ORIGINAL ARTICLE

Factor Substitution Possibilities, Labor Share Dynamics, and Inequality in an Age of Intangibles

Adnan Velic

Technological University Dublin

Correspondence: Adnan Velic (adnan.velic@tudublin.ie)

Accepted: 30 December 2024

Keywords: (in)tangible capital | factor substitution | growth | income inequality | labor income shares | management | productivity | skills

ABSTRACT

We examine the economy-wide degree of substitutability between intangible capital and other factor inputs in production using a large sample of advanced countries. In this context, we turn to studying the implications of intangible and tangible capital growth for labor income share dynamics. Compared to tangible capital, we find that intangible capital more strongly complements skilled labor. The analysis further indicates relative fungibility between tangible capital and a composite of intangible capital and skilled labor, in line with the rising prominence of knowledge-intensive tasks and AI-driven online platforms. The intrinsic nature of intangibles and their asymmetric effects across skilled and unskilled labor productivity based on our substitution elasticities suggest that intangible capital growth increases income inequality more aggressively.

JEL Classification: E2, J2, J3, O3, O4

1 | Introduction

In the context of neoclassical growth theory, reports of a declining labor share in income are shifting attention to factor substitution elasticities and productivity growth (Piketty 2014; Piketty and Zucman 2014; Lawrence 2015; Rognlie 2015; Boushey, DeLong, and Steinbaum 2017; Grossman and Oberfield 2022). Research, meanwhile, indicates that the capital deepening process is becoming more intangible intensive (Haskel and Westlake 2017, 2022). Industry leaders characterized by high profits tend to be firms that invest more heavily in intangible assets (Crouzet and Eberly 2018). According to the superstar firm hypothesis of Autor et al. (2017, 2020), more concentrated industries exhibit greater deterioration of the labor share. Intangibles can explain this market concentration not just through increasing productivity but also through decreasing competition, as they can yield barriers to entry (Philippon 2019; Eeckhout 2021). Such trends have implications for income inequality and redistributive taxation policy, especially in environments of low capital relative to labor taxes (Scheve and Stasavage 2016; Haskel and Westlake 2017; Saez and Zucman 2019; Aghion, Antonin, and Bunel 2021). In this article, we examine (i) the economy-wide substitution possibilities between intangible capital and other factor inputs in production, and in turn (ii) the implications for the relative skilled labor share.

We provide evidence on factor substitution elasticities within a production framework characterized by multi-level nesting, à la Krusell et al. (2000), that distinguishes between tangible and intangible capital. For a large sample of developed countries, our analysis reveals that intangibles exhibit significantly greater complementarity with skilled labor. These two inputs as a composite and tangible capital, moreover, are found to be substitutes. Such results are consistent with the structural transformation of advanced economies, which is expanding more data- and knowledge-oriented industries.

I thank Charles Engel, Menzie D. Chinn, Philip R. Lane, D.S. Prasada Rao, and two anonymous referees for very helpful comments.

We show that these differences in capital-skill complementarity across tangibles and intangibles imply greater income inequality in response to intangible, as opposed to tangible, capital growth. This is demonstrated analytically in the model by examining the income share of skilled labor relative to that of unskilled labor. Our estimates indicate that, for the given factor intensities, intangible capital growth imparts a stronger positive impact on the marginal product of skilled labor relative to that of unskilled labor than tangible capital growth of equal magnitude, noting that we find relative substitutability between unskilled labor and the remaining factor inputs. Therefore, investment in intangibles, compared to tangibles, places higher upward pressure on the relative demand for skilled labor at given factor prices. This ultimately yields higher relative skilled labor compensation.

The distinction between the two forms of capital is important because intangibles tend to exhibit greater spillover effects, synergies with other intangibles, and scalability. Institutions relying on such assets place a premium on skilled coordinators that are able to identify and maximize the synergies, as well as accordingly capture any positive spillovers. Intangible capital investment costs are also more likely to be sunk, which induces greater demand for highly skilled managers that can deal with the strong bargaining positions of workers in intangible-intensive firms. If social interaction is becoming an increasingly important facet of these work environments, it is not surprising that higher-order skills like patience, conscientiousness, critical thinking, and teamwork are growing in demand (Deming 2023).[1]

The literature further suggests that the largest growth slowdowns should occur in countries with the largest R&D slowdowns (Aghion, Antonin, and Bunel 2021). Corrado et al. (2024), on the other hand, highlight the higher relative efficiency of data capital, which tends to augment its contribution to labor productivity. This effect, however, is attenuated if greater levels of data hoarding are associated with a higher data intensity in the delivery of services/products. The latter can limit knowledge diffusion and in turn overall productivity growth, with gains skewed toward data- and skill-intensive market leaders. Corrado et al. (2024) suggest that data capital is the most important driver of labor productivity growth. More generally, Corrado, Hulten, and Sichel (2009), Roth and Thum (2013), and Bontadini et al. (2024) report that intangible capital improves labor productivity. In our framework, we allow for intangibles to impart heterogeneous effects on skilled and unskilled labor productivity. We show that these effects are contingent on more micro-level parameters such as factor substitution elasticities.

Intangible-intensive organizations are likely to be larger. If such entities are more profitable and skilled labor primarily shares in higher rents, then income inequality rises. Song et al. (2019) find that differences in wages between firms are a key source of income inequality. They report that over two-thirds of the rise in the inequality of earnings in the U.S. from the 1980s onward can be accounted for by a rising variance of earnings between firms, compared to within firms where the gap between occupations is still rising. Haskel and Westlake (2017) contend that firm performance and productivity spreads are larger in industries and countries that invest more in intangibles. Indeed, Hall, Jaffe, and Trajtenberg (2005) find that the stock market value of a company is strongly positively associated with its R&D spending and well-cited patents. Leaders pull away from laggards because they are more intangible-intensive and therefore enjoy outsized benefits given the features of intangibles.[2]This arises due to the leaders' superior ability to (i) create and manage scalable, synergistic assets, (ii) minimize the risks associated with them, and (iii) capture any advantageous spillovers both within and outside the firm. Conversely, laggards expect lower private returns and invest less in intangible capital. As dealing with knowledge assets requires both cognitive and non-cognitive skills, skilled labor will tend to be clustered in the high-paid jobs of intangible-intensive firms.

Schumpeter's paradigm of creative destruction implies that innovation rents and the associated income inequality are transitory. That is, new innovations and imitation destroy the rents of past innovations. Innovation fosters social and economic mobility as it enables new parties to enter the market (Aghion et al. 2019), while fully or partly displacing incumbents. Attempting to explain the dynamics of inequality at the top of the income distribution, Jones and Kim (2018) emphasize that creative destruction by outside innovators (new firm entrants) diminishes inequality.

The profit paradox described by Eeckhout (2021) paints a different picture. Intangibles are creating obstacles that discourage the entry of competitors, thereby increasing economies of scale for incumbents. Big data combined with artificial intelligence and machine learning software tenders a powerful means of building market dominance. In order to operationalize algorithmic applications, vast amounts of data are required. Such data collection, and thus learning, however, is typically a costly activity. This engenders a first-mover advantage for the firm that collates the data first. The large upfront investment produces a source of economies of scale and establishes market power that is difficult to contest as owners hoard data and hence stifle the training of competitors' algorithms. Similarly, dominant online platforms enjoy significant network externalities that make it difficult to penetrate the market.[3] Intangibles, therefore, can result in "winner-take-all" situations that carry exorbitant profits and returns to managers given the nature of the capital.[4] Akcigit and Goldschlag (2023) find for the U.S. that inventors are becoming increasingly concentrated in large incumbents where their earnings are notably higher compared to those in young firms.

In related work, Acemoglu and Restrepo (2020) stress that industrial robots impart robust negative effects on U.S. labor markets, while Acemoglu and Restrepo (2022) also find such effects on wages and employment in cohorts most exposed to "specialized software"-led automation. Frey and Osborne (2017) argue that almost half of U.S. jobs are threatened by computerization. Focusing on panels of developed economies, O'Mahony, Vecchi, and Venturini (2021) and Garcia-Lazaro and Pearce (2023) examine the heterogeneous effects of capital on the total labor share across asset types. The authors, nevertheless, adopt linear reduced-form analyses to reach their conclusions. In contrast, we directly estimate our underlying nonlinear theoretical frameworks and in turn derive implications for relative skilled wages and labor shares.[5]Thus, the sizes of the indirectly estimated intangible and tangible capital effects are explicitly mediated by the magnitudes of the estimated supply-side model parameters.

Correspondingly, such estimates can be used to corroborate reduced-form correlations observed in the data.

The remainder of the article is structured as follows. Section 2 outlines the production-based theoretical framework and derives the analytical expressions employed for the analysis of the "labor share"-"capital growth" nexus. In Section 3, we briefly describe the data. Estimation approach and empirical results are in turn documented in Section 4. Section 5 offers robustness checks and deeper discussion of findings in the context of some of the underlying skills complementing intangible capital and the wider business/regulatory environment. The section also provides some direction for future research. We conclude in Section 6.

2 | Production Nesting and Labor Share Dynamics

We employ a three-level nested CES production framework that distinguishes between (i) skilled and unskilled labor (L_S, L_U), and (ii) tangible and intangible capital (K_T, K_I).[6,7] The general normalized version of the four-factor model for output (Y), which encompasses the special case of Krusell et al. (2000) (i.e., $\sigma = 1$ at the first level), is

$$Y_t = \psi Y_0 \left[\delta_{10} \left(e^{\lambda_1 (t-t_0)} \frac{F_{1,t}}{F_{1,0}} \right)^{\frac{\sigma-1}{\sigma}} + \delta_{Z0} Z_t^{\frac{(\sigma-1)\rho}{(\rho-1)\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \quad (1)$$

$$Z_t = \left[\delta_{20} \left(e^{\lambda_2 (t-t_0)} \frac{F_{2,t}}{F_{2,0}} \right)^{\frac{\rho-1}{\rho}} + \delta_{X0} X_t^{\frac{(\rho-1)\nu}{(\nu-1)\rho}} \right] \quad (2)$$

$$X_t = \left[\delta_{30} \left(e^{\lambda_3 (t-t_0)} \frac{F_{3,t}}{F_{3,0}} \right)^{\frac{\nu-1}{\nu}} + \delta_{40} \left(e^{\lambda_4 (t-t_0)} \frac{F_{4,t}}{F_{4,0}} \right)^{\frac{\nu-1}{\nu}} \right]. \quad (3)$$

The point of normalization is defined in terms of either geometric or arithmetic averages of corresponding (growing or stationary) variables.[8] For input i (F_i), factor-augmenting productivity evolves according to $e^{\lambda_i (t-t_0)} \equiv \frac{A_{i,t}}{A_{i,0}}$ where λ is the constant of proportionality. The top-nest parameter σ in Equation (1) is the elasticity of substitution between F_1 and the compound input Z, as well as each of its individual components F_2, X, F_3, and F_4. The mid-level elasticity ρ in Equation (2) correspondingly governs the degree of substitutability between F_2 and composite input X, including its constituent parts F_3 and F_4. Finally, substitution elasticity ν of the bottom nest in Equation (3) gauges the ease with which one can switch between F_3 and F_4 inputs in production. With $\{\sigma, \rho, \nu\} \in (0, \infty)$, smaller below-unity values of these parameters imply stronger gross complementarity between factor input pairs, while higher above-unity values indicate greater gross substitutability between them. We also introduce an additional factor ψ with $\mathbb{E}[\psi] = 1$ due to the nonlinearity of the production function and the stochastic nature of the data. Distribution parameters, representing respective within-process factor income shares at the point of normalization, are defined as follows

$$\delta_{10} = r_{1,0}F_{1,0}/(r_{1,0}F_{1,0} + r_{2,0}F_{2,0} + r_{3,0}F_{3,0} + r_{4,0}F_{4,0}) = 1 - \delta_{Z0} \quad (4)$$

$$\delta_{20} = r_{2,0}F_{2,0}/(r_{2,0}F_{2,0} + r_{3,0}F_{3,0} + r_{4,0}F_{4,0}) = 1 - \delta_{X0} \quad (5)$$

$$\delta_{30} = r_{3,0}F_{3,0}/(r_{3,0}F_{3,0} + r_{4,0}F_{4,0}) = 1 - \delta_{40}, \quad (6)$$

where r_i are real factor returns. If, for example, $\nu < \sigma$, meaning complementarity between F_3 and F_4 is stronger than that between F_3 and F_1, then an increase in the use of input F_3 will ceteris paribus lead to an increase in the demand for input F_4 relative to F_1 and its relative price. In the case of $\rho < \sigma$, the same argument follows with F_2 instead of F_3.

The production function and corresponding first-order conditions in logarithmic form are

$$\ln \frac{Y_t}{Y_0} = \ln \psi + \frac{\sigma}{\sigma-1} \ln \left(\delta_{10} \left(e^{\lambda_1 (t-t_0)} \frac{F_{1,t}}{F_{1,0}} \right)^{\frac{\sigma-1}{\sigma}} + \delta_{Z0} Z_t^{\frac{(\sigma-1)\rho}{(\rho-1)\sigma}} \right) \quad (7)$$

$$\ln r_{1,t} = \frac{\sigma-1}{\sigma} \ln \psi + \ln \left(\frac{\delta_{10} Y_0}{F_{1,0}} \right) + \frac{\sigma-1}{\sigma} \lambda_1 (t-t_0) + \frac{1}{\sigma} \left(\ln \frac{Y_t}{Y_0} - \ln \frac{F_{1,t}}{F_{1,0}} \right) \quad (8)$$

$$\ln r_{2,t} = \frac{\sigma-1}{\sigma} \ln \psi + \ln \left(\frac{\delta_{Z0}\delta_{20} Y_0}{F_{2,0}} \right) + \frac{\rho-1}{\rho} \lambda_2 (t-t_0) + \frac{\sigma-\rho}{(\rho-1)\sigma} \ln Z_t + \frac{1}{\sigma} \ln \frac{Y_t}{Y_0} - \frac{1}{\rho} \ln \frac{F_{2,t}}{F_{2,0}} \quad (9)$$

$$\ln r_{3,t} = \frac{\sigma-1}{\sigma} \ln \psi + \ln \left(\frac{\delta_{Z0}\delta_{X0}\delta_{30} Y_0}{F_{3,0}} \right) + \frac{\nu-1}{\nu} \lambda_3 (t-t_0) + \frac{\sigma-\rho}{(\rho-1)\sigma} \ln Z_t + \frac{\rho-\nu}{(\nu-1)\rho} \ln X_t + \frac{1}{\sigma} \ln \frac{Y_t}{Y_0} - \frac{1}{\nu} \ln \frac{F_{3,t}}{F_{3,0}} \quad (10)$$

$$\ln r_{4,t} = \frac{\sigma-1}{\sigma} \ln \psi + \ln \left(\frac{\delta_{Z0}\delta_{X0}\delta_{40} Y_0}{F_{4,0}} \right) + \frac{\nu-1}{\nu} \lambda_4 (t-t_0) + \frac{\sigma-\rho}{(\rho-1)\sigma} \ln Z_t + \frac{\rho-\nu}{(\nu-1)\rho} \ln X_t + \frac{1}{\sigma} \ln \frac{Y_t}{Y_0} - \frac{1}{\nu} \ln \frac{F_{4,t}}{F_{4,0}}. \quad (11)$$

Using Equations (8–11), one can derive relative factor shares

$$\ln \frac{\omega_{4,t}/\omega_{4,0}}{\omega_{3,t}/\omega_{3,0}} = \frac{\nu-1}{\nu} (\lambda_4 - \lambda_3)(t-t_0) + \frac{1-\nu}{\nu} \ln \frac{F_{3,t}/F_{3,0}}{F_{4,t}/F_{4,0}} \quad (12)$$

$$\ln \frac{\omega_{k,t}/\omega_{k,0}}{\omega_{2,t}/\omega_{2,0}} = \left(\frac{\nu-1}{\nu} \lambda_k - \frac{\rho-1}{\rho} \lambda_2 \right)(t-t_0) + \frac{\rho-\nu}{(\nu-1)\rho} \ln X_t + \frac{1-\rho}{\rho} \ln \frac{F_{2,t}}{F_{2,0}} - \frac{1-\nu}{\nu} \ln \frac{F_{k,t}}{F_{k,0}} \quad (13)$$

$$\ln \frac{\omega_{k,t}/\omega_{k,0}}{\omega_{1,t}/\omega_{1,0}} = \left(\frac{\nu-1}{\nu} \lambda_k - \frac{\sigma-1}{\sigma} \lambda_1 \right)(t-t_0) + \frac{\sigma-\rho}{(\rho-1)\sigma} \ln Z_t + \frac{\rho-\nu}{(\nu-1)\rho} \ln X_t + \frac{1-\sigma}{\sigma} \ln \frac{F_{1,t}}{F_{1,0}} - \frac{1-\nu}{\nu} \ln \frac{F_{k,t}}{F_{k,0}} \quad (14)$$

$$\ln\frac{\omega_{2,t}/\omega_{2,0}}{\omega_{1,t}/\omega_{1,0}} = \left(\frac{\rho-1}{\rho}\lambda_2 - \frac{\sigma-1}{\sigma}\lambda_1\right)(t-t_0) + \frac{\sigma-\rho}{(\rho-1)\sigma}\ln Z_t + \frac{1-\sigma}{\sigma}\ln\frac{F_{1,t}}{F_{1,0}} - \frac{1-\rho}{\rho}\ln\frac{F_{2,t}}{F_{2,0}}, \quad (15)$$

where $\frac{\omega_{i,t}/\omega_{i,0}}{\omega_{j,t}/\omega_{j,0}} = \frac{r_{i,t}F_{i,t}/r_{i,0}F_{i,0}}{r_{j,t}F_{j,t}/r_{j,0}F_{j,0}}$ and $k \in \{3,4\}$. We set $F_1 = L_U$ and $F_4 = L_S$, so that the combination $F_1(F_2(F_3F_4))$ corresponds to either the $L_U(K_I(K_TL_S))$ or the $L_U(K_T(K_IL_S))$ configuration.[9] Thus L_U will always be separable from the compound input Z containing the remaining three factor inputs. This implies that unskilled labor and the technical change augmenting it will have no effect on relative factor prices or shares across the other three inputs, as can be seen from Equations (12) and (13). The pairing of skilled and unskilled labor at the bottom level of nesting completely disregards effects on relative labor earnings through the capital-skill complementarity channel.[10]The nesting of capital types at this level, meanwhile, would also be equally undesirable as it would constrain the potential for heterogeneous asset class effects via the aforementioned channel. Tangible and intangible capital would have differential effects on the skilled relative to unskilled labor share and skill premium only to the extent that their growth rates and/or intensities in aggregate capital were different.[11]

To examine the relation between the skilled relative to unskilled labor share and tangible or intangible capital, we can consider the following equations

$$\frac{\partial \ln \frac{\omega_{4,t}/\omega_{4,0}}{\omega_{1,t}/\omega_{1,0}}}{\partial \frac{F_{2,t}}{F_{2,0}}} = \delta_{20}\left(\frac{\sigma-\rho}{\sigma\rho}\right)\left(\frac{1}{Z_t}\right)\left(\frac{A_{2,t}}{A_{2,0}}\right)^{\frac{\rho-1}{\rho}}\left(\frac{F_{2,t}}{F_{2,0}}\right)^{-\frac{1}{\rho}} \quad (16)$$

$$\frac{\partial \ln \frac{\omega_{4,t}/\omega_{4,0}}{\omega_{1,t}/\omega_{1,0}}}{\partial \frac{F_{3,t}}{F_{3,0}}} = \delta_{30}\left[\delta_{X0}\left(\frac{\sigma-\rho}{\sigma\rho}\right)\left(\frac{1}{Z_t}\right)X_t^{\frac{\rho-\nu}{(\nu-1)\rho}} + \left(\frac{\rho-\nu}{\rho\nu}\right)\frac{1}{X_t}\right]\left(\frac{A_{3,t}}{A_{3,0}}\right)^{\frac{\nu-1}{\nu}}\left(\frac{F_{3,t}}{F_{3,0}}\right)^{-\frac{1}{\nu}}. \quad (17)$$

Alternatively, we can examine the growth expression for the relative labor share, which simplifies the relevant relations and allows for better comparability of effects across forms of capital. Differentiating Equation (14) with respect to time at the point of normalization $t = t_0$ where $Z = X = \frac{A_{i,t}}{A_{i,0}} = \frac{F_{i,t}}{F_{i,0}} = 1$ yields

$$g^{\omega_4/\omega_1} = \alpha g^{F_1} + \phi g^{F_2} + \gamma g^{F_3} + \beta g^{F_4} + TC. \quad (18)$$

Growth in variable m is defined as $g^m = \frac{\dot{m}}{m} \approx \ln m_{t_0+1} - \ln m_{t_0}$ and TC is a model parameters weighted average of factor-augmenting productivity growth rates. $\phi = \frac{\delta_{20}(\sigma-\rho)}{\sigma\rho}$ and $\gamma = \frac{\delta_{30}\delta_{X0}(\sigma-\rho)}{\sigma\rho} + \frac{\delta_{30}(\rho-\nu)}{\rho\nu}$ are the coefficients of interest as they govern the relation between growth in the relative skilled labor share and growth in the two types of capital. For the first (second) configuration of factor inputs, ϕ (γ) is relevant for the link with intangible capital while γ (ϕ) is relevant for the link with tangible capital.

It is clear that the response of the relative labor share to intangible and tangible capital growth is mediated by capital intensities and factor substitution elasticities. Specifically, for intangible capital to exhibit a stronger positive impact than tangible capital in the first (second) constellation of factor inputs, the following inequality must hold

$$\left(\delta_{20} - \delta_{30}\delta_{X0}\right)\left[\frac{\sigma-\rho}{\sigma\rho}\right] > (<)\ \delta_{30}\left[\frac{\rho-\nu}{\rho\nu}\right]. \quad (19)$$

When tangible capital and skilled labor are nested at the bottom level of the model (i.e., $F_3 = K_T$ and $F_4 = L_S$), a higher ν relative to ρ, ceteris paribus, makes it more likely that intangible capital growth delivers an economically more significant impact on the relative labor share. Conversely, a lower ν relative to ρ, ceteris paribus, increases this likelihood when the bottom level of nesting in the model comprises intangible capital and skilled labor (i.e., $F_3 = K_I$ and $F_4 = L_S$).

Figure 1 illustrates the message graphically in the first case where we set $\delta_{20} = \delta_{KI0} = 0.1$, $\delta_{X0} = 0.9$, $\delta_{30} = \delta_{KT0} = 0.6$, and $\sigma \in \{1.5, 2, 2.5\}$ in calibrations.[12] Figure 1a shows, holding all other parameters fixed, that lower values of ρ are associated with higher values of ϕ i.e. stronger intangible capital effects due to stronger complementarity between K_I and L_S. Furthermore, for a given ρ, a higher σ tends to augment the intangible capital effect (higher ϕ) because of the greater substitutability between K_I and L_U which weakens the response of unskilled wages to K_I growth.[13] Figures 1b–d meanwhile demonstrate that higher values of ν relative to ρ generate lower values of γ i.e. relatively weaker tangible capital effect due to stronger substitutability between K_T and L_S compared to that between K_I and L_S.[14] Panels 1b–d also indicate that, for given values of ν and ρ, greater substitutability between L_U and K_T (higher σ) is linked to stronger tangible capital effects on the relative skilled labor share (higher γ).

The core relations amongst parameters for the second model configuration are visually depicted in Figure 2 in the case of $\delta_{20} = \delta_{KT0} = 0.55$, $\delta_{X0} = 0.45$, $\delta_{30} = \delta_{KI0} = 0.2$, and $\sigma \in \{1.5, 2, 2.5\}$. Figure 2a now displays the inverse link between the tangible capital effect (ϕ) and the degree of substitutability between K_T and L_S (ρ), with greater substitutability between K_T and L_U (higher σ) increasing ϕ for a given ρ.[15] From Figures 2b–d, we observe that higher substitutability between K_I and L_S (higher ν) can offset higher substitutability between K_T and L_S (higher ρ) to maintain a constant intangible capital effect on the relative skilled labor share (constant γ). The graphs also highlight that lower values of ν for a given ρ value are tied to higher values of γ. That is, with greater complementarity between K_I and L_S, ceteris paribus, the intangible capital effect on the relative skilled labor share (γ) rises relative to that of tangibles (ϕ) as the marginal product of skilled labor becomes more sensitive to the accumulation of intangibles. Finally, the intangible capital effect (γ) increases for a given $\{\rho, \nu\}$ pairing as substitution between K_I and L_U becomes easier (higher σ), making unskilled labor productivity, and thus unskilled wages, less responsive to capital growth.

3 | Data

The system of Equations (7–11) is the general focus of estimation. Annual output, capital, and labor series are obtained from the EU KLEMS statistical repository based on national accounts.[16]

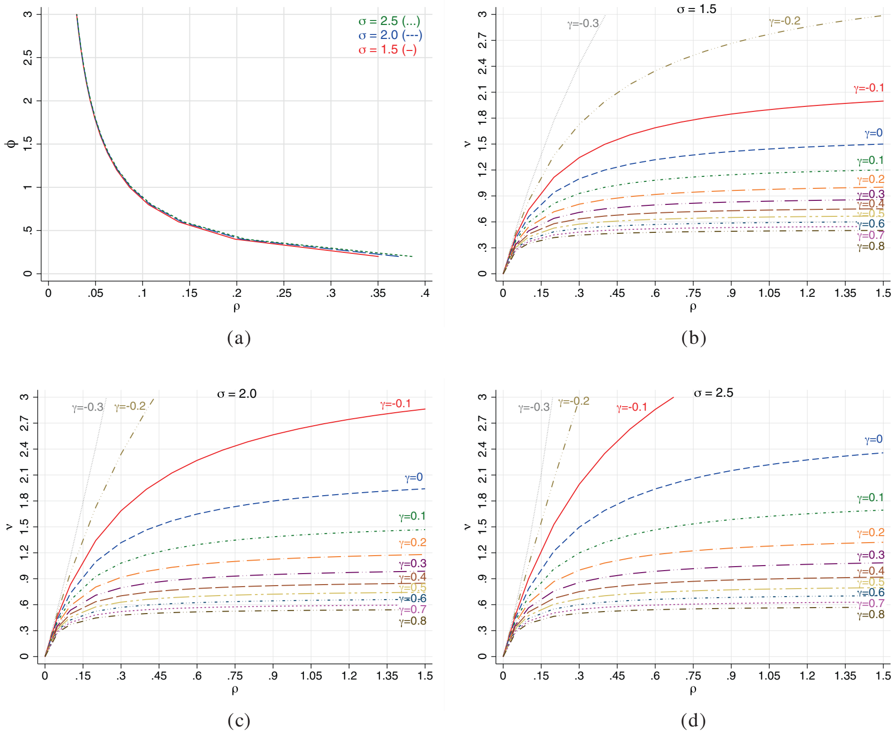

FIGURE 1 | (a–d) Intangible (ϕ) & Tangible (γ) capital coefficient calibrations for model configuration $L_U(K_I(K_T L_S))$. *Notes:* Author calculations of intangible and tangible capital growth slope coefficients $\phi = \frac{\delta_{20}(\sigma-\rho)}{\sigma\rho}$ and $\gamma = \frac{\delta_{30}\delta_{X0}(\sigma-\rho)}{\sigma\rho} + \frac{\delta_{30}(\rho-\nu)}{\rho\nu}$ for different combinations of underlying factor substitution elasticities in the case of $\delta_{20} = \delta_{KI0} = 0.1$, $\delta_{X0} = 0.9$, $\delta_{30} = \delta_{KT0} = 0.6$, and $\sigma \in \{1.5, 2, 2.5\}$.

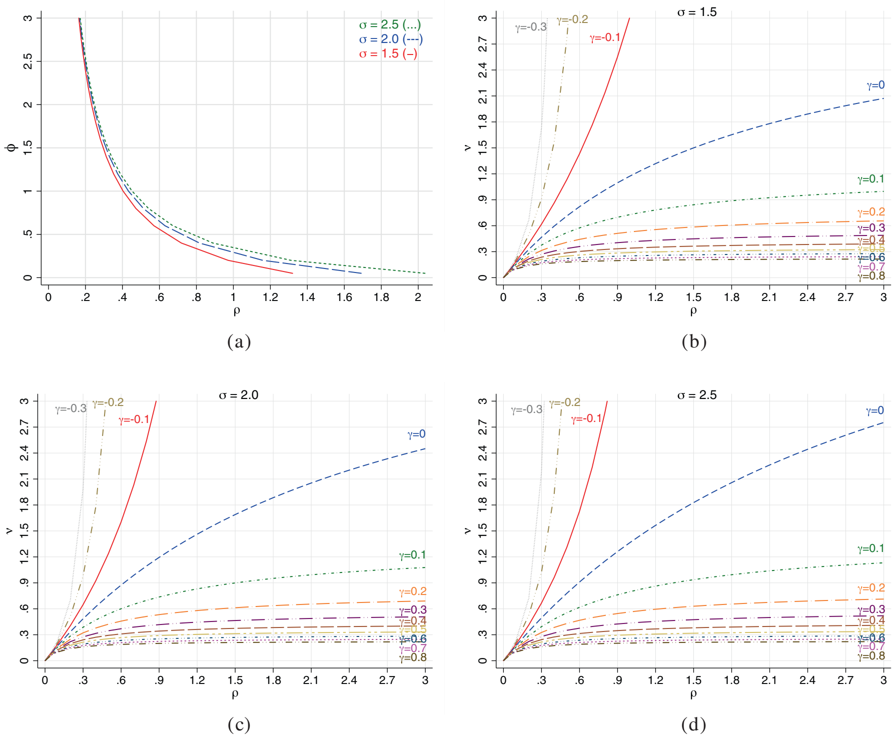

FIGURE 2 | (a–d) Intangible (γ) & Tangible (ϕ) capital coefficient calibrations for model configuration $L_U(K_T(K_I L_S))$. *Notes:* Author calculations of intangible and tangible capital growth slope coefficients $\gamma = \frac{\delta_{30}\delta_{X0}(\sigma-\rho)}{\sigma\rho} + \frac{\delta_{30}(\rho-\nu)}{\rho\nu}$ and $\phi = \frac{\delta_{20}(\sigma-\rho)}{\sigma\rho}$ for different combinations of underlying factor substitution elasticities in the case of $\delta_{20} = \delta_{KT0} = 0.55$, $\delta_{X0} = 0.45$, $\delta_{30} = \delta_{KI0} = 0.2$, and $\sigma \in \{1.5, 2, 2.5\}$.

All variables pertain to the total economy and cover 25 countries primarily over the period 1995–2015.[17,18] The data are in line with the ISIC 4 (NACE 2) industry classification and the new European System of National Accounts (ESA 2010). Real net capital stocks and numbers of persons engaged measure capital and labor inputs, respectively. Engaged labor includes employees, self-employed, and family workers.[19] The nominal rental price of capital services is computed as the ratio of total nominal capital income to the real capital stock. Similarly, the nominal wage rate for labor services is calculated as total nominal labor compensation divided by the total labor input. Real factor returns are then given as nominal returns divided by the GDP deflator. In EU KLEMS, the remuneration of labor is accordingly adjusted by changes in the number of self-employed (proprietors).[20] Factor shares in value added sum to unity.

Ten asset classes are provided by EU KLEMS in the statistical database under ESA 2010. We define these assets as either tangible or intangible in line with the classifications of Haskel and Westlake (2017). Tangible capital consists of residential structures, total non-residential structures, transport equipment, computing equipment (computer hardware), communications equipment, other machinery and equipment, and cultivated assets. Intangible capital, meanwhile, contains other intellectual property products (consisting of mineral exploration and artistic originals), research and development, and computer software and databases.

A breakdown of total capital compensation across asset types, however, is unavailable in the data. Instead, we construct asset-specific capital compensation as follows.[21] Adopting a similar approach to Hall and Jorgenson (1967), capital income for asset class κ in country c is estimated as

$$\widetilde{CAP}^{\kappa}_{c,t} = \left(i_{c,t} - \pi^{\kappa}_{c,t} + \xi^{\kappa} \right) K^{\kappa}_{c,t} P^{\kappa}_{c,t} \tag{20}$$

where i is the 10-year government bond yield retrieved from the FRED database of the Federal Reserve Bank of St. Louis, π^{κ} is the growth rate of the respective investment deflator, ξ^{κ} is the non-time- and non-country-varying capital depreciation rate, K^{κ} is the two-year end (moving) average of the respective real net capital stock, and P^{κ} is the corresponding (implied) capital stock deflator.[22,23] The sum $\widetilde{CAP}^{total}_{c,t} = \sum_{\kappa} \widetilde{CAP}^{\kappa}_{c,t}$ does not exactly coincide with total capital compensation over all assets in the EU KLEMS data, $CAP^{total}_{c,t}$.[24] The general trajectories of the two variables, on the other hand, are quite alike. Assuming that the shares of $CAP^{total}_{c,t}$ follow our generated capital shares, the real rentals of tangible and intangible capital evolve according to

$$r^{KT}_{c,t} = \frac{\left(\frac{\widetilde{CAP}^{KT}_{c,t}}{\widetilde{CAP}^{total}_{c,t}} \right) CAP^{total}_{c,t}}{K^{T}_{c,t} P_{c,t}} \quad \text{and} \quad r^{KI}_{c,t} = \frac{\left(\frac{\widetilde{CAP}^{KI}_{c,t}}{\widetilde{CAP}^{total}_{c,t}} \right) CAP^{total}_{c,t}}{K^{I}_{c,t} P_{c,t}} \tag{21}$$

where P_c is the GDP deflator of country c.

Total labor in EU KLEMS is disaggregated along the skill dimension into three groups: high-, medium-, and low-skilled.[25] The skill level is governed by educational attainment. The definition for high-skilled labor as those with a university degree or above is uniform across countries and time. The line of distinction between medium- and low-skilled labor conversely can vary across countries due to disparate educational systems, with these two cohorts together constituting levels of education up to and including secondary (high) school, vocational education and training, higher education below degree level, and some years of college (but not completed).[26] We decompose aggregate labor as a result into two skill groups: skilled labor (L_S) consisting of high-skilled workers and unskilled labor (L_U) comprising medium- and low-skilled workers. The corresponding labor share splits are also available. The overall average nominal wage per worker is therefore defined as $W = \frac{LAB}{L} \equiv \frac{L_S}{L}\frac{LAB_S}{L_S} + \frac{L_U}{L}\frac{LAB_U}{L_U} \equiv \frac{L_S}{L}W_S + \frac{L_U}{L}W_U$, where LAB is total labor compensation. Real skilled and unskilled wages are then given by $r^{LS} = \frac{LAB_S}{L_S P} \equiv \frac{W_S}{P}$ and $r^{LU} = \frac{LAB_U}{L_U P} \equiv \frac{W_U}{P}$ respectively.

4 | Empirical Assessment

Figure 3 establishes that skilled labor commands a disproportionately larger share of total labor compensation due to the existence of a skill premium. This is evident for all countries and years on display in the graphs, where countries further above the red dashed reference line are characterized by larger skilled-unskilled wage gaps. For some economies, vertical deviations from the 45-degree line have declined over time, pointing to an attenuation of skill premia and income inequality in line with a rising relative supply of skilled labor. For others, like Ireland and Lithuania, the divide has increased. We question how intangible capital compared to tangible capital has influenced these labor share dynamics, focusing on the so-called "capital-skill complementarity" channel.

Table 1 shows preliminary evidence on the relation between the relative skilled labor share and real capital stocks across the two core asset types of interest. The gross correlation coefficients indicate that both tangible and intangible capital are strongly positively associated with the income share of skilled labor relative to that of unskilled labor. They also suggest that the link is somewhat stronger for intangibles. Examining partial correlations that control for the other factor inputs, we now find a significantly more pronounced positive connection for intangibles compared to tangibles. The partial correlation moreover implies, assuming a linear model, that intangibles can explain 10% of the variation in the relative skilled labor share not attributable to other factor inputs, while tangibles display no such explanatory power. Figure 4 demonstrates that growth in the stock of intangible relative to tangible capital is related to growth in the relative skilled labor share.

We next turn to the formal, micro-founded, analysis of discrepancies in the effects of tangible and intangible capital growth on the relative skilled labor share as discussed in Section 2. Equations (7–11), consisting of the production function and corresponding first-order conditions, are estimated as a system of pooled (normalized) panel regressions using a two-step GMM estimator. The system imposes cross-equation restrictions on parameters and employs country-specific normalization points. Lags of covariates form the set of instruments in GMM estimation. Our decision on estimation approach thus takes into

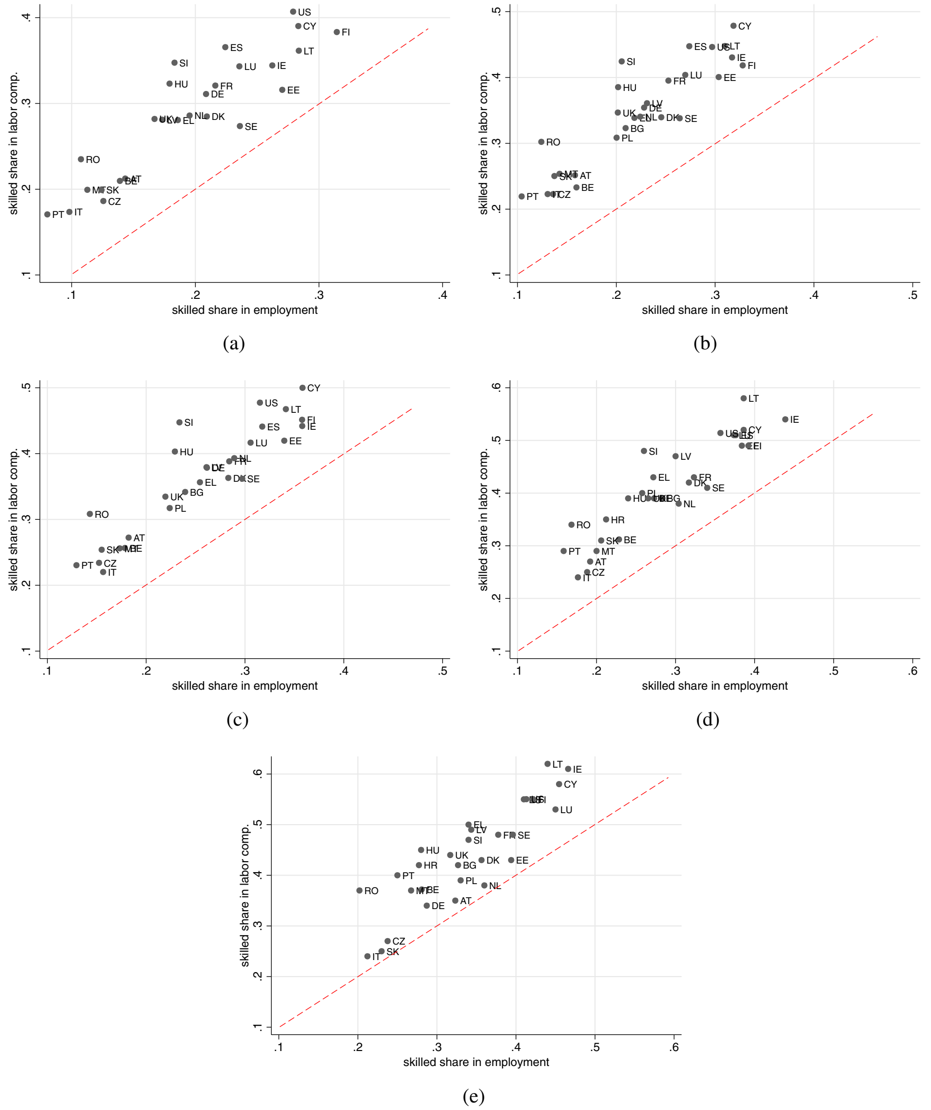

FIGURE 3 | Shares of skilled workers in employment and labor compensation, (a) 1995, (b) 2000, (c) 2005, (d) 2010, (e) 2015. *Notes:* Red dashed reference line represents equality of skilled labor shares in total employment and total labor compensation. Vertical distance above the line captures the strength of skill premia and income inequality i.e. countries further above the line are characterized by larger skilled-unskilled wage gaps and income inequality.

TABLE 1 | Baseline correlations: Relative skilled labor share versus capital.

	Capital type	
	(1)	**(2)**
Correlation coefficient	**Tangibles**	**Intangibles**
Gross	0.729	0.782
	[0.000]	[0.000]
Partial	0.023	0.314
	[0.644]	[0.000]

Note: Gross correlation is given by Pearson's coefficient. *Partial* correlation is obtained by fitting a linear regression of the relative skilled labor share on all factor inputs. The partial correlation coefficient is then computed as $t/(\sqrt{t^2+n-k})$ where t is the relevant variable's t-statistic, $n = 400$ is the number of observations, and $k = 5$ is the number of regressors including the constant. p-values are given in square brackets.

consideration the possibility of cross-equation correlations in residuals and endogeneity.

Estimates of factor-substitution elasticities and factor-augmenting productivity growth for each of the considered model configurations are reported in Table 2. Results pertaining to tests of cross-sectional dependence and non-stationarity on residuals of system regressions are meanwhile provided in Table 3. Looking at column (3) of Table 3, Pesaran (2004, 2015)'s test suggests that there is greater evidence of cross-section independence in residuals across system equations in the case of the first model configuration. Columns (1) and (2) of the same table, however, indicate that average and average absolute cross-sectional correlation coefficients, respectively, obtained from that test, are quite low in both configuration cases. Given the low correlations, we therefore adopt the assumption of independence following Pesaran (2004). Results of the first generation

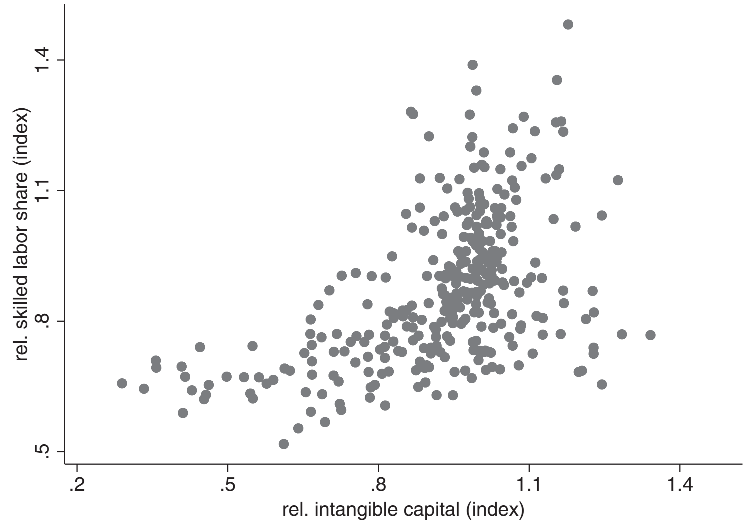

FIGURE 4 | Relative skilled labor share versus Relative intangible capital stock, 1995–2015. *Notes:* Skilled labor share in income is measured relative to the unskilled labor share in income. Real intangible capital stock is measured relative to the real tangible capital stock. Both indexes use 2010 as the base year. Pearson correlation coefficient: 0.70***. Spearman rank correlation coefficient: 0.65***. Partial correlation: 0.41*** (controls: skilled-to-unskilled labor ratio). *** significant at 1%.

Im, Pesaran, and Shin (2003) panel unit root test are shown in column (4), while those of the second generation Pesaran (2007) panel unit root test are displayed in column (5). The first test is also executed on cross-sectionally demeaned series in order to mitigate the impact of any cross-sectional dependence. The second test takes the possibility of cross-sectional dependence into account directly. The tests disclose a rejection of the null of non-stationarity at conventional statistical significance levels.

We rule out Cobb–Douglas forms for any of the nests or levels (top, middle, bottom) in the production function, as unitary elasticities of input substitution can be rejected in hypothesis tests. In Table 2, both model configurations show that the top-level substitution elasticity, σ, is estimated to be significantly above unity. Such a result specifies that unskilled labor and any of the other individual factor inputs or compound inputs are gross substitutes. $\sigma > 1$ on its own implies that, in percentage terms, an increase in the relative physical supply of capital or skilled labor relative to that of unskilled labor more than offsets the associated decrease in the corresponding relative factor price. These changes amount to an increase in the corresponding relative factor income share. Columns (13)–(18) report actual average annual growth in relative factor prices and income shares based on pooled data. Focusing on the skill premium, we find in column (15) that skilled relative to unskilled wages have declined on average over the sample by around two-fifths of a percent per annum (p.a.), while the relative skilled labor share has been increasing annually by approximately 3.2%. The trends are thus consistent with the predictions of $\sigma > 1$ if we ignore other influences.

The waning of skill premia across the U.S. and Europe in the twenty-first century, particularly after the global financial crisis (GFC), is also documented by Beaudry, Green, and Sand (2016), Crivellaro (2016), Valletta (2018), Green and Henseke (2021), and Velic (2023).[27] The typical explanation offered is that the relative demand for skilled labor is not keeping pace with the growth in relative supply. Crivellaro (2016) and Green and Henseke (2021) further highlight heterogeneity in wage, education, and labor market trends across European countries. Beaudry, Green, and Sand (2016) trace the reversal in the demand for cognitive tasks in the U.S. back to the tech bust of 2000. High-skilled labor responded by moving down the occupational ladder and displacing less educated labor in less skill-intensive posts. This pattern became more apparent after 2008 once jobs associated with the housing bubble vanished.[28] Finally, Beaudry, Green, and Sand (2016) and Haskel and Westlake (2022) contend that the post-GFC period is characterized by productivity, skilled labor demand, and skill premium growth slowdowns because of the weaker investment in intangible capital.

Turning attention to the middle and bottom level substitution elasticities (ρ and ν), both of the estimated systems reveal (i) strong complementarity between skilled labor and intangible capital and (ii) substitutability between skilled labor and tangible capital. Substitutability between these three inputs is furthermore far lower than that between unskilled labor and remaining inputs, as estimates indicate $\rho < \sigma$ and $\nu < \sigma$ across configurations.[29] The second model configuration in particular shows that skilled labor and intangible capital combined act as a gross substitute for tangible capital, consistent with the growing reliance on skill-complementary digital technologies to deliver consumer goods and services.[30] This is evident with the displacement of physical retail outlets, bank branches, consultancy offices[31], and certain health care facilities[32] by virtual spaces. The strong synergy between intangibles and skills (low ρ in the first constellation and low ν in the second constellation) implies a tight positive comovement between r_{LS}/r_{KI} and ω_{LS}/ω_{KI}. As columns (17) and (18) of Table 2 show, this is indeed suggested by the data.

Based on the estimated underlying model parameters, Table 4 presents estimates of ϕ and γ from growth Equation (18). The results indicate that the effects of intangible capital on the relative skilled labor share are economically and statistically different to those of tangible capital. These effects theoretically work

TABLE 2 | Four-factor system estimates for total economy.

	Parameter estimates							Actual relative factor price [Share] changes					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(13)	(14)	(15)	(16)	(17)	(18)
Model configuration	σ	ρ	ν	λ_{LU}	λ_{LS}	λ_{KT}	λ_{KI}	$d\ln\frac{r_2}{r_1}\left[\frac{\omega_2}{\omega_1}\right]$	$d\ln\frac{r_3}{r_1}\left[\frac{\omega_3}{\omega_1}\right]$	$d\ln\frac{r_4}{r_1}\left[\frac{\omega_4}{\omega_1}\right]$	$d\ln\frac{r_3}{r_2}\left[\frac{\omega_3}{\omega_2}\right]$	$d\ln\frac{r_4}{r_2}\left[\frac{\omega_4}{\omega_2}\right]$	$d\ln\frac{r_4}{r_3}\left[\frac{\omega_4}{\omega_3}\right]$
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	2.014***	0.064***	1.155***	0.004***	0.098***	−0.047***	−0.006***	0.035	−0.013	−0.004	−0.047	−0.035	0.009
	(0.210)	(0.009)	(0.032)	(0.001)	(0.010)	(0.009)	(0.002)	[0.065]	[0.008]	[0.032]	[−0.060]	[−0.028]	[0.027]
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	1.401***	1.273***	0.293***	−0.006**	0.048***	−0.022**	0.042***	−0.013	0.035	−0.004	0.047	0.009	−0.035
	(0.085)	(0.082)	(0.034)	(0.003)	(0.009)	(0.009)	(0.011)	[0.008]	[0.065]	[0.032]	[0.060]	[0.027]	[−0.028]

Note: * significant at 10%; ** significant at 5%; *** significant at 1%. Pooled normalized panel regressions employed. $n = 400$. Robust standard errors in parentheses. Average annual changes employed. For GMM estimation, null hypothesis of valid overidentifying restrictions in Sargan–Hansen (SH) test cannot be rejected and instrument proliferation is not a concern. SH test p-value equals 1.00 in first model and 0.99 in second model. The null hypotheses $\sigma = \rho = \nu$; $\sigma = \rho$; $\rho = \nu$; $\sigma = \nu$; $\sigma = 1$; $\rho = 1$; $\nu = 1$; $\lambda_{LU} = \lambda_{LS} = \lambda_{KT} = \lambda_{KI}$; $\lambda_{LU} = \lambda_{LS}$; and $\lambda_{KT} = \lambda_{KI}$ in each specification are rejected at conventional significance levels. Country-specific averages employed for distribution parameters at the point of normalization, $\{\delta_{10}, \delta_{Z0}, \delta_{20}, \delta_{X0}, \delta_{30}, \delta_{40}\}$, in system estimation. Based on pooled average (across countries and time) factor shares in value added, distribution parameters at point of normalization across the two factor configurations are $\{\delta_{LU0} = 0.38, \delta_{Z0} = 0.62, \delta_{KI0} = 0.10, \delta_{X0} = 0.90, \delta_{KT0} = 0.60, \delta_{LS0} = 0.40\}$ and $\{\delta_{LU0} = 0.38, \delta_{Z0} = 0.62, \delta_{KT0} = 0.55, \delta_{X0} = 0.45, \delta_{KI0} = 0.20, \delta_{LS0} = 0.80\}$. Pooled median factor shares are similar. Statistical database of EU KLEMS employed.

through the skill premium, as relative skilled labor supply and technical change effects are captured by α, β, and TC parameters/terms in the growth specification. For the first constellation of factor inputs, we find that intangible capital growth of one percent commands a 1.38% increase in the relative skilled labor share, while the same growth in tangible capital yields a negative effect of about three-fifths of a percent. For the second model configuration, both categories of capital exhibit a positive link with the relative labor share if standard errors are ignored. However, the coefficient on intangibles continues to be much stronger in this second case, standing at around 0.5, which is more than twelve times the size of the statistically insignificant coefficient on tangibles.

Intuitively, intangible capital growth raises the marginal product of skilled labor relative to that of unskilled labor. This occurs because of (i) strong complementarity between skilled labor and intangibles and (ii) substitutability between unskilled labor and intangibles. The more the corresponding substitution elasticities diverge (ρ and σ in the first system; ν and σ in the second system), the greater the increase in the aforementioned ratio of marginal products. Moreover, the impact is more pronounced for a higher intensity of intangibles in production, as reflected by the cost weight δ_2 in the first model and δ_3 in the second model. The change in labor productivity across skill types subsequently induces an increase in the relative demand for skilled labor at given factor prices. As excess demand for skilled labor builds up, upward pressure on the skill premium materializes. This culminates in a rise in the relative skilled labor share.[33]

Compared to intangibles, tangible capital exhibits much weaker complementarity (higher substitutability) with skilled labor. Tangible capital growth consequently ends up imparting much lower effects on skilled labor's relative marginal product, relative demand, wage premium, and relative income share. The weaker growth effect of tangibles reflects the fact that an increasingly larger proportion of skilled labor is specializing in intangible assets. This is consistent with the idea that attenuated investment in intangibles post GFC led to a productivity slowdown.

Finally, columns (4)–(7) in Table 2 report the estimates of factor-augmenting productivity growth that underpin the effects of technical change. The results suggest that growth in the effective supply of skilled relative to unskilled labor exceeds that of the physical ratio. Similarly, we find that the effective stock of intangibles relative to tangibles grows at a higher rate than that of the corresponding relative physical stock. Such trajectories in factor productivities enhance returns emanating from the "skilled labor"-"intangible capital" nexus, and thereby can widen the income gap across skill groups.

Asymmetric or factor-biased productivity growth in favor of skilled labor and intangible capital can be endogenized in the following way. Since skilled labor and intangibles remain relatively scarce inputs compared to unskilled labor and tangible capital, the output of industries/firms that use the former inputs intensively will be more constrained. This increases the relative price of "skilled labor"- and "intangible capital"-intensive goods and services, which makes investment in innovation (R&D) potentially more profitable in sectors specializing in such output. As more financial resources are diverted to "skilled labor"- and

TABLE 3 | Four-factor system residual diagnostics.

	Cross-section dependence			Panel unit root tests	
	(1)	(2)	(3)	(4)	(5)
Model configuration	$\overline{\rho}$	$\overline{\lvert\rho\rvert}$	**CSD**	**IPS**	**CIPS**
$L_U; \sigma; [K_I; \rho; (K_T; \nu; L_S)]$	0.01;0.01;–0.01;0.02	0.21;0.15;0.13;0.14	0.18;0.24;0.50;0.01	0.02;0.09;0.00;0.00	0.12;0.07;0.10;0.04
				0.00;0.18;0.00;0.00	
$L_U; \sigma; [K_T; \rho; (K_I; \nu; L_S)]$	0.03;0.02;0.04;0.00	0.25;0.16;0.13;0.15	0.00;0.01;0.00;0.84	0.00;0.08;0.00;0.01	0.07;0.01;0.00;0.05
				0.01;0.03;0.00;0.00	

Note: p-values are reported for cross-section dependence and panel unit root tests in columns (3) and (4)–(5), respectively. CSD refers to the cross-section dependence test of Pesaran (2004, 2015) where the null hypothesis can be interpreted either as that of strict cross-section independence (Pesaran 2004) or weak cross-section dependence in the case of relatively large N panels (Pesaran 2015). $\overline{\rho}$ and $\overline{|\rho|}$ are the average and average absolute cross-section correlation coefficients (off-diagonal elements) obtained from the Pesaran CSD test. Null hypothesis in Im, Pesaran, and Shin (2003), IPS, and Pesaran (2007), CIPS, tests is that all series are non-stationary. p-values in bold in column (4) are for IPS tests on cross-sectionally demeaned series. Choi (2001)'s Phillips–Perron Fisher panel unit root test yields results very similar to those of IPS.

TABLE 4 | Capital-skill complementarity effects on relative skilled labor share.

	Capital-skill complementarity effect		
	(1)	(2)	(3)
Model configuration	**Tangibles**	**Intangibles**	$H_0 : \phi = \gamma$
$L_U; \sigma; [K_I; \rho; (K_T; \nu; L_S)]$	−0.610***	1.382***	0.00
	(0.131)	(0.193)	
$L_U; \sigma; [K_T; \rho; (K_I; \nu; L_S)]$	0.040	0.510***	0.00
	(0.036)	(0.079)	

Note: * significant at 10%; ** significant at 5%; *** significant at 1%. $\phi = \frac{\delta_{20}(\sigma-\rho)}{\sigma\rho}$ and $\gamma = \frac{\delta_{30}\delta_{X0}(\sigma-\rho)}{\sigma\rho} + \frac{\delta_{30}(\rho-\nu)}{\rho\nu}$, where the corresponding system estimates of $\{\sigma, \rho, \nu\}$ and pooled averages of δ_i are used in calculations of ϕ for the impact of $g^{F_2} = 1\%$ and γ for the impact of $g^{F_3} = 1\%$. Standard errors in parentheses. p-values reported in column (3) for Wald-type test of coefficient equality. Delta method is employed for the calculation of standard errors and p-values.

"intangible capital"-intensive industries, their productivity levels outstrip those of other industries.[34]The divergence in productivity levels across these industries, in turn, acts to increase both inter-firm and inter-worker income inequality. The same logic applies within industries for firms characterized by heterogeneous factor intensities. We further note that our results suggest that productivity growth is net (skilled) labor augmenting, consistent with neoclassical growth theory and, in particular, the literature on balanced growth and structural transformation.[35]

5 | Discussion

The seminal works of Corrado, Hulten, and Sichel (2005, 2009); Corrado et al. (2017, 2018) and Haskel and Westlake (2017, 2022) offer an extended intangible capital framework that goes beyond the boundaries of the national accounts to include additional asset classes. The latter comprise market research and branding; industrial design; organizational capital; new financial product development; and vocational training (firm-specific human capital). To check whether our main results still hold with this augmented definition of intangibles, we repeat the core analysis with the corresponding analytical data of EU KLEMS (Bontadini et al. 2023) which contain the aforementioned supplementary asset categories alongside capital stocks from national accounts.

An abridged version of the new results is provided in Table 5.[36] The robustness check reveals that our key conclusions continue to be valid with the expanded definition of intangibles. As evident from the table, the pattern of factor substitution elasticities in each model still suggests that intangibles, compared to tangibles, demonstrate notably greater complementarity with skilled labor. The combination of these two highly synergistic inputs furthermore continues to provide a strong substitute for tangibles (i.e., $\rho \gg 1$ for the second configuration), while unskilled labor substitution possibilities also remain quite robust (column (1)). As before, columns (4)–(6) ultimately indicate that intangible capital unequivocally imparts more pronounced effects on the relative skilled labor share, widening the income inequality gap. Conversely, there is some evidence that tangible capital may be working in the opposite direction. Relative to the lower bound estimates of the effects of intangibles based on the more conservative statistical capital data, Table 5 now shows that intangible capital growth effects are almost double in size. This is partly due to the higher weight of intangibles in the overall capital stock, as signaled by a higher value of the distribution parameter δ_{KI0}. More precisely, column (5) implies that intangible capital growth of one percent is associated with a 1%–2% increase in the relative income share of skilled labor.

The intrinsic nature of intangibles implies that they engender greater uncertainty and contestedness. The riskiness of intangible investment is associated with its sunkedness. Put differently, the downside risk of intangibles is higher as it is more difficult to recover their value if the investment project fails. While intangibles are less valuable in the case of business failure, they also

TABLE 5 | Robustness check with augmented intangible capital stock.

	Model parameters			Capital-skill complementarity effect		
	(1)	(2)	(3)	(4)	(5)	(6)
Model configuration	σ	ρ	ν	**Tangibles**	**Intangibles**	$H_0 : \phi = \gamma$
$L_U; \sigma; [K_I; \rho; (K_T; \nu; L_S)]$	1.549***	0.092***	1.202***	−0.998***	2.036***	0.00
	(0.159)	(0.023)	(0.099)	(0.274)	(0.540)	
$L_U; \sigma; [K_T; \rho; (K_I; \nu; L_S)]$	1.359***	1.387***	0.268***	−0.006	1.020***	0.00
	(0.088)	(0.115)	(0.056)	(0.030)	(0.257)	

Note: * significant at 10%; ** significant at 5%; *** significant at 1%. $n = 309$. Robust standard errors in parentheses. p-values reported in column (6) for Wald-type test of coefficient equality. Delta method is employed for the calculation of standard errors and p-values in columns (4)–(6). Country-specific averages employed for distribution parameters at the point of normalization, $\{\delta_{10}, \delta_{Z0}, \delta_{20}, \delta_{X0}, \delta_{30}, \delta_{40}\}$, in system estimation. For the first model configuration, $\{\hat{\lambda}_{LU}, \hat{\lambda}_{KI}, \hat{\lambda}_{KT}, \hat{\lambda}_{LS}\} = \{0.005, -0.002, -0.022^{*}, 0.048^{***}\}$, $\{\delta_{LU0}, \delta_{Z0}, \delta_{KI0}, \delta_{X0}, \delta_{KT0}, \delta_{LS0}\} = \{0.38, 0.62, 0.20, 0.80, 0.54, 0.46\}$ based on pooled averages, and Sargan–Hansen test p-value (null of valid overidentifying restrictions) = 0.89. For the second model configuration, $\{\hat{\lambda}_{LU}, \hat{\lambda}_{KT}, \hat{\lambda}_{KI}, \hat{\lambda}_{LS}\} = \{-0.003, -0.023^{***}, 0.030^{***}, 0.029^{***}\}$, $\{\delta_{LU0}, \delta_{Z0}, \delta_{KT0}, \delta_{X0}, \delta_{KI0}, \delta_{LS0}\} = \{0.38, 0.62, 0.44, 0.56, 0.34, 0.66\}$ based on pooled averages, and Sargan–Hansen test p-value (null of valid overidentifying restrictions) = 0.67. Instrument proliferation is not a concern. Residual diagnostics across both model configurations indicate low average absolute cross-section correlations of around 0.20 or less and a rejection of the unit root hypothesis based on first- and second-generation panel unit root tests. $\phi = \frac{\delta_{20}(\sigma-\rho)}{\sigma\rho}$ is the slope on g^{F_2} and $\gamma = \frac{\delta_{30}\delta_{X0}(\sigma-\rho)}{\sigma\rho} + \frac{\delta_{30}(\rho-\nu)}{\rho\nu}$ is the slope on g^{F_3}. *Source:* LUISS EU KLEMS & INTANProd, analytical database.

yield much higher returns in the case of success due to their scalability, especially in the presence of network effects, and synergies. The return distribution of intangible investments is thus much wider. However, as intangible investments generate significant spillovers that are contestable outside the borders of the firm, estimating returns to the organization making the investment is fraught with issues.

Facing uncertainty over ownership of intangible investments due to ambiguity of property rules and valuation challenges, intangible-intensive firms deepen their search for well-networked, knowledgeable, individuals that can broker connections with wide-ranging partners in order to harness spillovers and fully exploit synergies. High-profile directors assuage concerns about contestable uncertainties and improve confidence amongst investors about new technologies and markets. This ultimately can increase share prices and relax financing constraints (Braggion and Moore 2013). These tendencies increase the power and value of managers displaying such qualities. Håkanson, Lindqvist, and Vlachos (2021). find that workers recruited by high-paying firms are indeed those that score well on tests for both cognitive and non-cognitive skills.[37] Haskel and Westlake (2017) contend that top-paying firms are more careful to sort and screen their workers as a response to the growing importance of intangibles.

An important trait of highly skilled influential directors in a world of intangibles is their ability to lead. In addition to countering the sometimes costly, distortive, aspects of authoritative management models, good leadership in the form of commitment and sacrifice, for example, increases the likelihood of loyalty to the firm and thus the ability to retain tacit intangible capital. Using data on more than one thousand political leaders between 1875 and 2004, Besley, Montalvo, and Reynal-Querol (2011) find that economic growth is higher under more educated leaders. In an intangible economy, leadership is decisive in systems innovation as described by Haskel and Westlake (2017), where new intangible project ventures may be highly dependent on the collaboration of a number of related industries. As synergies grow with the number of investments in intangibles, competent leaders that can persuade their network of partners and other institutions, including government and competitors, to follow their plans earn a premium.

Figure 5 graphs the intangible capital intensity of countries against their ease of doing business scores at the end of our sample period. The cross-section plot evinces a pronounced positive relation between the share of intangibles in total economy value added and regulatory performance, where higher scores for the latter indicate better regulatory practices. The dimensions of regulation include property registration/rights, taxation, contract enforcement, insolvency resolution, and protection of investors, amongst others. The basic correlation implies that countries characterized by better regulatory frameworks are more conducive to successful investments in intangibles and wider business prosperity. The laws and institutional arrangements of a country underlie its economic health and stability. If the rules are efficient, accessible, and simple to implement, then this can reduce some of the doubts surrounding the funding of intangible assets. Investors will be concerned with, for example, the defense of patents[38] and honoring of distribution rights. Less equivocal regulation means less uncertainty on these matters, greater confidence, and thus higher investment.

Favorable tax regimes also improve the intensity of intangibles in an economy. Focusing on mobility, Akcigit, Baslandze, and Stantcheva (2016) find that top-quality inventors and (R&D) scientists are primarily located in countries with lower tax rates. Akcigit et al. (2018). meanwhile report that increases in the highest marginal personal income and corporate tax rates disproportionately decrease the number of (i) patents filed, (ii) citations (in subsequent innovations), and (iii) inventors.[39] On the one hand, taxes can be used to fund productive investments that raise economic growth. On the other hand, for a given level of public spending, it disincentivizes innovation by diminishing net profits from innovation. Up to a certain tax rate, the positive effect outweighs the negative effect. According to Aghion et al. (2016), the threshold at which taxation begins to have a negative net effect on growth is declining with the level of government corruption.[40]

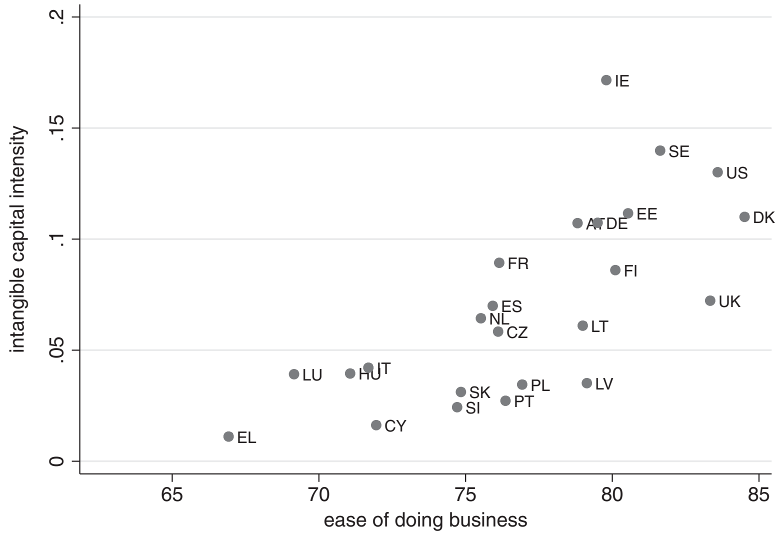

FIGURE 5 | Intangible capital income share versus Ease of doing business, 2015. *Notes:* Intangible capital intensity is measured as the share of intangible capital in total economy value added. Ease of doing business score ranges from 0 to 100, with a higher score reflecting a better regulatory environment that is more conducive to business success (*source*: World Bank). Pearson correlation coefficient: 0.72***. Spearman rank correlation coefficient: 0.76***. Plot with country *average* intangible capital income shares over the sample period is similar, where Pearson and Spearman correlation coefficients are 0.58*** and 0.53***, respectively. *** significant at 1%.

The World Management Survey (WMS), which measures management practices, as first described in Bloom and Van Reenen (2007), provides results that fall in line with the cross-country heterogeneity in the intensity of intangibles observed in Figure 5. We find that more intangible-intensive countries such as the U.S., Germany, and Sweden are typically characterized by higher average management scores (i.e., better practices). Less intangible-intensive countries such as Portugal and Greece conversely display weaker management scores.[41] One of the criteria in the survey is indeed how well loyalty is maintained amongst employees, which plays a crucial role in the growth of intangibles such as human and organizational capital. The link between management quality and the accumulation of intangible capital remains a fruitful avenue for future research at both aggregate economy and sectoral levels. Bloom, Sadun, and Van Reenen (2016) add that management is important in explaining large differences in both cross-country and within-country levels of total factor productivity.

6 | Conclusions

Income inequality and intangible capital growth are themes that have garnered significant attention in the economics literature over recent years e.g. Haskel and Westlake (2017, 2022), Oberfield (2023). We contribute to the discussion by examining whether intangibles impart differential growth effects on the skilled relative to unskilled labor share in income compared to tangibles. Our empirical analysis is based on a multi-factor, multi-level, supply-side framework that emphasizes the roles of factor substitution elasticities and factor intensities in the determination of "capital growth"-induced labor share dynamics.

Conducting the study at the total economy level, our results reveal that capital of the intangible variety demonstrates far greater complementarity with skilled labor, and that these two inputs as a composite form a strong substitute for tangible capital. Unskilled labor, meanwhile, exhibits the highest substitutability with remaining factor inputs. These elasticity estimates from our system of model equations indicate that intangible capital growth yields a more pronounced positive effect on the relative marginal product of skilled labor for the given factor intensities. Compared to tangibles, a larger stock of intangibles therefore induces a higher relative demand for skilled labor at given factor prices. This ultimately means a higher skill premium and relative skilled labor income than in the case of tangibles. In practice, the extent to which the gap between skilled and unskilled wages widens will hinge on the flexibility of the relative supply of skilled labor.

The findings suggest that investment in intangibles acts to more aggressively exacerbate income inequality than investment in tangibles. Software, large databases, and new management practices are leading to a replacement of egalitarian work cultures with systems driven by a robust reward-productivity nexus. This implies that the gap between the wages of the most talented skilled employees and those of remaining workers becomes more pronounced with the intensity of performance-tracking intangibles. More intangible-intensive economic activity further means that social capital will play a pivotal role, as negotiations, connections (networks), and competition over contested assets become increasingly important. In turn, underlying markers of social capital, such as education and class, will be in greater demand, thus reinforcing economy-wide income polarization.

Conflicts of Interest

The author declares no conflicts of interest.

Endnotes

[1] Research shows that these attributes are positively correlated with education. For example, Sunde et al. (2022) find a strong positive

link between patience, productivity, income, and years of schooling. Prada, Mareque, and Pino-Juste (2022) report that students' teamwork skills improve as they progress in their university studies, particularly those related to adaptability and decision-making. Studying psychological factors, Andersen et al. (2020), O'Connell and Marks (2022), and Bittmann (2022), amongst others, stress that conscientiousness, as characterized by carefulness, thoroughness, and deliberation, covaries positively with educational attainment.

[2] Bessen et al. (2020) find that investment in intangibles, especially software, by dominant firms is linked to reduced leapfrogging (industry dynamism/disruption) and greater persistence of the status quo in the industry.

[3] Investing in market research, product improvements, and advertising to develop brand loyalty generates further barriers to entry.

[4] The evolution of software, for example, has enabled CEOs to save time and increase the scope of their activities, such as the number of product lines controlled.

[5] We jointly model factor decompositions in a more flexible multi-level paradigm that allows for potentially heterogeneous degrees of substitutability across relevant input pairs.

[6] Applying some suitable combinations of the estimated parameters, this specification is able to closely approximate its two-level alternative. Our findings are not vastly altered with the latter model, which displays inferior fit and stationarity properties of estimated system residuals.

[7] Our paradigm is also closely related to the literature investigating automation in task-based models (Nakamura and Nakamura 2019).

[8] See Klump, McAdam, and Willman (2012) and Velic (2023) on the relevance of normalizing the CES production function and Krusell et al. (2000) on the problems associated with adopting a more general translog function.

[9] The inclusion of unskilled labor in the upper level, or nest, of the CES model is supported by the literature, as is the pairing of capital and skilled labor at bottom levels of nesting (Hamermesh 1993; Krusell et al. 2000). Pairing unskilled labor with capital in lower nests would imply that substitutability between capital and skilled labor is the same as that between unskilled labor and skilled labor, a restriction that is not lent any credence by previous research. Besides the literature, our choice of input configurations and specification design more generally are guided by information criteria, speed of parameter convergence, residual diagnostics (e.g., stationarity tests), sensibility of estimates, theoretical considerations, and the study's core objective.

[10] This is evident from Equation (12) with $F_4 = L_S$ and $F_3 = L_U$, or vice versa.

[11] This is evident from Equation (15), noting, for example, that $F_1 = L_U$, $F_2 = L_S$, $F_3 = K_T$, and $F_4 = K_I$. In particular, we would require differences in the physical capital growth rates g^{F_3} and g^{F_4}, and/or capital intensities δ_3 and δ_4, in the capital aggregator X found in compound input Z. Similar to Karabarbounis and Neiman (2014), amongst others, I discard formulations that effectively produce an aggregate labor or capital input in the bottom nest in order to avoid such inflexible settings.

[12] δ_{i0} are set in line with the corresponding pooled averages of factor income shares found in the benchmark data. The use of $\sigma > 1$ values within the defined interval follows evidence from the literature (e.g., Karabarbounis and Neiman (2014)) and our own empirical findings which indicate gross substitutability between unskilled labor and other factor inputs.

[13] Put differently, a higher σ diminishes growth in the relative marginal product of unskilled labor in response to capital growth. The negative impact of a higher σ on the unskilled labor return can be inferred from Equation (8).

[14] Generally, to yield a constant γ, it is evident from the graphs that ν must increase at a diminishing rate with ρ, given the δ_i weights.

[15] Noting again that a higher σ reduces unskilled labor returns by making the marginal product of unskilled labor less sensitive to capital growth.

[16] LUISS and TCB are the sources of our EU KLEMS data (see http://www.euklems.net).

[17] The list of countries is: Austria (AT), Belgium (BE), Cyprus (CY), Czech Republic (CZ), Denmark (DK), Estonia (EE), Finland (FI), France (FR), Germany (DE), Greece (EL), Hungary (HU), Ireland (IE), Italy (IT), Latvia (LV), Lithuania (LT), Luxembourg (LU), Netherlands (NL), Poland (PL), Portugal (PT), Slovak Republic (SK), Slovenia (SI), Spain (ES), Sweden (SE), United Kingdom (UK), United States (US).

[18] The time series for Denmark, Finland, France, and Sweden go back further than 1995, which leaves us with an unbalanced panel.

[19] Results are not qualitatively altered by only using the number of employees as the basic labor input measure.

[20] Labor compensation in EU KLEMS equals total compensation of employees times the ratio of hours worked by persons engaged to hours worked by employees, assuming the same hourly wages across employees and the self-employed.

[21] Estimation of the user cost of capital is based on the arbitrage equation produced by the neoclassical theory of investment.

[22] Typical production models feature $r = i - (1-\xi)\mathbb{E}[\pi] + \xi$ as the required rate of return on capital in equilibrium. The approximated return used in Equation (20) is more prevalent in the literature. For our data, the two returns generate similar results.

[23] Employing the full time period average growth rate of the investment deflator in Equation (20) does not alter results greatly. Similarly, results do not change markedly if start or end-of-year capital stocks are employed. These substitute measures are highly correlated with the ones in (20).

[24] The aggregate capital cost can be expressed as the nominal capital stock-weighted average of asset-specific required rates of return multiplied by the aggregate nominal capital stock: $\widetilde{CAP}^{total}_{c,t} \equiv \sum_{\kappa} \frac{P^{\kappa}_{c,t} K^{\kappa}_{c,t}}{\sum_s P^s_{c,t} K^s_{c,t}} \tilde{r}^{\kappa}_{c,t} \times \sum_{\kappa} P^{\kappa}_{c,t} K^{\kappa}_{c,t}$.

[25] These data in some cases are obtained from the WIOD's Socio Economic Accounts.

[26] Established national education attainment levels below the university grade do not always allow for direct comparability. Medium-skilled labor is defined as that with an intermediate level of education, while low-skilled labor is that with no formal qualifications in EU KLEMS. What classifies an intermediate level of education and no formal qualifications differs across nations.

[27] The first study focuses on the U.S., the next three on Europe, and the last one on both.

[28] Skill mismatching amongst college graduates is another factor, especially during recessions (Liu, Salvanes, and Sørensen 2016).

[29] A recent study by Acemoglu, Koster, and Ozgen (2023) finds that blue-collar workers performing routine tasks face lower employment and earnings as a result of robot adoption, while other workers indirectly gain. Acemoglu and Restrepo (2022), moreover, estimate negative effects on wages and employment in demographic groups most exposed to automation driven by specialized software e.g. clerical tasks in many industries experienced software-based automation.

[30] Among other implications, Bar-Gill, Brynjolfsson, and Hak (2023) find that digitization, including the rise of analytics tools, data-driven decision-making, and digital platforms, increases firm revenues.

[31] For example, for legal advisory services and insurance inquiries/purchases.

[32] For example, virtual doctors or psychologists in mental health care.

[33] The relative skilled wage bears the full burden of adjustment if the relative supply of skilled labor is fixed.

[34] Endogenous growth theory effectively indicates that technical change is directed toward scarce factors and goods.

[35] For example, see Acemoglu (2009) for an overview.

[36] The estimation is performed on a somewhat truncated overall sample due to missing augmented intangible capital data for a few countries.

[37] That is, highly educated individuals gifted with different forms of intelligence.

[38] That is, the ability to retain innovation rents for a period.

[39] These studies assume a fixed level of public investment.

[40] Where both of the aforementioned channels are adversely affected.

[41] See Bloom et al. (2014) and Bloom et al. (2016) for further details on rankings.

References

Acemoglu, D. 2009. *Introduction to Modern Economic Growth*. Princeton, NJ: Princeton University Press.

Acemoglu, D., H. R. A. Koster, and C. Ozgen. 2023. "Robots and Workers: Evidence from the Netherlands," NBER Working Paper No. 31009.

Acemoglu, D., and P. Restrepo. 2020. "Robots and Jobs: Evidence From U.S. Labor Markets." *Journal of Political Economy* 128, no. 6: 2188–2244.

Acemoglu, D., and P. Restrepo. 2022. "Tasks, Automation, and the Rise in US Wage Inequality." *Econometrica* 90, no. 5: 1973–2016.

Aghion, P., U. Akcigit, A. Bergeaud, R. Blundell, and D. Hémous. 2019. "Innovation and Top Income Inequality." *Review of Economic Studies* 86, no. 1: 1–45.

Aghion, P., U. Akcigit, J. Cagé, and W. R. Kerr. 2016. "Taxation, Corruption, and Growth." *European Economic Review* 86: 24–51.

Aghion, P., C. Antonin, and S. Bunel. 2021. *The Power of Creative Destruction: Economic Upheaval and the Wealth of Nations*. Cambridge, MA: Harvard University Press.

Akcigit, U., S. Baslandze, and S. Stantcheva. 2016. "Taxation and the International Mobility of Inventors." *American Economic Review* 106, no. 10: 2930–2981.

Akcigit, U., and N. Goldschlag. 2023. "Where Have All the "Creative Talents" Gone? Employment Dynamics of U.S. Inventors," NBER Working Paper No. 31085.

Akcigit, U., J. Grigsby, T. Nicholas, and S. Stantcheva. 2018. "Taxation and Innovation in the 20th Century," NBER Working Paper No. 24982.

Andersen, S. C., M. Gensowski, S. G. Ludeke, and O. P. John. 2020. "A Stable Relationship Between Personality and Academic Performance From Childhood Through Adolescence. An Original Study and Replication in Hundred-Thousand-Person Samples." *Journal of Personality* 88, no. 5: 925–939.

Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. Van Reenen. 2017. "Concentrating on the Fall of the Labor Share." *American Economic Review* 107, no. 5: 180–185.

Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. Van Reenen. 2020. "The Fall of the Labor Share and the Rise of Superstar Firms." *Quarterly Journal of Economics* 135, no. 2: 645–709.

Bar-Gill, S., E. Brynjolfsson, and N. Hak. 2023. "Helping Small Businesses Become More Data-Driven: A Field Experiment on eBay," NBER Working Paper No. 31089.

Beaudry, P., D. A. Green, and B. M. Sand. 2016. "The Great Reversal in the Demand for Skill and Cognitive Tasks." *Journal of Labor Economics* 34, no. S1: S199–S247.

Besley, T., J. G. Montalvo, and M. Reynal-Querol. 2011. "Do Educated Leaders Matter?" *Economic Journal* 121, no. 554: F205–F227.

Bessen, J., E. Denk, J. Kim, and C. Righi. 2020. "Declining Industrial Disruption," Boston University School of Law, Law & Economics Series Paper No. 20-28.

Bittmann, F. 2022. "Are Cognitive Ability and Conscientiousness Really More Important for Educational Attainment Than SES? A Replication and Extension of O 'Connell and Marks (2022)." *Collabra: Psychology* 8, no. 1: 37460.

Bloom, N., R. Lemos, R. Sadun, D. Scur, and J. Van Reenen. 2014. "The New Empirical Economics of Management." *Journal of the European Economic Association* 12, no. 4: 835–876.

Bloom, N., R. Lemos, R. Sadun, D. Scur, and J. Van Reenen. 2016. "Management and Productivity in the Private Sector," PEDL Policy Insights Series No.1.

Bloom, N., R. Sadun, and J. Van Reenen. 2016. "Management as a Technology?," NBER Working Paper No. 22327.

Bloom, N., and J. Van Reenen. 2007. "Measuring and Explaining Management Practices Across Firms and Countries." *Quarterly Journal of Economics* 122, no. 4: 1351–1408.

Bontadini, F., C. Corrado, J. Haskel, M. Iommi, and C. S. Jona-Lasinio. 2023. *EU KLEMS & INTANProd: Industry Productivity Accounts With Intangibles - Sources of Growth and Productivity Trends: Methods and Main Measurement Challenges*. Rome: LUISS Lab of European Economics.

Bontadini, F., C. Corrado, J. Haskel, M. Iommi, C. S. Jona-Lasinio, and T. Miyagawa. 2024. "Intangible Capital, TFP Growth and Green Shoots in New Productivity Data." In *International Productivity Monitor - Symposium on International Productivity Growth: The Role of Intangibles*, edited by A. Sharpe and B. van Ark, vol. 46, Spring, 3–37. Ottawa, ON: Centre for the Study of Living Standards (CSLS) & The Productivity Institute.

Boushey, H., J. B. DeLong, and M. Steinbaum. 2017. *After Piketty: The Agenda for Economics and Inequality*. Cambridge, MA: Harvard University Press.

Braggion, F., and L. Moore. 2013. "The Economic Benefits of Political Connections in Late Victorian Britain." *Journal of Economic History* 73, no. 1: 142–176.

Choi, I. 2001. "Unit Root Tests for Panel Data." *Journal of International Money and Finance* 20, no. 2: 249–272.

Corrado, C., J. Haskel, M. Iommi, and C. S. Jona-Lasinio. 2018. "Intangible Investment in the EU and US Before and Since the Great Recession and Its Contribution to Productivity Growth." *Journal of Infrastructure, Policy and Development* 2, no. 1: 11–36.

Corrado, C., J. Haskel, M. Iommi, C. S. Jona-Lasinio, and F. Bontadini. 2024. "Data, Intangible Capital, and Productivity." In *Technology, Productivity, and Economic Growth*, Studies in Income and Wealth, edited by S. Basu, L. Eldridge, J. Haltiwanger, and E. Strassner. Chicago, IL: University of Chicago Press.

Corrado, C., J. Haskel, M. Iommi, C. S. Jona-Lasinio, M. Mas, and M. O'Mahony. 2017. "Advancements in Measuring Intangibles for European Economies." *Eurostat Review on National Accounts and Macroeconomic Indicators* 2: 89–106.

Corrado, C., C. Hulten, and D. Sichel. 2005. "Measuring Capital and Technology: An Expanded Framework." In *Measuring Capital in the New Economy, Studies in Income and Wealth*, edited by C. Corrado, J. Haltiwanger, and D. Sichel, vol. 66, 11–46. Chicago, IL: University of Chicago Press.

Corrado, C., C. Hulten, and D. Sichel. 2009. "Intangible Capital and U.S. Economic Growth." *Review of Income and Wealth* 55, no. 3: 661–685.

Crivellaro, E. 2016. "The College Wage Premium Over Time: Trends in Europe in the Last 15 Years." In *Inequality: Causes and Consequences*, edited by L. Cappellari, S. W. Polachek, and K. Tatsiramos, vol.

43(Research in Labor Economics), 287–328. Bingley, UK: Emerald Group Publishing.

Crouzet, N., and J. Eberly. 2018. "Intangibles, Investment, and Efficiency." *AEA Papers and Proceedings* 108, no. May: 426–431.

Deming, D. J. 2023. "Multidimensional Human Capital and the Wage Structure," NBER Working Paper No. 31001.

Eeckhout, J. 2021. *The Profit Paradox: How Thriving Firms Threaten the Future of Work*. Princeton, NJ: Princeton University Press.

Frey, C. B., and M. A. Osborne. 2017. "The Future of Employment: How Susceptible Are Jobs to Computerisation?" *Technological Forecasting and Social Change* 114: 254–280.

Garcia-Lazaro, A., and N. Pearce. 2023. "Intangible Capital, the Labour Share and National Growth Regimes." *Journal of Comparative Economics* 51, no. 2: 674–695.

Green, F., and G. Henseke. 2021. "Europe's Evolving Graduate Labour Markets: Supply, Demand, Underemployment and Pay." *Journal for Labour Market Research* 55, no. 1: 1–13.

Grossman, G. M., and E. Oberfield. 2022. "The Elusive Explanation for the Declining Labor Share." *Annual Review of Economics* 14, no. 1: 93–124.

Håkanson, C., E. Lindqvist, and J. Vlachos. 2021. "Firms and Skills: The Evolution of Worker Sorting." *Journal of Human Resources* 56, no. 2: 512–538.

Hall, B. H., A. Jaffe, and M. Trajtenberg. 2005. "Market Value and Patent Citations." *RAND Journal of Economics* 36, no. 1: 16–38.

Hall, R. E., and D. W. Jorgenson. 1967. "Tax Policy and Investment Behavior." *American Economic Review* 57, no. 3: 391–414.

Hamermesh, D. S. 1993. *Labor Demand*. Princeton, NJ: Princeton University Press.

Haskel, J., and S. Westlake. 2017. *Capitalism Without Capital: The Rise of the Intangible Economy*. Princeton, NJ: Princeton University Press.

Haskel, J., and S. Westlake. 2022. *Restarting the Future: How to Fix the Intangible Economy*. Princeton, NJ: Princeton University Press.

Im, K. S., M. H. Pesaran, and Y. Shin. 2003. "Testing for Unit Roots in Heterogeneous Panels." *Journal of Econometrics* 115, no. 1: 53–74.

Jones, C. I., and J. Kim. 2018. "A Schumpeterian Model of Top Income Inequality." *Journal of Political Economy* 126, no. 5: 1785–1826.

Karabarbounis, L., and B. Neiman. 2014. "The Global Decline of the Labor Share." *Quarterly Journal of Economics* 129, no. 1: 61–103.

Klump, R., P. McAdam, and A. Willman. 2012. "The Normalized CES Production Function: Theory and Empirics." *Journal of Economic Surveys* 26, no. 5: 769–799.

Krusell, P., L. E. Ohanian, J.-V. Ríos-Rull, and G. L. Violante. 2000. "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis." *Econometrica* 68, no. 5: 1029–1053.

Lawrence, R. Z. 2015. "Recent Declines in Labor's Share in U.S. Income: A Preliminary Neoclassical Account," NBER Working Paper No. 21296.

Liu, K., K. G. Salvanes, and E. Ø. Sørensen. 2016. "Good Skills in Bad Times: Cyclical Skill Mismatch and the Long-Term Effects of Graduating in a Recession." *European Economic Review* 84: 3–17.

Nakamura, H., and M. Nakamura. 2019. "Production Function through Automation in a Task-Based Model," SSRN.

Oberfield, E. 2023. "Inequality and Measured Growth," NBER Working Paper No. 31096.

O'Connell, M., and G. N. Marks. 2022. "Cognitive Ability and Conscientiousness Are More Important Than SES for Educational Attainment: An Analysis of the UK Millennium Cohort Study." *Personality and Individual Differences* 188: 111471.

O'Mahony, M., M. Vecchi, and F. Venturini. 2021. "Capital Heterogeneity and the Decline of the Labour Share." *Economica* 88, no. 350: 271–296.

Pesaran, M. H. 2004. "General Diagnostic Tests for Cross Section Dependence in Panels," CESifo Working Paper No. 1229.

Pesaran, M. H. 2007. "A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence." *Journal of Applied Econometrics* 22, no. 2: 265–312.

Pesaran, M. H. 2015. "Testing Weak Cross-Sectional Dependence in Large Panels." *Econometric Reviews* 34, no. 6–10: 1089–1117.

Philippon, T. 2019. *The Great Reversal: How America Gave Up on Free Markets*. Cambridge, MA: Harvard University Press.

Piketty, T. 2014. *Capital in the Twenty-First Century*. Cambridge, MA: Harvard Univeristy Press.

Piketty, T., and G. Zucman. 2014. "Capital Is Back: Wealth-Income Ratios in Rich Countries 1700–2010." *Quarterly Journal of Economics* 129, no. 3: 1255–1310.

Prada, E. D., M. Mareque, and M. Pino-Juste. 2022. "Teamwork Skills in Higher Education: Is University Training Contributing to Their Mastery?" *Psicologia: Reflexão e Crítica* 35, no. 5: 1–13.

Rognlie, M. 2015. "Deciphering the Fall and Rise in the Net Capital Share: Accumulation or Scarcity?" *Brookings Papers on Economic Activity* 46, no. 1: 1–69.

Roth, F., and A.-E. Thum. 2013. "Intangible Capital and Labor Productivity Growth: Panel Evidence for the EU From 1998–2005." *Review of Income and Wealth* 59, no. 3: 486–508.

Saez, E., and G. Zucman. 2019. *The Triumph of Injustice: How the Rich Dodge Taxes and How to Make Them Pay*. New York: W.W. Norton & Company.

Scheve, K., and D. Stasavage. 2016. *Taxing the Rich: A History of Fiscal Fairness in the United States and Europe*. Princeton, NJ: Princeton University Press.

Song, J., D. J. Price, F. Guvenen, N. Bloom, and T. Von Wachter. 2019. "Firming Up Inequality." *Quarterly Journal of Economics* 134, no. 1: 1–50.

Sunde, U., T. Dohmen, B. Enke, A. Falk, D. Huffman, and G. Meyerheim. 2022. "Patience and Comparative Development." *Review of Economic Studies* 89, no. 5: 2806–2840.

Valletta, R. G. 2018. "Recent Flattening in the Higher Education Wage Premium: Polarization, Skill Downgrading, or Both?" In *Education, Skills, and Technical Change: Implications for Future U.S. GDP Growth*, edited by Charles R. Hulten and Valerie A. Ramey, 313–342. Chicago, IL: University of Chicago Press.

Velic, A. 2023. "Wages and the Role of Intangibles in Finance," TEP Working Paper No. 0323.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.