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Empirical Analysis of the Automation-Augmented Solow Growth Model and Income Differences in the South Korean Economy

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ABSTRACT

The integration of automation into production processes is emerging as a transformative force, impacting economic growth, labor market structures, and broader economic landscapes. Prettner's automation-augmented Solow Growth Model provides a novel theoretical framework for analyzing the role of automation capital in economic production, offering insights into its effects on both economic growth and income disparities between workers and business owners. This study investigates the impact of automation on economic growth and income inequality in South Korea, applying Prettner's automation-augmented Solow Growth Model. By incorporating automation capital into the production function, this model helps elucidate the broader economic implications of automation. South Korea, with its advanced manufacturing sector and rapid technological adoption, serves as an ideal case for examining these dynamics. Using time series data from 2011 to 2019 and the Ordinary Least Squares (OLS) method, our analysis reveals a positive correlation between automation capital and economic growth, highlighting automation's role in driving South Korea's economic progress. While the link between automation and income inequality is less clear, the study suggests that automation has the potential to significantly influence economic structures in South Korea. This emphasizes the need for further research to fully understand these relationships and inform policy decisions.

Keywords: Economic Growth, Automation, Labor Market, Empirical Analysis, Inequality

1. Introduction

In recent years, advancements in cutting-edge technologies, particularly in artificial intelligence (AI), have driven a significant shift across industries towards the adoption of automated systems over traditional human labor. This transformation is profoundly reshaping the landscape of global economic dynamics, prompting a reevaluation of established economic growth theories. Central to these discussions is the recognition of automation's pivotal role in transforming

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production processes and labor markets worldwide. Within the framework of economic growth theory, emphasis has traditionally been placed on human capital deepening and educational attainment to foster sustainable economic growth (Romer, 1990). Models such as the neoclassical Solow-Swan growth model (1956) have posited that economies converge towards a steady state where growth is driven primarily by exogenous technological advancements and investments in physical capital. However, with the introduction of automation in production processes, these traditional frameworks are facing increasing scrutiny regarding their relevance in explaining contemporary economic dynamics.

Of particular interest is the case of South Korea, a nation renowned for its heavy reliance on manufacturing industries and its leadership in transforming the labor market through automated systems. Korea's unique economic profile is characterized by a manufacturing-intensive economy and a significant presence in global exports. In the first quarter of 2024, the manufacturing sector accounted for 27% of South Korea's Gross Domestic Product (GDP), highlighting the central role of manufacturing in its economy, especially in electronics, automotive, and shipbuilding. (Statistics Korea, 2024a) However, the country faces demographic challenges, including the lowest birth rate among developed countries, with only 0.72 infants per mother, making it an exceptional case study for analyzing the impact of automation on economic growth and labor dynamics (Statistics Korea, 2024b). The robust manufacturing sector, coupled with a strategic emphasis on technological advancement, underscores South Korea's prominence in global discussions on automation and economic growth. This understanding is crucial for developing sustainable economic growth strategies and economic policies aimed at addressing income inequality in South Korea.

The discourse on economic growth has been significantly advanced by Prettner’s introduction of the automation-augmented version of neoclassical growth model (Prettner 2016). Prettner's model distinguishes between traditional capital and automation capital, treating automation capital as a perfect substitute for labor and an imperfect substitute for traditional capital within the production function. This theoretical framework asserts that continuous internal investments in automation capital alone can potentially drive perpetual economic growth, challenging the conventional emphasis on exogenous technological advancements as the primary driver of growth. Moreover, Prettner's analysis highlights not only the diminishing share of labor income but also the implications for wealth polarization in developed economies. By elucidating the role of automation in transforming production dynamics and factor returns, his model provides a foundational framework for understanding the broader impacts of automation on income inequality and wealth distribution.

Against the backdrop of South Korea's demographic challenges, including its record-low birth rate and significant income inequality, this paper aims to explore the impact of automation on

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overall output and economic dynamics. Additionally, it examines how the augmented model and its variables contribute to income inequality and wealth polarization within the Korean context.

2. Theoretical Framework

2.1. Prettner's Automation-Augmented Solow-Swan Growth Model

Over the years, numerous attempts have been made to explain the perpetual growth in developed economies. Solow (1956) attributed this growth to technological advancements as an exogenous variable, treating it as a public good for economies. In contrast, Shell (1967) defined technological advancements as a government imputed public good rather than a global public good. Romer (1990) suggested that human capital drives economic growth, which in turn fosters either effective labor or technological advancements. However, this paper follows the theoretical framework developed by Prettner (2016), the Automation-Augmented Solow-Swan Growth Model, to explore the relationship between the automation substituting traditional human labor and economic growth, and its potential impact on the income disparity between labor and employers.

According to Prettner (2016), there are two types of capital: traditional capital and automation capital. Traditional capital includes machinery and assembly lines, while automation capital encompasses robots and AI technology that replace human labor. Assuming time t evolves continuously and the workforce grows at rate n, with both types of accumulated capital depreciating at rate δ, the aggregate production function for an economy is defined as:

$$Y(t) = A(t)[L(t) + P(t)]^{1-\alpha} K(t)^{\alpha}, \tag{1}$$

where $Y(t)$ is aggregate output, $L(t)$ is labor, $P(t)$ is accumulated automation capital, $K(t)$ is the accumulated traditional capital, α is the elasticity of output with respect to traditional capital, and $A(t)$ denotes the level of technology, which has been normalized to 1 to isolate the effect of automation on the potential for perpetual economic growth.

Assuming perfect competition, where factor prices equal their marginal products, the factor rewards are:

$$w(t) = MPL = (1-\alpha)[\frac{K(t)}{L(t)+P(t)}]^{\alpha} \tag{2}$$

$$r_p(t) = MPP - \delta = w(t) - \delta = (1-\alpha)[\frac{K(t)}{L(t)+P(t)}]^{\alpha} - \delta \tag{3}$$

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$$r_k(t) = MPK - \delta = \alpha[\frac{L(t)+P(t)}{K(t)}]^{1-\alpha} - \delta \tag{4}$$

where $w(t)$ is wage rate, $r_p(t)$ is the interest rate for automation capital, and $r_k(t)$ is the interest rate for traditional capital (see Appendix A.1 for deriving equation (2) and (4)).

The no-arbitrage condition ensures that the returns on both types of capital are equalized, reflecting state of market equilibrium:

$$r_p(t) = r_k(t) \tag{5}$$

Equating the interest rate for both capitals and solving for $P(t)$ and $K(t)$,

$$P(t) = \frac{1-\alpha}{\alpha}K(t) - L(t) \tag{6}$$

$$K(t) = \frac{\alpha}{1-\alpha}(P(t)+L(t)) \tag{7}$$

Substituting the equation for traditional capital from equation (5) into the aggregate production function yields:

$$Y(t) = (\frac{\alpha}{1-\alpha})^{\alpha}(L(t)+P(t)), \tag{8}$$

This positive relationship between the accumulated stock of automation capital and the output. This indicates that with sufficient levels of savings, leading to continuous investment in automation capital, there is a possibility for perpetual growth and long-term growth if a positive accumulation rate of automation capital is maintained (see Appendix A.2 for deriving equation (8)).

Dividing the equation by the labor force to yield per capita GDP we get

$$y(t) = (\frac{\alpha}{1-\alpha})^{\alpha}(1+p(t)), \tag{9}$$

where $p(t)$ denotes the automation density, the number of automation capital in relation to the production (Abeliansky & Prettner 2023).

The following can be obtained by separating the production function from logs:

$$\ln y(t) = \ln(1+p(t)) + \alpha \ln(\frac{\alpha}{1-\alpha}) \tag{10}$$

Differentiating the production function with respect to time and simplifying it,

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$$\frac{y'(t)}{y(t)} = \frac{p(t)}{1+p(t)} \cdot \frac{p'(t)}{p(t)} \tag{11}$$

$$y_g = \frac{p(t)}{1+p(t)} \cdot p_g, \tag{12}$$

where y_g represents the growth rate of output and p_g denotes the growth rate of automation density. The model assumes that automation capital and labor are perfect substitutes for each other and that the returns to factor inputs are equal to their respective marginal products. These assumptions establish the link between automation capital and economic growth.

2.2. Impact of automation on labor compensation and inequality

A growing body of literature has explored the impact of automation on labor compensation and inequality, showing that automation has contributed to the decline of the labor share over recent decades (Charalampidis, 2020). Understanding this trend is a crucial macroeconomic challenge. Karabarbounis and Neiman (2014) argue that the decrease in the relative price of investment goods has led firms to substitute labor with capital inputs, accounting for half of the decline in the labor share. Building on this, Prettner (2016) proposes a theoretical negative relationship between the accumulation of automation capital and the labor share of income, as demonstrated by the following:

$$w(t)L(t) = (1-\alpha)[\frac{K(t)}{L(t)+P(t)}]^{\alpha}L(t) \tag{13}$$

$$LS = \frac{w(t)L(t)}{Y(t)} = (1-\alpha)\frac{L(t)}{L(t)+P(t)}, \tag{14}$$

where LS represents the labor income share, which is observed to decrease with the accumulation of automation capital.

2.3. Expansion of the Model:

This paper extends the model to address income differences by examining variations in factor returns. We make the following assumptions:

1. Employers derive returns from both traditional capital $K(t)$ and automation capital $P(t)$, while workers receive income solely from their labor, represented by wages $w(t)$.
2. Traditional capital $K(t)$ and automation capital $P(t)$ are accumulated and owned by the employers. Since automation capital substitutes for labor, it shifts the income distribution away from labor towards capital.

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3. As automation capital increases, the proportion of total income allocated to labor diminishes due to the reduced reliance on human labor and a greater dependence on automated processes.

In our case, the aggregate labor income, interest rate of traditional capita, and interest rate of automation capital are given by

$$w(t)L(t) = (1-\alpha)[\frac{K(t)}{L(t)+P(t)}]^{\alpha}L(t) \tag{15}$$

$$r_p(t)P(t) = (1-\alpha)[\frac{K(t)}{L(t)+P(t)}]^{\alpha}P(t) - \delta P(t) \tag{16}$$

$$r_k(t)K(t) = \alpha[\frac{L(t)+P(t)}{K(t)}]^{1-\alpha}K(t) - \delta K(t) \tag{17}$$

From equation (14), (15), and (16), the resulting difference in aggregate labor income and aggregate capital return are given as:

$$\Delta I = w(t)L(t) - [r_p(t)P(t) + r_k(t)K(t)], \tag{18}$$

where *ΔI* is the income share difference between employers and labor.

As of the no-arbitrage condition, letting $r_p(t) = r_k(t)$ using equation 4,

$$\Delta I = w(t)L(t) - [r_p(t)P(t) + r_p(t)K(t)] \tag{19}$$

$$= w(t)L(t) - r_p(P(t)+K(t)) \tag{20}$$

$$= (1-\alpha)[\frac{K(t)}{L(t)+P(t)}]^{\alpha}L(t) - [(1-\alpha)(\frac{K(t)}{L(t)+P(t)})^{\alpha} - \delta][P(t)+K(t)] \tag{21}$$

$$= (1-\alpha)[\frac{K(t)}{L(t)+P(t)}]^{\alpha}[L(t)-P(t)-K(t)] + [P(t)+K(t)]\delta \tag{22}$$

Dividing the equation by the total output, equation 1, to get the difference of income share,

$$\Delta I_Y = (1-\alpha)\frac{L(t)-P(t)-K(t)}{L(t)+P(t)} + \frac{P(t)+K(t)}{Y(t)}\delta \tag{23}$$

For simplicity purposes, the sum of labor and automation capital is defined as auto-labor capital, and the following variables are defined:

$$L_s = \frac{L(t)}{L(t)+P(t)} = \frac{1}{1+p(t)} \tag{24}$$

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$$P_s = \frac{P(t)}{L(t)+P(t)} = \frac{p(t)}{1+p(t)} \qquad (25)$$

$$K_s = \frac{K(t)}{L(t)+P(t)} = \frac{k(t)}{1+p(t)} \qquad (26)$$

$$TK = P(t) + K(t), \qquad (27)$$

where L_s is the ratio of labor to auto-labor capital, P_s is the ratio of automation capital to auto-labor capital, K_s is the ratio of traditional capital to auto-labor capital, $p(t)$is the automation density, $k(t)$ is the capital per worker, and TK is the total capital summing both traditional and automation capital.

By taking the logs of equation 22 and then differentiating with respect to time, we obtain:

$$\Delta\Delta I = L_{sg} - P_{sg} - K_{sg} + TK_g - Y_g, \qquad (28)$$

where $\Delta\Delta I$is rate of growth of income difference, L_{sg} is growth of L_s, the ratio of labor to combined labor and automation capital P_{sg} is growth of P_s, the ratio of automation capital to combined labor and automation capital, K_{sg} is growth of K_s, the ratio of traditional capital to combined labor and automation capital, TK_g is growth of total capital, sum of $P(t)$ and $K(t)$, and Y_g is growth of aggregate output (see Appendix A.3 for derivation of equation (28)).

Thus, the change in income differences between labor and employer is associated with the variables above. This hypothesis is tested for South Korea over the period of 2011-2019 by using the Ordinary Least Squares (OLS) regression. To test the model empirically, we estimate the following approximation of equation (12) and (28):

$$y_g = \beta_0 + \beta_1 X \cdot p_g + u_t \qquad (29)$$

$$\Delta\Delta I = \beta_0 + \beta_1 L_{sg} + \beta_2 P_{sg} + \beta_3 K_{sg} + \beta_4 TK_g + \beta_5 Y_g + u_t, \quad (30)$$

where $X$is defined as $\frac{p(t)}{1+p(t)}$ and $u_t$is the error term.

Based on the theoretical considerations, for the analysis regarding the relationship between automation density and the economic growth, we expect to find a positive coefficient for xp_g, the growth of automation density multiplied with $\frac{p(t)}{1+p(t)}$, where $p(t)$ is automation density. For the analysis regarding the income differences, we expect to find a positive coefficient for change in

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labor to auto-labor capital ratio and the growth of total capital. Negative coefficient is expected for change in automation capital to auto-labor capital ratio, change in traditional capital to auto-labor capital ratio, and economic growth.

3. Methodology

The study aims to investigate the relationships given in equations (12) and (28), focusing on the variables specified in these respective equations. The research is based on macroeconomic data collected over the period 2011 to 2019, primarily sourced from the Penn World Tables (PWT) 10.1, as described in Summers and Heston (1991), and the Korean Statistical Information Service (KOSIS) (Feenstra, et al. 2015). This time period was specifically chosen to cover the 2010s South Korean economy due to relatively restricted access to data from the 2020s whilst continued growth in automation density in the economy was observed over time. Since this study exclusively examines the South Korean economy, all data were collected at the country-level.

Economic growth is taken as the log-difference of real GDP at current prices, as given in the Penn World Tables (Feenstra, et al. 2015). For Xp_g, the value of X has been calculated using equation (12), and was multiplied to the growth rate of the automation density. For income differences, the aggregate labor income and aggregate capital return has been subtracted, while the yearly average wage and yearly average interest rate has been used as proxies for labor income and capital return respectively (Exchange rates 2017). Our proxy for the industrial automation density is the industrial robot density, which has been collected from the International Federation of Robotics (IFR) database (IFR, 2011~2019). The total aggregate labor is drawn from the total labor force, the total industrial robot is used as a proxy for the total automation capital, and the investment at current national prices in machinery and (non-transport) equipment is used as a proxy for the total traditional capital (Feenstra, et al. 2015). For statistical analysis, the econometrics software Gretl was used.

Table 1.
Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
y_g	9	0.03011533028	0.00981778071	0.01875003495	0.05171322826
Xp_g	9	0.131340087	0.04407724547	0.085659378	0.2084584885
$\Delta\Delta I$	9	0.01757161002	0.05016755241	-0.07520042791	0.06699551299
L_{sg}	9	-0.1149082694	0.033354577	-0.1724137931	-0.0788863109

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P_{sg}	9	0.0002585826995	0.0001497848727	0.000127877238	0.000600744924
K_{sg}	9	-0.08669120621	0.0491782409	-0.1899557707	-0.03742834558
TK_g	9	0.04398570623	0.02437199743	-0.00393848102	0.07106015544

Note: N refers to the number of observations, and St. Dev. denotes standard deviation.

Ordinary Least Squares (OLS) regression has been employed to analyze the data. To ensure that the OLS regression results adhere to the assumptions of time-series analysis, appropriate diagnostic tests, including the Durbin-Watson test, have been conducted.

4. Results

Table 2.

Xp_g ***and economic growth rate***

Panel A. Dependent Variable: y_g			
Method: Ordinary Least Squares			
Sample: 2011 2019			
Variables	**Coefficients**	**Std. error**	**t-Statistic [p-value]**
Constant	0.030115	0.00934780	1.369 [0.2132]
Xp_g	0.131838	0.0678569	1.943 [0.0931]
Mean dependent var	0.030115	S.E. of regression	0.008460
S.D. dependent var	0.009818	Sum squared resid	0.000501
R-squared	0.350337	Akaike criterion	−58.62494
Adjusted R-squared	0.257527	Schwarz criterion	−58.23049
F (1, 7)	3.774809	Log-likelihood	31.31247
P-value (F)	0.093138	Durbin-Watson	2.171384
Panel B. Diagnostic Tests			
Ramsey RESET Test		2.083097 [0.22]	

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Breusch-Pagan Test	1.846229 [0.174223]
Chi-square(2)	0.517 [0.77210]
Mean value of residual	-2.6985e-18

Note: Lags are given in () and p-values are stated in [].

Table 3.

Income Differences Between Capital Owners and the Labor Force

Panel A. Dependent Variable: $\Delta\Delta I$

Method: Ordinary Least Squares

Sample: 2011 2019

Variables	Coefficients	Std. error	t-Statistic [p-value]
Constant	−0.146204	0.232516	−0.6288 [0.5741]
Lsg	−2.47787	3.89064	−0.6369 [0.5695]
Psg	12.9478	427.545	0.03028 [0.9777]
Ksg	2.18342	2.73377	0.7987 [0.4829]
TKg	0.0193968	0.127457	0.1522 [0.8887]
Yg	0.984435	3.15043	0.3125 [0.7751]
Mean dependent var	0.017572	S.E. of regression	0.043250
S.D. dependent var	0.050168	Sum squared resid	0.005612
R-squared	0.721287	Akaike criterion	−28.88029
Adjusted R-squared	0.256767	Schwarz criterion	−27.69694
F (5, 3)	1.552756	Log-likelihood	20.44014
P-value (F)	0.380756	Durbin-Watson	1.959111

Panel B. Diagnostic Tests

Ramsey RESET Test	nan
Breusch-Pagan Test	2.516259 [0.774044]
Chi-square(2)	0.707 [0.7022]

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Mean value of residual	3.9706e-17

Note: Lags are given in () and p-values are given in [].

5. Discussion

The primary aim of this study is to empirically examine the relationship between automation capital and economic growth and how automation may influence income disparities between capital owners and labor in South Korea during the 2010s.

For model 1, the results indicate a relatively statistically significant positive correlation between automation capital function, Xp_g, and the economic growth rate, y_g. The coefficient for Xp_g is 0.131838, with a t-statistic of 1.943 and a p-value of 0.0931. This suggests that for each unit increase in automation capital, the economic growth rate is expected to rise by approximately 0.132 units. However, this result is only marginally significant, as the p-value exceeds the conventional threshold of 0.05 but is less than 0.10, indicating a trend toward significance. Additionally, the low R-squared value of 0.3503 and the adjusted R-squared of 0.2575 suggest that the model explains only a modest portion of the variance in economic growth. This indicates that there are other influencing factors not accounted for in this model.

In terms of diagnostic tests for the assumptions of regression of time-series analysis, Ramsey RESET test (p-value = 0.22) and the Breusch-Pagan test (p-value = 0.1742) indicate no significant evidence with model specification or heteroskedasticity. The chi-square test for normality of residuals yields a p-value of 0.7721, suggesting that the residuals of the regression model do not show significant departure from a normal distribution. Therefore, we can reasonably assume that the residuals are normally distributed.

For our model 2, which explores the impact of automation on income differences between capital owners and labor, our hypothesis was ultimately rejected. Specifically, L_{sg}, was found to be negatively correlated with income differences, contrary to our hypothesis. The coefficient for this variable is −2.47787 with a p-value of 0.5695, indicating a lack of statistical significance. Although the negative coefficient might suggest that an increase in labor relative to auto-labor capital could reduce income disparities — potentially leading to a more equitable distribution of income if the labor force grows faster than automation capital (Prettner & Strulik, 2020) — the lack of statistical significance and the small sample size warrant caution in interpreting these results. The results might differ with a larger dataset or in a different context.

The relationship with P_{sg} is also similar with that of L_{sg}. The coefficient for P_{sg} is 12.9478 with a p-value of 0.9777, which goes against our hypothesis. This high p-value suggests that P_{sg} does

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not significantly impact income differences between capital owners and the labor force. Although the large positive coefficient might initially suggest that increases in automation capital relative to auto-labor capital could widen income disparities. However, the lack of statistical significance means that we cannot confidently conclude that P_{sg} has any real effect in this context. Theoretically, if automation capital grows more rapidly than automation labor, it could indicate a shift in capital intensity (Moll et al., 2022) However, in this small sample, this relationship fails to show a significant impact on income inequality. The result could be attributed to the limited data available or underlying complexities not captured by the model.

For K_{sg}, the coefficient is 2.18342 with a p-value of 0.4829. This p-value, being well above the conventional significance threshold, implies that K_{sg} does not have a statistically significant effect on income differences. Despite the positive coefficient, which could suggest that a higher ratio of traditional capital to auto-labor capital might increase income differences, the lack of significance prevents us from asserting this relationship. Theoretically, traditional capital growth relative to auto-labor capital might impact income distribution by shifting economic benefits more towards capital owners (Prettner 2016). However, the result indicates that with the available data, no clear conclusion can be drawn, also possibly due to sample size limitations or other unaccounted factors.

The coefficient for TK_g is 0.0193968 with a p-value of 0.8887, indicating that TK_g does not significantly affect income differences. The very high p-value suggests that total capital growth does not have a substantial impact on income disparities between capital owners and the labor force in this dataset. Theoretically, one might expect total capital growth to influence income distribution by putting upward pressure on the wages, thereby reducing income differences. (Eichengreen et al., 2021). However, the insignificance of the coefficient in this study could be a result of the small sample size or because the total capital growth showed little fluctuation, it becomes challenging to detect its true influence on income disparities between capital owners and the labor force, which obscures its true effect.

Ultimately, for Y_g, the coefficient is 0.984435 with a p-value of 0.7751, indicating that Y_g also does not significantly impact income differences. Despite the positive coefficient suggesting a potential link between economic growth and income disparities, the high p-value implies that this effect is not statistically significant. Theoretically, one would expect that as the economy grows, income disparities might change due to varying impacts on different economic groups. However, in the context of this study, the insignificance of the coefficient could be attributed to the limited observations and potential model specification issues, which may have masked any real relationship.

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6. Conclusion

The results of this study reveal that for our model 1, xp_g, the automation function demonstrated a weak but some correlation with economic growth. In contrast, for our model 2, none of the variables examined— L_{sg}, K_{sg}, P_{sg}, TK_g, and Y_g, —show significant impacts with minimal evidence of correlation on income differences given the data. While the theoretical expectations suggested that automation and related factors would significantly affect income disparities, the empirical results obtained with this dataset do not strongly support these hypotheses. Given the small sample size and low degrees of freedom, the reliability of these findings is limited. This study highlights the need for further research with a larger sample size and possibly a comparative analysis across different countries to better understand the dynamics between automation, economic growth, and income inequality.

Despite these methodological constraints, the positive correlation found supports the hypothesis that automation capital might be a key driver of economic growth in South Korea. The marginal statistical significance and the positive coefficient provide a preliminary basis for future research. To strengthen the findings, future studies could benefit from a larger sample size, longer time periods, and additional variables to better capture the complexities of the relationship between automation, economic growth, and income distribution.

In summary, while the current study presents evidence suggesting a potential positive impact of automation on economic growth in South Korea, it provides limited evidence for the impact of automation capital and other factors of production on income differences.The limitations associated with the small sample size and degree of freedom warrant further investigation. The results offer a valuable starting point for exploring how automation may affect economic dynamics and income disparities, emphasizing the need for more comprehensive research in this field.

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Appendix

A Derivations

A.1 Derivation of equation (2), and (4)

Using equation (1), by differentiating with respect to labor,

$$\begin{aligned}\frac{dY(t)}{dL(t)} &= \frac{d}{dL(t)}[L(t)+P(t)]^{1-\alpha}K(t)^{\alpha} + [L(t)+P(t)]^{1-\alpha}[\frac{d}{dL(t)}K(t)^{\alpha}] \\ &= (1-\alpha)[L(t)+P(t)]^{-\alpha}K(t)^{\alpha} \\ &= (1-\alpha)[\frac{K(t)}{L(t)+P(t)}]^{\alpha} \\ w(t) &= (1-\alpha)[\frac{K(t)}{L(t)+P(t)}]^{\alpha}\end{aligned}$$

for equation (3), again differentiating equation (1) with respect to traditional capital,

$$\begin{aligned}\frac{dY(t)}{dK(t)} &= \frac{d}{dK(t)}[L(t)+P(t)]^{1-\alpha}K(t)^{\alpha} + [L(t)+P(t)]^{1-\alpha}[\frac{d}{dK(t)}K(t)]^{\alpha} \\ &= [L(t)+P(t)]^{1-\alpha}\cdot\alpha K(t)^{\alpha-1} \\ &= \alpha[\frac{L(t)+P(t)}{K(t)}]^{1-\alpha}\end{aligned}$$

Recognizing the depreciation of the capital,

$$r_k(t) = \alpha[\frac{L(t)+P(t)}{K(t)}]^{1-\alpha} - \delta$$

A.2 Solving for interest rate for automation capital and traditional capital

$$\alpha[\frac{L(t)+P(t)}{K(t)}]^{1-\alpha} - \delta = (1-\alpha)[\frac{L(t)+P(t)}{K(t)}]^{1-\alpha} - \delta$$

$$\alpha[\frac{L(t)+P(t)}{K(t)}][\frac{K(t)}{L(t)+P(t)}]^{\alpha} = [\frac{K(t)}{L(t)+P(t)}]^{\alpha} - \alpha[\frac{K(t)}{L(t)+P(t)}]^{\alpha}$$

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$$\alpha[\frac{L(t)+P(t)}{K(t)}]=1-\alpha$$

$$K(t)=\frac{\alpha}{1-\alpha}(L(t)+P(t))$$

$$P(t)=\frac{1-\alpha}{\alpha}K(t)-L(t)$$

Substituting $P(t)$ and $K(t)$ into equation (1),

$$Y(t)=[L(t)+\frac{1-\alpha}{\alpha}K(t)-L(t)]^{1-\alpha}K(t)^{\alpha}$$

$$Y(t)=[\frac{1-\alpha}{\alpha}]^{1-\alpha}K(t)^{1-\alpha}\cdot K(t)^{\alpha}$$

$$Y(t)=[\frac{\alpha}{1-\alpha}]^{\alpha}(L(t)+P(t))$$

A.3 Derivation of equation (28)

$$\Delta I_Y=(1-\alpha)\frac{L(t)-P(t)-K(t)}{L(t)+P(t)}+\frac{P(t)+K(t)}{Y(t)}\delta$$

Using definitions from equation (24), (25), (26), and (27),

$$\begin{aligned}\Delta I_Y&=(1-\alpha)[\frac{L(t)}{L(t)+P(t)}-\frac{P(t)}{L(t)+P(t)}-\frac{K(t)}{L(t)+P(t)}+\frac{TK}{Y(t)}\delta\\&=(1-\alpha)[L_s-P_s-K_s]+\frac{TK}{Y(t)}\delta\end{aligned}$$

By taking logs,

$$\begin{aligned}\ln\Delta I_Y&=\ln[(1-\alpha)L_s]-\ln[(1-\alpha)P_s]-\ln[(1-\alpha)K_s]+\ln(TK)-\ln(Y(t)+\ln(\delta)\\&=-\ln(1-\alpha)+\ln(L_s)-\ln(P_s)-\ln(K_s)+\ln(TK)-\ln(Y(t)+\ln(\delta)\end{aligned}$$

Then by differentiating with respect to time,

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$$
\begin{aligned}
\frac{d \ln \Delta I_Y}{dt} &= \frac{d}{dt}\ln(L_s) - \frac{d}{dt}\ln(P_s) - \frac{d}{dt}\ln(K_s) + \frac{d}{dt}\ln(TK) - \frac{d}{dt}\ln(Y(t)) \\
&= \frac{1}{L_s}\frac{dL_s}{dt} - \frac{1}{P_s}\frac{dP_s}{dt} - \frac{1}{K_s}\frac{dK_s}{dt} + \frac{1}{TK}\frac{dTK}{dt} - \frac{1}{Y(t)}\frac{dY(t)}{dt} \\
\Delta\Delta I &= L_{sg} - P_{sg} - K_{sg} + TK_g - Y_g
\end{aligned}
$$

