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Comparison of the Korean and US Stock Markets Using Continuous-time Stochastic Volatility Models†

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We estimate three continuous-time stochastic volatility models following the approach by Aït-Sahalia and Kimmel (2007) to compare the Korean and US stock markets. To do this, the Heston, GARCH, and CEV models are applied to the KOSPI 200 and S&P 500 Index. For the latent volatility variable, we generate and use the integrated volatility proxy using the implied volatility of short-dated at-the-money option prices. We conduct MLE in order to estimate the parameters of the stochastic volatility models. To do this we need the transition probability density function (TPDF), but the true TPDF is not available for any of the models in this paper. Therefore, the TPDFs are approximated using the irreducible method introduced in Aït-Sahalia (2008). Among three stochastic volatility models, the Heston model and the CEV model are found to be best for the Korean and US stock markets, respectively. There exist relatively strong leverage effects in both countries. Despite the fact that the long-run mean level of the integrated volatility proxy (IV) was not statistically significant in either market, the speeds of the mean reversion parameters are statistically significant and meaningful in both markets. The IV is found to return to its long-run mean value more rapidly in Korea than in the US. All parameters related to the volatility function of the IV are statistically significant. Although the volatility of the IV is more elastic in the US stock market, the volatility itself is greater in Korea than in the US over the range of the observed IV.

Key Word: Continuous-time Stochastic Volatility Model,
Integrated Volatility Proxy,
Maximum Likelihood Estimation
JEL Code: C22, C51, C58

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I. Introduction

Researchers such as Lee and Yu (2018), Choi and Cho (2017), and Yoon (2007) have reported evidence that Korean and US share prices move together using a variety of discrete- time econometric models. In addition, Kim (2010), Lee and Ryu (2013), Han *et al*. (2015), and Cho *et al*. (2015) studied the statistical properties of the VKOSPI and/or the VIX and suggested models to predict these. On the other hand, continuous-time diffusion models are widely employed to model and investigate the dynamics of stock prices. Diffusion models have been useful for stock prices because using them makes it more convenient to evaluate derivatives. Therefore, it is important and interesting to find a diffusion model that can describe the evolutions of stock prices well and to determine if two markets behave similarly in the context of a continuous-time model. The aim of this paper is not to look into the existence of co-movement in Korean and US stock prices but to estimate several stochastic volatility models for each country to find which one fits the data better. Moreover, we compare these two stock markets based on the estimation results to check whether or not the two countries' stock prices move analogously.

Although the Black-Scholes-Merton model (Black and Scholes, 1973; Merton, 1973) has been adopted quite often in descriptions of the dynamics of stock prices since the 1970s, researchers have found that this model is incapable of explaining certain stylized features of stock prices. These include the time-varying instantaneous volatility of stock prices and the phenomenon by which stock prices become more volatile when they decrease, well known as the leverage effect. Moreover, the implied volatility of options varies with time to maturity, strike prices, and maturities (Stein, 1989; Aït-Sahalia and Lo, 1998), which cannot be true if the stock price follows geometric Brownian motion. To address these issues, researchers have proposed a variety of continuous-time stochastic volatility models. Examples can be found in Hull and White (1987), Stein and Stein (1991), Heston (1993), and Lewis (2000).

Aït-Sahalia and Kimmel (2007) demonstrated that estimating continuous-time stochastic volatility models by maximum likelihood estimation (MLE) with approximate log-likelihood expansions produces accurate estimates of the parameters. In doing so, they generate and use an integrated volatility proxy for the latent volatility variable with the implied volatility of short-dated at-the-money option prices. Following their approach, we apply their estimation procedure to three stochastic volatility models, the Heston, GARCH and CEV (constant elasticity of volatility) processes, to compare the Korean and US stock markets. For the stock price and the implied variance of an at-the-money option with a maturity of 30 calendar days, the Korea Composite Stock Price Index 200 (KOSPI 200) and the VKOSPI for Korea and Standard & Poor's Composite 500 stock index (S&P 500 Index) and the VIX for the US were utilized. The data period is from April 13, 2009 until July 28, 2017, as the VKOSPI data series started to be announced on April 13, 2009, whereas more data are available for the other variables.

We conduct MLE in order to estimate the parameters of the stochastic volatility models considered in this paper. To do this we need the transition probability density function (TPDF). However, as is often the case even for a univariate diffusion process, the true TPDF is not available for any of the models in this paper. Although the true TPDFs of the stochastic volatility processes are unavailable, we can approximate them fairly accurately owing to Aït-Sahalia (2008), who suggests a method to approximate the true TPDF of a multivariate time-homogeneous diffusion model. Using the fact that the TPDF satisfies Kolmogorov forward and backward partial differential equations (PDEs), Aït-Sahalia (2002) and Aït-Sahalia (2008) respectively developed new ways to obtain an approximate TPDF of a univariate diffusion model and a log-TPDF expansion of a multivariate diffusion model in a closed form in the time-homogeneous case. His idea was extended to univariate time-inhomogeneous diffusion models by Egorov, Li, and Xu (2003); to multivariate time-inhomogeneous diffusion models by Choi (2013) and Choi (2015b); to a damped diffusion model by Li (2010); to a multivariate time-homogeneous jump diffusion model by Yu (2007), and to a multivariate time-inhomogeneous jump diffusion model by Choi (2015a). Other related papers include those by Bakshi, Ju, and Ou-Yang (2006); Stramer, Bognar, and Schneider (2010); and Chang and Chen (2011).

Among the three stochastic volatility models investigated, the Heston model and the CEV model are found to be best for the Korean and US stock markets, respectively. Based on these estimation results, we find that there exist relatively strong leverage effects in both countries. Even if the long-run mean level of the integrated volatility proxy (IV) was not statistically significant in either market, the speeds of the mean reversion parameters are statistically significant and meaningful in both. The IV is found to return to its long-run mean value more rapidly in Korea than in the US. All parameters related to the volatility function of the IV are statistically significant. The elasticity of the volatility of the IV is 0.50 for Korea and 0.62 in the US. Although it is more elastic in the US stock market, the volatility itself is greater in Korea than in the US over the range of the observed IV.

Looking at the overall estimations results, most parameters of the stochastic volatility models are quite accurately estimated for both countries. Furthermore, stochastic volatility models can capture well-known characteristics of share prices in both countries. This implies that introducing another stochastic factor for the instantaneous volatility of stock prices is desirable for a better fit of the data for both Korea and the US. Therefore, the stochastic volatility model appears to be more appropriate than the Black-Scholes-Merton model in explaining the movements of stock prices at least for these two countries.

The rest of this paper is organized as follows. We discuss certain features of the data and how to obtain a volatility proxy from the implied volatility. The next section introduces the three continuous-time stochastic volatility models employed in this article. After explaining the estimation method and how to derive the approximate log-likelihood for our models in **Section IV**, the estimation results and discussions are presented in **Section V**, after which we conclude the paper.

II. Data and Features

Daily time-series data of the Korea Composite Stock Price Index 200 (KOSPI

200) and the VKOSPI for the Korean stock market and those of Standard & Poor's Composite 500 stock index (S&P 500 Index) and the VIX for the US stock market were attained from Datastream for the period from April 13, 2009 to July 28, 2017. To compare the Korean and US stock markets, we used the same data period. Although the S&P 500, VIX, and KOSPI 200 data are available before April 13, 2009, we chose this data period because data for the VKOSPI series started to be released only on April 13, 2009.

The S&P 500 Index is a market-value weighted index of 500 large firms in the US and it is known to represent the U.S. stock market well. The Chicago Board Options Exchange (CBOE) publishes the VIX, which is an index of the implied volatility of options on the S&P 500. The VIX is calculated using a variety of 30-day European call and put options on the S&P 500 traded in the market. The KOSPI 200 is computed as the current market value of 200 large companies in Korea divided by the base market capitalization as of January 3, 1990. Because the KOSPI 200 accounts for more than 70% of the market value of all stocks in the KOSPI, it is a good measure of movements in the Korean stock market. Since April 13, 2009, the Korea Exchange (KRX) has calculated the VKOSPI using a method very similar to that of the VIX and has reported it to the public. The VKOSPI is the implied volatility of European call and put options on the KOSPI 200. See Choi and Han (2009) for more about the VKOSPI. As shown below, we take the logarithm of the stock price and construct a proxy for the volatility process of the stock price with the implied volatility to estimate the stochastic volatility models. The true instantaneous volatility variable is unobservable, and we use a proxy in place of this variable. Aït-Sahalia and Kimmel (2007) propose a means by which to create a volatility proxy out of the implied volatility utilizing an idea by Hull and White (1987) (see also Jones (2003)). This is referred to as the integrated volatility proxy (IV). Under a risk-neutral measure, the drift of the volatility process V_t for all models estimated here takes the form $a+bV_t$, where a and b are constants. In this case, we are able to obtain the integrated volatility proxy IV_t according to

(1)
$$IV_t = \frac{b\cdot\tau\cdot V_t^{imp} + a\cdot\tau}{\exp(b\cdot\tau)-1} - \frac{a}{b} \quad ,$$

where V_t^{imp} is the observed implied variance of an at-the-money option with a short-maturity τ. In our case V_t^{imp} is $(VKOSPI_t/100)^2$ and $(VIX_t/100)^2$ for the Korean and US stock markets, respectively.

In estimating the stochastic volatility models, we utilize a two-stage estimation procedure. The first stage estimation involves estimating the univariate CEV model for each case of $(VKOSPI_t/100)^2$ and $(VIX_t/100)^2$. For Korea (the US), we estimate

(2)
$$dY_t = \kappa(\gamma - Y_t)dt + \sigma Y_t^{\beta} dW_t$$

with $Y_t = (VKOSPI_t / 100)^2 (Y_t = (VIX_t / 100)^2)$ to acquire $a = \kappa\gamma$ and $b = -\kappa$ in equation (1). Using these and $V_t^{imp} = (VIX_t / 100)^2$ or $(VKOSPI_t / 100)^2$ and setting $\tau = 22/252$ because the time to maturity is 22 trading days (or 30 calendar days), we can construct the integrated volatility proxy, IV_t through equation (1) for both countries.[1] The method of maximum likelihood estimation is adopted to determine the parameter estimates of (2). In doing so, it is necessary to have the transition probability density function (TPDF) of model (2) but the true TPDF is unavailable. Therefore, we make use of the irreducible method in Aït-Sahalia (2008) to obtain an approximate transition log-likelihood function of diffusion process (2).[2]

Maximum likelihood estimates of the parameters of (2) and the formula used to determine IV_t for Korea and the US are provided in Table 1. For both countries, all parameter estimates are statistically quite significant. Comparing the Korean and US implied volatilities based on the estimation results, both the speed (κ) and the long-run average level (γ) to which the implied volatility reverts are greater in the US than in Korea. The parameter estimates of σ and β reveal that the VIX is more volatile than the VKOSPI and that the elasticity of the volatility of the implied volatility with respect to the implied volatility is close to 1 for both countries. The integrated volatility proxy formula is calculated through equation (1) and provided directly below each country's estimation results.

TABLE 1—PARAMETER ESTIMATES FOR THE UNIVARIATE CEV MODEL FOR VKOSPI AND VIX

	κ	γ	σ	β
Korea	4.27** (1.42)	0.031** (0.0053)	1.65** (0.037)	0.97** (0.0048)
	$IV_t = -0.0061 + 1.1979(KOSPI_t / 100)^2$			
US	5.41** (1.95)	0.037** (0.0070)	2.40** (0.060)	0.99** (0.0065)
	$IV_t = -0.0095 + 1.2545(VIX_t / 100)^2$			

Note: Maximum likelihood estimates of the parameters of the univariate CEV model for the VKOSPI and the VIX and their standard errors in parentheses are given in this table. The two asterisks next to the estimate indicate statistical significance at the 1% level. Directly below each country's estimation results, the integrated volatility proxy formula is calculated through equation (1) and provided.

[1]We could use $(VIX_t / 100)^2$ and $(VKOSPI_t / 100)^2$ as proxies of the true instantaneous volatility state variables for the US and Korea, respectively. However, as Aït-Sahalia and Kimmel (2007) argue, using these unadjusted Black-Scholes proxies introduces significant bias in the estimation of the elasticity of volatility parameter for the more general CEV model. They remedy this by correcting for the effect of the mean reversion of the volatility and provide equation (1) to calculate the integrated volatility proxy, IV_t from unadjusted Black-Scholes proxy, V_t^{imp}. In doing so, we need a and b in equation (1), which are estimated from equation (2).

[2]Because model (2) is univariate and reducible, the reducible method can be used to find the approximate TPDF. To use the reducible method, however, we need to consider three different cases, where $0 < \beta < 1$, $\beta = 1$ and $\beta > 1$, and find the approximate TPDF for each case, which can be cumbersome. See Aït-Sahalia (1999) for more on this. Instead, if we use the irreducible method, we do not have to take these three cases into account separately.

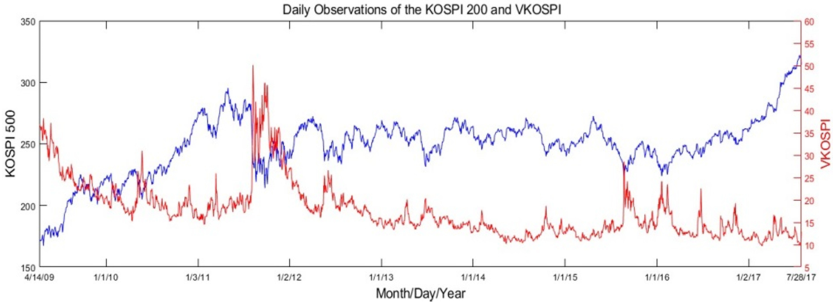

FIGURE 1. DAILY KOSPI 200 AND VKOSPI

Note: Daily observations of the KOSPI 200 and the VKOSPI data from April 13, 2009 to July 28, 2017 are depicted in Figure 1. The left y-axis is for the KOSPI 200 plot in blue and the right y-axis is for the VKOSPI plot in red.

Figure 1 displays daily time-series plots of KOSPI 200 and VKOSPI from April 13, 2009 to July 28, 2017. The left y-axis is for the KOSPI 200 plot in blue and the right y-axis is for the VKOSPI plot in red. A visual inspection of Figure 1 indicates that the implied volatility tends to increase, particularly when the stock price falls. This phenomenon is well known as the leverage effect. The sample correlation between the KOSPI 200 and VKOSPI in Table 2 is -0.60, which confirms the leverage effect in the Korean stock market. We also note that the VKOSPI tends to revert to a certain level, which we refer to as the long-run mean.

In the top panel of Figure 2, daily changes in the KOSPI 200 and the VKOSPI data are plotted. Here, the left y-axis and the right y-axis denote the changes in the

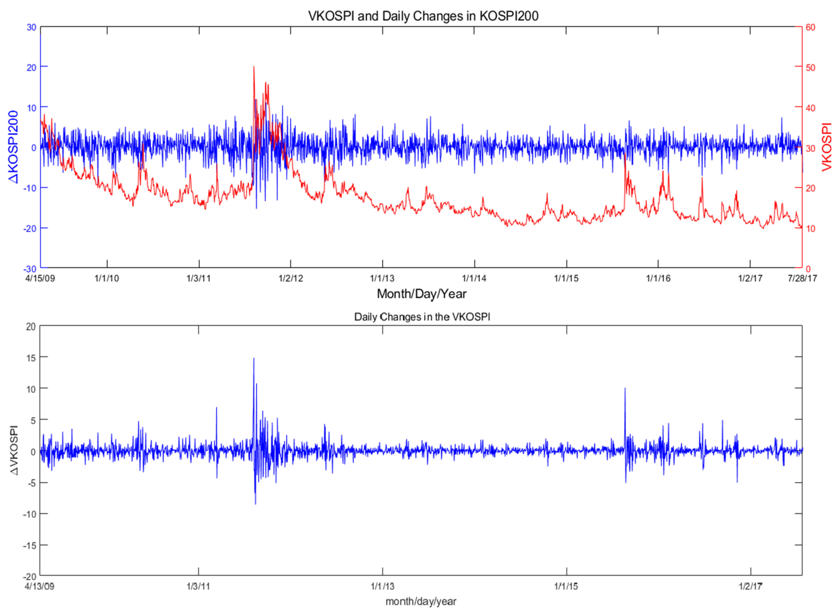

FIGURE 2. THE TREND OF THE GROWTH RATE OF PRODUCTIVITY

Note: In the top panel of Figure 2, daily changes in the KOSPI 200 and the VKOSPI data are plotted. Here, the left y-axis and the right y-axis denote the changes in the KOSPI 200 and the VKOSPI, respectively. Daily changes in the VKOSPI are graphed in the bottom panel of Figure 2.

KOSPI 200 and the VKOSPI, respectively. This figure shows that the implied volatility increases with the variance in the stock price. Daily changes in the VKOSPI graphed in the bottom panel of Figure 2 verify that the variability of the implied volatility is likely to increase as the implied volatility increases. Stochastic volatility models are capable of capturing these characteristics.

Descriptive statistics pertaining to the daily KOSPI 200 and the VKOSPI, $\ln(VKOSPI)$, and the integrated volatility from April 13, 2009 to July 28, 2017 are computed in Table 2. Here, the skewness coefficient, μ_3/σ^3 and the degree of excess, μ_4/σ^4-3 are respectively normalized measures of the asymmetry and the thickness of the tails of the distribution relative to the standard normal distribution. Note that for a random variable X_t, $\mu_i = E\left[(X_t-\mu)^i\right]$ and $\sigma^2 = E\left[(X_t-\mu)^2\right]$. Both the skewness coefficient and the degree of excess imply that none of these data series have normal distributions. Negative strong correlations between the KOSPI 200 and the VKOSPI, and $\ln(KOSPI\,200)$ and the IV, show there is a strong leverage effect in the Korean stock market. Again, what we use to estimate the stochastic volatility models are $\ln(KOSPI\,200)$ and the IV. Integrated volatility is nothing but a linear transformation of implied volatility, which does not affect the correlation, whereas taking the logarithm of the KOSPI 200 does. Even so, there is a solid negative correlation between $\ln(KOSPI\,200)$ and the IV.

Similarly to Figure 1, Figure 3 depicts the daily observations of the S&P 500 and the VIX from April 13, 2009 to July 28, 2017. The left y-axis is for the S&P 500 plot in blue and the right y-axis is for the VIX plot in red. We can observe a greater leverage effect in the US stock market than in the Korean stock market. Looking at Table 3, the sample correlation between the S&P 500 and the VIX is negative and greater than the corresponding Korean correlation in terms of the absolute value. The same is true for $\ln(S\&P\ 500)$ and the IV.

The top panel in Figure 4 depicts the daily changes in the S&P 500 and the VIX data. Here, the left y-axis is for the changes in the S&P 500 and the right y-axis is

TABLE 2—SUMMARY STATISTICS

	Obs.	Minimum	Maximum	Mean	Std. Dev	Skewness	Excess Kurtosis	corr
KOSPI 200	2165	167.24	322.01	248.71	23.95	-0.55	1.59	
VKOSPI	2165	9.72	50.11	17.56	6.09	1.70	3.45	-0.60
$\ln(KOSPI\,200)$	2165	5.12	5.77	5.51	0.10	-1.04	2.33	
IV	2165	0.0052	0.29	0.035	0.034	2.82	10.17	-0.57

Note: Descriptive statistics for the daily KOSPI 200, the VKOSPI, $\ln(KOSPI\,200)$, and the integrated volatility from April 13, 2009 to July 28, 2017 are computed. Here, the skewness coefficient μ_3/σ^3 and the excess kurtosis μ_4/σ^4-3 are respectively normalized measures of the asymmetry and the thickness of the tails of the distribution relative to the standard normal distribution. Note that for a random variable $X_t, \mu_i = E\left[(X_t-\mu)^i\right]$ and $\sigma^2 = E\left[(X_t-\mu)^2\right]$.

for the VIX. Daily changes in the VIX are graphed in the bottom panel of Figure 4. As in Figure 2, the changes in both the S&P 500 and the VIX are considerable, especially when the level of the VIX is high. This demonstrates that the volatility of stock prices depends on the implied volatility and that the volatility of the implied volatility appears to be an increasing function of the implied volatility.

We tabulate summary statistics of the S&P 500, the VIX, $\ln(S\&P\ 500)$, and the IV in Table 3. Examining the skewness coefficient and the degree of excess of all US data, they are far from normal. There exist leverage effects in the US stock market, and they are stronger than those in the Korean market because the sample

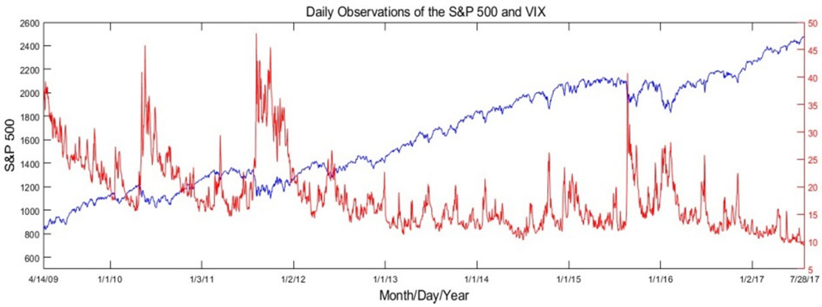

FIGURE 3. DAILY S&P 500 AND VIX

Note: Daily observations of the S&P 500 and the VIX from April 13, 2009 to July 28, 2017 are depicted in Figure 3. The left y-axis is for the S&P 500 plot in blue and the right y-axis is for the VIX plot in red.

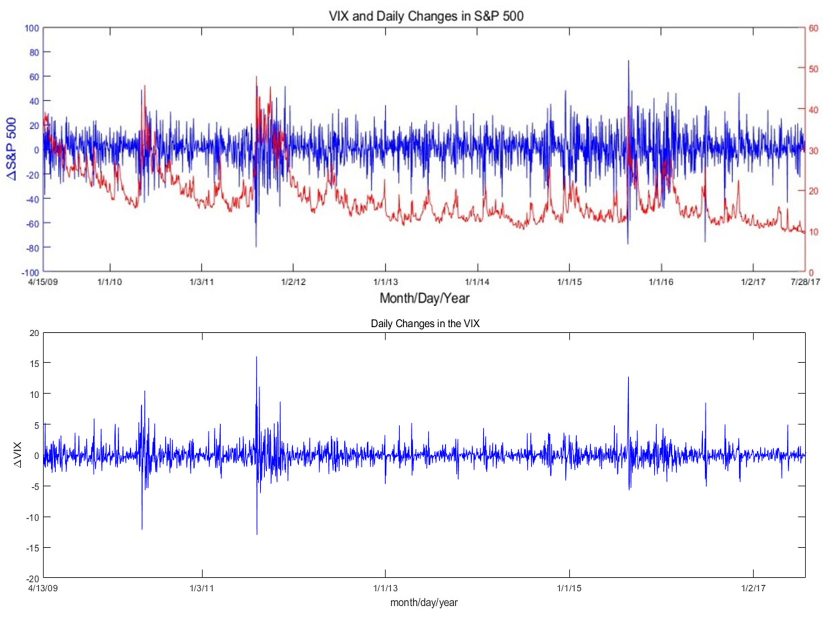

FIGURE 4. DAILY CHANGES IN THE S&P 500 AND THE VIX

Note: In the top panel of Figure 4, daily changes in the S&P 500 and the VIX data are plotted. Here, the left y-axis and right y-axis are for the changes in the S&P 500 and the VIX, respectively. Daily changes in the VIX are graphed in the bottom panel of Figure 4.

TABLE 3—SUMMARY STATISTICS

	Obs.	Minimum	Maximum	Mean	Std. Dev	Skewness	Excess Kurtosis	corr
S&P 500	2165	832.39	2477.83	1639.33	436.06	0.063	-1.32	
VIX	2165	9.36	48	18.22	6.34	1.37	1.79	-0.68
$\ln(S\&P\,500)$	2165	6.72	7.82	7.36	0.28	-0.23	-1.20	
IV	2165	0.0015	0.28	0.037	0.037	2.25	6.14	-0.64

Note: Descriptive statistics for the daily S&P 500, the VIX, $\ln(S\&P\,500)$ and the integrated volatility from April 13, 2009 to July 28, 2017 are computed. Here, the skewness coefficient μ_3/σ^3 and the excess kurtosis μ_4/σ^4-3 are respectively normalized measures of the asymmetry and the thickness of the tails of the distribution relative to the standard normal distribution. Note that for a random variable $X_t, \mu_i=E\left[(X_t-\mu)^i\right]$ and $\sigma^2=E\left[(X_t-\mu)^2\right]$.

correlations between the S&P 500 and the VIX and $\ln(S\&P\,500)$ and IV are all negative and closer to -1 than those for Korea.

Although we have discussed certain features of the Korean and US stock market data using data plots and descriptive statistics, it is more important to check if we can find any evidence to support the observations by estimating with appropriate econometric models, such as stochastic volatility models.

III. Three Stochastic Volatility Models

Three different continuous time stochastic volatility models have been used to describe the dynamics of the data. These are the Heston, GARCH and CEV models. The former two are nested by the CEV model.

A. *Heston Model*

The Black-Scholes-Merton model (Black and Scholes, 1973; Merton, 1973) has been quite popular because it provides a closed-form formula for a European option on an asset. In this model, the underlying asset price follows geometric Brownian motion which is, however, known not to explain the movements of this type of data well. To improve upon the Black-Scholes-Merton model Heston (1993) suggests the following stochastic volatility model.

$$d\begin{pmatrix} S_t \\ V_t \end{pmatrix} = \begin{bmatrix} (r-d)S_t \\ \kappa'(\gamma'-V_t) \end{bmatrix} dt + \begin{bmatrix} \sqrt{(1-\rho^2)V_t}\,S_t & \rho\sqrt{V_t}\,S_t \\ 0 & \sigma\sqrt{V_t} \end{bmatrix} d\begin{pmatrix} W_{1t}^Q \\ W_{2t}^Q \end{pmatrix}, \tag{3}$$

where W_{1t}^Q and W_{2t}^Q are independent Brownian motions under the risk neutral measure. And r is the instantaneous risk-free interest rate and d is the instantaneous dividend yield of the stock. As noted in the previous section, there is some evidence that continuously compounded stock returns are not normal and that their variances are not constant for the KOSPI 200 and the S&P 500 data. For this reason, the variance process V_t is introduced for the variance of S_t. In addition, the stock price is allowed to be correlated with the variance. The parameter ρ measures the correlation between S_t and V_t. The volatility process V_t obeys the square root process of Feller (1952), and Feller's condition $2k'\gamma' \geq \sigma^2$ must hold for the variance V_t to be positive.

Expressing (3) in terms of $s_t = \ln S_t$ and V_t, we obtain

$$(4) \qquad d\begin{pmatrix} s_t \\ V_t \end{pmatrix} = \begin{bmatrix} r - d - \frac{1}{2}V_t \\ \kappa'(\gamma' - V_t) \end{bmatrix} dt + \begin{bmatrix} \sqrt{(1-\rho^2)V_t} & \rho\sqrt{V_t} \\ 0 & \sigma\sqrt{V_t} \end{bmatrix} d\begin{pmatrix} W_{1t}^Q \\ W_{2t}^Q \end{pmatrix},$$

due to Ito's lemma. As in Aït-Sahalia and Kimmel (2007), we specify the market prices of risks as $\left[\lambda_1\sqrt{(1-\rho^2)V_t}, \lambda_2\sqrt{V_t}\right]^T$. Then, according to the Girsanov theorem, the joint dynamics of s_t and V_t under the objective measure P are determined by

$$(5) \qquad d\begin{pmatrix} s_t \\ V_t \end{pmatrix} = \begin{bmatrix} r - d + bV_t \\ \kappa(\gamma - V_t) \end{bmatrix} dt + \begin{bmatrix} \sqrt{(1-\rho^2)V_t} & \rho\sqrt{V_t} \\ 0 & \sigma\sqrt{V_t} \end{bmatrix} d\begin{pmatrix} W_{1t}^P \\ W_{2t}^P \end{pmatrix},$$

where $b = \lambda_1(1-\rho^2) + \lambda_2\rho - \frac{1}{2}$, $\kappa = \kappa' - \lambda_2\sigma$, and $\gamma = \left(\frac{\kappa'}{\kappa' - \lambda_2\sigma}\right)\gamma'$. One problem with (5) is that we cannot identify both λ_1 and λ_2 when we estimate the parameters of model (5) using the maximum likelihood estimation (MLE) method. To resolve this issue, we set $\lambda_2 = 0$ following Aït-Sahalia and Kimmel (2007). Model (5) reduced to

$$(6) \quad d\begin{pmatrix} s_t \\ V_t \end{pmatrix} = \begin{bmatrix} r - d + [\lambda_1(1-\rho^2) - \frac{1}{2}]V_t \\ \kappa(\gamma - V_t) \end{bmatrix} dt + \begin{bmatrix} \sqrt{(1-\rho^2)V_t} & \rho\sqrt{V_t} \\ 0 & \sigma\sqrt{V_t} \end{bmatrix} d\begin{pmatrix} W_{1t}^P \\ W_{2t}^P \end{pmatrix},$$

Thus, the parameter vector we need to estimate is $\theta = (\kappa, \gamma, \sigma, \rho, r, \lambda_1)$. The parameter κ indicates the speed of the mean reversion of V_t to its long-run mean level, γ and the parameter ρ measures the correlation between the innovations of the stock price and the volatility. We hold that there is a leverage effect when it takes a negative value.

B. *GARCH Model*

Another interesting model examined here is the GARCH model (Nelson, 1990; Meddahi, 2001). In this case, the stock price and its variance follow

$$d\begin{pmatrix} S_t \\ V_t \end{pmatrix} = \begin{bmatrix} (r-d)S_t \\ \kappa'(\gamma'-V_t) \end{bmatrix} dt + \begin{bmatrix} \sqrt{(1-\rho^2)V_t}S_t & \rho\sqrt{V_t}S_t \\ 0 & \sigma V_t \end{bmatrix} d\begin{pmatrix} W_{1t}^Q \\ W_{2t}^Q \end{pmatrix}, \tag{7}$$

under the risk-neutral measure. The lone difference between the Heston model and the GARCH model is that the volatility function of V_t for the latter is V_t while it is $\sqrt{V_t}$ for the former. The condition $\kappa'\gamma' \geq 0$ is required to ensure positivity of the variance V_t.

If we write model (7) in terms of (s_t, V_t) we obtain the following with Ito's lemma:

$$d\begin{pmatrix} s_t \\ V_t \end{pmatrix} = \begin{bmatrix} r-d-\frac{1}{2}V_t \\ \kappa'(\gamma'-V_t) \end{bmatrix} dt + \begin{bmatrix} \sqrt{(1-\rho^2)V_t} & \rho\sqrt{V_t} \\ 0 & \sigma V_t \end{bmatrix} d\begin{pmatrix} W_{1t}^Q \\ W_{2t}^Q \end{pmatrix}.$$

Using the same market price specification, $\left[\lambda_1\sqrt{(1-\rho^2)V_t},\, 0\right]^T$ as above, (s_t, V_t) obeys

$$d\begin{pmatrix} s_t \\ V_t \end{pmatrix} = \begin{bmatrix} r-d+bV_t \\ \kappa(\gamma-V_t) \end{bmatrix} dt + \begin{bmatrix} \sqrt{(1-\rho^2)V_t} & \rho\sqrt{V_t} \\ 0 & \sigma V_t \end{bmatrix} d\begin{pmatrix} W_{1t}^P \\ W_{2t}^P \end{pmatrix}, \tag{8}$$

under the physical measure P, where $b = \lambda_1(1-\rho^2) - \frac{1}{2}$, $\kappa = \kappa'$, and $\gamma = \gamma'$. The resulting model (8) contains the same set of parameters appearing in model (6). This model is also nested by the CEV model below.

C. *CEV Model*

The final model we consider is the CEV model.

$$d\begin{pmatrix} S_t \\ V_t \end{pmatrix} = \begin{bmatrix} (r-d)S_t \\ \kappa'(\gamma'-V_t) \end{bmatrix} dt + \begin{bmatrix} \sqrt{(1-\rho^2)V_t}S_t & \rho\sqrt{V_t}S_t \\ 0 & \sigma V_t^{\beta} \end{bmatrix} d\begin{pmatrix} W_{1t}^Q \\ W_{2t}^Q \end{pmatrix}, \tag{9}$$

The two models above are encompassed by this model given that we have the Heston model when $\beta = 1/2$ and the GARCH model when $\beta = 1$. Chan, Karolyi, Longstaff, and Sanders (1992) proposed the constant elasticity of volatility

(CEV) model for short-term interest rates. In this model, the volatility of the volatility process V_t follows the CEV process, which is why we refer to this model as the CEV model. Note that the parameter β indicates the elasticity of the volatility of V_t with respect to V_t. Lewis (2000) and Chacko and Viceira (2003) also adopted the CEV model for the volatility variable.

Again, if we write model (9) in terms of $(s_t = \ln(S_t), V_t)$,

$$d\begin{pmatrix} s_t \\ V_t \end{pmatrix} = \begin{bmatrix} r - d - \frac{1}{2}V_t \\ \kappa'(\gamma' - V_t) \end{bmatrix} dt + \begin{bmatrix} \sqrt{(1-\rho^2)V_t} & \rho\sqrt{V_t} \\ 0 & \sigma V_t^{\beta} \end{bmatrix} d\begin{pmatrix} W_{1t}^{Q} \\ W_{2t}^{Q} \end{pmatrix}.$$

With the same assumption for the market prices of risk, $\left[\lambda_1\sqrt{(1-\rho^2)V_t},\, 0\right]^T$ as in the Heston and GARCH models, according to the Girsanov theorem, the dynamics of the state variables are expressed as

$$(10) \qquad d\begin{pmatrix} s_t \\ V_t \end{pmatrix} = \begin{bmatrix} r - d + bV_t \\ \kappa(\gamma - V_t) \end{bmatrix} dt + \begin{bmatrix} \sqrt{(1-\rho^2)V_t} & \rho\sqrt{V_t} \\ 0 & \sigma V_t^{\beta} \end{bmatrix} d\begin{pmatrix} W_{1t}^{P} \\ W_{2t}^{P} \end{pmatrix},$$

where $b = \lambda_1(1-\rho^2) - \frac{1}{2}$, $\kappa = \kappa'$, and $\gamma = \gamma'$ under the physical measure P. We impose the restriction $1/2 \le \beta \le 1$ to ensure the uniqueness of option prices, as in Aït-Sahalia and Kimmel (2007).

IV. Estimation Method

To estimate the models considered in this paper, we use the maximum likelihood estimation (MEL) method. We only have discrete data for the continuous-time process, $X_t = (s_t, V_t)$ at discrete time points $t = i\Delta$ where $i = 0, 1, 2, \cdots, n$. The joint probability density function (pdf) of the data $(x_{n\Delta}, x_{(n-1)\Delta}, \cdots, x_{\Delta}, x_0)$ is then

$$\begin{aligned} & p(x_{n\Delta}, x_{(n-1)\Delta}, \cdots, x_{\Delta}, x_0; \theta) \\ &= p(x_{n\Delta} \mid x_{(n-1)\Delta}, \cdots, x_{\Delta}, x_0; \theta) \times p(x_{(n-1)\Delta} \mid x_{(n-2)\Delta}, \cdots, x_{\Delta}, x_0; \theta) \times \\ &\quad \cdots \times p(x_{2\Delta} \mid x_{\Delta}, x_0; \theta) \times p(x_{\Delta} \mid x_0; \theta) \times p(x_0; \theta) \\ &= p(x_{n\Delta} \mid x_{(n-1)\Delta}; \theta) \times p(x_{(n-1)\Delta} \mid x_{(n-2)\Delta}; \theta) \times \\ &\quad \cdots \times p(x_{2\Delta} \mid x_{\Delta}; \theta) \times p(x_{\Delta} \mid x_0; \theta) \times p(x_0; \theta). \end{aligned}$$

Here the first equality is due to the Bayes' rule and the second equality stems from the Markov property of a diffusion process. Taking the logarithm of the joint pdf and ignoring the initial observation, the log-likelihood function is written as

$$\ln(\theta) \equiv \sum_{i=1}^{n} \ln\left[p(x_{i\Delta} \mid x_{(i-1)\Delta};\, \theta) \right]. \tag{11}$$

Therefore, in order to carry out MLE, it is critical to have the transition density or log- likelihood function of stochastic volatility models. Unfortunately, the true transition density function is not known for any of the models we use in this paper, as is often the case for diffusion processes. Aït-Sahalia (2008) generalized Aït-Sahalia (2002) to obtain an explicit formula of an approximate transition density function of a multivariate time-homogeneous diffusion model. Since then, there have been more studies focusing on finding closed-form approximate transition density functions of diffusion processes, as discussed in Section 1. We employ the approach by Aït-Sahalia (2008) to obtain approximate transition densities of all models in this article.

In order to account for the method of Aït-Sahalia (2008) briefly for a general two-dimensional model, let us look at a two-dimensional diffusion process $X_t = (X_{1t}, X_{2t})'$,

$$\begin{pmatrix} dX_{1t} \\ dX_{1t} \end{pmatrix} = \begin{pmatrix} \mu_1(X_t;\, \theta) \\ \mu_2(X_t;\, \theta) \end{pmatrix} dt + \begin{pmatrix} \sigma_{11}(X_t;\, \theta) & \sigma_{12}(X_t;\, \theta) \\ \sigma_{21}(X_t;\, \theta) & \sigma_{22}(X_t;\, \theta) \end{pmatrix} dW_t. \tag{12}$$

A diffusion process is said to be reducible if it can be transformed into a unit diffusion whose volatility function is the identity matrix. If a diffusion model is reducible, an approximate log-likelihood function can be derived explicitly using the Hermite expansion or the Kolmogorov method. Aït-Sahalia (2008) and Choi (2013) present additional details of the reducible method. To determine if model (12) is reducible, it suffices to check the following necessary and sufficient conditions for a two-dimensional diffusion process,

$$\frac{\partial \sigma_{11}^{-1}(t,x)}{\partial x_2} = \frac{\partial \sigma_{12}^{-1}(t,x)}{\partial x_1} \text{ and } \frac{\partial \sigma_{22}^{-1}(t,x)}{\partial x_1} = \frac{\partial \sigma_{21}^{-1}(t,x)}{\partial x_2},$$

where $\sigma_{ij}^{-1}(x;\theta)$, $i = 1, 2$ is the (i, j) element of the inverse matrix of the volatility $\sigma(x;\theta)$ in (12). However, when checking these equalities for the Heston, GARCH, and CEV models, none of them are found to be reducible. In this case, although the reducible method is not applicable, the irreducible method can be adopted to obtain a closed-form approximate log-likelihood function. The irreducible method is more general than the reducible method, and it can be applied to any multivariate diffusion process, roughly speaking, as long as it has differentiable drift and volatility functions.

The starting point when deriving an approximate log-likelihood function employing the irreducible method is to surmise the functional form as that acquired for reducible diffusions:

$$(13)\quad \begin{aligned} &l_X^{(K)}(\Delta, x \mid x_0;\theta) \\ &= -\ln(2\pi\Delta) - D_\upsilon(x;\theta) + \frac{C_X^{(-1)}(\Delta, x \mid x_0;\theta)}{\Delta} + \sum_{k=0}^{K} C_X^{(K)}(\Delta, x \mid x_0;\theta)\frac{\Delta^k}{k!}. \end{aligned}$$

It is well known that the true log-likelihood function satisfies the Kolmogorov forward and backward partial differential equations (PDEs). The former is

$$(14)\quad \begin{aligned} \frac{\partial l_X(\Delta, x \mid x_0;\theta)}{\partial \Delta} &= -\sum_{i=1}^{2}\frac{\partial \mu_i(x;\theta)}{\partial x_i} + \frac{1}{2}\sum_{i,j=1}^{2}\frac{\partial^2 \upsilon_{ij}(x;\theta)}{\partial x_i \partial x_j} - \sum_{i=1}^{2}\mu_i(x;\theta)\frac{\partial l_X(\Delta, x \mid x_0;\theta)}{\partial x_i} \\ &+ \sum_{i,j=1}^{2}\frac{\partial \upsilon_{ij}(x;\theta)}{\partial x_i}\frac{\partial l_X(\Delta, x \mid x_0;\theta)}{\partial x_j} + \frac{1}{2}\sum_{i,j=1}^{2}\upsilon_{ij}(x;\theta)\frac{\partial^2 l_X(\Delta, x \mid x_0;\theta)}{\partial x_i \partial x_j} \\ &+ \frac{1}{2}\sum_{i,j=1}^{2}\frac{\partial l_X(\Delta, x \mid x_0;\theta)}{\partial x_i}\upsilon_{ij}(x;\theta)\frac{\partial l_X(\Delta, x \mid x_0;\theta)}{\partial x_j}. \end{aligned}$$

Therefore, if we substitute $l_X^{(K)}(\Delta, x \mid x_0;\theta)$ for $l_X(\Delta, x \mid x_0;\theta)$ in equation (14) and equate the same order terms of Δ, we can obtain the following PDEs of the coefficients $C_X^{(K)}(\Delta, x \mid x_0;\theta),\ k \geq -1.$

$$(15)\quad -2C_X^{(-1)}(\Delta, x \mid x_0;\theta) = \sum_{i,j=1}^{2}\upsilon_{ij}(x;\theta)\frac{\partial C_X^{(-1)}(\Delta, x \mid x_0;\theta)}{\partial x_i}\frac{\partial C_X^{(-1)}(\Delta, x \mid x_0;\theta)}{\partial x_j}.$$

$$(16)\quad -\sum_{i,j=1}^{2}\upsilon_{ij}(x;\theta)\frac{\partial C_X^{(-1)}(\Delta, x \mid x_0;\theta)}{\partial x_i}\frac{\partial C_X^{(0)}(\Delta, x \mid x_0;\theta)}{\partial x_j} = G_X^{(0)}(\Delta, x \mid x_0;\theta).$$

and for all $k \geq 1$

$$C_X^{(k)}(\Delta, x \mid x_0;\theta) - \frac{1}{k}\sum_{i,j=1}^{2}\upsilon_{ij}(x;\theta)\frac{\partial C_X^{(-1)}(\Delta, x \mid x_0;\theta)}{\partial x_i}\frac{\partial C_X^{(k)}(\Delta, x \mid x_0;\theta)}{\partial x_j} = G_X^{(k)}(\Delta, x \mid x_0;\theta),$$

where

$$\begin{aligned} &G_X^{(0)}(\Delta, x \mid x_0;\theta) \\ &= 1 - \sum_{i=1}^{2}\mu_i(x;\theta)\frac{\partial C_X^{(-1)}(\Delta, x \mid x_0;\theta)}{\partial x_i} + \sum_{i,j=1}^{2}\frac{\partial \upsilon_{ij}(x;\theta)}{\partial x_i}\frac{\partial C_X^{(-1)}(\Delta, x \mid x_0;\theta)}{\partial x_j} \\ &\quad - \sum_{i,j=1}^{2}\upsilon_{ij}(x;\theta)\frac{\partial C_X^{(-1)}(\Delta, x \mid x_0;\theta)}{\partial x_i}\frac{\partial D_\upsilon(x;\theta)}{\partial x_j} + \frac{1}{2}\sum_{i,j=1}^{2}\upsilon_{ij}(x;\theta)\frac{\partial^2 C_X^{(-1)}(\Delta, x \mid x_0;\theta)}{\partial x_i \partial x_j}, \end{aligned}$$

$$
\begin{aligned}
&G_X^{(1)}(\Delta, x \mid x_0;\theta)\\
&= -\sum_{i=1}^{2}\mu_i(x;\theta)\frac{\partial C_X^{(0)}(\Delta, x \mid x_0;\theta)}{\partial x_i} + \sum_{i,j=1}^{2}\frac{\partial \upsilon_{ij}(x;\theta)}{\partial x_i}\frac{\partial C_X^{(0)}(\Delta, x \mid x_0;\theta)}{\partial x_j}\\
&\quad -\sum_{i,j=1}^{2}\upsilon_{ij}(x;\theta)\frac{\partial C_X^{(0)}(\Delta, x \mid x_0;\theta)}{\partial x_i}\frac{\partial D_\upsilon(x;\theta)}{\partial x_j} + \frac{1}{2}\sum_{i,j=1}^{2}\upsilon_{ij}(x;\theta)\frac{\partial^2 C_X^{(0)}(\Delta, x \mid x_0;\theta)}{\partial x_i \partial x_j}\\
&\quad +\frac{1}{2}\sum_{i,j=1}^{2}\upsilon_{ij}(x;\theta)\frac{\partial C_X^{(0)}(\Delta, x \mid x_0;\theta)}{\partial x_i}\frac{\partial C_X^{(0)}(\Delta, x \mid x_0;\theta)}{\partial x_j}\\
&\quad -\sum_{i=1}^{2}\frac{\partial \mu_i(x;\theta)}{\partial x_i} + \frac{1}{2}\sum_{i,j=1}^{2}\frac{\partial^2 \upsilon_{ij}(x;\theta)}{\partial x_i \partial x_j} + \sum_{i=1}^{2}\mu_i(x;\theta)\frac{\partial D_\upsilon(x;\theta)}{\partial x_i} - \sum_{i,j=1}^{2}\frac{\partial \upsilon_{ij}(x;\theta)}{\partial x_i}\frac{\partial D_\upsilon(x;\theta)}{\partial x_j}\\
&\quad -\frac{1}{2}\sum_{i,j=1}^{2}\upsilon_{ij}(x;\theta)\left[\frac{\partial^2 D_\upsilon(x;\theta)}{\partial x_i \partial x_j} - \frac{\partial D_\upsilon(x;\theta)}{\partial x_i}\frac{\partial D_\upsilon(x;\theta)}{\partial x_j}\right].
\end{aligned}
$$

and when $k \geq 2$

$$
\begin{aligned}
&G_X^{(k)}(\Delta, x \mid x_0;\theta)\\
&= -\sum_{i=1}^{2}\mu_i(x;\theta)\frac{\partial C_X^{(k-1)}(\Delta, x \mid x_0;\theta)}{\partial x_i} + \sum_{i,j=1}^{2}\frac{\partial \upsilon_{ij}(x;\theta)}{\partial x_i}\frac{\partial C_X^{(k-1)}(\Delta, x \mid x_0;\theta)}{\partial x_j}\\
&\quad -\sum_{i,j=1}^{2}\upsilon_{ij}(x;\theta)\frac{\partial C_X^{(k-1)}(\Delta, x \mid x_0;\theta)}{\partial x_i}\frac{\partial D_\upsilon(x;\theta)}{\partial x_j} + \frac{1}{2}\sum_{i,j=1}^{2}\upsilon_{ij}(x;\theta)\frac{\partial^2 C_X^{(k-1)}(\Delta, x \mid x_0;\theta)}{\partial x_i \partial x_j}\\
&\quad +\sum_{i,j=1}^{2}\upsilon_{ij}(x;\theta)\frac{\partial C_X^{(0)}(\Delta, x \mid x_0;\theta)}{\partial x_i}\frac{\partial C_X^{(k-1)}(\Delta, x \mid x_0;\theta)}{\partial x_j}\\
&\quad +\frac{1}{2}\sum_{i,j=1}^{2}\upsilon_{ij}(x;\theta)\left[\sum_{h=1}^{k-2}\binom{k-1}{h}\frac{\partial C_X^{(h)}(\Delta, x \mid x_0;\theta)}{\partial x_i}\frac{\partial C_X^{(k-1-h)}(\Delta, x \mid x;\theta)}{\partial x_j}\right].
\end{aligned}
$$

It is important to note that $\upsilon(x;\theta) = \sigma(x;\theta)\sigma(x;\theta)^T$ and $\sigma(x;\theta)^T$ is the transpose of $\sigma(x;\theta)$.

When X_t is reducible, the explicit solutions of the above PDEs of $C_X^{(k)}(\Delta, x \mid x_0;\theta)$ can be found (see Choi (2015a)). Alternatively, X_t can be transformed into a unit diffusion process with the findings in Aït-Sahalia (2008) then used to obtain the closed-form approximate log-likelihood function. However, none of our models are reducible. Even so, we can turn to the irreducible method developed by Aït-Sahalia (2008). The major idea of the irreducible method is to Taylor-expand each coefficient $C_X^{(k)}(\Delta, x \mid x_0;\theta)$ and all of the other functions of x around x_0 in the above PDE. Subsequently, equating the same orders of $(x - x_0)$ yields an approximate coefficient of $C_X^{(k)}(\Delta, x \mid x_0;\theta)$. The approximation order j_k

of $C_X^{(k)}(\Delta, x \mid x_0; \theta)$ is set to have an approximation error identical to $O_p(\Delta^{K+1})$ of the approximate log-likelihood function. Specifically, $j_k = 2(K-k+1)$, for instance, when $k=2$, the orders of the Taylor expansion are $j_{-1}=8$, $j_0=6$, $j_1=4$, and $j_2=2$. We denote the j_k-th order Taylor expansion of $C_X^{(k)}(\Delta, x \mid x_0; \theta)$ by $C_X^{(k,j_k)}(\Delta, x \mid x_0; \theta)$, $k \geq -1$. The procedure of finding $C_X^{(k,j_k)}(\Delta, x \mid x_0; \theta)$ from the PDE of $C_X^{(k)}(\Delta, x \mid x_0; \theta)$ must be done from a low order to a high order recursively because the latter is generally dependent on all of the low-order terms. Moreover, $C_X^{(k,j_k)}(\Delta, x \mid x_0; \theta)$ must be retrieved in sequence from $k=-1$ sequentially because the PDE of $C_X^{(k)}(\Delta, x \mid x_0; \theta)$ usually contains all of the previous terms.[3] In this manner, we are able to obtain the approximate log-likelihood function up to any order.[4]

V. Estimation Results

We have estimated the Heston, GARCH and CEV models presented in Section 3 using daily observations of the KOSPI 200 for stock prices and the integrated volatility as a volatility proxy constructed from the daily VKOSPI data for Korea. We also conducted the same estimation using the daily S&P 500 and the VIX for the US stock market to compare the Korean and US stock markets. The estimation results are displayed in Table 4. Note that the CEV model encompasses the other two stochastic volatility models, as noted above.

MLE was carried out with the approximate log-likelihood function obtained by applying the irreducible method. In doing so, β is found to converge to 0.5, which amounts to the Heston model for Korea. However, this does not arise in the case of the US stock market. Therefore, we do not report estimation results of the CEV model for Korea. Two information criteria, AIC and BIC,[5] are reported in the last two rows of Table 4. Both AIC and BIC prefer the Heston model to the

[3] The Kolmogorov backward partial differential equation for the log-likelihood function of X_t is

$$\frac{\partial l_X(\Delta,x|x_0;\theta)}{\partial \Delta} = \sum_{i=1}^{2} \mu_i(x_0;\theta)\frac{\partial l_X(\Delta,x|x_0;\theta)}{\partial x_{0i}} + \frac{1}{2}\sum_{i=1,j}^{2} \upsilon_{ij}(x_0;\theta)\frac{\partial^2 l_X(\Delta,x|x_0;\theta)}{\partial x_{0i}} + \frac{1}{2}\sum_{i=1,j}^{2} \frac{\partial l_X(\Delta,x|x_0;\theta)}{\partial x_{0i}} \upsilon_{ij}(x_0;\theta)\frac{\partial l_X(\Delta,x|x_0;\theta)}{\partial x_{0j}}.$$

Employing the backward PDE instead of the forward PDE, we obtain the PDEs of the coefficients in x_0 and Δ. Using those PDEs of $C_X^{(k)}(\Delta,x|x_0;\theta)$, the same Taylor expansions of the coefficients can be retrieved. Thus, which PDE is used is irrelevant.

[4] We can also obtain an approximate transition probability density function. Choi (2015b) presents more information about how to obtain the approximate transition probability density function from the approximate log-likelihood function.

[5] $AIC = -\frac{2}{n}\ln L(x,\hat{\theta}_{ML}) + 2\frac{k}{n}$ and $BIC = -\frac{2}{n}\ln L(x,\hat{\theta}_{ML}) + \ln(n)\frac{k}{n}$, where n is the number of observations minus one and k is the number of parameters for each model. In addition, $L(x,\hat{\theta}_{ML})$ is the likelihood value evaluated at the maximum likelihood estimates.

GARCH model for Korea because the Heston model has smaller AIC and BIC values than the GARCH model. On the other hand, the CEV model is selected by AIC and BIC, as the CEV process yields the smallest AIC and BIC values among the three models.

The parameter ρ measures the correlation between the logarithm of the stock price and the integrated volatility proxy. For the Heston process of the Korean stock market, the estimate of ρ is -0.61 and is statistically different from zero at the 1% level. We also obtained similar results for p in the GARCH model. These estimates are quite analogues to the sample correlation between the $\ln(KOSPI\,200)$ and IV, which shows that there exists a strong leverage effect in the Korean stock market. Like the Korean stock market, the US stock market also appears to have a leverage effect. From the CEV model, we found that $\hat{\rho} = -0.62$, statistically significant at the 1% level, while $\hat{\rho} = -0.73$ and -0.70 for the Heston and GARCH processes, respectively. For the US, the CEV model engendered an estimate of the leverage effect of -0.64, much closer to the sample correlation between the $\ln(S\&P\ 500)$ and the IV as compared to the other two nested models.

The speed of reverting to the long-run mean level of the IV is very accurately estimated to be 6.09 for the Heston model, while it is 6.93 for the GARCH model for Korea. For the US stock market, the estimate of κ is 5.50 for the CEV process and

TABLE 4—MAXIMUM LIKELIHOOD ESTIMATION RESULTS OF STOCHASTIC VOLATILITY MODELS FOR KOREA AND THE US

	Korea			US		
	Heston	GARCH	CEV	Heston	GARCH	CEV
ρ	-0.61** (0.0040)	-0.63** (0.00022)	-	-0.73** (0.000046)	-0.70** (0.000061)	-0.62** (0.000079)
κ	6.09** (0.049)	6.93** (1.91)	-	2.85** (0.051)	2.59** (0.95)	5.50** (0.11)
γ	0.032 (0.18)	0.016 (3.44)	-	0.058 (0.34)	0.00013 (2.79)	0.035 (0.35)
σ	0.46** (0.0056)	1.34** (0.00048)	-	0.58** (0.00022)	1.14** (0.00014)	0.60** (0.0043)
λ	3.95** (0.15)	4.42** (0.31)	-	4.94** (0.13)	4.42** (0.12)	3.00** (0.12)
$r-d$	0.0000 (2.36)	0.0000 (2.87)	-	0.0005 (1.16)	0.0003 (2.33)	0.011 (1.31)
β	0.5	1	-	0.5	1	0.62** (0.0025)
log-lik	16114.25	14388.93	-	15450.66	22179.40	23880.50
AIC	-14.9198	-13.2975	-	-14.2788	-20.4976	-22.0698
BIC	-14.9172	-13.2949	-	-14.2762	-20.4950	-22.0672

Note: Maximum likelihood estimation results of the Heston and GARCH models for Korea and the Heston, GARCH, and CEV models for the US are tabulated in this table. No estimation results are given for the CEV model of Korea because the CEV model converges to the Heston model for the Korean data. The last three rows display the maximized log-likelihood, AIC and BIC values for each case. The two asterisks by each estimate imply statistical significance at the 1% level. From the second column to the seventh column, the estimation results for the Heston and GARCH models for Korea and for the Heston, GARCH and CEV models for the US are correspondingly presented.

2.85 and 2.59 for the other two models, correspondingly. All estimates of κ are statistically greater than zero at the 1% significant level. The volatility of the Korean stock market has been found to revert to its long-run mean more rapidly than that of the US stock market. Computing the expected time[6] it takes for the IV process to return to the middle value between the current value of IV and the long-run mean level of the IV based on the estimate of κ from the best model for each country, it is 28.68 business days for Korea and 31.76 business days for the US.

Even if we obtained statistically significant estimates of the speed of mean reversion for all cases, none of the long-run mean levels γ are statistically significant. Even so, the estimate of γ of the preferred model for each country, the Heston model for Korea and the CEV model for the US, is similar to the sample mean of the integrated volatility proxy variable. Figures 5 and 6 draw these

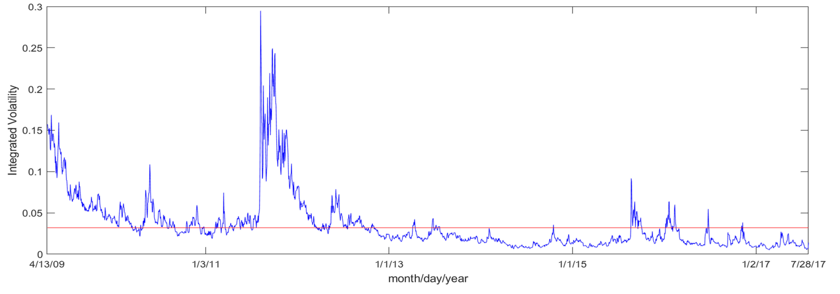

FIGURE 5. DAILY OBSERVATIONS OF THE INTEGRATED VOLATILITY AND $\hat{\gamma}$ FOR THE HESTON MODEL OF KOREA

Note: Figure 5 draws a daily time-series plot of the integrated volatility proxy of Korea. The horizontal line is the estimated long-run average from the Heston model.

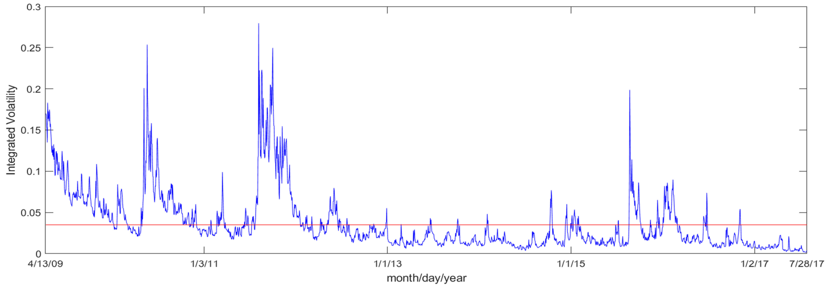

FIGURE 6. DAILY OBSERVATIONS OF THE INTEGRATED VOLATILITY AND $\hat{\gamma}$ FOR THE CEV MODEL OF THE US

Note: Figure 6 draws a daily time-series plot of the integrated volatility proxy of the US. The horizontal line is the estimated long-run average from the CEV model.

[6]The amount of expected time it takes for a mean-reverting process to revert halfway back to the long-run mean value is termed the half-life. For a diffusion process with a linear drift function $\kappa(X_t - \gamma)$, the half-life is $\ln(2)/\kappa$. Because we use daily observations, the number of half-life days can be calculated as $252 \cdot \ln(2)/\kappa$.

estimates of γ with the integrated volatility proxy values during the data period for Korea and the US. It appears to be reasonable to contend that the IV reverts to the estimated long-run mean value for both countries. We did not obtain a statistically significant estimate of γ most likely because there may be more than one data-generating process depending on the state of the economy. Using a regime-switching model, we may be able to attain statistically more significant estimates of γ, as found by Choi and Yuan (2018) for the US. It can be interesting to determine if there is more than one regime and, if so, how the estimates of the long-run mean and mean reversion speed differ in different regimes for the Korean stock market. This is left as future research.

Like the parameter γ, no significant estimate of $r-d$ was obtained for any of the models for any country.[7] The market price of risk for the stock price variable has been estimated to be significant in all cases. For Korea, these values are 3.95 and 4.42 for the Heston and GARCH models, respectively. In the case of the US, they are 4.94, 4.42 and 3.00 respectively for the Heston, GARCH, and CEV processes. Using the best model for each country, the market price of risk for the stock price is found to be more expensive in Korea.

Finally, looking at the parameters associated with the volatility function of the integrated volatility proxy, all of them are statistically greater than zero. In fact, it is more informative to draw and compare the volatility functions of the IV. Figure 7 depicts the volatility functions evaluated at the ML estimates with their 95% confidence bands over the range of the observed integrated volatility proxy for each country. The GARCH process underestimates (overestimates) the volatility of the IV when the IV is small (large), as indicated in the left panel of Figure 7 given the evidence that the Heston model is preferred to the GARCH model in Korea. The CEV model is better than the other two models and the Heston and GARCH processes overestimate the volatility of the IV for all observed values. Contrasting

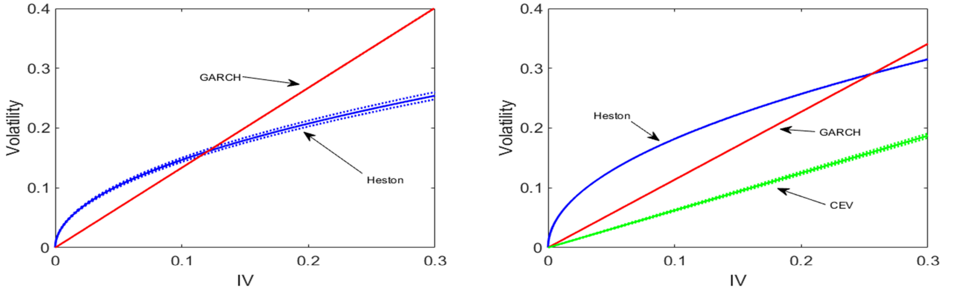

FIGURE 7. VOLATILITY FUNCTIONS OF THE INTEGRATED VOLATILITY FOR KOREA AND THE US

Note: The panel on the left and that on the right in Figure 7 depict the volatility functions of the integrated volatility proxy of Korea and the US, respectively. The volatility functions of the *IV* in the Heston and GARCH processes for Korea and those in the Heston, GARCH and CEV processes for the US are evaluated at the maximum likelihood estimates over the range of the IV observed. The dotted lines are 95% confidence bands.

[7] Aït-Sahalia and Kimmel (2007) did not estimate this parameter. In fact, the instantaneous interest rate and dividend yield for stocks were held fixed at 4% and 1.5% per year, respectively.

the Heston model of Korea and the CEV model of the US, the IV is more volatile in Korea than in the US for the entire range of the IV.

We have found that most estimates of the parameters of the stochastic volatility models examined here are quite accurate for both stock markets. Furthermore, stochastic volatility models can capture well-known characteristics of share prices in both countries. This implies that introducing another stochastic factor for the instantaneous volatility of the stock price is desirable to fit the data better for both Korea and the US. Therefore, the stochastic volatility model appears to be more appropriate than the Black-Scholes-Merton model in explaining the movements of stock prices at least for these two countries.

VI. Conclusion and Discussion

This article estimates the three continuous-time stochastic volatility models of the Heston, GARCH, and CEV models using daily data from KOSPI 200 and the VKOSPI for Korea and daily observations of the S&P 500 Index and the VIX for the US. We generate an integrated volatility proxy for an unobserved volatility variable using the implied volatility of an at-the-money option maturing in 30 calendar days. The VKOSPI and the VIX are the implied volatilities employed, respectively, for the Korean and US stock prices. MLE is utilized to estimate the parameters of these three models. To do this, we need the transition probability density functions (TPDFs) of our diffusion processes. However, the true TPDFs are not known for any of our models. Therefore, we adopt the irreducible method suggested by Aït-Sahalia (2008) to approximate the TPDF in a closed form accurately.

We were able to identify well-known features of stock prices in both countries. The Heston model and the CEV model are found to be best among the three models for the Korean and US stock markets, respectively, according to the information criteria, AIC and BIC. From the estimation results, we find that there are relatively strong leverage effects in both countries. The long-run mean level of the integrated volatility proxy (IV) was not statistically significant in either market. This appears to be due to the fact that we attempt to fit the data using only one data-generating process. It may be more reasonable to contend that stock prices are governed by more than one data-generating process depending on the economic weather. The CEV model converges to the Heston model for Korean stock prices possibly for the same reason. The speeds of mean reversion parameters are statistically significant in both markets. The IV is found to return to its long-run mean value more rapidly in Korea than in the US. All parameters related to the volatility function of the IV are statistically significant. The elasticity of the volatility of the IV is 0.50 for Korea and 0.62 in the US. Although it is more elastic in the US stock market, the volatility itself is greater in Korea than in the US over the range of observed IV outcomes. The mean-reversion speed and the volatility of the IV may vary depending on the economic conditions. If we allow the parameters to change over time, we may be able to obtain more interesting results. Choi and Yuan (2018) found strong evidence of regime-switching in the US stock market. It would be valuable to investigate Korean stock markets using regime-switching stochastic volatility models, which is an ongoing research topic.

Finally, we found evidence that there exists a strong leverage effect in both countries. This means that investors who buy stocks on margin are more likely to suffer large losses, particularly when the stock market is in a downturn. Therefore, in order to stabilize the stock market, it appears to be necessary for policymakers to prohibit excessive purchases of stocks on credit.

REFERENCES

Aït-Sahalia, Y. 1999. "Transition Densities for Interest Rate and Other Nonlinear Diffusions," *Journal of Finance*, 54: 1361-1395.

Aït-Sahalia, Y. 2002. "Maximum Likelihood Estimation of Discretely Sampled Diffusions: A Closed-Form Approximation Approach," *Econometrica*, 70(1): 223-262.

Aït-Sahalia, Y. 2008. "Closed-Form Likelihood Expansions for Multivariate Diffusions," *Annals of Statistics*, 36(2): 906-937

Aït-Sahalia, Y. and R. Kimmel. 2007. "Maximum likelihood estimation of stochastic volatility models," *Journal of Financial Economics*, 83: 413-452.

Aït-Sahalia, Y. and A. Lo. 1998. "Nonparametric estimation of state-price-densities implicit in financial asset prices," *Journal of Finance*, 53: 499-547.

Bakshi, G., N. Ju, and H. Ou-Yang. 2006. "Estimation of Continuous-time Models with an Application to Equity Volatility," *Journal of Financial Economics*, 82: 227-249.

Black, F., and M. Scholes. 1973. "The Pricing of Options and Corporate Liabilities," *Journal of Political Economy*, 81(3): 637-654.

Chacko, G., and L. M. Viceira. 2003. "Spectral GMM Estimation of Continuous-Time Processes," *Journal of Econometrics*, 116: 259-292.

Chan, K., Karolyi, F. Longstaff, and A. Sanders. 1992. "An Empirical Comparison of Alternative Models of the Short-Term Interest Rate," *The Journal of Finance*, 47(3), 1209-1227.

Chang, J., and S. X. Chen. 2011. "On the Approximate Maximum Likelihood Estimation for Diffusion Processes," *Annals of Statistics*, 39(6): 2820-2851.

Cho, J. K., W. S. Choi, and K. S. Choe. 2015. "An Asymmetric Nature of the VKOSPI Index," *The Journal of Eurasian Studies*, 12(4): 21-43.

Choi, H., and S. Han. 2009. "Explanation of the VKOSPI and empirical analysis," KRX Market.

Choi, K., and D. Cho. 2017. "Time-varying Co-movement and Dynamic Spillover Effect among Korean, Chinese, and U.S. Stock Markets," *Review of International Money and Finance*, 7(2): 5-31.

Choi, S. 2013. "Closed-Form Likelihood Expansions for Multivariate Time- Inhomogeneous Diffusions," *Journal of Econometrics*, 174(2): 45-65.

Choi, S. 2015a. "Approximate Transition Probability Density Function of a Multivariate Time-inhomogeneous Jump Diffusion Process in a Closed-Form Expression," Working paper, University of Seoul.

Choi, S. 2015b. "Explicit Form of Approximate Transition Probability Density Functions of Diffusion Processes," *Journal of Econometrics*, 187: 57-73.

Choi, S. and D. Yuan. 2018. "Maximum Likelihood Estimation of Continuous-Time Stochastic Volatility Models with Regime Shifts," Working paper, University of Seoul.

Egorov, A. A., H. Li, and Y. Xu. 2003. "Maximum Likelihood Estimation of Time Inhomogeneous Diffusions," *Journal of Econometrics*, 114: 107-139.

Feller, W. 1952. "The Parabolic Differential Equations and the Associated Semi-Groups of Transformations," *Annals of Mathematics* 55(3): 468-519.

Han, H., A. M. Kutan, and D. Ryu. 2015. "Effects of the US Stock Market Return and Volatility on the VKOSPI," *Economics: The Open-Access, Open-Assessment E-Journal*, 9: 1-34.

Heston, S. L. 1993. "A Closed-Form Solution for Options with Stochastic Volatility with Applications to Bond and Currency Options," *Review of Financial Studies*, 6(2): 327-343.

Hull, J., and A. White. 1987. "The pricing of options on assets with stochastic volatilities," *Journal of Finance*, 42: 281-300.

Jones, C. S. 2003. "The dynamics of stochastic volatility: evidence from underlying and options markets," *Journal of Econometrics*, 116: 181-224.

Kim, S. W. 2010. "A Study on Developing a VKOSPI Forecasting Model via GARCH Class Models for Intelligent Volatility Trading Systems," *Journal of Intelligent Information Systems*, 16(2): 19-32.

Lee, B. S., and D. Ryu. 2013. "Stock returns and implied volatility: A new VAR approach," *Economics: The Open-Access, Open-Assessment E-Journal*, 7: 1-20.

Lee, J., and B. K. Yu. 2018. "What Drives the Stock Market Co-movements between Korea and China, Japan and the US?" Working paper, Bank of Korea.

Lewis, A. 2000. *Option Valuation Under Stochastic Volatility*. Finance Press, Newport Beach.

Li, M. 2010. "A damped diffusion framework for financial modeling and closed-form maximum likelihood estimation," *Journal of Economic Dynamics and Central*, 34: 132-157.

Meddahi, N. 2001. "An eigenfunction approach for volatility modeling," Working paper, Université de Montréal.

Merton, R. C. 1973. "Theory of Rational Option Pricing," *Bell Journal of Economics and Management Science*, 4: 141-183.

Nelson, D. 1990. "ARCH models as diffusion approximations," *Journal of Econometrics*, 45: 7-38.

Stein, E., and J. Stein. 1991. "Stock Price Distributions with Stochastic Volatility: An Analytic Approach," *Review of Financial Studies*, 4: 727-752.

Stein, J. 1989. "Overreactions in the options market," *Journal of Finance*, 44: 1011-1023.

Stramer, O., M. Bognar, and P. Schneider. 2010. "Bayesian Inference for Discretely Sampled Markov Processes with Closed-Form Likelihood Expansions," *Journal of Financial Econometrics*, 8(4): 450-480.

Yoon, J. I. 2007. "The Evaluations and the International Comparisons of the Integration with U.S. Stock Market," *Journal of Money and Finance*, 21(1): 55-92.

Yu, J. 2007. "Closed-Form Likelihood Approximation and Estimation of Jump-Diffusions with an Application to the Realignment Risk of the Chinese Yuan," *Journal of Econometrics*, 141: 1245-1280.

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Effects of Technology Transfer Policies on the Technical Efficiency of Korean University TTOs

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The Korean government has provided various policy devices to boost technology transfers between academia and industry since the establishment of the Technology Transfer Promotion Act in 2000. Along with the enactment of the law, the Korean government mandated the establishment of a technology transfer office at national and public universities and encouraged technology transfer activities. Despite the quantitative expansion of technology transfer offices (TTOs), operational inefficiency was brought up. As a supplementary policy, the Korean government implemented a line of projects to support the labor and business expenses of leading TTOs. This research questions whether the project greatly affected the technical efficiency of TTOs. We analyze publicly available university panel data from 2007 to 2015 using a one-step stochastic frontier analysis. The results suggest that the program was marginally effective at shifting the technical efficiency distribution to the right on average, but it failed to maximize its impact by diversifying the policy means based on targets. The marginal effects of the program on technical efficiency differ according to the research capability and size of each school. We also compare technical efficiency against the licensing income at the start and end of the program. Technical efficiency increased for the leading TTOs, and both measures show improvements for unsupported TTOs. Our empirical results imply that diversifying the program for universities with different characteristics may have improved the effectiveness of the policy.

Key Word: Technology Transfer, Technology Transfer Office, Efficiency, Stochastic Frontier Analysis,
JEL Code: L24, O32, O38, I28

I. Introduction

The assessment that the Bayh–Dole Act positively affected the commercialization of publicly funded research has led to the implementation of similar policies in

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many countries. A few policies focus on legal reformations related to the ownership of intellectual property rights produced by publicly funded research to facilitate commercialization. Another set of policies concerns the establishment or fostering of intermediaries for the technology transfer functions of universities. Several researchers were critical of these policies and skeptical about their effectiveness. Mowery and Sampat (2005) argued that the success of Bayh–Dole is actually due to universities' efforts to engage in university-industry collaboration and technology transfers even before the enactment of the law and that these efforts are rooted in the scale and structure of the U.S. higher education system. They predicted that such efforts to emulate the Bayh–Dole policy will not achieve great success. Indeed, industry–academia cooperation in Western European countries, Japan, and Korea still tends to be led by the respective governments, and an atmosphere of autonomous cooperation with the private sector is not easily formed.

Nonetheless, due to the increasing complexity and diversity of technological advances, voluntary activities for knowledge spillover by the private sector are required, and governments continue to make efforts to create ecosystems in which such activities can thrive. In countries without a lengthy history of university–industry collaboration, such as the United States, various policy interventions have attempted to achieve smooth transfers of public research outcomes. The Korean government's technology transfer policies have also been part of the efforts. The Korean government has provided various policy devices to boost technology transfers between academia and industry since the establishment of the Technology Transfer Promotion Act (TTPA) in 2000 and the Industrial Education Enhancement and Industry-Academia Research Cooperation Promotion Act in 2003.[1]

Despite the efforts of the Korean Government, university—industry cooperation is not considered active. In particular, technology transfer offices (TTO), which are responsible for patents, licensing, and commercialization, are still judged to lack expertise and competence, despite the fact that they are legally required to be established.[2] As the government led the establishment of TTOs at national and public universities, the expansion of university TTOs has been more quantitative within a short period. However, TTOs suffered from operational inefficiency because most of them did not have enough experience and/or specialists such as patent attorneys and technology valuation specialists. These problems are not

[1]In Korea, several laws were enacted or revised by benchmarking the Bayh–Dole act. Three representative acts are the Technology Transfer Promotion Act (enacted in 2000), the Industry Education Enhancement and Industry—Academia—Research Cooperation Promotion Act (amended in 2003; IARC Promotion Act hereafter), and the Invention Promotion Act (amended in 2006). The enactment of TTPA made it possible to manage intellectual property through TTOs, but this law encompasses not only universities but also the TTOs of government research institutions. Meanwhile, the amendment of the IARC Promotion Act in 2003 made it possible for the Industry-Academia Cooperation Foundation to acquire legal status and handle integrated issues such as intellectual property rights management, affairs of technology transfers, and researcher compensation. The amendment of the Invention Promotion Act in 2006 allowed teaching staff of a national or public school to have a non-exclusive license for employee invention. Accordingly, detailed policy devices related to the laws originated from the spirit of the Bayh–Dole act, and some of the policy programs implemented according to each law may resemble each other. For example, the *Leaders in Industry-University Cooperation + (LINC+) project* is similar to but more comprehensive than the *Leading TTO Cultivation Project*. In this paper, we focus on the policy effects of the *Leading TTO Cultivation Project* and our results are therefore limited in that we cannot address all of the complicated relationships between policies.

[2]On the basis of TTPA, the government mandated the establishment of technology transfer offices (TTOs) at national and public universities and encouraged technology transfer activities.

easily solved because the corresponding universities have not provided sufficient funding for the operation of the TTOs. The government recognized the structural problems and attempted to enhance the capabilities of TTOs through supplementary financial support. For this reason, starting in 2006 the government began to implement the financial support project known as the *Leading TTO Cultivation Project* to subsidize the labor and business expenses of TTOs which have shown relatively high performance capabilities.

At the moment when the *Leading TTO Cultivation Project*, which was originally planned for five years, was extended for another five years, the TTOs of Korean universities were evaluated to have better competence in terms of the number of experts, technology transfer income, and patent registrations. However, it is not known how much of the improvement is due to the policy. The purpose of this paper is quantitatively to evaluate the effects of the policy and present future policy directions.

Technology transfer is a topic studied from a wide variety of aspects. Bozeman (2000) and Bozeman *et al.* (2015) found several major directions in the broader technology transfer literature under the dimensions of the contingent effectiveness model. In particular, Bozeman *et al*. (2015) found that the discussion of recent studies is centered on university settings. While many studies focus on the impact and effectiveness of technology transfers, factors affecting the effectiveness of technology transfers are still being explored (Caldera and Debande, 2010). As technology transfers involve many actors and the final outputs of TTOs vary according to the institutional goal, various determinants are being studied. Although the output of TTOs is not singular but rather mixed, the number of technology transfers, royalty income, and licensing fees are recognized as the main outputs (Thursby and Kemp, 2002; Carlsson and Fridh, 2002; Siegel *et al*., 2007). Often, intellectual property rights ownership, start-ups, or spin-offs based on technologies invented in university labs are considered to be the outputs of TTOs (Thursby and Kemp, 2002; Carlsson and Fridh, 2002; Friedman and Silberman, 2003).

A large portion of the studies on technology transfers focus on finding the determinants of technology transfers, and many factors have been explored in different countries. Listing each factor is difficult because previous studies identify many determinants of a technology transfer. One of the reasons for the various and complicated determinants is that technology transfers are complex activities that involve multiple stages. Defining a typical production function as one for the manufacturing sector is challenging. Various determinants can be categorized as the primary inputs for invention, secondary inputs for technology transfers, and other environmental factors. Interestingly, the outputs from technology production are actually the important intermediate inputs for the stage of the technology transfer. Another portion of studies attempts to estimate the production function and productivity of technology transfer units, which are TTOs in most cases (Siegel *et al*., 2003; Thursby and Kemp, 2002; Thursby and Thursby, 2002). These studies seek to find the determinants of the improved technical efficiency of technology transfer units.

Several countries have implemented technology transfer policies under government initiatives, but few empirical studies have examined how these policies affect technology transfers. Goldfarb and Henrekson (2003) showed that policy efficiency can change according to the policy delivery structure by comparing cases in Sweden and the United States. In particular, they argued that the top-down nature of Swedish policies may be an obstacle to the commercialization of academic achievements, whereas competition between universities and researchers for research funding has allowed academics to interact with industry actively. The lack of empirical research on the effectiveness of policies may be due to the failure to find a policy environment that influences technology transfers independently in many countries. A major contribution of the present study lies in identifying the policy environment and conducting an empirical analysis to confirm the effectiveness of a policy.

In this study, we analyze the effects of the *Leading TTO Cultivation Project* implemented by the Korean government from 2011 to 2015 on the technical efficiency of university TTOs. In particular, we utilize a one-step stochastic frontier analysis with publicly available university panel data of Korea from 2007 to 2015. The main finding is that the TTO policy effectively improved the technical efficiency of university TTOs on the average, whereas the effects of the policy could be improved if it were fine-tuned according to the characteristics of the TTOs and universities.

The remaining parts of the paper are organized as follows. In the next section, we introduce the technology transfer policy in Korea and the financial support program for TTOs, which is the main policy instrument analyzed in section III. In section III, we analyze the impacts of the TTO support program by using a one-step stochastic frontier analysis. We review the one-step stochastic frontier model suggested by Wang and Schmidt (2002), and illustrate the results from an empirical analysis. Finally, section IV concludes the paper.

II. Technology Transfer Policy in Korea

To facilitate exchanges of knowledge and technology between science and technology academia and industry, the Korean government has enacted laws and implemented various plans and support projects accordingly. Korea had emphasized linkages between industry and academia during the process of industrialization in the 1960s, but only in a few cases were the research outcomes of public research institutes (PRIs) transferred or put into practical use by the end of the 1990s. The TTPA was enacted in 2000 to promote the development of science and technology and the commercialization of achievements in these areas. The Science and Technology Innovation Office[3] began to manage and utilize research results with government support starting in 2005. In 2006, the TTPA was amended to increase the incentives for the technology commercialization of PRIs. In addition, the Korean government has enacted various laws for the protection of intellectual property rights, the promotion of university–industry collaboration,

[3]The Science and Technology Innovation Office is a subordinate organization of the Ministry of Science and Technology. It is responsible for the coordination of the related departments of S&T policies, industry, manpower, and regional innovation policies, along with the allocation of the R&D budget and performance evaluations.

support for the development of new technology, the creation of a proper ecosystem, and participation by private companies.

Along with such legal assistance, the Technology Transfer and Commercialization Plan (TTCP) was implemented in 2001. The plan aims to integrate the management of the details of various ministries involved in technology transfer and commercialization activities. At the beginning, the plan focused on building infrastructures (e.g., the technology trading market, National Technology Bank) and establishing intermediary organizations such as an industry–academia cooperation foundation, TTOs, and technology evaluation institutions. In the second phase of the plan, the emphasis was on building a system for technologically innovative businesses by allowing technology in-kind contributions and expanding technology finance. Owing to these efforts, social awareness of technology transfers and commercialization spread in a short period and a quantitative expansion was possible. However, the lack of links between detailed projects and a policy that prioritizes quantitative achievements were obstacles to smooth collaboration between researchers and industry. To solve these problems, the plan focused on establishing a technology-oriented ecosystem and encouraging voluntary participation by the private sector. To this end, the role of the technology transfer intermediaries has been to attract attention, and the organizational expertise of TTO has been incorporated into the detailed goals of the plan since 2012.

The Korean government's technology transfer policy has expanded quantitatively with the TTCP, but these efforts have generally resulted in projects targeting SMEs. Relatively little attention has been paid to universities, even if policy programs that qualify for universities and their subordinate organizations actually require company participation or are intended to help SMEs that are technology consumers. In other words, only few policies have attempted to solve the problems of university TTOs on the side of the technology provider. Technology transfer policies have been centered on enterprises because policy authorities took the existence of intermediary organizations for granted and did not recognize that the intermediaries had not been developed sufficiently.

The *Leading TTO Cultivation Project* is one of the few policies aimed at university TTOs. The project was actually initiated by the Small and Medium Business Administration in 2001 and continued on a very small scale until 2006. In 2006, the Ministry of Knowledge Economy and the Ministry of Education, Science, and Technology expanded this project and started a new project called *Connect Korea*, benchmarking the CONNECT program of the University of California, San Diego (UCSD). The project was planned as a five-year project, three years to complete the first half and two years for the second half, and 18 universities and their TTOs were supported by the project. At its beginning, TTOs were still being established in many universities, implying that this project contributed to the spreading of TTOs throughout the country and to expanding professional employment (Table 1) rather than contributing to the actual growth of the TTOs.

In 2010, when the project ended, Korean universities were still in a poor situation. TTOs are operated as subordinate organizations of the University–Industry Collaboration Foundation, which is responsible for more complex tasks. Hence, concentrating on technology transfers was difficult, and only four or five

TABLE 1—PROFESSIONAL EMPLOYMENT IN TTOS AFTER THE *CONNECT KOREA PROGRAM*

Year	Specialists			Non-specialists	Total
	PA[1]	TTA[2]	CVA[3]		
2006	-	-	-	72	72
2007	7	8	-	99	114
2008	8	19	15	73	115
2009	10	26	23	103	162
2010	17	27	41	88	173

Note: 1) [1]Patent Attorneys; [2]Technology Transfer Agents; [3]Certified Valuation Analysts, 2) Figures are the workforce of 18 universities which participated in the *Connect Korea program*. The *Connect Korea program* ran from 2001 to 2005.

staff members were involved. Although the number of experts increased, this was limited to universities with the proper financial leeway.

After the end of the project, the government expanded its scale and implemented a new project termed the *Leading TTO Cultivation Project* from 2011 onwards. A major difference from the previous support project is that TTOs with superior performance capabilities are prioritized while second-best TTO groups are supported by a type of consortium. TTOs are divided into two types according to their existing technology transfer performances and their capacities. At the time of the project in 2011, leading TTOs received KRW 150 million to KRW 300 million, and the TTOs of the consortium received KRW 50 million. This project was also planned as a five-year project, with two years allocated for the first half and three years for the second half. In total, 24 TTOs were supported in the first half of the project and 30 TTOs were supported in the second half. The subsidies were designated to be used to cover labor costs, technology discovery, evaluations, and marketing. The project also provided educational programs for technology transfers, but this was not the main part. Essentially, the project was a simple program to support the operating expenses of TTOs.

In the next section, we examine the impact of the *Leading TTO Cultivation Project* on efficiency improvements at TTOs through an empirical analysis.

III. Impacts of a Financial Support Program

A. *One-step Stochastic Frontier Analysis*

The stochastic frontier analysis (SFA) and the data envelopment analysis (DEA) methods are widely used methodologies which analyze how efficient decision-making units are. The SFA is based on the idea that no economic unit can exceed a theoretical production frontier; therefore, the degree of inefficiency can be estimated by the gap between the ideal production frontier and the productivity of each economic unit. The main goal of the conventional SFA is an empirical estimation of the relative inefficiency (or efficiency) of individual economic units compared to the best practice unit.

A simple stochastic frontier model can be written as follows:

$$
\begin{aligned}
y_{it} &= x_{it}^{'}\beta + \varepsilon_{it} \\
\varepsilon_{it} &= v_{it} - u_{it}
\end{aligned}
\tag{1}
$$

Eq. (1) is a log-transformation of a Cobb–Douglas production function. The empirical literature on the production function generally seeks to estimate the parameters of the production function that passes through the middle of data points. Arguments in the stochastic frontier literature redirected attention from the production function to deviations from that function (Greene, 2008). Generally, SFA focuses on estimations of the deviation from the production frontier with the assumption that the error term includes unobserved productivity, which is additive to the white noise. The error term ε_{it} can then be decomposed into the unobservable inefficiency term u_{it} and white noise v_{it}. If an economic unit, for instance $i = m$, is producing on the production frontier, then its inefficiency is zero by definition; i.e., $u_{mt} = 0$, whereas the inefficiencies of other economic units are greater than zero; i.e., $u_{it} > 0$, where $i \neq m$. In other words, a one-sided distribution can be assumed for the inefficiency term u_{it}. Under this assumption, the relative inefficiency is comparable by estimating the inefficiency distribution and parameters of the production function using, in this case, Eq. (1).

Although efficiency[4] is essentially unobservable, we can think of the sources of efficiency. The early literature on the sources of efficiency constructed what was termed an efficiency equation using the estimated efficiency measure shown in Eq. (1) as a dependent variable, estimating it separately. These studies, using what is known as the two-step approach, consider efficiency factors exogenous to the independent variables of Eq. (1).

However, the endogeneity issue is prevalent as long as we cannot control the relevant variables precisely, and the estimates are biased when we ignore the endogeneity problem. For this reason, a set of studies after Kumbhakar *et al.* (1991) stressed the usefulness of the one-step approach, which estimates the system of the production function and the efficiency equation at the same time. In particular, Wang (2002) and Wang and Schmidt (2002) showed that estimates from two-step approach can be biased, with the following reasoning. First, there is a possibility of a correlation between the explanatory variables for the production function and the determinants for the efficiency equation. Second, it is challenging to exclude the possibility that omitted variables exist in the efficiency model used in the second step. Third, it is highly probable that the estimated efficiency in the first step without considering the determinants of efficiency is downwardly biased.

A simple means of introducing influences in the inefficiency model is to consider the location and scale of the distribution. Studies such as those by Kumbhakar *et al.* (1991), Huang and Liu (1994), and Battese and Coelli (1995) proposed the parametrization of the mean of the pre-truncated inefficiency distribution. As an extension, Caudill and Ford (1993) and Caudill *et al.* (1995) put

[4]The relative inefficiency term can be transformed into the relative efficiency measure through a negative exponential function. Hence, efficiency and inefficiency terms are used interchangeably in this paper.

forward the parameterization of the mean and variance of the pre-truncated inefficiency distribution to allow heteroscedasticity in u_{it} and/or v_{it}. Additionally, Wang (2002) introduced a methodology to allow non-monotonic efficiency effects owing to the possibility that the effects of determinants on the efficiency distribution are not monotonic. For example, the accumulation of experience by farmers can enhance production efficiency even if the marginal effect of age on efficiency is negative.

In the present study, we apply the methodology suggested by Wang (2002) to estimate the marginal effects of policy intervention on the technical efficiency of university technology transfer offices. The main model is expressed in the following system of equations,

(2) $$y_{it} = x_{it}'\beta + \varepsilon_{it},$$

(3) $$\varepsilon_{it} = v_{it} - u_{it},$$

(4) $$v_{it} \sim N(0, \sigma_v^2),$$

(5) $$u_{it} \sim N^+(\mu_{it}, \sigma_{it}^2),$$

(6) $$\mu_{it} = z_{it}\delta,$$

(7) $$\sigma_{it}^2 = \exp(z_{it}\gamma),$$

where z_{it} denotes the vector of the determinants of inefficiency. As noted above, Eq. (2) represents a log-transformed production function, and Eq. (3) is the composed error of the inefficiency and white noise. We assume that the white noise follows a normal distribution with zero mean and variance of σ_v^2. Inefficiency, u_{it}, is assumed to have a truncated normal distribution,[5] whose pre-truncated distribution has a mean of μ_{it} and variance of σ_{it}^2. Following Wang (2002), we parametrize both the mean and variance of the pre-truncated efficiency distribution, as expressed in Eq. (6) and Eq. (7).

Given that μ_{it} and σ_{it}^2 represent the mean and variance of the pre-truncated distribution, respectively, δ and γ are not precise measures of the effects of z_{it} on the efficiency distribution. Instead, Wang (2002) provided the functional form of the marginal effects of each determinant on the location of the efficiency distribution, as follows[6]:

(8) $$\frac{\partial E(u_{it})}{\partial z[k]} = \delta[k]\left[1 - \Lambda\left(\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right) - \left(\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right)^2\right] + \gamma[k]\frac{\sigma_{it}}{2}\left[(1+\Lambda^2)\left(\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right) + \left(\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right)^2\right]$$

[5]A one-sided distribution of inefficiency can be modeled in various ways. The widely used distributional forms are the truncated normal, half normal, exponential, and gamma distribution.

[6]Wang (2002) also provided the functional form of the marginal effects of determinant on the variance of efficiency. We do not present the functional form here, as our main interest is on the location rather than the dispersion of the efficiency distribution.

Here, $z[k]$ denotes the k th element of the determinants, $\Lambda = \mu_{it} / \sigma_{it}$, and ϕ and Φ represent the probability density function and cumulative distribution function of the standard normal, respectively.

B. *Data Description*

The data sources of this paper are three fold. The primary data source is the *Information Service of Higher Education* (ISHE) in Korea. It provides publicly available information and regulated relevant details of all universities in Korea. The variables we collected from this source include operational details of the office of research affairs, research activities and funding, and general information pertaining to universities. We also collect the number of patents owned by each university from the *Worldwide Patent Statistical Database* (PATSTAT) of the European Patent Office and the *Korea Institute of Patent Information* (KIPI). Finally, we obtain information about the recipients of government financial support programs from business description materials held by the *Ministry of Science, ICT, and Future Planning* (MSIP) and the *Ministry of Education* (MOE).

The number of technology transfers and royalty income are collected on the basis of the information reported by the university–industry cooperation foundations based on the contracts for technology transfers. In this case, technology transfers are limited to cases in which the developed technology is purchased or licensed, and transfers of technology that has not been developed, such as technical consultations, industrial joint research, and personnel exchanges, are excluded. Royalty income refers to the amount of money actually deposited in the survey year, regardless of the contract year, excluding VAT, and the number of contracts means the number of contracts for technology transfers made in the survey year. The operating expenses for university–industry cooperation were collected based on closed accounts data. This variable refers to expenditures on operating expenses for industry-academia cooperation among the accounting categories of the Industry-Academia Collaboration Foundation. This item is composed of industry-academy cooperation research funds, educational administration fees, intellectual property rights operation and transfer fees, school facility fees, industry-university cooperation rewards, and other industry-academic cooperation fees.[7] Next, research funds include only cash in the amounts agreed upon during the base year. Among these, the amounts for government subsidies are research funds supported by the central government and ministries and not local governments. Total financial support means grants through financial support projects. A financial support project refers to a project that is managed through an on-campus institution and that meets one of the following conditions: improvement of educational conditions, development and operation of the curriculum, improvement of the undergraduate system, cooperation between industry and academia, and research and development by professors and students.

The range of data is nine years, from 2007 to 2015 inclusive. The number of

[7] The operating expenses for university–industry cooperation do not include remuneration for TTO employees. Therefore, there is no problem with duplicated calculations between the number of TTO staff members and labor costs in the selection of input factors.

TABLE 2—SUMMARY STATISTICS

Classification	Variables	Obs.	Mean	S.D.	Min	Max
TTO Operational Details	No. of Technology Transfers	1,039	17.8	21.6	0	141
	Royalty Income	885	430.9	727.7	0.3	7,065
	No. of TTO Staff Members	976	3.5	3.5	0	25.8
	Operating Expenses	927	7	18.8	0	335
Research Activities	Total Research Funding	1,110	33.3	58.9	0	502
	Gov't Research Funding	1,110	25.4	48.5	0	450
	Private Research Funding	1,110	4.3	9.0	0	66
	Local Research Funding	1,110	1.3	1.7	0	12
General Information	Total Financial Support	1,068	57.1	1,000	0	32,800
	No. of Students (Thousands)	937	13.2	8.3	0	39.5
	No. of Faculty Members	1,110	455	340	15	2,248
	Total Education Expenses	937	168	164	0	1,220
IPR	Domestic Patents Granted	1,102	257.5	590.7	0	7,080
	Foreign Patents Granted	1,102	29.2	108.5	0	1,086

Note: The data source for *TTO Operational Details*, *Research Activities*, and *General Information* is ISHE. *Domestic and Foreign Patents* are from KIPI and EPO PATSTAT, respectively. All monetary variables are in KRW. Units of *Operating Expenses*, *Total Research Funding*, *Government / Private / Local Research Funding*, *Total Financial Support*, and *Total Education Expenses* are in billions of KRW and *Royalty Income* is in millions of KRW in this table.

institutions of higher education in Korea has gradually increased.[8] Such institutions exist in various forms and pursue different purposes. Some do not aim to transfer technology, or this activity is impossible because they do not have technologies to sell. Therefore, we limit the sample to universities that are capable of technology transfers. We exclude universities that did not have technology transfer revenue for the sample period. In addition, universities within the lower 10% in terms of average royalty income for the three years between 2013 and 2015 inclusive are excluded. The final sample collected on this basis is an unbalanced panel with 127 observations per year. All nominal variables are adjusted to real variables with a GDP deflator for 2010. The summary statistics are displayed in Table 2, and the correlation coefficients between the variables are given in Table A1 in the Appendix.

C. *Empirical Results*

As we have discussed in Section I, there is only a rough consensus on the outputs and inputs of the TTOs' production function. Although TTOs aim to support researchers' patent activities and ultimately to increase the number of patents owned by universities, it is also an important operational goal to increase technology transfer income by selling patents already owned. For this reason, one may regard patents as a part of the outcome that TTOs produce. However, the

[8]There were 408 institutions of higher education in 2007, and this number increased to 431 in 2015.

contributions of TTOs during this process are not research activities for patent production but rather overall an auxiliary role for the registration and management of IP. Naturally, we consider IP as an intermediate input for TTOs to create technology transfer outcomes. In this study, we assume that the intellectual property rights of each university are intermediate inputs that can be utilized by TTOs.

To sum up, the number of technology transfer contracts and the amounts of royalty income are considered as outputs, and inputs consist of operating expenses of TTOs, the number of TTO employees and the cumulative numbers of domestic and foreign patents owned by the affiliate university. The other variables include a policy dummy and control variables describing the university research environments. The policy dummy indicates a value of 1 for all years *i* in which the TTO policy subsidizes university *j*, and 0 otherwise. The control variables for university research environments include the size of the university as measured by the funding amount, the number of faculty members, the number of students, or total education expenses, the size of the TTO proxied by operating expenses, and other variables to control for the general characteristics of universities, such as the location of the university or whether a university is private or public.

With these variables, we estimated the system of equations, Eq. (2) to Eq. (7), by means of maximum likelihood estimations, as in Battese and Coelli (1995). All variables but dummy variables are logarithmic, and lagged values of the TTO policy dummy, operating expenses, are used. Because there is a possibility of a sample selection problem with regard to the TTO policy dummy, we used the estimated inverse Mill's ratio from a probit model[9] for the TTO policy dummy.

Table 3 illustrates the parameter estimates. Table 3 consists of the estimation results of *Frontier Equation* Eq. (2) and *Inefficiency Equation* Eq. (5). The table shows the results from seven specifications. We keep the input variables for the *Frontier Equation* unchanged, whereas the specification for the *Inefficiency Equation* varies. We take logarithm of the output and input variables; therefore, the estimated coefficients for the *Frontier Equation* can be interpreted as the output elasticities of each input factor. We assume that there is no exogenous variable that affects the efficiency of the TTO operation in specification (1), which is our baseline model. In this case, the output elasticities of all variables but operating expenses are significant and positive. The output elasticity of domestic patents granted is the largest, whereas that of foreign patents granted is the smallest. The coefficient estimates of the *Frontier Equation* are stable across specifications; therefore, the estimation of the *Frontier Equation* is robust for this model.

We set μ_{it} as a function of the TTO policy in specification (2). The magnitudes of the coefficient estimates of the *Frontier Equation* do not change much, and the coefficient for operating expenses is estimated to be positive and significant. The result revealed that the effect of the TTO policy on the mean of the inefficiency distribution is negative but statistically insignificant. For specifications (1) and (2), the constant term is estimated as negative but insignificant. This implies that inefficiencies are likely to be distributed near zero, which is ideal but unrealistic. In

[9]The determinants of the probit model are total research funding, the number of TTO staff members, domestic and foreign patent amounts, operational expenses, total financial support, and the number of faculty members.

TABLE 3—PARAMETER ESTIMATES FOR ONE-STEP SFA MODELS

Dep. Var.	Royalty Income (logged)						
Specifications	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Frontier Equation							
Operating Expenses	0.024	0.027*	0.025	0.025	0.041**	0.025	0.024
	(0.017)	(0.016)	(0.016)	(0.016)	(0.020)	(0.016)	(0.015)
TTO employment	0.334***	0.260***	0.256***	0.256***	0.249***	0.252***	0.257***
	(0.071)	(0.059)	(0.050)	(0.049)	(0.048)	(0.046)	(0.047)
Domestic Patents	0.537***	0.526***	0.470***	0.469***	0.433***	0.446***	0.423***
	(0.049)	(0.046)	(0.047)	(0.047)	(0.050)	(0.048)	(0.048)
Foreign Patents	0.179***	0.146***	0.142***	0.142***	0.139***	0.140***	0.151***
	(0.043)	(0.039)	(0.039)	(0.039)	(0.039)	(0.038)	(0.038)
Constant	9.033***	9.179***	9.596***	9.602***	9.641***	9.802***	9.888***
	(0.289)	(0.269)	(0.269)	(0.273)	(0.304)	(0.282)	(0.285)
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inefficiency Equation							
Mu							
TTO Policy (t-1)		-11.672	-4.797*	-4.786*	-3.234*	-3.272*	-2.861*
		(7.161)	(2.746)	(2.744)	(1.872)	(1.901)	(1.722)
Faculty			-0.006***	-0.006***	-0.003**	-0.003**	-0.003***
			(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Public Univ.				-0.059	0.441	0.334	0.376
				(0.552)	(0.468)	(0.464)	(0.436)
Gov't R&D					-0.530*		
					(0.281)		
Private R&D					-0.057		
					(0.185)		
Local R&D					-0.013		
					(0.164)		
Total R&D						-0.529***	
						(0.201)	
Total Financial Support							-0.844***
							(0.233)
Constant	-9.690	-3.919	1.237*	1.317	9.773***	9.146***	14.266***
	(10.676)	(3.126)	(0.724)	(1.004)	(2.919)	(2.782)	(3.311)
Usigma							
Constant	2.354***	1.839***	1.260***	1.259***	0.998***	0.993***	0.910***
	(0.868)	(0.468)	(0.294)	(0.295)	(0.252)	(0.264)	(0.222)
Vsigma							
Constant	-1.242***	-1.437***	-1.632***	-1.633***	-1.731***	-1.743***	-1.775***
	(0.230)	(0.248)	(0.248)	(0.247)	(0.262)	(0.259)	(0.255)
Obs.	741	741	741	741	715	741	728
Log pseudolikelihood	-1,011.97	-990.42	-961.96	-961.95	-923.58	-954.94	-925.22

Note: 1) Numbers in parentheses are Huber-White Robust Standard Errors, 2) *p<.1, **p<.05, ***p<.01.

specification (3), we added the number of faculty members, which is a proxy for research capacity, as a determinant of inefficiency. Along with the TTO policy variable, the number of professors has a negative and significant effect on the mean of the inefficiency distribution. In other words, the efficiency of TTO improves distributionally as the number of professors increases or if a TTO is supported by a governmental financial support policy.

In specification (4), we added a public dummy that indicates whether the universities to which a TTO belongs are public or private. Given that the estimates from this specification are comparable to those from specification (3) and the coefficient estimate of the public dummy is insignificant, it can be concluded that the university type does not affect the efficiency of the TTO.

Specifications (5)-(7) include two funding variables as inefficiency determinants: Research Funding from various sources and *Total Financial Support*. When research funding for each source is included in (5), only government research funding reduces inefficiency significantly. The magnitude of the impact of government research funding in (5) is comparable to that of total research funding in (6). This is reasonable considering that nearly 71% of total research funding comes from the government for universities in Korea. The results from specifications (6) and (7) indicate that either total research funding or total financial support improves the efficiency of TTOs.

Because specifications (1)-(4) are nested into specification (5), we perform likelihood ratio tests on the hypotheses that nested models are preferred in specification (5). The results suggest that specifications (1)-(4) are rejected in favor of specification (5) at the 5% level.

It should be noted that the estimates displayed in Table 3 are not the marginal effects of determinants on the mean of the inefficiency distribution, $E(u_{it})$ despite the fact that the signs coincide. In Eq. (6), μ_{it} is not the mean of inefficiency; rather, it is the mean of the pre-truncation of the inefficiency distribution because we assume that the distribution of inefficiency takes a half-normal form. The marginal effects of determinants on the mean of the inefficiency distribution can be expressed by Eq. (8) from Wang (2002). The marginal effects can be derived for each of the observations.

In Table 4, the sample mean of the marginal effects are listed. The negative sign of the estimated marginal effect means that the inefficiency is alleviated on average as the corresponding determinants become larger. One can find that all but the public university dummy have negative marginal effects on mean inefficiency. In addition, the TTO policy has the greatest marginal effects, indicating that the TTO policy played an important role in reducing the operational inefficiency of TTOs on average.

Figure 1 and 2 illustrate the observation-wise marginal effects of the inefficiency determinants. The horizontal axis represents the determinant and the vertical axis is the marginal effect. Figure 1 is generated from specification (5), as is shows the largest log-pseudolikelihood.[10] First, Panel (a) shows the differences in the marginal

[10]Note that the observation-wise marginal effects of the TTO policy and faculty size are estimated to be similar in all specifications. This can be inferred by the comparable coefficient estimates in Table 3 and Table 4.

TABLE 4—MARGINAL EFFECTS OF INEFFICIENCY DETERMINANTS ON $E(u_{it})$

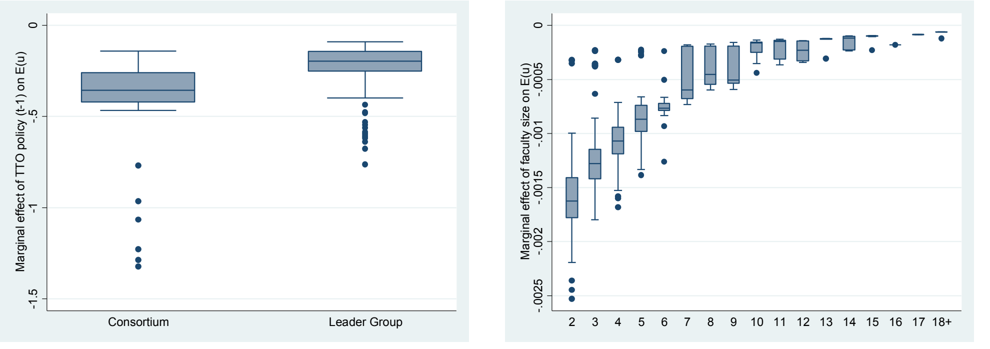
Specifications	(2)	(3)	(4)	(5)	(6)	(7)
TTO Policy (t-1)	-1.517 (0.014)	-1.208 (0.019)	-1.207 (0.019)	-1.067 (0.019)	-1.092 (0.019)	-1.035 (0.019)
Faculty		-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)
Public Univ.			-0.015 (0.000)	0.145 (0.003)	0.111 (0.002)	0.136 (0.003)
Gov't R&D				-0.175 (0.003)		
Private R&D				-0.019 (0.000)		
Local R&D				-0.004 (0.000)		
Total R&D					-0.177 (0.003)	
Total Financial Support						-0.305 (0.006)

Note: Numbers in parentheses are 1,000 bootstrap standard errors.

effects of the TTO policy by support type. As discussed in Section II, the financial support program for TTOs was implemented and aimed at two groups: leader groups and consortia. As indicated by the policy name, this policy was designed for leading TTOs, but it also provided an opportunity for the remaining TTOs for which the performance levels were second-best. Support for this non-leader group was provided in the form of a consortium, and eight universities were selected for the program. From Panel (a), the marginal effects of both types are skewed towards the larger side, which means that most of the TTOs have small marginal effects, and only a few TTOs enjoy relative greater improvements in efficiency by the policy. The horizontal line in the box plot represents the median of the distribution. We can find that the median of the leader group is higher than that of the consortium, which demonstrates that the marginal improvement of efficiency in the consortium is greater when TTOs are supported by the financial support policy. Note that the variance of the marginal effects in the leader group is smaller than that in the consortium. This provides a rationale for the need to investigate how the effects of the policy differ with the characteristics of each university.

Panel (b) of Figure 1 shows the marginal effects of faculty size. We categorize faculty size into 100 units, and the largest category is the group of universities with more than 1800 faculty members. The results show that the marginal effects of faculty size are positive but non-monotonic. In particular, smaller universities are more likely to have a greater efficiency improvement than larger universities when the faculty size increases.

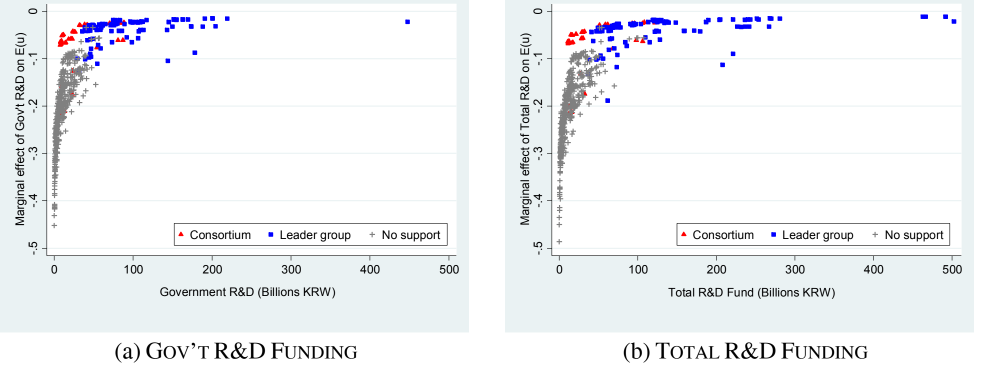
Figure 2 displays the marginal effects of different type of funding on TTOs' technical efficiency levels, as estimated in specifications (5) – (7). The tendencies of the three panels are similar, as the three funding types are highly correlated. The leader group is indicated by the blue squares, the consortium is shown by the red triangles, and unsupported TTOs are denoted by the gray crosses. Mostly, the leader group tends to be larger in terms of how much funding they receive. Notably, a larger amount of funding received means a smaller marginal effect. Overall, the



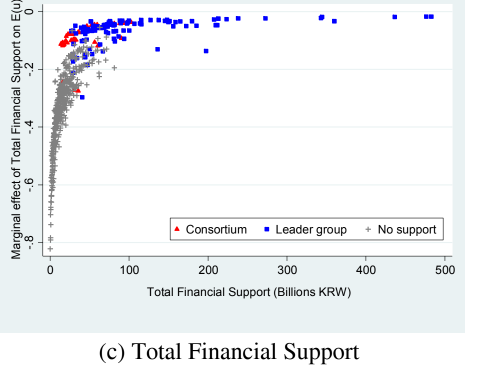
(a) SUPPORT TYPE (b) FACULTY SIZE

FIGURE 1. MARGINAL EFFECTS OF THE SUPPORT TYPE AND FACULTY SIZE ON THE INEFFICIENCY DISTRIBUTION

Note: The horizontal axis represents the determinant and the vertical axis is the marginal effect. The horizontal line in the box-whisker plot is the median and the dots are outliers. In panel (b), the unit of faculty size (horizontal axis) is one hundred and 18+ indicates a faculty size of more than 1,800 professors.



(a) GOV'T R&D FUNDING (b) TOTAL R&D FUNDING



(c) Total Financial Support

FIGURE 2. MARGINAL EFFECTS OF R&D FUNDING AND FINANCIAL SUPPORT ON THE INEFFICIENCY DISTRIBUTION

Note: The observation-wise marginal effects of government R&D funding, total R&D funding, and total financial support are estimated in specifications (5), (6), and (7), respectively.

relationship between the marginal effects of funding and the funding size is positive and concave. However, the magnitude and variation in the marginal effects are much larger among unsupported TTOs.

In sum, the results imply that the marginal effects of efficiency determinants are non-monotonic and increase as the research capacity of the affiliate university becomes smaller. Interestingly, the marginal effect of the TTO support policy is greater for TTOs supported in the consortium group. Taken together, the marginal effect of the TTO policy on mitigating inefficiency was greater for TTOs whose universities have less research funding and lower capacities. This result is somewhat out of line with the intent of the policy. We expect larger marginal effects for the leader group because the goal of the policy was to assist with the growth of TTOs which had shown better performance by supporting their operating and personnel expenses. The deviating policy effect is due to the uniform policy enforcement, which does not take into account the various characteristics of each university and/or TTO. Moreover, although many TTOs complain about difficulties due to a lack of professional manpower, there appears to be no relationship between the marginal effect of this policy and TTO employment. This implies that a policy that only supports personnel and business expenses does not solve the fundamental problem of TTO expert deficiency.

Finally, Figure 3 illustrates technical efficiency scores against royalty income in 2011 and 2015. The technical efficiency score can be derived from the estimated inefficiency, $\hat{u}_{it}$, via $-\exp(\hat{u}_{it} \mid \varepsilon_{it})$. In this figure, we can observe the change of

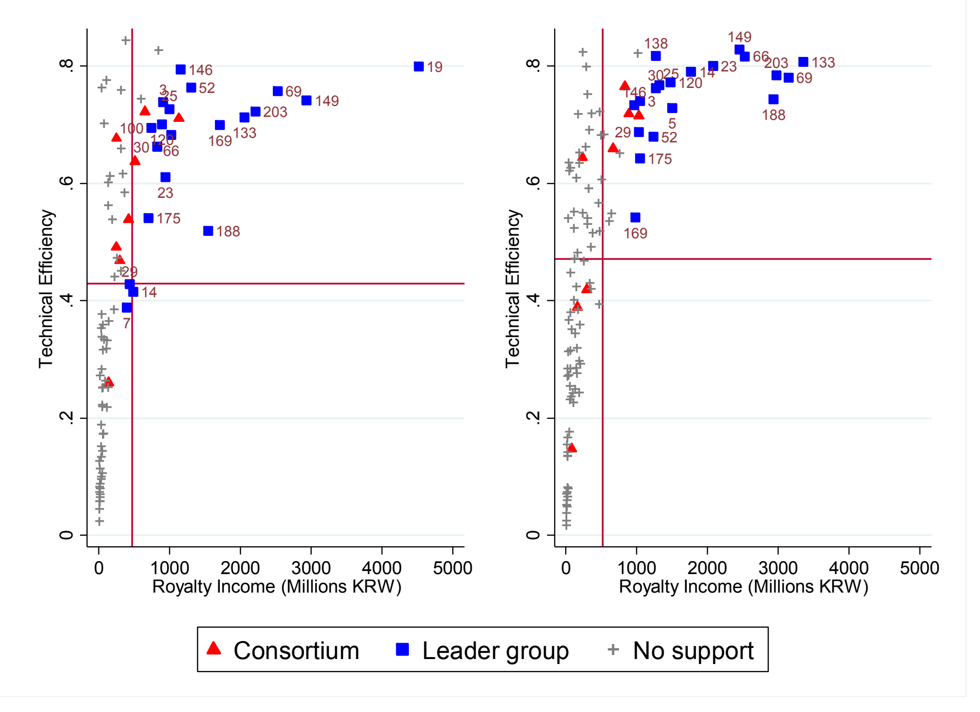


FIGURE 3. TECHNICAL EFFICIENCY VERSUS ROYALTY INCOME IN 2011 AND 2015

each of the TTO's positions. Royalty income is a measure for the final output of the TTO, whereas technical efficiency is a measure showing how efficiently it has operated through the ratio of input to output. As the TTO policy started in 2011 and ended in 2015, it is possible to check whether it has induced only external growth of the final output or caused an actual capacity enhancement of productivity or efficiency. In Figure 3, the vertical and horizontal lines for each panel are the averages of royalty income and technical efficiency, respectively. Although the average of royalty income did not change much, the average technical efficiency was improved. The efficiency level of the leader group has improved overall, while the variance in output (royalty income) was smaller. The efficiency of TTOs that were below the average efficiency score in 2011, in this case #14 and #29, was greatly improved in 2015.[11] In contrast, it is difficult to find a systematic difference between 2011 and 2015 for the consortium group. The plot shows that the relative efficiency of TTOs in the consortium group was exacerbated, or at least was not improved. Interestingly, the unsupported group improved in terms of both outcome and efficiency.

D. *Additional Empirical Analysis*

More technology transfer contracts and greater amounts of royalty income are commonly the major objectives of TTOs, but each TTO may assign different weights to these goals depending on the strategies they employ. TTOs with high-value technologies may try to focus on transferring technologies at higher prices. On the other hand, we can conjecture that the majority of TTOs may try to increase their overall revenue by signing more contracts. Figure 4 shows a scatter plot of the number of technology transfers contracts against royalty income. The two variables are positively correlated[12] but the data points are more dispersed with an increase in either the number of contracts or royalty income. This reflects the possibility that the behavior of the TTO becomes diversified as the TTO's capacity increases. Therefore, it is worthwhile to estimate our model with the *number of technology transfers contracts* as the dependent variable.

Table 5 presents the coefficient estimates and Table 6 provides the associated marginal effects of the inefficiency determinants. We compare the results with the estimates in Section III-C. Regarding the estimation of the *Frontier Equation*, the coefficients of TTO employment and domestic patents are estimated to be similar to the previous results. However, the sign of the foreign patent coefficient is estimated to be negative and significant. This is an interesting result in that it implies that when more foreign patents are owned, fewer technology transfers occur. This may be in line with our conjecture that TTOs with potentially high-value technologies may seek to focus on raising the value of their technology rather than on the quantity of their contracts.

The most noticeable difference between the inefficiency equation estimation results shown in Table 5 against Table 3 is that the magnitude of the overall coefficient

[11]TTO #29 was excluded from the support list starting in 2013.

[12]The correlation coefficient between the number of technology transfer contracts and royalty income in our sample is only about 0.68.

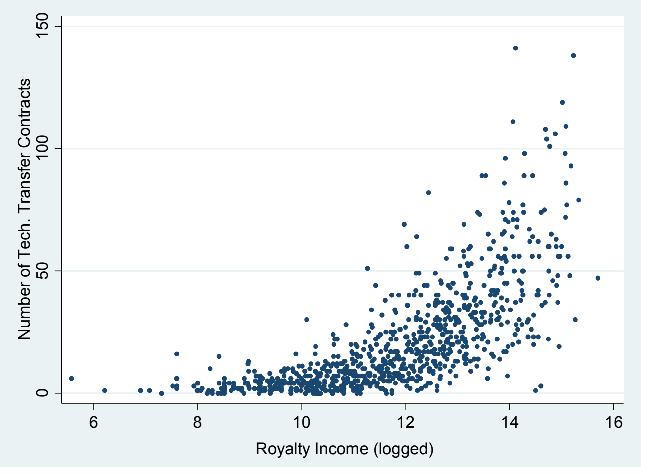


FIGURE 4. CORRELATION BETWEEN THE NUMBER OF TECHNOLOGY TRANSFERS AND ROYALTY INCOME

estimates is reduced. In addition, the signs of the public university dummy become negative and the standard errors shrink, even if we cannot reject from specifications (A5) – (A7), showing that R&D funding does not have significant effects on the inefficiency distribution, whereas an increase in total financial support helps reduce the inefficiency of TTOs. The marginal effects of the inefficiency determinants are also estimated to be comparable with slightly decreased magnitudes, as displayed in Table 6.

TABLE 5—PARAMETER ESTIMATES WITH THE NUMBER OF TECH. TRANSFER CONTRACTS

Dep. Var.	Number of Tech. Transfer Contracts (logged)						
Specifications	(A1)	(A2)	(A3)	(A4)	(A5)	(A6)	(A7)
Frontier Equation							
Operating Expenses	-0.002	-0.001	-0.006	-0.005	-0.017	-0.004	0.000
	(0.024)	(0.025)	(0.019)	(0.019)	(0.020)	(0.018)	(0.017)
TTO employment	0.324***	0.259***	0.239***	0.236***	0.224***	0.232***	0.215***
	(0.066)	(0.065)	(0.067)	(0.067)	(0.069)	(0.067)	(0.067)
Domestic Patents	0.494***	0.478***	0.407***	0.377***	0.395***	0.365***	0.316***
	(0.051)	(0.047)	(0.052)	(0.054)	(0.060)	(0.057)	(0.058)
Foreign Patents	-0.077**	-0.109***	-0.103***	-0.085**	-0.096**	-0.084**	-0.073**
	(0.037)	(0.039)	(0.035)	(0.035)	(0.038)	(0.035)	(0.034)
Constant	0.896**	1.097***	1.716***	1.864***	1.979***	1.942***	2.204***
	(0.395)	(0.413)	(0.321)	(0.325)	(0.314)	(0.316)	(0.299)
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inefficiency Equation							
Mu							
TTO Policy (t-1)		-4.908**	-2.015**	-1.775**	-1.518**	-1.589**	-0.963*
		(2.106)	(0.902)	(0.777)	(0.726)	(0.763)	(0.539)
Faculty			-0.003***	-0.003***	-0.002***	-0.002***	-0.001***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Public Univ.				-0.515*	-0.294	-0.423	-0.196
				(0.310)	(0.306)	(0.309)	(0.239)
Gov't R&D					-0.155		
					(0.163)		
Private R&D					-0.049		
					(0.100)		
Local R&D					-0.028		
					(0.100)		
Total R&D						-0.117	
						(0.134)	
Total Financial Support							-0.460***
							(0.125)
Constant	-1.821	-0.952	1.496***	2.220***	5.278***	3.940**	9.292***
	(1.638)	(1.034)	(0.402)	(0.507)	(1.791)	(1.981)	(1.921)
Usigma							
Constant	0.836*	0.748**	0.292	0.260	0.158	0.215	-0.006
	(0.449)	(0.307)	(0.193)	(0.182)	(0.179)	(0.183)	(0.143)
Vsigma							
Constant	-1.557***	-1.780***	-2.259***	-2.352***	-2.394***	-2.431***	-2.783***
	(0.180)	(0.186)	(0.284)	(0.311)	(0.291)	(0.348)	(0.528)
Obs.	738	738	738	738	711	738	725
Log pseudolikelihood	-841.70	-823.50	-790.76	-786.92	-750.33	-785.82	-755.04

Note: 1) Numbers in parentheses are Huber-White Robust Standard Errors, 2) *p<.1, **p<.05, ***p<.01.

TABLE 6—MARGINAL EFFECTS OF THE INEFFICIENCY DETERMINANTS ON THE NUMBER OF TRANSFER CONTRACTS

Specifications	(A2)	(A3)	(A4)	(A5)	(A6)	(A7)
TTO Policy (t-1)	-1.084 (0.010)	-0.825 (0.011)	-0.767 (0.010)	-0.706 (0.011)	-0.731 (0.010)	-0.554 (0.019)
Faculty		-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)
Public Univ.			-0.223 (0.003)	-0.137 (0.002)	-0.195 (0.003)	-0.113 (0.002)
Gov't R&D				-0.072 (0.001)		
Private R&D				-0.023 (0.000)		
Local R&D				-0.013 (0.000)		
Total R&D					-0.054 (0.001)	
Total Financial Support						-0.264 (0.004)

Note: Numbers in parentheses are 1,000 bootstrap standard errors.

IV. Conclusion

Korea's R&D investment is steadily increasing, along with the share of government and public resources. In the early 2000s, the Korean government began to recognize the importance of technology transfers and put forward policies to promote them. The *Leading TTO Cultivation Project* is one of these technology transfer promotion policies, which is relevant in that it directly supports technology transfer intermediaries. This policy has had a positive effect in that TTOs and related experts at universities have expanded quantitatively and the interest in technology transfers has increased.

This study empirically analyzed the effects of exogenous variations, in this case the research capacity, amounts of funding and financial aid, and the university type, as well as policy interventions, on the operational efficiency of TTOs. We use a production function approach, in particular a stochastic frontier analysis, to estimate the efficiency scores for each TTO and the marginal effects of exogenous variables. Our empirical results suggest that the smaller the research capacity and the amount of financial aid for the university to which the TTO belongs, the larger the marginal effects of exogenous variables. More importantly, the marginal effect of the *Leading TTO Cultivation Project* was not monotonic and was greater for the TTO group which was supported as a type of consortium than for the leader group. The policy originally aimed to support TTOs which showed excellent performance initially, followed by help for the growth of late-runner TTOs. Our results imply that the policy goal is not fully achieved in that the effects on the target group did not outperform the effects on the other group. Nevertheless, the implementation of the project helped to reduce inefficiency on average. This result is unchanged when we estimate the model with the number of technology transfer contracts as a dependent variable.

Therefore, we conclude that the policy may have been more effective if a detailed policy design had been provided considering the different conditions of TTOs. If more subsidies are provided to late-runners and non-monetary support such as technology promotions and the easing of legal constraints could be provided to the front-runners, the policy effect may be maximized. In addition, the policy effect can be maximized if different policy devices are implemented considering each university's research capacity, financial environment, and the characteristics of the TTOs.

As noted above, there are more policies for the purpose of vitalizing industry-university cooperation and the growth of TTOs than the *Leading TTO Cultivation Project* analyzed in this study. Therefore, it is difficult to conclude that the government policy is too monotonous based solely on the analysis conducted here. Nevertheless, this study has significance in that it quantitatively assessed the effectiveness of the TTO operating-cost support policy and pointed out that this policy could be further improved.

In addition, it is important to point out that the direction of the government's TTO support policy must be clearly defined. The *Leading TTO Cultivation Project* aims to support TTOs already equipped with technology transfer capabilities to reach a higher level of TTO. However, as shown in this study, the policy effects associated with efficiency improvements were greater in the second-tier group than in the leader group and were larger in relatively small colleges and in those that lack capacity. This confirms that there is a gap between the current policy goals and the means by which to realize them. If the government wants to maintain its current goal of increasing the growth of leading TTOs, the size of the subsidy should be increased to match the size and capacity of the school. However, if the government wants gradually to reduce support for leading TTOs and enhance support for latecomer TTOs, the current criteria for the selection of support colleges should be changed.

Finally, it should be noted that the analysis in this paper does not consider the production of research outcomes. In other words, even when the research production performance of a school is poor and the outcome is not continuously produced, the school is classified as highly efficient if the technology transfer performance against input is excellent. This case was not addressed separately, but the desirable policy direction for such cases would be to secure the mobility of skilled technical transfer personnel to other schools and to provide support for research capacity improvements of such colleges.

APPENDIX

TABLE A1—CORRELATION MATRIX

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
[1]	1.000											
[2]	0.678	1.000	.									
[3]	0.445	0.515	1.000									
[4]	0.584	0.567	0.432	1.000								
[5]	0.679	0.742	0.411	0.495	1.000							
[6]	0.631	0.776	0.469	0.520	0.920	1.000						
[7]	0.669	0.695	0.462	0.812	0.766	0.808	1.000					
[8]	0.702	0.787	0.488	0.815	0.809	0.832	0.870	1.000				
[9]	0.756	0.818	0.435	0.550	0.868	0.803	0.710	0.834	1.000			
[10]	0.505	0.732	0.368	0.282	0.818	0.836	0.554	0.684	0.836	1.000		
[11]	0.437	0.611	0.393	0.368	0.625	0.754	0.576	0.625	0.533	0.604	1.000	
[12]	0.657	0.810	0.493	0.553	0.915	0.990	0.825	0.865	0.835	0.850	0.733	1.000

Note: [1]: No. of technology transfers, [2]: royalty income, [3]: No. of TTO staff members, [4]: operational expenses, [5]: government research funding, [6]: total research funding, [7]: total financial support, [8]: No. of students, [9]: No. of faculty members, [10]: total education expenses, [11]: domestic patents granted, [12]: foreign patents granted.

REFERENCES

Battese, G. E. and T. J. Coelli. 1995. "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data." *Empirical Economics* 20(2): 325-332.

Bozeman, B. 2000. "Technology Transfer and Public Policy: A Review of Research and Theory." *Research Policy* 29: 627-655.

Bozeman, B., H. Rimes, and J. Youtie. 2015. "The Evolving State-of-art in Technology Transfer Research: Revisiting the Contingent Effectiveness Model." *Research Policy* 44: 34-49.

Caldera, A. and O. Debande. 2010. "Performance of Spanish Universities in Technology Transfer: An Empirical Analysis." *Research Policy* 39: 1160-1173.

Carlsson, B. and A.-C. Fridh. 2002. "Technology Transfer in United states universities." *Journal of Evolutionary Economics* 12: 199-232.

Caudill, S. B. and J. M. Ford. 1993. "Biases in Frontier Estimation due to Heteroscedasticity." *Economic Letters* 41(1): 17-20.

Caudill, S. B., J. M. Ford, and D. M. Gropper. 1995. "Frontier Estimation and Firms-specific Inefficiency Measures in the Presence of Heteroscedasticity." *Journal of Business and Economics Statistics* 13(1): 105-111.

Friedman, J. and J. Silberman. 2003. "University Technology Transfer: Do Incentives, Management, and Location Matter?" *The Journal of Technology Transfer* 28: 17-30.

Goldfarb, B. and M. Henrekson. 2003. "Bottom-up versus Top-down Policies towards the Commercialization of University Intellectual Property." *Research Policy* 32: 639-658.

Greene, W. H. 2008. "The Econometric Approach to Efficiency Analysis." in H. O. Fried, C. K. Lovell, and S. S. Schmidt (Eds.), *The Measurement of Productivity Efficiency and Productivity Growth,* Chapter 2, Oxford University Press, pp.92-250.

Huang, C. J. and J. T. Liu. 1994. "Estimation of a Non-neutral Stochastic Frontier Production Function." *Journal of Productivity Analysis* 5: 171-180.

Kumbhakar, S. C., S. Ghosh, and J. T. McGuckin. 1991. "A Generalized Production Frontier Approach for Estimating Determinants of Inefficiency in U.S. Dairy Farms." *Journal of Business and Economics Statistics* 9(1): 279-286.

Mowery, D. C. and B. N. Sampat. 2005. "The Bayh–dole Act of 1980 and University-industry Technology Transfer: A Model for other OECD Government?" *The Journal of Technology Transfer* 30: 115-127.

Siegel, D. S., R. Veugelers, and M. Wright. 2007. "Technology Transfer Offices and Commercialization of University Intellectual Property: Performance and Policy Implications." *Oxford Reviews of Economic Policy* 23(4): 640-660.

Siegel, D. S., D. Waldman, and A. Link. 2003. "Assessing the Impact of Organizational Practices on the Relative Productivity of University Technology Transfer Offices: An Exploratory Study." *Research Policy* 32: 27-48.

Thursby, J. and S. Kemp. 2002. "Growth and Productive Efficiency of University Intellectual Property Licensing." *Research Policy* 31: 109-124.

Thursby, J. and M. Thursby. 2002. "Who is selling the Ivory Tower? Sources of Growth in University Licensing." *Management Science* 48(1): 90-104.

Wang, H.-J. 2002. "Heteroscedasticity and Non-monotonic Efficiency Effects of a Stochastic Frontier Model." *Journal of Productivity Analysis* 18(3): 241-253.

Wang, H.-J. and P. Schmidt. 2002. "One-step and Two-step Estimation of the Effects of Exogenous Variables on Technical Efficiency Levels." *Journal of Productivity Analysis* 18(2): 129-144.

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Government R&D Support for SMEs: Policy Effects and Improvement Measures

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Government R&D grants for SMEs have risen to three trillion Korean won a year, placing Korea second among OECD nations. Indeed, analysis results have revealed that government support has not only expanded corporate R&D investment and the registration of intellectual property rights but has also increased investment in tangible and human assets and marketing. However, value added, sales and operating profit have lacked improvement owing to an ineffective recipient selection system that relies solely on qualitative assessments by technology experts. Nevertheless, if a predictive model is properly applied to the system, the causal effect on value added could increase by more than two fold. Accordingly, it is important to focus on economic performance rather than technical achievements to develop such a model.

Key Word: R&D Policy, SMEs, Program Evaluation
Genetic Matching, Heterogeneous Causal Effect
JEL Code: O32, O38

I. Introduction

An amount of 8.1 trillion won, 40 percent of the entire national annual R&D budget (19 trillion won) was allocated for economic growth¯including industrial and infrastructure development, in 2016. Among these funds, three trillion was earmarked for the innovation of SMEs in the form of R&D grants, making Korea the second largest spender in absolute amounts among OECD members, next to the US and ahead of Germany and Japan. Moreover, due to the government's direct grants and indirect tax benefits, the yearly R&D investment of Korean SMEs exceeded 13 trillion won during the same year (36,026 affiliated research institutes). Korea also ranks fourth in total corporate R&D and second in SME R&D among OECD nations, as shown in Table 1.[1] In particular, small firms

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TABLE 1— INTERNATIONAL COMPARISON OF TOTAL CORPORATE R&D INVESTMENT AND GOVERNMENT-FUNDED R&D COSTS BY FIRM SIZE

(Unit: 1 million dollar, PPP exchange rate)

Number of Employees	Korea (2013)	US (2011)	Japan (2013)	Germany (2013)	France (2013)
1-49	6,033 (914)	21,842 (2,066)	1,135 (49)	2,448 (544)	4,292 (492)
50-249	5,955 (662)	21,996 (1,515)	4,620 (99)	4,230 (499)	4,881 (261)
SME subtotal	11,988 (1,576)	43,838 (3,581)	5,755 (148)	6,678 (1,043)	9,173 (753)
250-	41,442 (1,384)	250,255 (27,730)	117,776 (1,162)	62,235 (1,272)	28,331 (2,281)
Total	53,430 (2,961)	294,092 (31,630)	123,531 (1,310)	68,914 (2,316)	37,503 (3,035)

Note: Figures in parentheses denote government-funded R&D costs.

Source: Main Science and Technology Indicators (OECD Stat webpage). Cited from Park *et al*. (2016) pp.24-25.

with fewer than 50 employees, including startups, were found to invest more actively in R&D than medium-sized firms.[2]

Prior literature on the performance evaluation of R&D support projects have mainly focused on how support contributes to increasing corporate R&D investment and intellectual property (IP) rights, and the majority of outcomes have shown a positive relationship. However, with the exception of Oh and Kim (2017), very few studies have dealt with the economic gains of R&D support. Oh and Kim (2017) looked at growth indicators (sales, employment, assets, and liabilities), profitability indicators (ROA, ROE, operating margin), and R&D investments by firms to assess the economic gains from governmental R&D support. This study adds value added and various strategic assets to the list of economic indicators. Value added is the most comprehensive indicator, and not only knowledge capital such as R&D but also physical capital, human capital, and relational capital may contribute to the growth of value added. Indeed, with governmental R&D grants for SMEs reaching the three trillion won mark, this study attempts to assess the contribution of government support projects comprehensively along with other strategic assets and to seek ways to enhance the effectiveness of these sources of funding.

II. Government R&D Support Projects for SMEs

The Small Business Innovation Research (SBIR) program is the main R&D support program for SMEs in the US. In 2015, the SBIR program distributed about $2.5 billion via eleven departments.

[1]China has rapidly expanded R&D investment and risen to become the world's second largest provider (no statistics available on SME R&D).

[2]Largely due to the government's fund of funds, Korea's ratio of venture capital investment to GDP rose to 0.13% in 2015, standing below that of the US (0.33%) and China (0.24%) but far higher than those of Japan, Germany and France (approx. 0.03%) (Park *et al*., 2016).

Edison (2010) examined 1,460 companies applying for US Department of Defense (DOD) SBIR funding in 2003 and found a significant causal effect of increased sales of recipients by \$0.15 million during the following year (\$0.37 million in 2004-2006). In addition, Howell (2017) analyzed the earnings of 5,021 companies applying for US Department of Energy (DOE) SBIR funding in 1995-2013 and confirmed that grants awarded during Phase Ⅰ (the proof-of-concept stage with funds up to \$0.15 million for 6-9 months) increased the average 10% probability of venture capital funding by +10%p and \$2 million in sales by \$1.3-\$1.7 million. The results also revealed that the increases were not due to the effects of government certification; instead, they stemmed from the effects of proof-of-concept demonstrated via prototypes. Moreover, increases in venture capital funding were particularly strong among firms without patents and young startups less than two years old (+6%p and +14%p). On the other hand, the extensive grants given during Phase Ⅱ (the subsequent full-scale R&D with funds reaching \$1 million for a period of 24 months) had little economic impact. Accordingly, Howell (2017) concluded that rather than offering large long-term funding to a few medium-sized firms, it would be more effective to award small lump sums to numerous small-sized firms. Germany and Finland operate similar programs, providing small grants and research consulting services to such firms and startups which lack R&D experience. Most R&D support programs in advanced economies have transparent and convenient online management systems that accommodate free competition for bottom-up research designs.

Based on the SBIR, the Korean government established the Korea Small Business Innovation Research (KOSBIR) program in 1998 and has steadily increased this budget since. Indeed, the expenditure for SME-operated government R&D projects reached 2,897 billion won in 2016, equivalent to 15.2% of the government's total R&D investment amount and similar to the US SBIR's total grant amount.[3] According to the National Science and Technology Knowledge Information Service (NTIS) database, which includes information pertaining to the management of all government R&D projects, among the 30,448 R&D projects awarded to firms in 2010-2014, the median funding amount was 200 million won, while the top 20% ranged from 525 million to 54.7 billion won and the bottom 20% accounted for less than 100 million won. In the US, Phase Ⅰ projects (about \$0.10 million per project) outnumbered Phase Ⅱ projects by two to three fold. However, in Korea, nearly 80% of projects were funded at more than 100 million won per project, implying a strong tendency to omit the initial proof-of-concept stage and begin with full-fledged support.

Governments evaluate R&D support projects in terms of patents and publications. Patent applications for SMEs continued to soar due to their strong commitment in acquiring more patents, rising from 34,547 in 2013 to 46,813 in 2016.[4] On the other hand, that number for large enterprises declined from 48,045 to 38,800 over the same period following a shift in the evaluation focus of R&D divisions to the creation of economic value after it was deemed that practices such

[3]Ministry of Science and ICT·Korea Institute of Science & Technology Evaluation and Planning, *2016 National R&D Project Report and Analysis*, 2017 (in Korean).

[4]Korea Intellectual Property Office, *Intellectual Property Statistics FOCUS*, 2014; 2017 (in Korean).

as stockpiling unused patents simply to demonstrate technological prowess was a waste of financial (patent applications and renewal fees) and research resources.

III. Comparison of Recipients and Non-recipients

This study used the Korea Enterprise Data (KED) (2010-2015) to analyze the economic effects of government support programs. Research subjects were limited to incorporated enterprises with more than ten employees. The 2010-2015 financial performance outcomes of a total of 212,245 firms were analyzed of which 165,023 small-sized firms and 42,770 medium-sized firms were the main focus of the analysis. In this study, 70% or 21,265 cases in the NTIS were linked to our dataset.

TABLE 2—BASIC SME STATISTICS COMPARISON

Variable (Unit: 1 million won)		Non-recipient SMEs (control group: 670,760)		Recipient SMEs (experimental group: 18,980)	
		Average	Standard deviation	Average	Standard deviation
Basic	Firm age	9.10	8.26	10.72	7.80
	IPO ratio	0.13	0.33	0.36	0.48
	Ratio of venture firm	0.10	0.30	0.57	0.50
Operating Performance	Value added	1,389	19,100	3,008	5,988
	Increment (Δ_{t+2})	195	26,400	43	9,792
	Increment (Δ_{t+3})	330	31,200	163	10,400
	Sales	6,733	21,900	13,600	30,500
	Rate of increase (Δ_{t+2})	0.36	2.11	0.13	1.06
	Rate of increase (Δ_{t+3})	0.41	2.16	0.17	1.09
	Operating profit	255	2,826	559	3,105
	Increment (Δ_{t+2})	8	3,067	-155	3,639
	Increment (Δ_{t+3})	8	3,134	-203	3,969
Financing	Debt	4,030	32,100	7,820	17,400
	Rate of increase (Δ_{t+2})	0.32	1.25	0.22	0.66
	Rate of increase (Δ_{t+3})	0.42	1.31	0.29	0.75
	Equity	2,360	18,500	7,505	20,900
	Increment (Δ_{t+2})	447	7,077	1,046	13,300
	Increment (Δ_{t+3})	750	8,821	1,758	14,600
Capabilities/ assets	R&D investment	64	1,377	741	1,718
	Rate of increase (Δ_{t+2})	0.22	4.23	-0.77	5.36
	Rate of increase (Δ_{t+3})	0.34	4.71	-1.17	5.69
	IP rights registration	0.12	1.94	1.86	12.90
	Rate of increase (Δ_{t+2})	0.01	0.30	0.11	0.73
	Rate of increase (Δ_{t+3})	0.01	0.32	0.10	0.76
	Tangible assets	2,160	11,600	5,277	14,900
	Rate of increase (Δ_{t+2})	0.41	2.06	0.24	1.19
	Rate of increase (Δ_{t+3})	0.52	2.23	0.34	1.33
	Human capital	830	2,567	1,718	2,753
	Rate of increase (Δ_{t+2})	0.33	1.68	0.13	0.88
	Rate of increase (Δ_{t+3})	0.41	1.73	0.19	0.95
	Marketing investment	79	913	163	937
	Rate of increase (Δ_{t+2})	0.20	3.84	-0.01	3.52
	Rate of increase (Δ_{t+3})	0.25	4.13	0.01	3.74

Based on the financial data, this study extracted ten performance indicators pertaining to the following three aspects: operating performance (value added, sales and operating profit), financing (debt and equity) and capabilities/assets.[5] Value added is the most comprehensive indicator, as it covers all value distributed to various stakeholders, including employees (labor cost), shareholders (dividends), government (taxes and dues), creditors (interest), and firms (net profit + depreciation cost). Additionally, despite the significance of economies of scale in the past, the scalability of intangible assets has grown in importance, as shown by Uber and Airbnb. Thus, in terms of performance indicators for capabilities/assets, this study used R&D investment, IP rights registrations and marketing investment in conjunction with tangible assets and human capital investment.[6]

Table 2 shows that recipients considerably outperformed non-recipients on average in terms of most indicators, specifically operations, financing and capabilities/assets when they receive subsidies. The differences are statistically significant, and the differences in the operating profit and R&D investment indicators widen by more than twenty times. However, there is a visible reverse in this trend two to three years after the reception of support, except for IP rights registrations. Even operating profit and R&D investment decrease.[7] When large enterprises are included in the comparison, negative growth can also be observed in value added and marketing investment.

IV. Estimation of the Causal Effect of Government Support

Existing econometric studies usually estimate causal effects with a parametric model, which is created by assuming the form of the functions and distribution of the data. However, models based on hard-to-verify assumptions always run the risk of misspecifications. Matching methods (matching observations which have different values of the treatment variable and similar values of other covariates) are widely used to estimate causal effects from observed data in the absence of random experimental data, although the matching method cannot account for the effects of unobserved variables. Matching methods, as non-parametric preprocessing approaches, can compensate for the weaknesses of parametric models. Ho, Imai, King and Stuart (2007) suggest a two-step unified estimation approach which integrates a non-parametric matching method and the parametric regression model. The two-step approach can accurately estimate causal effects even when only one of the two steps is properly specified. Hence, it is doubly robust and can also estimate the effects of other covariates.

[5]The distribution of corporate performance tends to skew to the right as it is influenced by large firms. As such, this raw data underwent logarithmic transformation while the raw data for value added, operating profit, and equity were used as they were considering that many of these values were negative.

[6]Based on financial statements: tangible asset data was used as tangible assets; the sum of labor-related costs, welfare benefits, education and training costs and stock compensation was used as a proxy variable for human capital investment; the sum of R&D expenditures in income statements and manufacturing cost statements and the increments of intangible asset development costs was used as a proxy for intellectual property investment; and the sum of advertising costs, sales promotion costs, entertainment expenses and overseas marketing expenses was used as the proxy variable for relational assets.

[7]With regard to equity financing, recipients posted larger increments but smaller growth rates.

In this study, diverse methods were attempted in the matching phase. Propensity score matching (PSM) satisfies the unconfoundedness assumption $\left(Y_i(1), Y_i(0)\right) \perp T_i \mid \mathrm{X}$ by replacing multi-dimensional covariates (X) with propensity scores $\left(\mathrm{P}(\mathrm{X})\right)$. PSM usually uses parametric models such as the logistic and probit models to convert multivariate covariates into one-dimensional propensity scores. The values of the closest propensity scores in the experimental group and the control group are then matched one-to-one with each other. Alternatively, the weight is given in proportion to the proximity of the propensity score. However, King and Nielsen (2016) suggest that alternative matching methods should also be tested because PSM can aggravate imbalance, inefficiency, model dependence and bias. Specifically, it is difficult to satisfy the conditional independence between the covariate and treatment variable depending on a single parametric model given that there is a complex decision-making system in reality. The lack of computing power in the past made PSM useful, but matching based on multi-dimensional covariates has become affordable owing to the advancements in computing power.

Mahalanobis Distance Matching (MDM) is also one of the most widely used matching methods. PSM and MDM are equal-percent bias-reducing (EPBR) methods, meaning that they reduce the bias by the same rate through a linear combination of covariates (Kim, 2016). EPBR methods can reduce bias only when the dataset of covariates can be modeled using a Gaussian (normal) distribution. Because the distribution of real data is often not Gaussian, a matching method based on a linear combination may rather increase the bias.

Iacus, King, and Porro (2009) developed the Coarsened Exact Matching (CEM) method, which divides the covariates into coarse intervals and then precisely matches the same interval units. Imbalances cannot be larger than the block range predefined by a researcher and an improvement in the balance for one covariate does not affect the imbalance of the other covariates. However, CEM may leave many cases in the treatment group unmatched with the control group. If the interval of the covariate blocks is widened to increase the matching rate, imbalances will increase as a trade-off.

Another alternative matching method is Genetic Matching (GM), which optimizes the balance of covariates using a genetic algorithm (Sekhon, 2011).[8] The Mahalanobis distance is defined as follows:

$$\text{(1)} \qquad \mathrm{md}(X_i, X_j) = \left((X_i - X_j)^T S^{-1} (X_i - X_j)\right)^{\frac{1}{2}}$$

In equation (1), S is the sample covariance matrix of X. If the covariate contains continuous variables, there is a bias that does not disappear (Abadie and Imbens, 2006). The GM algorithm adds a square matrix of weights W to generalize the Mahalanobis metric when the Mahalanobis distance does not optimally approach equilibrium. The equation for the GM algorithm is as follows:

[8]The matching package can be downloaded at CRAN.R-project.org/package=Matching.

$$\mathrm{d}(X_i, X_j) = (X_i - X_j)^T (S^{-\frac{1}{2}})^T W S^{-\frac{1}{2}} (X_i - X_j)^{\frac{1}{2}} \quad (2)$$

In equation (2), $S^{\frac{1}{2}}$ is the Cholesky decomposition of S, and the matrix of the weights W is a diagonal matrix that has zeros without diagonal elements. If the diagonal elements of W are 1, it becomes the Mahalanobis distance. GM uses a genetic algorithm to search for the optimal solution of W iteratively such that the maximum unbalance among the covariates of the control and experimental groups is minimized.

Ho, Imai, King, and Stuart (2007) suggest that various matching methods must be assessed to find the most robust results. This study used as many as 17 covariates, including the seven firm attributes of age, size, region, industry, IPO status, venture firm status, and affiliation status as well as ten performance indicators. First, the propensity score matching method allowed overlapping when matching the nearest cases and assigning weights in proportion to the similarity of the propensity scores. In the case of CEM, the block interval of the covariates was coarsened (widened) such that at least 70% of the firms could be matched. The GM computation took much more time than that needed by the other matching methods due to the greater computational complexity.

Table 3 shows to what extent the mean difference between recipients and non-recipients can be reduced using the PSM, CEM, and GM methods. All of the mean differences became smaller than that in the raw data. GM reduced the mean differences the most, by an average of 85%, and PSM reduced these values by about 70%. However, even if the overall average is similar, differences in individual pairs can still be large. A deviation from exact matching is referred to as an imbalance. The imbalance of the raw data was reduced the most using GM and then to a lesser extent by PSM and CEM.

TABLE 3—COMPARISON OF MEAN DIFFERENCE AND REDUCTION RATE BY THE MATCHING METHOD

(Unit: 1 million won; log transformation of 1,000 won)

Covariates	Mean Difference				Reduction Rate		
	Raw data	PSM	CEM	GM	PSM	CEM	GM
Value added	-21,499	-14,942	-1,849	-5,635	0.305	0.914	0.738
ln (sales)	-1.45277	-0.26676	-0.65236	0.05180	0.816	0.551	0.964
Equity financing	-112,292	-81,024	-5,622	-33,117	0.278	0.950	0.705
ln (debt)	-1.63607	-0.24761	-1.08969	-0.04096	0.849	0.334	0.975
Operating profit	-11,813	-9,104	-344	-4,774	0.229	0.971	0.596
ln (tangible assets)	-2.68170	-0.31424	-1.78535	-0.01798	0.883	0.334	0.993
ln (human capital)	-1.59099	-0.19074	-0.80534	-0.02787	0.880	0.494	0.982
ln (marketing investment)	-3.30725	-0.60767	-3.11299	-0.12307	0.816	0.059	0.963
ln (R&D investment)	-9.29562	-0.68442	-8.79407	-0.40304	0.926	0.054	0.957
ln (IP rights registrations)	-0.62686	-0.23760	-0.32307	-0.03511	0.621	0.485	0.944
Firm age	-2.98611	-0.64181	-1.68229	-0.37315	0.785	0.437	0.875
Firm size	-0.25449	-0.06970	-0.15041	-0.00268	0.726	0.409	0.989
Ratio of venture firms	-0.44578	-0.05481	-0.45277	-0.00028	0.877	-0.016	0.999
Firm region	-0.07900	-0.01670	-0.12711	-0.08145	0.789	-0.609	-0.031
Industry group	-0.80774	-0.13427	-0.74409	-0.02822	0.834	0.079	0.965
IPO ratio	-0.29116	-0.05620	-0.23131	0.00005	0.807	0.206	1.000
Ratio of affiliate firms	-0.01923	0.00766	-0.00158	-0.00127	0.602	0.918	0.934
Mean					0.707	0.386	0.856

When Q-Q plots (quantile-quantile plots) were drawn for each covariate variable, the balance improves as the values of the experimental group and control group are arranged close to the 45-degree line. Figure 1 shows Q-Q plots of the sales

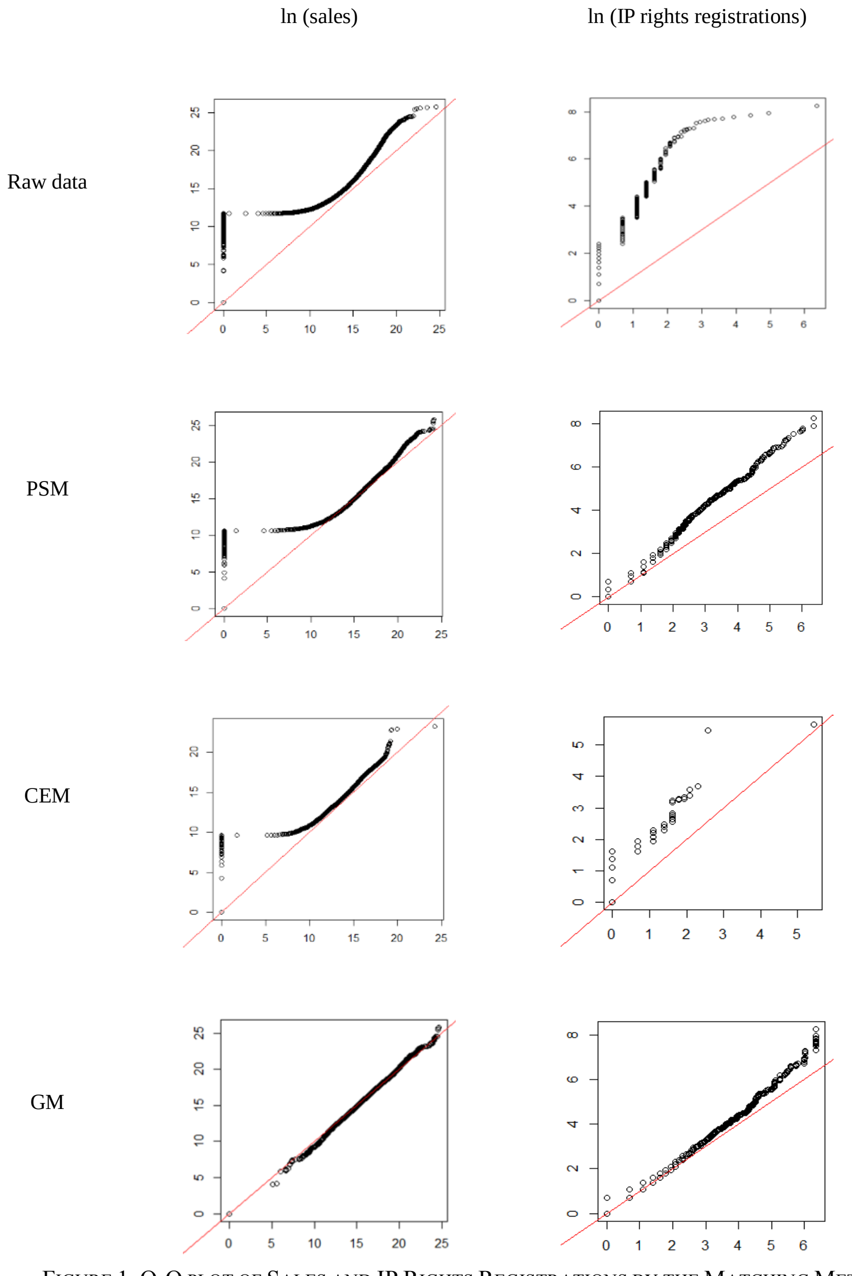


FIGURE 1. Q-Q PLOT OF SALES AND IP RIGHTS REGISTRATIONS BY THE MATCHING METHOD

Note: In all plots, the horizontal axis represents the value of non-recipients and the vertical axis represents value of recipients.

and IP rights registrations, which are relatively high in terms of the mean difference and imbalance. The matched pair values move closer to the 45-degree line than the raw data, and the values from GM move closest to the 45-degree line. Because the GM method has proved to be the best given all of the matching evaluation criteria, subsequent analyses will use the matched dataset derived from GM as a control group.

Table 4 shows the OLS regression model using the matched dataset. The dependent variable is the value added change (Δ_{t+2}) after two years, and seventeen firm-specific attribute and performance values in the supported year are controlled for as independent variables. Because this analysis applied the difference-in-differences (DID), matching method and multiple regression together, it can estimate the causal effect more robustly than a mere difference-in-differences matching method. This proves that the inferior value added growth of the recipient SMEs shown in Table 2 is not due to the treatment effects of government support.

TABLE 4¯ OLS ANALYSIS OF VALUE ADDED INCREMENT (Δ_{t+2}) IN THE MATCHED DATASET

(Unit: 1,000 won)

Variables (at year *t*)	Matched SMEs	
	Estimate	Significance
R&D support treatment	**38,159**	**0.672**
Value added	-0.633	0.000**
ln (sales)	133,147	0.002**
Operating profit	0.287	0.000**
Equity financing	-0.026	0.000**
ln (debt)	-260,714	0.000**
ln (tangible asset)	28,016	0.415
ln (human capital)	495,701	0.000**
ln (marketing investment)	12,730	0.291
ln (R&D investment)	-12,099	0.289
ln (IP rights registrations)	344,400	0.000**
Firm age	6,891	0.625
Firm age (squared)	490	0.113
Firm size (medium business)	1,940,460	0.000**
Firm size (mid-size company)	-	-
Firm size (major company)	-	-
Ratio of venture firms	-173,183	0.072
IPO ratio	912,434	0.000**
Ratio of affiliate firms	5,434,900	0.000**
Firm region (Chungcheong)	-52,145	0.706
Firm region (Jeolla)	236,958	0.183
Firm region (Kyungsang)	39,668	0.730
Firm region (others)	187,213	0.488
Industry group 2	37,908	0.728
Industry group 3	19,271	0.874
Year (2011)	-52,310	0.693
Year (2012)	119,433	0.348
Year (2013)	177,735	0.165
Constant	-4,715,643	0.000**
Number of observations	25,542	
Adjusted R^2	0.122	

Note: * and ** correspondingly denote statistical significance at the 5% and 1% levels.

Multiple regression estimates the effects of other covariates on the performance indicator as well. The relationship between value added in the supported year and the value added increase after two years is negative and statistically significant. That is, the incremental growth diminishes as the value added of the company increases.

OLS analyses (Table 4) are repetitively conducted with two-year increments (Δ_{t+2}) of the ten performance indicators as dependent variables. Table 5 extracts the coefficient estimates and significance of the government R&D support treatment variable to summarize the OLS results. Table 5 compares the estimation that integrates the difference-in-differences, the matching method and the OLS regression with only the DID OLS regression and DID matching estimation methods. Compared to the other outcomes, the two-stage integrated analysis (DID+Matching+OLS) demonstrates a statistically significant causal effect on most performance indicators, except for the value added increment.

In sum, government R&D support has contributed significantly to debt and equity financing of SMEs. Utilizing such funds, firms expanded their investments in intellectual property, relational assets, tangible assets and human capital. The recipients of government support achieved an approximate 5%p increase in debt financing and an increase of over 300 million won in equity financing due to their advantageous position in acquiring the government's technology guarantees and fund of funds.[9] Among the indicators of capabilities/assets, R&D investment and IP rights registrations have consistently shown considerable gains of 100%p and 30%p, respectively, while marketing investment, deemed to be strongly complementary with regard to intellectual property, gained over 20%p. Tangible assets and human capital posted small but significant gains in investment growth. However, while R&D support has served successfully as a catalyst for private-sector investment, it has not enhanced the operating performances of the recipients. Most have failed to see improvements in their value added compared to their non-recipient counterparts, even recording significant negative growth in sales and operating profit.[10]

Table 6 summarizes the treatment effect according to the amount of support. This table shows that the negative effects on value added, operating profit and sales

[9]SMEs are significantly influenced by the government's fund of funds, while large and mid-range firms that rely on the public stock market are less influenced by whether or not they receive government support.

[10]The analysis of the increments after three years reveals similar results. Two- or three-year performance tracking after the completion of R&D may appear to be too short to evaluate the economic effects, but according to the *2016 Survey on Technology of SMEs* (2017), SMEs reported that it took an average of 10.4 months from technology development to commercialization (5.4 months for development → 5.0 months for commercialization) and an additional 7.9 months to establish sales channels. Most R&D support programs for SMEs are more akin to short-term projects that are focused on improving competitiveness in existing products, and thus enough time is given to evaluate the performance of the support program. In the empirical analysis of the US SBIR program by Edison (2010), a significant increase in sales was observed starting one year after the support. This study intended to check whether the additional government support could improve recipients' economic performances significantly compared to those of non-recipients whose investment amounts for all capabilities including R&D were similar to those of their counterparts. In particular, value added embraces input indicators such as R&D investment, meaning that an increase in this metric would exceed the average if the operating profit does not shrink to offset the increase in inputs. Furthermore, when the evaluation targets longer periods, the effects from the respective support methods tend to dissipate due to the growing impact from other noise sources. Oh and Kim (2017) confirmed waning or stagnating effects in all indicators, except for the debt increase rate, beyond three years after the support was provided.

TABLE 5—SUMMARY ANALYSIS OF THE TREATMENT EFFECT ON THE INCREMENT OF TEN PERFORMANCE INDICATORS AMONG SMEs IN THE MATCHED DATASET

(Unit: 1,000 won; log transformation)

Dependent variables (Δ_{t+2})	DID+OLS Benefit	DID+OLS Significance	DID+Matching Benefit	DID+Matching Significance	DID+Matching+OLS Benefit	DID+Matching+OLS Significance
Value added	-106,153	0.258	-196,123	0.039*	38,159	0.672
Operating profit	-119,247	0.000**	-70,437	0.069	-109,879	0.001**
ln (sales)	-0.069	0.000**	0.015	0.253	-0.045	0.000**
ln (debt)	-0.013	0.170	0.050	0.000**	0.047	0.000**
Equity financing	212,583	0.004**	86,742	0.509	344,495	0.008**
ln (R&D investment)	1.002	0.000**	0.870	0.000**	1.140	0.000**
ln (IP rights registrations)	0.294	0.000**	0.289	0.000**	0.289	0.000**
ln (human capital)	0.004	0.783	0.019	0.091	0.024	0.026*
ln (tangible assets)	-0.085	0.000**	0.059	0.000**	0.048	0.000**
ln (marketing investment)	0.215	0.000**	0.212	0.000**	0.239	0.000**

Note: * and ** correspondingly denote statistical significance at the 5% and 1% levels.

TABLE 6—OLS ANALYSIS COMPARISON OF TREATMENT EFFECTS BY FUND SIZE: MATCHED SMEs

(Unit: 1,000 won; log transformation)

Dependent variables (Δ_{t+2})	0-100 million won Estimate	0-100 million won Signif.	100-200 million Estimate	100-200 million Signif.	200-500 million Estimate	200-500 million Signif.	500-million Estimate	500-million Signif.	Adj. R^2
Value added	168,283	0.323	72,059	0.598	180,450	0.152	-324,564	0.033*	0.122
Operating profit	-13,125	0.835	-56,782	0.260	-35,028	0.451	-367,146	0.000**	0.275
ln (sales)	-0.057	0.004**	-0.024	0.135	-0.023	0.111	-0.098	0.000**	0.346
ln (debt)	0.039	0.003**	0.046	0.000**	0.048	0.000**	0.052	0.000**	0.166
Equity financing	197,290	0.421	271,809	0.166	358,833	0.048*	526,427	0.016*	0.043
ln (R&D investment)	0.826	0.000**	1.241	0.000**	1.237	0.000**	1.099	0.000**	0.220
ln (IP rights registrations)	0.209	0.000**	0.235	0.000**	0.278	0.000**	0.437	0.000**	0.331
ln (human capital)	-0.061	0.003**	0.022	0.174	0.038	0.010*	0.068	0.000**	0.130
ln (tangible assets)	0.071	0.004**	0.043	0.031*	0.047	0.010*	0.038	0.089	0.137
ln (marketing investment)	0.184	0.016*	0.322	0.000**	0.146	0.009**	0.319	0.000**	0.158

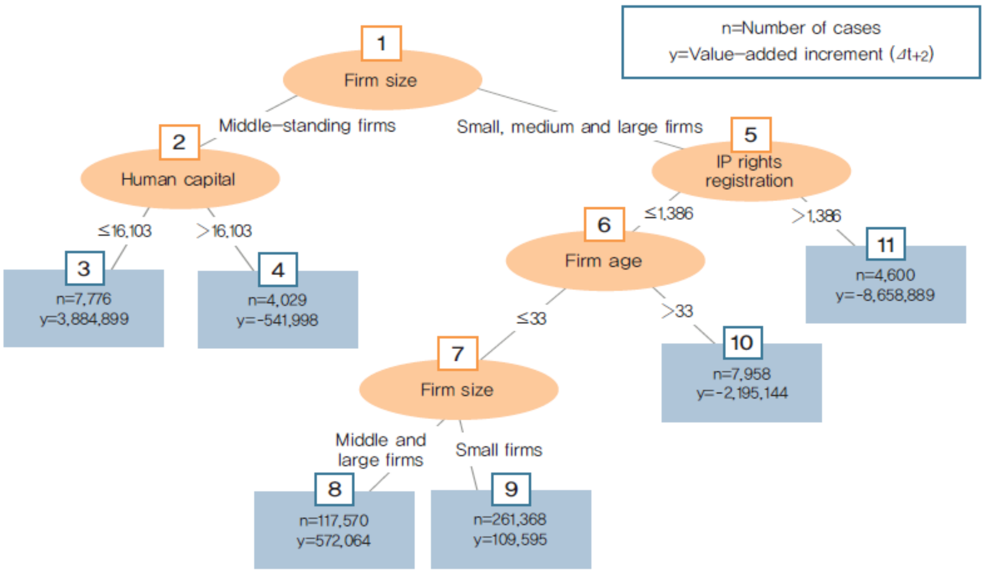
Note: * and ** correspondingly denote statistical significance at the 5% and 1% levels.

are substantial and statistically significant when the support amount exceeds 500 million won. The positive effect on debt is statistically significant for all sizes and increasing moderately along with the size of support. The positive effect on equity financing is statistically significant only when the support amount exceeds 200 million won. The positive effect on R&D investment is the largest in the 100-500 million won range, and the positive effect on IP rights registrations and human capital investment is the largest when support exceeds 500 million won.

V. Exploratory Models to Improve the Selection of Recipients

Because firms that receive government support tend to have superior capabilities to non-recipient firms, causal effects must be cautiously estimated to avoid overestimation from a simple comparison between recipients and non-recipients. However, contrary to expectations, Table 2 revealed lower growth rates of recipient firms, and an ensuing estimation of the causal effects in Table 4-6 demonstrated that they were not due to negative treatment effects in most cases. Consequently, we can suspect that government support tends to be distributed to firms with low-growth potential rather than to firms with high-growth potential. To verify our suspicion, a prediction model of the value added increment after two years is tested.

A decision-tree algorithm builds a tree top-down from a root node and partitions the data into subsets that contain similar values through a reduction of the Gini index or variance. As the nodes and layers of a decision tree increase, the predictive power of the algorithm improves but its visualization becomes more difficult. To optimize the trade-offs when presenting results, we limit the number of final nodes to less than ten. Figure 2 shows the population split into six subgroups (nodes) after applying a decision-tree model known as the 'causal conditional inference trees algorithm' to the value added increment after two years using our 17 covariates. According to the figure, firms with three or more IP rights registrations per year (node 11) account for a mere 1% of all firms but 11% of the recipients. It is probable that they were selected based on technology competence indicators, but their value added exhibits the largest decrement of -8.7 billion won. On the other



Number of firms	Final Node 3	4	8	9	10	11	Total
Non-recipients	7,150 (1.8%)	3,253 (0.8%)	113,580 (29.2%)	253,914 (65.3%)	7,661 (2.0%)	2,996 (0.8%)	388,554 (100%)
Recipients	626 (4.2%)	776 (5.3%)	3,990 (27.1%)	7,454 (50.5%)	294 (2.0%)	1,604 (10.9%)	14,744 (100%)
Total	7,776 (1.9%)	4,029 (1.0%)	117,570 (29.2%)	261,368 (64.8%)	7,958 (2.0%)	4,600 (1.1%)	403,301 (100%)

FIGURE 2. DECISION-TREE MODEL THAT PREDICTS THE VALUE ADDED INCREMENT (Δ_{t+2})

hand, small firms (node 9) with two or fewer IP rights registrations per year account for two thirds of all firms but only half of the recipients despite the fact that their value added increment is large at 100 million won on average. In other words, firms with high growth prospects were the majority but a smaller proportion were selected as recipients, while those with low growth prospects were in the minority but a larger proportion were recipients. Consequently, the value added growth of the recipients is lower than average.

Even if the average causal effect of a policy on the entire population is statistically significant, some subgroups may be affected either insignificantly or in the opposite direction. On the other hand, policies with insignificant average effects on the population may affect some subgroups either positively or negatively to a statistically significant level.

Athey *et al*. (2016) develop a causalTree algorithm that adopts a random-forest prediction algorithm to estimate heterogeneous treatment effects. Random-forest algorithms allow for the flexible modeling of high-dimensional interactions by building a large number of decision trees from randomly extracted bootstrap samples and averaging their predictions. Wager and Athey (2017) require the individual trees to satisfy a fairly strong condition, which they call honesty: a tree is honest if, for each training example i, it only uses the response Y_i to estimate the within-node treatment effect or to decide where to place the splits, but not both. When placing splits, an honest tree approach ignores the outcome data Y_i and instead trains a classification tree for the treatment assignments. Such "propensity trees" are particularly useful in observational studies because selection bias due to variations in $e(x)$ can be minimized. This approach, which matches training examples based on the estimated propensity, is similar to propensity score matching. Although a randomized experiment is ideal, heterogeneous treatment effects for subgroups can be estimated from observational data if matched samples from the control group are very similar to those in the treatment group (Prust and Prasad, 2015).

Subgroups are derived using performance indicators and the 17 covariates and are sorted in descending order of the low treatment effects and aggregated into decimal groups. Table 7 shows the average causal effect on the value added increment for each decimal group. It compares the causal effect and observed difference for each decile group and indicates the portion of the beneficiary companies in each group, along with the average firm attribute values (across the 17 covariates) of both the experimental and control groups that belong to each decimal subgroup.

Figure 3 shows that deciles 1-4 are positive and deciles 5-10 are negative. These results imply that government support had an insignificant impact on the value added increment of the entire population, not because there was no positive impact at all but because the significant positive effect experienced by numerous recipients was offset by the negative impact experienced by the majority. The bottom decile 10 in particular shows the largest negative effect, with most firms having high value added and high equity levels, numerous IP rights registrations, long histories and high proportions of IPOs at the time of the support.

The model that estimates heterogeneous treatment effects can predict the subgroup

TABLE 7— COMPARISON OF THE CAUSAL EFFECT ON VALUE ADDED INCREMENT (Δ_{t+2}) FOR EACH DECIMAL SUBGROUP OF THE MATCHED SMES

(Unit: 1,000 won; log transformation)

Characteristics	Decile										Total
	1	2	3	4	5	6	7	8	9	10	
Observations	2,760	2,587	2,584	2,497	2,488	2,525	2,548	2,507	2,656	2,425	25,577
Causal effect	319	91	39	6	-21	-48	-82	-136	-298	-1,690	-171
Observed difference	-47	313	199	179	140	152	229	256	279	-317	140
Portion of recipients	0.504	0.508	0.467	0.481	0.493	0.506	0.492	0.476	0.497	0.655	0.507
Value added	5,994	2,442	1,778	1,552	1,476	1,671	1,898	2,517	4,835	7,280	3,162
Sales	16.699	15.527	15.154	14.935	14.824	14.901	15.126	15.349	16.238	16.469	15.534
Operating profit	1,727	608	404	352	326	360	419	581	1,132	998	701
Equity financing	10,773	3,987	2,720	2,249	2,141	2,344	2,790	3,783	8,241	30,224	6,870
Debt	15.922	14.791	14.420	14.246	14.127	14.250	14.485	14.789	15.633	16.469	14.920
Tangible assets	15.134	13.661	13.223	13.001	12.911	13.126	13.539	13.885	14.948	15.817	13.933
Human capital	14.555	13.570	13.298	13.172	13.127	13.247	13.440	13.633	14.324	14.724	13.716
Marketing investment	10.009	8.042	7.452	6.854	6.497	6.568	6.782	7.338	8.697	9.796	7.823
R&D investment	12.212	10.883	10.914	10.809	10.904	11.211	11.213	11.379	11.627	11.722	11.295
IP rights registrations	0.701	0.508	0.463	0.435	0.423	0.396	0.453	0.466	0.588	0.890	0.533
Firm age	13.641	10.153	8.997	8.917	8.846	9.047	9.631	10.435	12.944	15.670	10.844
Firm size	1.756	1.375	1.245	1.198	1.178	1.189	1.237	1.336	1.589	1.733	1.387
Ratio of venture firms	0.559	0.595	0.615	0.633	0.637	0.633	0.603	0.594	0.553	0.477	0.590
IPO ratio	0.782	0.372	0.246	0.188	0.169	0.198	0.246	0.373	0.666	0.842	0.411
Ratio of affiliate firms	0.001	0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.001	0.005	0.001
Firm region	1.927	2.234	2.184	2.035	2.065	2.025	2.057	1.990	2.351	2.139	2.101
Industry group	1.993	1.928	1.940	1.983	1.982	2.013	1.987	1.977	2.022	2.151	1.997

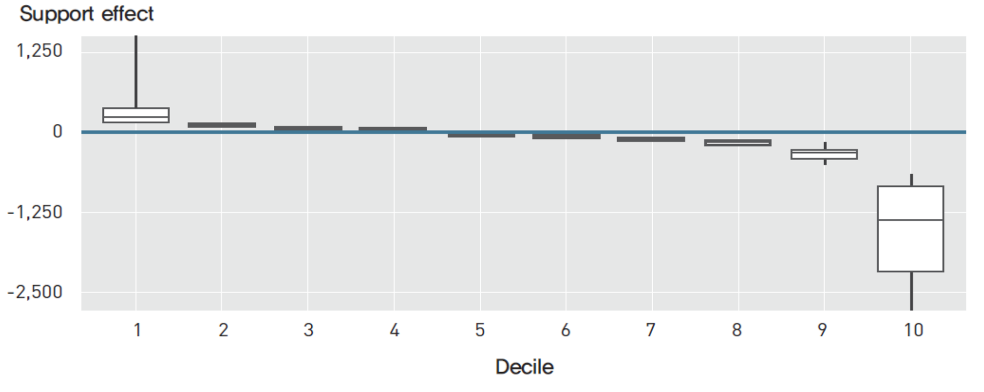


FIGURE 3. COMPARISON OF TREATMENT EFFECTS BY DECILE: VALUE ADDED INCREMENT IN MATCHED SMES

into which each firm will fall. Accordingly, if government support assigned for recipients in the bottom six deciles (that are expected to exhibit negative effects) is redistributed to non-recipients in the top four deciles (that are expected to exhibit the opposite), positive treatment effects would expand two fold or more.

Although we introduced the prediction model and the heterogeneous causal effect model only for the value added increment in this article, we can also do this for the nine other performance indicators as well. Depending on the future application, one can select a few of the performance indicators or allocate appropriate weights to set up a customized model for analysis.

If the aforementioned models that predict the growth potential and heterogeneous causal effect are elaborated further in subsequent studies, it would be possible to select recipient firms with more growth potential and better treatment effects, which will in turn help to accelerate their growth. There exist sufficient records of support for medium-sized firms with which one can accurately predict their growth prospects and treatment effects. However, this is not the case for small firms with little experience in R&D and IP rights registrations, which means that there is not enough data, as of yet, to develop a predictive model to produce accurate estimates of policy effects in these cases. Therefore, this study suggests that experiments to expand support to smaller firms should be undertaken to explore the corresponding causal effects.

VI. Conclusion and Policy Suggestions

When consumer needs are ambiguous or change rapidly, the sequential completion of R&D is likely to result in a waste of time and money. Rather, the agile development method may be more effective, as it enables the early release of prototypes to potential customers so that firms receive feedback and make prompt changes. In other words, shortening the 'time to the market' has become imperative, and such an environment offers more opportunities to SMEs and startups whose business strengths are in speed and flexibility. To keep pace with the rapid evolution of today's business R&D climate, government R&D support programs must be upgraded with more flexible operating systems in which active exchanges of feedback take place between those involved in R&D experiments and market verification.

First, with respect to recipient selection, a predictive model should be developed and utilized in phases while shifting away from the existing selection model, which is heavily dependent on qualitative evaluations by technology experts. As of 2016, 22 special agencies for R&D management in Korea spent more than two trillion won on operating costs, which exceeds 10% of the national R&D budget.[11] Government R&D support programs for the private sector have incurred massive administrative costs on ex-ante, mid-term and ex-post evaluations, but recipients have exhibited slower growth than non-recipients. Howell (2017) found that even US programs saw no correlation between proposal review scores and corporate growth rates. Owing to the large uncertainties in the initial stages of research, even experts are unable to predict success more accurately than prediction models. Hence, it is cost-efficient to let prediction models select which firm should receive

[11]The Hankyoreh, "Government R&D Budget Wasted on Management Expenses, Instead of Researchers," Oct. 7th, 2016 (in Korean).

a small amount of research funding.[12] More policy experiments should be attempted to provide small grants to small firms, which have often been neglected in the recipient selection process. The government will be able to become a supporter rather than a manager by delegating the selection process to an algorithm. Only then can it focus on providing the necessary advice that can help inexperienced recipients conduct research in a more systematic manner. After the recipient firm completes the research, experts can judge the research output qualitatively and decide whether to provide follow-up funding instead of relying on the prediction model. However, it is not necessary to extend government support if the research result and commerciality are both excellent and hence the firm is likely to receive private financial support. Additional government support will be welcome only if the research result is satisfactory but its commercial viability remains ambiguous at that point.

Secondly, evaluations should be focused on broader economic performance outcomes and not only on publications, IP rights and amounts of R&D investment. Accordingly, a selection model should be developed to optimize the evaluation results. The aforementioned evidence shows that firms with three or more patents registered per year exhibit negative growth on average. The government must now discard the old belief that more patents automatically lead to greater corporate growth. The Korean government already has integrated data on ministerial R&D projects, which could be used to formulate evidence-based policies. However, insufficient action has been taken thus far with regard to policy planning, implementations and evaluations in relation to market and financial data. Attempts to realize such policy formulations should be initiated by those in ministries working for industrial innovation, with the goal of driving the fourth industrial revolution.

REFERENCES

Abadie, A. and G. Imbens. 2006. "Large Sample Properties of Matching Estimators for Average Treatment Effects," *Econometrica*, 74: 235-267.

Athey, S., G. Imbens, Y. Kong, and V. Ramachandra. 2016. "An Introduction to Recursive Partitioning for Heterogeneous Causal Effects Estimation Using the causalTree Package."

Edison, T. R. 2010. "Estimation of the Department of Defense Small Business Innovation Research Program Treatment Effect," RAND Dissertation.

Ho, D. E., K. Imai, G. King, and E. A. Stuart. 2007. "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference," *Political Analysis*, 15: 199-236.

Howell, S. T. 2017. "Financing Innovation: Evidence from R&D Grants," *American Economic Review*, 107(4): 1136-1164.

Iacus, S. M., G. King, and G. Porro. 2009. "CEM: Software for Coarsened Exact Matching," *Journal of Statistical Software*, 30(9): 1-27.

Kim, Sangsin. 2016. "Understanding and Using the CEM Method: Focusing on the Effect of Public R&D Subsidies." *The Korean Journal of Economic Studies*, 64(3): 125-151 (in Korean).

[12]Even when the predictive model is used, certain involvement by experts is necessary to determine whether to pass or fail a proposal and, if needed, to provide coaching support to candidate firms.

King, G. and R. Nielsen. 2016. "Why Propensity Scores Should Not Be Used for Matching," Working Paper, Harvard Institute for Quantitative Social Science (http://j.mp/2ovYGsW).

Korea Federation of SMEs. 2017. *2016 Survey on Technology of SMEs*, Small and Medium Business Administration (in Korean).

Korea Intellectual Property Office. 2014. *Intellectual Property Statistics FOCUS*, Vol. 4 (in Korean).

Korea Intellectual Property Office. 2017. *Intellectual Property Statistics FOCUS*, Vol. 9 (in Korean).

Ministry of Science and ICT·Korea Institute of Science & Technology Evaluation and Planning. 2017. *2016 National R&D Project Report and Analysis* (in Korean).

OECD. Main Science and Technology Indicators, http://www.oecd.org/sti/msti.htm (accessed October 31, 2017).

Oh, Seunghwan and Sunwoo Kim. 2017. "R&D Support for SMEs: Current Status and Performance Analysis," *STEPI Insight*, Vol. 211, Science and Technology Policy Institute (in Korean).

Park, Chansu, Chaeyoon Im, and Dongwoo Lee. 2016. *Evaluating SME's Innovation Capability and Analyzing SME Innovation Policy Ⅶ*, Research Paper 2016-10, Science and Technology Policy Institute (in Korean).

Prust, A. C. and R. H. H. Prasad. 2015. "Application of Uplift Modeling and Propensity Score Matching to Develop an Industrialized Marketing Progression Service," *DMA Analytics Journal*.

Sekhon, J. S. 2011. "Multivariate and Propensity Score Matching Software with Automated Balance Optimization: The Matching Package for R," *Journal of Statistical Software*.

The Hankyoreh. "Government R&D Budget Wasted on Management Expenses, Instead of Researchers," (October 7, 2016) (in Korean).

Wager, S. and S. Athey. 2017. "Estimation and Inference of Heterogeneous Treatment Effects using Random Forests," Stanford University.

LITERATURE IN KOREAN

과학기술정보통신부·한국과학기술기획평가원, 『2016년도 국가연구개발사업 조사·분석 보고서』, 2017.

김상신, 「CEM (Coarsened Exact Matching) 방법의 이해와 활용: 연구개발 보조금 효과를 중심으로」, 『경제학연구』, 제64집 제3호, 2016, pp.125~151.

박찬수·임채윤·이동우, 『중소기업 기술혁신 역량평가 및 글로벌 정책 분석 사업 Ⅶ』, 조사연구 2016-10, 과학기술정책연구원, 2016.

오승환·김선우, 「중소기업 R&D 지원의 현황과 성과분석」, 『STEPI Insight』, 제211호, 과학기술정책연구원, 2017.

중소기업중앙회, 『2016 중소기업 기술통계조사』, 중소기업청, 2017.

특허청, 「지식재산 통계 FOCUS」, 통권 제4권, 2014.

특허청, 「지식재산 통계 FOCUS」, 통권 제9권, 2017.

『한겨레』, 「정부 R&D예산, 연구보다 관리비로 '펑펑'」, 2016. 10. 7.

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Higher Education, Productivity Revelation and Performance-pay Jobs†

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This paper examines the differences between the subsequent careers of high school and college graduate workers based on a direct role of college graduation with regard to the revelation of workers' individual abilities. Using NLSY79, we document a positive relationship between off-the-job training/performance-pay jobs and ability for high school graduates at the early stages of their careers. However, this relationship is less prominent for college graduates. Moreover, we show that high ability is associated with more jobs, which reflects higher job mobility, only for high school graduates. We argue that these patterns are the result of productivity-revealing behavior of high school graduates, whose individual abilities, unlike college graduates, is not observed precisely at the beginning of their careers.

Key Word: Productivity Revealing, Off-the-job Training, NLSY79, Performance-pay Jobs, Job Mobility, College Education
JEL Code: I20, J24

I. Introduction

Since Spence (1973), one of well-known functions of higher education has been to signal ability. In the traditional signaling model, individuals with high ability reveal their ability by sorting into higher education. However, a recent paper by Arcidiacono, Bayer, and Hizmo (2010) (ABH (2010) hereafter) finds that college graduation plays a direct role in revealing the productivity of individuals to the labor market rather than simply categorizing these individuals as college graduates. In particular, ABH (2010) documents how the wages of college graduates are

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correlated with their own abilities, whereas this is not the case for the wages of high school graduates, at least not in the beginning of their careers.[1] There are several additional studies that document the pooling of young high school graduates. For instance, Bishop (1994) and Rosenbaum (1990) demonstrate that having both cognitive and non-cognitive skills—both of which are believed to be related to productivity—is not reflected in the wages of young high school graduates. Thus, at the early stages of their careers, high-ability high school graduates tend to be "pooled" with low-ability high school graduates.

The goal of this paper is to document the effects of higher education on the post-schooling careers of workers based on the role of higher education, i.e., to reveal ability. In particular, based on evidence of the role of higher education in revealing ability, we argue that this role yields clear implications regarding workers' productivity-revealing behaviors after they enter the job market. To be more accurate, if the individual abilities of high school graduates are not directly observable, high-ability high school graduates will not be appropriately compensated. Thus, their wages will be set based on the average ability of high school graduates. As a result, it is likely that high-ability high school graduates will engage in activities that will separate them from low-ability high school graduates after they start their careers. More specifically, we predict that high-ability high school graduates will be more likely to obtain off-the-job training and more likely to sort themselves into performance-pay jobs in which wages are closely related to individual ability.

Unlike high school graduates, high-ability college graduates are not expected to engage in costly activities to separate themselves from those with low ability given that the abilities of college graduates are already apparent from the beginning of their careers. Thus, the probability of participating in off-the-job training and sorting into performance-pay jobs would not be positively correlated with the measure of ability among college graduates at the early stages of their careers. Moreover, we expect that high-ability high school graduates tend to have more jobs than their low-ability counterparts considering that they move to better jobs. However, college graduates will not necessarily exhibit this pattern. Specifically, as college graduates are assigned to jobs according to their abilities from the beginning of their careers, they do not have to change jobs at the cost of firm-specific human capital. Thus, job mobility among college graduates will be determined by factors that are not related to worker abilities, such as a random job match between an employer and an employee.

We examine these patterns of worker's post-schooling behaviors using NLSY79 data by documenting different relationships between AFQT scores and productivity-revealing activities across high school and college graduates. These patterns coincide with the prediction of the signaling model under a different degree of asymmetric information between employers and workers across the two groups.

This paper contributes to the literature by illustrating the role of post-schooling

[1]Many aspects of college education can identify the abilities of young college graduates; in Hoxby (1997), college students' abilities are homogeneous within a university but heterogeneous across universities. Given the sorting of students by the ranking or selectivity of colleges, potential employers can obtain fairly accurate information about college graduates via the names of their alma maters.

signaling as a possible mechanism explaining how the wages of workers with only a high school degree eventually reflect their individual abilities. Since the seminal work of Farber and Gibbons (1996), the role of the employer learning on wage dynamics—young workers' wages eventually being positively related to AFQT scores—is well documented by several papers (Altonji and Pierret, 2001; Bauer and Haisken-Denew, 2001). The basic employer learning model hinges on public or symmetric employer learning, assuming that the current employer's information about the workers is shared with *all* potential employers. However, the existence of private or asymmetric learning of employers—and the game theory issues related to it—can complicate the plausible mechanism of employer learning. As a result, only a small number of papers such as Schönberg (2007) and Pinkston (2009) have proposed an employer learning mechanism that explains wage dynamics under private or asymmetric learning of employers. However, given the high mobility of high school graduates in the early stages of their career (Topel and Ward, 1992), it seems unrealistic that information about average young workers could be accumulated in a short time and then passed to outside employers through a rather complicated process without significant losses of the information.

By focusing on the incentives of high-ability workers to reveal their productivity, this paper provides an alternative story regarding the wage dynamics of young workers. Unlike employers who do not have an incentive to reveal information about their high-ability workers, high-ability workers have a strong incentive to reveal their abilities to their potential employers through productivity-revealing activities. Because the worker will signal their abilities to all potential employers, one does not have to consider the transmission of information across employers. Moreover, explaining wage dynamics using workers' incentives is more intuitive than relying on employer learning, as it emphasizes the role of workers who will actually gain from the revelation of productivity and its related wage increases.[2]

The rest of this paper is organized into the following sections. Section II provides an overview of NLSY79 and the sample construction process. In Section III, we describe individuals' sorting behaviors into higher education and draw testable implications regarding subsequent aspects of post-schooling careers followed by the identification strategy and the estimating equations. In Section IV, we present the main empirical results that verify the hypotheses regarding productivity-revealing activities and the number of jobs. Section V presents concluding remarks.

II. Data

To verify our hypotheses regarding workers' post-school behaviors empirically, we use NLSY79 data for the period of 1979-2006. This dataset has been compiled at regular intervals (annually since 1979 and biannually since 1994). The respondents were aged between 14 and 22 at the beginning of the survey. The data have a number of advantages for analyzing post-schooling signaling behaviors. In particular, NLSY79 focuses on the early stage of respondents' careers, when

[2]Employers will be indifferent about the wage distribution in this setting as long as the average wage equals the average productivity of workers.

productivity-revealing activities are most likely to have an impact. Moreover, for the focused analysis of post-school behaviors here, information regarding workers' abilities is essential. NLSY79 contains the results of AVSAB tests, which can be converted into AFQT scores. AFQT scores in NLSY79 are widely accepted as a pre-market measure of ability. Lastly, the data contain detailed information about the training of workers and their job characteristics, including the payment structures of jobs.

For the main analysis, we restrict the sample to white males in order to avoid tracking career variations that may arise from differences in race and/or gender.[3] Following ABH (2010), we also limit the sample to the respondents who have completed 12 or 16 years of education and exclude high school dropouts and individuals who have completed some college education. We exclude respondents who have military jobs or, jobs without pay, who are self-employed in CPS (main) jobs, or who work for a family business. We also drop labor market experience accumulated before individuals left school for the first time. Furthermore, we restrict our scope of the analysis to individuals for whom the potential experience duration is less than 13 years, thereby focusing on the early stages of their careers.[4] Another reason for this sample construction stipulation, as explained in ABH (2010), is to keep the analysis simple by focusing on the approximately linear region of the relationship between log wages, AFQT scores, and potential experience.

The measure of ability, i.e., the AFQT score, is constructed using the definition provided by the Department of Defense and is standardized according to the age of the individual at the time of the test. The construction of the performance-pay indicator variable follows the method used by Lemieux, MacLeod, and Parent (2009). The performance-pay indicator variable takes a value equal to one if the wages of CPS jobs include a variable-pay component, such as a bonus, commission or piece-rate structure. With regard to the off-the-job training variable, we follow Parent (1999) and reclassify 12 training categories into three groups: on-the-job training (OJT), off-the-job training (OFT) and apprenticeships. In particular, the OFT indicator variable takes a value equal to one if the respondent took any form of OFT, such as by attending a business college, a nursing program or a vocational-technical institute, in a given year. We use the hourly wage rate of CPS jobs from the work history file as a measure of wages and obtain the real wage using the CPI index. The number of jobs in a given year is used as a proxy for the job mobility of workers.

Table 1 shows the summary statistics of the main analysis of the sample. As expected, the average of log wages and the average AFQT scores are higher for college graduates than for high school graduates. College graduates are more likely to take performance-pay jobs and to obtain training. Additionally, the compositions of training differ between the two groups, as high school graduates are more likely to obtain OFT and apprenticeships and are less likely to obtain OJT. However, there

[3]In Appendix, we include results based on all racial groups. These results are consistent with our main findings.

[4]Potential experience is defined as the number of years since a respondent initially finished their schooling.

TABLE 1—SUMMARY STATISTICS

	High School		College		Total	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
AFQT	0.323	0.797	1.272	0.454	0.595	0.835
Potential Experience	6.213	3.309	5.346	3.051	5.966	3.261
Log of Real Wage	6.409	0.474	6.837	0.537	6.530	0.529
Number of Jobs	4.621	3.746	2.982	2.588	4.156	3.535
Performance-pay Jobs (%)	24.12		38.94		28.93	
Training (%)	11.22		18.42		13.25	
Off-the-Job Training (%)	50.63		38.11		45.73	
On-the-Job Training (%)	41.79		67.19		51.73	
Apprenticeship (%)	11.11		3.54		8.15	
Region (%)						
Northeast	19.94		27.88		22.18	
North Central	35.87		28.44		33.77	
South	27.20		28.77		27.64	
West	16.99		14.91		16.40	
Urban Residence (%)	71.85		87.48		76.24	
Number of Observations	7,716		3,058		10,774	
Number of Individuals	988		437		1,425	

Note: The average and standard deviations are calculated over individual-by-year observations coming from a panel of 1979-2006. S.D. stands for standard deviation. Please refer to Section II for a detailed description of the variables.

is little difference in the number of jobs per year between college and high school graduates.

III. Empirical Framework

In this section, we describe individual's sorting behavior into higher education and draw testable implications regarding subsequent aspects of post-schooling careers. This is followed by descriptions of the identification strategy and the estimating equations.

In order to illustrate workers' postgraduate productivity-revealing activities, we assume that each worker has innate ability a, distributed as $F(a)$, and that employers do not have direct information about any individual worker's innate ability. First, an individual decides whether they will sort themselves into higher education or not. Under the commonly acknowledged assumptions of returns and the cost of engaging in higher education, a certain percentage of individuals from the top of the ability distribution have incentives to participate in higher education. Specifically, there is an ability cutoff a^* such that individuals whose ability is greater than a^* would receive higher education. Individuals who decide to receive higher education become college graduates and individuals who decide not to enter higher education remain high school graduates.[5] After individuals finish their schooling and enter the job market, they then decide whether to engage in activities that will further reveal their abilities. Employers know that the average ability of college graduates is higher than the average ability of high school graduates. Moreover, given the role of higher education in revealing ability, college graduates will receive wages according to their individual abilities. However, with regard to wages, high school graduates will be pooled at the beginning of their careers, as employers cannot verify the individual abilities of fresh high school graduates. Thus, the wages of college graduate workers are positively correlated with their ability a, whereas the wages of high school graduates at the beginning of their careers will be the expected ability of high school graduate workers, $E(a \mid a < a^*)$, regardless of individual abilities a assuming a perfectly competitive labor market.

Thus, given these initial wages of high school graduates, some portion of high-ability high school graduates have incentives to engage in productivity-revealing activities to separate themselves from low-ability high school graduates and ultimately to gain compensation for their individual abilities. However, high-ability college graduates will not engage in costly productivity-revealing activities because they are already separated from both high school graduates and low-ability college graduates. We exploit this predicted difference in productivity-revealing activities, such as participation in off-the-job training and taking performance-pay jobs, between high school and college graduates to identify the effects of higher education on an individual's postgraduate career. In addition, we argue that job mobility will exhibit different patterns among high school and college graduates.

A. *Off-the-Job Training*

The literature on training mainly focuses on the human-capital-mediated effect of training on wage increases or job mobility (Lynch, 1991; 1992; Parent, 1999). In contrast, here we view training mainly as a means of revealing worker productivity. In particular, off-the-job training (OFT) is similar to schooling in the sense that the worker pays the cost of the training, while the contents of the training are not firm-specific. Given the similarities between off-the-job training and schooling, off-the-job training can be used as a signaling device. Thus, as traditional signaling theory (Spence, 1973) would predict, high-ability workers will be more likely to obtain OFT than their low-ability counterparts if they are not differentiated from their low-ability counterparts.

Therefore, for high school graduates whose abilities are not revealed at the beginning of their careers, the probability of receiving off-the-job training will be positively related to their AFQT scores, as high-ability high school graduates would participate in OFT to reveal their ability. However, for college graduates whose individual abilities are already apparent, the probability of obtaining OFT will not necessarily depend positively on measured ability. Moreover, because the

[5]It is important to note that the predictions and implications drawn in this section will be independent of whether the return is from signaling or human capital accumulation. That is, motivation for education does not matter as long as high-ability individuals proceed to higher education.

return from being separated from low-ability workers decreases with time, the probability of obtaining OFT will decrease more rapidly with experience for high-ability high school graduates compared to their low-ability counterparts. In other words, the experience gradient will be steeper for high-ability high school graduates whose motivation for taking OFT is positively affected by both signaling (productivity revealing) and human capital accumulation. However, we do not expect different experience gradients across abilities among college graduates given that high-ability college graduates do not have additional incentives to receive OFT in the early stages of their careers.

If OFT functions as a productivity-revealing device, one may consider that high-ability high school graduates would also be separated from low-ability high school graduates as soon as they take OFT and thus would be paid according to their ability. However, the strength of the signal from OFT is weaker than that of college education. Therefore, the ability of high school graduate workers with OFT would be revealed gradually, unlike college graduates.

B. *Performance-pay Jobs*

A recent paper by Lemieux, MacLeod, and Parent (2009) asserts that due to imperfect information about workers, high-ability workers will have an incentive to sort themselves into performance-pay jobs so that they can reveal their high productivity and receive wages that more closely reflect their abilities. Lemieux, MacLeod, and Parent (2009) supports this argument by comparing the average AFQT score for workers in performance-pay jobs with that of workers in non-performance-pay jobs. Adopting their view on performance-pay jobs, one can categorize sorting behavior into performance-pay jobs as a means to reveal the productivity of individual workers. Thus, given the role of higher education, the relationship between ability and having a performance-pay job among high school graduates will be different from that among college graduates.

To be more specific, because high school graduates are pooled with each other at the beginning of their careers, high-ability high school graduates would try to take performance-pay jobs and receive pay in relation to their individual abilities. However, unlike high school graduates, high-ability college graduates are already distinguished from their low-ability counterparts at the beginning of their careers. Thus, high-ability college graduates will have little incentive to choose to take performance-pay jobs and pay additional monitoring costs to reveal their high abilities. In other words, it is not necessary for high-ability college graduates to sort themselves into performance-pay jobs; in fact it could be considered wasteful in the early stages of their careers.

In sum, the probability of obtaining performance-pay jobs will depend positively on AFQT scores among high school graduates in the early stages of their careers, whereas among college graduates, the correlation between the probability of working at a performance-pay job and the AFQT score will not be positive.[6]

[6]A difference in the probability of working at performance-pay jobs between high school and college graduate workers can still exist, as college graduates are more likely to sort themselves into performance-pay jobs. This fact does not contradict our explanation given that the difference between average high school and college graduates can be explained by other factors, such as differences in the job characteristics of college and high school

C. *Number of Jobs*

The positive relationship between wage increases and job mobility for young high school graduates has been well documented by Topel and Ward (1992). They interpret the results as supportive evidence of the search theory, viewing job mobility as an important means of wage increases and as a step toward stable long-term employment for high school graduates.[7]

In our paper, we examine the number of jobs that workers take in a given year. This number is regarded as a measure reflecting the job mobility of workers. In particular, high-ability high school graduates will be more likely to exhibit higher job mobility than low-ability high school graduates as they engage in productivity-revealing activities to differentiate themselves from their low-ability counterparts and to move to better jobs. Thus, there will be a positive relationship between wage increases and the number of jobs among high school graduates, as high-ability high school workers seek and switch to better jobs with higher wages. Moreover, as high-ability high school graduates obtain the jobs they deserve, the incentive to move to other jobs will decrease over time and their careers will eventually stabilize. This implies that the negative relationship between the number of jobs and potential experience will be stronger for the high-ability high school graduates than for low-ability high school graduates.

However, high-ability college graduate workers will not have an incentive to move between jobs at the cost of firm-specific human capital, as college graduates are offered jobs according to their individual abilities from the beginning of their careers. That is, high-ability college graduate workers will not have to engage in costly job searches and endure the related job mobility to separate themselves from their low-ability counterparts in the early stages of their careers.

D. *Estimating Equation*

In this section, we document the different patterns of the relationship between ability and outcomes among high school and college graduates discussed in the earlier part of this section. We claim this difference as evidence supporting the effects of higher education on the subsequent careers of workers. To be specific, we verify a positive relationship between the incidence of productivity-revealing activities and ability among high school graduates, while we find a non-positive relationship among college graduates. We attribute this difference between the two groups to differences in their participation rates of productivity-revealing activities given the role of college graduation.

The main empirical specification closely follows employer learning literature and regresses the outcome variable on a measure of ability, potential experience, and the interaction between the two (Altonji and Pierret, 2001). The following equation will be estimated separately for high school graduate and college graduate workers,

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graduates.

[7]Unlike Topel and Ward (1992), Neumark (2002) views job mobility as a wasteful procedure. He argues that judgments of job mobility can differ between high school and college graduates.

$$(1) \quad Y_{it} = \beta_0 + \beta_1 AFQT_i + \beta_2 AFQT_i \times Exper_{it} + f(Exper_{it}) + \mathrm{X}_{it}'\Phi + \delta_t + e_{it},$$

where Y_{it} is the outcome variable, in this case the wage of worker i in time t, the number of jobs held in a given year, and a dummy variable for having a performance-pay job and engaging in off-the-job training. $Exper_{it}$ represents i's potential experience at time t and $f(Exper_{it})$ is a function of $Exper_{it}$. In the main analysis, we adopt a third-order polynomial function for potential experience. X_{it} includes the control variables such as the region of residence. The error term e_{it} is clustered at the individual level.

The coefficient of $AFQT_i$, β_1, indicates the correlation between the outcome variable and AFQT score at the beginning of an individual's career—when their potential experience is equal to zero. The coefficient of the interaction term, β_2, captures the difference in the correlation between experience and outcome across workers with different abilities. Our hypothesis will be supported by examining the differences in the statistical significance and the signs of the coefficients in each group.

IV. Results

This section provides empirical results that verify our hypotheses regarding participation in the productivity-revealing activities and job mobility of workers. We perform a regression analysis using equation (1) with various dependent variables, in this case indicators of receiving OFT and taking performance-pay jobs separately for high school graduate and college graduate samples. Tables 2 through 5 report the results from the regression for each group of workers for the dependent variables, and they also provide p-values from tests comparing the coefficients based on the two different samples. Specifically, columns (1) and (3) of each table report the result of estimating equation (1) *without* the interaction term between AFQT and potential experience for high school and college graduates, respectively. Therefore, the estimated coefficients of AFQT in columns (1) and (3) indicate the overall relationship between AFQT and the outcome variable for the first 13 years of the workers' careers. Columns (2) and (4) report the estimation result of the equation (1) for high school and college graduates, respectively.

A. *Does Higher Education Fulfill the Role of Revealing Ability? Replication of ABH (2010)*

Before we present our main results, we present the regression result using wage as a dependent variable, which will confirm that our main sample exhibits a result regarding wage dynamics identical to that in ABH (2010). That is, we show that the wages of college graduate workers are correlated with their own abilities at the beginning of their careers, while the wages of high school graduate workers are not, at least in the beginning of their careers. Table 2 presents the results from estimating equation (1) with the log of real wage as an outcome variable separately for high school graduates and college graduates. It shows that our results regarding wages are qualitatively similar to those in ABH (2010). In particular, the AFQT coefficient in column (2) is positive but small and statistically insignificant, which implies that the wages of high school graduates do not reflect their cognitive abilities at the beginning of their careers — when their potential experience is zero. The positive and significant coefficient of the interaction term between AFQT scores and potential experience implies that the wages of high school graduates eventually reflect their individual abilities. In other words, high school graduates are pooled with each other at the beginning of their careers but are eventually separated by their AFQT scores. On the other hand, the coefficient of the AFQT score estimated with the college graduate sample, shown in column (4), is sizable, positive and significant, whereas the interaction term is small and insignificant. This result implies that college graduates are separated by their AFQT scores from the beginning of their careers and that the additional separation associated with experience is insignificant, unlike high school graduates. Taking into account that the variations in the AFQT scores are much smaller among college graduates than among high school graduates, this result appears to provide strong support for the argument that higher education has a productivity-revealing role.

TABLE 2—REPLICATING ABH (2010)

	High School		College		Test: College=HS P-value	
	(1)	(2)	(3)	(4)	(5)	(6)
AFQT	0.0765*** (.016)	0.00150 (.0173)	0.191*** (.0431)	0.152** (.0599)	0.013	0.015
Exper/10	1.192*** (.1931)	1.172*** (.1937)	1.314*** (.3793)	1.185*** (.3718)	0.775	0.976
AFQT*Exper/10		0.113*** (.0243)		0.0617 (.0902)		0.582
Adjusted R-squared	0.133	0.154	0.139	0.150		
N	7,406	7,194	2,970	2,850		
Additional Controls	No	Yes	No	Yes	No	Yes

Note: All specifications include a year fixed effect and squared and cubic terms for potential experience. Specifications (2) and (4) additionally control for the location of the residence and an urban residence. In columns (5) and (6), we report the p-values for the difference in the coefficients from specifications (1) and (3) as well as (2) and (4), respectively. Standard errors in parentheses are clustered at the individual level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

B. *Off-the-Job Training*

Table 3 summarizes the results regarding off-the-job training separately for the high school graduate and college graduate samples. For high school graduates, the AFQT coefficient in column (2) is positive and statistically significant, which implies that high-ability high school graduates are more likely to engage in OFT than their low-ability counterparts at the beginning of careers. Moreover, the negative coefficient of the interaction term between AFQT scores and potential experience implies that high-ability high school graduates are more likely to undertake an OFT at the beginning of their careers compared to low-ability high school graduates. This result also supports our hypotheses, as the return for revealing productivity through OFT is higher in the early stages of a career. Thus, high-ability high school graduates will engage in OFT more intensively in the earlier stages of their careers.

The results based on the college graduate sample show a different pattern. They show that the probability of engaging in OFT does not depend positively on the AFQT scores in the early stages of their careers, as the AFQT coefficient in column (4) is not statistically significant. The positive coefficient of the interaction term between AFQT scores and potential experience is evidence against the possibility of OFT being used as a productivity-revealing device for high-ability college graduates. If OFT is used as a productivity-revealing device for high-ability college graduate workers, they would have received OFT more in the early stages of their careers and the coefficient of AFQT and the interaction term would accordingly have exhibited the same patterns as they do for high school graduates. Overall, the evidence supports the contention that for college graduates, revealing productivity is not a dominant motivation for receiving OFT.

TABLE 3—OFF-THE-JOB TRAINING

	High School		College		Test: College=HS P-value	
	(1)	(2)	(3)	(4)	(5)	(6)
AFQT	0.0121*** (.0038)	0.0258*** (.0075)	0.000374 (.0129)	-0.0396 (.0245)	0.382	0.010
Exper/10	-0.497*** (.1219)	-0.481*** (.1237)	-0.0561 (.1857)	-0.152 (.1989)	0.047	0.160
AFQT*Exper/10		-0.0235** (.0114)		0.0790** (.0364)		0.007
Adjusted R-squared	0.008	0.009				
N	6,769	6,573	2,683	2,576		
Additional Controls	No	Yes	No	Yes	No	Yes

Note: All specifications include a year fixed effect and squared and cubic terms for potential experience. Specifications (2) and (4) additionally control for the location of the residence and an urban residence. In columns (5) and (6), we report the p-values for the difference in the coefficients from specifications (1) and (3) as well as (2) and (4), respectively. Standard errors in parentheses are clustered at the individual level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

C. *Performance-pay Jobs*

As discussed earlier in Section III. B, high school graduates with high ability would have an incentive to work at performance-pay jobs in the early stages of their careers in order to receive pay reflecting their individual abilities, whereas college graduates would have limited incentives to choose performance-pay jobs. Therefore, if our hypotheses are correct, we would find a positive coefficient of AFQT scores for high school graduates according to equation (1) with an indicator of having a performance-pay job as an outcome variable. For college graduates, we expect a non-positive AFQT coefficient.

Note that our main specification for the result regarding performance-pay jobs will only have the AFQT score and measure of potential experience as the main independent variables due to data limitations. The data from the question about performance-pay jobs were collected between 1988 and 1990 and between 1996 and 2000, when most of respondents had already gained approximately from 7 to 8 years of potential experience. As a result, the estimation of β_1 in equation (1), which estimates the AFQT scores and the outcome at the beginning of workers' careers, will be unreliable when we include the interaction between AFQT scores and potential experience. Moreover, because the collection of information about performance pay is not continuous, β_2, which estimates the relationship between performance pay and experience, will also be unreliable. Thus, we only look at whether sorting into a performance-pay job depends on AFQT for the first 13 years of the workers' careers. Thus, the our hypotheses will be verified by examining whether there is a difference in the relationship between having a performance-pay job and ability in the first 13 years of an individual's career across the two groups.

TABLE 4—PERFORMANCE-PAY JOBS

	High School		College		Test: College=HS P-value	
	(1)	(2)	(3)	(4)	(5)	(6)
AFQT	0.0351** (.0138)	0.153** (.0605)	-0.0334 (.0481)	-0.209** (.0939)	0.171	0.002
Exper/10	1.275 (1.176)	0.858 (1.227)	2.213*** (.7505)	2.103*** (.7695)	0.501	0.390
AFQT*Exper/10		-0.118* (.0669)		0.307** (.1436)		0.007
Adjusted R-squared	0.003	0.007	0.018	0.027		
N	1,917	1,898	933	922		
Additional Controls	No	Yes	No	Yes	No	Yes

Note: All specifications include a year fixed effect and squared and cubic terms for potential experience. Specifications (2) and (4) additionally control for the location of the residence and an urban residence. In columns (5) and (6), we report the p-values for the difference in the coefficients from specifications (1) and (3) as well as (2) and (4), respectively. Standard errors in parentheses are clustered at the individual level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Our estimation results support the described different patterns of taking performance-pay jobs between high school and college graduate workers. As shown in column (1) of Table 4, the probability of having a performance-pay job depends positively on the AFQT score for high school graduates in the first 13 years of their careers. This result is consistent with our hypotheses that high-ability high school graduates will work at performance-pay jobs to reveal their ability in the early stages of their careers.

However, for college graduates, AFQT scores are not positively associated with the probability of obtaining performance-pay jobs during the early stages of their careers, as the coefficient in column (3) is negative and statistically insignificant. The estimation result for college graduates shows that high-ability college graduates have little incentive to take performance-pay jobs under productivity-revealing motives, unlike high school graduate workers.

D. *Number of Jobs*

In order to examine our hypotheses described in Section III. C regarding number of jobs, we use the number of jobs in a given year as a dependent variable in equation (1), and Table 5 documents the results. As the coefficient of AFQT in column (2) is positive, the number of jobs is positively related to ability among high school graduates at the beginning of their careers. In particular, an increase of one standard deviation in the AFQT scores is associated with 0.15 more jobs in the early stages of high school graduates' careers. The coefficient of the interaction term is negative for high school graduates. This result implies that the number of jobs among high-ability high school graduates will eventually stabilize over time.

TABLE 5—NUMBER OF JOBS

	High School		College		Test: College=HS P-value	
	(1)	(2)	(3)	(4)	(5)	(6)
AFQT	0.0613*** (.0193)	0.152*** (.0364)	-0.138*** (.0499)	-0.143 (.1006)	0.000	0.006
Exper/10	-1.445*** (.4669)	-1.377*** (.4657)	-3.500*** (.5976)	-3.393*** (.7047)	0.007	0.017
AFQT*Exper/10		-0.148*** (.0471)		0.0117 (.1575)		0.330
Adjusted R-squared	0.026	0.029	0.071	0.071		
N	7,406	7,194	2,970	2,850		
Additional Controls	No	Yes	No	Yes	No	Yes

Note: All specifications include a year fixed effect and squared and cubic terms for potential experience. Specifications (2) and (4) additionally control for the location of the residence and an urban residence. In columns (5) and (6), we report the p-values for the difference in the coefficients from specifications (1) and (3) as well as (2) and (4), respectively. Standard errors in parentheses are clustered at the individual level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

However, the results for college graduates display different patterns. The result in column (4) suggests that unlike high school graduates, the number of jobs does not depend positively on AFQT scores for college graduates. The coefficients for both AFQT scores and the interaction term are either negative and/or statistically insignificant for college graduate workers. These results suggest that other factors that do not depend on the abilities of workers may be the major determinants of job mobility among young college graduates.

Overall, the results show that for the number of jobs, different patterns emerge among high school and college graduate workers. These differences could shed light on the source of the return from job mobility described in Topel and Ward (1992). As the number of jobs reflects job mobility, our results suggest that the return from the number of jobs among high school graduates arises from the correlation between ability—which is positively related to wages in the long run—and job mobility.

V. Conclusion and Discussion

In this paper, we document the difference between the subsequent careers of high school and college graduate workers based on the role of higher education in revealing abilities. In particular, we argue that high-ability high school graduates will actively engage in productivity revealing-activities while high-ability college graduates will not actively participate in those activities. Moreover, we expect that high-ability high school graduates will tend to have more jobs than low-ability high school graduates at the beginning of their careers as they move to better jobs. Unlike high school graduates, college graduates do not exhibit such a pattern in the number of jobs given that high-ability college graduates will have decent jobs from the beginning of their career and will not have an incentive to move between jobs at the cost of firm-specific human capital. Using NLSY79 data, we test our hypotheses by regressing the measure of productivity-revealing activities and the number of jobs on the measure of ability separately for high school graduates and college graduates. Overall, the empirical pattern is fairly consistent with our hypotheses. Therefore, our findings highlight the importance of the role of higher education to understand the post-schooling behavior of high school and college graduates.

APPENDIX

Although our main results are based on a sample of white males, we also perform the same analysis based on a sample containing all racial groups – white, black and Hispanic. The sample used in this Appendix is restricted to males only. Table A1 documents the regression results using the estimating equation (1) with the same dependent variables used in the main text. In addition to the control variables in the main analysis, we included dummy variables indicating racial groups. The results are qualitatively and quantitatively similar to the main results.

TABLE A1—RESULTS BASED ON ALL RACIAL GROUPS

	High School		College		Test: College=HS P-value	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dependent Variable=Log Real Wage						
AFQT	0.0800*** (.0112)	0.00100 (.017)	0.172*** (.0343)	0.153** (.0593)	0.011	0.013
AFQT* Exper/10		0.114*** (.0242)		0.0647 (.0869)	0.002	0.316
Panel B: Dependent Variable=OFT						
AFQT	0.0108*** (.0029)	0.0259*** (.0075)	-0.00172 (.0102)	-0.0412* (.0242)	0.238	0.001
AFQT* Exper/10		-0.0233** (.0113)		0.0808** (.0359)		0.009
Panel C: Dependent Variable=Performance-pay Jobs						
AFQT	0.0315** (.0111)	0.116** (.0572)	-0.00750 (.0335)	-0.196** (.092)	0.268	0.196
AFQT* Exper/10		-0.0985 (.0636)		0.298** (.1413)		0.306
Panel D: Dependent Variable=Number of Jobs						
AFQT	0.0647*** (.0146)	0.149*** (.0361)	-0.0723* (.0377)	-0.151 (.0988)	0.001	0.004
AFQT* Exper/10		-0.146*** (.0467)		0.0276 (.1553)	0.271	0.519
Additional Controls	No	Yes	No	Yes	No	Yes

Note: All specifications include a year fixed effect and squared and cubic terms for potential experience. Specifications (2) and (4) additionally control for the location of the residence and an urban residence. In columns (5) and (6), we report the p-values for the difference in the coefficients from specifications (1) and (3) as well as (2) and (4), respectively. Standard errors in parentheses are clustered at the individual level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

REFERENCES

Altonji, J. G., and C. R. Pierret. 2001. "Employer learning and statistical discrimination," *Quarterly Journal of Economics*, *116*(1): 313-350.

Arcidiacono, P., P. Bayer, and A. Hizmo. 2010. "Beyond signaling and human capital: Education and the revelation of ability," *American Economic Journal: Applied Economics*, *2*(4): 76-104.

Bauer, T. K., and J. P. Haisken-Denew. 2001. "Employer learning and the returns to schooling," *Labour Economics*, 8: 104-123.

Bishop, J. H. 1994. "Signaling the competencies of high school students to employers," *CAHRS Working Paper Series*, *Working Paper* 94-18.

Farber, H. S., and R. Gibbons. 1996, November. "Learning and wage dynamics," *The Quarterly Journal of Economics*, 111(4): 1007-1047.

Hoxby, C. M. 1997. "How the changing market structure of U.S. higher education explains college tuition," *NBER Working Paper Series* (6323).

Lemieux, T., W. B. MacLeod, and D. Parent. 2009. "Performance pay and wage inequality," *Quarterly Journal of Economics*, 124(1): 1-49.

Lynch, L. M. 1991. "The role of off-the-job vs on-the-job training for the mobility of women workers," *American Economic Review: Papers and Proceedings*, 81: 151-156.

Lynch, L. M. 1992. "Private-sector training and the earning of young workers," *American Economic Review*, 82(1): 299-312.

Neumark, D. 2002. "Youth labor markets in the United States: Shopping around vs. staying put," *Review of Economics and Statistics*, 84(3): 462-482.

Parent, D. 1999. "Wages and mobility : The impact of employer-provided training," *Journal of Labor Economics*, 17(2): 298-317.

Pinkston, J. C. 2009. "A model of asymmetric employer learning with testable implications," *Review of Economics Studies*, 76: 367-394.

Rosenbaum, J. 1990. "Do school achievements affect the early jobs of high school graduates? Results from the high school and beyond surveys in the US and Japan," *Northwestern University*, *Mimeo*.

Schönberg, U. 2007. "Testing for asymmetric employer learning," *Journal of Labor Economics*, *25*(4): 651-691.

Spence, A. M. 1973. "Job market signaling," *The Quarterly Journal of Economics*, 87(3): 355-374.

Topel, R. H., and M. P. Ward. 1992. "Job mobility and the careers of young men," *Quarterly Journal of Economics*, 107(2): 439-479.