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How AI Innovation Contributes to Technological Progress in Terms of the Solow–Cobb–Douglas Production Function

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Abstract

We investigate the degree to which artificial intelligence (AI) innovations contribute to technological progress. Herein, we note the total factor productivity (TFP) concept that will be a proxy variable of the Solow–Cobb–Douglas production function's coefficient. Thereafter, we conduct empirical analyses of AI innovation in advanced countries to determine the degree of penetration of AI innovation. If we use multiple regression analysis, the value of TFP and the parameters of capital and labor will remain constant in the Solow–Cobb–Douglas production function model. However, the value of TFP and the parameters of capital and labor change over time. Therefore, we use the Kalman filter technique to stochastically imitate their real changes.

Keywords: *innovation, artificial intelligence, total factor productivity, Solow–Cobb–Douglas production function, Kalman filter technique*

INTRODUCTION

We investigate the degree to which artificial intelligence (AI) innovations contribute to technological progress. Herein, we use the total factor productivity (TFP) concept that will be a proxy variable of Solow–Cobb–Douglas production function's coefficient. Thereafter, we conduct empirical analyses of AI innovation in advanced countries to establish the degree of penetration of AI innovation. If we use regression analysis, the value of TFP and the parameters of capital and labor will remain constant in the Solow–Cobb–Douglas production function model. However, the value of TFP and the parameters of capital and labor change over time. Therefore, we use the Kalman filter technique to stochastically imitate their real changes.

The previous works related to our research are as follows:

Munguia et al. (2019) present a novel approach for estimating the Solow–Cobb–Douglas economic growth model. In this study, an extended Kalman filter is used to estimate the system state of a Solow–Cobb–Douglas economic growth model. The proposed method is intended to simultaneously estimate the time-varying model parameters as well as the state of the dynamic system from a subset of available economic data measurements. Three time periods, namely, the convergence, testing, and prediction periods, are defined for the experiments.

Inglesi-Lotz et al. (2014) examine the importance of technological progress to aggregate economic growth in South Africa. Quantifying the contribution of technological progress to economic growth has become imperative, considering the outcome of a simple growth accounting exercise. The findings of this study indicate that the contribution of technological growth to aggregate economic growth has increased substantially over the past three decades. The ultimate purpose of this study is to describe the evolution of the contribution of technological progress captured by total factor productivity (TFP) or the Solow residual to economic growth.

Economic growth is modelled through a Cobb–Douglas production function, employing a Kalman filter to determine the evolution of the Solow residual over time. The Solow residual represents both technological progress and structural change. According to the Kalman filter results, technological progress has been characterized by an upward trend since the 1980s, with a steeper slope since the 2000s. Their results show that technological progress has become a factor as important to production as capital stock and labor, which policymakers should consider to boost economic growth.

Through the Solow–Cobb–Douglas production function, we examine the degree of AI innovations that contribute to technological progress in several advanced countries via linear regression and the Kalman filter technique.

MODEL

In the factor analysis of economic growth, we consider the Solow–Cobb–Douglas production function model. The original Cobb–Douglas production function at time t is given by

$$Y_t = K_t^{\alpha} L_t^{\beta} \quad \ldots 1),$$

where Y_t is the output of a country (GDP), sales volume of a specified company, and production volume. Capital, K_t , denotes the input volume of capital, such as equipment, factories, and lands. Labor, L_t, denotes the input volume of labor, such as labor hours and number of employees. However, α and β are between 0 and 1 ($\because \alpha+\beta=1$). In addition, α and β indicate that the contribution ratio to the output increases when the input volume of capital and labor increases by one unit. If all the inputs are doubled, the output will exactly double. Thus, it is evident that this production function exhibits constant returns to scale. Another feature of this Cobb–Douglas production function is that α indicates the elasticity of production against labor,

$$\frac{\partial Y_t}{\partial K_t} = \alpha K_t^{\alpha-1} L_t^{\beta} = \alpha \frac{K_t^{\alpha} L_t^{\beta}}{K_t} = \alpha \frac{Y_t}{K_t} \quad ,$$

$$\therefore \alpha = \frac{\partial Y_t / Y_t}{\partial K_t / K_t} \quad \ldots 2)$$

Similarly, β indicates the elasticity of production against capital,

$$\therefore \beta = \frac{\partial Y_t / Y_t}{\partial L_t / L_t} \quad \ldots 3)$$

Here, we follow the Solow model and introduce technological progress into the Cobb–Douglas production function. If we add a technology variable A_t to the production function, the Solow–Cobb–Douglas production function is expressed as:

$$Y_t = A_t K_t^{\alpha} L_t^{\beta} \quad \ldots 4)$$

Thus, the technology variable A_t is deemed as "labor-augmenting" or "Harrod-neutral." Generally, technological progress occurs when A_t increases over time. For example, a unit of labor will be more productive when the level of technology is higher. Here, we can find that sustained growth occurs only in the presence of technological progress.

Capital accumulation reduces returns without technological progress. However, improvements in technology continue to compensate for decreasing returns with technological progress. Consequently, labor productivity has grown owing to technology advancements. These improvements can be achieved through additional capital accumulation. If we take natural logs and completely differentiate Equation 4, we can derive the key formula for growth accounting. Equation 5 indicates that output growth is equal to the growth rate of A_t plus the weighted average of capital and labor growth.

$$\frac{\Delta Y_t}{Y_t} = \frac{\Delta A_t}{A_t} + \alpha \frac{\Delta K_t}{K_t} + \beta \frac{\Delta L_t}{L_t} \quad \ldots 5)$$

If we transform Equation 5, we can take the

Solow residual as the TFP in Equation 6.

$$\frac{\Delta A_t}{A_t} = \frac{\Delta Y_t}{Y_t} - \left(\alpha \frac{\Delta K_t}{K_t} + \beta \frac{\Delta L_t}{L_t} \right) \ldots 6)$$

While $\frac{\Delta A_t}{A_t}$ is referred to as technological progress factor, TFP growth, or multifactor productivity growth. To apply linear regression analysis in Equation 4, we have to add the observation error term $e^{\tilde{e}_t}$ for Equation 4.

Namely,

$$Y_t = A_t K_t^{\alpha} L_t^{\beta} e^{\tilde{e}_t} \ , \quad \tilde{e}_t \sim N(0, \sigma_t^2) \ldots 7)$$

As Equation 7 is nonlinear, we take the natural log of both sides of Equation 7 to linearize the equation. We execute a linear regression analysis in Equation 8.

$$\ln Y_t = \ln A_t + \alpha \ln K_t + \beta \ln L_t + \tilde{e}_t \ldots 8)$$

If we assume that the technological progress rate is constant over time, we can rewrite Equation 8 as follows, where, T_t represents the technological progress rate at time t.

$$\ln Y_t = \lambda + \gamma T_t + \alpha \ln K_t + \beta \ln L_t + \tilde{e}_t \ldots 9)$$

$$(\because \ln A_t = \lambda + \gamma T_t)$$

The problem associated with applying regression analysis entails the assumption that the values of α and β are constant through the observation period. If we will use the Kalman filter technique, we can notice how α and β change stochastically over time. Concerning the scale, we can also determine whether returns will diminish, remain constant, and increase in each case. Therefore, we use state-space models with constraints for the state variables under the same supposition of the linear regression analysis.

Observation equation:

$$\ln \tilde{Y}_t = \ln \tilde{A}_t + \tilde{\alpha}_t \ln K_t + \tilde{\beta}_t \ln L_t + \tilde{e}_t = \lambda + \gamma \tilde{T}_t + \tilde{\alpha}_t \ln K_t + \tilde{\beta}_t \ln L_t + \tilde{e}_t \quad \ldots 10)$$

$$(\because \ln A_t = \lambda + \gamma T_t)$$

State equation:

$$\ln \tilde{A}_t = \phi \ln \tilde{A}_{t-1} + \tilde{\varepsilon}_{\ln A_t, t} \ldots 11)$$

$$\tilde{\alpha}_t = \varphi_1 \tilde{\alpha}_{t-1} + \tilde{\varepsilon}_{\alpha,t} \ldots 12)$$

$$\tilde{\beta}_t = \varphi_2 \tilde{\beta}_{t-1} + \tilde{\varepsilon}_{\beta,t} \ldots 13)$$

State constraints:

$$\tilde{\alpha}_t + \tilde{\beta}_t + \tilde{\varepsilon}_{c,t} = 1 \ldots 14)$$

The Solow–Cobb–Douglas production function in the Observation Equation 10 is linearized by taking a natural log for state variables with given technological progress, while State Equation 11 reveals the state variables indicating technological progress. State Equations 12 and 13 are state variables indicating the contribution ratio to the output of capital $\tilde{\alpha}_t$ and labor $\tilde{\beta}_t$, respectively. State Constraint Equation 14 is almost true for the constant returns to scale concept.

EMPIRICAL RESULTS

First, we conduct an empirical analysis of the Solow–Cobb–Douglas production function using a multiple regression analysis. The databases of these analyses are based on World Bank national accounts data and OECD national accounts data files. The data period is from 1990 to 2019, on an annual basis. We divide the data period into three from 1990 to 1999, 2000 to 2009, and 2010 to 2019 to observe the trend of change in technological progress. Table 1 shows that the coefficients of λ, T_t, and ln K_t are significant at the 5% confidence level, except for ln K_t, from 2000 to 2009 and λ, T_t, and ln K_t and from 2010 to 2019. In addition, the adjusted R-squared value in each case shows a relatively high level in their figures. Here, A_t, which is a proxy variable for technological progress, shows a 1.61% increase over the past three decades (from 1990 to 2019). Strictly speaking, the first decade (from 1990 to 1999) shows a 2.77%, however, the second decade (from 2000 to 2009) shows a 1.02% increase, and the third decade (from 2010 to 2019) showed a 2.71% decrease.

After the collapse of the bubble economy in 1990, Japanese companies intentionally increased their retained earnings owing to a huge loss of investment activities.

In particular, A_t marked a 2.77% increase, implying that the technological progress rate was constant from 1990 to 1999 with more research

Table 1: Multiple Regression Analysis: Japan

Period	Variable	Coefficient	Standard Error	t-Statistic	Prob.	R-squared	Adj. R-squared	A_t
1990-2019	λ	-11.7769	0.7014	-16.7895	0.0000	0.9443	0.9402	0.0161
	T_t	0.4977	0.0273	18.2001	0.0000			
	$\ln K_t$	0.5205	0.0596	8.7271	0.0000			
1990-1999	λ	-8.5793	1.0454	-8.2069	0.0001	0.9839	0.9793	0.0277
	T_t	0.3751	0.0400	9.3686	0.0000			
	$\ln K_t$	0.6517	0.0785	8.3051	0.0001			
2000-2009	λ	-11.9443	3.3721	-3.5421	0.0094	0.7994	0.7421	0.0102
	T_t	0.4986	0.1290	3.8645	0.0062			
	$\ln K_t$	0.3421	0.1978	1.7299	0.1273			
2010-2019	λ	-13.5178	10.5134	-1.2858	0.2394	0.9160	0.8920	-0.0271
	T_t	0.5684	0.3926	1.4476	0.1910			
	$\ln K_t$	0.6234	0.5112	1.2195	0.2621			

Table 2: Multiple Regression Analysis: U.S.A.

Period	Variable	Coefficient	Standard Error	t-Statistic	Prob.	R-squared	Adj. R-squared	A_t
1990-2019	λ	-9.9290	0.8107	-12.2468	0.0000	0.9963	0.9961	0.0207
	T_t	0.3937	0.0279	14.0988	0.0000			
	$\ln K_t$	0.1166	0.0637	1.8292	0.0784			
1990-1999	λ	-6.9466	3.8338	-1.8119	0.1129	0.9905	0.9878	0.0189
	T_t	0.2831	0.1366	2.0728	0.0769			
	$\ln K_t$	0.1925	0.2119	0.9087	0.3937			
2000-2009	λ	-11.0810	0.8936	-12.3998	0.0000	0.9915	0.9891	0.0204
	T_t	0.4414	0.0328	13.4632	0.0000			
	$\ln K_t$	0.2338	0.0524	4.4641	0.0029			
2010-2019	λ	-5.3368	0.7698	-6.9323	0.0002	0.9990	0.9987	0.0104
	T_t	0.2328	0.0273	8.5112	0.0001			
	$\ln K_t$	0.3565	0.0350	10.1897	0.0000			

and development (R&D)-intensive investments. In addition, the values of A_t decrease after 2000 lies in the shift from capital-intensive to labor-intensive with the consideration of employment. Another reason is that companies save retained earnings with fewer investments.

Table 2 shows that the coefficients of λ, T_t, and $\ln K_t$ are significant at the 5% confidence level, except for $\ln K_t$, from 1990 to 2019 and λ and $\ln K_t$, from 1990 to 1999. In addition, the adjusted. R-square value in each case shows a relatively high level in their figures. Here, A_t shows a 2.07% increase over the past three decades (from 1990 to 2019). Strictly speaking, the first decade (from 1990 to 1999) shows a 1.89% increase; however, the second decade (from 2000 to 2009) shows a 2.04% increase, and the third decade (from 2010 to 2019) shows a 1.04% increase.

Therefore, the value of A_t fluctuates each decade under the steady technological progress rate of T_t. However, the values of the coefficient in $\ln K_t$ increase in each decade for the growth of labor productivity.

Table 3 shows that the coefficients of λ, T_t, and $\ln K_t$ are significant at the 5% confidence level, except for $\ln K_t$, from 1990 to 1999 and λ, T_t, and $\ln K_t$, from 2010 to 2019. In addition, the adjusted R-square value in each case shows a relatively high level in their figures. Here, A_t shows a 0.90% increase over the past three decades (from 1990

Table 3: Multiple Regression Analysis: U. K.

Period	Variable	Coefficient	Standard Error	t-Statistic	Prob.	R-squared	Adj. R-squared	A_t
1990-2019	λ	-5.6623	1.2320	-4.5960	0.0001	0.9826	0.9813	0.0090
	T_t	0.2809	0.0459	6.1168	0.0000			
	$\ln K_t$	0.5454	0.1120	4.8709	0.0000			
1990-1999	λ	-18.2261	6.0863	-2.9946	0.0201	0.9325	0.9132	0.0296
	T_t	0.7890	0.2412	3.2717	0.0136			
	$\ln K_t$	0.2055	0.2924	0.7027	0.5049			
2000-2009	λ	-8.9289	1.1819	-7.5544	0.0001	0.9952	0.9938	0.0195
	T_t	0.4090	0.0458	8.9227	0.0000			
	$\ln K_t$	0.4146	0.0664	6.2410	0.0004			
2010-2019	λ	16.3518	15.7524	1.0381	0.3338	0.4772	0.3278	-0.0114
	T_t	-0.5922	0.6162	-0.9611	0.3685			
	$\ln K_t$	1.0389	0.5645	1.8404	0.1083			

Table 4: Multiple Regression Analysis: Germany

Period	Variable	Coefficient	Standard Error	t-Statistic	Prob.	R-squared	Adj. R-squared	A_t
1990-2019	λ	-5.2687	0.7980	-6.6020	0.0000	0.9698	0.9675	0.0117
	T_t	0.2564	0.0293	8.7516	0.0000			
	$\ln K_t$	0.6586	0.0844	7.8057	0.0000			
1990-1999	λ	-3.4517	1.3435	-2.5692	0.0371	0.9729	0.9651	0.0092
	T_t	0.1883	0.0515	3.6555	0.0081			
	$\ln K_t$	0.7915	0.1157	6.8391	0.0002			
2000-2009	λ	16.3003	2.1287	-7.6576	0.0001	0.9907	0.9881	0.0543
	T_t	0.6778	0.0802	8.4559	0.0001			
	$\ln K_t$	0.2008	0.1171	1.7156	0.1299			
2010-2019	λ	7.2453	2.3297	3.1099	0.0171	0.8808	0.8468	-0.0069
	T_t	-0.2306	0.0902	-2.5579	0.0377			
	$\ln K_t$	0.8159	0.0965	8.4547	0.0001			

to 2019). Strictly speaking, the first decade (from 1990 to 1999) shows a 2.96% increase; however, the second decade (from 2000 to 2009) shows a 1.95% increase, and the third decade (from 2010 to 2019) shows a 1.14% decrease.

The value of A_t decreases in each decade. However, the values of the coefficient in $\ln K_t$ increase in each decade for the growth of labor hours, and not productivity in the UK case.

Table 4 shows that the coefficients of λ, T_t, and $\ln K_t$ are significant at the 5% confidence level, except for $\ln K_t$, from 2000 to 2009. In addition, the adjusted R-square value in each case shows a relatively high level in their figures. Here, A_t shows a 1.17% increase over the past three decades (from 1990 to 2019). Strictly speaking, the first decade (from 1990 to 1999) shows a 0.92% increase; however, the second decade (from 2000 to 2009) shows a 5.43% increase, and the third decade (from 2010 to 2019) shows a 0.69% decrease. The value of A_t fluctuates in each decade. However, the values of the coefficient in $\ln K_t$ fluctuate in each decade. Germany's Industry 4.0, will lead to the growth of labor productivity.

Table 5 shows that the coefficients of λ, T_t, and $\ln K_t$ are significant at the 5% confidence level, except for λ from 1990 to 2019, $\ln K_t$ from 1990 to 1999, and λ, T_t, and $\ln K_t$ from 2010 to 2019. In addition, the adjusted R-square value in each case shows a relatively high level in their figures.

Table 5: Multiple Regression Analysis: French

Period	Variable	Coefficient	Standard Error	t-Statistic	Prob.	R-squared	Adj. R-squared	A_t
1990-2019	λ	-3.3206	2.2531	-1.4738	0.1520	0.9793	0.9778	0.00036
	T_t	0.1798	0.0875	2.0546	0.0500			
	ln K_t	0.5652	0.1184	4.7726	0.0001			
1990-1999	λ	-23.8272	8.6885	-2.7424	0.0290	0.7987	0.7412	-0.0061
	T_t	0.9877	0.3495	2.8257	0.0260			
	ln K_t	-0.2478	0.2663	-0.9306	0.3830			
2000-2009	λ	-9.2342	1.3352	-6.9160	0.0002	0.9984	0.9979	0.00349
	T_t	0.4166	0.0524	7.9452	0.0001			
	ln K_t	0.4353	0.0574	7.5743	0.0001			
2010-2019	λ	-7.7175	11.8188	-0.6530	0.5350	0.7543	0.6841	0.00017
	T_t	0.3588	0.4657	0.7706	0.4660			
	ln K_t	0.6429	0.3602	1.7848	0.1180			

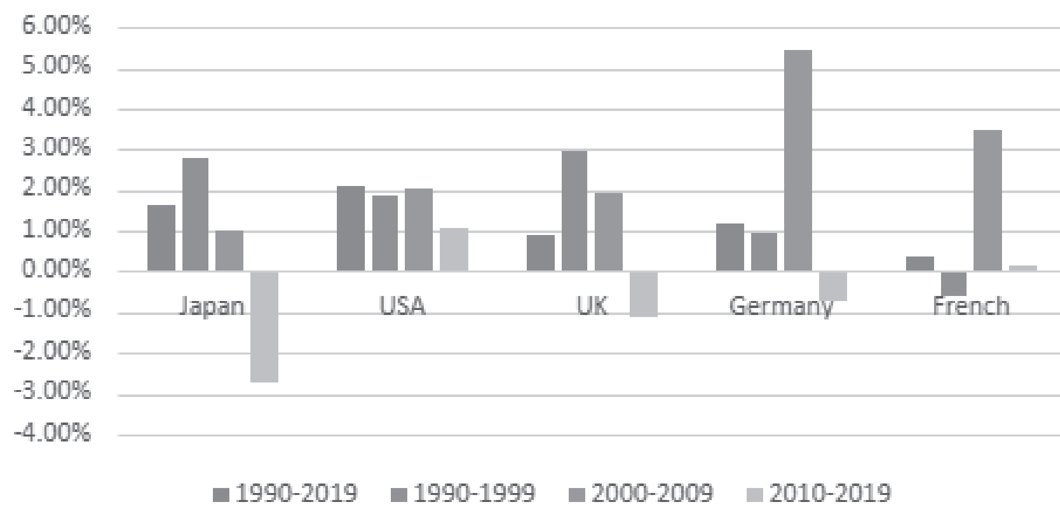

Figure 1: Technological Progress and A_t

Here, A_t shows a 0.36% increase over the past three decades (from 1990 to 2019). Strictly speaking, the first decade (from 1990 to 1999) shows a 0.61% decrease; however, the second decade (from 2000 to 2009) shows a 3.49% increase, and the third decade (from 2010 to 2019) shows a 0.17% increase.

The value of A_t fluctuates in each decade. However, the values of the coefficient in ln K_t increase in each decade for the AI investment strategy of the French government.

The following Figure 1 summarizes the above-mentioned empirical results graphically.

Some countries, such as Japan, the UK, and Germany, show a decrease from 2010 to 2019.

However, constant technological progress can be observed in every country from 1990 to 2019.

Meanwhile, we can show the results of the Kalman filter technique as follows:

Basically, the database and method of analysis are the same as in the multiple regression analysis that we conduct here. The results of the state variables in Japan are shown in Table 6. For example, the final states of the estimated values of the state variables are LN_TP_Y_ and ALPHA, respectively. In the past three decades, the mean of LN_TP_Y_ is 1.3176, the root-mean square error is 0.0936, and the z-statistic is 1.3176/0.0936 = 14.0779. The mean of ALPHA is 0.8855, the root-mean square error

Table 6: Kalman Filter Analysis : Japan

Period	Variable	Final State	RMSE	z-Statistic	Prob.
1990-2019	LN_TP_Y_	1.3176	0.0936	14.0779	0.0000
	ALPHA	0.8855	0.1204	7.3569	0.0000
1990-1999	LN_TP_Y_	1.2256	0.0886	13.8385	0.0000
	ALPHA	0.8912	0.1316	6.7709	0.0000
2000-2009	LN_TP_Y_	1.0354	0.1326	7.8109	0.0000
	ALPHA	0.3779	0.1701	2.2216	0.0263
2010-2019	LN_TP_Y_	1.4660	0.0675	21.7226	0.0000
	ALPHA	1.0772	0.0919	11.7199	0.0000

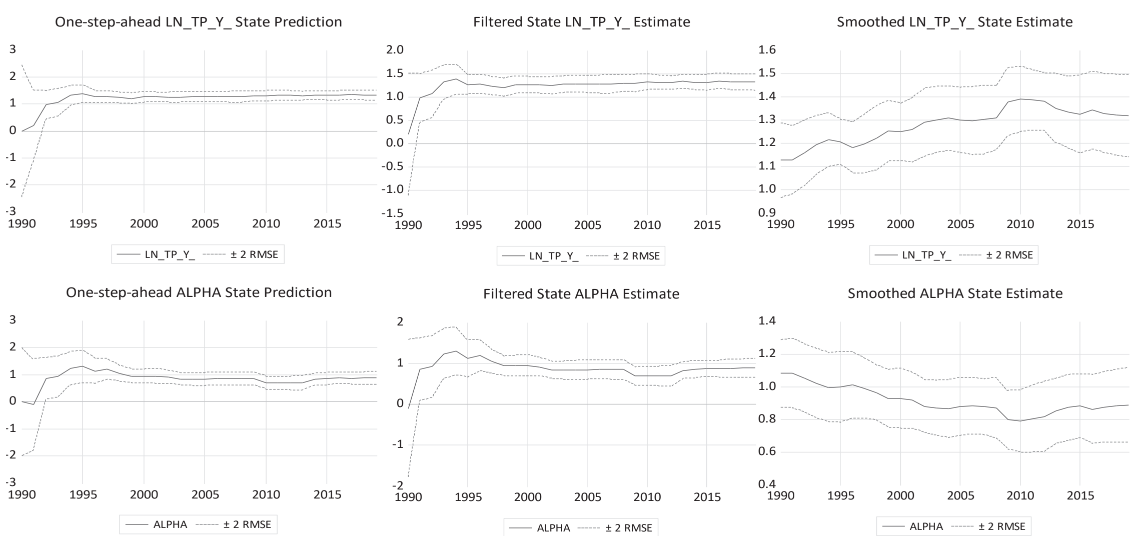

Figure 2: Three Estimates of States Variables: Japan (1990–2019)

is 0.1204, and the z-statistic is 0.8855/0.1204 = 7.3569. Judging from the values of the final state in each decade, the mean of LN_TP_Y_ is 1.4660 and the mean of ALPHA is 1.0772 in the third decade (from 2010 to 2019). Thus, we can surmise that technological progress by AI is conspicuous from the value of LN_TP_Y_, and the capital-intensive trend can be seen from the value of ALPHA in the third decade by the increase of labor productivity.

There are three types of estimated values for the state variables. These are the one-step-ahead predicted states, filtered state estimates, and smoothed state estimates. For example, one-step-ahead predicted states predict the mean and variance of the state variables at time *t* using information at time *t*-1. Filtered state estimates calculate the mean and variance of state variables in time *t* by using the information at time *t*. Smoothed state estimates also calculate the mean and variance of state variables in time *t* by using the information at time *T*. Concerning the figures of the three estimates of state variables, we omit each decade's results due to space limitations. In other words, we refer only to the past three decades.

The means of state variables such as LN_TP_Y_ and ALPHA can be depicted by the time series graphs of the ±2×Root MSE from Figure 2. More precisely, one-step-ahead is an initial next-period prediction, and the filtered state filters the one-step-ahead prediction.

The predicted states at this moment and the smoothed state trace back all the periods from the final period. Thus, for practical convenience, we mainly refer to the movements of a smoothed state.

Table 7: Kalman Filter Analysis: U.S.A

Period	Variable	Final State	RMSE	z-Statistic	Prob.
1990-2019	LN_TP_Y_	0.8187	0.0157	52.2559	0.0000
	ALPHA	0.1587	0.0139	11.4170	0.0000
1990-1999	LN_TP_Y_	0.6963	0.1552	4.4865	0.0000
	ALPHA	0.3881	0.1262	3.0767	0.0021
2000-2009	LN_TP_Y_	0.5849	0.1122	5.2138	0.0000
	ALPHA	0.1274	0.0838	1.5209	0.1283
2010-2019	LN_TP_Y_	1.0952	0.0783	13.9793	0.0000
	ALPHA	0.4852	0.0860	5.6432	0.0000

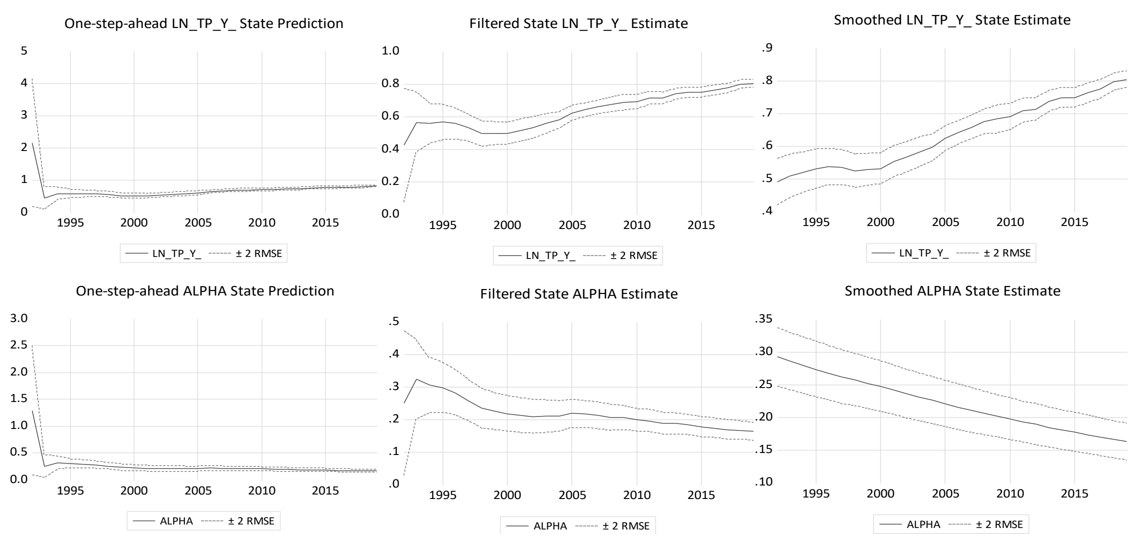

Figure 3: Three Estimates of States Variables: U.S.A (1990–2019)

From Figure 2, it is evident that the smoothed state estimate in LN_TP_Y_ gradually increases from 1990 to 2010 and decreases from 2010 to 2019. However, the smoothed state estimate in ALPHA decreases from 1990 to 2010 and increases from 2010 to 2019. This is because LN_TP_Y_ expands steadily around R&D until 2010, and supports technological progress. However, after 2010, it grows at a sluggish pace. ALPHA decreases for companies that have saved retained earnings with less investments from 1990 to 2010. However, investments grow from 2010 to 2019.

Based on Table 7 and Figure 3., the value of LN_TP_Y_ increases with R&D and AI progress from 1990 to 2019 in the United States. In addition, the value of ALPHA increases with an increase in labor productivity and investment. This leads to economic growth and an improvement in the employment environment.

Based on the data in Table 8 and Figure 4, the value of LN_TP_Y_ maintains a high value from 1990 to 2019. However, this means that the high value of LN_TP_Y_ from 2000 to 2009 lies in R&D investments. However, ALPHA increases with an increase in labor productivity and investment from 2000 to 2009.

Based on Table 9 and Figure 5, the value of LN_TP_Y_ is stagnant due to the high level of R&D investment. The value of ALPHA increases because of the increase in labor productivity and investment since 1990. This coincides with the EU's lowest unemployment rate.

Based on Table 10 and Figure 6, the value of LN_TP_Y_ increases constantly from 1990 to 2019.

Table 8: Kalman Filter Analysis: U.K.

Period	Variable	Final State	RMSE	z-Statistic	Prob.
1990-2019	LN_TP_Y_	1.3623	0.0901	15.1234	0.0000
	ALPHA	0.7098	0.0825	8.6023	0.0000
1990-1999	LN_TP_Y_	0.3597	0.1304	2.7577	0.0058
	ALPHA	-0.0336	0.0990	-0.3395	0.7342
2000-2009	LN_TP_Y_	1.3794	0.0773	17.8457	0.0000
	ALPHA	0.6377	0.0588	10.8531	0.0000
2010-2019	LN_TP_Y_	0.5297	0.0617	8.5798	0.0000
	ALPHA	0.0000	0.0000	0.0000	1.0000

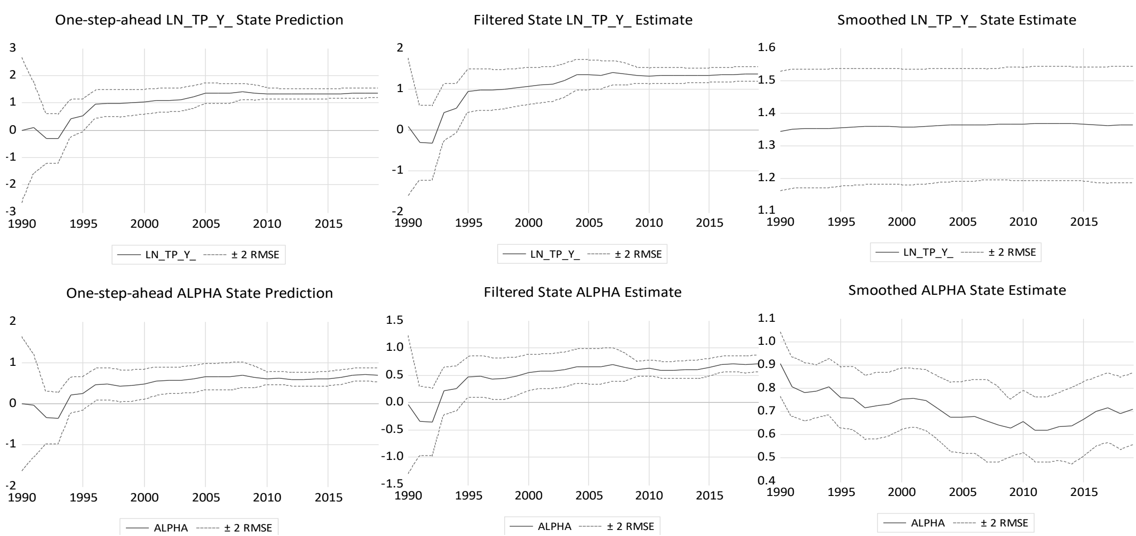

Figure 4: Three Estimates of States Variables: U.K. (1990–2019)

Table 9: Kalman Filter Analysis: Germany

Period	Variable	Final State	RMSE	z-Statistic	Prob.
1990-2019	LN_TP_Y_	1.1795	0.0596	19.7917	0.0000
	ALPHA	0.6555	0.0633	10.3629	0.0000
1990-1999	LN_TP_Y_	0.1713	0.0718	2.3851	0.0171
	ALPHA	0.0000	0.0000	0.0000	1.0000
2000-2009	LN_TP_Y_	1.1381	0.1242	9.1617	0.0000
	ALPHA	0.5168	0.1164	4.4397	0.0000
2010-2019	LN_TP_Y_	1.1675	0.0687	16.9998	0.0000
	ALPHA	0.6444	0.0642	10.0417	0.0000

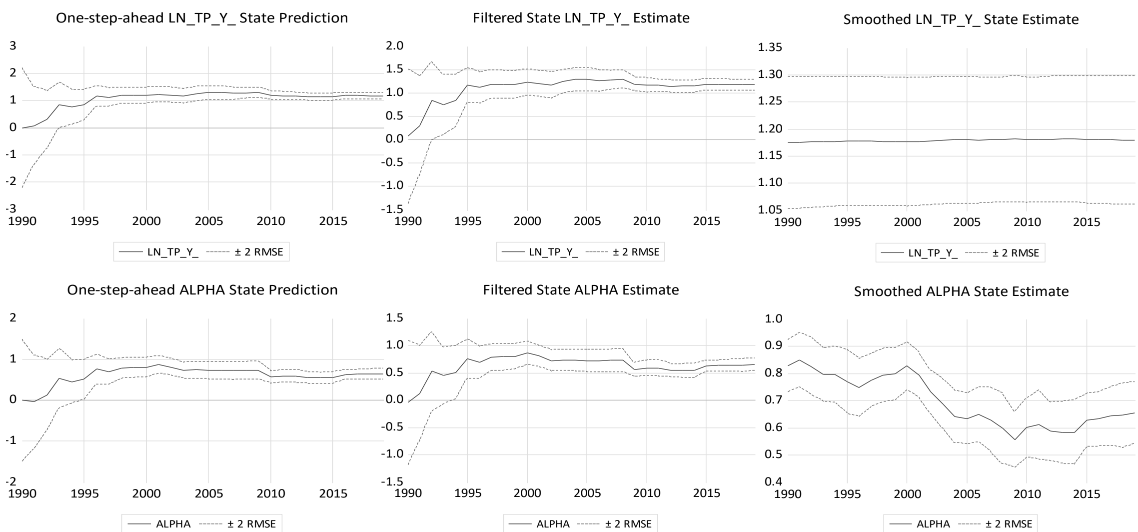

Figure 5: Three Estimates of States Variables: Germany (1990–2019)

Table 10: Kalman Filter Analysis: French

Period	Variable	Final State	RMSE	z-Statistic	Prob.
1990-2019	LN_TP_Y_	1.2335	0.0448	27.5505	0.0000
	ALPHA	0.7596	0.0653	11.6369	0.0000
1990-1999	LN_TP_Y_	0.3921	0.0325	12.0807	0.0000
	ALPHA	0.0150	0.0523	0.2862	0.7747
2000-2009	LN_TP_Y_	1.2188	0.0517	23.5713	0.0000
	ALPHA	0.5960	0.0699	8.5229	0.0000
2010-2019	LN_TP_Y_	1.2898	0.0619	20.8516	0.0000
	ALPHA	0.8316	0.0811	10.2566	0.0000

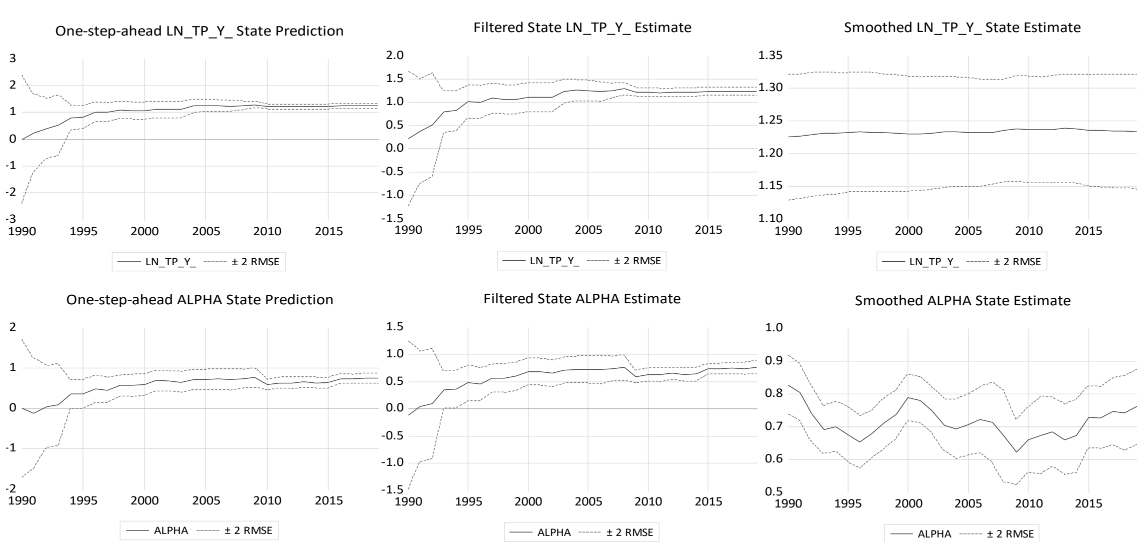

Figure 6: Three Estimates of States Variables: French (1990–2019)

In particular, the AI investment strategy implemented by the French government has been effective since 2018. The value of ALPHA also increases constantly with an increase in labor productivity and investment from 1990 to 2019.

THE FUTURE OF AI

Notably, AI will make predictions cheaper, faster, and more accurate with the progress of deep learning using neural network systems. It is well known that when the accuracy of predictions exceeds a certain threshold, it will have a profound impact on the strategy. Furthermore, AI will understand, interpret, and mimic human emotions sooner than later, and it will eventually replace human-to-human interactions. People who use these emotions will have an interest in privacy intrusion and manipulation. As AI progresses, it will depend less on bottom-up big data and more on top-down reasoning, which mimics the way humans approach problems and tasks. This trend will make it possible to apply AI more widely than ever before, creating opportunities for early adopters, even in businesses and activities wherein AI has previously seemed inappropriate.

CONCLUSION

We use the TFP concept as a proxy variable of the Solow–Cobb–Douglas production function's coefficient, A_t.

Through the Solow–Cobb–Douglas production function, we examine the degree of AI innovations that contribute to technological progress in five advanced countries by using multiple regression analysis and the Kalman filter technique.

Although multiple regression analysis only analyzes the data at one point in time, the Kalman filter technique analyzes the data throughout the entire period. Thus, we note that the Kalman filter technique reinforces the data analyses made via multiple regression analysis in this study.

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