the directions. Market access appears to have a 0.01%p impact on population change. In addition, population growth is slow in densely populated cities. The effects of years of education and age are similar to those of employment, but these results are not as significant as before.

In sum, market access is closely associated with employment growth as well as population growth in Korean cities. Employment in cities with high market access tends to increase rapidly. On the other hand, regions with low market access, located far from hub cities, appear to have grown slowly or even to have declined. These results are more prominent in the Seoul metropolitan area than in non-SMA regions. In addition, employment growth in the manufacturing sector occurs more rapidly than in the service sector.

VI. Concluding Remarks

This study examines the relationship between market access and urban growth and analyzes the effect of market access, which is high with nearby large populations. Market access is a variable representing the aggregation effect of the nearby cities. The empirical results show that market access has a significant impact on regional employment development.

I also documented the urban population growth patterns of Korean cities, finding that the population distributions of cities in Korea follow Zipf's law. Moreover, it appears that Zipf's law holds very well with the recent population distribution, while this cannot be confirmed in the period of 1975 to 1995. Gibrat's law also has different implications because the relationship between population size and its growth varies over time. Population growth from 1975 to 1995 showed a different trend from that of 1995 to 2015. This appears to have major policy implications. Since the 1970s, industrialization policies had led people to move to large cities. In the 1990s, on the other hand, the policies aimed to ease overcrowding in metropolitan cities and to distribute industrial facilities nationwide. As a result, the growth of medium-size cities has been prominent. However, behind the population growth of these middle cities, there was a decline of small cities, recently referred to as extinction areas, raising awareness of this local crisis.

This study introduces the concept of market access as a factor that influences urban growth. Market access, a concept introduced in the international trade, measures the geographical and economic advantages of cities. The market access of a city is calculated from the population of and the distances from the surrounding regions. Therefore, cities located close to populated cities show high market access, and regions far from a large city or regional hub city have low market access.

An empirical analysis of the relationship between market access and urban growth using data from 1995 to 2015 shows that employment in cities with high market access has rapidly increased. On the other hand, regions with low market access appear to have undergone slower growth. These results are more prominent in the Seoul metropolitan area than in non-SMA regions. In addition, employment in the manufacturing sector has risen more prominently than that in the service sector.

Next, we discuss policy implications for balanced national development. Korea is striving for balanced national development, and various policies have been implemented with the goal of 'evenly developing regions'. As discussed in the introduction, however, the gap between the SMA and non-SMAs is broadening. Metropolitan cities in non-SMA regions are showing decreasing populations. As shown in this study, the gap between the SMA and non-SMA regions can be explained by differences in market access and agglomeration effects. In other words, cities with low market access in non-SMA regions have experienced little development in employment, whereas cities with high market access near Seoul have grown rapidly. Compared to non-SMA cities with low market access, cities with high market access near non-SMA metropolitan cities also benefited from nearby large cities, with employment rising. These are the agglomeration effects of large cities on regional development.

Currently, the shrinking populations of local metropolitan cities imply the possibility that it is not merely a matter related to these cities but a risk that can impede the development of the corresponding regions. To prevent this trend, policies that help local hub cities find a starting point for development without causing a decline in the overall development of the region are needed. When investing in local areas via policies such as the relocation of public institutions, the relocation area selected should be an investment worthy as a place for regional development, not for political gains. If Korea’s second city grows due to such an investment, it will contribute not only to the region but also to the growth rate of the whole country. Moreover, many regions with low market access should be compact, with investments to strengthen a network with neighboring hub cities.

Finally, it is important to discuss the limitations of this study. The analysis here focuses on quantitative growth of cities in terms of population and employment. Therefore, the study fails to analyze qualitative growth in order to improve the quality of life. Quantitative growth outcomes of employment and population cannot be achieved in non-urban areas with poor market access, but the qualitative growth of productivity and income per capita can improve. This can have a positive impact on the quality of lives of local residents. The analysis in this study does not take this into account, as it is limited to an analysis of quantitative growth.

APPENDIX

A. *Definition of Cities*

To look at the population distributions of cities, we need to define what a city is. In other words, we need to determine the spatial scope of a city. With this definition, we will study the population distribution of Korea by looking at how many people live in each geographically defined city.

A city is a place where people live and work, and a city can differ essentially from an administrative division. However, the literature has often defined spatial units of research as administrative divisions, as a variety of factors are needed for a strict definition of a city. Administrative divisions are used in many fields, including politics, and various types of statistical data are collected on this basis. Based on the administrative divisions, basic living zones are termed Si (city), Gun (county), and Gu (district) in Korea. Existing studies have utilized these distinctions as a spatial scope. In a metropolitan area, however, people's living zones are wider than administrative divisions. In this study, it is necessary to divide regions into those similar to people's living areas as precisely as possible.

Here, I define basic living zones as Si (city) and Gun (county) and define cities among living zones by using Si (city) and not Gun (county). To clarify this, we consider the administrative divisions in Korea. Table A1 shows the areas and populations of Korea's administrative divisions. Korea is divided into eight metropolitan cities, including Seoul and Sejong, and nine general and special autonomous provinces. Metropolitan cities as autonomous municipalities have autonomous districts (Gu) and autonomous counties (Gun), and such provinces have general administrative cities (Si) and counties (Gun). As shown in Table A1, Seoul has 25 Gu and Busan has 15 Gu and one Gun. There may be a general municipality which has general Gu and Gun, particularly when their populations exceed 500,000. This division is distinct from the autonomous districts of metropolitan cities. Suwon, the capital of Gyeonggi-Do, has four general Gu, and there are 17 general Gu in Gyeonggi-Do. Si (city), Gun (county), and Gu (district) refer to general cities, general counties, and autonomous districts, respectively. A city in this sense differs from a metropolitan city in a metropolitan municipality.

For the purposes of this study, cities are defined as metropolitan cities and general cities. This does not include the autonomous districts of metropolitan cities. In this regard, cities in this study are distinguished from a city as defined by Si (city), Gun (county), and Gu (district). Because general cities and metropolitan cities are regarded as the same types of cities, cities are also different from metropolitan economic zones in that the provinces are divided into cities and counties. Finally, cities are distinguished from Gun (county). Article 7 of the Local Autonomy Act provides the criteria for the promotion of a county or town to a city. Gun (counties) with population of 50,000 or more or Eup (towns) with population of 20,000 or more can be a Si (city). The Act states that a Gun or Eup should be in the form of a city, more than 60% of the population must live in the city's urban area, and a high proportion of people must be engaged in urban industries. Moreover, a city's population density is expected to be higher than the average population density of cities with populations of 100,000 or less. According to the Local Autonomy Act,

TABLE A1— ADMINISTRATIVE REGIONS IN SOUTH KOREA

Region	Area (km²)	Population	Si	Gun	Gu
Seoul	605.23	9,857,426	-	-	25
Busan	770.04	3,470,653	-	1	15
Daegu	883.54	2,475,231	-	1	7
Incheon	1,063.10	2,948,542	-	2	8
Gwangju	501.18	1,463,770	-	-	5
Daejeon	539.46	1,502,227	-	-	5
Ulsan	1,061.18	1,165,132	-	1	4
Sejong	464.85	280,100	-	-	-
Gyeonggi-Do	10,186.29	12,873,895	23	3	(17)
Gangwon-Do	16,875.04	1,550,142	7	11	-
Chungcheongbuk-Do	7,407.66	1,594,432	3	8	(4)
Chungcheongnam-Do	8,227.45	2,116,770	8	7	(2)
Jeollabuk-Do	8,069.01	1,854,607	6	8	(2)
Jeollanam-Do	12,335.14	1,896,424	5	17	-
Gyeongsangbuk-Do	19,032.20	2,691,706	10	13	(2)
Gyeongsangnam-Do	10,539.83	3,380,404	8	10	(5)
Jeju-Do	1,850.16	657,083	(2)	-	-
Total	100,411.36	51,778,544	75	82	69

Note: The numbers in parenthesis are different types of divisions. For example, cities (Si) in a province (Do) cannot have autonomous districts (Gu) but can have general districts (Gu), which is a type of division for administrative purposes.

Source: Administrative division and population (2017); Ministry of the Interior and Safety.

there are 75 cities with current status of Si (city).

Next, I would like to compare Gun (county) with Si (city) defined as explained above. In Table A2, 162 Si (cities) and Gun (counties) in Korea are divided into 85 cities and 77 counties. Their differences are determined by their population, population density, employment, and industry structure. First, cities have on average approximately 12 times more people than counties. In addition, the population density is more than 20 times higher than that in counties, showing remarkable differences in terms of the population size and density. Similar to the population, there is a major difference in terms of the number of employees. It is important to note that the variations across cities are greater than those across counties. The standard deviations for population and employment were more than double in urban areas compared to those in rural areas. The maximum population and employment values for cities are 249 times and 577 times higher than the corresponding minimum values, while the respective differences are only 13 times and 15 times in the counties. In contrast, in terms of the industrial structure, cities and counties do not show much of a difference. On average, the share of manufacturing is higher in urban areas, and the service sector is higher in rural areas, but the differences are slight.

Figure A1 shows more clearly the differences in population and population densities between cities and counties. In all samples, the density of the population is

TABLE A2— COMPARISON BETWEEN SI AND GUN

Administrative Region	Variable	Mean	Standard Deviation	Min	Max
Si (cities)	Population	529,550	1,123,505	37,690	9,394,807
	Population Density	1,832	3,016	54	15,522
	Employment	229,661	579,270	8,851	5,108,828
	Ratio of Manufacture	22.7%	13.6%	1.1%	53.7%
	Ration of Service	70.5%	12.4%	42.6%	91.4%
Gun (counties)	Population	43,218	19,562	8,392	112,446
	Population Density	77	59	18	421
	Employment	17,753	11,120	4,073	64,542
	Ratio of Manufacture	19.0%	13.7%	3.8%	58.5%
	Ration of Service	71.1%	12.5%	37.3%	88.2%

Note: These basic statistics are from 85 Si (cities) and 77 Gun (counties). is a type of division for administrative purposes.

Source: Population Census (2015) and Census on Establishments (2015); Statistics Korea.

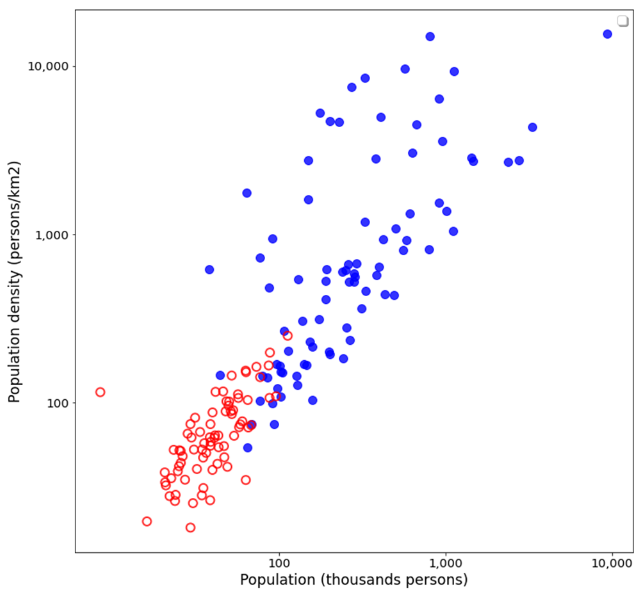

FIGURE A1. COMPARISON BETWEEN SI AND GUN: POPULATION VERSUS POPULATION DENSITY

Note: Both axes are in log scale. Si (cities) is represented by blue dots and Gun (counties) is denoted by red circles.

Source: Population Census (2015); Statistics Korea.

strongly correlated with the number of people, and counties in general have smaller populations than cities. However, the fact that some counties are larger than smaller cities that have nearly 100,000 persons and a density of 100 persons/km^2 suggests that the distinction between cities and counties does not simply reflect the size of the population. Therefore, if only urban areas are included in the analysis, such large counties will be excluded. In this regard, the analysis should be robust in terms of sample selection among the 162 regions used. To this end, I will conduct an analysis with various samples.

Cities are defined as a part of a Si (city) and Gun (county) at the regional level because these criteria are actually most similar to people's living zones. In cities and counties with small populations, people rarely live and work beyond this administrative boundary, and people in large cities tend to extend their livelihoods across these boundaries due to the expanded transportation facilities. Therefore, the autonomous districts of Gu in metropolitan cities are too small to serve as a spatial unit. In particular, the Seoul metropolitan area, which includes the vicinity of Seoul in Gyeonggi-Do, can be seen as a living zone because many people commute to Seoul from various cities of Gyeonggi-Do, and people consider the entire metropolitan area as their living area. According to the Seoul Metropolitan Living Population in Seoul, the average population of those living in Seoul in the fourth quarter of 2017 was 11.5 million, which is about 1.7 million more than the 9.8 million registered residents in Seoul. When taking into account people who live in Seoul but work outside of Seoul, approximately two million people can be said to live near Seoul but work mainly in Seoul on weekdays.

However, it is not easy to define such living zones, as there is no information about where the living population of Seoul resides, either outside of Seoul or vice versa. In addition, other metropolitan cities apart from Seoul lack statistical data pertaining to the living population to define their living zones. I did not find any information about the living population of Busan, the second city of Korea, and where these people live and commute to or from the city center. On the other hand, even with this information, it is known that living zones tend to grow as the cities expand. Therefore, in this study I define cities using Si (cities) and Gun (counties).

It also should be noted that a considerable amount of the literature on regions defines regions as closely as possible to living zones. In the United States, a CBSA (core-based statistical area) is defined separately from administrative divisions and is used for statistics-based research. Most papers on Zipf's law, discussed in the next section, also find cities or statistical areas of administrative divisions based on these living areas. Accordingly, this study establishes cities as close to the living zone as the spatial units of research.

B. *Statistical Test of Empiric laws*

We estimate the coefficients of linear trends according to Zipf. Here, we denote the population of city i by S_i. According to Zipf's law, the city population has the following characteristics.

$$\ln(rank) = A - B\ln S_i.$$

In this equation, Zipf's law holds if B equals 1. To determine whether Zipf's law holds in Korea, we conduct a cross-sectional regression analysis. Table A3 shows the coefficient estimates for B in the equation for Zipf's law. From 1975 to 1985, the early data period, the estimates are between 1.1 and 1.3. This appears to be due to the fact that there are many medium-sized cities with relatively small populations at that time, before the population grew. Hence, the slope of the trend

TABLE A3— ZIPF'S LAW AND HHI OF CITIES' POPULATIONS

Year	Number of Cities	Estimates	p-value $H_0: \beta_1 = 1$	R^2	*HHI*
1975	67	1.291 (0.031)	0.0000	0.964	0.0943
1980	67	1.212 (0.024)	0.0000	0.974	0.1047
1985	67	1.150 (0.017)	0.0000	0.985	0.1092
1990	71	1.092 (0.010)	0.0000	0.995	0.1049
1995	72	1.037 (0.010)	0.0003	0.994	0.0909
2000	73	1.034 (0.013)	0.0101	0.989	0.0804
2005	71	1.029 (0.016)	0.0862	0.983	0.0750
2010	69	1.034 (0.020)	0.1039	0.975	0.0712
2015	70	1.037 (0.021)	0.0912	0.972	0.0675

Note: In the column of estimates, the standard errors are given in parentheses. The rank is technically defined by (rank-0.5). See Gabaix and Ibragimov (2011) in more details. The p-value is the probability of obtaining the observed results under the null hypothesis of $H_0: \beta_1 = 1$. *HHI* is the Herfindahl-Hirschman Index on urban populations.

Source: Population Census (1975~2015); Statistics Korea.

line appears to be steeper than a 45-degree line. After this point, however, the coefficient estimates become smaller, reaching 1 mostly due to the rapid growth of medium-sized cities. Table A3 also shows the statistical significance of the Zipf's law coefficient estimates. The null hypothesis that the coefficient for the slope of the line is 1 can be tested. The table shows the p-values of the test of the null hypothesis. From 1975 to 1990, the p-values are all close to zero, allowing rejection of the null hypothesis. In other words, there is no statistical significance until 1990 to support the contention that the estimated line has a slope of 1, which means that Zipf's law does not hold. Since 2000, the p-value increased until 2010, and the null hypothesis could not be rejected at the significance level of 1%. This means that the coefficient estimate recently approached 1. The recent populations distributions of Korean cities satisfy Zipf's law and show linearity with a slope of 1, which is consistent with the graph discussed above.

Moreover, I add a concentration indicator to the results table to highlight the change of the urban population distribution in Korea. The indicator is the Herfindahl-Hirschman Index (HHI), which is widely applied in the field of industrial organization. Similar to observing concentrations or competition in a market, this index for urban population indicates how much of a population is concentrated in a small number of cities. The index is calculated as follows:

$$HHI = \sum_{i=1}^{N} S_i^2,$$

TABLE A4— GIBRAT'S LAW: RELATIONSHIP BETWEEN POPULATION AND GROWTH RATE

Dependent Variable: △ln Population	Year: 1975~1995		Year: 1995~2015	
Explainable Variables	(1)	(2)	(1)	(2)
ln Population	-0.215***	-3.218***	-0.055	-0.211
	(0.072)	(0.774)	(0.044)	(0.664)
(ln Population)^2	-	0.123***	-	0.006
	-	(0.032)	-	(0.026)
Constant	2.904***	21.095***	0.855	1.851
	(0.868)	(4.738)	(0.546)	(4.266)
R^2	0.096	0.237	0.018	0.019
Number of Cities	85	85	85	85

Note: The dependent variable is the annual growth rate of population over the period described.

Source: Population Census (1975~2015); Statistics Korea.

where S_i is the population share of city i over the total population in the country. If all cities have the same population, this index will be $1/N$, where N is the total number of cities. On the other hand, the index would be close to one when the total population is clustered in one city. Thus, the index value must be between $1/N$ and 1. The index as calculated from census data varies over time. It increased until 1985, when the HHI showed its maximum value of 0.1092. Since 1985, the index has declined, reaching 0.0675 in 2015.

Gibrat's law can be confirmed through the regression analysis of population growth. Table A4 shows statistical results to verify the trends in Figure 4 in Chapter 2, Section B. I run regressions of the population growth on population size and the corresponding squared value. In the period between 1975 and 1995, the coefficient of the population squared is positive, implying a parabolic curve. All coefficients estimated are statistically significant at the 1% level. In the next two decades, on the other hand, the significance of the estimates falls, and it is difficult to identify any relationship between population and population growth. This suggests that population growth over the last 20 years is independent of the population size. As a result of analyzing the relationship between population and population growth through a basic regression analysis and graphs without any other explanatory variables, we can confirm the applicability of Gibrat's law here.

C. *City List sorted by market access*

TABLE A5— NON-SMA SI (CITY) LIST WITH THE HIGHEST MARKET ACCESS

Rank (of Non-SMA)	Si (Do)	Rank (of Non-SMA)	Si (Do)
1	Gyeryong (Chungcheongnam-Do)	11	Asan (Chungcheongnam-Do)
2	Kimhae (Gyeongsangnam-Do)	12	Gunsan (Jeollabuk-Do)
3	Jeonju (Jeollabuk-Do)	13	Taebaek (Gangwon-Do)
4	Yangsan (Gyeongsangnam-Do)	14	Mokpo (Jeollanam-Do)
5	Gyeongsan (Gyeongsangbuk-Do)	15	Gwangyang (Jeollanam-Do)
6	Naju (Jeollanam-Do)	16	Busan (Busan)
7	Gimjae (Jeollabuk-Do)	17	Iksan (Jeollabuk-Do)
8	Nonsan (Chungcheongnam-Do)	18	Cheonan (Chungcheongnam-Do)
9	Sejong (Sejong)	19	Samcheock (Gangwon-Do)
10	Sacheon (Gyeongsangnam-Do)	20	Gongju (Chungcheongnam-Do)

Source: Population Census (2015) and Census on Establishments (2015); Statistics Korea.

D. *Robustness Checks*

TABLE A6— RELATIONSHIP BETWEEN EMPLOYMENT GROWTH AND MARKET ACCESS BY CITY DEFINITION

Dependent Variable: △ln Employment	Cities as of 1995		All Cities and Counties	
Explainable Variables	(1)	(2)	(1)	(2)
ln Market Access	0.0197***	0.0184***	0.0204***	0.0183***
	(0.00649)	(0.00656)	(0.00572)	(0.00586)
ln Population Density	-0.0641***	-0.0695***	-0.0558***	-0.0609***
	(0.0129)	(0.0149)	(0.00897)	(0.0104)
Education years	0.0117**	0.0140**	0.0139***	0.0152***
	(0.00562)	(0.00575)	(0.00347)	(0.00362)
Age	0.00182	0.0262	0.00201	0.0232
	(0.00242)	(0.0272)	(0.00188)	(0.0153)
Age^2	-	-0.0305	-	-0.0260
		(0.0341)		(0.0179)
Ratio of Service	0.113***	0.105***	0.127***	0.120***
	(0.0282)	(0.0316)	(0.0174)	(0.0195)
Cities	-	-	-0.00352	-0.00161
			(0.00654)	(0.00664)
Constant	0.447**	-0.0299	0.336***	-0.0857
	(0.180)	(0.535)	(0.115)	(0.324)
Fixed-effect	YES	YES	YES	YES
R^2	0.787	0.788	0.677	0.679
# of Observation	272	272	636	636
# of Cites	68	68	159	159

Note: 1) The dependent variable is the average annual growth rate of employment over the 5-year period. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively, 2) The robust standard errors are in parentheses, and clustered by cities, 3) Year fixed-effect and city fixed-effect are included.

Source: Population Census (1975~2015); Statistics Korea.

TABLE A7— RELATIONSHIP BETWEEN EMPLOYMENT GROWTH AND MARKET ACCESS WITH DENSITY SQUARED

Dependent Variable: △ln Employment	Pooled OLS		Fixed-effect model	
Explainable Variables	(1)	(2)	(1)	(2)
ln Market Access	0.00234***	0.00238***	0.0189***	0.0168***
	(0.000457)	(0.000456)	(0.00641)	(0.00614)
ln Population Density	-0.00334	-0.00502	0.0124	0.0131
	(0.00766)	(0.00789)	(0.0693)	(0.0648)
(ln Population Density)^2	-0.0421	-0.0323	-0.508	-0.568
	(0.0537)	(0.0549)	(0.529)	(0.491)
Education years	0.00679**	0.00646**	0.0156***	0.0195***
	(0.00310)	(0.00311)	(0.00509)	(0.00591)
Age	-0.00316**	0.0234**	0.00173	0.0410
	(0.00129)	(0.0116)	(0.00242)	(0.0260)
Age^2		-0.0331**		-0.0488
		(0.0145)		(0.0325)
Ratio of Service	0.00749	0.00579	0.111***	0.101***
	(0.0116)	(0.0117)	(0.0231)	(0.0253)
Cities	-0.0253***	-0.0237***	-0.00802	-0.00687
	(0.00799)	(0.00793)	(0.00707)	(0.00667)
Constant	0.140*	-0.379*	0.127	-0.685
	(0.0750)	(0.228)	(0.269)	(0.603)
Year Fixed-effect	YES	YES	YES	YES
Citi Fixed-effect	NO	NO	YES	YES
F-statistics	-	-	177.51	183.65
R^2	0.603	0.606	0.725	0.729
# of Observation	332	332	332	332
# of Cites	83	83	83	83

Note: 1) The dependent variable is the average annual growth rate of employment over the 5-year period. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively, 2) The robust standard errors are in parentheses, and clustered by cities, 3) Among 85 cities, Jeju and Seoguipo are excluded.

Source: Population Census (1995~2015); Statistics Korea.

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Do Patents Lead to an Increase in Firm Value? Evidence from Korea†

By JANGWOOK LEE*

Patents are widely used in the literature as a measure of firm-level innovation. It is regarded that patents improve a firm's operational environment and ultimately increase the value of the firm. However, the relationship between patents and firm value in Korea is under-explored in the literature due to the difficulty of constructing datasets. This paper examines whether patents in Korea increase the market value of a firm. To do this, I exploit novel data on firm-level patents and financial information of all listed Korean companies during the period of 1993-2015 and estimate the non-linear production-function type of Tobin's q equations on R&D, patents, and citations. Surprisingly, I find that patents and citations are weakly associated with firm value, while R&D is strongly associated with an increase in firm value. These results direct imply that policymakers in Korea should enhance patenting incentives to encourage firms to innovate.

Key Word: Innovation, Firm Value, Tobin's q, R&D, Patent
JEL Code: O30, O32, O34

I. Introduction

It has been extensively documented that innovative capabilities are important for firms' growth and performance. Measuring innovation by firms has always attracted much attention from researchers in economics. One method by which to do this is to measure innovation with R&D expenditures, but one problem is that not all R&D leads to technological progress, and they are an input into innovation processes, not an outcome of these processes. Patents are another frequently used measure of firms' innovative capabilities in the literature. The value of a patent is recognized in part by the patent office, which allows us to infer technological progress. The patent system requires three conditions to be met for the granting of a patent: utility, novelty, and non-obviousness.

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† This paper is based on Lee, Jangwook, 2019(forthcoming), "A study on firm-level effects of knowledge capital: focusing on patents and citations of firms," KDI *(in Korean)*. I am grateful to Shiyun Roh for her outstanding assistance and to two anonymous referees for their valuable comments. All remaining errors are mine.

A large body of research has studied the relationship between patents and firm value. Since Griliches (1981) found a positive relationship between the market value of a firm and its patents, much subsequent research has shown that patents and their characteristics are associated with firm value. Hall, Jaffe, and Trajtenberg (2005) find that the quality of patents as measured by patent citations is correlated with firm value. Since then, citations have become a popular proxy for firms' technological advances.

However, one area less studied is whether the patents of a firm do in fact lead to an increase in firm value in the Korean context. Because patent systems differ across countries, the legal rights and economic value of a patent can vary depending on where it is granted. Considering patents as a proxy for innovation is relatively common in the research on Korean firms, and it is an important empirical question as to whether the relationship between patents and firm value still holds in Korea as it does in foreign contexts.

Several studies have assessed the effects of firms' patents in Korea, though these have limitations. Youn (2004) represents one of the first papers to investigate the relationship between patents and firm value in Korea. The author finds a positive effect of patents on firm value, but the analysis includes only 242 firms, excluding non-renewed patents. Jeong and Kim (2017) demonstrate a relationship between US patents held by Korean firms and firm value, but they focus only on firms with US patents, not Korean patents. It is difficult to uncover implications pertaining to the Korean patent system in such a case. Recently, there has been some effort to construct large-scale firm-level patent data for Korean firms. Lee, Lim, Kim, Song, and Jeong (2019) match firms in FnGuide with patents. However, they focus on constructing patent-firm data itself, not providing an analysis of the effects of patents.

This paper exploits the commercial database ORBIS Intellectual Properties (IP) provided by Bureau Van Dijk. By merging ORBIS IP with FnGuide 5.0, I construct panel data for all listed firms in Korea with patent grant information from 1993 through 2015. To the best of my knowledge, this is the first paper to investigate whether the patents of a firm do in fact increase firm value with large-scale firm-level patents and financial data in Korea.

This paper investigates how the characteristics of the patents of Korean firms affect the firms' market value. I estimate firm value (Tobin's q) equations driven by the Cobb-Douglas production function by means of non-linear least squared estimation, a standard approach in the literature. This specification enables me to compare the effects of patents in Korea with the results from overseas studies. I use three variables for measuring firms' innovation: R&D stock/assets, patent stock/R&D stock, and citation stock/patent stock (hereafter referred to as R&D/asset, patent/R&D, and citation/patent, respectively).

Interestingly, contrary to the expectation that patents in Korea lead to an increase in firm value, the coefficient of patent/R&D is positive but not statistically significant. The coefficient of citation/patent is found to be statistically significant, but the magnitude is low compared to those in earlier work. Tobin's q increases by 0.5% with a one-unit increase in citation/patent, which is weak compared to prior studies. On the other hand, R&D/asset is strongly correlated with Tobin's q. As R&D/asset increases by 1%p, Tobin's q increases by about 1%. The magnitude of the R&D/asset effect is similar to or greater than those in previous studies conducted overseas.

I also investigate whether the effects of patents on firm value vary across industries. Given that the importance of technology differs depending on the industry, the effect of patents on firm value can also differ across industries. Consistent with my expectation, I find that the effects of patents on firm value in knowledge-intensive industries such as pharmaceuticals are very strong, whereas conventional manufacturing industries such as metals show weak effects. These findings corroborate the previous analysis results of the paper.

Prior research suggests that citations represent importance differentially depending on the type. Who cites who indicates a linkage between technology (Li, Chambers, Ding, Zhang, and Meng, 2014) and knowledge flows (Alcácer and Gittelman, 2006). Self-citations, citations coming from subsequent patents owned by the same firm, are known to be strongly associated with the market value of a firm (Hall, Jaffe, and Trajtenberg, 2005). Based on prior research, this paper undertakes a closer examination of whether self-citations increase the market value of Korean firms more so than normal citations do (including both self- and non-self-citations). Self-citations closely related to the market value of a firm may mean that the analyses in this paper are consistent with those in the literature. The results show that self-citations are positively correlated with market value and that the economic significance is approximately five times larger than that associated with normal citations.

It is widely understood in financial economics that firm value represents the discounted sum of the income of the future. If patents are associated with firm value, the patents should be linked to future performance measures such as net income and sales. To find how firm value and patents are related, I estimate panel regressions of patent variables on firm performance variables. This analysis sheds light on the linkage between patents and firm value. Specifically, a variable that shows a strong effect on firm value, such as self-citations, is expected to predict future earnings better. Consistent with the previous analysis, the estimation results show that self-citation/patent does predict future earnings while patent/asset and citation/patent do not show a correlation with future earnings.

My sample includes all patents of listed Korean firms granted in all countries around the world. The sample enriches the credibility of the analysis by measuring exclusive rights to use technologies in the global market. However, one may raise the concern that multiple patents in the same patent family contain the same technology, meaning that patents can be over-counted relative to the knowledge contained in them. However, this is not the case here because the value of patents not only comes from the technology itself but also originates from legal protections. Nonetheless, I construct the sample only with the first patents in the patent families and check the robustness of the analysis. The results are consistent with the previous analysis, showing that patents and citations in Korea are weakly associated with the market value of a firm. I also check the robustness of the results by excluding the 1997-1998 Asian financial crisis and the 2008 global financial crisis periods to rule out the effect of exceptional economic shocks. The results are consistent with the main findings.

This paper has valuable implications for policymakers in Korea. The results imply that the Korean patent system does not play a critical role in increasing the market value of a firm. There have been studies positing that legal protection rights are weak in Korea compared to those in foreign countries. Ryu (2019) argues that the Korean patent system is very conservative in setting punitive damages in infringement cases and that there is no clear standard of willful infringement. Not only does the patent system weaken patent value per se, but also it reduces incentives for firms to file patents for valuable technologies. There is also the possibility that firms prefer to choose to keep their technologies secret instead of pursuing patent protection (Chung, 2017). Retaining secrecy of technology may be optimal for a firm but may not be socially optimal in that there would be no knowledge spillover. This paper provides evidence that the patent system in Korea should be improved. To promote knowledge spillover and achieve a socially optimal level of innovation, policymakers in Korea should enhance patenting incentives to promote innovation in Korea.

Patent incentives refer to the appropriability from which a firm can create economic value. It can take the form of strong exclusive rights with regard to the technology in patents. Heavy punishments in cases of patent infringement are one good example. Prior research suggests that the Korean patent system is not good at providing proper protection in infringement cases. This could result in a weak association between patents and firm value. Thus, I suggest that policymakers should improve the actual rights of patents so that firms have more of an incentive to file patents and furthermore to invest more resources in innovation.

The remainder of this paper proceeds as follows. Section 2 describes the patent data and financial data used in the analysis. Section 3 develops the estimation equations of patent variables and firm value. Section 4 presents the estimation results, and Section 5 reports robustness checks. Lastly, section 6 closes with a conclusion.

II. Data

I construct the sample by combining two large datasets, ORBIS intellectual property (IP) and FnData 5.0. ORBIS IP, provided by the commercial data provider Bureau Van Dijk, offers worldwide patent information. It includes approximately 115 million patents and also offers the information about which firm had ownership of the patents when they were granted. Prior studies usually match the names of companies to the names of the patent assignees on a one-by-one basis, a method subject to mismatching. ORBIS IP, as a commercial data provider, argues that they have developed their own matching algorithm over 30 years. It is less likely that the data contains matching errors compared to a hand-collected dataset.

I use Dataguide from FnData as a source of financial information pertaining to listed companies in Korea, such as accounting variables and stock returns. The database of FnData, a commercial data provider in Korea, is widely used in Korean financial academia and industries. The sample periods are from 1993 to 2015. Patent data is available prior to 1993, but the availability of research and development accounting in Dataguide began in 1993. Firms that are granted at least one patent during the sample period are included in the sample, and the total number of those firms is 1,931.

A. *Patent truncation issue*

When analyzing patent data, the data truncation issue can naturally arise. There are two types of truncation issues. The first stems from the time lag between the application and the grant. This usually appears when analyzing US patent data. In the US, not all applied patents were made available to the public before 1999, as only granted patents were published. This issue generates bias when constructing the sample.

The data in this paper is less subject to be affected by the application-grant lag issue. Korea became a member of the World Intellectual Property Organization (WIPO) in 1979 and joined in Paris Convention for the Protection of Industrial Property in 1980. Since then, all patents applied for in Korea are released 18 months after the application date regardless of their status. It is not likely for firms to discontinue the patent process deliberately after applying given that the contents of the patent will be released anyway. ORBIS IP originally included patent information published until 2018, and this paper analyzes patent data up to 2015 considering the 18-month lag between the application and publication. The data in this paper include all patents applied for during the sample period.

The second issue is the truncation of citations. The number of citations increases over time. Earlier patents will have more citations than later patents regardless of their true value. To handle this issue, I determine the distribution of the number of years until the patents are cited and assign weights to these numbers of citations. I assume a 30-year lifetime of patents and calculate the proportions of citations for each year. In this way, I can obtain the cumulative distribution function of grant-citation lag years. The adjusted numbers of citations are obtained by dividing the total number of citations observed in the last year of the sample by the cumulative distribution function value. For example, assume that a patent applied for in 2013 is cited twice up to the last year we can observe. I record the number of patent citations for March of 2019 (the end of the database) to utilize the maximum amount of information available.

Because I truncate the sample period to 2015, I assume that the patent has been cited through three years, 2013, 2014, and 2015. Then there are 27 years during which the patent may be cited later. I assume that citations of this patent will follow the cumulative distribution function and divide the citation number of ‘2’ in this case by the CDF value of ‘3’ years.

B. *Data and variables*

I consider only granted patents as valid patents of the firms. If a patent is not granted until the end of the sample period, it is not counted. I count a patent at the time of its application, not when it is granted. In other words, when the patent application is made, it is considered as knowledge capital accumulation, but only for patents that are granted eventually at the end of the sample period.

Figure 1 reports the number of patents granted and the average number of citations for the listed companies in Korea. It shows a pattern consistent with those in previous studies. The number of granted patents has increased over time. Though it was less than 20,000 in 1993, it exceeded 60,000 by 2015. As the scale of the economy grows,

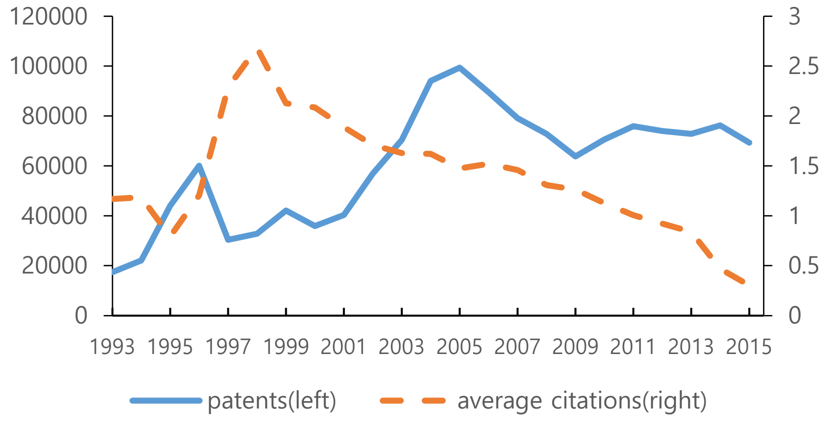

FIGURE 1. NUMBER OF GRANTED PATENTS AND AVERAGE FORWARD CITATIONS PER PATENT FOR LISTED COMPANIES IN KOREA

the importance of intellectual property on our economy also increases.

Figure 2 shows the total number of patents over the total R&D, the total citations over the total R&D, and the adjusted citations over the total R&D over the sample period. The denominators and the numerators are the aggregate quantities across firms. The R&D amounts are all adjusted according to the 2015 CPI level. Total patents over total R&D decreases from 1993 to 2015. In the early 1990s, firms obtained approximately 20 patents per billion won of R&D spending but obtained 1.5 patents per billion won in 2015. Both total patents and total R&D increase over time, but total R&D rises more rapidly. Total citations over total R&D decreases, but it is not clear as to whether adjusted citations over R& are decreased. The adjusted citations over R&D decreased during the 2000s but started to increase from 2010.

The independent variables in the following analysis, R&D/asset, patent/R&D, and citation/patent, are stock variables. They are defined as follows,

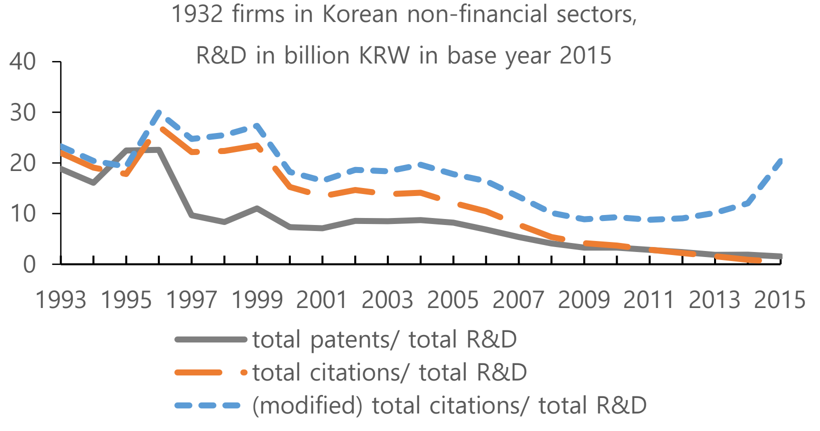

FIGURE 2. PATENTS AND CITATIONS PER R&D IN KOREA

Source: Orbis IP.

$$stock_t = (1 - dep) \times stock_{t-1} + input_i,$$

where $stock_t$ denotes R&D, patent, and citation stocks in year t, and dep is the depreciation rate, set here to 0.15, assuming that only 85% of knowledge capital remains and that 15% of it disappears every year. In addition, $input_i$ represents the annual flow of R&D, patents, and citations in year t. I use the R&D account in the financial statement footnote.

Calculating the citation stock value requires attention. At the firm level, the total truncation-corrected citation number in year τ from the patents granted in year t is represented by $C(t,\tau)$. The number of citation in year t for a firm is then defined as follows:

$$C(t) = \sum_{\tau=t}^{2019} C(t,\tau)$$

Citation stock increases when the patent is granted. This measure takes all of the citation information up to 2019 into account when the patent is granted. In this way, I address the issue of the time lag between the grant and the citation.

C. *Sample statistics*

I exclude observations with negative total assets, zero or negative market value, no R&D/total assets, no citations/patents, and no Tobin's Q. I replace no patents /R&D with zeros. Table 1 [Panel A] reports the sample statistics. The sample includes 1,931 firms and 21,460 observations. Variables in this sample show high skewness. Not only financial variables such as total assets and total liabilities but also patent variables such as patents stocks and citations stocks are skewed to the right. The high skewness features of the patent variables are similar to those found in earlier work.

Table 1 [Panel B] reports the correlations among R&D/Asset, patent/R&D, and citation/patent. The variables are not highly correlated with each other. Conventional

TABLE 1— SAMPLE STATISTICS

[Panel A] Summary Statistics

	Mean	Median	SD	Min	Max
Total assets (in bn KRW)	1,180	108	7,123	0.491	242,180
Total liabilities (in bn KRW)	710.9	49.2	4,216	0.188	131,976
Market values (in bn KRW)	515.9	52.6	4,089	0.186	224,190
R&D stocks (in bn KRW)	68.7	4.0	1,018	0	66,864
Patent stocks	335.5	6.7	4,052	0.004	139,488
Citation stocks (modified)	839.4	9.6	15,841	0	1,068,000
R&D/asset	0.084	0.036	0.267	0	16.92
Patent/R&D	32.3	1.7	868.2	0	67,375
Citation/patent	2.2	1.3	5.548	0	241.1
Q	1.3	1.0	1.1	0.212	38.4

Note: The total number of observation is 21,460 with 1,931 firms and the sample period is from 1993 to 2015.

TABLE 1— SAMPLE STATISTICS (CONT'D)

[Panel B] Correlation Coefficients

	R&D/total assets	Patents/R&D	Citations/patents
R&D/total assets	1		
Patents/R&D	-0.0108	1	
Citations/patent	0.0457	-0.0074	1

wisdom is that R&D firms may have a more efficient patent production and/or citation process, but the data shows that not all active R&D firms are efficient in terms of gaining patents or receiving citations.

III. Empirical specification

I construct the relationship between Tobin's q for a firm and associated patent variables and R&D expenditures as defined in the previous section. A firm generates revenue and earnings with its physical capital and knowledge. The value of the firm can be thought of as a function of these variables. I follow the standard form of the knowledge production function in the literature.[1] An advantage of this specification is that I can compare the estimation results with those in earlier studies conveniently and obtain policy implications for Korea through such a comparison. The firm value function is expressed as shown below:

$$V_{i,t} = q_t(A_{i,t} + \gamma K_{i,t}) \tag{1}$$

Firm t 's value in year t is $V_{i,t}$, consisting of physical capital $A_{i,t}$ and knowledge capital $K_{i,t}$, as shown in equation (1). This type of function assumes that the constant-return-to-scale and marginal shadow price of capital, q_t is identical across firms. The parameter γ is the price of knowledge capital relative to that of physical capital.

Taking the log on both sides of the equation (1) gives

$$\log V_{i,t} = \log q_t + \log A_{i,t} + \log\left(1 + \frac{K_{i,t}}{A_{i,t}}\right).$$

Subtracting $\log A_{i,t}$ on both sides yields the following equation,

$$\log Q_{i,t} = \log\left(\frac{V_{i,t}}{A_{i,t}}\right) = \log q_t + \log\left(1 + \gamma\frac{K_{i,t}}{A_{i,t}}\right) + \varepsilon_{i,t},$$

[1] Hall, Jaffe, and Trajtenberg (2005).

where $\varepsilon_{i,t}$ is a statistical error.

For convenience, I decompose knowledge capital to physical capital $\frac{K_{i,t}}{A_{i,t}}$ into three parts: R&D/Asset $\frac{R_{i,t}}{A_{i,t}}$, patent/R&D $\frac{P_{i,t}}{R_{i,t}}$, and citations/patent $\frac{C_{i,t}}{P_{i,t}}$. I assume that the linear combination of $\frac{R_{i,t}}{A_{i,t}}$, $\frac{P_{i,t}}{R_{i,t}}$, and $\frac{C_{i,t}}{P_{i,t}}$ can approximate $\frac{K_{i,t}}{A_{i,t}}$. This gives the following equation:

$$(2) \qquad \log Q_{i,t} = \log q_t + \log\left(1 + \gamma_1 \frac{R_{i,t}}{A_{i,t}} + \gamma_2 \frac{P_{i,t}}{R_{i,t}} + \gamma_3 \frac{C_{i,t}}{P_{i,t}}\right) + \varepsilon_{i,t}$$

This paper uses equation (2) for the analysis. I estimate γ_1, γ_2, and γ_3 by means of non-linear least squared estimation. Each parameter correspondingly measures the effects of R&D/Asset, patent/R&D, and citations/patent on the value of the firm.

IV. Estimation

A. *Estimation*

This section reports the estimation results of the equations presented in the previous section. Table 2 shows the non-linear least squared estimation results according to equation (2). Column (1) presents how R&D/asset and patent/R&D affect Tobin's q of the firm. Interestingly, although the coefficient of R&D/asset is positive and statistically significant, the coefficient of patent/R&D is negative. This result is not consistent with prior studies in a foreign context, which report a positive relationship between patents and the market value of a firm.

The variable D in the table is a dummy variable that takes a value of one when there is no R&D stock and is zero otherwise. The coefficient of D is positive but not statistically significant, meaning that patent stock or citation stock without R&D does not affect the market values of firms.

Table 2 column (2) reports the coefficients of all three independent variables, i.e., R&D/asset, patent/R&D, and citation/patent. While R&D/asset and citation/patent have positive and statistically significant coefficients, the coefficient of patent/R&D is not significant. The coefficients of R&D/asset and citation/patent are 1.151 and 0.006, respectively. The economic significance of the citation/patent variable is not as large as in prior studies. The magnitude of the citation coefficient is nearly ten times larger in foreign studies than in the results here.

One possibility is that legal protection in the Korean patent system is not strong enough to boost firm value. There have been many legal studies pointing out the weaknesses of this protection. Ryu (2019) reports that the Korean patent system is very conservative with regard to imposing punitive damages in cases of infringement. Punitive damages were introduced in 2019 in Korea. Therefore, there are too few

TABLE 2— NON-LINEAR REGRESSIONS OF TOBIN'S Q ON PATENT VARIABLES

	(1)	(2)	(3)
R&D/asset	1.140***	1.151***	1.109***
	(6.26)	(6.22)	(6.11)
Patent/R&D	-4.15e-06	-3.97e-06	-3.68e-06
	(-1.53)	(-1.47)	(-1.38)
Citation/patent		0.00589***	
		(4.22)	
D (R&D = 0)	0.0474	0.0484	0.0505*
	(1.54)	(1.58)	(1.65)
Citation/patent Dummy Variables			
1-1.3			0.0320
			(1.61)
1.3-2.5			0.0475***
			(2.84)
2.5-6.5			0.0676***
			(3.75)
6.5 or above			0.0931**
			(2.55)
Year-fixed effects	Y	Y	Y
R-squared	0.1437	0.1462	0.1471
# of obs.	21,460	21,460	21,460

Note: Standard errors are cluster-robust errors at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

judicial precedents to establish a clear standard of willful infringement. Furthermore, the responsibility of proving that the patents are infringed falls on the patent owners. The cost is substantial for patent owners to be given actual legal protection in Korea.

The other possibility is that firms intentionally do not apply for a patent for their valuable technologies. Chung (2017) empirically shows that firms choose strategically between secrecy and pursuing patent protection depending on the risk of information disclosure. The weaker the patent protection is, the less incentive there is for firms to apply for a patent. Firms would instead choose to keep their valuable technologies secret.

Although the economic significance of the citation/patent variable on firm value is not as strong as in prior studies, the estimation result does not at all imply that citations have no economic effect on the market value of a firm. I also analyze the effect of the citation/patent variable by constructing citation/patent dummy variables and examining the effects of each of these. I break citation/patent into five groups: less than 1, 1-1.3, 1.3-2.46, 2.46-6.5, and greater than 6.5. They correspondingly represent less than 42%, 42%-50%, 50%-75%, 75%-95%, and greater than 95% in the sample. Table 2 column (3) reports the results of the estimation with the dummy variables depending on citation/patent percentile included in the regression. The economic significance of dummy variables with higher percentiles is greater. Firms with 1-1.3 citations/patent have a 0.032 higher log q than those with less than one citation/patent. The effect increases as firms enter a higher citation/patent group, implying that the citation/patent variable does play a role to some extent with regard to increasing the value of a firm, and not only for a specific group of firms.

To understand the previous analysis quantitatively, I calculate the degree of semi-

TABLE 3— SEMI-ELASTICITIES

	Mean	Median
R&D/asset	0.084	0.036
Patent/R&D	32.3	1.7
Citation/patent	2.2	1.3
Elasticity		
Partial logQ/ partial (R&D/asset)	1.036	1.097
Partial logQ/ partial (patent/R&D)	n/a	n/a
Partial logQ/ partial (citation/patent)	0.005	0.006

elasticity. This enables us to interpret the magnitude of the effects of patents and R&D conveniently. Taking the derivatives of each independent variable in equation (2) yields the following equation:

$$\frac{\partial \log Q}{\partial X_i} = \hat{\gamma}_i (1 + \hat{\gamma}_1 X_1 + \hat{\gamma}_2 X_2 + \hat{\gamma}_3 X_3)^{-1}.$$

The independent variables are R&D/asset, patent/R&D, and citation/patent.

Table 3 reports the semi-elasticity outcomes of the R&D/asset and citation/patent variables on log q. When R&D/asset increases by 1%p, Tobin's q increases by approximately 1%. One unit of increase in citation/patent is associated with a 0.5% increase in Tobin's q. The semi-elasticity of patent/R&D is not reported because it is not statistically significant in the previous estimation.

Consistent with the previous analysis, R&D/asset plays a more important role in increasing firm value, while the effect of citation/patent on firm value is limited. This implies that the patents of Korean firms are weakly associated with an increase in firm value.

B. *Cross-industry analysis*

A cross-industry analysis is implemented to investigate further the impact of patents on firm value. The importance of patents can vary across industries because technologies work in different ways depending on the market environment. Technology in some industries, such as pharmaceuticals, is crucial for sustaining the competitiveness of a firm, while other components, such as the scale of the economy, may be more important in other industries. Thus, it is necessary to check whether knowledge-intensive industries enjoy stronger effects of patents.

Five industries[2] are chosen to represent the various degrees of patenting activity.[3] I add those industry dummy variables and interaction terms to equation (2). Industries are categorized according to KSIC (Korea Standard Industry Code) two-digit codes. Chemicals, pharmaceuticals, metals, electronic parts, and medical

[2]It is not possible to report the analysis results of all industries because there are more than 50 industries with KSIC two-digit codes. My findings for other industries are available upon request.

[3]Most patents were granted in electric parts during the sample period. Companies categorized into the chemicals, pharmaceuticals, and medical precision groups are so categorized in the order of the number of granted patents, with metals firms having the fewest patents granted in the sample.

precision categories are selected for use here. Chemical firms according to KSIC 20 are involved in the "manufacture of chemicals and chemical products; except pharmaceuticals and medicinal chemicals." Pharmaceuticals according to KSIC 21 are involved in the "manufacture of pharmaceuticals, medicinal chemical and botanical products." For metals, KSIC 25 stipulates the "manufacture of fabricated metal products, except machinery and furniture." Electronic parts companies according to KSIC 26 undertake the "manufacture of electronic components, computers; visual, sounding and communication equipment." Lastly, companies in the medical precision KSIC 27 group undertake the "manufacture of medical, precision and optical instruments, watches and clocks."

The most noteworthy industry is pharmaceuticals in the sense that it is a highly R&D-intense industry, and patent protection is crucial for firms to earn revenue, as developing new drugs requires considerable time and effort, whereas copying developed drugs is relatively easy.

The estimation equation with the industry effect is as follows.

$$(3)\quad \log Q_{i,t} = \log q_t + \log\left(\begin{array}{l} 1+\gamma_1 \dfrac{R_{i,t}}{A_{i,t}} + \gamma_2 \dfrac{P_{i,t}}{R_{i,t}} + \gamma_3 \dfrac{C_{i,t}}{P_{i,t}} \\ +\gamma_4 D_j \dfrac{R_{i,t}}{A_{i,t}} + \gamma_5 D_j \dfrac{P_{i,t}}{R_{i,t}} + \gamma_6 D_j \dfrac{C_{i,t}}{P_{i,t}} \end{array}\right) + \sum\nolimits_j \gamma_j D_j + \varepsilon_{i,t}$$

In equation (3), the dummy variable D_j and the parameter γ_7 denotes the industry fixed effects and the corresponding coefficient. The parameters γ_4, γ_5, and γ_6 are correspondingly the coefficients of the interaction effects between the industry and knowledge capital variables for the R&D/asset, patent/R&D, and citation/patent variables.

Table 4 reports the estimation results of equation (3). The effect of the patent variables on firm value is strong in knowledge-intensive industries such as pharmaceuticals. Column (1) is the baseline result in Table 3. Column (2) is the result without the interaction effect. Firms in the pharmaceuticals and medical precision groups have a high book-to-market ratio in general. A high book-to-market ratio usually implies a high marginal product of capital. It is natural that pharmaceutical and medical precision firms are such industries. As such, the industry effect on firm value is consistent with the findings of prior research.

Table 4 column (3) shows interesting results. For firms in the chemicals category, the interaction term coefficient of R&D/asset offsets the coefficient of R&D/asset, meaning that R&D/asset does not affect firm value for these firms. On the other hand, patent/R&D affects firm value negatively for firms in the chemicals category.

In the pharmaceutical industry, the citation/patent variable is important for increasing firm value. The effect of the dummy variable itself on log q is 0.156 in column (2), but the statistical significance disappears when considering an interaction effect with independent variables. This implies that the high q in pharmaceutical firms comes from the effects of R&D and patent variables and not from unobserved factors in this industry. The coefficient of the citation/patent

TABLE 4—NON-LINEAR REGRESSIONS OF TOBIN'S Q ON PATENT VARIABLES: INDUSTRY EFFECTS

	(1)		(2)		(3)	
Chemical			-0.0192	(-0.57)	0.0476	(1.20)
Pharmaceutical			0.156***	(3.77)	0.0347	(0.65)
Metal			-0.0430	(-1.11)	-0.0725	(-1.35)
Electronic parts			0.00352	(0.19)	0.135***	(4.69)
Medical precision			0.137***	(2.92)	0.188**	(2.11)
R&D/asset interaction	1.151***	(6.22)	1.076***	(5.77)	1.647***	(9.79)
Chemicals					-1.661***	(-9.19)
Pharmaceuticals					0.622	(0.77)
Metals					1.560	(0.98)
Electronic parts					-1.418***	(-5.96)
Medical precision					-0.738	(-1.22)
patent/R&D interaction	-3.97e-06	(-1.47)	-3.28e-06	(-1.09)	-1.44e-05**	(-2.13)
Chemicals					0.00147	(1.01)
Pharmaceuticals					0.00254	(1.09)
Metals					1.57e-05**	(2.29)
Electronic parts					0.000634	(1.45)
Medical precision					0.00243	(0.48)
citation/patent interaction	0.00589***	(4.22)	0.00602***	(4.32)	0.00600***	(4.50)
Chemicals					0.00539	(0.59)
Pharmaceuticals					0.0459**	(2.00)
Metals					0.00665	(0.63)
Electronic parts					-0.00381	(-1.30)
Medical precision					-0.00478	(-0.97)
D (R&D = 0)	0.0484	(1.58)	0.0511	(1.68)	0.0697**	(2.33)
Year-fixed effects	Y		Y		Y	
R-squared	0.1462		0.1543		0.1727	
# of obs.	21460		21460		21460	

Note: Standard errors are cluster-robust errors at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

variable in pharmaceuticals increases drastically from 0.006 to 0.052 when interaction effects are considered.

Firms in the metal industry appear to be irrelevant with regard to patent variables. The interaction effects on the metal group are not statistically significant, except for patent/R&D. The interaction effect for patent/R&D is 0.0000157, which reduces the effect of patent/R&D to nearly zero for the metal group. In the electronic parts industry, the effect of R&D/asset decreases compared to the benchmark case. In medical precision firms, the effects of R&D/asset, patent/R&D, citation/patent do not deviate much from the benchmark levels. In sum, the role of patents in increasing firm value varies across industries, and knowledge-intensive industries such as pharmaceuticals show a strong effect of the citation/patent variable.

C. *Self-citations*

elf-citations are citations associated with patents for which the assignee firm is identical to that of the cited patent. A self-citation is a special type of citation, and it has important meanings. Prior research shows that the importance of self-citations with regard to technological advances is higher than citations by others. We can keep track of the evolution of technology with self-citations. In this section, I more closely

TABLE 5— NON-LINEAR REGRESSIONS OF TOBIN'S Q ON PATENT VARIABLES: SELF-CITATIONS

	(1)	(2)	(3)
R&D/asset	1.151***	1.140***	1.166***
	(6.22)	(6.24)	(5.96)
Patent/R&D	-3.97e-06	-4.01e-06	-3.90e-06
	(-1.47)	(-1.48)	(-1.42)
Citation/patent	0.00589***		
	(4.22)		
		0.0350**	0.0336**
		(2.23)	(2.05)
[Self-citation/patent] * log(patent portfolio)			0.00453
			(0.57)
D(R&D = 0)	0.048	0.048	0.054
	(1.58)	(1.58)	(1.49)
Year-fixed effects	Y	Y	Y
R-squared	0.1462	0.1448	0.1475
# of obs.	21,460	21,460	19,392

Note: Standard errors are cluster-robust errors at the firm level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

examine the effects of self-citations on the market value of a firm. If self-citation more aptly captures technology, it should have strong effects on firm value.

When dealing with self-citations, it is important to consider the patent portfolio, which is the number of patents of a firm. If a firm owns many patents, the number of self-citations grows naturally. One should control for the patent portfolio; otherwise, the effect of self-citations is actually the effect of the patent portfolio.

Table 5 reports the estimation results of equation (2), including self-citations. The self-citation/patent variable is a stock variable identical to citation/patent except that the numerator is the self-citation stock. It has the same depreciation rate of 0.15, and it only increases when a firm cites the patent whose owner is the firm itself. Consistent with expectations here, the coefficients of the self-citation/patent variable is larger than that of the citation/patent variable. Table 5 column (1) presents the baseline result. Column (2) includes the coefficient of the self-citation/patent variable. The effects of self-citation/patent are approximately five times that of the citation/patent variable.

Column (3) includes the interaction term of self-citation/patent with a log patent portfolio. The interaction term is assumed to control for the number of patents owned by a firm. After controlling for the patent portfolio, the effect of self-citation/patent on firm value is economically and statistically significant as well.

D. *Firm's operating performance and patents*

In this section, I investigate whether R&D, patents, and citations can predict the future operating performances of firms. In the previous sections, I examined the relationship between only patent variables and firm value by utilizing the Cobb-Douglas production function. Because firm value is ultimately the sum of the present value of future earnings, there should be predictability of future earnings for variables that are strongly associated with firm value, such as self-citations. I adopt panel regressions to examine this because the purpose of this analysis is to determine simple predictability outcomes.

In panel regressions, I use the following equation for the estimation.

$$Y_{i,t} = \beta_1 + \beta_2 \frac{R_{i,t-1}}{A_{i,t-1}} + \beta_3 \frac{P_{i,t-1}}{R_{i,t-1}} + \beta_4 \frac{C_{i,t-1}}{R_{i,t-1}} + control + \varepsilon_{i,t}$$

Here, $Y_{i,t}$ is a firm operation variable. It is net-income/asset, operating-income/asset, and sales/asset. The control variables, $control$, include the log of market capitalization, firm-fixed-effect dummy variables, and year-fixed-effect dummy variables. The independent variables are R&D to assets, patents to R&D, and citations to patents, as defined in the previous sections.

The sample is identical to that used in the previous analysis. All variables are winsorized at the 1% and 99% level and normalized to a standard deviation of one to exclude the effects of extreme value observations.

Table 6 reports the panel regressions results. R&D/asset is negatively correlated with net-income/asset and operating-income/asset. A one standard deviation increase in R&D/asset is associated with a 0.16 standard deviation decrease in net-income/asset and operating-income/asset, as R&D is expensed and decreases current profits mechanically. Patent/R&D is not correlated with net-income/asset, operating-income/asset, or sale/asset.

The coefficients of citation variables are interesting in that citation/patent is negatively correlated with the profit and sales variables, while self-citation/patent is positively correlated with the dependent variables. A one standard deviation increase in citation/patent decreases the market value by approximately 0.038–0.04 standard deviations. On the other hand, a one standard deviation of self-citation/patent boosts market value by 0.033-0.038 standard deviations. Consistent with the previous analysis, these results implies that self-citations are closely related to technological advances and that their importance is much higher.

TABLE 6— REGRESSIONS OF OPERATING PERFORMANCE VARIABLES ON PATENT VARIABLES

VARIABLES	(1) Net income/asset	(2) Operating income/asset	(3) Sales/asset
R&D/asset	-0.163***	-0.158***	0.00369
	(-7.972)	(-8.327)	(0.225)
Patent/R&D	-0.00529	-0.00262	0.00565
	(-0.636)	(-0.305)	(0.674)
Citation/patent	-0.0381***	-0.0400***	-0.0369***
	(-2.925)	(-3.367)	(-3.406)
Self-citation/patent	0.0343***	0.0377***	0.0328***
	(4.352)	(4.260)	(4.080)
Size	-0.100***	-0.183***	-0.639***
	(-3.322)	(-6.727)	(-25.94)
Year-fixed effects	Y	Y	Y
Firm-fixed effects	Y	Y	Y
# of obs.	19,507	19,507	19,507
R-squared	0.497	0.520	0.635

Note: Standard errors are cluster-robust errors at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 7— REGRESSIONS OF OPERATING PERFORMANCE VARIABLES ON PATENT VARIABLES: LONG-RUN EFFECT

Variables	(1) Net income/asset	(2) Operating income/asset	(3) Sale/asset
R&D/asset	-0.0411**	-0.0592***	-0.0197
	(-2.032)	(-3.379)	(-1.397)
Patent/R&D	0.00554	-0.00381	-0.00485
	(0.611)	(-0.417)	(-0.548)
Citation/patent	-0.0277**	-0.0322***	-0.00445
	(-2.157)	(-2.641)	(-0.405)
Self-citation/patent	0.0254***	0.0244***	0.00607
	(3.335)	(2.789)	(0.737)
Size	-0.346***	-0.293***	-0.190***
	(-11.09)	(-11.01)	(-7.371)
Year-fixed effects	Y	Y	Y
Firm-fixed effects	Y	Y	Y
# of obs.	15,912	15,912	15,912
R-squared	0.624	0.661	0.725

Note: Standard errors are cluster-robust errors at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

A patent has the characteristic of a real option (Bloom and Reenen, 2002). It can take several years for firms to utilize the technology of a patent. In such cases, current patents can affect firm value through future operational outcomes in the long run. It takes a long time to initiate the effect of patents, and the effects last for long periods of time. A one-year time lag may not be enough to capture the predictability of patent variables. To address this concern, I construct three-year cumulative dependent variables. The estimation equation is as follows.

$$Y_{i,t,t+2} = \beta_1 + \beta_2 \frac{R_{i,t-1}}{A_{i,t-1}} + \beta_3 \frac{P_{i,t-1}}{R_{i,t-1}} + \beta_4 \frac{C_{i,t-1}}{R_{i,t-1}} + control + \varepsilon_{i,t}$$

$Y_{i,t,t+2}$ denotes the three-year cumulative dependent variables.

Table 7 displays the long-run effect of knowledge capital on a firm's operation. The results are consistent with the previous analysis. R&D/asset is negatively correlated with the profit variables. A one standard deviation increase in R&D/asset is associated with a 0.04 standard deviation decrease in three-year cumulative net-income/asset. The coefficient is 0.11-0.12 standard deviations smaller than the coefficients of a one-year lag analysis. A one standard deviation increase in citation/patent leads to a 0.027-0.045 standard deviation decrease in profit variables. On the other hand, a one standard deviation increase in self-citation/patent is associated with a 0.025 standard deviation increase in profit variables. In sum, the cumulative technological advance is positively associated with long-term profit generation.

V. Robustness Check

This section presents the results of additional analyses as a robustness check. The Korean economy experienced major economic shocks during the 1997-1998 Asian financial crisis and during the 2008 global financial crisis. At those times, firm values depreciated abruptly. To mitigate the concern that the results in the previous section stem from those extreme periods, I run a subsample analysis to determine if the results still hold after excluding such periods.

Table 8 reports the estimations with the same analysis of equation (2) with the subsample period of 2010-2015. The results are not different from the baseline results. R&D/asset plays a crucial role in increasing firm value, while the coefficient of patent/R&D is not economically or statistically significant. Citation/patent is positively associated with firm value increase as well.

The scope of the knowledge capital captured by patents consists of two features: the knowledge itself contained in the patents and the right of legal protection. Patent protection is limited to the country where the patent is granted. Hence, it quite often occurs that firms file patents in multiple countries with the same technology. Similar or the same technology patents in different countries are collectively referred to as a "patent family." In the previous analysis, I count patents without considering patent families, as the value of patents comes not only from the technology itself but also originates from legal protection as well.

However, one may raise the concern that patent families can inflate the number of patents. To address this point, I consider the first patent in the patent family as the effective case and compute the patent stock with that item. This is a very conservative approach because the remaining patents in the family are considered as valueless.

Table 9 reports the estimation results with alternative patent stock data. Similar to the previous results, patent/R&D does not affect firm value. The effect of citation/patent increases slightly to 0.008. In short, after excluding patent families, R&D/asset is the most important factor with regard to increasing firm value in Korea.

TABLE 8— NON-LINEAR REGRESSIONS OF TOBIN'S Q ON PATENT VARIABLES: 2010-2015

	(1)	(2)
R&D/asset	1.2450***	1.2680***
	(8.55)	(8.52)
Patent/R&D	-3.14E-06	-2.91E-06
	(-1.58)	(-1.49)
Citation/patent		0.006954***
		(3.13)
D (R&D = 0)	0.1656***	0.1656***
	(4.03)	(4.04)
Year-fixed effects	Y	Y
R-squared	0.1465	0.1496
# of obs.	8,488	8,488

Note: Standard errors are cluster-robust errors at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 9— NON-LINEAR REGRESSIONS OF TOBIN'S Q ON PATENT VARIABLES: PATENT FAMILY ADJUSTED VARIABLES

	(1)	(2)
R&D/asset	1.2521***	1.2665***
	(7.28)	(7.24)
Patent/R&D	-6.30E-06	-6.04E-06
	(-1.69)	(-1.63)
Citation/patent		0.00838***
		(4.74)
D (R&D = 0)	0.0512***	0.0508***
	(1.67)	(1.66)
Year-fixed effects	Y	Y
R-squared	0.1502	0.154
# of obs.	21,265	21,265

Note: Standard errors are cluster-robust errors at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

VI. Conclusion

By taking advantage of a novel patent database, I investigate the relationship between firm-level patents and firm value in Korea. I estimate the non-linear production-function type of Tobin's q equations on R&D, patents, and citations. The effect of R&D/asset is much higher in Korea than the effects reported in the literature, though surprisingly, patent/R&D is not associated with an increase in firm value. Firm value rises with citation/patent, but the magnitude is much smaller than the results in prior studies. Self-citation, which can track the technological advance of a firm, plays an important role in the increase in firm value. Overall, the results of the analysis here imply that the patent system in Korea does not play a role in boosting firm value.

The findings can be interpreted in two ways. One is that the patent system in Korea does not provide adequate protection. There have been many legal studies pointing out the weakness of patent protection in Korea. Proving infringement and accessing potential damage are too costly and burdensome for firms in Korea. Even if firms prove that an infringement took place, economic compensation is too low compared to the actual damage from the infringement. In many cases, patents in Korea may not be giving actual exclusive rights to the patent assignee, which can lead to a weak association between patents and firm value.

The second possible interpretation is that firms do not file patents with valuable technologies that have a risk of information disclosure, as Chung (2017) argues that firms choose strategically between secrecy and pursuing patent protection. Due to the weak patent protection in Korea, firms tend to choose secrecy when there is a risk that their technologies will be replicated by competitors.

Regardless of which mechanism better explains the main findings of this paper, the results provide clear implications for policies pertaining to the patent system in Korea. Policymakers in Korea should set up proper institutional and legal systems so that patents held by Korean firms can increase the value of these firms. Reinforcing patent protection will lead to the active patenting of valuable technologies, as firms will have more of an incentive to apply for a patent. If firms tend to apply for more patents, knowledge spillover in the economy will be stimulated. Thus, policymakers in Korea should enhance patenting incentives to promote innovation in Korea.

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Disability and Occupational Labor Transitions: Evidence from South Korea†

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*We examine how certain occupational physical requirements affect labor transitions of disabled workers by exploiting a unique feature of South Korean Disability Insurance (DI), where award rules are based solely on an applicant's medical condition, independent of his previous occupations. We estimate the labor market response to a health shock by constructing a physical intensity measure from O*NET and applying it to longitudinal South Korean household panel data. Our results suggest that health shocks initially lead to a 14 to 20 percent drop in employment and that this effect is greater for workers who previously held physically demanding occupations. Those who remain part of the labor market exhibit higher occupational mobility toward less physically demanding jobs. These findings imply that the magnitudes of income risks associated with health shocks vary depending on occupational and skill characteristics.*

Key Word: Disability, Labor Supply, Occupation, O*NET
JEL Code: I10, J24, J62

I. Introduction

A decline in an individual's health status can affect his economic circumstances in several ways. After the onset of disability, workers often face higher medical expenses, such that these expenses account for one-third of consumer bankruptcies in the United States (Livshits *et al.,* 2007). Numerous studies have shown, along with the burden of medical expenses, that the financial status of disabled workers often deteriorates, as they tend to spend more time searching for jobs, work fewer hours, and earn less.[1,2] One possible explanation for unhealthy workers' underperforming labor

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[1]See Low and Pistaferri (2015), Kim and Rhee (2018), and De Nardi *et al*. (2018), among others.

[2]These patterns can be found in other countries too. For instance, Campolieti (2002) and Cai and Kalb (2005) use Canadian and Australian datasets, respectively, to show a decline in labor force participation after the onset of disability. Kwon (2018) finds similar results among South Korean males.

market outcomes compared to their healthier counterparts could be their lack of work capacity as a result of poor health. This leads to the questions of which types of workers are at risk of losing their work capacity, and to what extent?

In this paper, we answer this question while focusing on the physical requirements of occupations and examine whether those of previous jobs can differentially affect labor market outcomes after the onset of disability. In their influential paper, Kambourov and Manovskii (2009a) show that individuals accumulate occupation-specific skills and that occupational mobility can account for substantial changes in wage.[3] If occupation-specific experiences constitute a significant part of human capital in the labor market, then workers in physically demanding occupations could be exposed to higher income risks after the onset of disability. Similarly, we expect workers in less demanding occupations to keep participating in the labor market even after the onset of disability, therefore being less affected by their health status. Therefore, knowing the link between the physical requirements of a job and the decrease in a person's work capacity could be useful for incentivizing work-capable DI recipients to rejoin the workforce.

Unfortunately, it is not straightforward to examine this relationship between occupation-level requirements and labor market outcomes because most advanced countries provide social insurance against a loss of work capacity, but not a poor health status. That is, DI award rules consider both the applicant's occupation history (and, thus, occupational characteristics, including physical intensity level) and his future job prospects.[4] Therefore, it is not straightforward to distinguish between individuals who opt out owing to a lack of occupation-specific requirements and those who leave the labor force to take DI.

A unique institutional feature of the DI program in South Korea can be useful to address this challenge. In South Korea, the award of DI is based solely on an applicant's medical condition. As a result, the award probability is independent of an individual's occupational history and his labor market prospects. Furthermore, the presence of the DI program itself is relatively insignificant in South Korea; total government spending on the DI program is 0.05% of the country's GDP, whereas, on average, OECD countries spend 1.3% of GDP on DI recipients.[5] Most importantly, DI recipients do not lose their benefits when they work, thus DI does not distort their labor supply decisions.[6]

We construct a measure of physical intensity for each occupation and use this index to examine how occupation-level physical requirements affect the labor supply after the onset of disability. Here, we use a longitudinal data set on South Korean households to estimate a standard fixed-effects panel regression model. Similarly to Gertler and Gruber (2002), our analysis is restricted to working-age individuals with

[3]Recent studies of the role of occupational characteristics in labor market outcomes expand this framework by estimating the labor transitions, summarizing occupations as sets of tasks that require multidimensional skills (e.g., see Lise and Postel-Vinay, 2019 and Guvenen *et al.,* 2020).

[4]The US Social Security Administration (SSA) applies more generous criteria to older, less educated, non-English-speaking applicants because they are expected to have greater difficulty in developing skill sets for new occupations (Wixon and Strand, 2013).

[5]In terms of the scale of recipients, only 1.1% of the South Korean working-age population is currently enrolled as DI recipients. In other OECD countries, 6% of their working-age populations receive DI payments on average (source: https://data.oecd.org/healthres/health-spending.htm).

[6]Indeed, about 37% of working-age individuals registered as disabled for work-related events are currently employed in South Korea (source: disability survey of KLIPS, 9th wave).

employment and good health prior to potential disability events. By restricting our samples to ex ante (seemingly) healthy workers with strong labor market attachment, we control for potential unobservable characteristics.

Our results suggest that after the onset of disability, poor health reduces employment by 19 percentage points (*pp*). Furthermore, this decline lasts at least two years and is more profound among individuals who previously worked in physically demanding occupations. More specifically, compared with the average "white-collar" occupation, high-intensity occupation holders experience an additional 14.4 *pp* decline in employment after disability occurs.

Although the short-run effect of occupational physical intensity on the employment rate is negative and significant, we find no significant effects in the long term. We study the reasons for this finding by examining the patterns of occupational mobility after the onset of disability. The results suggest that while workers tend to move to less demanding occupations overall, this transition becomes more apparent after disability occurs. Quantitatively, our estimation suggests that a reduction in physical intensity is comparable to switching occupations from a hairdresser to a general salesperson. These findings suggest that workers who currently have physically demanding occupations are exposed to additional health risks but that their endogenous response can partially mitigate this effect.

A. *Related Literature*

This study is directly related to a broad body of literature on the role of health in labor market outcomes. Currie and Madrian (1999) provide an extensive survey on this subject, illustrating multiple ways in which poor health can influence an individual's welfare. Recently, Autor *et al.* (2019) and Lee (2019) noted that households respond to a breadwinner's bad health event by adjusting the spousal labor supply, implying that the welfare consequences of bad health go beyond the individual. On an aggregate level, De Nardi *et al.* (2018) document how poor health outcomes accumulate over the life cycle and shape economic inequality in the United States. Our analysis quantifies the interplay between the effects of occupation-level characteristics and poor health on the labor supply decisions of individuals.

Extensive research has been conducted in an effort to quantify the effects of health on labor supply decisions. French (2005) studies the labor supply of old-age workers and examines the relationship between health, social security, and retirement decisions. Using data from an Australian household survey, Cai and Kalb (2005) examine the effects of poor health on the labor supply across age and gender groups, finding a more significant decline among older people and females. Kwon (2018) explores a South Korean medical panel dataset and finds that poor health outcomes result in a decline in employment among middle-aged workers. The present study contributes to the literature by examining whether the effects of poor health on the labor supply depend on a worker's previous occupational characteristics.

Our analysis builds on the idea of occupation-specific human capital, which is explored empirically in Kambourov and Manovskii (2009a), Kambourov and Manovskii (2009b), and Groes *et al*. (2015). These studies find that occupation-specific human capital exists and that individuals' labor market outcomes and aggregate distributions are strongly related to their occupational mobility patterns.

This concept has been widely adopted in the studies of labor market transitions, including those that account for skill-biased technological change (Lindenlaub, 2017) and those that analyze long-term US unemployment rates (Wiczer, 2015).

Recent empirical analyses have explored the underlying factors defining occupation-specific human capital using a task-based approach (Autor, 2013). Guvenen *et al.* (2020) categorize occupation-specific requirements into cognitive and non-cognitive skills and study the extent of the mismatch in the labor market. Lise and Postel-Vinay (2019) decompose occupation characteristics into analytical, verbal, and social skills and study how these three types of skills evolve over a worker's occupation tenure. This study considers physical ability as an occupation-specific characteristic and examines how this requirement affects the labor supply of the disabled.

The remainder of the paper is organized as follows. Section 2 discusses the award criteria of the DI program in South Korea and compares its features with those of the US DI program. Section 3 describes our data and constructs the physical intensity measure used in the empirical analyses. In Section 4, we explain our empirical approach and document its results. Section 5 concludes the paper.

II. Background: DI Award Criteria in South Korea

South Korea has two income-support programs for the disabled: DI and a disability pension (DP). DI is a social insurance funded by employer- and employee-paid taxes, whereas DP is a welfare program comparable to Supplemental Security Income (SSI) in the United States. In this section, we focus on the DI program and explain its award criteria. However, it is important to note that both programs follow strict medical impairment criteria to determine applicants' eligibility.

A. *The Degree Rule*

In South Korea, a non-elderly individual is eligible for DI when he meets the following two conditions.[7] First, he must be an active contributor with a sufficient record of earned income tax payments. The former checks whether applicants have shown recent labor market activity, and the latter verifies whether applicants have accumulated a sufficient employment history. These are similar to the work tests—the recent work test and the duration of work test—in the United States.

Second, the applicant needs to pass a medical examination administered by the National Pension System (NPS). The medical exam is conducted twice, 18 months apart, in order to take into account potential recovery. For each exam, an applicant's impairment is classified into one of 13 types of disabilities and evaluated on a four-degree scale, where a degree of one represents the most severe impairments.[8] Each disability type may contain subcategories and provides extremely detailed medical

[7]The lower age bound for eligibility is 18, and the upper bound gradually increases depending on the applicant's birth year: age 61 for those born in the years 1953–1956, age 62 for those born in the years 1957–1960, age 63 for those born in the years 1961–1964, age 64 for those born in the years 1965–1968, and age 65 for those born after 1969.

[8]The categories are vision, hearing, speech, arm/leg/spine, mental disorders, respiratory disorders, cardiovascular system, digestive system, liver disease, hematological disorders, abdomen/pelvic organs, facial disorders, and cancer.

TABLE 1— DI ALLOWANCE BY DEGREE IN SOUTH KOREA

	No. of Cases	Percent (%)
Degree 1 (most severe)	3,376	11.43
Degree 2	10,363	35.08
Degree 3	5,155	17.45
Degree 4 (least severe)	4,568	15.46
Insufficient impairment	5,141	17.40
Disqualification	942	3.19
Total	29,545	100

Note: Table 1 documents the 2018 award statistics of the DI program allowance in South Korea. Grounds for disqualification include an ineligible application and insufficient medical evidence.

Source: 2018 NPS Statistical Yearbook.

TABLE 2— THE DISTRIBUTION OF THE MONTHLY DI BENEFITS

DI Benefit Amount (1,000 won)	Total	Male	Female
Less than 200	49	31	18
200 to 400	30,412	21,763	8,649
400 to 600	29,982	25,411	4,571
600 to 800	7,456	6,920	536
800 to 1,000	2,051	1,962	89
1,000 to 1,300	816	781	35
1,300 to 1,600	101	99	2
1,600 to 2,000	5	5	0
More than 2,000	0	0	0
Total	70,872	56,972	13,900

Note: Table 2 documents the number of DI recipients by DI benefit amount as of May 2020.

Source: NPS Monthly Statistics, September 8, 2020.

conditions for determining the degree of impairment. After the recovery period, applicants labelled as degree one, two, or three on their second medical exam become eligible for DI payments (Lee *et al.*, 2010). Those labelled as degree four, the least severe degree, receive a one-time lump-sum compensation equivalent to 225% of the regular DI payment. Applicants not assigned a degree do not qualify for DI. The allowance results are summarized in Table 1. Once approved, applicants start collecting monthly DI benefits, as determined by their contribution history and severity of impairments. Table 2 reports the distribution of monthly benefits among the DI beneficiaries. As of May of 2020, 85% of DI recipients collect less than 600,000 Korean won per month.[9]

Another important feature of the South Korean DI program is that applicants can maintain their beneficiary status regardless of their labor market status as long as their medical condition remains. Therefore, beneficiaries' labor supply decisions are not distorted by their DI status. Indeed, approximately one-third of the DI recipients are employed in South Korea.[10]

[9]The average monthly income for an urban household of one in the year 2019 is 2,545,147 Korean won, which is 4.24 times greater than 600,000 Korean won.

[10]Data source: Special Supplement on Disability from KLIPS 9th wave.

B. *DI Criteria Independent of Work Capacity*

To illustrate the unique features which apply when determining disabilities independent of work capacity, we compare the South Korean DI programs to the US DI decision process, focusing on applicants with hand amputations. Table 3 lists the severity of impairments for corresponding degrees related to hand amputees in South Korea. Regardless of an individual's socioeconomic characteristics, his amputation level determines the results of medical exams (and thus DI eligibility). In 2018, of 906 applications related to hand/arm amputees, 367 cases (40.5%) were awarded DI (National Pension System, 2019).

In contrast, medical evidence evaluations in the United States include three steps and examine applications while considering multiple factors. Once the degree of impairment meets the necessary conditions, the SSA verifies whether the medical condition is sufficiently severe for the applicant to receive DI.[11] In the case of a hand amputation, the sufficient medical condition is the loss of both hands, which is equivalent to degree one in South Korea. However, if the applicant's amputation condition is less severe, the disability status is determined after a subsequent evaluation of his work capacity, referred to as the residual functional capacity test.[12]

During the residual functional capacity test, the SSA examines the applicant's capacity with regard to past and alternative occupations. The SSA defines individuals as disabled when their health status prevents them from doing their previous work and from adjusting to alternative jobs. The assessment rules vary with the applicants' age, work experience, and education to reflect their current and potential skill sets. For instance, the SSA does not consider age as a constraint to learning new skills for applicants below the age of 50, whereas more lenient criteria are applied for older workers.[13] Thus, eligibility results may vary in the United States for the same health status depending on an individual's characteristics. These application procedures allow the government to award DI based on the residual of work capacity as a result of poor health, not based on poor health itself.

TABLE 3— DI AWARD CRITERIA: DEGREE RULES FOR AMPUTATION

Degree	Amputation level
1	Removal of the both hands above the wrist
2	Removal of one hand above the wrist
3	Missing the thumb and index fingers on one hand

Note: Table 3 lists the physical conditions to receive DI owing to hand amputations. Source: NPS Disability Award Rules.

[11]The Listing of Impairments (also known as the Blue Book), which contains the type of disability with sufficient medical conditions for DI eligibility, is available on the SSA webpage (Listing of Impairments).

[12]Since 1985, DI awards based on residual functional capacity increased threefold (Michaud *et al.,* 2018). In 2010, 13.6% of applicants received DI for proving sufficiently severe medical conditions, and 16.8% received DI after the residual capacity evaluation (Wixon and Strand, 2013).

[13]Chen and van der Klaauw (2008) exploit this institutional feature to estimate the labor supply distortion created by DI using a regression discontinuity method. Their results suggest that DI recipients' labor supply would have increased by 20 *pp* had none received benefits.

III. Data

In this section, we describe the two main data sources used in our analysis: O*NET for occupational skill requirements and the Korean Labor & Income Panel Study (KLIPS). First, we construct a measure of occupational physical intensity using O*NET, after which we apply this measure to longitudinal survey data on Korean workers for the estimation.

A. *O*NET*

The US Department of Labor provides occupational information pertaining to more than 967 professions, covering both subjective characteristics (e.g., style, value, interests) and the qualifications (e.g., abilities, skills, knowledge) of each occupation. "Physical abilities" is one such qualification measure, indicating the physical abilities needed to perform an occupation's main tasks. We focus on this category to construct a measure for occupational physical intensity.

1. Physical Intensity of Occupation

"Physical abilities" consists of 18 components, reported on a scale between 0 and 100.[14] Because these measures are highly correlated, we initially apply a principal component analysis (PCA) rather than using them as independent regressors.[15] The PCA is known for reducing data dimensions (and thus improving the computational efficiency of the estimation of the second stage) while retaining the variation of the original data.[16] Specifically, our dataset is a matrix of $K = 18$ measures of physical abilities for $N = 967$ occupations. We denote this $N \times K$ matrix as P, where the element p_{nk} represents ability k required for occupation n. Using the PCA, we transform the original data points into $q_n = A(p_n - \overline{p})$, where A is the $K \times K$ matrix of principal components ($\{f_k\}$) and $\overline{p}$ is the mean vector.

We find that the first component explains the majority of the correlation between the ability requirements and thus use it as a physical intensity index. Technically, the physical intensity measure $\hat{p}_j$ of occupation j is an orthogonal projection of the original data point onto the first principal component ($k = 1$). Figure 2 confirms that the measure reflects the relative difference in physical intensity.

[14]These are the level and importance of the following nine characteristics: dynamic flexibility, dynamic strength, explosive strength, extent flexibility, gross body coordination, gross body equilibrium, stamina, static strength, and trunk strength. The importance score reflects how relevant it is with regard to performing the main tasks of an occupation, while the level score indicates the difficulty required when performing occupational tasks.

[15]Indeed, the overall Kaiser–Meyer–Olkin measure of sampling adequacy is 0.933, indicating that our sample is appropriate for a PCA (Kaiser, 1974).

[16]A similar approach can be found in Lise and Postel-Vinay (2019), who map more than 200 O*NET job descriptors into three skill requirements— mathematical, mechanical, and social skills —and estimate a structural job search model of multidimensional skills. Guvenen *et al*. (2020) process multiple test scores available in NLSY79 into three ability measures for individuals (math, verbal, and social skills) using a PCA and gauge the degree of mismatch in the US labor market.

(a) Principal Component Estimates

f_k	Eigenvalue	Diff.	Proportion	Cum.
1	14.091	12.682	0.783	0.783
2	1.409	0.302	0.078	0.861
3	1.108	0.741	0.062	0.923
4	0.367	0.144	0.020	0.943
5	0.223	0.039	0.012	0.955

(b) Cumulative Variation Explained

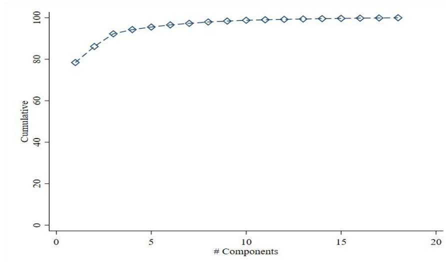

FIGURE 1. PRINCIPAL COMPONENTS: CORRELATION AND CUMULATIVE VARIATION

Note: The left panel reports the first five principal component estimates using physical abilities from O*NET. The right panel reports the cumulative variation explained by the number of principal components.

(a) $\hat{p}_j^{(1)}$ (b) $\hat{p}_j^{(2)}$

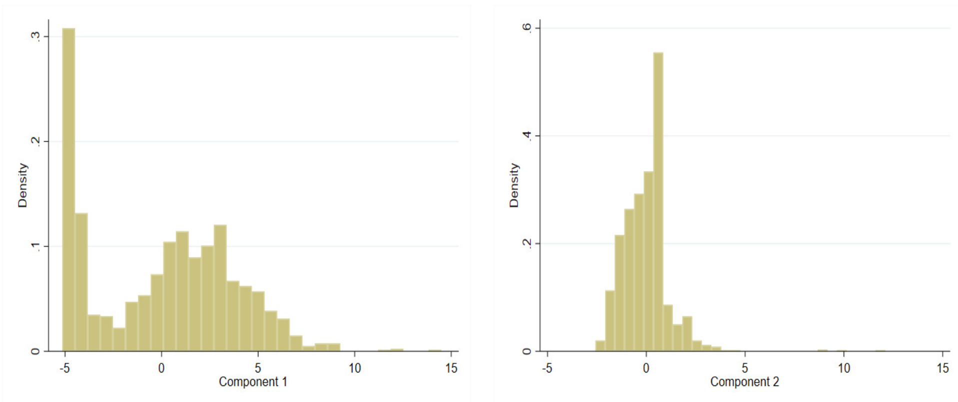

FIGURE 2. PHYSICAL INTENSITY INDEX DISTRIBUTION: $\hat{p}_j^{(1)}$ AND $\hat{p}_j^{(2)}$

Note: Figure 2 illustrates the distribution of physical ability of occupations available from O*NET. The graph shows that the majority of variation in the physical intensity measure is explained by the first principal component.

TABLE 4— MOST AND LEAST PHYSICALLY INTENSIVE OCCUPATIONS

Most Intensive	Least Intensive
Dancers	Music composers and arrangers
Choreographers	Dispatchers (except police, fire, and ambulance)
Fitness trainers and aerobics instructors	Survey researchers
Athletes and sports competitors	Regulatory affairs managers
Municipal firefighters	Water/wastewater engineers

Note: Table 4 reports the most and least physically demanding occupations from O*NET, based on the author's calculations.

B. *KLIPS*

The labor market data used in our analysis are taken from KLIPS, a longitudinal survey representing the labor market activities of Korean urban households. In this section, we briefly explain how we link the physical requirement information from O*NET to KLIPS and introduce the key variables used in our empirical analysis.

1. Occupation

There are two major differences between the occupational classification criteria of O*NET and KLIPS. First, O*NET records the occupational characteristics of the Standard Occupational Classification (SOC) of the Office of Management and Budget (OMB), whereas KLIPS provides individuals' occupational variables according to the Korea Standard Classification of Occupation (KSCO). In addition, O*NET reports occupational characteristics at the four-digit level, whereas KLIPS adopts a more aggregated three-digit level. We reconcile these differences using the following two-step procedure. We address the first issue by linking the four-digit occupation classification of the SOC to the four-digit KSCO table using the International Standard Classification of Occupation (ISCO). Then, we construct the physical intensity indices for the three-digit level occupation as the (weighted) mean of the four-digit codes. We find that 75.3% of Korean occupation codes can be mapped into five or fewer occupations in the US occupational classification codes. Detailed matching rates for each process are reported in Appendix A.1.[17] This gives us an aggregated physical intensity measure for 147 occupations in the KSCO.

One possible concern when using U.S. job characteristics in an analysis of the Korean labor market is that those characteristics can be misleading, as identically labeled occupations may require different sets of skills and abilities due to country-specific factors. To mitigate this concern, we examine the relationship between the occupational physical intensity measures and other individual-level socioeconomic characteristics in the two countries. Figure 3 illustrates the relationship between the subjective health measures and the physical requirement indices, and Table 6 summarizes the correlation between other socioeconomic characteristics and the physical requirement indices. Both suggest that the occupational physical requirements and other variables exhibit no significant differences between the two countries.

TABLE 5— SUMMARY STATISTICS: PHYSICAL INTENSITY MEASURE

Category		Mean	SD
Gender	male	0.510	(3.085)
	female	-0.008	(2.536)
Education	less than college	1.733	(2.628)
	college or more	-0.934	(2.483)
Age (less than college)	less than 50	1.458	(2.666)
	above 50	2.183	(2.501)
Age (college or more)	less than 50	-0.955	(2.462)
	above 50	-0.766	(2.636)

Note: Table 5 presents the means and standard errors of the physical intensity measures of occupation by respondents' socioeconomic status. Statistics are computed using cross-sectional weights.

[17]Multiple matches mostly occur in occupations in information technology and healthcare, where the SOC adopts more granular definitions, whereas the KSCO and ISCO use broader classifications.

TABLE 6— PHYSICAL REQUIREMENTS AND INDIVIDUAL CHARACTERISTICS: US VS. SOUTH KOREA

		Variable				
		College	Female	Hours	Wage	Age
U.S.		-0.343	-0.207	0.008	-0.186	-0.095
South Korea	Local area labor force survey	-0.425	-0.135	0.092	-0.250	-0.061
	KLIPS	-0.652	-0.145	0.127	-0.157	-0.089

Note: Table 6 reports the correlation between the physical requirement index and individual-level characteristics using the March CPS data, the Local Area Labor Force Survey, and KLIPS. The observations are employed workers aged between 18 and 64. The wage variable is adjusted based on the annual CPI indices.

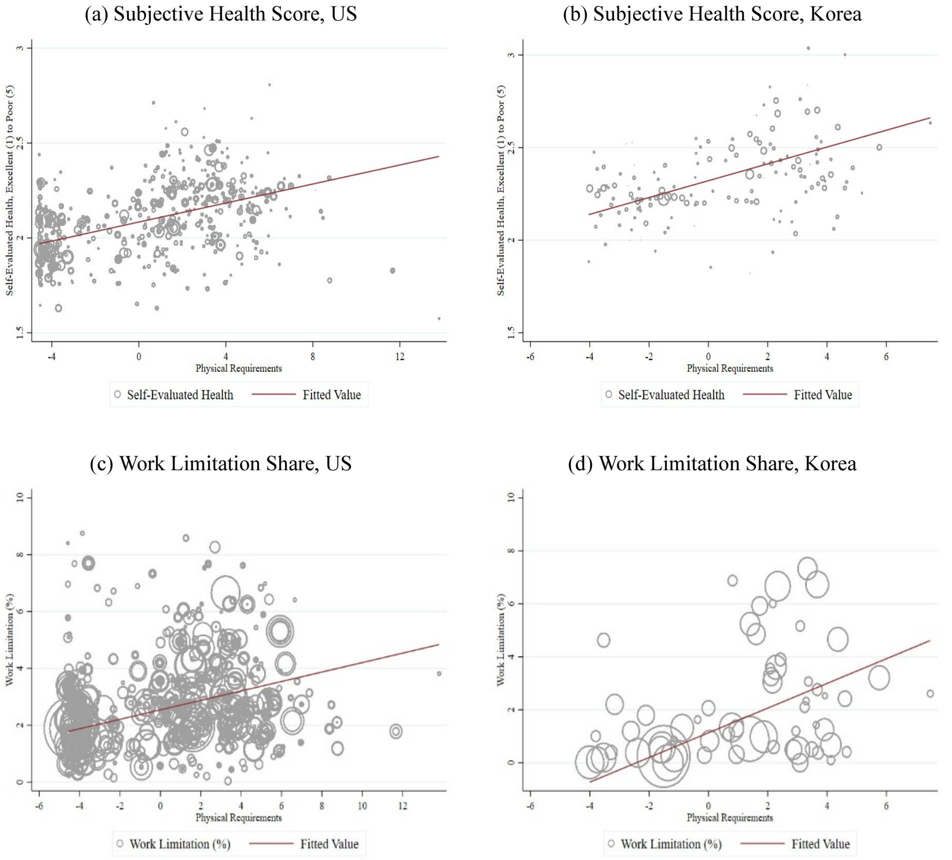

FIGURE 3. PHYSICAL REQUIREMENTS AND HEALTH OUTCOMES: US VS. SOUTH KOREA

Note: These graphs illustrate the relationship between the physical requirements and health outcomes, the subjective health score and work limitations, based on the March supplement of the US Current Population Survey (CPS) and KLIPS. The size of each circle represents the population weight, and solid lines are population-weighted linear approximations.

2. Disability Measure

KLIPS provides three sets of health variables that we can use to infer health shocks. First, it asks directly whether a respondent has an impairment that causes a disability. According to this definition, 2.95% report being disabled in our sample. Although this variable is similar to the technical definition of a health shock in our analysis, Korean households may interpret the definition of a disability too narrowly and thus may answer in the negative despite their restricted work capacity. To address this concern, we complement the variable with two other health-related variables: a subjective evaluation and work limitations. KLIPS provides three categorical variables of subjective health evaluation, with scores ranging from one (excellent) to five (very poor). Individuals are asked to assess their current health status and then to compare it with that of the general public and with their own health status from the previous year. In our benchmark analysis, we use the evaluation of the current health status to define a disability.[18] Although these measures are useful for obtaining an overall picture of a respondent's health status, they may be unrelated to the respondent's work capacity. For instance, if a person with a hearing impairment is a painter, he may score his overall health status below average, but his capacity to work as a painter may not be limited by his physical characteristics. To address this shortcoming, we also combine the subjective evaluation measures with "work limitation," which asks whether the respondent's health status restricts his job-related activities.[19] In our benchmark analysis, we define individuals with a disability as those who report either physical or sensory disabilities and those with poor health and work limitations. According to this definition, approximately 4.8% of the sample observations are considered disabled.[20] Table 7 presents the means of the key variables, and Table 8 reports the summary statistics of the health variables.

TABLE 7— DESCRIPTIVE STATISTICS

Variable		Mean	SD
Demographics	Age (years)	37.81	(14.21)
	College degree	0.527	(0.499)
	Married	0.502	(0.500)
Labor market	Employment	0.619	(0.486)
	Regular contract worker	0.738	(0.440)
	Weekly working hours	44.22	(15.45)
	Physical intensity	0.510	(3.085)
Health	Share disabled	0.048	(0.214)
	Subjective health below average	0.080	(0.272)
	Transition probability: non-disabled to disabled	0.031	(0.173)
	transition probability: disabled to non-disabled	0.394	(0.489)
	Share of population with transition	0.045	(0.208)
Number of obs.	56,698		

Note: Table 7 presents the means and standard errors of the key variables used in the analyses. Statistics are computed using cross-sectional weights.

[18]The current health evaluation and relative evaluation results are strongly correlated (≈ 0.8).

[19]Specifically, the survey asks whether a respondent has experienced difficulties in job-related activities owing to his health status.

[20]We conduct robustness analyses using alternative strict definitions of disability and find qualitatively similar results. The robustness analyses are reported in Section 4.2.

TABLE 8— SUMMARY STATISTICS: HEALTH-RELATED VARIABLES IN KLIPS

(a) Descriptive statistics

Variable	Mean	SD
Government registered disabilities*	0.0159	(0.125)
Physical or sensory disabilities	0.0295	(0.169)
Work limitation	0.0398	(0.195)
Subjective health below average	0.0664	(0.249)

(b) Relationships across health variables

Health measures	Government registered disabled*			
	Non-disabled		Disabled	
Physical or sensory disabilities	0.0036	(0.0597)	0.3259	(0.4693)
Work limitation	0.0043	(0.0651)	0.2505	(0.4337)
Subjective health below average	0.0047	(0.0686)	0.1328	(0.3396)

Note: *This variable reports the fraction of working-age individuals who went through government's medical examination and were approved at severe degrees (1, 2, and 3) for their impairments. This variable is also included in a part of the special supplement during the 9th wave of KLIPS. The top panel presents the means and standard errors of the health-related variables available in KLIPS. The bottom panel presents the share of government-registered disabled according to the three disability measures. Statistics are computed using cross-sectional weights.

IV. Estimation

A. *Model*

We consider the following fixed-effects regression model as our benchmark specification:

$$y_{it} = X_{it}'\beta + \sum_{k=-2}^{2} \{\delta_k + \lambda_k \overline{p}_{i,-3}\} \times I_{itk} + u_i + \theta_t + \varepsilon_{it}, \quad (1)$$

where the dependent variable y_{it} is the labor market outcome of individual i at time t . The independent variable X_{it} contains a set of individual-level characteristics, including age and education. We denote the dummy variables for individual and time fixed effects as u_i and θ_t, respectively, and ε_{it} represents a standard error term.

Our main interest is in the coefficients δ_k and λ_k associated with the dummy variable I_{itk}, which takes a value of one if individual i reports a health shock at time $t+k$, for $k \in \{-2, -1, 0, 1, 2\}$. The variable $\overline{p}_{i,-3}$ is the physical intensity of the occupation of individual i three periods prior to the onset of disability. Thus, the coefficient δ_k represents a common change in response to a health shock, and the coefficient λ_k is the interaction between a worker's health status and his occupation three years prior to the occurrence of the negative health shock. We fix the occupational characteristics three years before the onset of the disability because we restrict our sample to those individuals who reported good health and who worked at that time. This restriction controls for unobservable characteristics, thus helping us to measure the effects of a health shock on labor market outcomes.

B. *Results*

1. Employment to Non-employment

The first estimation reports the effects of disability on employment, which takes a value one if individual i orts that they have either a part- or full-time job. We report the estimation results for equation (1) in Table 9. As indicated in the first column (δ_k), a disability event is associated with a persistent negative impact on employment. However, the coefficient estimates for pre-disability dummies turn out to be statistically insignificant. These outcomes suggest that our sample selection criteria, which limit the analysis to individuals with employment and good health three periods prior to the potential disability, can usefully control for potential unobservable characteristics. We can also observe the common impact of a disability on the employment estimates over time in Figure 4.

The second column (λ_k) of Table 9 reports the interaction between a worker's previous occupation and his disability status. Similar to the case of common effect estimates, we find no significant relationship between occupation and health on employment prior to the disability event. In contrast, the onset of disability induces a decline in employment, and this negative effect is amplified in period t. The estimated coefficient suggests that if the physical requirement of an occupation increases by one, there is an additional decline in the employment probability of 1.54*pp.*[21]

In our sample, the score 4.94 corresponds to the top 5% intensity measure, while

TABLE 9. EFFECTS OF DISABILITY ON EMPLOYMENT OVER TIME: ESTIMATION RESULTS

Coefficient	Disability (δ_k)	Physical intensity × Disability (λ_k)
t-2	0.0099 (0.0240)	0.0074 (0.0068)
t-1	-0.0260 (0.0202)	-0.0023 (0.0056)
t (disability event)	-0.1903*** (0.0218)	-0.0154** (0.0062)
t+1	-0.0853*** (0.0176)	0.0084 (0.0052)
t+2	-0.0154 (0.0181)	-0.0014 (0.0051)
# of obs.	35,527	
R-sq	0.0527	

Note: Table 9 reports the estimation results based on employed individuals aged between 15 and 65 with no reported disability at time *t-3*. Other regressors are age, education, and the dummy variables for industry, time, and location. Numbers in parentheses are robust standard errors, clustered by individual. ***p < 1%, **p < 5%, and *p < 10%.

[21]The coefficient estimate for physical intensity is 0.00039 with 95% CI [-0.0030,0.0038] and are thus omitted for brevity.

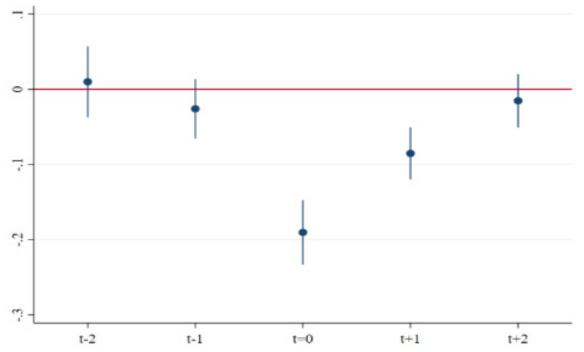

FIGURE 4. EFFECTS OF DISABILITY ON EMPLOYMENT

Note: Figure 4 illustrates the common effects of disability on employment based on our coefficient estimates in Table 9. Blue dots indicate point estimates, and the vertical line represents the 95 percent confidence interval.

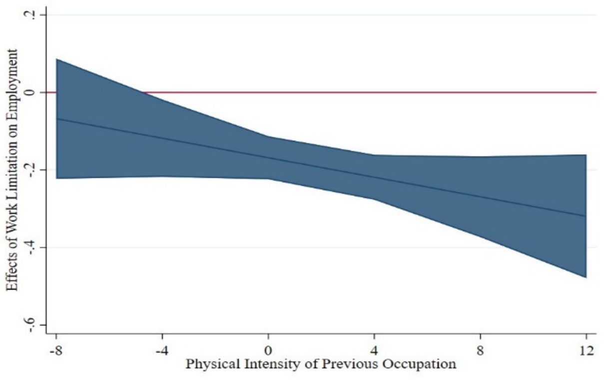

FIGURE 5. EFFECTS OF WORK LIMITATION ON EMPLOYMENT:
PHYSICAL INTENSITY OF THE PREVIOUS OCCUPATION

Note: Figure 5 reports the marginal effects of disability on employment, as indicated by the physical intensity measures, based on our estimation results. The shaded area reports the 95 percent confidence interval.

-4.39 represents the bottom 5%. Thus, the employment rates from the onset of disability vary significantly. Indeed, Figure 5 illustrates the magnitude of the decline in employment according to the degree of physical intensity of the previous occupation. Figure 5 suggests that we can expect the difference in employment to be around 14.4 *pp*.

a. Robustness Analyses

1) Demographic Subgroups

Here, we initially conduct a robustness analysis by estimating equation (1) according to different demographic subgroups. In our benchmark analysis, we focus on the labor supply of both male and female workers. We change this sample selection criterion and separately estimate female samples and male samples. The results are reported in Table 10. The results remain significant when we separately estimate the male and female samples, although the role of previous occupational requirements becomes more significant when we limit the observations to female

TABLE 10— ESTIMATION RESULTS BY GENDER

Coefficient	(1) Male only		(2) Female only		(3) Male + Female	
	Disability	Intensity × Disability	Disability	Intensity × Disability	Disability	Intensity × Disability
t-2	-0.0056 (0.0313)	0.0121 (0.0079)	0.0227 (0.0368)	0.0008 (0.0135)	0.0099 (0.0240)	0.0074 (0.0068)
t-1	-0.0445* (0.0248)	0.0083 (0.0064)	-0.0005 (0.0312)	-0.0233** (0.0101)	-0.0260 (0.0202)	-0.0023 (0.0056)
t	-0.1684*** (0.0283)	-0.0126* (0.0076)	-0.1993*** (0.0333)	-0.0280*** (0.0108)	-0.1903*** (0.0218)	-0.0154** (0.0062)
t+1	-0.0624*** (0.0228)	0.0052 (0.0063)	-0.1073*** (0.0278)	0.0113 (0.0094)	-0.0853*** (0.0176)	0.0084 (0.0052)
t+2	-0.0015 (0.0242)	-0.0033 (0.0057)	-0.0307 (0.0275)	0.0006 (0.0102)	-0.0154 (0.0181)	-0.0014 (0.0051)
# of obs.	21,514		14,013		35,527	
R-sq	0.0900		0.0141		0.0527	

Note: Table 10 reports the estimation results based on employed individuals aged between 15 and 65 with no reported disability at time *t-3*. Other regressors are age, education, and the dummy variables for industry, occupation, time, and location. The numbers in parentheses are robust standard errors, clustered by individual. ***p < 1%, **p < 5%, and *p < 10%.

workers. This observation is in line with the literature, where the labor supply decisions of female workers are more responsive to health shocks (Low and Pistaferri, 2020).

Another interesting robustness exercise is to compare older and younger workers. Although we include age and its square as regressors to control for possible age effects in the benchmark estimation, there could be systematic patterns that may not be well captured using the quadratic equation. This robustness analysis has potential policy implications, as the current US DI award process applies lenient rules to older workers. Using age 45 as our cutoff, we divide the sample into two groups: older and younger workers. The results in Table 11 show that negative health shocks tend

TABLE 11— ESTIMATION RESULTS BY GENDER

Coefficient	(1) Older workers only		(2) Younger workers only	
	Disability	Intensity × Disability	Disability	Intensity × Disability
t-2	0.0458 (0.0311)	-0.0035 (0.0083)	-0.035 (0.0409)	0.0143 (0.0139)
t-1	-0.0339 (0.0270)	-0.0040 (0.0073)	0.0249 (0.0357)	-0.0026** (0.0109)
t	-0.1921*** (0.0294)	-0.0175** (0.0079)	-0.1539*** (0.0362)	-0.0021 (0.0117)
t+1	-0.0638*** (0.0233)	0.0015 (0.0067)	-0.0945*** (0.0298)	0.0151 (0.0093)
t+2	-0.0269 (0.0271)	0.0018 (0.0074)	-0.0031 (0.021)	-0.0113 (0.0074)
# of obs.	16,197		19,330	
R-sq	0.0466		0.0007	

Note: Table 11 reports the estimation results based on employed individuals with no reported disability at time t-3. Samples are divided into two groups: those aged above 45 and below 45. Other regressors are age, education, and the dummy variables for industry, occupation, time, and location. The numbers in parentheses are robust standard errors, clustered by individual. ***p < 1%, **p < 5%, and *p < 10%.

(a) Relation with occupational experience

Dependent variable: Occupational experience

Variable	Coefficient
Physical intensity	-0.1938*** (0.0096)
Female	-1.3433*** (0.0494)
College or more	0.8459*** (0.0547)
# of obs.	54,223
R-sq	0.3285

(b) Average Years of Experience by Age

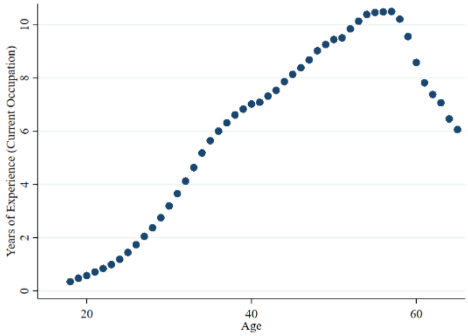

FIGURE 6. SUMMARY STATISTICS: EXPERIENCE

Note: The left panel reports the regression estimation, where the dependent variable is years of experience in the current occupation. Other regressors are age, age square, and dummies for time and industry. The numbers in parentheses are robust standard errors. ***p < 1%, **p < 5%, and *p < 10%. The right panel illustrates the average years of experience in the current employment among individuals aged between 18 and 65, computed using the cross-sectional weights.

to decrease employment but that the effect is weaker among younger workers. We also find that the physical intensity of past occupation is statistically insignificant among younger workers.

2) Occupation Tenure

If the loss of occupation-related skills is the main factor affecting the negative sign of the coefficient λ_k, we expect more profound effects among those who have accumulated long experience in the same occupation. We examine this hypothesis using the variable containing the start year of current employment. Figure 6 summarizes the basic relationship between occupation tenure and the other variables and illustrates the life-cycle pattern of experience for South Korean workers. Overall, the physical intensity measure shows a negative relationship with occupation tenure. However, this result could be affected by composition changes, driven mainly by the fact that starting around their mid-50s, workers switch from their main job to a temporary job in South Korea. Therefore, in this analysis, we restrict our sample to individuals aged between 18 and 50. We categorize the samples into five groups using the relative ranking of accumulated experience and create indicator variables for each group.

Given the intensity λ_k for non-disabled least experienced workers as our base, we expand the benchmark regression by including a disability-by-rank group for λ_k:

$$(2) \qquad y_{it} = X_{it}^{'}\beta + \sum_{s=1}^{5}\sum_{k=-2}^{2}\{\delta_k + \lambda_{d,k,s} \times \overline{p}_{i,-3}\} I_{itk} \times I_{is} + u_i + \theta_t + \varepsilon_{it},$$

where the indicator variable I_{itk} takes a value one if individual i is disabled at time t at time $t+k$ for $k \in \{-2, -1, 0, 1, 2\}$ and the indicator variable I_{is} denotes individual i's rank s. The results are summarized in Table 12. We find

TABLE 12— ESTIMATION RESULTS BY EXPERIENCE

Coefficient	Intensity × Experience	
	Non-disabled	Disabled
Experience ≤ 2	-	-0.0222 (0.0190)
Experience = 3	-0.0009 (0.0020)	-0.0024** (0.0232)
4 ≤ Experience ≤ 6	0.0029 (0.0019)	-0.0469** (0.0216)
7 ≤ Experience ≤ 12	0.0075*** (0.0067)	-0.0287 (0.0195)
Experience ≥ 13	0.0061** (0.0028)	0.0081 (0.0218)
# of obs.	20,287	
R-sq	0.0018	

Note: Table 12 reports the estimation results based on employed individuals aged between 18 and 50 with no reported disability at time *t-3*. Samples are divided into five groups using the relative ranks of their accumulated experience. Other regressors are age, education, and the dummy variables for time and location. The numbers in parentheses are robust standard errors, clustered by individual. ***p < 1%, **p < 5%, and *p < 10%.

that overall, the duration of the occupation tenure has a negative effect on employment rates among the disabled, consistent with the prediction of the theory of human capital.

3) Alternative Definitions for Health Shocks

In our benchmark analysis, we define a health shock based on self-reports of physical/sensory impairments, work limitations, or very poor health status. Table 13 summarizes the estimation results for the alternative health measures, showing qualitatively similar patterns across alternative definitions, though the effects of occupation tend to increase with a more selective measure of disability.

TABLE 13— ESTIMATION RESULTS BY DEFINITION OF DISABILITY

Coefficient	(1) Physical/sensory Impairments		(2) Work limitation		(3) Benchmark	
	Disability	Intensity × Disability	Disability	Intensity × Disability	Disability	Intensity × Disability
t-2	-0.0170 (0.0321)	0.0125 (0.0090)	0.0223 (0.0304)	0.0027 (0.0082)	0.0099 (0.0240)	0.0074 (0.0068)
t-1	-0.0467 (0.0285)	-0.0097 (0.0080)	-0.0361 (0.0263)	-0.0059 (0.0070)	-0.0260 (0.0202)	-0.0023 (0.0056)
t	-0.1442*** (0.0280)	-0.0282*** (0.0078)	-0.2440*** (0.0263)	-0.013* (0.0072)	-0.1903*** (0.0218)	-0.0154** (0.0062)
t+1	-0.0562** (0.0224)	-0.0098 (0.0065)	-0.1146*** (0.0213)	0.0102 (0.0062)	-0.0853*** (0.0176)	0.0084 (0.0052)
t+2	0.0196 (0.0213)	-0.0159** (0.0062)	-0.0330 (0.0250)	0.0053 (0.0066)	-0.0154 (0.0181)	-0.0014 (0.0051)
# of obs.	35,684		35,594		35,527	
R-sq	0.0448		0.0566		0.0527	

Note: Table 13 reports the estimation results based on alternative health measures. Samples are employed workers aged between 18 and 65 with no reported disability at time *t-3*. Other regressors are age, education, and the dummy variables for time and location. Numbers in parentheses are robust standard errors, clustered by individual. ***p < 1%, **p < 5%, and *p < 10%.

2. Occupational Mobility

Although we find negative effects of physically intensive occupations, these effects turn out to be less persistent. One possible explanation for this outcome could be the workers' endogenous response of changing to a job with less physical intensity. To verify this mechanism, first we verify the frequency of employer changes by health status. In Figure 7, we compare the accumulated years of experience in the current employment by health status, conditional on being non-disabled for the past two years. The histograms suggest that a higher fraction of individuals who recently experienced the onset of a disability exhibit changes in employment.

Given this finding, we more closely examine the frequency of occupational mobility by health status. These results are reported in Table 14. Of the non-disabled workers employed in period t, more than 90% were still working three years later. In contrast, this employment-to-employment (E-to-E) transition drops for workers with disabilities in period t, consistent with our estimates in Table 9. When we compute the share of occupation switchers among all E-to-E transitions, we find that overall, approximately 10% of employees switch occupations, while the share turns out to be moderately higher for individuals with disabilities.

At this point, we compare the occupational measures of physical intensity among individuals who switched occupations. The overall distributions are reported in Figure 8. We find that there is a shift toward less physically demanding occupations

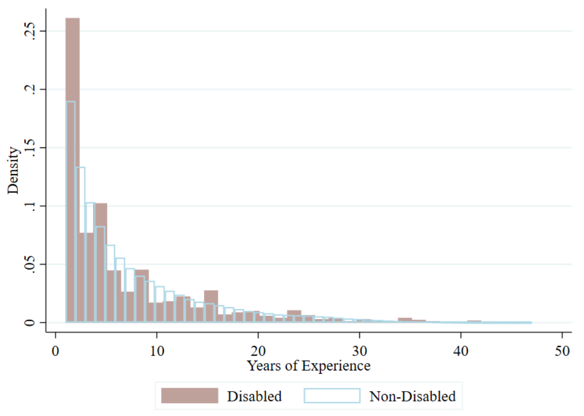

FIGURE 7. DISTRIBUTION OF EMPLOYMENT TENURE: RECENTLY DISABLED VS. NON-DISABLED

Note: Figure 7 compares the employment tenure of the non-disabled (blue line) and the disabled (red shaded area).

TABLE 14— ESTIMATION RESULTS BY DEFINITION OF DISABILITY

Statistics (%)	Health status	Duration $t+1$	$t+2$	$t+3$
Employment to employment	Non-disabled	93.67	92.03	90.87
	Disabled	84.35	73.61	76.51
Occupation changes	Non-disabled	9.41	11.34	12.61
Among the employed	Disabled	11.09	11.50	18.14

Note: Table 14 reports the summary statistics of labor market transitions among male workers aged between 15 and 65. Statistics are weighted using the cross-sectional weights.

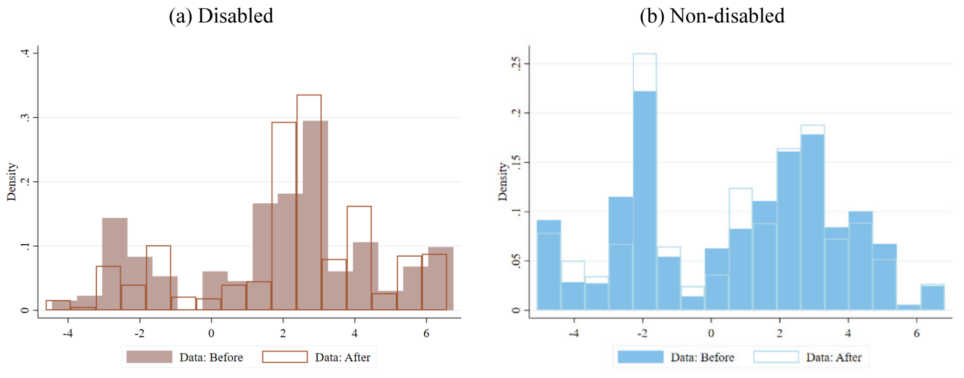

FIGURE 8. PHYSICAL INTENSITY BEFORE AND AFTER OCCUPATIONAL CHANGES

Note: These figures report the distribution of occupational physical intensity measures before and after the change in occupation. We define occupation switchers as individuals who reported changes in occupation over a two-year spell. The left and right panels illustrate the distributions for the disabled and non-disabled, respectively. The bars with lines depict the previous occupation measures, and the shaded area represents the current occupation measures.

within two years of the onset of disability. To examine our idea formally, we estimate the following regression:

$$\Delta p_{it} = X_{it}'\beta + (\alpha + \gamma I_{it}) \times \overline{p}_{i,-3} + u_i + \theta_t + \varepsilon_{it}, \tag{3}$$

where the dependent variable Δp_{it} represents the difference in the physical intensity measures between the current and previous occupations. If the variable is positive, then an individual switched to a more demanding occupation, and vice versa. Along with the previous criteria, we further restrict the sample by limiting it to individuals with labor market participation in both t and $t+3$. The remaining regressors are identical to those in the benchmark analysis.

The results are summarized in Table 15. We find that working in a physically demanding occupation in period t tends to lead to a change toward a less demanding job. We also find that this trend becomes more apparent when an individual experiences a negative health shock when we reduce the intensity score by 3.5 points. The magnitude is comparable to a change from a hair stylist (0.14) to a general salesperson (-3.78).

TABLE 15— ESTIMATION RESULTS: OCCUPATION CHANGES

Coefficient	Estimation
Physical intensity	-0.5780*** (0.1507)
Physical intensity × Disability	-3.5231* (2.1055)
# of obs.	1,467
R-sq	0.0181

Note: Table 15 reports the summary statistics of the estimation results. The sample includes workers aged between 15 and 64. Statistics are weighted using the cross-sectional weights. ***p < 1%, **p < 5%, and *p < 10%.

a. Robustness Analysis

KLIPS conducted a one-time supplemental survey on disability in its ninth wave (year 2006), collecting information about the timing of disabilities and corresponding degrees from the government's medical exams. We restrict our sample to those who experienced the onset of a disability between the first and ninth waves so that we can compare his pre- and post-disability labor market outcomes based on the government's definition of a disability. Table 16 summarizes statistics according to the degree of the disability. The employment rate of the least severely disabled group is around 41%, and it gradually decreases with the severity of the disability status.

Due to the limited observations, we do not conduct statistical tests for equation (3). Instead, we compare the group mean of the physical intensity measures before and after the disability event. These results are presented in Figure 9. We find, in line with our benchmark definition, that employment declines after the onset of a disability and that those who remain the labor market work at occupations with fewer physical requirements. This approach excludes individuals who became disabled before the first KLIPS survey. There is a possibility that our comparison is compounded by aging effects, as the post physical intensity distribution consists of

TABLE 16— SUMMARY STATISTICS BY GOVERNMENT REGISTERED DISABILITY STATUS

Health		Population share	Employment	Age	Female share	College share	# of obs.
Disabled	Degree 1	0.0038 (0.0618)	0.1626 (0.3749)	44.36 (13.44)	0.2678 (0.4499)	0.0845 (0.2827)	535
	Degree 2	0.0058 (0.0759)	0.2886 (0.4576)	43.83 (13.39)	0.4039 (0.4956)	0.2351 (0.4283)	795
	Degree 3	0.0061 (0.0781)	0.4124 (0.4967)	49.75 (10.90)	0.1316 (0.3411)	0.2131 (0.4132)	850
Non-disabled		0.9749 (0.1566)	0.5811 (0.4934)	38.86 (13.58)	0.5083 (0.5000)	0.4039 (0.4907)	10,448

Note: Table 16 reports the summary statistics of the sample according to the government's medical exam degree ratings. The sample includes workers aged between 15 and 65. Statistics are weighted using the cross-sectional weights.

(a) Summary statistics

	Statistics	
	Before	After
Employment rate	0.5704 (0.4954)	0.3933 (0.4894)
# of obs.	695	266
Physical intensity	1.9556 (2.5031)	0.4185 (3.0104)
# of obs.	395	99

(b) Physical intensity

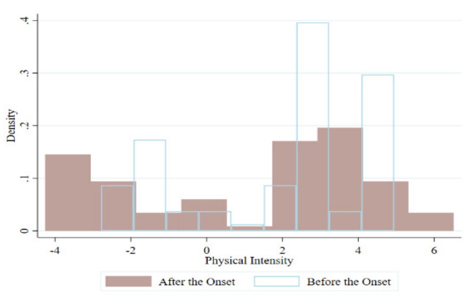

FIGURE 9. LABOR MARKET OUTCOMES BEFORE AND AFTER THE ONSET OF DISABILITY: BY GOVERNMENT REGISTERED DISABILITY STATUS

Note: The left panel reports the summary statistics of the employment and physical intensity measures according to the timing of the disability. The right panel illustrates the distribution of the intensity measures. The sample includes workers aged between 15 and 65. Statistics are weighted using the cross-sectional weights.

an older population.[22] We vary the range of the time interval and compute the statistics, finding that the differences by disability in the statistics are robust.

3. Wage and Working Hours

To gain a better understanding of the effects of negative health shocks on other labor market performance outcomes, we estimate the changes in the average (log) weekly earnings and working hours before and after the onset of disability. While the coefficients for after-disability working hours are negative, the results are not significant. The coefficients for the earnings regressions are not significant either, suggesting that the extensive margin is relatively more important to understand the labor market risk for the disabled.[23]

TABLE 17— DISABILITY EFFECTS ON HOURS AND EARNINGS

Coefficient	Working hours	Log weekly earnings	Log hourly wage rate
t-2	0.2761 (0.8638)	-0.0132 (0.0207)	-0.0214 (0.0241)
t-1	0.0264 (0.7937)	-0.02272 (0.0206)	-0.0275 (0.0223)
t	0.5827 (0.9412)	-0.0087 (0.0223)	-0.0219 (0.0230)
t+1	-0.4618 (0.6917)	-0.0168 (0.041)	-0.0138 (0.0258)
t+2	-0.7417 (0.7198)	0.0214 (0.0193)	0.0385* (0.0214)
# of obs.	16,770	16,750	16,750
R-sq	0.0001	0.0188	0.0027

Note: Table 17 reports the fixed-effect regression coefficients. The sample includes workers aged between 15 and 65. We use the nation-level annual consumer price index (CPI) to deflate the wage variables. Statistics are weighted using the cross-sectional weights.

C. *Policy Implication*

Thus far, we empirically illustrate a pattern which shows that at the onset of disability, previous occupational requirements in physical abilities have statistically significant negative effects on employment in South Korea, where the DI award rules are independent of applicants' employment histories. In this section, we briefly introduce the model of Diamond and Sheshinski (1995) and map it with empirical observations to discuss policy implications.

1. Model

a. Environments and Preferences

Consider an economy populated by a unit measure of workers. Workers have one

[22]The average ages before and after the disability event are 48.9 and 52.7 years.
[23]In our sample, the share of full-time workers among the employed is 92.3%.

unit of labor that can be turned into output y. If working, a worker suffers disutility depending on his health condition θ, which is unobservable to the government and distributed according to $F \sim [0,\infty]$. The utility of non-labor market participants is denoted by $u(c)$, and the utility of an employed worker is $u(c)-\theta$. $u(\cdot)$ is a standard utility function with $u'(c)>0$ and $u''(c)<0$. Instead of working, he can apply for DI. Given that the government does not observe θ, the award DI rule is based on other observable characteristics θ_e. $g(\theta_e;\theta)$ is the corresponding CDF. We can consider θ to be the true work capacity (or disutility from work), whereas θ_e is an observable variable related to θ, such as medical exam records. The government sets the DI award criteria θ^* in the form of θ_e. That is, with probability $p(\theta)=1-G(\theta_e^*;\theta)$, his DI application is approved, and he receives $b+d$ units of consumption. Otherwise, his consumption will be b, which is the combined value of unemployment insurance and possible home production.

b. Government's Problem

Given the policy rule $\{p(\theta),t,d,b\}$, workers make optimal decisions as to whether to apply for DI and participate in the labor market. With our assumptions about preferences, we know that the optimal solutions will be cut-off rules. We denote θ_d as the threshold that makes workers indifferent with regard to receiving DI or being employed: $u(y-t)-\theta_d=u(b+d)$. Similarly, θ_b solves $u(y-t)-\theta_b=u(b)$.[24] Combining the two definitions, we find that $\theta_d<\theta_b$. Therefore, we can classify workers into three groups according to their optimal choices: workers who always work ($\theta<\theta_d$), workers who apply for DI but work if denied ($\theta_d<\theta<\theta_b$), and workers who apply fort DI and opt out of the labor market if denied ($\theta>\theta_b$).

At this stage, we expand the basic model by introducing additional heterogeneity. The underlying work capacity distribution $F(\theta)$ is common, but $G(\theta_e\,|\,\theta)$ varies by type: $G(\theta_e\,|\,\theta)<G_j(\theta_e\,|\,\theta)$ for $i<j$. This assumption means that if the government applies the common DI award rule θ^*, then for same underlying work capacity, the approval rate of type-i will be higher than that of type-j.

If the government still applies universal criteria, $\overline{\theta}^*$ for all, the maximization problem is

[24]For simplicity, we consider the case where both values of θ are strictly positive.

$$\max_{\bar{\theta}^*,b,d,t} \sum_{i=1}^{n} \omega_i \begin{pmatrix} \int_0^{\theta_d} \{u(y-t)-\theta\} dF(\theta) + \\ \int_{\theta_d}^{\theta_b} [(1-p_i(\theta))\{u(y-t)-\theta\} + p_i(\theta)u(b+d)] dF(\theta) + \\ \int_{\theta_b}^{\infty} [(1-p_i(\theta))u(b) + p_i(\theta)u(b+d)] dF(\theta) \end{pmatrix}$$

$$s.t. \quad R + \sum_{i=1}^{n} \omega_i t \left\{ \int_0^{\theta_d} dF(\theta) + \int_{\theta_d}^{\theta_b} (1-p_i(\theta)) dF(\theta) \right\}$$
$$= \sum_{i=1}^{n} \omega_i \left[\int_{\theta_b}^{\infty} (1-p_i(\theta)) b dF(\theta) + \int_{\theta_d}^{\infty} p_i(\theta)(b+d) dF(\theta) \right].$$

Taking the first-order conditions with respect to $\bar{\theta}^*$, we find that the type-specific trade-offs are weighted using the corresponding population size:

$$\Delta_d \sum_{i=1}^{n} \omega_i \int_{\theta_b}^{\infty} g_i(\bar{\theta}^* \mid \theta) dF + \Delta_e \sum_{i=1}^{n} \omega_i \int_{\theta_d}^{\theta_b} g_i(\bar{\theta}^* \mid \theta) dF + \sum_{i=1}^{n} \omega_i \int_{\theta_d}^{\theta_b} \theta g_i(\bar{\theta}^* \mid \theta) dF = 0.$$

The solution to this maximization is worse than the solution to the more generalized maximization problem with type-dependent award rule θ_i^*. With the type-dependent rule, we can always find two types below and above the aggregate mean θ over (θ_d, θ_b) interval and improve the welfare by means of redistribution across types.

2. Welfare Analysis

Here, we initially adjust the model environments to calibrate the underlying parameters based on data from South Korean non-college graduates and use the calibration results to conduct a policy analysis.

a. Functional Form Assumptions

Work capacity θ follows an exponential distribution $F(\theta) = 1 - \exp(-\gamma\theta)$ with $\theta \in [0, \infty]$. The DI award rule is based on medical condition θ_e, which is correlated with the true work capacity θ such that $\theta_e = h_i(\theta) + \varepsilon$, where ε is the standard measurement error following a normal distribution. The function $h_i(\theta)$ reflects possible systematic differences in the relationship between θ_e and θ for type-i workers. $G(\theta_e \mid \theta)$ denotes the cumulative density of θ_e given θ for type-i.

Individuals have a constant-returns-to-scale (CRRA) utility function over consumption $\frac{c^{1-\sigma}}{1-\sigma} - \theta I_{\{emp=1\}}$. Once approved, workers receive DI independent of their employment status. Thus, given our utility function, it is always optimal to apply DI. Using the definitions of θ_d and θ_b, workers are categorized into three groups according to their optimal labor market behaviors: (i) those who apply DI and work regardless of the outcome, (ii) those who apply DI and work only when they are rejected for DI, and (iii) those who apply DI and do not work when their DI application is rejected.

b. Data Moments and Calibration

We construct calibration moments using the 9th wave of KLIPS on disability. To do this, we initially categorize the sample with government-registered disabilities into four groups: DI status and two physical intensity levels of pre-disability occupation, denoted by high (H) and low (L). Using the average intensity among high school graduates as the cut-off, we find that 68% of the population is considered as type- H . With these two characteristics, the observed labor market statistics are as follows:

TABLE 18— MOMENTS

Moments	Statistics	Simulation
DI share among population (%)	1.12	1.05
Conditional employment rates (%)		
type-L & DI	78.93	72.53
type-L & no DI	82.40	96.66
type-H & DI	17.18	17.04
type-H & no DI	40.92	43.03

Note: Table 18 reports the moments of the sample according to the medical exam degree (one, two, or three) and the occupational physical intensity level. The sample includes workers aged between 15 and 65 with a high school education and recent employment history. Statistics are weighted using the individual survey weights.

TABLE 19— CALIBRATION PARAMETERS: RESULTS

A. Parameters calibrated outside the model

Variable	Definition	Value
σ	Risk-aversion parameter	0.5
y	Average earning (output)	20
b	Consumption level of the non-employed	6
d	DI benefits	4.24

B. Parameters calibrated inside the model

Variable	Definition	Value
$\bar{\theta}^*$	The DI award rule for θ_e	78,819
γ	Scale parameter of θ distribution	0.115
α	Difference between θ and θ_e	0.688
μ_η	Leisure preference parameter for type-H	-25.148

Note: Table 19 presents the calibration results for the model targeting the moments in Table 18.

Table 19 summarizes the parameter calibration process. The variable of labor market earnings is normalized to 20. The size of the DI benefit d is taken from the average benefit-to-income ratio among the DI beneficiaries (National Pension System, 2019). The minimum consumption level b is set to 30% of the median income of households, which is the South Korean poverty line.

The scale parameter γ for capacity distribution $F(\theta)$ and the DI standard $\overline{\theta}^*$ are calibrated to match the aggregate share of the population with medical degrees 1–3 (1.21%) among workers with less than a college education. Assuming that type-L is the baseline with $\theta_e = \theta$, we parameterize $h_H(\theta) = \alpha\theta$. We find that, to be consistent with the moments, the award rule systematically underestimates disutility from work for type-H workers, i.e. that their observed medical condition is less severe ($\alpha < 1$). The current model is abstracting other crucial heterogeneities (such as the education level and wealth) that may affect the labor supply decision, and including these elements would deliver a better prediction at a magnitude of α.

c. Counter-factual Experiments

Given the current DI policy, the welfare of type-i workers consists of three parts:

$$\begin{aligned} W_i = &\int_0^{\theta_d} [(1-p_i(\theta))\{u(y-t)-\theta\} + p_i(\theta)\{u(y+d-t)-\theta\}]dF(\theta) \\ &+ \int_{\theta_d}^{\theta_b} [(1-p_i(\theta))\{u(y-t)-\theta\} + p_i(\theta)u(b+d)]dF(\theta) \\ &+ \int_{\theta_b}^{\infty} [(1-p_i(\theta))u(b) + p_i(\theta)u(b+d)]dF(\theta), \end{aligned}$$

and the aggregate welfare is the weighted average of W_i with the corresponding population share $\omega_i : W = \sum_{i\in\{H,L\}} \omega_i W_i$. We now compare the welfare implications of alternative DI, focusing on the case in which the screening process for type-H improves. We can consider this experiment as a case where the South Korean government factors in work experience and skill sets when evaluating θ, along with medical conditions.

To make the comparison reasonable, we assume that both policies must be budget-neutral.[25] Total spending cannot exceed the expenditures from the benchmark analysis, and any additional spending must be financed with lump sum tax t. This results in a moderate increase in taxes, meaning that employed workers pay around 0.5% additionally as income tax. These results are presented in Table 20. Under the new DI program, type-H workers face a less strict disability standard, whereas that of type-L becomes tightened. This results in a decline in employment by 10 *pp*.

[25]Under the current DI program, the benchmark economy is spending 12.20% of average labor productivity for social insurance. Because we are analyzing only high school graduates, we may consider this result as redistribution toward high school graduates.

TABLE 20— POLICY EXPERIMENTS

Variable		Status quo L	Status quo H	Vocational grids L	Vocational grids H
Share, disabled		1.35	0.91	1.34	2.48
Employment	Disabled	72.53	17.04	73.08	7.11
	Non-disabled	96.66	43.03	96.90	43.67

Note: Table 20 compares the economies under the current DI programs to the Vocational Grids.

V. Conclusion

This study examines the relationship between labor market outcomes and individuals' health status, taking into account occupational requirements. Applying a PCA to O*NET measurements of physical ability, we construct an index of the physical intensity of an occupation and use it to quantify the role of occupation in labor market outcomes by health status.

Our estimation is based on longitudinal South Korean panel data. Using a South Korean household survey has several advantages when studying the relationship between health and occupation. First, unlike most advanced countries, South Korea has a very strict DI program. The share of DI recipients is 1.1% among the working-age population, compared to the OECD average of 6%. Furthermore, the South Korean DI program evaluates its applicants based solely on medical conditions. Thus, the award criteria are independent of the applicants' occupation histories, unlike in other advanced countries, which consider possible vocational limitations due to disabilities. Moreover, the continuation of the DI benefit is independent of the labor market status of the recipient. These institutional features help us to examine the interplay between occupational characteristics and health shocks in the labor market, alleviating the potential bias caused by DI.

Our analysis shows several interesting results. First, working in a highly physically intense occupation tends to reduce employment rates after the onset of disability, suggesting that vocational consideration would be a reasonable policy to mitigate negative income risks. When we divide the sample by gender, we find that the baseline results remain the same for both groups, although female workers are more responsive. However, when we divide the sample by age, we find that workers below age 45 remain in the market, regardless of their previous occupational characteristics. We also find that younger workers are more likely to switch occupations after the onset of disability. This endogenous response against health shocks tends to be directed, such that workers switch to less demanding occupations. In contrast, all else being equal, exiting the labor market is more common when individuals have accumulated relatively more occupational experience.

Overall, our results suggest that having occupational requirements on physical abilities is important with regard to the labor market outcomes of the disabled. Individuals with less demanding occupational requirements are more apt to be employed, thus remaining in the same occupation. Hence, these workers are subject to lower income risks than are workers with physically demanding occupations. However, as the results suggest, not all individuals with the same occupation face the same risks. Some workers exit the labor market, while others switch to alternative occupations. Understanding the relationship between health requirements and other job skills helps us to understand these varying responses.

APPENDIX

A. *Data Appendix*

In this section, we provide further details of the data construction process used for our empirical analyses.

1. Linking the Occupational Codes

We match the occupation-level characteristics surveyed by the U.S. Department of Labor to a South Korean panel dataset by linking the two country-specific occupational classifications using the International Standard Classification of Occupation (ISCO). The following paragraphs describe the detailed procedure that matches the ISCO with the country-level occupational codes.

a. The International Standard Classification of Occupation (ISCO)

Since 1949, the International Labour Organization (ILO) has provided a comparable list of occupational classifications called the International Standard Classification of Occupation (ISCO). The ISCO categorizes the list of occupations using four layers of occupational classifications. First, the finest occupational descriptions are available for 436 occupations, where each occupation is assigned a four-digit number. Further, two additional layers of occupational classifications group a set of four-digit occupations into 130 cases with three-digit numbers (minor classification) and 43 cases with two-digit numbers (sub-major classification). Finally, these occupations are linked to ten major categories of occupations. Table A1 summarizes

TABLE A1— STRUCTURE OF ISCO-08

Major classification	Sub-major (two-digit)	Minor (three-digit)	Detailed (four-digit)
Managers	4	11	31
Professionals	6	27	92
Technicians and associate professionals	5	20	84
Clerical support workers	4	8	29
Service and sales workers	4	13	40
Skilled agricultural, forestry & fishery workers	3	9	18
Craft and related trades workers	5	14	66
Plant and machine operators, & assemblers	3	14	40
Elementary occupations	6	11	33
Armed forces occupations	3	3	3
Total number of classifications	43	130	436

Note: Table A1 shows the structure of ISCO-08. Numbers are the sub-classification counts associated with each major classification.

the structure of the most recent ISCO, which was released in 2008.

b. The Korea Standard Classification (KSCO)

The South Korean Statistics Department (KOSTAT) provides a list of occupations called the Korea Standard Classification (KSCO) to collect and compare occupation-related data consistently. Analogous to the ISCO, the KSCO adopts a four-layer system of occupational classifications over 400 occupations (Table A2), and eight out of ten major classifications in the KSCO share definitions identical to those of ISCO-08. The other two categories can also be linked by either merging or dividing two major classifications of ISCO-08.[26]

The similarities between the two classifications help us to link the KSCO into ISCO-08. KOSTAT provides the official crosswalk table between ISCO-08 and the 6th KSCO.[27] According to the crosswalk table, 318 out of 426, or 74.6% of four-digit occupations have a one-to-one relationship from the KSCO to ISCO-08 (KOSTAT, 2018) The remaining 108 occupations of KSCO have multiple matched occupations in ISCO-08 (Table A3). As a result, we have 596 possible combinations between ($318+72\times 2+19\times 3+12\times 4+2\times 5+2\times 6+1\times 7$) the 6th KSCO and ISCO-08. It is important to note that this does not imply that there are 318 unique one-to-one matches. Different occupations in the KSCO (called A and B) may be separately linked to one occupation x in ISCO-08, generating two one-to-one matches $A:x$ and $B:x$. As a result, inverse matching from ISCO-08 to the KSCO shows different outcomes.[28]

TABLE A2— THE STRUCTURE OF THE 6TH KSCO

Major classification	Sub-major (two-digit)	Minor (three-digit)	Detailed (four-digit)
Managers	5	15	24
Professionals & related workers	8	41	153
Clerks	4	9	26
Service workers	4	10	33
Sales workers	3	4	13
Skilled agricultural, forestry & fishery workers	3	5	12
Craft & related trades workers	9	20	73
Equipment, machine operating & assembling workers	9	31	65
Elementary workers	6	12	24
Armed forces occupations	1	2	3
	52	149	426

Note: Table A2 shows the structure of the 6th KSCO. Numbers are the sub-classification counts associated with each major classification.

[26]Instead of "service and sales workers" in ISCO-08, the KSCO adopts the two separate categories of "service workers" and "sales workers." While ISCO-08 has two separate categories for "professionals" and "technicians and associated professionals," the KSCO combines the two categories into "professionals and related workers."

[27]While its most recent 7th revision was introduced in 2017, we decided to use the 6th KSCO as our main classification because the panel dataset for the main analysis is reported based on the previous occupational codes.

[28]For instance, the KSCO separately labels "Company Grade Officers" and "Field Grade Officer or Higher Ranks," but ISCO-08 labels both occupations as "Commissioned Armed Force Officers."

TABLE A3— LINKAGE BETWEEN THE 6TH KSCO AND THE ISCO-08

Type of match: the KSCO to ISCO-08		No. of occupations	Share (%)
One-to-one matches		318	74.65
Multiple matches	one-to-two	72	16.90
	one-to-three	19	4.46
	one-to-four	12	2.82
	one-to-five	2	0.47
	one-to-six	2	0.47
	one-to-seven	1	0.23
Total		426	100

Note: Table A3 reports the results of the matching of the 6th KSCO to ISCO-08 using the crosswalk table provided by KOSTAT.

c. The U.S. Occupational Classification

Although the U.S. Standard Occupational Classification (SOC) was recently modified in 2018, the most recent crosswalk table between ISCO-08 and the SOC is based on the 2010 version of the codes. Thus, we match ISCO-08 with the SOC in terms of four-digit level based on the 2010 SOC. As the Bureau of Labor Statistics (BLS) uses 23 major classifications, the resulted linkage from ISCO-08 to the 2010 SOC more frequently involves a merging of multiple occupations. Nonetheless, 67.5% of the occupations can be represented by the matching of an occupation in ISCO-08 with three or fewer occupations in the 2010 SOC (Table A4).[29]

TABLE A4— LINKAGE BETWEEN ISCO-08 AND THE 2010 SOC

Type of match: the ISCO-08 to the 2010 SOC		No. of occupations	Share (%)
One-to-one matches		155	35.39
Multiple matches	one-to-two	141	32.19
	one-to-three	61	13.93
	one-to-four	28	6.39
	one-to-five	19	4.34
	one-to-six	13	2.97
	one-to-seven	4	0.91
	one-to-eight	6	1.37
	one-to-nine	2	0.46
	ten or more	9	2.06
Total		438	100

Note: Table A4 reports the match results of the 2010 SOC to the ISCO-08 using the crosswalk table provided by the BLS.

d. Linking the Occupational Codes across Countries

Here, we describe how we linked the KSCO and the 2010 SOC using ISCO-08. As shown in Table A3, 318 out of 426 (74.6%) occupations in the KSCO form a

[29]The official crosswalk table is available for download from the webpage of the BLS. The crosswalk table between 2010 and 2018 SOC is also available from the BLS webpage.

TABLE A5— LINKAGE BETWEEN THE 6TH KSCO AND THE 2010 SOC

Type of match: the KSCO to the 2010 SOC		No. of occupations	Share (%)
One-to-one matches		80	18.82
Multiple matches	one-to-two	96	22.59
	one-to-three	60	14.12
	one-to-four	41	9.65
	one-to-five	43	10.12
	one-to-six	34	8.00
	seven or more	71	16.70
Total		425	100

Note: This table reports the results of the matching of the 6th KSCO to the 2010 SOC via ISCO-08 using the official crosswalk tables provided by KOSTAT and the BLS. There is no match from ISCO-08 (5343) to the SOC, leaving one of the KSCO codes (5301) unmatched.

unique match with ISCO-08, and 409 of 426 (96%) occupations in the KSCO can be described with three or fewer occupations in ISCO-08. Based on the results in Tables A3 and A4, we link all possible matching combinations of ISCO-08 and the 2010 SOC to each occupation in the KSCO.

B. *A Model without Heterogeneity*

The government's objective function is

$$
\begin{aligned}
&\max_{\theta^*,b,d,t} \int_0^{\theta_d} \{u(y-t)-\theta\} dF(\theta) + \\
&\int_{\theta_b}^{\infty} [(1-p(\theta))u(b)+p(\theta)u(b+d)] dF(\theta) + \\
&\int_{\theta_d}^{\theta_b} [(1-p(\theta))\{u(y-t)-\theta\}+p(\theta)u(b+d)] dF(\theta) \\
s.t.\quad & R+t\left\{\int_0^{\theta_d} dF(\theta)+\int_{\theta_d}^{\theta_b}(1-p(\theta))dF(\theta)\right\} \\
&= \int_{\theta_b}^{\infty}(1-p(\theta))b\,dF(\theta)+\int_{\theta_d}^{\infty} p(\theta)(b+d)dF(\theta),
\end{aligned}
\tag{A1}
$$

where R represents additional resources available. Setting the Lagrangian problem for equation (A1), we obtain the following four first-order conditions:

$$
\begin{aligned}
\frac{\partial L}{\partial t}:\quad & (u'(y-t)-\lambda)\left(\int_0^{\theta_d} dF+\int_{\theta_d}^{\theta_b} G(\theta^*\mid\theta)dF\right) \\
&= -\lambda u'(y-t)\begin{bmatrix}(b+t)G(\theta^*\mid\theta_b)f(\theta_b)+ \\ (b+d+t)(1-G(\theta^*\mid\theta_d))f(\theta_d)\end{bmatrix}
\end{aligned}
\tag{A2}
$$

$$
\begin{aligned}
\frac{\partial L}{\partial d}:\quad & (u'(b+d)-\lambda)\int_{\theta_d}^{\infty}(1-G(\theta^*\mid\theta))dF \\
&= \lambda u'(b+d)(b+d+t)(1-G(\theta^*\mid\theta_d))f(\theta_d)
\end{aligned}
\tag{A3}
$$

$$\text{(A4)}\quad \frac{\partial L}{\partial b}:\ (u'(b)-u'(b+d)-\lambda)\int_{\theta_b}^{\infty} G(\theta^*\mid\theta)dF+(u'(b+d)-\lambda)\int_{\theta_d}^{\theta_b}(1-G(\theta^*\mid\theta))dF$$
$$=\lambda[u'(b)(b+t)G(\theta^*\mid\theta_b)f(\theta_b)+u'(b+d)(t+b+d)(1-G(\theta^*\mid\theta_d))f(\theta_d)]$$

$$\text{(A5)}\quad \frac{\partial L}{\partial\theta^*}:\ \int_{\theta_d}^{\theta_b} g(\theta^*\mid\theta)\{u(b+d)-u(y-t)+\theta)dF+\int_{\theta_b}^{\infty} g(\theta^*\mid\theta)(u(b+d)-\upsilon(b))dF$$
$$=\lambda\left[\int_{\theta_b}^{\theta_d}(t+b+d)g(\theta^*\mid\theta)dF+\int_{\theta_b}^{\infty} dg(\theta^*\mid\theta)dF\right].$$

The first two conditions show that it is optimal to provide partial insurance due to moral hazard concerns: $y-t>b+d$.[30] equation (A5) states that at the optimum criteria for disability θ^*, additional welfare changes among DI beneficiaries must be equal to the corresponding financial costs. We denote the net welfare of marginal DI recipients switching from non-employment as $\Delta_d \equiv u(b+d)-u(b)-d\lambda$ and, similarly, the net welfare change from employment as $\Delta_e+\theta \equiv u(b+d)-u(y-t)+\theta-\lambda(t+b+d)$. Using these notations, equation (A5) can be written as

$$\text{(A6)}\qquad \Delta_d\int_{\theta_b}^{\infty} g(\theta^*\mid\theta)dF+\Delta_e\int_{\theta_d}^{\theta_b} g(\theta^*\mid\theta)dF+\int_{\theta_d}^{\theta_b}\theta g(\theta^*\mid\theta)dF=0.$$

The last term of the equation above is strictly positive; thus, at the optimum, the first two terms have opposite signs. Assuming standard concave utility functions, we can show that $\frac{u(b+d)-u(b)}{(b+d)-b}>u'(b+d)$, where $u'(b+d)\geq\lambda$. Therefore, $u(b+d)-u(b)>\lambda d$ and Δ_d is strictly positive. This result implies that the optimal DI cutoff is set at the level with a positive net welfare gain for those who have no work capacity. The optimality condition in the more generalized setup is the weighted average of equation (A6) with its population size.

[30]Solving for λ, we can show that $\frac{1}{\lambda}$ is the weighted average of the inverse marginal utilities. Because the RHSs of the first-order conditions are non-negative, $u'(b)>u'(b+d)\geq\lambda$, or $\frac{1}{u'(b)}<\frac{1}{u'(b+d)}\leq\frac{1}{\lambda}$. Therefore, it must be the case that $\frac{1}{u'(y-t)}>\frac{1}{\lambda}$, i.e. $u'(y-t)<\lambda$.

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