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# Analysis on the Determinants of Labor Share and Its Policy Implications

Yaein Baek Associate Research Fellow, Int'l Macroeconomics Team, Int'l Macroeconomics & Finance Dept. (yibaek@kiep.go.kr)
Minsoo Han Assistant Professor, Department of International Trade, Inha University (minsoo.han@inha.ac.kr)
Wongi Kim Assistant Professor, Department of Economics, Sungshin Women's University (wgkim@sungshin.ac.kr)
Hyunsuk Kim Researcher, Int'l Macroeconomics Team, Int'l Macroeconomics & Finance Dept.

## I. Introduction

There has been a significant decline in the global labor share, leading to numerous studies about the cause of this drop. The labor share is used as one of the main indicators of inequality because a decrease in the labor share can lead to aggravation of income inequality. This is because low-skilled workers can be greatly affected by such a decline in the labor share and the main source of income for the low-income class, including the self-employed, is labor income. Among various indicators of inequality, this study analyzes the determinants of the change in labor share. Technological changes such as adoption of robots, advancements in information and communications technology (ICT) and the Fourth Industrial Revolution (4IR) are expected to change the labor market. Hence, this study analyzes the impact of technological changes on labor share and suggests policy responses.

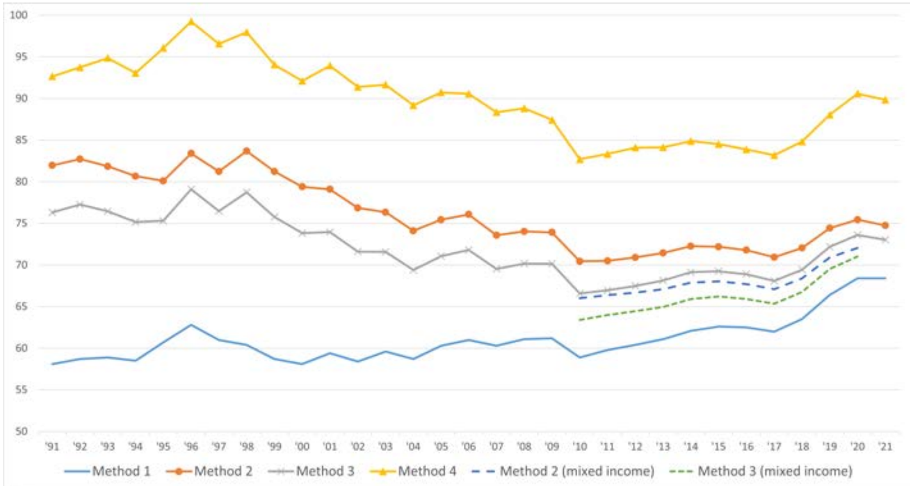
## II. The Trend of Labor Share in Korea

The definition of labor share is simple but there is a lack of consensus in its measurement, mainly due to the issue of how to handle the income of self-employed. An et al. (2019) estimates the trend of Korea's labor share using various measurement methods suggested from previous studies. Likewise, we apply the methods used in An et al. (2019) to a more recent dataset and estimate the trend of Korea's labor income share. In addition, we examined changes in the components of labor share. We address the measurement issue of income for the self-employed in two ways. First, we applied four methods proposed in previous studies to macro data and analyzed the adjusted series. The first method (Method 1 in Figure 1) is defined as the share of the compensation of employees in the national income. Gollin (2002) points out this method does not incorporate the income of self-employed workers. The second method (Method 2) is defined as the share of compensation for employees and self-employment income in the national income. The self-employment income is measured using the operating surplus of private unincorporated enterprises (OSPUE), as Gollin (2002) suggests. The third method (Method 3) is the share of the compensation of employees in the national income, subtracted by the self-employment income. Lastly, the fourth method (Method 4) assumes the average labor income of the self-employed is the same as that of wage employees. Then we separately estimate labor share using firm-level micro data in which measurement issues do not arise.

Main takeaways from these analyses are summarized as follows. First, the level and trend of the labor share in Korea change greatly when we adjust for the earnings from the self-employed. Most importantly, unlike the traditional labor share (Method 1), the adjusted series exhibit a downward trend from the mid-1990s to the financial crisis. The difference arises due to relatively stagnant OSPUE compared to rising total employee compensation. Second, short-term changes in labor share are mainly attributed to fluctuations in capital income rather than components of labor income (employee compensation and OSPUE). In particular, fluctuations in net operating profit drive variations in the labor share across time and industries. Third, statistics from various international organizations show that Korea's overall labor income share has been relatively higher than those of other countries, but the gap is narrowing due to the declining share of self-employed workers.

**Figure 1. Korea's Labor Share**

(Unit: %)




Source: Update of Figures 2-2, 2-3 in An et al. (2019)

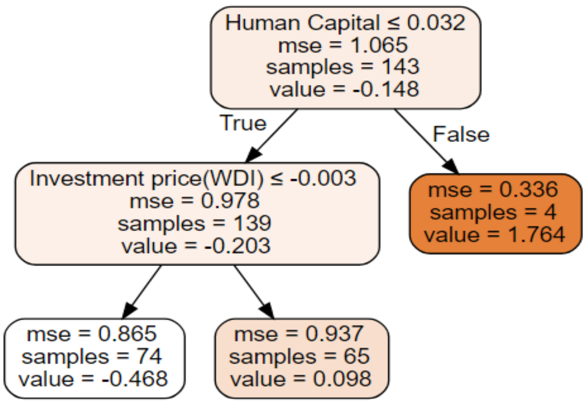
## III. Determinants of Labor Share as Predictors

Grossman and Oberfield (2022) provides an extensive literature review on the declining labor share, which highlights the main determinants of the change in labor share as being technological change, globalization, increased product market power, declining market power of workers, and demographic and education factors. We examine whether the determinants of labor share are meaningful as predictors. We estimate a regression tree model, which is a machine learning method, for forecasting labor share and obtain variables with predictive power.

Figure 2 shows the regression tree for predicting the labor share in the corporate sector (Karabarbounis and Neiman 2014) in six developed countries. The results show that human capital and the relative price of investment goods are found to be the most important. In addition, the non-linear relationship between human capital and the relative price of investment goods can be important in predicting the labor share.

Figure 3 shows the regression tree forecasting the change in labor share in developed countries (left) and emerging countries (right). Human capital and education are important in predicting the labor share in developed countries, whereas demographic change and ICT development play a key role in emerging countries.

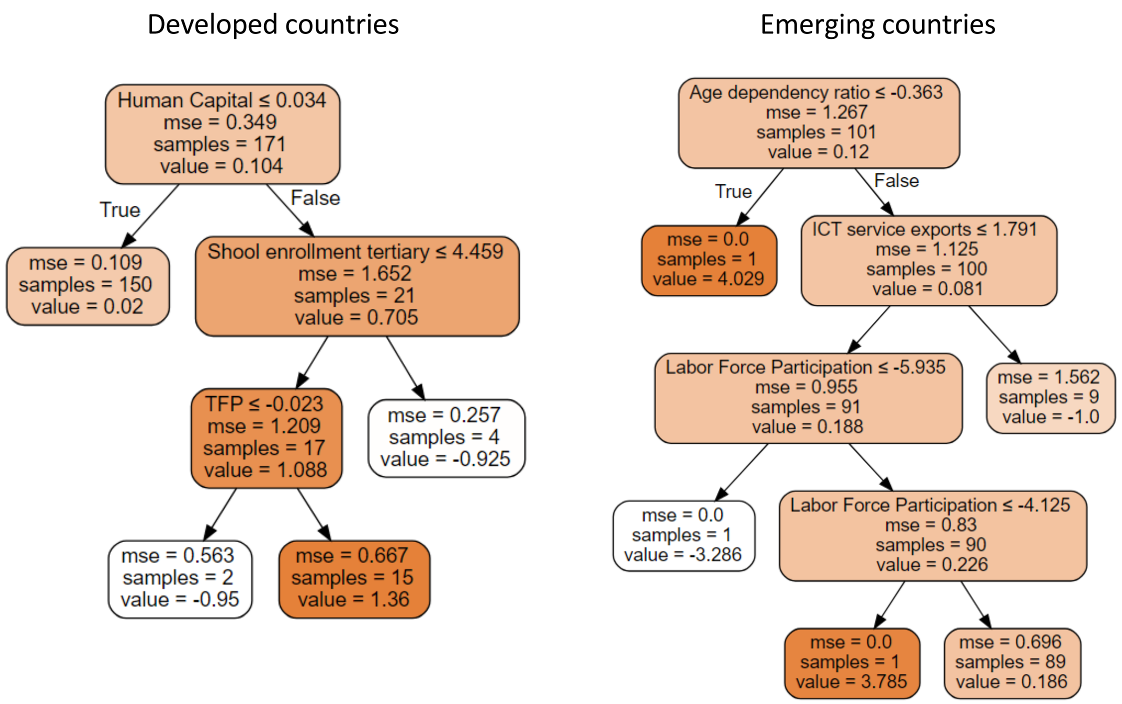
**Figure 2. Corporate Labor Share Prediction Regression Tree**




Note: Optimal minimal cost-complexity pruning parameter $\alpha = 0.0775$.
Source: Authors' calculation based on Karabarbounis and Neiman (2014), Penn World Table (PWT version 10.0), OECD Structural Analysis Database (STAN)

The regression tree model is estimated for each of the eight developed economies (South Korea, USA, Germany, Japan, France, Italy, Spain, UK). The estimation results suggest that human capital is important in five out of the eight developed countries, and the importance of ICT change varies across countries. In short, it was found that human capital and education are not only important determinants of changes in the labor share but also in prediction, and technological change such as advances in ICT are also important predictors in both advanced and emerging countries.

**Figure 3. Labor Share Prediction Regression Tree**




Note: Optimal minimal cost-complexity pruning parameter $\alpha = 0.0551$ (left), $\alpha = 0.1207$ (right).
Source: Authors' calculation based on Penn World Table (PWT version 10.0), World Development Indicator.

## IV. Robots and the Labor Market

The impact of robots on the labor market are examined by conducting empirical analysis with two different data sets. The first analysis estimates the effect of robots on labor share and labor productivity using various panel models by merging data from KLEMS and the International Federation of Robots (IFR). The following model is estimated with the annual panel data of 15 industries from 17 countries.

$$y_{i,t} = \beta robot_{ijt} + \Gamma' X_{ijt} + \alpha_{ij} + \alpha_t + \varepsilon_{ijt}$$

The second analysis studies the impact of the 4IR including robots and AI on labor share and labor productivity. The following panel model is estimated at the firm level using the company activity survey data from the National Statistical Office of Korea from 2017 to 2019.

$$y_{i,t} = \beta tech_{it} + \Gamma' X_{it} + \alpha_i + \alpha_t + \varepsilon_{it}$$

### Table 1. Panel Analysis with Country-industry Fixed Effects

| | Dependent variable: Labor Share × 100 | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | All industries | All industries | Manufacturing | Manufacturing | Country | Country |
| log(1+Robot) | -0.232** | -0.237** | -0.290** | -0.352*** | -0.522 | -0.506 |
| | (0.102) | (0.113) | (0.120) | (0.135) | (0.748) | (0.654) |
| log(wage) | 3.594*** | 4.831*** | 5.123*** | 5.171** | 3.863 | 7.071* |
| | (1.072) | (1.667) | (1.761) | (2.162) | (2.213) | (3.390) |
| log(capital price) | -3.109** | -3.225** | -5.227* | -5.897* | -3.440 | -3.064 |
| | (1.429) | (1.496) | (2.776) | (3.130) | (2.318) | (2.378) |
| log(TFP) | -0.064*** | -0.059*** | -0.068*** | -0.061*** | -0.142** | -0.093 |
| | (0.017) | (0.017) | (0.023) | (0.021) | (0.060) | (0.059) |
| Year dummy | X | O | X | O | X | O |
| obs | 4,472 | 4,472 | 2,954 | 2,954 | 306 | 306 |
| groups | 244 | 244 | 159 | 159 | 17 | 17 |

Notes: ***, **, * denote statistical significance at 1%, 5%, 10% respectively. Numbers in parentheses are robust (country-industry cluster) standard errors. In the case of (5) and (6) country-industry fixed effects are replaced with country fixed effects and robust (country cluster) standard errors are used.

Source: Authors' calculation

### Table 2. Company Activity Survey Data Panel Analysis Results

| | Dependent variable: Labor Share × 100 | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| 4th industrial technology | -0.419** | -0.374* | -0.387* | -0.369* |
| | (0.211) | (0.213) | (0.206) | (0.209) |
| log(TFP) | -0.549*** | -0.551*** | -0.553*** | -0.553*** |
| | (0.0105) | (0.0109) | (0.0110) | (0.0114) |
| log(wage) | 0.467*** | 0.469*** | 0.516*** | 0.517*** |
| | (0.0112) | (0.0118) | (0.0137) | (0.0142) |
| log(capital price) | 14.30*** | 6.951 | 68.89*** | 61.90*** |
| | (4.072) | (6.212) | (17.24) | (22.52) |
| leverage | | | 4.945* | 4.810 |
| | | | (2.989) | (2.967) |
| log(1+patent) | | | -0.257*** | -0.245*** |
| | | | (0.0662) | (0.0733) |
| log(1+exports) | | | -0.0349 | -0.0242 |
| | | | (0.0238) | (0.0229) |
| Industry, region, listing dummy | O | O | O | O |
| Year dummy | X | O | X | O |
| obs | 14,079 | 14,079 | 14,079 | 14,079 |
| groups | 6,035 | 6,035 | 6,035 | 6,035 |

Notes: ***, **, * denotes statistical significance at 1%, 5%, 10% respectively. Numbers in parentheses are robust (firm cluster) standard errors.

Source: Authors' calculation

Tables 1 and 2 show the estimation results from each of the two analyses. Both results show that the introduction of robots lowers the labor share. In addition, as robot adoption increases, labor productivity tends to improve, which implies that the use of robots and AI technology has a positive effect on labor productivity. As discussed in previous studies, the introduction of robots can have opposite effects, such as reducing employment by replacing labor (substitution effect) and increasing productivity by lowering production costs and increasing employment (productivity effect). According to our results, the fact that the adoption of robots improves labor productivity is consistent with the theoretical model in the literature and the decline in the labor share suggests that the productivity effect may be smaller than the substitution effect.

## V. Policy Implications

Based on the results of our research, we suggest labor, education and industrial policies that support human capital are required by companies in the changed technological environment. According to our empirical analysis, the benefits of technological progress are concentrated only on the high-skilled workers group, and this could lead to job losses for low-skilled workers. Therefore, efforts at the institutional level need to be put into developing the workforce in response to technological progress, toward which we suggest three policy directions. First, vocational training and lifelong learning systems should be improved so that workers can respond to the adoption of new technology at work. Second, it is necessary to enhance the flexibility of the labor market and the dynamism of the corporate sector while maintaining a strong social safety net. Lastly, it is also necessary to check the overall governance of the government for these policies to be properly implemented. KIEP

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