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The University of Dublin

Wages and the Role of Intangibles in Finance

Adnan Velic

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Adnan Velic†

Technological University Dublin

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Abstract

We investigate the role of intangible capital in the growth of relative finance wages using i) a production framework entailing multi-level nesting and ii) reduced-form analysis. We find that the degree and effects of complementarity between skilled labor and intangible capital are much more pronounced in finance than in the rest of the market economy. The stronger positive effects of such complementarity on finance skill premia are reinforced by relatively stronger unskilled labor substitution possibilities and technical change in the sector. Despite accounting for under a tenth of overall economic activity, finance offsets up to almost a third of declines in skilled-unskilled wage disparities nationally. We thereby find that finance contributes inordinately to income inequality. Intensified intangible capital growth in the industry stands to exacerbate this trend. Finally, our study suggests that financial deregulation, globalization, banking competition, and domestic credit expansion positively affect relative finance wages. Stricter labor market protection meanwhile dampens the impact of banking competition.

Keywords: skill premium, inequality, intangible capital, finance, factor substitution, productivity growth, factor-income shares, multi-level nesting

JEL: G2, J2, J3, O3, O4

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†Email: adnan.velic@tudublin.ie
Address: School of Accounting, Economics, and Finance, College of Business, Technological University Dublin, Aungier Street, Dublin 2, Ireland.

1 Introduction

The shift toward skill-intensive service-based economies in the developed world (Herrendorf *et al.*, 2014; Baldwin, 2019; Autor *et al.*, 2021) has been met by a significant rise in intangible capital (Gutiérrez and Philippon, 2017; Haskel and Westlake, 2017; West, 2018; Philippon, 2019). One area that is at the forefront of these trends is finance. The prominent rise of artificial intelligence (AI) and big data in the sector has translated into the automation of various services such as those pertaining to payments, loans, investment, and data analytics. By assisting skilled labor, it is acting as a critical enabler of innovative forms of research and asset trading (Aldridge and Krawciw, 2017). Although zero-wage competition from white-collar digital robots is posing a threat to certain work previously shielded in finance, it is creating opportunities in programming and other related areas (Baldwin, 2019; Laboure and Deffrennes, 2022). Such advances (i.e. FinTech algorithms) are improving financial inclusion by reducing negative prejudice in credit markets compared to face-to-face lending (Philippon, 2020; Prasad, 2021; Bartlett *et al.*, 2022). Simultaneously, increasing financialization is leading to conclusions that finance is disproportionately contributing to aggregate-level income inequality (Philippon and Reshef, 2012; Denk, 2015).

In this paper, we focus on advanced economies and investigate the role of intangible capital in the evolution of relative finance wages, which have sustained an upward trajectory over time. The first half of our study displays a finance-growth nexus in that we adopt a multi-level nested production framework to examine the relative factor substitution possibilities and technical change of the financial sector. We find that the degree of complementarity between skilled labor and intangibles is much stronger in finance than in the remainder of the market economy. Thus, the leveraging of new skill-complementary intangible technologies that increase efficiency is likely to be higher in finance. Unskilled labor and intangible capital, on the other hand, are notably less substitutable in non-finance. Analytically, these differences in sectoral elasticities of substitution for the given factor intensities engender a more pronounced positive relation between the skill premium and intangible capital in finance. The relative finance skill premium is moreover reinforced by larger technical change effects in the sector.

Expanding on this micro-level theoretical foundation, we subsequently conduct a reduced-form analysis of the covariates of relative finance wages in the second half of the paper. We find that increases in the intensity of intangibles in finance relative to non-finance, ceteris paribus, are tied to a bolstering of relative finance aggregate and skilled wages. This materializes because of i) sectoral discrepancies in skill-capital complementarities and unskilled labor substitution possibilities, which imply that skilled (unskilled) labor productivity is more sensitive to intangible capital in finance (non-finance) and ii) relative capital stock volume amplification effects. These channels yield upward pressures on the skilled-to-unskilled ratio of marginal products in finance relative to that in non-finance, and in turn relative finance demand for skilled labor at given factor input prices. As we find that finance, relative to its economic size, inordinately promotes economy-wide income inequality, elevated intangible capital growth in the industry stands to aggravate its resistance to narrowing the income divide.

The literature tenders a variety of reasons for capital deepening including globalization (Elsby *et al.*, 2013), declining investment goods prices (Karabarbounis and Neiman, 2014), deteriorating growth in the face of a constant savings rate (Piketty, 2014), and automation (Acemoglu and Restrepo, 2018, 2020). Most notably, there has been a pronounced shift in the composition of investment toward intangible assets, such that intangible capital today commands a significant share in both aggregate capital and income. While secular stagnation after the global financial crisis (GFC) features lower overall investment, the curtailment is far less severe for intangibles. We find that the intensity of intangibles in firm operations is much greater in finance than in the non-financial market economy. Real intangible capital growth in finance since the mid-nineties has averaged 7.4 percent per annum (p.a.) compared to 4.2 percent in non-finance. Moreover, the share of intangibles in income relative to that of tangibles grows annually two to three times faster in finance.

The relative rise of intangibles in finance reflects the data intensity of the sector and growing influence of FinTech. The distinction between tangible and intangible capital in the capital deepening process is important as intangible assets exhibit a number of properties that make them more likely to induce higher skilled labor compensation. Firstly, intangible investment costs are highly likely to be sunk. This increases demand for highly skilled managers that can handle skilled labor with powerful bargaining positions. Second, they are more scalable. In the investment advisory industry for instance, a single robo-advisor can provide portfolio management services to many clients. Thus computer algorithms relax time constraints on other activities and overall increase the productivity of skilled labor. Third, the combination of intangibles tends to generate greater synergies and positive spillovers (e.g. network effects of new software or merging ideas across divisions), where the whole is much larger than the sum of individual parts. The latter three features can produce bigger organizations and hence higher demand for highly skilled labor. Larger profits and rents associated with firm size can translate to improved pay packages amongst the skilled, thereby increasing income inequality. Intangibles are also able to create entry barriers that further consolidate the higher rents and salaries of incumbents. Additionally, intangible capital is harder to tax as it can be moved across borders more easily (Haskel and Westlake, 2017).

Our paper is the first to consider intangible capital as a separate factor input within a multi-level production setup à la Krusell *et al.* (2000) and Ohanian *et al.* (2021), and its implications for skill premia in both financial and non-financial sectors. Factor input decompositions, more generally, enable identification of the specific winners and losers of reported aggregate factor share changes. Such insights allow for better targeted heterogeneous policy responses across stakeholders. By adopting a more elaborate framework, we are able to exploit the availability of more granular factor data and relax restrictions pertaining to elasticities of substitution in conventional models. Furthermore, the approach is useful to those studying economy-wide patterns in labor share dynamics through the lens of sectoral discrepancies in supply-side characteristics such as factor substitution elasticities, factor-augmenting productivities (technical change bias), and factor intensities in production. Our work is therefore also directly related to the growth literature examining structural change drivers and balanced growth (Kongsamut *et al.*, 2001; Ngai and Pissarides, 2007; Acemoglu and Guerrieri, 2008; Herrendorf *et al.*, 2014; Herrendorf *et al.*, 2015; Comin *et al.*, 2021).

We find that the share of labor in income on average declines in both sectors, and by significantly more in the non-financial market economy. Unskilled labor is responsible for the deterioration across the two sectors. Skilled labor, conversely, exerts pressures in the opposite direction and yields a much stronger counteracting force in finance. The sector's share of skilled labor relative to that of unskilled labor in particular grows 6.3 percent p.a. on average in contrast to only 2.4 percent in non-finance. The relative finance skill premium, meanwhile, trends upwards, with the cross-country weighted average skill premium in finance overtaking that in non-finance in the early 2000s. Unlike the non-finance skill premium which is characterized by a downward trajectory from the mid-nineties, the finance skill premium grows up until the GFC. Our analysis further highlights that skill composition matters for relative finance wage growth, and that finance disproportionately contributes to growth in the market economy skill premium. Although it constitutes around a tenth of overall economic activity, finance offsets up to almost a third of declines in skilled-to-unskilled wage disparities nationally. As we show, skilled labor (including wage and intensity changes) accounts for most of the shifts in relative finance aggregate wages.

The growth of financial services and financial sector compensation has garnered much attention in the literature (Greenwood and Scharfstein, 2013; Glode and Lowery, 2016). Nevertheless, despite the growing palpable influence of intangibles such as FinTech-related R&D, organizational design, and machine learning in finance and the wider market economy, the *interaction* between tangibles, intangibles, and labor skills in formal production frameworks, and its role in wage determination, remain unexplored.[1] This gap in the field has partly been driven by data availability issues (Corrado *et al.*, 2009; Haskel and Westlake, 2017). Our study shows that intangible capital has differential implications for the marginal products of skilled and unskilled labor across finance and non-finance.[2] If the skills associated with intangibles are clustered in highly intangible-intensive financial institutions characterized by large informational rents, our results imply an exacerbation of the dichotomy between the rich and the poor.

In related work, in their model attempting to explain U.S. labor demand shifts, Autor *et al.* (2003) contend that computer capital substitutes with "routine labor" (explicit codifiable tasks) and complements labor specializing in "abstract" tasks (creativity, high-level problem solving).[3] The remaining "non-routine manual" tasks (food preparation, janitorial work) are assumed to be much less affected by such capital. While Autor *et al.* (2015) confirm that employment polarization is evident in U.S. local labor markets, they report that computerization does not reduce net employment. Frey and Osborne (2017) estimate that 47 percent of U.S. employment is at risk to computerization, reporting evidence of a strong inverse relation between wages / educational attainment and an occupation's probability of computerization.[4] The intensity with which a particular class of workers is employed will vary across heterogeneous production technologies in equilibrium (Choné and Kra-

[1]Intangible capital is more pervasive in finance. Machine learning is yielding analytics engines that are flexible and robust over time, thus delivering faster, cheaper, and more effective portfolio-optimized solutions in different market environments. Algorithmic trading is responsible for about half of all trading on the stock market, with real-time risk evaluation, while insurance companies are employing AI systems to calculate policyholder payouts. Credit ratings and loan pricing are now available through online platforms that harness quantitative credit-modeling approaches to produce quick and reliable estimates. Many firms are offering analytics in "software-as-a-service", while subscriptions to big data sources are driving profitability in the industry. Digital automation and big data are making detection of risk events less arduous. Machine learning algorithms, moreover, are ubiquitous in customer service departments e.g. Amelia in Swedish bank SEB.

[2]Intangible capital growth benefits skilled labor productivity more in finance, while inducing greater substitution of less skilled labor which releases additional resources and increases profits in the sector.

[3]The authors use a Cobb-Douglas production function featuring a composite of routine labor and computer capital which enter additively so that they are characterized by perfect substitutability, thus making computers and the remaining input, non-routine tasks, relative complements.

[4]Our work is closely tied to the literature on automation in task-based models (Nakamura and Nakamura, 2019).

marz, 2021). One might anticipate that market returns to a particular skill type should be higher in settings where the technology is likely to be more intensively using that skill (Skans *et al.*, 2023).

Assessing the other covariates in reduced-form regressions, we find strong evidence of a positive relation between relative finance wages and financial deregulation, financial globalization, banking competition under flexible labor markets, relative ICT intensity, and domestic credit growth. In contrast, relative finance skilled labor supply and labor market rigidity in the presence of bank competition each display an inverse link. Our results indicate that greater employment protection encumbers the effects of competition in finance, whereby higher competition intensity can be associated with lower relative finance wages given highly regulated labor markets.

The remainder of the paper is structured as follows. Section 2 outlines the underlying supply-side paradigm implemented for the theoretically-grounded analysis of skill premia. Specifically, section 2.1 expounds the multi-factor, multi-level, nested CES models comprising decompositions of aggregate factor inputs, and derives analytical expressions for sectoral skill premia in terms of relative skilled labor supply, capital growth, and technical change. As we demonstrate, the links between the latter three components and skill premia are determined by factor-substitution elasticities, factor-augmenting productivity growth, and factor intensities in production. In section 3, we discuss some of the motivations underpinning the covariates included in our complementary reduced-form assessment of relative finance wages and skill premia. The data and estimation methodologies employed are comprehensively detailed in section 4. The section further provides insight into the relevance of i) skilled labor for relative finance wages and ii) finance for the economy-wide skill premium. Section 5 commences the core empirical analysis. In particular, sections 5.1 and 5.2 tender the three-factor and four-factor model results respectively, while section 5.3 evaluates findings from reduced-form regressions. We conclude in section 6.

2 Theoretical Framework

The decomposition of the market-wide skilled (S), unskilled (U), or total (T) labor share over the financial sector (F) and the remainder of the market economy (NF) can be written as

$$\underbrace{\frac{w_t^v L_t^v}{P_t Y_t}}_{\text{aggregate labor share}} \equiv \sum_{\forall \tau \in I_\tau} \underbrace{\frac{w_{\tau,t}^v L_{\tau,t}^v}{P_{\tau,t} Y_{\tau,t}}}_{\text{sector } \tau\text{'s labor share}} \times \underbrace{\frac{P_{\tau,t} Y_{\tau,t}}{P_t Y_t}}_{\text{sector } \tau\text{'s output share}} \tag{1}$$

where $v \in \{S, U, T\}$, $\tau \in \{F, NF\}$, and $Y_t = \left[\sum_\tau \delta_\tau Y_{\tau,t}^{\frac{\epsilon-1}{\epsilon}}\right]^{\frac{\epsilon}{\epsilon-1}}$. $\delta_\tau \in (0,1)$ is the intensity of sector τ's output in final market output Y_t with $1 - \delta_F = \delta_{NF}$, while ϵ reflects the degree of complementarity between sectoral outputs in Y_t. Under sectoral Cobb-Douglas production functions, sectoral factor shares are constant. Therefore, in the presence of heterogeneous production technologies across sectors (i.e. capital intensities), aggregate factor share dynamics will be driven by sectoral output shares. A deviation from factor substitution elasticities of unity through a more general constant elasticity of substitution (CES) production structure enhances flexibility, as it allows aggregate factor share changes to be also influenced by sectoral factor shares. We next outline the multi-level nested CES paradigms employed in our analysis, moving from aggregated to disaggregated capital inputs.

2.1 Multi-Level CES Nesting Approach

With normalization in our three-level (two-level) CES case, estimation solely focuses on the three (two) constant substitution elasticities and the four (three) factor-augmenting technical change parameters as highlighted in the next sections. By comparison, the more general translog production function alternative has many more parameters for estimation, which reduces degrees of freedom and thus can be problematic in small samples. In addition to this and other issues[5], translog substitution elasticities vary over time which would complicate quantifying the effects of factor input changes on relative factor prices and factor shares over our sample period. Finally, we note that the benefit of going beyond a one-step production function is flexibility. Reducing the number of levels in the production system acts to restrict the substitution elasticities between factors.

2.1.1 Baseline Sectoral Model

Decomposing labor, we first consider a two-level nested CES model that combines skilled labor (L_S), unskilled labor (L_U), and total capital (K) to produce output (Y). Omitting subscript τ for brevity, the general three-factor setup in each sector is provided by

$$Y_t = A\left[\delta_1(A_{1,t}F_{1,t})^{\frac{\sigma-1}{\sigma}} + \delta_X X_t^{\frac{(\sigma-1)\nu}{(\nu-1)\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

where

$$X_t = \left[\delta_2(A_{2,t}F_{2,t})^{\frac{\nu-1}{\nu}} + \delta_3(A_{3,t}F_{3,t})^{\frac{\nu-1}{\nu}}\right]. \tag{3}$$

The configuration of production factors $F_1(F_2F_3)$ can correspond to $L_U(L_SK)$, $L_S(L_UK)$, or $K(L_SL_U)$. For example, the first case indicates that a composite of skilled labor and total capital is combined with unskilled labor at the top level of nesting. The constant parameters $\delta_i \;\forall i \in \{1, X\}$ and $\delta_{j\neq i}\delta_X$ are factor intensities in output with $\delta_1 + \delta_X = 1$ while $\delta_j \;\forall j \in \{2,3\}$ are cost weights in aggregate X compensation with $\delta_2 + \delta_3 = 1$. The productivity variables allow for factor-biased technical progress and are defined as $A_{i,t} = A_{i,0}e^{\lambda_i t} \;\forall i \in \{1,2,3\}$, with λ representing the constant of proportionality. The elasticity of substitution between factor input F_1 and the aggregate input X is given by σ. Meanwhile, ν is the elasticity of substitution between factor inputs F_2 and F_3 at the bottom level of nesting.

The presence of more than two factors of production complicates the notion of a substitution elasticity, thus leading to multiple definitions. We additionally adopt the Morishima elasticity of substitution which is defined as the difference between cross-price and own-price elasticities $\frac{\partial \ln F_j}{\partial \ln r_i} - \frac{\partial \ln F_i}{\partial \ln r_i} \equiv \varepsilon_{j,i} - \varepsilon_{i,i} = \eta_{i,j}$. As nesting separates the links between different levels of the production function, the Morishima elasticity can be asymmetric in a nested CES setup. The Morishima elasticity accounts for all factor substitution possibilities. For example, the standard Hicksian top level elasticity σ would not account for substitution possibilities within the bottom level X_t process. Furthermore, the Morishima elasiticity of substitution (η) can be directly linked to changes in the ratio of factor income shares $\frac{\partial \ln \frac{r_iF_i}{r_jF_j}}{\partial \ln \frac{r_i}{r_j}} = 1 - \eta_{i,j}$.

[5] Including those pertaining to constrained translog functions.

Consider two nests (processes) N_r and N_s within a nested CES function. Define σ_I as the interprocess elasticity and $\sigma_{r(s)}$ as the intraprocess elasticity pertaining to nest $N_{r(s)}$. Then for our three-factor nested CES function, the average Morishima elasticities are provided by

$$\eta_{a,b} = \eta_{b,a} = \sigma_{r(s)},\ a,b \in N_{r(s)} \Rightarrow \eta_{2,3} = \eta_{3,2} = \nu \tag{4a}$$

$$\eta_{a,b} = \delta_a^r \sigma_I + (1-\delta_a^r)\sigma_r,\ a \in N_r,\ b \in N_s \Rightarrow \eta_{1,2} = \eta_{1,3} = \sigma \tag{4b}$$

$$\eta_{b,a} = \delta_b^s \sigma_I + (1-\delta_b^s)\sigma_s,\ a \in N_r,\ b \in N_s \Rightarrow \eta_{2,1} = \delta_2\sigma + (1-\delta_2)\nu \tag{4c}$$

$$\eta_{b,a} = \delta_b^s \sigma_I + (1-\delta_b^s)\sigma_s,\ a \in N_r,\ b \in N_s \Rightarrow \eta_{3,1} = \delta_3\sigma + (1-\delta_3)\nu. \tag{4d}$$

While the Morishima intra-nest elasticities are symmetric, the Morishima inter-nest elasticities can be asymmetric. In particular, changes in r_1 affect relative factor prices r_1/r_j. Hence the difference between $\eta_{1,j}$ and $\eta_{j,1}$ arises because a change in r_1 does not affect the relative price r_2/r_3.

Normalizing equation (2), we obtain

$$Y_t = \psi Y_0 \left[\delta_{10} \left(e^{\lambda_1(t-t_0)} \frac{F_{1,t}}{F_{1,0}} \right)^{\frac{\sigma-1}{\sigma}} + \delta_{X0} X_t^{\frac{(\sigma-1)\nu}{(\nu-1)\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{5}$$

where

$$X_t = \left[\delta_{20} \left(e^{\lambda_2(t-t_0)} \frac{F_{2,t}}{F_{2,0}} \right)^{\frac{\nu-1}{\nu}} + \delta_{30} \left(e^{\lambda_3(t-t_0)} \frac{F_{3,t}}{F_{3,0}} \right)^{\frac{\nu-1}{\nu}} \right]. \tag{6}$$

The point of normalization is defined in terms of averages of the underlying variables. Geometric means are employed for variables that are growing over time, while arithmetic means are used for variables that are approximately stationary.[6] An additional factor ψ with $\mathbb{E}[\psi] = 1$ is introduced due to the nonlinearity of the production function and the stochastic nature of the data. The distribution parameters now possess data identifiable interpretations given by

$$\delta_{10} = r_{1,0}F_{1,0}/(r_{1,0}F_{1,0} + r_{2,0}F_{2,0} + r_{3,0}F_{3,0}) = 1 - \delta_{X0} \tag{7}$$

$$\delta_{20} = r_{2,0}F_{2,0}/(r_{2,0}F_{2,0} + r_{3,0}F_{3,0}) = 1 - \delta_{30}. \tag{8}$$

Payments to factors of production are consistent with marginal products in equilibrium. Specifically, the production function and first-order conditions in logarithmic form are

$$\ln \frac{Y_t}{Y_0} = \ln \psi + \frac{\sigma}{\sigma-1} \ln \left(\delta_{10} \left(e^{\lambda_1(t-t_0)} \frac{F_{1,t}}{F_{1,0}} \right)^{\frac{\sigma-1}{\sigma}} + \delta_{X0} X_t^{\frac{(\sigma-1)\nu}{(\nu-1)\sigma}} \right) \tag{9}$$

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

$$\ln r_{2,t} = \frac{\sigma-1}{\sigma} \ln \psi + \ln \left(\frac{\delta_{X0}\delta_{20} Y_0}{F_{2,0}} \right) + \frac{\nu-1}{\nu} \lambda_2(t-t_0) + \frac{\sigma-\nu}{\sigma(\nu-1)} \ln X_t + \frac{1}{\sigma} \ln \frac{Y_t}{Y_0} - \frac{1}{\nu} \ln \frac{F_{2,t}}{F_{2,0}} \tag{11}$$

$$\ln r_{3,t} = \frac{\sigma-1}{\sigma} \ln \psi + \ln \left(\frac{\delta_{X0}\delta_{30} Y_0}{F_{3,0}} \right) + \frac{\nu-1}{\nu} \lambda_3(t-t_0) + \frac{\sigma-\nu}{\sigma(\nu-1)} \ln X_t + \frac{1}{\sigma} \ln \frac{Y_t}{Y_0} - \frac{1}{\nu} \ln \frac{F_{3,t}}{F_{3,0}}. \tag{12}$$

where the r_i are factor returns. Subtracting equation (11) from equation (12), and (10) from either

[6] Using sample averages as base variable values attenuates the size of cyclical and stochastic components in the normalization point. See Klump *et al.* (2012) for a discussion on the relevance of normalization for estimation.

(11) or (12) yields

$$\ln\frac{r_{3,t}}{r_{2,t}} = \ln\left(\frac{\delta_{30}/F_{3,0}}{\delta_{20}/F_{2,0}}\right) + \frac{\nu-1}{\nu}(\lambda_3-\lambda_2)(t-t_0) + \frac{1}{\nu}\ln\left(\frac{F_{2,t}/F_{2,0}}{F_{3,t}/F_{3,0}}\right) \tag{13}$$

$$\ln\frac{r_{j,t}}{r_{1,t}} = \ln\left(\frac{\delta_{X0}\delta_{j0}/F_{j,0}}{\delta_{10}/F_{1,0}}\right) + \left(\frac{\nu-1}{\nu}\lambda_j - \frac{\sigma-1}{\sigma}\lambda_1\right)(t-t_0) + \frac{\sigma-\nu}{\sigma(\nu-1)}\ln X_t + \frac{1}{\sigma}\ln\frac{F_{1,t}}{F_{1,0}} - \frac{1}{\nu}\ln\frac{F_{j,t}}{F_{j,0}}. \tag{14}$$

Enhanced insight into the drivers of relative factor prices can be obtained by differentiating equations (13)-(14) with respect to time at the point of normalization $t = t_0$ where $X = F_{i,t}/F_{i,0} = 1$. Defining $g^N = \dot{N}/N \approx \ln N_{t_0+1} - \ln N_{t_0}$, the corresponding growth expressions for relative input prices are

$$g^{r_2/r_3} = \underbrace{\frac{1}{\nu}\left(g^{F_3}-g^{F_2}\right)}_{relative\ supply} + \underbrace{\frac{\nu-1}{\nu}\left(\lambda_2-\lambda_3\right)}_{technical\ change} \Leftrightarrow g^{r_3/r_2} = \underbrace{\frac{1}{\nu}\left(g^{F_2}-g^{F_3}\right)}_{relative\ supply} + \underbrace{\frac{\nu-1}{\nu}\left(\lambda_3-\lambda_2\right)}_{technical\ change} \tag{15}$$

$$g^{r_j/r_1} = \underbrace{\frac{1}{\sigma}g^{F_1} - \left[\frac{\delta_{i0}\sigma+\delta_{j0}\nu}{\sigma\nu}\right]g^{F_j}}_{relative\ supply} + \underbrace{\left[\frac{\delta_{i0}(\sigma-\nu)}{\sigma\nu}\right]g^{F_i}}_{F_1-F_i\ complementarity} + \underbrace{\left[\frac{1-\sigma}{\sigma}\right]\lambda_1 + \left[\frac{\nu-1}{\nu}+\frac{\delta_{j0}(\sigma-\nu)}{\sigma\nu}\right]\lambda_j + \left[\frac{\delta_{i0}(\sigma-\nu)}{\sigma\nu}\right]\lambda_i}_{technical\ change} \tag{16}$$

where $j = 2$ when $i = 3$ and vice versa, $g^{r_2/r_3} = -g^{r_3/r_2}$, and $g^{r_1/r_j} = -g^{r_j/r_1}$.[7] In equation (16), the specific condition that needs to hold for a negative relative supply effect on corresponding relative factor price growth is $\left[\delta_{j0}+\delta_{i0}\frac{\sigma}{\nu}\right]g^{F_j} > g^{F_1}$.[8] The key to understanding this condition is the discrepancy between substitution elasticities σ and ν. If $\sigma > \nu$, then substitution between F_1 and F_i is relatively easier than substitution between F_j and F_i. Thus an increase in the relative supply of F_j ($g^{F_j} > g^{F_1}$) under $\sigma \geq \nu$ has an unequivocal effect, requiring a fall in the relative price r_j/r_1. With $g^{F_j} \geq g^{F_1}$, $\sigma > \nu$ ensures a negative relative supply effect. This in turn leads to a decline in the relative factor share if the fall in the relative factor price is larger than the increase in relative factor supply. Examining the relative supply effect on $g^{r_jF_j/r_1F_1} \equiv g^{\omega_j} - g^{\omega_1}$, the parallel condition for a negative effect on the relative factor share is $\left[\frac{\delta_{i0}}{1-\sigma}\frac{\sigma}{\nu} + \frac{\delta_{j0}}{1-\sigma} - \frac{\sigma}{1-\sigma}\right]g^{F_j} > g^{F_1}$. For $\sigma < \nu$ on the other hand, depending on the relative size of ν, a positive effect on relative prices can arise even when $g^{F_j} > g^{F_1}$. Stronger complementarity between F_1 and F_i places pressure on r_1 to decline by a disproportionately larger amount when $g^{F_1} > 0$ which may result in a rise in r_j/r_1. However, the sign of the relative supply effect at the bottom level of nesting solely depends on $g^{F_3} - g^{F_2}$ while ν mediates the absolute magnitude of the effect as shown in equation (15). This is because inputs 2 and 3 form a compound input that is separable from input 1.

Regarding the second term in equation (16), the sign of the partial effect of g^{F_i} on g^{r_j/r_1} relies on $\sigma - \nu$. Growth in factor i will impart a positive effect on the relative price if its use is more complementary with factor j than factor 1 i.e. $\sigma > \nu$. In this case, the demand for input j relative to 1 will rise leading to a rise in its relative price. Note that while a stronger $\sigma > \nu$ inequality enhances the positive complementarity effect, it also enhances the negative relative supply effect under the aforementioned growth condition. The final part of the equation is a model-parameters-

[7] $g^{r_m/r_n} = \dot{(r_m/r_n)}/(r_m/r_n) = d\ln(r_m/r_n)/dt = -d\ln(r_n/r_m)/dt = -g^{r_n/r_m}$.

[8] Naturally, in the case of g^{r_1/r_j}, the opposite inequality must hold for a negative relative supply effect.

weighted average of factor-augmenting technical change terms. The effect on relative prices is again ambiguous. It is evident nevertheless that technical change yields no effect if $\lambda_m = \lambda \ \forall m = 1, i, j$ or if $\sigma = \nu$ and $\lambda_1 = \lambda_j$. Moreover, for $\lambda_m > 0$, technical change effects are positive if $\sigma < 1$, $\sigma > \delta_{j0}\nu/(\nu - 1 + \delta_{j0})$, and $\sigma > \nu$. We note finally that at the bottom level of nesting higher factor-augmenting technical change in favor of input 3 (i.e. $\lambda_3 > \lambda_2$), raising ceteris paribus its relative effective supply, combined with $\nu > 1$, or the configuration $\lambda_3 < \lambda_2$ with $\nu < 1$, has a positive effect on g^{r_3/r_2} and $g^{r_3F_3/r_2F_2} \equiv g^{r_3/r_2} + g^{F_3/F_2} = \frac{\nu-1}{\nu}(\lambda_3 - \lambda_2 + g^{F_3} - g^{F_2})$.

2.1.2 Augmented Sectoral Model

Next, our framework is extended to also differentiate between the different types of capital of interest. As well as tangible and intangible capital, we consider ICT and non-ICT capital in an adjacent secondary analysis. These capital types are respectively denoted by K_T, K_I, K^y_{ict}, and K^n_{ict}. Specifically, we accommodate this additional disaggregation on the capital side by adopting a three-level nested CES production function, where the primary constellations of interest are $L_U(K_T(K_I L_S))$, $L_U(K_I(K_T L_S))$, and $L_U(K^n_{ict}(K^y_{ict} L_S))$.[9] The general normalized four-factor specification for output, which encompasses the special case of Krusell *et al.* (2000) (i.e. σ=1 at the first level), is

$$Y_t = \psi Y_0 \left[\delta_{10} \left(e^{\lambda_1 (t-t_0)} \frac{F_{1,t}}{F_{1,0}} \right)^{\frac{\sigma-1}{\sigma}} + \delta_{Z0} Z_t^{\frac{(\sigma-1)\rho}{(\rho-1)\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{17}$$

$$Z_t = \left[\delta_{20} \left(e^{\lambda_2 (t-t_0)} \frac{F_{2,t}}{F_{2,0}} \right)^{\frac{\rho-1}{\rho}} + \delta_{X0} X_t^{\frac{(\rho-1)\nu}{(\nu-1)\rho}} \right] \tag{18}$$

$$X_t = \left[\delta_{30} \left(e^{\lambda_3 (t-t_0)} \frac{F_{3,t}}{F_{3,0}} \right)^{\frac{\nu-1}{\nu}} + \delta_{40} \left(e^{\lambda_4 (t-t_0)} \frac{F_{4,t}}{F_{4,0}} \right)^{\frac{\nu-1}{\nu}} \right]. \tag{19}$$

The distribution parameters, representing respective within-process factor income shares at the point of normalization (i.e. sample averages), are defined as follows

$$\delta_{10} = r_{1,0}F_{1,0}/(r_{1,0}F_{1,0} + r_{2,0}F_{2,0} + r_{3,0}F_{3,0} + r_{4,0}F_{4,0}) = 1 - \delta_{Z0} \tag{20}$$

$$\delta_{20} = r_{2,0}F_{2,0}/(r_{2,0}F_{2,0} + r_{3,0}F_{3,0} + r_{4,0}F_{4,0}) = 1 - \delta_{X0} \tag{21}$$

$$\delta_{30} = r_{3,0}F_{3,0}/(r_{3,0}F_{3,0} + r_{4,0}F_{4,0}) = 1 - \delta_{40}. \tag{22}$$

If, for example, $\nu < \rho$, meaning complementarity between F_3 and F_4 is stronger than that between F_2 and F_4, then an increase in the use of input F_4 will ceteris paribus lead to an increase in the demand for input F_3 relative to F_2 and its relative price. The corresponding log system of output and factor return equations is

$$\ln \frac{Y_t}{Y_0} = \ln \psi + \frac{\sigma}{\sigma - 1} \ln \left(\delta_{10} \left(e^{\lambda_1 (t-t_0)} \frac{F_{1,t}}{F_{1,0}} \right)^{\frac{\sigma-1}{\sigma}} + \delta_{Z0} Z_t^{\frac{(\sigma-1)\rho}{(\rho-1)\sigma}} \right) \tag{23}$$

[9]With some suitable combinations of the estimated parameters, it turns out that this model can closely approximate its two-level alternative e.g. see Caselli (2017). Our conclusions overall do not change vastly with the latter system, which tends to display inferior fit and stationarity properties of the estimated system residuals.

$$\ln r_{1,t} = \frac{\sigma-1}{\sigma}\ln\psi + \ln\left(\frac{\delta_{10}Y_0}{F_{1,0}}\right) + \frac{\sigma-1}{\sigma}\lambda_1(t-t_0) + \frac{1}{\sigma}\left(\ln\frac{Y_t}{Y_0} - \ln\frac{F_{1,t}}{F_{1,0}}\right) \tag{24}$$

$$\ln r_{2,t} = \frac{\sigma-1}{\sigma}\ln\psi + \ln\left(\frac{\delta_{Z0}\delta_{20}Y_0}{F_{2,0}}\right) + \frac{\rho-1}{\rho}\lambda_2(t-t_0) + \frac{\sigma-\rho}{(\rho-1)\sigma}\ln Z_t + \frac{1}{\sigma}\ln\frac{Y_t}{Y_0} - \frac{1}{\rho}\ln\frac{F_{2,t}}{F_{2,0}} \tag{25}$$

$$\ln r_{3,t} = \frac{\sigma-1}{\sigma}\ln\psi + \ln\left(\frac{\delta_{Z0}\delta_{X0}\delta_{30}Y_0}{F_{3,0}}\right) + \frac{\nu-1}{\nu}\lambda_3(t-t_0) + \frac{\sigma-\rho}{(\rho-1)\sigma}\ln Z_t + \frac{\rho-\nu}{(\nu-1)\rho}\ln X_t + \frac{1}{\sigma}\ln\frac{Y_t}{Y_0} - \frac{1}{\nu}\ln\frac{F_{3,t}}{F_{3,0}} \tag{26}$$

$$\ln r_{4,t} = \frac{\sigma-1}{\sigma}\ln\psi + \ln\left(\frac{\delta_{Z0}\delta_{X0}\delta_{40}Y_0}{F_{4,0}}\right) + \frac{\nu-1}{\nu}\lambda_4(t-t_0) + \frac{\sigma-\rho}{(\rho-1)\sigma}\ln Z_t + \frac{\rho-\nu}{(\nu-1)\rho}\ln X_t + \frac{1}{\sigma}\ln\frac{Y_t}{Y_0} - \frac{1}{\nu}\ln\frac{F_{4,t}}{F_{4,0}}. \tag{27}$$

The differences between equations (27) and (26), (27) or (26) and (25), (27) or (26) and (24), and (25) and (24) give relative factor prices

$$\ln\frac{r_{4,t}}{r_{3,t}} = \ln\left(\frac{\delta_{40}/F_{4,0}}{\delta_{30}/F_{3,0}}\right) + \frac{\nu-1}{\nu}(\lambda_4-\lambda_3)(t-t_0) + \frac{1}{\nu}\ln\left(\frac{F_{3,t}/F_{3,0}}{F_{4,t}/F_{4,0}}\right) \tag{28}$$

$$\ln\frac{r_{k,t}}{r_{2,t}} = \ln\left(\frac{\delta_{X0}\delta_{k0}/F_{k,0}}{\delta_{20}/F_{2,0}}\right) + \left(\frac{\nu-1}{\nu}\lambda_k - \frac{\rho-1}{\rho}\lambda_2\right)(t-t_0) + \frac{\rho-\nu}{(\nu-1)\rho}\ln X_t + \frac{1}{\rho}\ln\frac{F_{2,t}}{F_{2,0}} - \frac{1}{\nu}\ln\frac{F_{k,t}}{F_{k,0}} \tag{29}$$

$$\ln\frac{r_{k,t}}{r_{1,t}} = \ln\frac{\delta_{Z0}\delta_{X0}\delta_{k0}/F_{k,0}}{\delta_{10}/F_{1,0}} + \left(\frac{\nu-1}{\nu}\lambda_k - \frac{\sigma-1}{\sigma}\lambda_1\right)(t-t_0) + \frac{\sigma-\rho}{(\rho-1)\sigma}\ln Z_t + \frac{\rho-\nu}{(\nu-1)\rho}\ln X_t + \frac{1}{\sigma}\ln\frac{F_{1,t}}{F_{1,0}} - \frac{1}{\nu}\ln\frac{F_{k,t}}{F_{k,0}} \tag{30}$$

$$\ln\frac{r_{2,t}}{r_{1,t}} = \ln\left(\frac{\delta_{Z0}\delta_{20}/F_{2,0}}{\delta_{10}/F_{1,0}}\right) + \left(\frac{\rho-1}{\rho}\lambda_2 - \frac{\sigma-1}{\sigma}\lambda_1\right)(t-t_0) + \frac{\sigma-\rho}{(\rho-1)\sigma}\ln Z_t + \frac{1}{\sigma}\ln\frac{F_{1,t}}{F_{1,0}} - \frac{1}{\rho}\ln\frac{F_{2,t}}{F_{2,0}}. \tag{31}$$

We set $F_1 = L_U$ and $F_4 = L_S$, so that the combination $F_1(F_2(F_3F_4))$ corresponds to one of the highlighted configurations of $L_U(K_I(K_TL_S))$, $L_U(K_T(K_IL_S))$, or $L_U(K^n_{ict}(K^y_{ict}L_S))$. Thus L_U will always be separable from the compound input Z containing the remaining three factor inputs. This implies that the development of unskilled labor and the technical change augmenting it will have no effect on relative prices across the other three inputs, as can be seen from equations (28) and (29). The pairing of capital and skilled labor at the bottom level of nesting meanwhile tends to be supported by past research. Relating to equation (30), the growth expression of interest is

$$g^{r_k/r_1} = \underbrace{\frac{1}{\sigma}g^{F_1} - \left[\frac{(\delta_{i0}\rho+\delta_{k0}\nu)\sigma + \delta_{k0}\delta_{X0}\nu(\rho-\sigma)}{\sigma\rho\nu}\right]g^{F_k}}_{relative\ \ supply} + \underbrace{\left[\frac{\delta_{20}(\sigma-\rho)}{\sigma\rho}\right]g^{F_2}}_{F_1-F_2\ \ complementarity} + \underbrace{\left[\frac{\delta_{i0}\delta_{X0}(\sigma-\rho)}{\sigma\rho} + \frac{\delta_{i0}(\rho-\nu)}{\rho\nu}\right]g^{F_i}}_{F_1-F_i\ \ complementarity} + \underbrace{\left[\frac{1-\sigma}{\sigma}\right]\lambda_1 + \left[\frac{\delta_{20}(\sigma-\rho)}{\sigma\rho}\right]\lambda_2 + \left[\frac{\nu-1}{\nu} + \frac{\delta_{k0}\delta_{X0}(\sigma-\rho)}{\sigma\rho} + \frac{\delta_{k0}(\rho-\nu)}{\rho\nu}\right]\lambda_k + \left[\frac{\delta_{i0}\delta_{X0}(\sigma-\rho)}{\sigma\rho} + \frac{\delta_{i0}(\rho-\nu)}{\rho\nu}\right]\lambda_i}_{technical\ \ change} \tag{32}$$

where $k = 3$ when $i = 4$ and vice versa. For $g^{r_4/r_1} \equiv g^{r_{LS}/r_{LU}}$ in equation (32), the condition required for a negative relative supply effect is $\left[\delta_{30}\frac{\sigma}{\nu} + (\delta_{20}\frac{\sigma}{\rho} + \delta_{X0})\delta_{40}\right]g^{F_4} > g^{F_1}$. If σ is higher than both ρ and ν, substitution between F_1 and F_2 or F_3 is easier than substitution between F_2 and F_4, as well as between F_3 and F_4. Therefore, ceteris paribus, an increase in the supply of F_4 relative to F_1 ($g^{F_4} > g^{F_1}$) in the case of $\sigma \geq \{\rho, \nu\}$ necessitates a fall in the corresponding relative price of r_4/r_1.

Similarly, $\sigma \geq \max[\rho; \nu]$ confirms a negative relative supply effect when $g^{F_4} \geq g^{F_1}$. Coefficients on g^{F_2} and g^{F_3} in equation (32) are relevant for the analysis of the "skill premium"-"capital growth" nexus across the various capital types. Both coefficients are functions of factor intensities and substitution elasticities. These underlying model parameters thus also underpin our discussion of capital growth effects in later sections.

3 Reduced Form Approach

The determination of relative wages and skill premia in finance can also be analyzed through alternative factors such as financial deregulation and globalization in a less refined reduced-form manner. However, such an approach is not orthogonal to the one based on the analytical expressions described in section 2. These determinants can all naturally be viewed through the lens of factor-substitution elasticities and factor-augmenting technical change. In this section, in addition to the relative intangible or ICT capital stock and skill composition of labor, we consider the roles of financial deregulation, financial globalization, banking competition, labor market flexibility, and domestic credit expansion in the determination of finance wages. Thus a total of seven separate regressors feature in our supplementary reduced-form regression analysis. We next briefly discuss some of the underlying theoretical channels through which these factors may affect finance wages.

3.1 Intangible and ICT Capital

In the presence of complementarity (substitutability) between skilled labor and intangible or ICT capital, an increase in the latter production input can raise (attenuate) demand for more educated workers and corresponding wages.[10] A rise in the intensity of such capital in production increases the skill premium if complementarity for unskilled labor is weaker. Given greater complementarity between skilled labor and intangible or ICT capital in finance than in the non-finance market economy, combined with an increase in the usage intensity of such capital in finance relative to non-finance, an increase in the relative finance wage (of skilled workers) may arise.

Intangible capital deepening may also impart opposite pressures on skilled labor wages via the technical progress channel.[11] If advances in artificial intelligence or deep learning algorithms result in technical change that is skilled-labor augmenting, then, ceteris paribus, the *effective* skilled labor to intangible capital ratio may rise despite a falling or stable *physical* ratio. The return to skilled labor would fall in this case (i.e. due to effective skilled labor supply increase), along with its share in income provided there is complementarity between the two aforementioned inputs. Assuming that the technical change effect is stronger in finance, which is almost entirely data analysis driven, than in the rest of the economy, the skilled wage in finance relative to that in non-finance declines. Skill-biased productivity growth can however yield the opposite wage configuration if it induces sufficiently strong (positive) demand side effects in favor of skilled labor in finance.

[10] Complementarity refers to the curvature of the isoquant, and thus ease of substitution between inputs.
[11] Technical progress refers to (non-parallel) shifts in isoquants.

3.2 Skill Composition of Labor

The standard labor market clearing condition indicates that, ceteris paribus, as the supply of a particular class of workers rises relative to another, the corresponding relative reward falls. Nevertheless, if skilled labor commands a higher return and lower weight in total employment, an increase in the share of skilled workers in finance relative to that in non-finance can reduce the relative finance skilled wage while improving the relative aggregate wage. The response of the latter relative wage will depend on the sensitivities of labor returns across skill groups to corresponding labor supply changes.

3.3 Financial Deregulation

Opaque financial activities, such as those of shadow banks, are often linked to excessive deregulation which engenders conditions beyond the scope of conventional regulatory frameworks. By enabling financial operations that are more subject to asymmetric information, complexity, and socially inefficient risk taking, deregulation can raise the demand for sophisticated capital and skilled labor. As moral hazard is associated with informational rents, it exacerbates excessive risk taking by management boards.[12] Incentive payments, moreover, may increase with the complexity of tasks. Given the ubiquitous nature of asymmetric information in finance relative to other sectors, one would expect deregulation to impart differential effects in finance (Philippon and Reshef, 2012, 2013; Philippon, 2019).

3.4 Financial Globalization

The activities of domestic financial institutions pertaining to foreign investment demand tend to be more complicated in nature (e.g. legal aspects) and hence more skilled-labor intensive. Heightened exposure to such tasks consequently intensifies the search for highly skilled workers. However, if the growth in the supply of skilled labor falls short of that of corresponding demand, then upward pressure will be placed on skilled labor wages. As lower communication and transportation costs fuel international financial integration within a given regulatory paradigm (i.e. extent of capital controls), we may therefore observe a rise in the relative finance wage.

3.5 Banking Competition

Fluctuations in bank concentration over time tend to be a good proxy of developments in overall financial sector concentration. Greater competition amongst financial institutions for customers can manifest itself in enhanced competition for skilled employees. In turn, ceteris paribus, this translates to higher returns to skilled labor. Deregulation can stimulate such competition by weakening barriers to entry. Market/Banking competition furthermore promotes financial innovation and augments productivity that can reinforce skilled wage growth. Competitive pressures may on the other hand lead to consolidation (i.e. strategic responses such as mergers) and, in turn, greater risk taking. Higher market concentration yields bigger payouts to skilled staff in the relevant organizations if

[12] More non-transparent financial activity is correlated with higher informational rents.

profits are shared with workers.[13] Autor *et al.* (2020) more generally find that the labor share declines with rising concentration, or less competition, as output is reallocated toward market leaders (superstars) that are characterized by higher mark-ups. Philippon (2020) notes that technological advances and rising competition in some parts of the finance industry in post crisis years have reduced the costs of financial intermediation. Finally, competition effects should be stronger with more flexible labor markets. That is, inter-firm mobility of workers tends to improve remuneration.

3.6 Domestic Credit

A surge in the demand for credit within a particular regulatory paradigm can strengthen skilled labor recruitment efforts in the financial sector.[14] In the face of such demand conditions, a larger skilled workforce may be required to screen the larger volume of loan applications. Additionally, the borrowers and associated risks must be monitored and managed over time. This pushes up skilled labor returns in finance, with monitoring perhaps necessitating efficiency wages in order to diminish the likelihood of shirking or moral hazard.

4 Data and Estimation

We collect data on output, capital, and labor from the EU KLEMS repository. The data are provided at the annual frequency level. Coverage of the aggregate "market economy" and 1-digit level "financial intermediation" sector, alternatively labeled as "financial and insurance activities", is available for 30 countries over the period 1995-2017.[15] The data are consistent with the ISIC 4 (NACE 2) industry classification scheme and the new European System of National Accounts (ESA 2010).

The raw quality-unadjusted capital and labor inputs are the real net capital stock and the number of persons engaged. The latter includes employees, self-employed, and family workers.[16] 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 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 labor quality and the number of self-employed (proprietors).[17] Factor shares in value added sum to unity.

[13] Skilled workers primarily would capture the rents allocated to labor.

[14] Note that financial deregulation itself can raise demand for credit e.g. i) relaxation of loan-to-income and loan-to-value ratios for household mortgages, or percentage caps on lenders' portfolios accounted for by high loan-to-value mortgages, in the context of macroprudential policy or ii) loosening (stress-test, counter-cyclical, conservation) capital buffer requirements that would increase credit supply and decrease interest rates thus stimulating demand (Jiménez *et al.*, 2017; Berrospide and Edge, 2019; Gropp *et al.*, 2019).

[15] The list of countries comprises Austria (AT), Belgium (BE), Bulgaria (BG), Croatia (HR), Cyprus (CY), Czech Republic (CZ), Germany (DE), Denmark (DK), Estonia (EE), Greece (EL), Spain (ES), Finland (FI), France (FR), Hungary (HU), Ireland (IE), Italy (IT), Japan (JP), Lithuania (LT), Luxembourg (LU), Latvia (LV), Malta (MT), Netherlands (NL), Poland (PL), Portugal (PT), Romania (RO), Sweden (SE), Slovenia (SI), Slovakia (SK), United Kingdom (UK), and United States (US).

[16] Using just the number of employees as the basic labor input measure does not alter results significantly.

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

As highlighted in sub-section 2.1.2, we distinguish between tangible and intangible capital as well as ICT and non-ICT capital. The asset classes covered by the statistical database of EU KLEMS under ESA 2010 are residential structures, total non-residential structures, transport equipment, computing equipment (computer hardware), communications equipment, other machinery and equipment, cultivated assets, other intellectual property products (consisting of mineral exploration and artistic originals), research and development, and computer software and databases. Following Haskel and Westlake (2017), the final three categories form the intangible capital stock while the remaining categories together define the tangible capital stock. In addition, we employ the analytical database of EU KLEMS which includes supplementary intangible asset classes that are outside the boundaries of national accounts. Consistent with Haskel and Westlake (2017), the definition of intangible capital is expanded to include: advertising, market research and branding; design and other product developments; purchased organizational capital; own-account organizational capital; and vocational training. ICT capital meanwhile comprises computing equipment, communications equipment, and computer software and databases.

A disaggregation of total capital compensation across asset types, however, is not available in the data. To obtain these capital compensation components and corresponding rental rates, we proceed as follows.[18] First, similar to Hall and Jorgenson (1967), we directly estimate the capital income for asset class κ in industry j of country c as

$$\widetilde{CAP}^{\kappa}_{j,c,t} = \left(i_{c,t} - \pi^{\kappa}_{j,c,t} + \xi^{\kappa}_{j}\right) K^{\kappa}_{j,c,t} P^{\kappa}_{j,c,t} \tag{33}$$

where i is the 10-year government bond yield obtained 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.[19,20] The sum $\widetilde{CAP}^{total}_{j,c,t} = \sum_{\kappa} \widetilde{CAP}^{\kappa}_{j,c,t}$ does not exactly coincide with total capital compensation over all assets in the EU KLEMS data, $CAP^{total}_{j,c,t}$.[21] The general developments of the two variables instead are quite similar. Second, assuming that the shares of $CAP^{total}_{j,c,t}$ follow our generated capital shares, the real rental trajectories of tangible and intangible capital are given by

$$r^{KT}_{j,c,t} = \frac{\left(\frac{\widetilde{CAP}^{KT}_{j,c,t}}{\widetilde{CAP}^{total}_{j,c,t}}\right) CAP^{total}_{j,c,t}}{K^{T}_{j,c,t} P_{c,t}} \quad \text{and} \quad r^{KI}_{j,c,t} = \frac{\left(\frac{\widetilde{CAP}^{KI}_{j,c,t}}{\widetilde{CAP}^{total}_{j,c,t}}\right) CAP^{total}_{j,c,t}}{K^{I}_{j,c,t} P_{c,t}} \tag{34}$$

where P_c is the GDP deflator of country c. Those for ICT and non-ICT capital are defined analo-

[18]Our approach to estimating the user cost of capital is based on the arbitrage equation yielded by the neoclassical theory of investment.

[19]In typical models of production, the required rate of return on capital in equilibrium is $r = i - (1-\xi)\mathbb{E}[\pi] + \xi$. The approximated return specified in equation (33) is more prevalent in the literature. For our data, the two returns yield similar results.

[20]Using instead the full time period average growth rate of the investment deflator in equation (33) does not alter results greatly. This is also the case if start or end of year capital stocks are employed. All of these substitute measures are highly correlated with the one in (33).

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

gously, namely,

$$r_{j,c,t}^{KICT} = \frac{\left(\frac{\widetilde{CAP}_{j,c,t}^{KICT}}{\widetilde{CAP}_{j,c,t}^{total}}\right) CAP_{j,c,t}^{total}}{K_{j,c,t}^{ict,y} P_{c,t}} \quad \text{and} \quad r_{j,c,t}^{KNICT} = \frac{\left(\frac{\widetilde{CAP}_{j,c,t}^{KNICT}}{\widetilde{CAP}_{j,c,t}^{total}}\right) CAP_{j,c,t}^{total}}{K_{j,c,t}^{ict,n} P_{c,t}}. \tag{35}$$

EU KLEMS decomposes labor along the skill dimension into three groups: high-, medium- and low-skilled.[22] The skill level is determined by educational attainment. The definition for high-skilled labor as those with a university degree or above is consistent across countries and time. The effective line of distinction between medium- and low-skilled labor on the other hand can vary across countries due to differences in 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).[23] We therefore partition aggregate labor 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 wage per worker is thus defined as $w = \frac{LAB}{L} \equiv \frac{L_s}{L}\frac{LAB_S}{L_S} + \frac{L_U}{L}\frac{LAB_U}{L_U} \equiv \frac{L_S}{L}w_S + \frac{L_U}{L}w_U$.

The production function and corresponding first-order conditions, or combinations of the optimality conditions, in each supply-side framework form our systems of equations for estimation. We estimate systems of pooled normalized panel specifications with cross-equation restrictions by applying the procedures of nonlinear seemingly unrelated regressions (NLSUR) and general method of moments (GMM). An iterated feasible generalized nonlinear least squares estimator is employed for NLSUR. Either a two-step or an iterative estimator is used for GMM. Normalization points are country-specific. Our estimator choices are motivated by the likelihood of cross-equation correlations in residuals, the potential to maximize information and improve efficiency, and possible endogeneity issues. Instruments in GMM estimation of our normalized supply-side system consist of lags of the employed variables. Residuals of regressions are tested for cross-sectional dependence and non-stationarity.

Our reduced-form regression analysis entails estimating the panel specification

$$\ln \zeta_{c,t} = \alpha_t + \boldsymbol{\beta}'\mathbf{X}_{c,t-l} + u_{c,t} \tag{36}$$

where $\zeta \in \left\{\frac{w_F^T}{w_{NF}^T}, \frac{w_F^S}{w_{NF}^S}, \frac{w_F^S}{w_F^T}\Big/\frac{w_{NF}^S}{w_{NF}^T}, \frac{w_F^S}{w_F^U}\Big/\frac{w_{NF}^S}{w_{NF}^U}\right\}$, α_t are time fixed effects, and $\mathbf{X}$ is the vector of controls in log or level form. The presence of time dummies permits the link between the finance relative wage ζ and covariate x_i for country c at time t to be gauged relative to sample-wide common patterns in ζ and x_i at time t. Pooled panel OLS and GMM estimation are considered as well as the specification with $\alpha_t = \alpha$. In contrast to the country fixed effects estimator which focuses only on the data variation along the within-country dimension, the pooled estimator takes advantage of the full cross-sectional variation in the data.

[22]For the U.S., these data are partly retrieved from the WIOD's Socio Economic Accounts.

[23]Established national education attainment levels below the university grade are not always directly comparable. Medium-skilled labor is classified as that with an intermediate level of education, while low-skilled labor is that with no formal qualifications in EU KLEMS. What defines intermediate level of education and no formal qualifications differs across countries.

Relative Wages: If $\zeta = \frac{w_F^T}{w_{NF}^T} = \frac{L_F^S}{L_F^T}\frac{w_F^S}{w_{NF}^T} + \frac{L_F^U}{L_F^T}\frac{w_F^U}{w_{NF}^T} \equiv \zeta^{\{1\}}$, we note that

$$\Delta\zeta^{\{1\}} = \underbrace{\left[\Delta\left(\frac{L_F^S}{L_F^T}\right)\cdot\overline{\left(\frac{w_F^S}{w_{NF}^T}\right)} + \Delta\left(\frac{w_F^S}{w_{NF}^T}\right)\cdot\overline{\left(\frac{L_F^S}{L_F^T}\right)}\right]}_{skilled} + \underbrace{\left[\Delta\left(\frac{L_F^U}{L_F^T}\right)\cdot\overline{\left(\frac{w_F^U}{w_{NF}^T}\right)} + \Delta\left(\frac{w_F^U}{w_{NF}^T}\right)\cdot\overline{\left(\frac{L_F^U}{L_F^T}\right)}\right]}_{unskilled} \tag{37}$$

$$= \underbrace{\sum_{v\in\{S,U\}}\Delta\left(\frac{L_F^v}{L_F^T}\right)\cdot\overline{\left(\frac{w_F^v}{w_{NF}^T}\right)}}_{between\ \ changes} + \underbrace{\sum_{v\in\{S,U\}}\Delta\left(\frac{w_F^v}{w_{NF}^T}\right)\cdot\overline{\left(\frac{L_F^v}{L_F^T}\right)}}_{within\ \ changes}. \tag{38}$$

Examining the change over the sample period in the decomposition of equation (37), we find for each country that the skilled component is positive while the unskilled counterpart is negative[24], and for the majority of countries (18/30) that the skilled component predominantly drives the relative finance wage i.e. skilled component outweighs unskilled component. In particular, the median contribution of skilled labor to relative finance wage growth, $\Delta\zeta^{\{1\}}$, is 127 (147) percent based on the statistical (analytical) database of EU KLEMS. Figures 1 and 2 indeed indicate that relative aggregate and relative skilled wages are highly correlated.[25] Turning to equation (38), 17 countries (16 in analytical database) show that "within" skill group wage changes in absolute terms matter more than skill composition led ("between") wage changes for overall relative finance wage development. "Between" wage changes are driven by skilled labor intensity growth and are positive over the period for all countries, except Croatia, while "within" wage changes are positive for around half the sample (14/30). The median share of "within" group wage changes in $\Delta\zeta^{\{1\}}$ is 70 (59) percent based on the statistical (analytical) database, thus suggesting a more even split and notable role for skill composition shifts.

To obtain an idea of how much finance contributes to the skill premium of the overall market economy or private sector (M), we can employ $\frac{w_M^S}{w_M^U} = \frac{L_F^S}{L_M^S}\frac{w_F^S}{w_M^U} + \frac{L_{NF}^S}{L_M^S}\frac{w_{NF}^S}{w_M^U}$ to show that

$$\Delta\left(\frac{w_M^S}{w_M^U}\right) = \underbrace{\left[\Delta\left(\frac{L_F^S}{L_M^S}\right)\cdot\overline{\left(\frac{w_F^S}{w_M^U}\right)} + \Delta\left(\frac{w_F^S}{w_M^U}\right)\cdot\overline{\left(\frac{L_F^S}{L_M^S}\right)}\right]}_{finance} + \underbrace{\left[\Delta\left(\frac{L_{NF}^S}{L_M^S}\right)\cdot\overline{\left(\frac{w_{NF}^S}{w_M^U}\right)} + \Delta\left(\frac{w_{NF}^S}{w_M^U}\right)\cdot\overline{\left(\frac{L_{NF}^S}{L_M^S}\right)}\right]}_{non-finance} \tag{39}$$

$$= \underbrace{\sum_{\tau\in\{F,NF\}}\Delta\left(\frac{L_\tau^S}{L_M^S}\right)\cdot\overline{\left(\frac{w_\tau^S}{w_M^U}\right)}}_{between\ \ changes} + \underbrace{\sum_{\tau\in\{F,NF\}}\Delta\left(\frac{w_\tau^S}{w_M^U}\right)\cdot\overline{\left(\frac{L_\tau^S}{L_M^S}\right)}}_{within\ \ changes}. \tag{40}$$

We find that finance contributes positively to market economy relative skilled wage growth in 19 countries, while the non-financial sector contributes negatively in 25 cases (in both databases). Moreover, the non-finance component outweighs the finance component for 27 countries, with only 6 countries exhibiting positive market economy skill premium growth over the sample period. The finance sector on average across all countries is able to offset 12 percent of the negative non-finance effect, and 27 percent when we restrict the sample to the 18 countries that observed a positive finance effect and

[24]The only exception is in the statistical database for the UK which displays a marginally positive unskilled share.
[25]Both gross Spearman rank and Pearson correlation coefficients are approximately 0.94 in Figure 2.

a negative non-finance effect. Given that the finance sector on average across countries over the sample period commands around 8 percent of both skilled labor and real/nominal output in the market economy, we can conclude that its effects on the market economy skill premium are disproportionate and contribute to rising income inequality. Thus the importance of the finance sector is non-negligible. "Within" sector wage changes drive skill premium changes in the market economy in our sample. The "within" change is negative for 24 countries while the "between" change, capturing the effects of skilled labor reallocation across sectors, is positive for 24 nations. In absolute terms, "within" wage changes are larger than "between" changes in all but two cases (Cyprus and Japan), and notably so, with the "within" share in $\Delta(w_M^S/w_M^U)$ lying close to 100 percent on average across countries. In finance, however, the average (median) "between" change, which is positive, more than offsets the negative average (median) "within" change. The "between" change in particular is 3 (5) times the size of the "within" change in absolute terms based on mean (median) values in this sector. On a more granular level in finance, 13 countries display a positive "within" wage change while 25 countries feature a positive "between" component, where 23 economies see the "between" component outweighing the corresponding "within" component over the period.

Non-"Factor Input" Correlates: Regarding covariates in equation (36), financial deregulation data are obtained from Denk and Gomes (2017) who extend the dataset of Abiad *et al.* (2010). Deregulation data are given in index form with higher values indicating greater liberalization or fewer restrictions. The index covers seven dimensions of financial policy reform. These include credit controls, interest rate controls, entry barriers, international capital flows, privatization, securities market policies, and banking supervision & prudential regulation.[26] According to Bernanke *et al.* (2020), the financial regulatory system relative to post crisis was notably weaker in the years leading up to the global financial crisis, as reflected for example by the introduction of the Dodd-Frank Act in the U.S. in 2010.[27] Denk and Gomes (2017) highlight that ownership and supervision are two key areas that have changed most visibly since the crisis, with bank recapitalizations by governments increasing state ownership and regulatory initiatives such as the Basel III accord enhancing oversight of risk. The regulatory index overall shows non-negligible variation over time and cross-section dimensions in the sample, where a number of countries such as Japan, Ireland, and the United Kingdom have seen a decrease in the index post the 2007/08 crisis which roughly marks our sample period mid-point.[28]

Financial globalization is captured by the volume-based measure of international financial integration of Lane and Milesi-Ferretti (2007, 2018), which is defined as the sum of external assets and liabilities divided by GDP.[29] As shares of GDP, domestic credit provided by the financial sector, domestic credit to the private sector, domestic credit to the private sector by banks, and private credit by deposit money banks (and other financial institutions) are obtained from World Bank's (WB)

[26] Central banks now, occupying a much larger space, lie at the heart of such regulation as a distinct autonomous component of the regulatory state, having emerged from the GFC with more responsibilities and powers unlike after the stock market crash of 1929 and Great Depression when their status waned significantly e.g. central banks were bystanders at the Bretton Woods accords. The more prominent role of central banks in recent times can be partly attributed to the abject failure of non central bank regulators in the run-up to the financial crisis (Tucker, 2018).

[27] With a view to promoting financial stability, the reform also directed the Fed to apply stricter supervisory standards to non-bank financial institutions deemed to be systemically important.

[28] The global financial crisis more generally halted the financial liberalization of the preceding three decades.

[29] The 2021-updated external wealth of nations database of Lane and Milesi-Ferretti (2018) covers our sample period.

World Development Indicators (WDI) and Global Financial Development (GFD) databases. All four of these comoving variables generate similar results. Consequently, findings are only reported for the second option which offers the broadest gauge while excluding the role of government.

We examine four different measures of banking competition from WB's GFD repository, namely, bank concentration, the Boone indicator, the H-statistic, and the Lerner index. Bank concentration gauges the share of assets for the three largest banks in the country. The Boone indicator is calculated as the elasticity of profits to marginal costs with more negative values of the indicator reflecting higher competition intensity. The H-statistic measures the elasticity of bank revenues relative to input prices, where lower values of the statistic are typically associated with less competition. Finally, the Lerner index is defined as the difference between output prices and marginal costs (relative to prices), meaning that higher values of the index signal less bank competition. However, in regression analysis, we only report results with bank concentration as it is the sole measure that provides full sample coverage. Over the available observations, movements in the four variables are quite synchronized for most countries, where bank concentration is positively correlated with the Boone indicator and the Lerner index while negatively correlated with the H-statistic.[30] We employ the OECD's employment protection index based on collective and individual dismissals to gauge labor market flexibility as higher job security is associated with weaker inter-firm/job mobility according to theory. Higher values of the index indicate stricter protection.

5 Empirical Analysis

5.1 Three Factor Model

Table 1 reports results for our three-factor CES model which disaggregates labor into skilled and unskilled components.[31] For each of the three factor input configurations, systems of four or three panel equations comprising production function (9) and optimality conditions (10)-(12) or (10) and (13) are estimated by NLSUR and GMM approaches.[32] Panel A gives results for finance while panel B provides them for non-finance. Correspondingly, Table 2 displays residual diagnostics for the estimated systems, which generally indicate relatively weak cross-sectional dependence and a rejection of the unit root hypothesis.

[30]Gross Pearson and Spearman rank correlations are predominantly economically and statistically significant. This implies that competition intensity declines as bank concentration rises consistent with Philippon (2019) and Prasad (2021). We note that reduced-form relative wage regression results with the other three measures are qualitatively similar overall although sample size is diminished.

[31]Quality-unadjusted factor inputs are only employed as quality-adjusted data are unavailable for the labor decomposition. Based on unreported estimates from the conventional aggregate two-factor model, conclusions should be similar across both types of data.

[32]Inverse optimality conditions in the same spirit as Lawrence (2015) and Grossman and Oberfield (2022) are used at times, implying that factor quantities are regressed on factor prices. Such specifications circumvent parameter convergence issues and provide more sensible estimates where employed. Specification tests, diagnostics, and theory also guide this selection and the choice between a three or four equation system.

5.1.1 First Inputs Configuration

Inspecting estimates for the first configuration of inputs where skilled labor and aggregate capital in the sector are combined at the bottom level of nesting, we find that skilled labor primarily drives complementarity between aggregate labor and capital. This suggests that the productivity gains from schooling are capital using and vice versa. Column (2) of Table 1 shows that the substitution elasticity between skilled labor and overall capital (ν) is lower in the financial sector. Estimates of ν in finance are 0.17 (NLSUR) and 0.33 (GMM) compared to 0.24 and 0.45 in non-finance. Unskilled labor, meanwhile, exhibits relatively high substitutability with the compound input X and the corresponding individual factor inputs, skilled labor and capital, based on estimates of $\sigma = \eta_{1,2} = \eta_{1,3}$ (column (1)) and Morishima elasticities $\eta_{2,1}$ (column (6)) and $\eta_{3,1}$ (column (7)). $\eta_{2,1}$ and $\eta_{3,1}$ values across sectors in particular suggest that substitutability between capital and unskilled labor is stronger than substitutability between skilled and unskilled labor. Substitutability between unskilled labor and remaining factor inputs, moreover, appears to be stronger in finance, where skilled labor growth has also been higher (4.4 percent p.a. in finance compared to 3.1 percent p.a. in non-finance while counterpart figures for unskilled labor are -2 and 0). Estimates of, for example, σ in finance are 1.46 (NLSUR) and 1.23 (GMM) compared to 1.18 and 0.72 in non-finance. This pattern may reflect the more pronounced rise of skilled-labor-dependent automation in finance driven by big data and machine learning (intangible capital). Indeed, capital's share in output stands at around 0.45 on average in finance relative to 0.35 in non-finance.

Results for the first production function configuration further indicate that productivity growth augmenting unskilled labor (column (3)) is primarily negative across sectors, with the decline more notable in finance. Conversely, while evidence is weaker in non-finance, growth in skilled labor-augmenting productivity (column (4)) is mainly positive. Similarly, capital-augmenting productivity growth (column (5)) tends to be positive across panels A and B, and support for this upward trend is stronger in finance.

Pooled average annual relative factor price and factor share changes in the data are reported in columns (8)-(10) of Table 1. We find in column (8) corresponding to the first inputs configuration that skilled labor's share of income relative to that of unskilled labor in the financial sector has been increasing at around 6.3 percent p.a. compared to only 2.4 percent p.a. in non-finance. This disparity is clearly evident over time in i) Figure 2 which tracks the cross-country weighted average sectoral skilled shares in value added and ii) Figure 1 which plots the ratio of the former i.e. finance to non-finance.

According to the graphs, skilled labor enjoys a significantly higher (mostly growing) share of output in finance than in non-finance across all years. The aggregate labor share in non-finance has been decreasing on average across countries by around 0.3 percent per annum and by less than 0.1 percent in the financial sector. This means that unskilled labor is responsible for the decline in the aggregate labor share in both sectors, noting that skilled labor exhibits a greater counteracting force in finance. While average annual growth in the skill premium has been close to zero (marginally negative) in finance, column (8) in panel B indicates that the wage gap in non-finance decreases by about 0.01 log points annually over the sample period, or $\Delta(w^S_{NF}/w^U_{NF}) \approx -1\%$ p.a. As Figure 2 shows, the cross-country weighted average skilled-unskilled wage in finance displays a general upward trend up until the global financial crisis of 2007/08, with a downward trend thereafter, although there was also some deterioration in the relative wage around the time of the dot com crash. On the other hand, the graph highlights that the skill premium in non-finance, while always positive, is on a downward path throughout the sample period. It is also evident that the relative skilled wage, and thus skill premium in percentage terms, in finance overtakes that in non-finance in the early 2000s. The plot of the skilled-to-unskilled wage in finance relative to that in non-finance in Figure 1 reflects these details, showing a general upward trajectory in the series with a tapering off post the GFC starting point.

Since our estimates of σ, equaling the Morishima elasticity $\eta_{1,2}$, are mostly greater than unity, they are qualitatively consistent with the inverse relation between the aforementioned relative factor prices and factor shares in the data, noting that $1-\eta_{1,2}$ predicts the percentage change in the relative unskilled labor share in response to a 1 percent increase in the relative unskilled wage. In line with the data, the magnitude of the predicted effect is more pronounced in finance.

Next we find that the rental rate relative to the unskilled wage has been increasing in finance and decreasing in non-finance (column (9) for first configuration). The corresponding relative income share of capital, nevertheless, is increasing annually on average in both sectors, with higher growth in finance. The positive relation between the former relative factor shares and factor prices in finance is predicted by the Morishima elasticity $\eta_{3,1}$, although the anticipated magnitude is much weaker. On the other hand, the inverse relation in non-finance is captured by $\sigma = \eta_{1,3}$ under NLSUR estimation. Finally, the rental rate relative to the skilled wage (column (10) for first configuration) has on average grown annually by the same amount in both sectors, while the share of capital relative to that of skilled labor has declined annually in both and more strongly in finance. This inverse link nonetheless is not forecasted by estimates of $\nu = \eta_{2,3} = \eta_{3,2}$.

In panels A of Table 7, we show the computed relative skilled labor supply, capital-labor complementarity, and technical change contributions to finance and non-finance skill premia based on equation (16) in the case of our first three-factor configuration. Columns (1) and (7) firstly show that the conditon for a negative relative skilled labor supply effect in the baseline case of $g^{L_U} \approx g^{L_S} > 0$ is satisfied in both sectors (RSC > 1).[33] Given that the effect is negative in the lower bound instance of similar skilled and unskilled labor growth rates, it must be even stronger for clearer cases of $g^{L_U} < g^{L_S}$.[34] In our data, we observe $g^{L_U} < 0 < g^{L_S}$ on average across sectors, which under our estimates of σ and ν yields negative relative supply coefficients. The baseline lower bound case of roughly equal (positive) growth rates across skilled and unskilled labor allows for comparability in effects across sectors.[35] Columns (2) and (8) report the magnitudes of these comparable minimum negative effects in finance and non-finance respectively. We find that a 1 percent joint increase in the supplies of skilled and unskilled labor corresponds to a reduction of relative skilled wage growth by around 3.12 (NLSUR) or 1.35 (GMM) percentage points in finance, suggesting an elastic response.[36] These coefficients are effectively equivalent to those for marginal increases in the supply of skilled relative to unskilled labor, with larger increases mapping to larger inverse correlations. The

[33]The estimate however is not statistically different from unity for finance in the case of GMM.

[34]If both growth rates are negative and g^{L_U} is insufficiently more negative than g^{L_S}, this can result in an increase in the relative skilled wage despite an increase in the relative supply of skilled labor.

[35]The disparity in these growth rates is much greater in finance and thus obscures the role of cross-sectoral differences in factor substitution elasticities.

[36]Ignoring other factors, this implies a decline in the relative skilled wage.

decrease in non-finance is smaller at 2.10 (NLSUR) or 0.54 (GMM) percentage points, where the latter GMM estimate is statistically insignificant. This difference arises because capital and skilled labor are more complementary in finance, while capital and unskilled labor are less substitutable in non-finance. Thus, as the relative supply of skilled labor rises, finance relative skilled wages need to fall by more in order for the additional labor to be absorbed by the sector.

By definition of equation (16), sectoral aggregate capital growth ($g^{F_i} = g^K > 0$) should have the opposite role to that of relative supply in the formation of the skill premium. Given the previous factor growth conditions, as σ rises or ν falls, or both, not only is the positive contribution of g^K enhanced, but so is the negative contribution of relative supply. Due to stronger complementarity between skilled labor and capital, than that between unskilled labor and capital, the relative marginal product of skilled labor rises from investment in the capital stock, thus increasing its relative return.[37] Columns (3) and (9) of Table 7 indicate that increases in capital have a more prominent role in finance, where the positive "aggregate capital"-"skilled labor" complementarity coefficient is stronger for more pronounced discrepancies between estimates of σ and ν in Table 1.

Turning attention to columns (6) and (12) in panels A of Table 7, we find that technical change (a constant) in both sectors is associated with positive changes in the skill premium on an annual basis. However, the contribution of technical change is more economically significant in finance. One of the reasons behind this difference is the more negative growth in unskilled labor augmenting productivity in finance, combined with higher substitutability between skilled and unskilled labor in the sector. Given the lack of complementarity between the two types of labor in finance, a deterioration in unskilled labor augmenting productivity unambiguously reduces unskilled labor's relative marginal product and return. Another reason is that, coupled with relatively strong capital-augmenting productivity growth in finance, capital and skilled labor are stronger complements while capital and unskilled labor are stronger substitutes in finance. Therefore, as capital-augmenting productivity (and subsequently effective capital) rises in either sector, the marginal product of skilled labor relative to that of unskilled labor improves by more in finance, and in turn the corresponding relative wage. Using GMM (NLSUR) parameter estimates, ceteris paribus, technical change is linked to 7.8 (11.2) percent growth p.a. in finance relative skilled wages compared to 4.7 (2.5) percent in non-finance.

5.1.2 Second Inputs Configuration

In this section we examine results for the second configuration of inputs where unskilled labor and capital are now in the bottom level of nesting in the two-level three-factor model. The NLSUR estimate of σ in panel A suggests that skilled labor and compound input X are perfect complements in finance. However, given the earlier findings, we know that this result is being driven by the high degree of complementarity between skilled labor and capital. In relative terms, the NLSUR estimate of ν points to greater substitutability between capital and unskilled labor in finance. Technical change parameters now show rising (declining) unskilled (skilled) labor-augmenting productivity and weak growth in capital-augmenting productivity. GMM estimates for finance on the other hand are more consistent with results for the first configuration. The GMM estimate of σ in finance is

[37] Grossman *et al.* (2017) require a sufficient degree of complementarity between capital and schooling for balanced growth in the economy under capital-augmenting technological progress and a non-unitary substitution elasticity.

0.35, while the corresponding Morishima elasticity $\eta_{3,1}$ is 0.62. These estimates are more reflective of the degree of complementarity between skilled labor and capital found in the first configuration. The estimates are a little higher than in the first configuration because unskilled labor is now found in aggregator X which tends to increase substitutability. Additionally, the GMM estimate of $\nu = 1.08$ at the bottom level of nesting points to gross substitutability between unskilled labor and capital in line with σ estimates obtained for the first configuration. Overall, NLSUR and GMM estimates (including Morishima elasticities) in finance again indicate greater substitutability between unskilled labor and capital relative to the link between skilled labor and capital. Regarding technical change, GMM estimates show negative unskilled labor augmenting productivity growth in finance, providing support for the corresponding result in the first configuration.

For the wider non-financial market economy (panel B), we also find complementarity between skilled labor and compound input X, driven by capital, in contrast to substitutability between unskilled labor and capital accroding to NLSUR and GMM estimates. Importantly, consistent with results in the previous section, we again find much stronger complementarity between skilled labor and capital in finance than in non-finance. More specifically, the calculated Morishima elasticity $\eta_{3,1}$ is 0.08 (NLSUR) or 0.62 (GMM) in finance compared to 1.13 (NLSUR) or 1.48 (GMM) in non-finance. The latter estimates in fact imply substitutability between skilled labor and capital in non-finance, unlike $\sigma = \eta_{1,3}$ estimates which average at 0.55 in the sector versus 0.17 in finance. Across NLSUR and GMM systems in non-finance, growth in skilled labor augmenting productivity is negative while there is some evidence of rising unskilled labor augmenitng productivity.

The only Morishima elasticity consistent with the directions of corresponding relative factor prices and shares in finance is $\eta_{3,2} = \eta_{2,3} = \nu$ in the case of NLSUR estimates (see column (10)). On the other hand, Morishima elasticities $\eta_{3,2} = \eta_{2,3} = \nu$, $\eta_{2,1}$, and $\eta_{3,1}$ in non-finance are all in line with the direction of relative factor price and share changes in the sector (see columns (8)-(10)). In terms of magnitude, the GMM estimate of ν in non-finance suggests that a 1 percent increase in the rental on capital relative to the unskilled wage is associated with a 1.45 percent decrease in the relative share of capital (vis-à-vis L_U). The related column (10) data indeed line up with the predicted elastic change in the relative factor share.

Panel A in Table 7 for the second configuration indicates that the negative relative supply condition (RSC < 1) is met in all estimation cases across sectors, where the equation of $g^{r_1/r_2} = -g^{r_2/r_1}$ is now the focus (see negative of equation (16)). NLSUR-based coefficient values imply that the baseline inverse comovement between relative skilled labor and relative skilled wage growth is much stronger in finance than non-finance. The RS coefficient in finance nonetheless is statistically insignificant and inflated due to the insignificant, approximately zero, NLSUR estimate of σ. Similarly, although statistically insignificant, NLSUR-based KLC and TC estimates are more pronounced in finance. For GMM, the role of technical change continues to be stronger in finance, in contrast to relative supply and factor complementarity coefficients which are now more prominent in non-finance.

Relative to the first configuration in section 5.1.1, the second model configuration is less preferable based on information criteria and some of the unrealistic, outsized, parameter estimates obtained for the latter model. Faster convergence of parameter estimates in the first configuration further tilts preference in its direction. Overall, although treating skilled labor as separable from capital, meaning L_S does not play a role in the path of r_K/w_U, is counterintuitive and arguably implausible, there are still many parallels in findings across the two configurations.

5.1.3 Third Inputs Configuration

The final three factor input configuration nests skilled and unskilled labor at the bottom level of the model. Thus, by aggregating over skill types, the separable compound input X is comparable to sectoral aggregate labor. While the third configuration creates a correspondence to the conventional two-factor model, it crucially provides an extra layer of detail over the latter framework via the weighted average or Armington-type representation of aggregate labor.

We find complementarity between capital and compound input X in both sectors, with notably greater complementarity in finance. Earlier results imply that skilled labor in the labor aggregator is driving the complementarity. Morishima elasticities $\eta_{2,1}$ and $\eta_{3,1}$ for the current inputs configuration certainly affirm this argument for the finance sector. NLSUR and GMM estimates of σ in finance are indeed quite low at 0.10 and 0.40 respectively, relative to 0.64 and 0.72 in non-finance. Estimates of ν conversely indicate substitutability between skilled and unskilled labor across sectors, with substitution occurring more easily in finance. More specifically, the average estimate of ν in finance is 1.39 compared to 1.13 in non-finance.

Distinguishing between types of labor, Morishima elasticities $\eta_{2,1}$ and $\eta_{3,1}$ further add that complementarity between skilled labor, specifically, and capital is much stronger in finance, while there is evidence of greater complementarity between unskilled labor and capital in non-finance. $\eta_{2,1}$ in fact offers some indication that skilled labor and capital in non-finance may be substitutes given the above unity GMM-based Morishima elasticity. Morishima elasticities $\eta_{1,3} = \sigma$, $\eta_{3,1}$, and $\eta_{3,2} = \eta_{2,3} = \nu$ fall in line with the directions of corresponding relative factor price and share changes in finance. In the non-financial sector, the same can be said for $\eta_{3,2} = \eta_{2,3} = \nu$ and GMM-based $\eta_{2,1}$.

Technical change parameters reveal similar trends to those in the case of the first configuration. Relative to the non-financial market economy, unskilled labor productivity deteriorates faster and capital-augmenting productivity growth is stronger in finance. Capital-augmenting productivity in non-finance is either stable or declining. The upward trajectory in skilled-labor augmenting productivity moreover is steeper in finance based on GMM estimates. On the whole, the estimates suggest net labor-augmenting technical change in both sectors.

As skilled and unskilled labor are separable from capital in the third configuration, relative skilled wages evolve independent of capital growth. Panel A in Table 7 consequently does not report a KLC coefficient for the third configuration. Equation (15) in particular is of interest for relative skilled wage growth in the third constellation of factor inputs.

The relative supply condition now hinges on the difference between factor growth rates, while the elasticity of substitution between the two types of labor mediates the magnitude of the correlation between relative factor prices and quantities. If substitution between skilled and unskilled labor is relatively easy, as captured by a higher ν, then factor quantity changes can be absorbed with relatively smaller movements in associated factor prices, and vice versa. Thus a higher ν tends to act in the offsetting direction to an increasing relative supply. Columns (1) and (7) inform us that the condition for an inverse relation between relative skilled wages and relative skilled labor is satisfied in all cases across sectors. Finance is characterized by higher growth in relative skilled labor and greater substitutability between skill types compared to the non-finance sector. While the higher substitutability between skilled and unskilled labor in finance assists in attenuating the effects of the gap in relative supplies across sectors, the net results in columns (2) and (8) respectively still point to a significant difference in RS coefficients, where finance displays the more pronounced negative relation. Annually over the period, ceteris paribus, the increase in finance (non-finance) relative skilled labor on average is associated with a 4-5 (3) percent drop in finance (non-finance) relative skilled wages.

Skill premium growth continues to be positively linked to technical change in both sectors, with the latter displaying a more pronounced role in finance. More precisely, technical progress is related to a 4-4.5 percent p.a. increase in the finance relative skilled wage, compared to around 1.5-2 percent in non-finance. The difference across sectors is due to finance's i) greater excess growth in skilled labor augmenting productivity over unskilled labor augmenting productivity and ii) production technology that allows for greater substitutability between skill types in labor. Intuitively, higher net skilled labor augmenting productivity growth $(\lambda_{LS} - \lambda_{LU})$ increases the effective quantity of skilled labor relative to that of unskilled labor, thereby raising the relative marginal product of skilled labor. At the same time, greater substitutability between labor types reduces the downward pressure on the relative skilled wage that coincides with an increase in the relative effective volume of skilled labor.

Although the third configuration has been useful in corroborating a number of our previous findings, its inability to incorporate the role of capital-labor complementarities in skill premia dynamics due to the (aforementioned) unrealistic separability assumption remains a key disadvantage. This drawback, along with results of information criteria, ultimately tilt preference toward the first configuration again.

5.2 Four Factor Model

Building on the decomposition of labor in section 5.1, we in addition disaggregate capital in this section by focusing on the distinction between either i) intangible and tangible capital, or ii) ICT and non-ICT capital. The systems that are estimated consist of equations (23)-(27) or (23)-(25) and (28). Information criteria, residual diagnostics, speed of convergence in parameter estimates, and sensibility of estimates guide the decision between four and five equation frameworks and selected input constellations. Considering the analysis of section 5.1, unskilled labor is always treated as separable from other factor inputs in our three-level four-factor models. For the three designated four factor configurations, Tables 3 and 5 present system estimates in the cases of statistical and analytical databases respectively, where the latter database augments the definition of intangible capital as discussed in section 4. Corresponding Tables 4 and 6 provide residual diagnostics for system equations, which typically lead to the conclusions of relatively low cross-sectional correlation and mean reversion.

5.2.1 Capital Decomposition I: Intangibles & Tangibles

5.3.1.1 First Inputs Configuration

The first configuration of the four factor inputs in Tables 3 and 5 places intangible capital in the second level of the model, while nesting tangibles and skilled labor in composite input X in the third or bottom level. This setup may for instance be congruous with examining the extent to which robo-advisors and optimized low-cost exchange traded funds (ETFs), which require little to no human involvement, are displacing active portfolio managers and associated capital equipment, as well as unskilled labor, in wealth management services. Using either statistical or analytical data, the tables show that, while intangible capital, tangible capital, and skilled labor are complementary inputs in both sectors, finance is characterized by greater complementarity in those inputs. Furthermore, substitutability between these inputs and unskilled labor is notably greater in finance. The substitution elasticities in finance imply that, rather than net replacing human asset managers or financial advisors, computer algorithms alongside big data and R&D are net assisting skilled labor in catering to client needs while automating menial tasks handled by unskilled labor (e.g. call centres or support services, certain loan origination functions).[38] Such trends may have contributed to further increases in demand for skilled labor that is proficient in computer coding. The volume of assets managed solely by robo-advisors, although on the rise, still remains a relatively small fraction of total assets in the U.S. and Europe.[39]

Column (3) of the tables provides estimates of the elasticity of substitution between tangible capital and skilled labor, $\nu = \eta_{3,4} = \eta_{4,3}$. With higher values in non-finance across both estimators and databases, we obtain estimates of ν ranging from 0 to 0.17 in finance, and 0.01 to 0.40 in non-finance. The corresponding average sectoral estimates are 0.06 and 0.15. The complementarity implies that factor price changes dominate (oppositely signed) factor quantity changes such that factor shares move in the same direction as the former. However, the predicted positive link between w_S/r_{KT} and the relative share of skilled labor is only evident for finance based on pooled average annual changes in column (18).

For estimates of $\rho = \eta_{2,3} = \eta_{2,4}$ which gauges the substitutability between intangible capital and compound input X, as well as each of its underlying components (tangible capital and skilled labor), column (2) again reports that values in all cases are higher in non-finance. Values of ρ span from 0.02 to 0.22 in finance, and 0.05 to 0.85 in non-finance, while corresponding sectoral averages are 0.11 and 0.30 respectively. Reinforcing this result, columns (11) and (12) in Tables 3 and 5 show that Morishima elasticities $\eta_{3,2}$ and $\eta_{4,2}$ are also higher in non-finance. In all cases across both sectors, we find that ρ, $\eta_{3,2}$, and $\eta_{4,2}$ are greater than ν. This suggests that there is greater substitutability between intangible capital and tangible capital or skilled labor than there is between tangible capital and skilled labor.

On the one hand, estimates of ρ less than unity appear natural as intangibles such as software and tangibles such as computer hardware (ICT equipment) can be viewed as net complementary. On the other hand, AI-driven online platforms and services in the cloud, where AI generates new algorithms through machine learning to meet evolving consumer needs, can reduce such complementarity by diminishing growth in the overall volume of physical premises, equipment, and workers required. Higher estimates of ρ in the wider non-finance market economy may suggest that the latter effects

[38] Prasad (2021) suggests that new technologies are likely to be more skill complementary in investment banking than commercial banking. Each customized financial derivative, new securitization product, or merger and acquisition exhibits its own idiosyncratic attributes that still requires the experience and (potentially prescient) intuition of skilled labor in interpreting the data. AI can augment such labor qualities by elucidating non-apparent trends and expediting intermediate analytical processes.

[39] This adoption is less pronounced in the latter region as European investors tend to be more risk-averse relative to their U.S. counterparts. Fees associated with such transactions are also higher in Europe due to differences in national regulations.

are more pronounced in this sector. This is evident for example in the retail sector where growth in the number of physical retail outlets and associated equipment has significantly declined (on net) due to the shift toward online consumption (Laboure and Deffrennes, 2022). Up until the end of 2003 average annual growth in tangibles is lower in the non-finance sector. While average annual growth in non-finance's real net stock of tangibles over 2008-2017 is down by about 1 percentage point, or 43 percent, relative to 1995-2007, it still remains higher than in the financial sector which observes a steeper decline. Equally, growth in intangibles is always higher in finance, but the decline in the growth over the same two periods is more pronounced in finance.[40]

Although tangible capital continues to maintain a larger share in the aggregate capital stock across sectors, Figures 3(c) and 3(d) show that the cross-country weighted average ratio of nominal or real intangible to tangible capital is rising strongly over the sample period in both sectors. Figures 3(a) and 3(b) also highlight that the share of intangibles in total capital over time is higher in finance than in the remainder of the market economy, with non-finance narrowing the gap in the post crisis years. In relative terms, intangible capital requires more skilled labor such as developers for software and databases, or scientists for R&D. Corresponding to the greater weight of intangibles in finance, which has seen 7.4 percent growth p.a. in its real stock on average compared to 4.2 percent in non-finance[41], Figure 1 indicates that the share of skilled labor in total employment in finance has been more than twice that in non-finance over the period studied. As evident from the plot, finance's relative share of skilled workers is also growing up until the GFC, and declining thereafter.

Columns (16) and (17) of Tables 3 and 5 reveal that the directions of average changes in relative factor prices r_{KT}/r_{KI} and w_S/r_{KI}, and corresponding relative factor shares fall in line with the positive price-share links predicted by ρ, $\eta_{3,2}$, and $\eta_{4,2}$ estimates. To illustrate, consider GMM estimates of $\rho = \eta_{2,4}$ and $\eta_{4,2}$ for the financial sector (panel A) in Table 5. The former estimate signals that a 1 percent decrease in the return to intangibles relative to that of skilled labor is associated with a 0.85 percent decrease in the output share of intangibles relative to that of skilled labor. Looking at the inverses of these ratios, the $\eta_{4,2}$ estimate suggests a 0.88 percent drop in the relative skilled labor share. Matching up quite closely with these correlations, cloumn (17) of Table 5 reports that the skilled wage relative to the intangibles rental on average falls annually by around 1.8 percent in finance, while the relative skilled labor share in the analytical data deteriorates by about 1.4 percent p.a. (implying a 0.80 per 1 percent change).

The output share of intangibles relative to that of tangibles is, on average, increasing annually in both sectors based on either statistical or analytical data according to column (16) in the tables, with finance featuring the higher growth. Using augmented capital stocks (Table 5), we find that the relative income share of intangibles is rising by 7.2 percent p.a. in finance which is almost three times the growth rate of the non-finanical sector. The statistical database (Table 3) meanwhile indicates that it is almost twice as high. Apart from a brief dip around the GFC period, Figures 5(c) and 5(d) demonstrate that the cross-country weighted average intangible capital share is trending upward over time in both sectors. For the augmented capital stock (analytical database), Figure 5(d) shows that finance's intangibles share in sectoral output is higher than in the rest of the market economy throughout almost the entire period. For the statistical database, this is evident mainly in years after

[40] This fall in investment post GFC is often referred to as secular stagnation in the literature.

[41] Based on the statistical database.

the GFC. However, differences in relative output shares of intangibles $r_{KI}K_I/r_{KT}K_T$ across sectors are more amplified partly because of the higher growth of tangibles in the non-financial sector. Over the sample period, the real stock of tangible capital is expanding on average across countries by 1.8 percent p.a. in non-finance compared to 1 percent p.a. in finance. The lower growth of tangible capital in finance reflects the fact that finance is a significantly more data-intensive industry and the dwindling reliance on physical outlets in the sector. Growing demand for intangibles relative to tangibles in finance has also raised its relative return, standing above that in non-finance, as captured by Figures 6(c) and 6(d). Lastly, Figures 5(a) and 5(b) stress that the share of intangibles in total capital compensation in finance is on average always greater than that in non-finance over the period.

Turning attention to column (1) in Tables 3 and 5, we find that the elasticity of substitution between unskilled labor and composite input Z, or any of the remaining individual factor inputs composing it, tends to be around 1.40 in finance and 1.18 in non-finance. Alongside the aforementioned $\sigma = \eta_{1,2} = \eta_{1,3} = \eta_{1,4}$ estimates, the majority of the corresponding estimates of Morishima elasticities $\eta_{2,1}$, $\eta_{3,1}$, and $\eta_{4,1}$ across tables too reflect greater substitutability between unskilled labor and remaining inputs in finance. For instance, the average Morishima substitution elasticity between skilled labor and unskilled labor $\eta_{4,1}$ is 0.77 in finance compared to 0.60 in non-finance. These results are consistent with the parallel three-factor model conclusions where gross or relative substitutability between unskilled labor and aggregate capital, or skilled labor, is similarly found in each sector, as well as greater ease of this substitution in finance. The sectoral estimates (σ, $\eta_{LS,LU}$) however are larger on average in the four-factor model: while NLSUR estimates are more alike, GMM estimates are notably smaller in the three-factor framework. Between them, σ, $\eta_{2,1}$, $\eta_{3,1}$, and $\eta_{4,1}$ are able to capture the directions of corresponding average relative factor price and share changes in the data reported in columns (13)-(15).

Columns (4)-(7) focus on factor-augmenting productivity growth. We find in column (4) that the effective supply of unskilled labor is declining more rapidly in the financial sector. As this implies that real unit labor costs in terms of unskilled workers are increasing faster in finance, financial institutions will be more inclined to choose technologies that maximize the efficiency of other factor inputs. Column (6) suggests that growth in tangible capital augmenting productivity is higher in finance, with column (7) in Table 3 in particular suggesting the same for intangible capital. Such trends in capital productivity across sectors ultimately prompt even higher growth in finance relative to non-finance demand for skilled labor given our estimates of substitution elasticities.

The roles of skill intensity, capital-labor complementarities, and technical change in the evolution of skill premia across sectors are assessed for the first configuration in panels B and C of Table 7. Columns (1) and (7) establish that the condition for a negative relation between relative skilled wages and relative skilled labor, namely RSC > 1, is met in both sectors based on the various estimates. Columns (2) and (8) subsequently record the magnitude of the link in each case, disclosing that coefficients are larger in finance. For example, based on GMM estimates of substitution elasticities, panel B (C) indicates that for negligible growth in the relative quantity of skilled labor assuming that $g^{L_U} = 0.01$ (lower bound case of $g^{L_U} \approx g^{L_S}$), the decline in the relative skilled wage is approximately 3 (6) percent in finance while 1 (5) percent in non-finance. This difference is driven by the fact that σ relative to ρ and ν is significantly higher in finance compared to non-finance. As substitution between unskilled labor and tangible or intangible capital is easier in finance, while complementarity between skilled labor and the two capital types is weaker in non-finance, equal growth in skilled and unskilled labor necessitates a greater fall in the skilled wage relative to the unskilled wage in finance. Finance NLSUR estimates are outsized relative to mean GMM estimates because of relatively small ρ and ν.

The connection between growth in the intangible capital stock and skill premium is given in column (4) for finance and column (10) for non-finance in Table 7. Aligned with finance's stronger complementarity between skilled labor and intangible capital ($\rho_F < \rho_{NF}$), and stronger substitutability between unskilled labor and intangible capital ($\sigma_F > \sigma_{NF}$), cloumn (4) reports the larger positive correlations. Given that the within Z process intangibles income share, $\delta_{20} = \delta_{KI0}$, is higher in finance, we note that the difference $\sigma - \rho$ also receives greater weight in finance than non-finance when calculating the KLC$_2$ coefficient. For a 1 percent increase in the real stock of intangible capital, the associated increase in the finance relative skilled wage ranges from 0.64 to 11.02 percent ignoring all other factors. The range across estimates in non-finance meanwhile is 0.03 to 1.91 percent. Average coefficients indicate that the change in the finance relative skilled wage is more than four times that of the non-finance sector, standing at 4.84 percent versus 1.14 percent. Put differently, the marginal product of skilled labor relative to that of unskilled labor in finance benefits more from a higher real stock of intangibles. From a factor substitution perspective, larger disproportionate increases in the skilled wage are required in finance in order to absorb the extra intangible capital in place of a small number of skilled workers. The greater increase in the productivity of skilled labor in finance however results in a higher net rise in the demand for skilled workers in the sector, thus further increasing the relative finance skill premium.

Denoted by KLC$_3$, the complementarity effects of tangible capital are gauged in columns (5) and (11) of Table 7. Coefficients are positive in both sectors. The financial sector, however, exhibits the more economically significant values, while statistical insignificance occurs for its two NLSUR-based estimates. Examining GMM-based results in panel B, we find that when real tangible capital grows by 1 percent, the relative skilled wage in finance improves by 2.31 percent which is almost 2.5 times the corresponding change obtained in non-finance's relative wage. This outcome is partly driven by the stronger complementarity between skilled labor and tangible capital found in finance ($\nu_F < \nu_{NF}$), and the weaker substitutability between unskilled labor and tangible capital in non-finance ($\sigma_F > \sigma_{NF}$). As substitution between unskilled labor and tangible capital goes through two levels or nests in the production function, namely via compound inputs Z and X respectively, the mid-level elasticity ρ also plays a role in mediating the KLC$_3$ coefficient. Specifically, σ and ν are measured relative to ρ, with differences $\sigma - \rho$ and $\rho - \nu$ being of concern. As KLC$_3$ estimates suggest that the unit labor costs related to skilled labor are declining more in finance relative to non-finance with tangible capital growth, finance should observe higher upward pressure on the demand for skilled labor for similar g^{K_T} across sectors.[42]

Technical change (TC) coefficients are positive in both sectors but are notably more economically significant in finance. Only GMM-based estimates are statistically significant. In the case of GMM in panel B of Table 7, columns (6) and (12) show that technical change, reflecting a weighted average of

[42]Even for observed pooled average annual tangible capital growth rates $g_F^{KT} = 0.01$ and $g_{NF}^{KT} = 0.018$, skill premium growth in finance is higher.

factor-augmenting productivity growth rates, is associated with a 12 percent annual appreciation of the relative skilled wage in finance, compared to only 3.4 percent in non-finance. Given corresponding substitution and distribution parameter values, analyzing the λ_i estimates and technical change component in equation (32) reveals that this disparity can be primarily ascribed to sectoral differences in λ_{LU} and λ_{KI}. First, $\lambda_{LU} < 0$ is almost twice as large in finance, which is also characterized by a higher σ. Thus as the productivity and effective volume of unskilled labor in finance relative to non-finance declines, ceteris paribus, the relative finance unskilled wage is pushed down.[43] Furthermore, as substitutability between skilled and unskilled labor is higher in finance, the marginal product of skilled labor is less affected in the sector. These two points combined imply that the financial sector observes the larger increase in the skill premium. Second, λ_{KI} estimates point to financial sector increases in productivity that augments the sector's intangible capital, and the opposite in non-finance. The implication is a divergence in the relative marginal products of skilled labor across sectors, with finance (non-finance) displaying an increase (a decrease) in the ratio. Although the lower weight of intangibles, lower L_S-K_I complementarity (higher ρ tempering $\mathrm{MPL_S}$ fall), and lower L_U-K_I substitutability (lower σ deepening $\mathrm{MPL_U}$ fall) in non-finance attenuate the negative impact in the sector, the net result is a drop in the non-finance skill premium. An increase meanwhile materializes in finance. This two-fold trend produces magnified growth in the skill premium of finance over non-finance.

5.3.1.2 Second Inputs Configuration

In the second inputs configuration of Tables 3 and 5, intangible capital and skilled labor are combined in the bottom nest of the model, while tangible capital now appears at the second level. With the rising prominence of FinTech platforms including online banking, this permutation of factors in finance can for instance reflect the notion that computer programmers and analysts are being combined with software, databases, and R&D to deliver services and reduce the net volume of bank branches (physical structures), associated equipment (e.g. telephones, ATMs, as consumers transition to digital transactions), and relatively unskilled labor such as security guards. In our sample, northern European countries have the most advanced online banking industry, with Nordic and Dutch banks having curtailed branch numbers by about 50 percent (Laboure and Deffrennes, 2022). In non-finance the configuration may be representative of the idea that data-driven online services merged with skilled labor are displacing tangible outlets and in turn unskilled labor. For example online shopping could require only a couple of central warehouses and delivery system without multiple stores and shop assistants.

Buchak *et al.* (2018) report that FinTech lenders can offer greater speed and convenience for mortgage loans even for borrowers with access to traditional banks, thus implying some degree of substitution. Tang (2019) finds that peer-to-peer lending is a substitute for conventional bank lending in terms of serving infra-marginal bank borrowers, while complementing small loans from banks. Focusing on the U.S. Paycheck Protection Program (PPP), Erel and Liebersohn (2020) find that, although statistically significant, the degree of substitution between FinTech lending and traditional bank lending is economically small, implying that FinTechs have not markedly closed the gap in

[43] $\sigma > 1$ in equation (24) means that λ_{LU} and the real return to unskilled labor move unequivocally in the same direction due to gross substitutability between unskilled labor and other inputs.

financial services in areas where bank branches operate.[44] The study concludes that FinTech and traditional bank lending markets are relatively segmented, with FinTech attending to new distinct markets comprising borrowers that are underserved by the traditional banking system. By serving firms and households with weak ties to traditional banks or in regions with fewer bank branches, that otherwise would not receive credit, FinTech acts to expand the credit supply and complement traditional banking. Our results for the financial sector show congruence with such complementarity in the literature e.g. amongst others see Di Maggio and Yao (2021) and Prasad (2021).

The first point to highlight in Tables 3 and 5 for the second configuration is that the inequality $\rho > \nu$ still persists in both sectors. The implication of this result in the first two configurations is that the degree of substitutability between tangible and intangible capital is higher than between either tangible capital and skilled labor, or intangible capital and skilled labor. Estimates of $\rho = \eta_{2,3} = \eta_{2,4}$, $\nu = \eta_{3,4} = \eta_{4,3}$, $\eta_{3,2}$, and $\eta_{4,2}$ again emphasize complementarity between tangible capital, intangible capital, and skilled labor in both sectors, with much stronger complementarity in finance as captured by notably lower values of the afermentioned elasticities. As intangibles are characterized by greater within-synergies and spillover effects, relative to tangible capital, their impact on other factor inputs will be more pronounced in finance where intangibles enjoy a higher weight.[45]

From column (3) in the tables we see that ν is significantly smaller for finance in the case of both estimators and databases. On average, the estimate of ν is only 0.07 in finance. This is less than half the size in non-finance where the mean estimate is 0.16. The difference coincides with the fact that most large financial institutions, especially banks, have been writing their own software which has equated to increasing numbers of programmers on the books. Indeed, Citibank over a period employed more programmers than Microsoft.[46] Costs associated with intangible capital are also more likely to be sunk. Therefore relatively "intangible capital"-intensive industries such as finance will generate greater demand for highly skilled managers that can minimize the profligate costs of hold-up and haggling emanating from the powerful bargaining positions of skilled workers. For example, replacing old legacy user-specific codes of big banks is almost impossible i.e. they are long-lasting and non-fungible. As intangibles engender greater synergies through effective coordination, where the whole is significantly larger than the sum of the parts, scale increases resulting in bigger firms and in turn higher demand for highly skilled labor.[47] With more knowledge- and data-intensive organizations, there is greater reliance on knowledge sharing and knowledge workers, especially if the knowledge is tacit. This places further upward pressures on the demand for skilled co-ordinators and executives that can successfully communicate information, promote appropriate organizational design, and maintain loyalty amongst staff. Lastly, in both sectors, the positive comovement between w_S/r_{KI} and $w_S L_S/r_{KI} K_I$ implied by estimates of ν is consistent with the observed signs of average annual changes in these ratios reported in column (18).

All estimates of ρ but one in non-finance lie approximately in the interval (0.34,0.38), with the

[44]A 10 percent decrease in traditional bank lending causes a 0.4 percent increase in FinTech lending (although substitution may be higher in ZIP codes where fewer branches operate and FinTech loans tend to be more common).

[45]The income share of intangible capital in finance is twice that in non-finance on average.

[46]It is also true that in recent times banks have begun to outsource such tasks to the tech sector due to regulatory compliance issues and maintenance costs.

[47]By their very nature, intangibles are more scalable and transferrable within an expanding organization experiencing a rising market share or sales volume.

overall average standing at 0.31. The typical value of ρ in finance is about 0.14, with only one estimate exceeding this mean (Table 3). Similar sectoral discrepancies in corresponding Morishima elasticities in columns (11) and (12) can be found. The results of the second configuration thus continue to suggest that complementarity between tangible capital and intangible capital or skilled labor is stronger in finance. We also see evidence of this complementarity in finance being greater than complementarity between intangible capital and skilled labor in non-finance e.g. ρ, $\eta_{3,2}$, and $\eta_{4,2}$ in finance are less than ν in non-finance based on NLSUR estimates in Table 3.[48] Consider the distinction between *using* and *producing* intangible assets. If on average, compared to the other sector, the non-financial market economy uses intangible assets more intensively, while the financial sector engages more intensively in the production of research (speculation, forecasting etc.) and knowledge sharing, then that may partly explain the relatively high ν in non-finance.

Estimates of the elasticity of substitution between unskilled labor and remaining factor inputs, σ, are very similar to those from the first configuration. In finance, σ values are now more tightly concentrated around the repeated average estimate of 1.40, ranging from 1.37 to 1.42. Substitutability in non-finance again is notably lower with all estimates lying quite near the typical value of 1.20. These results for σ encapsulate the more pronounced polarization of skilled and unskilled income shares in finance relative to non-finance and match the documented divergence of sectoral skill premia (column (15) and Figure 1). If capital accumulation combined with financial deregulation intensified knowledge-oriented activities and automation of lower-tier jobs within finance relative to non-finance, then this may have produced a higher σ and facilitated the steeper decline in unskilled labor in the sector.[49] For example, using the optimal routing technology in an Amazon warehouse does not necessarily require more skilled labor. Growth in ICT and organizational design have enabled more efficient monitoring and thus an expansion in some types of non-autonomous unskilled work in many non-finance firms such as Amazon. The capital in such cases acts as a substitute for more autonomous skilled labor, often referred to in the literature as power-biased technological change (Guy, 2014; Haskel and Westlake, 2017).

Columns (4)-(7) of Tables 3 and 5 lead to conclusions about factor-augmenting productivities that are generally similar to those for the first configuration. Morishima elasticities in columns (8)-(12), and those equal to σ or ρ, meanwhile are qualitatively consistent with most of the corresponding pairwise changes in relative factor prices and factor shares given in columns (13)-(17). Table 7 in the case of the second configuration reiterates that skill premium growth in finance, compared to non-finance, is more strongly positively linked to intangible and tangible capital growth as well as technical change, while exhibiting a stronger inverse link with the relative supply of skilled labor. In finance, we find that the relation between intangible capital growth and the relative skilled wage is more pronounced than in the case of tangibles ($\mathrm{KLC}_3 > \mathrm{KLC}_2$) in all instances of this configuration. In non-finance, however, the evidence is mixed, with panel B showing that tangibles matter about twice as much as intangibles. The latter result is driven by the relatively low weight of intangibles in non-finance in the statistical database and the higher corresponding ν estimates indicating lower complementarity between skilled labor and intangible capital.

[48] Average estimates across tables indicate the same.

[49] A higher σ, ceteris paribus, reduces the marginal product of unskilled labor relative to that of skilled labor in the face of capital growth.

5.2.2 Capital Decomposition II: ICT & Non-ICT

The third and final configuration demarcates ICT capital from non-ICT capital instead, placing ICT capital and skilled labor in the bottom nest of the model. The results in column (3) of Tables 3 and 5 allow us to conclude overall that ICT capital and skilled labor are more complementary in the financial sector which is characterized by an average ν estimate of 0.05.[50] Column (1) on the other hand highlights that substitutability between unskilled labor and ICT capital, or any of the remaining inputs, is markedly weaker in the non-financial market economy. In particular, the relevant substitution elasticity σ hovers around 1.42 in finance while averaging approximately 1.09 in non-finance. GMM estimates in Table 5 actually indicate that σ is twice as large in finance relative to non-finance. Clustered quite compactly in each sector, values of the Morishima elasticity $\eta_{3,1} \equiv \eta_{ICT,LU}$ in column (9), additionally, are at least twice as big in finance.

At the more general level over sectors, our findings support the conclusions of Autor *et al.* (1998) and Autor *et al.* (2003) who suggest that computerization tends to i) complement workers in more complex non-routine problem-solving operations thus increasing the demand for such labor, and ii) substitute for routine cognitive and manual labor following explicit rules (i.e. codifiable tasks) thereby reducing employment of less skilled labor e.g. self-service facilities. At a more granular sectoral level, our results for finance lend further credence to the notion that ICT investment affects job complexity and optimal organization in banking as expounded by Autor *et al.* (2002) and Morrison and Wilhelm (2004, 2008). As a whole, the finance industry relies more heavily on data collation and analytics than non-finance, which explains the sectoral discrepancies in σ, $\eta_{3,1}$, and ν estimates. This also suggests that the reward to skilled labor from investment in ICT is higher in finance. As depicted in Figure 4, while the real stock of ICT to non-ICT capital is rising in both sectors on average across countries ((c) and (d)) commensurate with declining relative ICT user costs (Figures 6(c) and 6(d)), ICT intensity in finance continuously more than doubles that in non-finance.[51,52] Figure 5, moreover, illustrates that the shares of ICT in total capital compensation ((a) and (b)) and output ((c) and (d)) in finance significantly outstrip the corresponding non-finance shares, with proof of relative finance growth.

Column (2) meanwhile shows that complementarity between non-ICT capital and ICT capital, skilled labor, or the composite of the latter two inputs X is much greater in finance. Specifically, average estimates of the corresponding substitution elasticity ρ in finance and non-finance are 0.19 and 0.49 respectively. The elasticity magnitudes and sectoral difference align with the fact that intangibles, which are present in both ICT and non-ICT capital and carry a significantly higher weight in finance, are more synergistic, yielding greater scale and positive spillovers. Along the tangibles dimension, ICT hardware and the structures that store them are highly complementary. Morishima elasticities $\eta_{3,2} \equiv \eta_{ICT,NICT}$ in column (11) and $\eta_{4,2} \equiv \eta_{LS,NICT}$ in column (12) across sectors are qualitatively consistent with sectoral discrepancies in ρ estimates. However, they suggest that the cross-sectoral asymmetry in complementarity between skilled labor and non-ICT capital

[50] ν estimates imply that the "skilled wage"-"ICT rental" ratio and corresponding ratio of output shares display a positive comovement. Column (18) in both tables however shows that only trends in finance match up with this prediction, suggesting other factors are at play in non-finance.

[51] ICT adoption is notably more pervasive in finance in pre GFC years. The intensity gap between sectors although narrows in post GFC years. Note that if $K_{ICT}/K_{NICT} = x$, then $K_{ICT}/(K_{ICT} + K_{NICT}) = x/(1 + x)$.

[52] Pooled simple average annual changes in ratios are obtainable from column (16) of Tables 3 and 5.

is far more pronounced than that between ICT and non-ICT capital. This is consistent with the relatively high degree of complementarity found between skilled labor and intangibles for finance in earlier configurations, given that non-ICT capital contains most intangibles such as R&D and organizational design. Based on Morishima elasticities $\eta_{3,2}$ and $\eta_{4,2}$, we find in both sectors that complementarity between ICT capital and non-ICT capital ($\eta_{3,2}$) is weaker than complementarity between ICT capital and skilled labor (ν) but stronger than that between skilled labor and non-ICT capital ($\eta_{4,2}$). Average values of $\eta_{3,2}$ and $\eta_{4,2}$ in finance are 0.09 and 0.15 respectively, while 0.13 and 0.42 in non-finance. These statistics are also in line with the stronger $\rho > \nu$ inequality in non-finance, reflecting the greater interchangeability between different capital types and skilled labor in non-finance.

In column (7) of Tables 3 and 5 we find that ICT-augmenting productivity growth ranges from 1 to 3 percent p.a. in finance while non-finance estimates predominantly fall below zero. This implies that effective real ICT capital growth exceeds physical stock growth in the financial sector, and the opposite in non-finance or at best that effective and physical ICT capital are approximately equal in the sector based on the NLSUR estimate in panel B of Table 5. According to Acemoglu (2002), a higher relative quantity of skilled labor pushes more innovation in the direction of capital that is more complementary to upper levels of education. Therefore $\lambda_F^{KICT} > \lambda_{NF}^{KICT}$ makes sense in the context of Figure 1 which shows much stronger skill intensity in finance that moreover experiences relative growth over time. Regarding the other factor inputs, unskilled labor augmenting productivity growth continues to be more negative in finance, while average values and GMM estimates of growth in skilled and non-ICT augmenting productivity are higher in finance. Thus technical change is directed further away from unskilled labor in finance.

Table 7 shows that technical change and relative skilled wage growth are positively linked in finance and negatively linked in non-finance (columns (6) and (12)). The negative association in non-finance is partly engendered by $\lambda_F^{KICT} \leq 0$ and the importance of ICT capital for skilled labor, as gauged by ν, in the sector. We also see from columns (4)-(5) in finance and columns (10)-(11) in non-finance that growth in either non-ICT or ICT capital is positively correlated with the skill premium in both sectors. More precisely, these capital-labor complementarity coefficients (KLC$_i$) tend to be i) larger in the case of ICT capital in both sectors and ii) more prominent in finance, in line with the estimated substitution elasticities and capital intensities (distribution parameters δ_{KNICT0} and δ_{KICT0}) across sectors.

5.3 Reduced-Form Analysis

Tables 8-11 report the results of our reduced-form analysis of the covariates of relative finance wages as proposed in section 3. Annual data are used in Tables 8-9. A more long-term perspective on the other hand is taken in Tables 10-11 where non-overlapping four-year average data points that attenuate the effects of short-term business cycle movements are employed. Amongst regressors, Tables 8 and 10 consider the role of intangible capital, while Tables 9 and 11 feature ICT capital. The panel regressions in each table consider the four different, but related, dependent variables: i) relative finance aggregate wage (w_F^T/w_{NF}^T), ii) relative finance skilled wage (w_F^S/w_{NF}^S), iii) skilled to aggregate wage ratio in finance relative to non-finance ($\frac{w_F^S/w_F^T}{w_{NF}^S/w_{NF}^T}$), and iv) skilled to unskilled wage ratio in finance relative to non-finance ($\frac{w_F^S/w_F^U}{w_{NF}^S/w_{NF}^U}$). Figures 1 and 2 illustrate that these four relative wage series are positively correlated. All variables are in logarithmic form apart from banking competition, labor market flexibility, and their interaction. Specifications in columns (1)-(4) exclude time dummies. Those in columns (5)-(8) meanwhile include time fixed effects, either annual (Tables 8-9) or period (Tables 10-11), which account for global factors and hence related cross-section comovements. In each of the tables, panel A (B) provides pooled OLS (GMM) estimates. The tables indicate that regression residuals exhibit relatively low average and absolute average cross section correlations with the overwhelming majority of CSD tests failing to reject the null of either independence or weak dependence. All regression residuals are stationary according to panel unit root tests at conventional significance levels (last rows). R-squared values on average suggest that covariates capture around half of the variation in relative finance wages.

We find across the tables that relative finance wages are positively associated with both i) the intensity of real intangible capital in finance relative to that in non-finance and ii) the intensity of real ICT capital in finance relative to that in non-finance. Corresponding point estimates for the relative finance skilled wage (columns (2) and (6)) are larger than those for the relative finance aggregate wage (columns (1) and (5)). Such an outcome is reasonable given aggregate wages are a labor-weighted average of skilled and unskilled wages, and the comparatively lower sensitivity of finance unskilled wages to capital growth based on σ estimates. Noting that $\frac{w_F^S/w_F^T}{w_{NF}^S/w_{NF}^T}$ can be re-written as $\frac{w_F^S/w_{NF}^S}{w_F^T/w_{NF}^T}$, the positive coefficient on relative capital intensity in column (3) is consistent with the aforementioned inequality across columns (1) and (2). The same applies to the result in column (7), vis-à-vis the discrepancy across columns (5) and (6). Compared to columns (3) and (7) respectively, columns (4) and (8) report larger correlations for the skill premium gap $\ln(w_F^S/w_F^U) - \ln(w_{NF}^S/w_{NF}^U)$, which again makes sense in the context of sectoral skill intensities and our factor substitution elasticity estimates i.e. given capital-skill complementarity in finance with unskilled (skilled) wages that are less (more) sensitive to capital growth in finance relative to non-finance. That is, we expect the inequality $\%\Delta w^T > \%\Delta w^U$ tied to intangible or ICT capital growth to be met most strongly in finance. As Table 7 hints, the skill premium gap still increases in favor of finance even if the intensity of intangibles or ICT grows equally across sectors. Therefore relative finance capital growth acts to amplify this result.

The magnitudes of coefficients on relative intangible and ICT capital intensity tend to be marginally higher for the lower frequency data set comprising 4-year averages (Tables 10-11). In particular, average estimates on intangible capital across pooled OLS and GMM specifications with and without time fixed effects for relative finance wages $\left\{\frac{w_F^T}{w_{NF}^T}, \frac{w_F^S}{w_{NF}^S}, \frac{w_F^S/w_F^T}{w_{NF}^S/w_{NF}^T}, \frac{w_F^S/w_F^U}{w_{NF}^S/w_{NF}^U}\right\}$ based on annual observations are 0.10, 0.13, 0.03, and 0.06 compared to 0.10, 0.14, 0.04, and 0.08 based on 4-year observations. Here we can see that the third value in both cases quite conveniently equals the difference between the first two averages. For coefficients on ICT capital intensity, the corresponding averages are 0.03, 0.04, 0.05, and 0.11 based on annual data, compared to 0.05, 0.07, 0.06, and 0.13 based on 4-year data.

A 5 percent increase in relative finance intangible or ICT capital intensity is thus typically associated with, for example, a ~0.5 percent increase in the relative finance skilled-to-unskilled wage. Intuitively, assuming $g^{K_I} > 0$ or $g^{K_{ICT}} > 0$ in both sectors, a higher relative finance intangible or ICT capital intensity raises the ratio of marginal products $\mathrm{MPL}_S/\mathrm{MPL}_U$ in finance relative to that in non-finance. This occurs because of i) greater complementarity between intangible or ICT capital and skilled labor in finance, ii) lower substitutability between intangible or ICT capital and unskilled labor in non-finance, and iii) higher relative growth in these capital types in finance. The first two points imply that the productivity of skilled labor is more sensitive to intangibles and ICT in finance relative to non-finance, while the productivity of unskilled labor is more sensitive to that capital in non-finance relative to finance. Both act to enhance the discrepancy in $\text{MPL}_S/\text{MPL}_U$ changes across sectors in favor of finance. The third point amplifies this discrepancy. In turn, at given factor input prices, the demand for skilled relative to unskilled labor in finance increases by more than in the non-financial sector. Excess demand ultimately places proportionate upward pressure on the relative finance skill premium.

While in columns (2)-(4) and (6)-(8) we find that an increase in finance's skilled labor intensity in total sectoral employment relative to that of non-finance in a given labor market regime correlates negatively with relative finance skilled wages and skill premia, columns (1) and (5) show positive comovement with relative finance aggregate wages. Although relative skilled wages decline, the relative aggregate wage may rise if the skilled labor intensity $\frac{L_S}{L}$ is initially less than the unskilled labor intensity $\frac{L_U}{L}$ in the aggregate wage definition, such that $|\%\Delta\frac{L_S}{L}| > |\%\Delta\frac{L_U}{L}|$. A larger skill premium, moreover, improves the likelihood of unskilled wage increases more than offsetting skilled wage decreases in percentage terms. The dichotomy between coefficients from the perspective of labor alone is also in tune with the finding of gross substitutability between skilled and unskilled workers in our more micro-founded analysis i.e. $\sigma > 1$. The latter implies that, in absolute terms, percentage changes in skilled relative to unskilled wages are smaller than those in corresponding relative quantities.[53] Given the positive coefficient estimates on relative finance skilled labor intensity in the case of $\frac{w_F^T}{w_{NF}^T}$, negative estimates should be stronger for $\frac{w_F^S/w_F^T}{w_{NF}^S/w_{NF}^T}$ than for $\frac{w_F^S}{w_{NF}^S}$, which is what we find in the tables. Lastly, controlling for other variables, we find that coefficients pertaining to relative capital intensity, especially intangibles, are generally economically larger than those for relative skill intensity in the cases of relative finance skilled wages and skill premia.

Financial globalization, or volume-based international financial integration, covaries positively with relative finance wages. Estimates are primarily statistically significant for relative finance aggregate and skilled wages, with economic significance usually less than that for intangible or ICT capital intensity. Financial globalization elevates the bargaining power of capital relative to labor by tendering exit options for capital. Namely, investment capital can flow across borders to outsource labor-intensive, including skill-intensive, tasks via FDI. This shrinks median wages and the labor share, particularly in non-finance, while increasing dividend and interest payments (Dünhaupt, 2017).[54] Higher capital shares subsequently may bolster activity in finance through demand for investment, advisory, and consultancy services. The openness of international capital markets within a given regulatory framework can rise due to, for example, lower information costs. If such openness induces specialization patterns that are in line with comparative advantage, labor in the non-financial market economy incurs greater losses as the output composition of developed economies shifts toward "skilled labor"-intensive *services* such as those in finance.[55] This, together

[53] As observed in the data based on pooled averages with the sectoral disparity in line with $\sigma_F > \sigma_{NF}$.

[54] Dünhaupt (2017) finds that shareholder value orientation is inversely related to the labor share.

[55] Where the unit cost of finanical intermediation is declining.

with the rising complexity of financial products in an increasingly interconnected world, can exert upward pressure on relative finance average skilled wages.

A 1 percent increase in financial deregulation is associated with a 0.5 to 1 percent increase in the relative finance skilled-to-unskilled wage ratio (columns (4) and (8)). Remaining coefficients are only robustly statistically significant for the relative finance skilled-to-aggregate wage ratio (columns (3) and (7)), in which case the correlation continues to be positive but weaker in magnitude, equaling about half the size of the former estimates. Examining the impact of bank deregulation on income inequality in the U.S., Beck *et al.* (2010) find that the removal of intra-state branching restrictions tightened the income distribution by increasing the relative wages and working hours of unskilled labor, while having little affect on incomes above the median.[56] If this trend is most pronounced in non-finance, the relative finance skill premium can still rise. Delis *et al.* (2014) who study a range of financial regulatory policies obtain support overall for the results in Beck *et al.* (2010), but report a substantial increase in income inequality when securities markets are liberalized.

Philippon and Reshef (2012), in contrast, conclude that finanical deregulation in the U.S. disproportionately raises the demand for skilled labor in finance relative to non-finance over the long run. By enhancing creative freedom, deregulation encourages banks to attract highly skilled labor that is capable of producing innovative complex financial instruments, particularly in investment banking and market operations, which ultimately raise profits and wage premiums over non-finance workers. This mechanism can also deliver the rise in the relative finance skill premium that we report, and is more likely than the one outlined in Beck *et al.* (2010) to be the underlying driver given that we control for bank competition in regressions. Our estimates for relative skilled wages although are statistically insignificant.[57] Philippon and Reshef (2012) find that the financial sector contributes significantly to income inequality growth over the period of study. Jerzmanowski and Nabar (2013) meanwhile consider the same deregulation case as Beck *et al.* (2010) but reach opposing results, emphasizing increased wage rate differentials across skill levels.

While improved credit growth is likely to favor skilled workers in finance, what about those in non-finance? Credit expansion can enhance investment in the non-financial market economy that creates entrepreneurial activity, employment opportunities, and wage growth at the lower end of the income distribution. Conversely, it can heighten income inequality if it flows disproportionately to market leaders or larger firms in the sector. Greater credit access, furthermore, allows for organizational structural change in line with comparative advantage that increases labor reallocation as the share of firms specializing in skilled or unskilled labor-intensive tasks rises (Jerzmanowski and Nabar, 2013). This bids up the skill premium if new entrants to the market prefer the former work. A misallocation of resources, accompanied by lower destruction and creation rates, alternatively arises with higher credit if financial institutions face distorted incentives e.g. avoidance of non-performing loans that inefficiently diverts credit (Caballero *et al.*, 2008). The distributional effects of credit growth thus appear to be theoretically equivocal. Our empirical results are quite unidirectional, overwhelmingly indicating that relative finance wages benefit from the expansion of domestic credit.

[56]The deregulation had the affect of increasing competition in retail banking, thus enhancing bank operating efficiency and lowering the price of capital. Studying the French banking reforms of 1985, Bertrand *et al.* (2007) suggest that efficiency improving reforms, while increasing employment amongst firms, suppress wage growth.

[57]Under different specifications in unreported robustness checks we are able to retrieve statistically significant positive estimates for relative skilled wages too.

Higher banking competition is unambiguously related to higher relative finance wages in our regressions, assuming flexible labor markets. The link is ubiquitous across all specifications which in particular show that a 1 percentage point decline in the bank concentration ratio is typically associated with a 1-2 percent increase in the relative finance skilled wage and skilled-to-unskilled wage ratio. On the one hand, intensified competition in finance can increase the scarcity and bargaining power of skilled labor from the perspective of individual financial institutions due to higher demand, hence diverting resources away from different projects and increasing the factor's return in the sector (Thanassoulis, 2012; Acharya *et al.*, 2016). The higher skill intensity in finance makes these pressures particularly pronounced. On the other hand, as competitive pressures induce efficiency gains in finance, the cost of financial capital can drop thereby disproportionately benefitting the lower end of the income distribution in non-finance (Beck *et al.*, 2010).[58] If the market structure developments in finance translate to greater competition in non-finance through better targeted credit flows and higher rates of firm entry and exit, outsourcing in non-finance may increase and correspondingly reduce average wages in the sector (Bertrand *et al.*, 2007). Competition in both sectors may, additionally, prompt swifter adoption of new technologies (compositional changes) that complement skilled labor and strengthen its marginal product in finance relative to non-finance.[59] All of these channels are capable of generating a rise in relative finance wages.

Stricter employment protection legislation including unionization, equating to more rigid labor markets, covaries negatively with relative finance wages in all cases given a competitive financial sector. More precisely, a 0.01 point increase in the employment protection index correlates with approximately a 0.3-0.5 percent deterioration of the relative finance skilled-to-unskilled wage ratio, while coefficients for relative finance skilled-to-aggregate and skilled wages are normally about half the size or marginally smaller. Less flexible labor markets can reduce wage volatility and stifle innovation and productivity growth by creating firm operating inflexibilities that raise costs, including those of equity, and risks (Chen *et al.*, 2011). If hiring, managing, and firing staff is more difficult, then investment in new intangibles slows down. Upgrading intangibles often necessitates an adjustment to the way workers operate, with changes in organizational design, and may carry higher risks that increase the probability of future failure. Tighter labor market regulations that impede workforce flexibility therefore deter such investment and diminish the marginal product of complementary skilled labor, particularly in finance. As market demand changes, legal restrictions hinder the ability of firms to adjust their inputs. Returns to skilled labor in finance consequently may suffer most due to the exorbitant rents in the presence of moral hazard that accompany financial innovation (Axelson and Bond, 2015), especially when characterized by higher levels of complex, opaque, activity (Bolton *et al.*, 2016; Biais and Landier, 2020). Job or firm-to-firm mobility plays a central role in the excessive short-run compensations, rent-seeking, and long-term risk-taking observed in finance according to theory (Godechot, 2008; Acharya *et al.*, 2016; Bénabou and Tirole, 2016; Bijlsma *et al.*, 2018).[60]

The interaction term between bank competition and labor market flexibility uniformly highlights that the effects of lower bank concentration, reflecting lower market power, on relative finance wages

[58]Note also that, on average, low-to-middle income households are net borrowers while high income households are net savers.

[59]Given the higher complementarity in finance.

[60]The project or asset specificity of the work of skilled managers in finance augments their wage bargaining power in fluid competitive labor markets, where demand for skilled labor is strong.

are blunted by stricter employment protection laws which tend to constrain labor mobility. Noting that the employment protection index varies between 0.1 and 4.6 in the entire sample with an average or median value of around 2.3, we can see that greater competition in finance is linked to lower relative finance wages in highly rigid labor markets. This can occur if firms allocate more resources to long-term investment projects and risk management, instead of socially inefficient bonuses and pay packages, in the pursuit of higher productivity and cost efficiency under stronger competition, knowing that hiring/firing obstacles and job security that weaken labor mobility reduce employees' credible threats of departure and rent extraction powers. Conversely, abnormal profits in finance resulting from higher market power may be more likely to be shared with long-term (skilled) staff in less mobile labor markets.[61,62] Moreover, low rates of managerial churning allow longer run assessments of managers within the organization and thus better identification of talented executives deserving of commensurate rewards (Acharya *et al.*, 2016).

6 Conclusions

Structural transformation is shifting the output composition of developed economies toward high-paying skill-intensive services. At the same time, investment in intangible relative to tangible capital is rising, accompanied by a growing ICT intensity. Such trends imply an increasing reliance on data, information sharing, systems, and ideas. We focus on the financial sector by examining the role of intangible capital, as well as ICT, in the evolution of relative finance wages, which have displayed a striking upward trajectory over time. Exorbitant wage growth in the industry naturally raises concerns about whether finance is excessively contributing to economy-wide income inequality.

Applying a multi-level nested production framework, we find that synergies between skilled labor and the different types of capital are notably larger in finance than in the non-financial market economy. Unskilled labor and various forms of capital, meanwhile, are less fungible in the non-financial sector. These discrepancies in sectoral elasticities of substitution, given factor intensity differences, analytically yield a more pronounced positive link between the skill premium and intangible or ICT capital growth in finance. Stronger technical change in finance further enhances the relative skill premium.

Building on our theoretically-founded micro level approach, subsequent reduced-form analysis highlights that increases in intangible or ICT capital intensity in finance relative to non-finance, ceteris paribus, are associated with improvements in relative finance aggregate and skilled wages. This occurs through i) sectoral disparities in skill-capital complementarities and unskilled labor substitution possibilities, and ii) relative capital stock volume amplification effects.

Our study further suggests that financial deregulation, finanical globalization, banking competition under flexible labor markets, and domestic credit expansion comove positively with relative finance wages. Meanwhile, relative skilled labor supply and labor market rigidity given healthy firm competition exhibit the opposite relation. Robust evidence from our regressions shows that labor

[61] Besides job security and inter-firm mobility barriers, long-term worker loyalty or tenure is also induced by the fact that there are fewer options for workers in monopsony-style situations i.e. low firm competition environments.

[62] Stiglitz (2019) points out that corporations with market power in twentieth-century capitalism shared monopoly rents with their unionized workers, while in twenty-first century capitalism there is less rent sharing although market power may be higher on average.

market protection hampers the effects of competition in finance. Overall, our analysis indicates that skill composition matters for relative finance wage growth, particularly in the face of elevated intangible capital investment. We find that skilled labor predominantly drives finance wages which in turn disproportionately contribute to growth in the market economy skill premium. If the economically marginalized have limited access to digital information-processing services or lack the financial literacy, intangible product innovations in finance may reinforce income and wealth inequality along the "access" dimension as well.

Declarations

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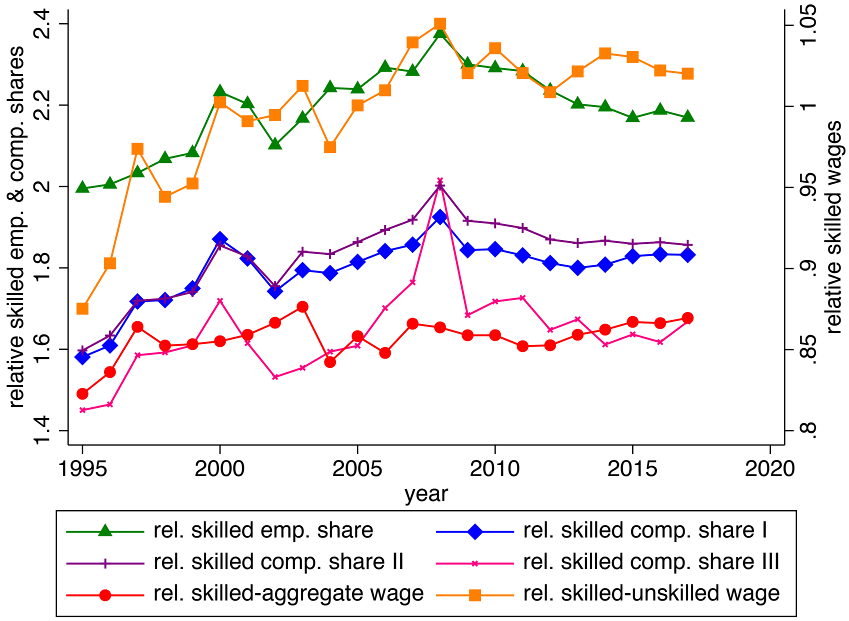
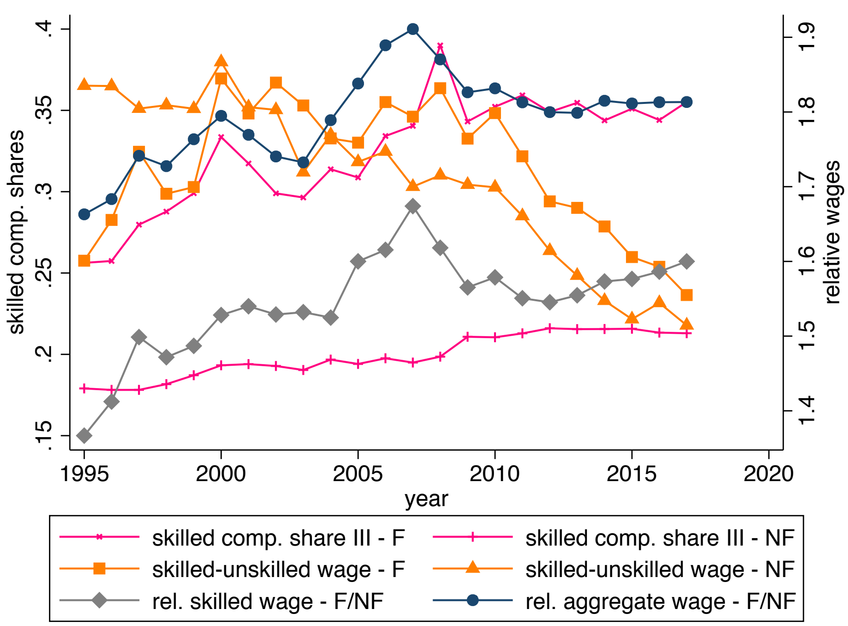
Figure 1: Relative Finance Skilled Employment Share, Compensation Share, and Wage



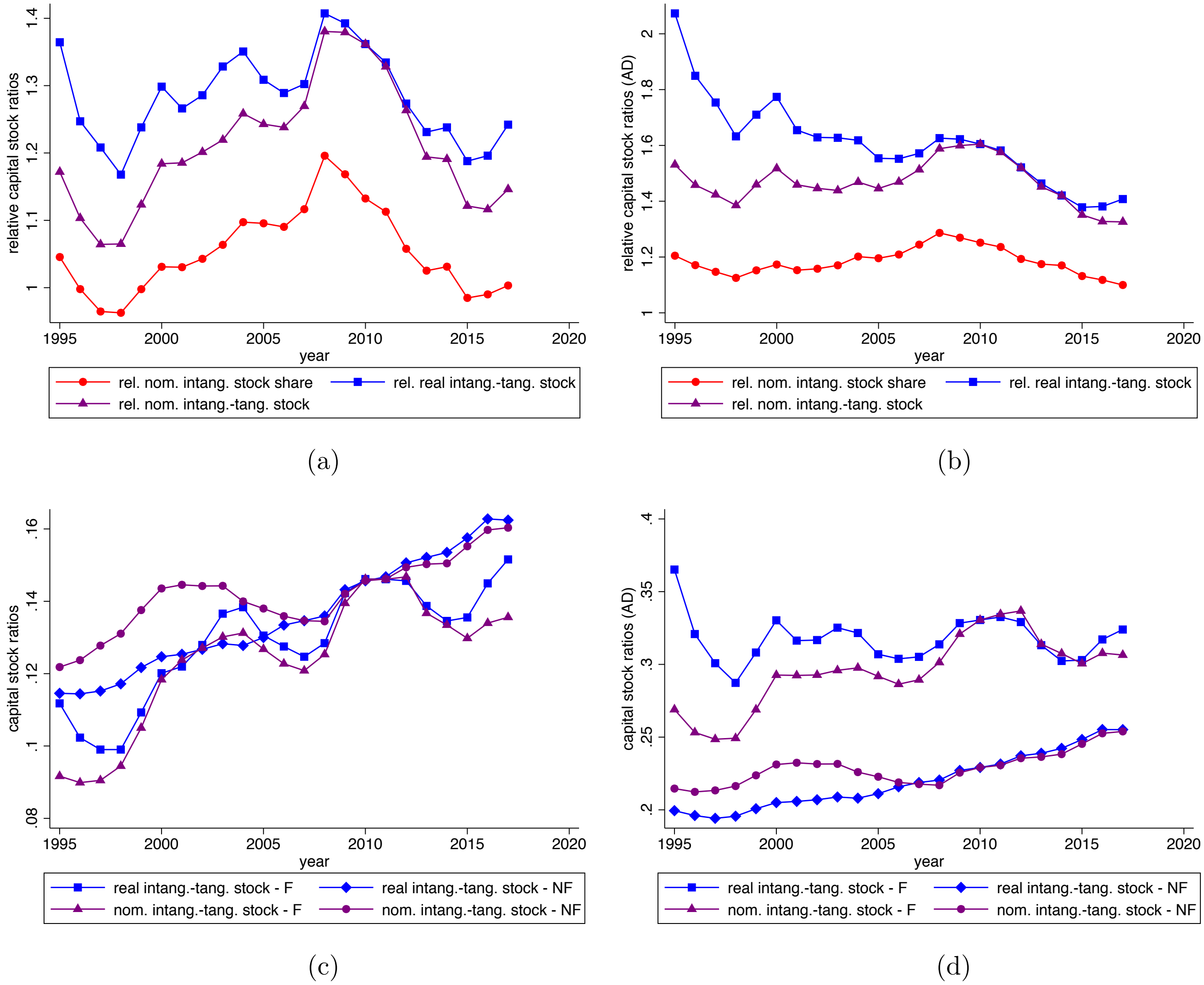
Notes: Cross-country weighted average finance relative to non-finance variables for full sample of 30 countries are plotted. *Relative skilled employment share* and *relative skilled-aggregate (-unskilled) wage* in a given year are weighted by a country's share in cross-section full sample market economy employment. *Relative skilled compensation share I (II)* pertains to shares in total labor compensation and in a given year is weighted by a country's share in cross-section full sample market economy euro-denominated labor compensation (employment). *Relative skilled compensation share III* pertains to shares in value added and in a given year is weighted by a country's share in cross-section full sample market economy euro-denominated value added. Author calculations based on EU KLEMS statistical database.

Figure 2: Sectoral Skilled Compensation Shares, Sectoral Skilled-Unskilled Wages, and Relative Finance Skilled & Aggregate Wages



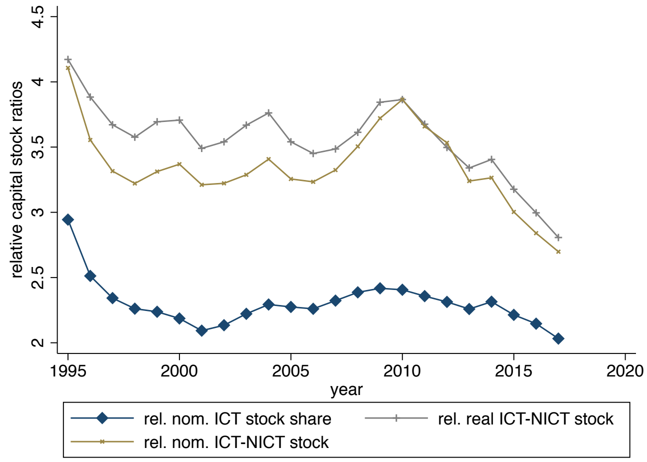
Notes: Cross-country weighted average variables for full sample of 30 countries are plotted. F and NF denote finance and non-finance sectors respectively. *Skilled compensation share III - F (NF)* gauges the skilled labor share in value added in the financial (non-financial) sector and in a given year is weighted by a country's share in cross-section full sample finance (non-finance) euro-denominated value added. *Skilled-unskilled wage - F (NF)* in a given year is weighted by a country's share in cross-section full sample finance (non-finance) employment. *Relative skilled (aggregate) wage - F/NF* gauges finance relative to non-finance wages and in a given year is weighted by a country's share in cross-section full sample market economy employment. Author calculations based on EU KLEMS statistical database.

Figure 3: Relative Finance and Sectoral Intangible Capital Stock Ratios

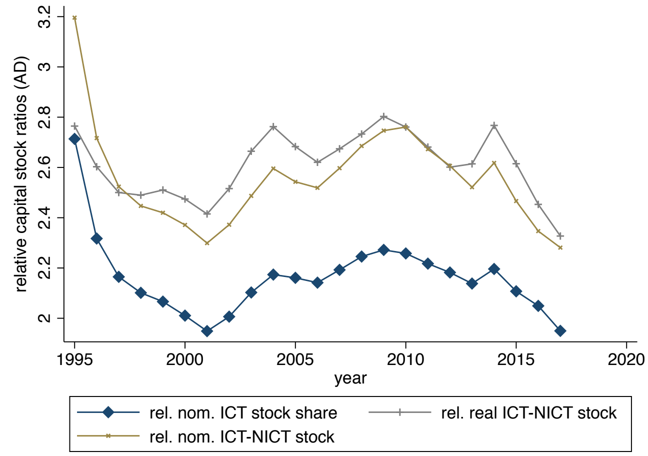


Notes: Cross-country weighted average variables for full sample of 30 countries are plotted. Finance relative to non-finance variables provided in panels (a) and (b). Sectoral variables provided in panels (c) and (d). F and NF denote finance and non-finance sectors respectively. *Relative nominal intangible stock share* pertains to the nominal intangible-aggregate capital stock ratio and in a given year is weighted by a country's share in cross-section full sample market economy nominal euro-denominated aggregate capital stock. *Relative real (nominal) intangible-tangible stock* ratio in a given year is weighted by a country's share in cross-section full sample market economy nominal euro-denominated aggregate capital stock. *Real (nominal) intangible-tangible stock - F (NF)* in a given year is weighted by a country's share in cross-section full sample finance (non-finance) nominal euro-denominated aggregate capital stock. Author calculations based on EU KLEMS statistical database in graphs on left (panels (a) and (c)), while based on EU KLEMS analytical database (AD) in graphs on right (panels (b) and (d)).

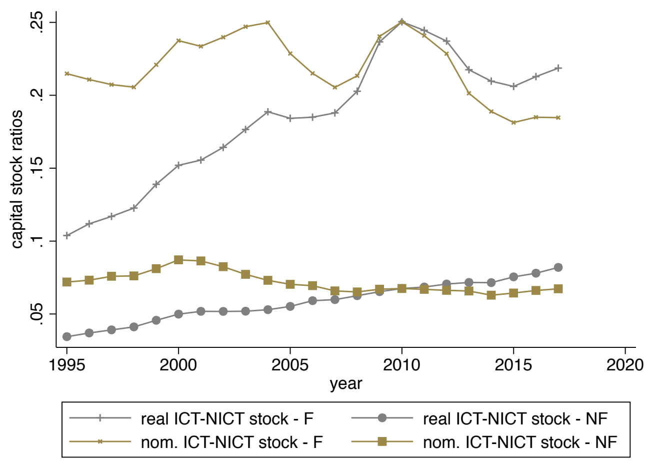
Figure 4: Relative Finance and Sectoral ICT Capital Stock Ratios



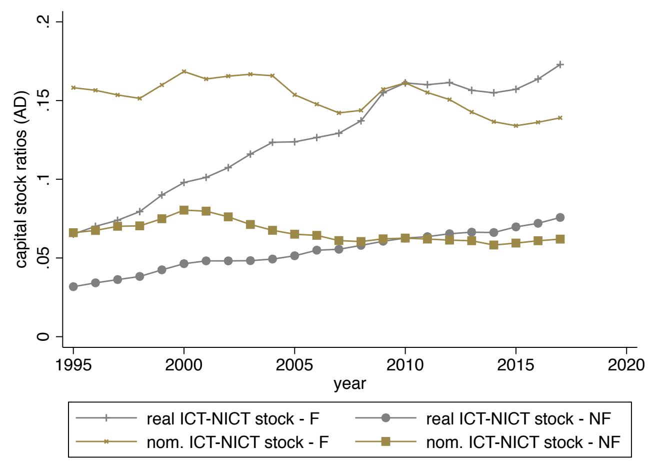
(a)



(b)



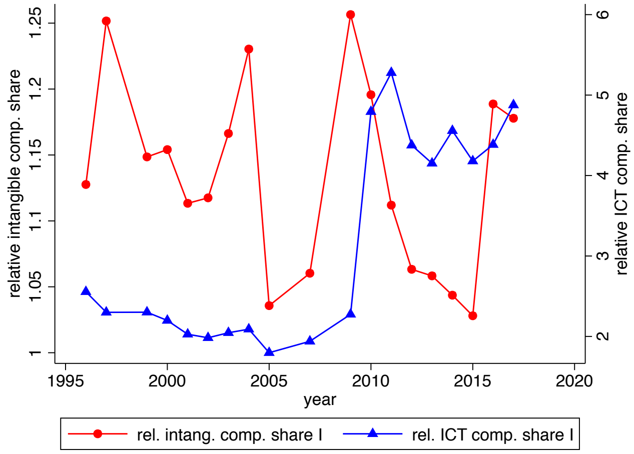
(c)



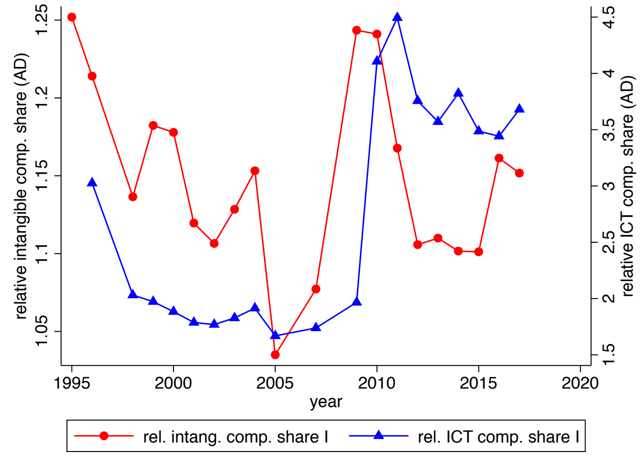
(d)

Notes: Cross-country weighted average variables for full sample of 30 countries are plotted. Finance relative to non-finance variables provided in panels (a) and (b). Sectoral variables provided in panels (c) and (d). F and NF denote finance and non-finance sectors respectively. *Relative nominal ICT stock share* pertains to the nominal ICT-aggregate capital stock ratio and in a given year is weighted by a country's share in cross-section full sample market economy nominal euro-denominated aggregate capital stock. *Relative real (nominal) ICT-NICT stock* ratio in a given year is weighted by a country's share in cross-section full sample market economy nominal euro-denominated aggregate capital stock. *Real (nominal) ICT-NICT stock - F (NF)* in a given year is weighted by a country's share in cross-section full sample finance (non-finance) nominal euro-denominated aggregate capital stock. Author calculations based on EU KLEMS statistical database in graphs on left (panels (a) and (c)), while based on EU KLEMS analytical database (AD) in graphs on right (panels (b) and (d)).

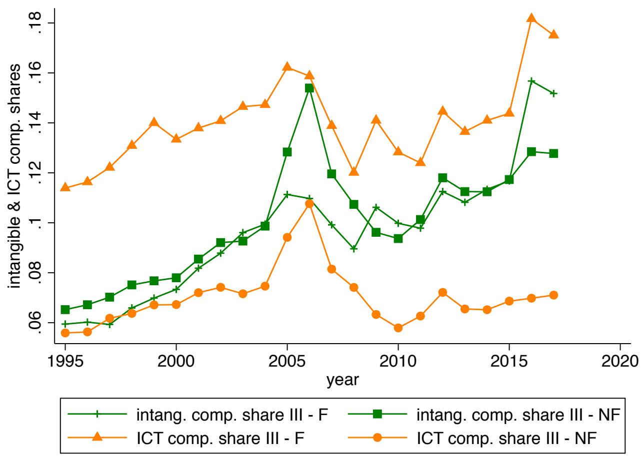
Figure 5: Relative Finance and Sectoral Intangible & ICT Capital Compensation Shares



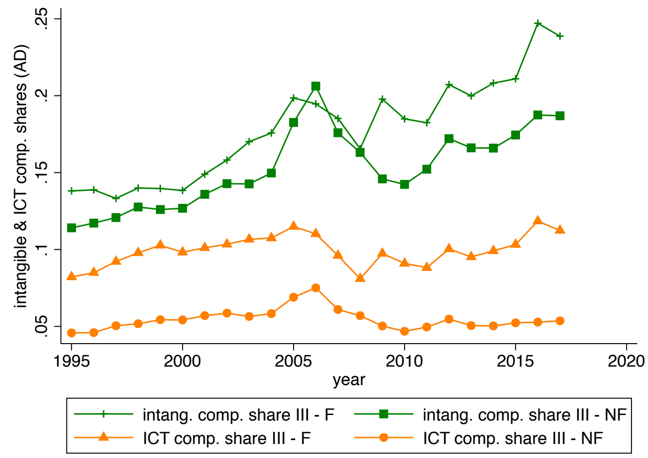
(a)



(b)



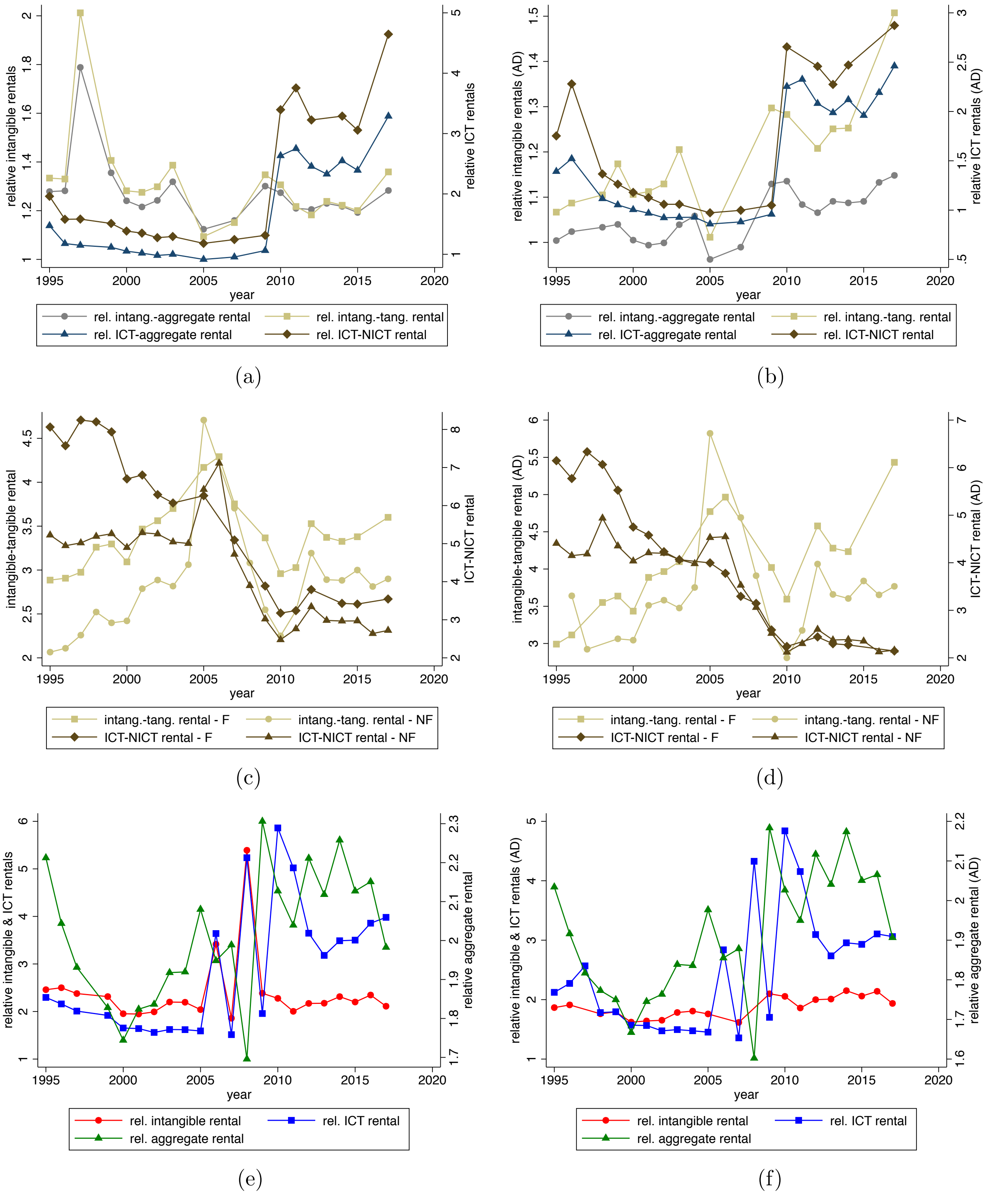
(c)



(d)

Notes: Cross-country weighted average variables for full sample of 30 countries are plotted. Finance relative to non-finance variables provided in panels (a) and (b). Sectoral variables provided in panels (c) and (d). F and NF denote finance and non-finance sectors respectively. *Relative intangible (ICT) compensation share I* pertains to shares in total capital compensation and in a given year is weighted by a country's share in cross-section full sample market economy euro-denominated capital compensation. *Intangible compensation share III - F (NF)* gauges the intangible capital share in value added in the financial (non-financial) sector and in a given year is weighted by a country's share in cross-section full sample finance (non-finance) euro-denominated value added. *ICT compensation share III - F (NF)* gauges the ICT capital share in value added in the financial (non-financial) sector and in a given year is weighted by a country's share in cross-section full sample finance (non-finance) euro-denominated value added. Author calculations based on EU KLEMS statistical database in graphs on left (panels (a) and (c)), while based on EU KLEMS analytical database (AD) in graphs on right (panels (b) and (d)).

Figure 6: Relative Finance and Sectoral Intangible & ICT Rental Ratios



Notes: Cross-country weighted average variables for full sample of 30 countries are plotted. Finance relative to non-finance variables provided in panels (a), (b), (e) and (f). Sectoral variables provided in panels (c) and (d). F and NF denote finance and non-finance sectors respectively. *Relative intangible-aggregate (-tangible) rental* and *relative ICT-aggregate (-NICT) rental* in a given year are weighted by a country's share in cross-section full sample market economy nominal euro-denominated aggregate capital stock. *Intangible-tangible rental - F (NF)* and *ICT-NICT rental - F (NF)* in a given year are weighted by a country's share in cross-section full sample finance (non-finance) nominal euro-denominated aggregate capital stock. *Relative intangible (ICT) (aggregate) rental* in a given year is weighted by a country's share in cross-section full sample market economy nominal euro-denominated intangible (ICT) (aggregate) capital stock. Author calculations based on EU KLEMS statistical database in graphs on left (panels (a), (c) and (e)), while based on EU KLEMS analytical database (AD) in graphs on right (panels (b), (d) and (f)).

Table 1: Three-Factor System Estimates for Financial Sector (A) and Non-Financial Market Economy (B)

Regression	**Parameter Estimates**					**Morishima Elasticities**		**Actual Relative Factor Price [Share] Changes**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	σ	ν	λ_{LU}	λ_{LS}	λ_K	$\eta_{2,1}$	$\eta_{3,1}$	$d\ln\frac{r_2}{r_1}[\frac{\omega_2}{\omega_1}]$	$d\ln\frac{r_3}{r_1}[\frac{\omega_3}{\omega_1}]$	$d\ln\frac{r_3}{r_2}[\frac{\omega_3}{\omega_2}]$
A. System: NLSUR										
$L_U;\sigma;(L_S;\nu;K)$	1.455***	0.173***	−0.060**	0.021**	0.048***	0.673***	0.955***	0.000	0.004	0.004
	(0.175)	(0.021)	(0.030)	(0.010)	(0.011)	(0.069)	(0.107)	[0.063]	[0.041]	[-0.022]
$L_S;\sigma;(L_U;\nu;K)$	0.001	0.218***	0.063***	−0.017***	0.009*	0.138***	0.082***	-0.000	0.004	0.004
	(0.019)	(0.052)	(0.008)	(0.004)	(0.005)	(0.034)	(0.024)	[-0.063]	[-0.022]	[0.041]
$K;\sigma;(L_S;\nu;L_U)$	0.104***	1.525***	−0.042***	0.072***	0.013***	0.772***	0.857***	-0.004	-0.004	-0.000
	(0.027)	(0.096)	(0.014)	(0.013)	(0.005)	(0.049)	(0.054)	[0.022]	[-0.041]	[-0.063]
A. System: GMM										
$L_U;\sigma;(L_S;\nu;K)$	1.233***	0.331***	−0.157***	0.056***	0.084***	0.683***	0.881***	0.000	0.004	0.004
	(0.053)	(0.034)	(0.047)	(0.013)	(0.012)	(0.027)	(0.033)	[0.063]	[0.041]	[-0.022]
$L_S;\sigma;(L_U;\nu;K)$	0.345***	1.077***	−0.295***	−0.025***	0.235***	0.806***	0.616***	-0.000	0.004	0.004
	(0.132)	(0.023)	(0.104)	(0.005)	(0.054)	(0.055)	(0.086)	[-0.063]	[-0.022]	[0.041]
$K;\sigma;(L_S;\nu;L_U)$	0.398***	1.240***	−0.102***	0.131***	0.006*	0.792***	0.842***	-0.004	-0.004	-0.000
	(0.042)	(0.061)	(0.041)	(0.030)	(0.003)	(0.033)	(0.035)	[0.022]	[-0.041]	[-0.063]
B. System: NLSUR										
$L_U;\sigma;(L_S;\nu;K)$	1.179***	0.242***	−0.050***	0.054***	0.058***	0.579***	0.841***	-0.008	-0.004	0.004
	(0.037)	(0.090)	(0.010)	(0.010)	(0.009)	(0.049)	(0.023)	[0.024]	[0.020]	[-0.004]
$L_S;\sigma;(L_U;\nu;K)$	0.867***	1.340***	−0.005	−0.058***	0.067***	1.075***	1.132***	0.008	0.004	-0.004
	(0.041)	(0.137)	(0.013)	(0.018)	(0.014)	(0.069)	(0.083)	[-0.024]	[-0.004]	[0.020]
$K;\sigma;(L_S;\nu;L_U)$	0.644***	1.112***	−0.023	0.137***	−0.021***	0.967***	0.789***	-0.004	0.004	0.008
	(0.021)	(0.044)	(0.020)	(0.045)	(0.006)	(0.034)	(0.024)	[0.004]	[-0.020]	[-0.024]
B. System: GMM										
$L_U;\sigma;(L_S;\nu;K)$	0.720***	0.448***	0.057***	−0.042***	−0.027***	0.546***	0.622***	-0.008	-0.004	0.004
	(0.065)	(0.145)	(0.010)	(0.009)	(0.008)	(0.106)	(0.081)	[0.024]	[0.020]	[-0.004]
$L_S;\sigma;(L_U;\nu;K)$	0.239***	2.451***	0.018***	−0.012***	0.009***	1.212***	1.478***	0.008	0.004	-0.004
	(0.006)	(0.325)	(0.002)	(0.001)	(0.002)	(0.141)	(0.181)	[-0.024]	[-0.004]	[0.020]
$K;\sigma;(L_S;\nu;L_U)$	0.717***	1.155***	−0.039***	0.098***	0.005	1.019***	0.853***	-0.004	0.004	0.008
	(0.075)	(0.040)	(0.013)	(0.028)	(0.007)	(0.037)	(0.054)	[0.004]	[-0.020]	[-0.024]

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Pooled normalized panel regressions employed. Robust standard errors in parentheses. Average/Median annual changes employed. For GMM estimation, null hypothesis of valid overidentifying restrictions (i.e. population moment conditions hold) in Sargan/Hansen test cannot be rejected and instrument proliferation is not relevant. The null hypotheses $\sigma = \nu$; $\sigma = 1$; $\nu = 1$; $\eta_{2,1} = \eta_{3,1}$; and $\lambda_{LU} = \lambda_{LS} = \lambda_K$ in each specification are rejected at conventional significance levels. Country-specific averages employed for distribution parameters at point of normalization, $\{\delta_{10}, \delta_{X0}, \delta_{20}, \delta_{30}\}$, in system estimation. Pooled average (across countries and time) factor shares in sector value added for finance and non-finance are $\{\omega_{LS} = 0.29, \omega_{LU} = 0.26, \omega_K = 0.45\}^F$ and $\{\omega_{LS} = 0.20, \omega_{LU} = 0.45, \omega_K = 0.35\}^{NF}$ respectively. Thus, using pooled averages, distribution parameters at point of normalization across the three factor configurations are $\{\delta_{LU0} = 0.26, \delta_{X0} = 0.74, \delta_{LS0} = 0.39, \delta_{K0} = 0.61\}^F$, $\{\delta_{LU0} = 0.45, \delta_{X0} = 0.55, \delta_{LS0} = 0.36, \delta_{K0} = 0.64\}^{NF}$; $\{\delta_{LS0} = 0.29, \delta_{X0} = 0.71, \delta_{LU0} = 0.37, \delta_{K0} = 0.63\}^F$, $\{\delta_{LS0} = 0.20, \delta_{X0} = 0.80, \delta_{LU0} = 0.56, \delta_{K0} = 0.44\}^{NF}$; $\{\delta_{K0} = 0.45, \delta_{X0} = 0.55, \delta_{LS0} = 0.53, \delta_{LU0} = 0.47\}^F$, $\{\delta_{K0} = 0.35, \delta_{X0} = 0.65, \delta_{LS0} = 0.31, \delta_{LU0} = 0.69\}^{NF}$. The latter shares are used in Morishima elasticity calculations. Pooled median factor shares are identical. Statistical database of EU KLEMS employed.

Table 2: Three-Factor System Residual Diagnostics for Financial Sector (A) and Non-Financial Market Economy (B)

Regression	**Cross-Section Dependence**			**Panel Unit Root Tests**			
	(1) $\overline{\rho}$	(2) $\overline{\lvert\rho\rvert}$	(3) CSD	(4) LLC	(5) F-PP	(6) IPS	(7) CIPS
A. System: NLSUR							
$L_U;\sigma;(L_S;\nu;K)$	0.04; 0.07; 0.06; 0.07	0.31; 0.39; 0.39; 0.33	0.00; 0.00; 0.00; 0.00	0.00; 0.00; 0.00; 0.00 **0.00;0.00;0.00;0.00**	0.00; 0.00; 0.00; 0.00 **0.00;0.04;0.00;0.34**	0.00; 0.01; 0.00; 0.02 **0.00;0.01;0.00;0.45**	0.00; 0.03; 0.06; 0.03
$L_S;\sigma;(L_U;\nu;K)$	0.01; 0.04; 0.00	0.32; 0.37; 0.39	0.22; 0.00; 0.96	0.00; 0.00; 0.00 **0.00;0.00;0.00**	0.00; 0.00; 0.57 **0.00;0.00;0.49**	0.00; 0.00; 0.39 **0.00;0.00;0.34**	0.00; 0.00; 0.05
$K;\sigma;(L_S;\nu;L_U)$	0.02; 0.01; 0.13	0.31; 0.35; 0.40	0.36; 0.33; 0.00	0.00; 0.00; 0.12 **0.00;0.00;0.02**	0.01; 0.02; 0.06 **0.01;0.02;0.46**	0.00; 0.01; 0.34 **0.01;0.02;0.34**	0.00; 0.00; 0.29
A. System: GMM							
$L_U;\sigma;(L_S;\nu;K)$	0.11; 0.02; 0.09; 0.05	0.37; 0.39; 0.36; 0.28	0.00; 0.03; 0.00; 0.50	0.00; 0.00; 0.00; 0.00 **0.00;0.00;0.00;0.00**	0.01; 0.01; 0.00; 0.00 **0.01;0.03;0.00;0.03**	0.01; 0.01; 0.00; 0.00 **0.01;0.01;0.00;0.04**	0.01; 0.20; 0.03; 0.00
$L_S;\sigma;(L_U;\nu;K)$	0.04; 0.05; 0.00	0.39; 0.23; 0.19	0.00; 0.00; 0.95	0.01; 0.00; 0.00 **0.01;0.00;0.00**	0.04; 0.00; 0.00 **0.00;0.00;0.01**	0.68; 0.00; 0.00 **0.33;0.00;0.01**	0.01; 0.00; 0.00
$K;\sigma;(L_S;\nu;L_U)$	0.05; 0.00; 0.13	0.33; 0.31; 0.30	0.00; 0.76; 0.00	0.00; 0.00; 0.01 **0.00;0.00;0.00**	0.00; 0.00; 0.04 **0.01;0.00;0.34**	0.05; 0.00; 0.07 **0.31;0.02;0.24**	0.01; 0.00; 0.11
B. System: NLSUR							
$L_U;\sigma;(L_S;\nu;K)$	0.19; 0.04; 0.17; 0.16	0.39; 0.39; 0.36; 0.39	0.00; 0.00; 0.00; 0.00	0.00; 0.00; 0.00; 0.00 **0.00;0.01;0.00;0.00**	0.04; 0.02; 0.08; 0.00 **0.46;0.37;0.43;0.00**	0.13; 0.07; 0.00; 0.02 **0.53;0.29;0.00;0.00**	0.18; 0.03; 0.02; 0.00
$L_S;\sigma;(L_U;\nu;K)$	0.18; 0.14; 0.05; 0.31	0.38; 0.39; 0.29; 0.39	0.00; 0.00; 0.00; 0.00	0.00; 0.00; 0.00; 0.00 **0.00;0.00;0.00;0.00**	0.50; 0.44; 0.01; 0.01 **0.77;0.66;0.05;0.00**	0.28; 0.41; 0.01; 0.00 **0.69;0.57;0.03;0.00**	0.23; 0.01; 0.03; 0.00
$K;\sigma;(L_S;\nu;L_U)$	0.12; 0.15; 0.08; 0.09	0.31; 0.30; 0.38; 0.38	0.00; 0.00; 0.00; 0.00	0.02; 0.00; 0.04; 0.01 **0.01;0.00;0.01;0.00**	0.50; 0.00; 0.85; 0.31 **0.07;0.00;0.30;0.04**	0.79; 0.00; 0.94; 0.79 **0.75;0.00;0.91;0.53**	0.09; 0.00; 0.03; 0.05
B. System: GMM							
$L_U;\sigma;(L_S;\nu;K)$	0.08; 0.07; 0.07	0.39; 0.39; 0.33	0.00; 0.00; 0.00	0.00; 0.01; 0.00 **0.00;0.00;0.00**	0.00; 0.09; 0.00 **0.00;0.07;0.00**	0.13; 0.14; 0.00 **0.13;0.09;0.00**	0.02; 0.19; 0.00
$L_S;\sigma;(L_U;\nu;K)$	0.16; 0.16; 0.11; 0.04	0.34; 0.31; 0.34; 0.37	0.00; 0.00; 0.00; 0.00	0.00; 0.00; 0.00; 0.00 **0.00;0.00;0.00;0.00**	0.29; 0.39; 0.02; 0.05 **0.10;0.50;0.06;0.04**	0.15; 0.17; 0.04; 0.04 **0.07;0.28;0.06;0.03**	0.05; 0.01; 0.03; 0.03
$K;\sigma;(L_S;\nu;L_U)$	0.14; 0.00; 0.06	0.32; 0.32; 0.28	0.00; 0.98; 0.00	0.00; 0.00; 0.00 **0.01;0.00;0.00**	0.00; 0.00; 0.90 **0.06;0.00;0.99**	0.06; 0.00; 0.84 **0.46;0.00;0.99**	0.09; 0.00; 0.29

Notes: P-values reported for cross section dependence and panel unit root tests in columns (3) and (4)-(7) respectively. CSD refers to the cross section dependence or CD 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 Levin *et al.* (2002), LLC, Choi (2001)'s Phillips-Perron Fisher, F-PP, Im *et al.* (2003), IPS, and Pesaran (2007), CIPS, tests is that all series are non-stationary. P-values in bold in columns (4)-(6) are for LLC, F-PP, and IPS tests on series net of cross-section means.

Table 3: Four-Factor System Estimates for Financial Sector (A) and Non-Financial Market Economy (B)

Regression	**Parameter Estimates**							**Morishima Elasticities**					**Actual Relative Factor Price [Share] Changes**					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	σ	ρ	ν	λ_{LU}	λ_{LS}	λ_{KT}^{KNICT}	λ_{KI}^{KICT}	$\eta_{2,1}$	$\eta_{3,1}$	$\eta_{4,1}$	$\eta_{3,2}$	$\eta_{4,2}$	$d\ln\frac{r_2}{r_1}[\frac{\omega_2}{\omega_1}]$	$d\ln\frac{r_3}{r_1}[\frac{\omega_3}{\omega_1}]$	$d\ln\frac{r_4}{r_1}[\frac{\omega_4}{\omega_1}]$	$d\ln\frac{r_3}{r_2}[\frac{\omega_3}{\omega_2}]$	$d\ln\frac{r_4}{r_2}[\frac{\omega_4}{\omega_2}]$	$d\ln\frac{r_4}{r_3}[\frac{\omega_4}{\omega_3}]$
A. System: NLSUR																		
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	1.380***	0.028**	0.002*	−0.097**	0.033***	0.075***	0.022*	0.258***	0.719***	0.663***	0.016**	0.015**	0.024	-0.011	-0.000	-0.035	-0.026	0.008
	(0.140)	(0.014)	(0.001)	(0.041)	(0.013)	(0.013)	(0.014)	(0.027)	(0.073)	(0.067)	(0.008)	(0.008)	[0.119]	[0.021]	[0.063]	[-0.099]	[-0.056]	[0.042]
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	1.417***	0.125**	0.057***	−0.057**	0.016*	0.060***	−0.003	0.694***	0.451***	1.022***	0.077***	0.105**	-0.011	0.024	-0.000	0.035	0.008	-0.026
	(0.147)	(0.055)	(0.022)	(0.028)	(0.010)	(0.010)	(0.011)	(0.071)	(0.045)	(0.104)	(0.030)	(0.045)	[0.021]	[0.119]	[0.063]	[0.099]	[0.042]	[-0.056]
$L_U;\sigma;[K_{ict}^n;\rho;(K_{ict}^y;\nu;L_S)]$	1.426***	0.017*	0.003	−0.053**	0.016*	0.054***	0.011	0.538***	0.515***	0.913***	0.008*	0.012*	-0.003	-0.014	-0.000	-0.011	-0.000	0.011
	(0.163)	(0.009)	(0.002)	(0.026)	(0.009)	(0.009)	(0.010)	(0.061)	(0.059)	(0.105)	(0.005)	(0.007)	[0.027]	[0.061]	[0.063]	[0.034]	[0.035]	[0.001]
A. System: GMM																		
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	1.402***	0.224***	0.172***	−0.099***	0.039***	0.083***	0.005*	0.424***	0.812***	0.762***	0.199***	0.197***	0.024	-0.011	-0.000	-0.035	-0.026	0.008
	(0.054)	(0.009)	(0.023)	(0.013)	(0.003)	(0.005)	(0.003)	(0.009)	(0.034)	(0.033)	(0.011)	(0.012)	[0.119]	[0.021]	[0.063]	[-0.099]	[-0.056]	[0.042]
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	1.373***	0.279***	0.129***	−0.099***	0.036***	0.083***	0.018***	0.760***	0.490***	1.012***	0.173***	0.236***	-0.011	0.024	-0.000	0.035	0.008	-0.026
	(0.044)	(0.016)	(0.017)	(0.012)	(0.004)	(0.004)	(0.005)	(0.020)	(0.023)	(0.035)	(0.010)	(0.009)	[0.021]	[0.119]	[0.063]	[0.099]	[0.042]	[-0.056]
$L_U;\sigma;[K_{ict}^n;\rho;(K_{ict}^y;\nu;L_S)]$	1.393***	0.264***	0.050***	−0.089***	0.036***	0.082***	0.031**	0.682***	0.540***	0.913***	0.133***	0.190***	-0.003	-0.014	-0.000	-0.011	-0.000	0.011
	(0.083)	(0.083)	(0.019)	(0.028)	(0.012)	(0.008)	(0.014)	(0.071)	(0.033)	(0.054)	(0.031)	(0.052)	[0.027]	[0.061]	[0.063]	[0.034]	[0.035]	[0.001]
B. System: NLSUR																		
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	1.162***	0.050***	0.004**	−0.028***	0.039***	0.044***	0.019*	0.161***	0.687***	0.479***	0.031***	0.023***	0.028	-0.005	-0.008	-0.033	-0.036	-0.003
	(0.056)	(0.010)	(0.002)	(0.011)	(0.009)	(0.010)	(0.012)	(0.012)	(0.033)	(0.022)	(0.006)	(0.004)	[0.070]	[0.013]	[0.024]	[-0.058]	[-0.047]	[0.011]
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	1.196***	0.375***	0.225***	−0.048***	0.046***	0.069***	0.013	0.818***	0.419***	1.002***	0.255***	0.345***	-0.005	0.028	-0.008	0.033	-0.003	-0.036
	(0.032)	(0.116)	(0.026)	(0.008)	(0.007)	(0.009)	(0.011)	(0.049)	(0.021)	(0.026)	(0.039)	(0.095)	[0.013]	[0.070]	[0.024]	[0.058]	[0.011]	[-0.047]
$L_U;\sigma;[K_{ict}^n;\rho;(K_{ict}^y;\nu;L_S)]$	1.216***	0.377***	0.034***	−0.040***	0.036***	0.063***	−0.001	0.847***	0.246***	1.003***	0.095***	0.315***	-0.002	-0.032	-0.008	-0.030	-0.006	0.025
	(0.045)	(0.140)	(0.013)	(0.009)	(0.008)	(0.011)	(0.010)	(0.059)	(0.011)	(0.036)	(0.035)	(0.117)	[0.015]	[0.040]	[0.024]	[0.025]	[0.009]	[-0.017]
B. System: GMM																		
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	1.184***	0.850***	0.396***	−0.053***	0.062***	0.085***	−0.100***	0.884***	0.861***	0.719***	0.664***	0.582***	0.028	-0.005	-0.008	-0.033	-0.036	-0.003
	(0.019)	(0.032)	(0.065)	(0.005)	(0.005)	(0.003)	(0.025)	(0.029)	(0.034)	(0.043)	(0.030)	(0.038)	[0.070]	[0.013]	[0.024]	[-0.058]	[-0.047]	[0.011]
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	1.247***	0.381***	0.215***	−0.039***	0.028***	0.063***	0.009	0.849***	0.421***	1.041***	0.248***	0.348***	-0.005	0.028	-0.008	0.033	-0.003	-0.036
	(0.031)	(0.027)	(0.028)	(0.007)	(0.006)	(0.006)	(0.007)	(0.021)	(0.025)	(0.027)	(0.025)	(0.025)	[0.013]	[0.070]	[0.024]	[0.058]	[0.011]	[-0.047]
$L_U;\sigma;[K_{ict}^n;\rho;(K_{ict}^y;\nu;L_S)]$	1.235***	0.599***	0.060***	−0.041***	0.016**	0.070***	−0.009	0.955***	0.264***	1.022***	0.149***	0.500***	-0.002	-0.032	-0.008	-0.030	-0.006	0.025
	(0.032)	(0.064)	(0.007)	(0.004)	(0.008)	(0.006)	(0.012)	(0.042)	(0.009)	(0.026)	(0.013)	(0.052)	[0.015]	[0.040]	[0.024]	[0.025]	[0.009]	[-0.017]

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Pooled normalized panel regressions employed. Robust standard errors in parentheses. Average/Median annual changes employed. For GMM estimation, null hypothesis of valid overidentifying restrictions (i.e. population moment conditions hold) in Sargan/Hansen test cannot be rejected and instrument proliferation is not a concern. The null hypotheses $\sigma = \rho = \nu$; $\sigma = \rho$; $\rho = \nu$; $\sigma = \nu$; $\sigma = 1$; $\rho = 1$; $\nu = 1$; $\eta_{2,1} = \eta_{3,1} = \eta_{4,1} = \eta_{3,2} = \eta_{4,2}$; $\lambda_{LU} = \lambda_{LS} = \lambda_{KT}^{knict} = \lambda_{KI}^{kict}$; $\lambda_{LU} = \lambda_{LS}$; and $\lambda_{KT}^{knict} = \lambda_{KI}^{kict}$ in each specification are rejected at conventional significance levels. Country-specific averages employed for distribution parameters at point of normalization, $\{\delta_{10}, \delta_{Z0}, \delta_{20}, \delta_{X0}, \delta_{30}, \delta_{40}\}$, in system estimation. Pooled average (across countries and time) factor shares in sector value added for finance and non-finance are $\{\omega_{LS} = 0.29, \omega_{LU} = 0.26, \omega_{KI} = 0.13, \omega_{KT} = 0.32, \omega_{KICT} = 0.17, \omega_{KNICT} = 0.28\}^F$ and $\{\omega_{LS} = 0.20, \omega_{LU} = 0.45, \omega_{KI} = 0.06, \omega_{KT} = 0.29, \omega_{KICT} = 0.04, \omega_{KNICT} = 0.31\}^{NF}$ respectively. Thus, using pooled averages, distribution parameters at point of normalization across the three factor configurations are $\{\delta_{LU0} = 0.26, \delta_{Z0} = 0.74, \delta_{KI0} = 0.17, \delta_{X0} = 0.83, \delta_{KT0} = 0.52, \delta_{LS0} = 0.48\}^F$, $\{\delta_{LU0} = 0.45, \delta_{Z0} = 0.55, \delta_{KI0} = 0.10, \delta_{X0} = 0.90, \delta_{KT0} = 0.59, \delta_{LS0} = 0.41\}^{NF}$; $\{\delta_{LU0} = 0.26, \delta_{Z0} = 0.74, \delta_{KT0} = 0.44, \delta_{X0} = 0.56, \delta_{KI0} = 0.30, \delta_{LS0} = 0.70\}^F$, $\{\delta_{LU0} = 0.45, \delta_{Z0} = 0.55, \delta_{KT0} = 0.54, \delta_{X0} = 0.46, \delta_{KI0} = 0.21, \delta_{LS0} = 0.79\}^{NF}$; $\{\delta_{LU0} = 0.26, \delta_{Z0} = 0.74, \delta_{KNICT0} = 0.37, \delta_{X0} = 0.63, \delta_{KICT0} = 0.36, \delta_{LS0} = 0.64\}^F$, $\{\delta_{LU0} = 0.45, \delta_{Z0} = 0.55, \delta_{KNICT0} = 0.56, \delta_{X0} = 0.44, \delta_{KICT0} = 0.18, \delta_{LS0} = 0.82\}^{NF}$. The latter shares are used in Morishima elasticity calculations. Pooled median factor shares are identical. Statistical database of EU KLEMS employed.

Table 4: Four-Factor System Residual Diagnostics for Financial Sector (A) and Non-Financial Market Economy (B)

Regression	**Cross-Section Dependence**			**Panel Unit Root Tests**		
	(1) $\overline{\rho}$	(2) $\overline{\lvert\rho\rvert}$	(3) CSD	(4) LLC	(5) IPS	(6) CIPS
A. System: NLSUR						
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	0.01;0.02;0.00;0.13;0.01	0.28;0.33;0.38;0.36;0.30	0.48;0.05;0.98;0.00;0.51	0.00;0.00;0.00;0.00;0.00 **0.00;0.00;0.00;0.00;0.00**	0.00;0.02;0.21;0.00;0.00 **0.00;0.02;0.34;0.09;0.00**	0.00;0.07;0.05;0.01;0.03
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	0.03;0.08;0.11;-0.01;0.05	0.27;0.37;0.32;0.35;0.32	0.00;0.00;0.00;0.28;0.00	0.00;0.00;0.00;0.00;0.00 **0.00;0.00;0.00;0.00;0.00**	0.00;0.00;0.00;0.01;0.00 **0.00;0.02;0.00;0.03;0.00**	0.00;0.01;0.01;0.03;0.00
$L_U;\sigma;[K^n_{ict};\rho;(K^y_{ict};\nu;L_S)]$	0.00;0.08;0.13;-0.01;0.04	0.25;0.36;0.29;0.28;0.28	0.47;0.00;0.00;0.37;0.00	0.00;0.00;0.00;0.00;0.00 **0.00;0.00;0.00;0.00;0.00**	0.00;0.00;0.07;0.00;0.00 **0.01;0.02;0.01;0.03;0.00**	0.00;0.01;0.00;0.03;0.00
A. System: GMM						
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	0.02;0.02;0.01;0.03	0.31;0.38;0.30;0.35	0.02;0.02;0.11;0.00	0.00;0.00;0.00;0.00 **0.00;0.00;0.00;0.00**	0.00;0.09;0.00;0.05 **0.01;0.02;0.00;0.00**	0.00;0.00;0.00;0.00
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	0.02;0.02;0.04;0.01	0.30;0.38;0.27;0.35	0.01;0.05;0.00;0.06	0.00;0.00;0.00;0.00 **0.00;0.00;0.00;0.00**	0.01;0.04;0.00;0.00 **0.01;0.02;0.00;0.00**	0.00;0.00;0.00;0.00
$L_U;\sigma;[K^n_{ict};\rho;(K^y_{ict};\nu;L_S)]$	0.01;0.02;0.09;-0.01;0.02	0.30;0.38;0.26;0.29;0.29	0.30;0.02;0.00;0.33;0.10	0.00;0.00;0.00;0.00;0.00 **0.00;0.00;0.00;0.00;0.00**	0.05;0.05;0.00;0.09;0.00 **0.01;0.03;0.05;0.09;0.00**	0.00;0.09;0.01;0.08;0.00
B. System: NLSUR						
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	0.05;0.16;-0.01;0.09;0.25	0.37;0.39;0.39;0.30;0.42	0.00;0.00;0.50;0.00;0.00	0.00;0.00;0.00;0.00;0.00 **0.00;0.01;0.00;0.00;0.00**	0.00;0.04;0.01;0.00;0.03 **0.00;0.09;0.05;0.01;0.00**	0.04;0.00;0.06;0.00;0.02
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	0.17;0.02;0.03;0.11;0.14	0.38;0.38;0.27;0.39;0.34	0.00;0.01;0.00;0.00;0.00	0.00;0.00;0.00;0.00;0.00 **0.01;0.01;0.00;0.00;0.00**	0.00;0.06;0.00;0.07;0.00 **0.07;0.05;0.00;0.01;0.00**	0.05;0.09;0.00;0.00;0.04
$L_U;\sigma;[K^n_{ict};\rho;(K^y_{ict};\nu;L_S)]$	0.11;0.02;0.08;0.07;0.16	0.32;0.38;0.26;0.34;0.31	0.00;0.00;0.00;0.00;0.00	0.00;0.00;0.00;0.00;0.00 **0.00;0.01;0.00;0.02;0.00**	0.05;0.05;0.00;0.11;0.00 **0.25;0.10;0.00;0.03;0.00**	0.05;0.03;0.01;0.10;0.00
B. System: GMM						
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	0.12;0.02;0.06;0.06	0.39;0.38;0.24;0.34	0.00;0.02;0.00;0.00	0.00;0.00;0.00;0.00 **0.00;0.00;0.00;0.00**	0.04;0.10;0.00;0.00 **0.28;0.09;0.00;0.00**	0.05;0.09;0.00;0.00
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	0.16;0.02;0.00;0.06	0.38;0.38;0.28;0.33	0.00;0.05;0.94;0.00	0.00;0.00;0.00;0.00 **0.00;0.00;0.00;0.00**	0.00;0.07;0.00;0.01 **0.07;0.04;0.00;0.02**	0.02;0.08;0.00;0.00
$L_U;\sigma;[K^n_{ict};\rho;(K^y_{ict};\nu;L_S)]$	0.14;0.02;0.01;0.02;0.19	0.33;0.39;0.24;0.28;0.31	0.00;0.03;0.17;0.02;0.00	0.00;0.00;0.00;0.00;0.00 **0.00;0.00;0.00;0.00;0.00**	0.02;0.07;0.00;0.03;0.00 **0.10;0.04;0.00;0.06;0.00**	0.07;0.08;0.00;0.10;0.00

Notes: P-values reported for cross section dependence and panel unit root tests in columns (3) and (4)-(6) respectively. CSD refers to the cross section dependence or CD 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 Levin *et al.* (2002), LLC, Im *et al.* (2003), IPS, and Pesaran (2007), CIPS, tests is that all series are non-stationary. P-values in bold in columns (4)-(5) are for LLC and IPS tests on series net of cross-section means. Choi (2001)'s Phillips-Perron Fisher, F-PP, panel unit root test yields results similar to those of IPS.

Table 5: Four-Factor System Estimates II for Financial Sector (A) and Non-Financial Market Economy (B) Based on Augmented Intangible Capital Stock

Regression	Parameter Estimates							Morishima Elasticities					Actual Relative Factor Price [Share] Changes					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	σ	ρ	ν	λ_{LU}	λ_{LS}	λ_{KT}^{KNICT}	λ_{KI}^{KICT}	$\eta_{2,1}$	$\eta_{3,1}$	$\eta_{4,1}$	$\eta_{3,2}$	$\eta_{4,2}$	$d\ln\frac{r_2}{r_1}[\frac{\omega_2}{\omega_1}]$	$d\ln\frac{r_3}{r_1}[\frac{\omega_3}{\omega_1}]$	$d\ln\frac{r_4}{r_1}[\frac{\omega_4}{\omega_1}]$	$d\ln\frac{r_3}{r_2}[\frac{\omega_3}{\omega_2}]$	$d\ln\frac{r_4}{r_2}[\frac{\omega_4}{\omega_2}]$	$d\ln\frac{r_4}{r_3}[\frac{\omega_4}{\omega_3}]$
A. System: NLSUR																		
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	1.344***	0.026**	0.002	−0.100**	0.039***	0.078***	0.043***	0.408***	0.579***	0.767***	0.012**	0.016**	0.015	-0.025	-0.000	-0.040	-0.018	0.022
	(0.131)	(0.013)	(0.002)	(0.044)	(0.014)	(0.014)	(0.014)	(0.039)	(0.056)	(0.075)	(0.006)	(0.008)	[0.077]	[0.006]	[0.063]	[-0.072]	[-0.014]	[0.057]
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	1.420***	0.012	0.002	−0.066**	0.025**	0.061***	0.029***	0.448***	0.598***	0.824***	0.006	0.008	-0.025	0.015	-0.000	0.040	0.022	-0.018
	(0.157)	(0.010)	(0.002)	(0.031)	(0.011)	(0.011)	(0.011)	(0.052)	(0.066)	(0.091)	(0.006)	(0.007)	[0.006]	[0.077]	[0.063]	[0.072]	[0.057]	[-0.014]
$L_U;\sigma;[K^n_{ict};\rho;(K^y_{ict};\nu;L_S)]$	1.425***	0.108**	0.063***	−0.052**	0.014*	0.053***	0.008	0.674***	0.472***	1.016***	0.077***	0.095**	0.002	-0.022	-0.000	-0.024	-0.005	0.019
	(0.172)	(0.051)	(0.023)	(0.027)	(0.009)	(0.010)	(0.010)	(0.080)	(0.054)	(0.121)	(0.031)	(0.042)	[0.034]	[0.052]	[0.063]	[0.019]	[0.028]	[0.010]
A. System: GMM																		
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	1.466***	0.149***	0.075***	−0.076***	0.033***	0.072***	0.027***	0.532***	0.675***	0.870***	0.109***	0.119***	0.015	-0.025	-0.000	-0.040	-0.018	0.022
	(0.054)	(0.015)	(0.013)	(0.010)	(0.004)	(0.004)	(0.004)	(0.019)	(0.026)	(0.032)	(0.009)	(0.009)	[0.077]	[0.006]	[0.063]	[-0.072]	[-0.014]	[0.057]
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	1.400***	0.127***	0.092***	−0.087***	0.034***	0.072***	0.035***	0.521***	0.641***	0.850***	0.107***	0.112***	-0.025	0.015	-0.000	0.040	0.022	-0.018
	(0.047)	(0.007)	(0.013)	(0.013)	(0.004)	(0.005)	(0.005)	(0.016)	(0.025)	(0.031)	(0.008)	(0.007)	[0.006]	[0.077]	[0.063]	[0.072]	[0.057]	[-0.014]
$L_U;\sigma;[K^n_{ict};\rho;(K^y_{ict};\nu;L_S)]$	1.436***	0.380***	0.092***	−0.080***	0.026**	0.075***	0.022*	0.834***	0.495***	1.032***	0.178***	0.293***	0.002	-0.022	-0.000	-0.024	-0.005	0.019
	(0.127)	(0.139)	(0.020)	(0.032)	(0.014)	(0.009)	(0.014)	(0.105)	(0.040)	(0.089)	(0.047)	(0.099)	[0.034]	[0.052]	[0.063]	[0.019]	[0.028]	[0.010]
B. System: NLSUR																		
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	1.201***	0.121***	0.082**	−0.043***	0.051***	0.057***	0.043***	0.337***	0.675***	0.608***	0.103***	0.101***	0.012	0.004	-0.008	-0.008	-0.020	-0.012
	(0.045)	(0.036)	(0.036)	(0.010)	(0.010)	(0.010)	(0.010)	(0.031)	(0.027)	(0.026)	(0.034)	(0.034)	[0.047]	[0.022]	[0.023]	[-0.025]	[-0.024]	[0.001]
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	1.205***	0.148***	0.063***	−0.041***	0.047***	0.057***	0.042***	0.603***	0.463***	0.806***	0.093***	0.118***	0.004	0.012	-0.008	0.008	-0.012	-0.020
	(0.047)	(0.029)	(0.012)	(0.010)	(0.010)	(0.009)	(0.010)	(0.025)	(0.020)	(0.031)	(0.015)	(0.021)	[0.022]	[0.047]	[0.023]	[0.025]	[0.001]	[-0.024]
$L_U;\sigma;[K^n_{ict};\rho;(K^y_{ict};\nu;L_S)]$	1.203***	0.313***	0.107***	−0.040***	0.040***	0.060***	0.003	0.820***	0.271***	1.038***	0.138***	0.282***	-0.005	-0.023	-0.008	-0.018	-0.002	0.016
	(0.044)	(0.126)	(0.034)	(0.009)	(0.007)	(0.010)	(0.009)	(0.048)	(0.027)	(0.035)	(0.047)	(0.112)	[0.015]	[0.049]	[0.023]	[0.034]	[0.009]	[-0.026]
B. System: GMM																		
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	1.206***	0.153***	0.100***	−0.049***	0.051***	0.062***	0.047***	0.363***	0.686***	0.620***	0.128***	0.125***	0.012	0.004	-0.008	-0.008	-0.020	-0.012
	(0.013)	(0.013)	(0.005)	(0.003)	(0.003)	(0.003)	(0.004)	(0.011)	(0.009)	(0.008)	(0.006)	(0.005)	[0.047]	[0.022]	[0.023]	[-0.025]	[-0.024]	[0.001]
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	1.201***	0.339***	0.121***	−0.050***	0.045***	0.069***	0.041***	0.710***	0.499***	0.823***	0.197***	0.263***	0.004	0.012	-0.008	0.008	-0.012	-0.020
	(0.020)	(0.017)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.009)	(0.008)	(0.013)	(0.007)	(0.012)	[0.022]	[0.047]	[0.023]	[0.025]	[0.001]	[-0.024]
$L_U;\sigma;[K^n_{ict};\rho;(K^y_{ict};\nu;L_S)]$	0.723***	0.648***	0.040***	0.051***	−0.068***	0.001	−0.094***	0.691***	0.142***	0.620***	0.131***	0.557***	-0.005	-0.023	-0.008	-0.018	-0.002	0.016
	(0.030)	(0.130)	(0.008)	(0.005)	(0.020)	(0.016)	(0.023)	(0.056)	(0.008)	(0.025)	(0.023)	(0.118)	[0.015]	[0.049]	[0.023]	[0.034]	[0.009]	[-0.026]

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Pooled normalized panel regressions employed. Robust standard errors in parentheses. Average/Median annual changes employed. For GMM estimation, null hypothesis of valid overidentifying restrictions (i.e. population moment conditions hold) in Sargan/Hansen test cannot be rejected and instrument proliferation is not a concern. The null hypotheses $\sigma = \rho = \nu$; $\sigma = \rho$; $\rho = \nu$; $\sigma = \nu$; $\sigma = 1$; $\rho = 1$; $\nu = 1$; $\eta_{2,1} = \eta_{3,1} = \eta_{4,1} = \eta_{3,2} = \eta_{4,2}$; $\lambda_{LU} = \lambda_{LS} = \lambda_{KT}^{knict} = \lambda_{KI}^{kict}$; $\lambda_{LU} = \lambda_{LS}$; and $\lambda_{KT}^{knict} = \lambda_{KI}^{kict}$ in each specification are rejected at conventional significance levels. Country-specific averages employed for distribution parameters at point of normalization, $\{\delta_{10}, \delta_{Z0}, \delta_{20}, \delta_{X0}, \delta_{30}, \delta_{40}\}$, in system estimation. Pooled average (across countries and time) factor shares in sector value added for finance and non-finance are $\{\omega_{LS} = 0.29, \omega_{LU} = 0.26, \omega_{KI} = 0.22, \omega_{KT} = 0.23, \omega_{KICT} = 0.13, \omega_{KNICT} = 0.32\}^F$ and $\{\omega_{LS} = 0.20, \omega_{LU} = 0.45, \omega_{KI} = 0.11, \omega_{KT} = 0.24, \omega_{KICT} = 0.04, \omega_{KNICT} = 0.31\}^{NF}$ respectively. Thus, using pooled averages, distribution parameters at point of normalization across the three factor configurations are $\{\delta_{LU0} = 0.26, \delta_{Z0} = 0.74, \delta_{KI0} = 0.29, \delta_{X0} = 0.71, \delta_{KT0} = 0.43, \delta_{LS0} = 0.57\}^F$, $\{\delta_{LU0} = 0.45, \delta_{Z0} = 0.55, \delta_{KI0} = 0.20, \delta_{X0} = 0.80, \delta_{KT0} = 0.53, \delta_{LS0} = 0.47\}^{NF}$; $\{\delta_{LU0} = 0.26, \delta_{Z0} = 0.74, \delta_{KT0} = 0.31, \delta_{X0} = 0.69, \delta_{KI0} = 0.42, \delta_{LS0} = 0.58\}^F$, $\{\delta_{LU0} = 0.45, \delta_{Z0} = 0.55, \delta_{KT0} = 0.43, \delta_{X0} = 0.57, \delta_{KI0} = 0.35, \delta_{LS0} = 0.65\}^{NF}$; $\{\delta_{LU0} = 0.26, \delta_{Z0} = 0.74, \delta_{KNICT0} = 0.43, \delta_{X0} = 0.57, \delta_{KICT0} = 0.30, \delta_{LS0} = 0.70\}^F$, $\{\delta_{LU0} = 0.45, \delta_{Z0} = 0.55, \delta_{KNICT0} = 0.57, \delta_{X0} = 0.43, \delta_{KICT0} = 0.15, \delta_{LS0} = 0.85\}^{NF}$. The latter shares are used in Morishima elasticity calculations. Pooled median factor shares are identical. Analytical database of EU KLEMS employed.

Table 6: Four-Factor System Residual Diagnostics II for Financial Sector (A) and Non-Financial Market Economy (B)

Regression	**Cross-Section Dependence**			**Panel Unit Root Tests**		
	(1) $\overline{\rho}$	(2) $\overline{\lvert\rho\rvert}$	(3) CSD	(4) LLC	(5) IPS	(6) CIPS
A. System: NLSUR						
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	0.01;0.02;0.01;0.11;0.01	0.33;0.35;0.37;0.36;0.33	0.23;0.05;0.16;0.00;0.51	0.00;0.00;0.00;0.00;0.00 **0.00;0.00;0.00;0.00;0.00**	0.01;0.01;0.03;0.00;0.00 **0.01;0.02;0.06;0.01;0.00**	0.00;0.08;0.05;0.05;0.01
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	0.00;0.04;0.09;0.03;0.03	0.30;0.36;0.34;0.36;0.30	0.74;0.00;0.00;0.00;0.00	0.00;0.00;0.00;0.00;0.00 **0.00;0.00;0.00;0.00;0.00**	0.00;0.00;0.05;0.07;0.00 **0.00;0.02;0.12;0.10;0.00**	0.00;0.02;0.03;0.04;0.00
$L_U;\sigma;[K^n_{ict};\rho;(K^y_{ict};\nu;L_S)]$	0.01;0.09;0.13;-0.02;0.02	0.25;0.36;0.33;0.31;0.25	0.41;0.00;0.00;0.08;0.06	0.00;0.00;0.00;0.00;0.00 **0.00;0.00;0.00;0.00;0.00**	0.01;0.01;0.05;0.04;0.00 **0.01;0.04;0.02;0.02;0.00**	0.00;0.01;0.00;0.06;0.00
A. System: GMM						
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	0.02;0.02;0.00;0.02	0.31;0.36;0.31;0.36	0.01;0.05;0.42;0.00	0.00;0.00;0.00;0.00 **0.00;0.00;0.00;0.00**	0.00;0.03;0.00;0.09 **0.00;0.02;0.00;0.00**	0.00;0.00;0.00;0.00
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	0.02;0.02;0.02;0.01	0.29;0.38;0.28;0.36	0.02;0.04;0.03;0.22	0.00;0.00;0.00;0.00 **0.00;0.00;0.00;0.00**	0.00;0.02;0.05;0.02 **0.00;0.02;0.00;0.00**	0.00;0.00;0.09;0.00
$L_U;\sigma;[K^n_{ict};\rho;(K^y_{ict};\nu;L_S)]$	0.02;0.02;0.05;-0.01;0.02	0.27;0.38;0.22;0.29;0.28	0.03;0.04;0.00;0.15;0.02	0.00;0.00;0.00;0.00;0.00 **0.00;0.00;0.00;0.00;0.00**	0.01;0.03;0.00;0.07;0.00 **0.03;0.02;0.00;0.01;0.00**	0.00;0.03;0.00;0.02;0.00
B. System: NLSUR						
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	0.20;0.02;0.01;0.08;0.22	0.38;0.36;0.34;0.35;0.42	0.00;0.01;0.22;0.00;0.00	0.00;0.00;0.00;0.00;0.00 **0.00;0.01;0.00;0.00;0.00**	0.02;0.03;0.00;0.01;0.08 **0.20;0.07;0.00;0.01;0.00**	0.10;0.04;0.01;0.00;0.04
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	0.19;0.03;0.04;0.02;0.18	0.36;0.38;0.37;0.36;0.38	0.00;0.00;0.00;0.02;0.00	0.00;0.00;0.00;0.00;0.00 **0.01;0.01;0.00;0.00;0.00**	0.03;0.05;0.02;0.00;0.00 **0.13;0.07;0.00;0.00;0.03**	0.04;0.02;0.08;0.00;0.00
$L_U;\sigma;[K^n_{ict};\rho;(K^y_{ict};\nu;L_S)]$	0.17;0.03;0.06;0.11;0.17	0.34;0.37;0.29;0.34;0.34	0.00;0.00;0.00;0.00;0.00	0.00;0.00;0.00;0.02;0.00 **0.02;0.01;0.00;0.00;0.00**	0.01;0.03;0.00;0.08;0.00 **0.10;0.07;0.00;0.10;0.00**	0.00;0.02;0.01;0.03;0.00
B. System: GMM						
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	0.20;0.02;0.01;0.06;0.18	0.38;0.37;0.35;0.35;0.39	0.00;0.05;0.09;0.00;0.00	0.00;0.00;0.00;0.00;0.00 **0.00;0.00;0.00;0.00;0.00**	0.00;0.05;0.00;0.05;0.00 **0.09;0.09;0.00;0.02;0.00**	0.07;0.08;0.00;0.08;0.01
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	0.20;0.02;0.02;0.03;0.14	0.39;0.37;0.28;0.34;0.36	0.00;0.05;0.02;0.00;0.00	0.00;0.00;0.00;0.00;0.00 **0.00;0.00;0.00;0.00;0.00**	0.00;0.03;0.00;0.00;0.00 **0.10;0.07;0.00;0.00;0.07**	0.03;0.08;0.01;0.00;0.09
$L_U;\sigma;[K^n_{ict};\rho;(K^y_{ict};\nu;L_S)]$	0.09;0.05;0.00;0.04;0.17	0.39;0.36;0.29;0.30;0.29	0.00;0.00;0.66;0.00;0.00	0.00;0.00;0.00;0.00;0.00 **0.00;0.00;0.00;0.00;0.00**	0.09;0.06;0.00;0.09;0.00 **0.09;0.05;0.00;0.12;0.00**	0.05;0.04;0.00;0.09;0.01

Notes: P-values reported for cross section dependence and panel unit root tests in columns (3) and (4)-(6) respectively. CSD refers to the cross section dependence or CD 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 Levin *et al.* (2002), LLC, Im *et al.* (2003), IPS, and Pesaran (2007), CIPS, tests is that all series are non-stationary. P-values in bold in columns (4)-(5) are for LLC and IPS tests on series net of cross-section means. Choi (2001)'s Phillips-Perron Fisher, F-PP, panel unit root test yields results similar to those of IPS.

Table 7: Relative Supply, Capital-Labor Complementarity, and Technical Change Effects on Skill Premium in Finance & Non-Finance

Model	**Finance (1)-(6)**						**Non-Finance (7)-(12)**					
	(1) RSC	(2) RS	(3) KLC	(4) KLC_2	(5) KLC_3	(6) TC	(7) RSC	(8) RS	(9) KLC	(10) KLC_2	(11) KLC_3	(12) TC
A. System: NLSUR												
$L_U;\sigma;(L_S;\nu;K)$	5.531***	−3.115***	3.115***			0.112***	3.475**	−2.100**	2.100**			0.025*
	(0.909)	(0.440)	(0.440)			(0.023)	(1.229)	(0.995)	(0.995)			(0.013)
$L_S;\sigma;(L_U;\nu;K)$	0.374***	-469.296	469.296			34.041	0.845***	−0.179***	0.179***			0.021***
	(0.053)	(6551.71)	(6551.71)			(471.758)	(0.029)	(0.036)	(0.036)			(0.003)
$K;\sigma;(L_S;\nu;L_U)$	−0.065***	−0.042***				0.039***	−0.031***	−0.028***				0.016***
	(0.004)	(0.003)				(0.005)	(0.002)	(0.001)				(0.002)
A. System: GMM												
$L_U;\sigma;(L_S;\nu;K)$	2.660***	−1.347***	1.347***			0.078***	1.389	−0.540	0.540			0.047***
	(0.263)	(0.193)	(0.193)			(0.006)	(0.302)	(0.432)	(0.432)			(0.008)
$L_S;\sigma;(L_U;\nu;K)$	0.572***	−1.241*	1.241*			0.146**	0.603***	−1.663***	1.663***			0.083***
	(0.076)	(0.693)	(0.693)			(0.067)	(0.006)	(0.066)	(0.066)			(0.003)
$K;\sigma;(L_S;\nu;L_U)$	−0.065***	−0.052***				0.045***	−0.031***	−0.027***				0.018***
	(0.004)	(0.003)				(0.005)	(0.002)	(0.001)				(0.003)
Source: Table 1												
B. System: NLSUR												
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	333.589	-241.038		5.959*	235.080	9.968	206.023*	-176.394**		1.905***	174.489*	0.945
	(223.838)	(158.347)		(3.238)	(155.463)	(6.748)	(111.608)	(90.980)		(0.399)	(90.962)	(0.895)
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	11.148**	−7.162**		3.200**	3.962**	0.086	2.809***	−1.513***		0.989**	0.523***	0.021**
	(4.363)	(2.967)		(1.555)	(1.634)	(0.069)	(0.532)	(0.428)		(0.449)	(0.090)	(0.009)
$L_U;\sigma;[K^n_{ict};\rho;(K^y_{ict};\nu;L_S)]$	232.248	-162.199		22.216*	139.983	0.058	8.411**	−6.096**		1.024*	5.072**	−0.142**
	(190.548)	(137.064)		(13.310)	(127.044)	(0.889)	(3.246)	(2.567)		(0.558)	(2.094)	(0.066)
B. System: GMM												
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	5.139***	−2.953***		0.639***	2.314***	0.120***	2.191***	−1.006***		0.033***	0.973***	0.034***
	(0.527)	(0.401)		(0.033)	(0.411)	(0.018)	(0.275)	(0.240)		(0.005)	(0.241)	(0.003)
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	5.002***	−2.915***		1.254***	1.661***	0.066***	2.943***	−1.558***		0.984***	0.574***	0.036***
	(0.265)	(0.258)		(0.093)	(0.320)	(0.013)	(0.215)	(0.172)		(0.100)	(0.114)	(0.004)
$L_U;\sigma;[K^n_{ict};\rho;(K^y_{ict};\nu;L_S)]$	10.087***	−6.523***		1.138***	5.385***	0.058*	5.700***	−3.805***		0.481***	3.324***	−0.047***
	(2.644)	(1.912)		(0.433)	(1.954)	(0.034)	(0.568)	(0.479)		(0.093)	(0.461)	(0.018)
Source: Table 3												
C. System: NLSUR												
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	268.612	-199.115		11.023*	188.092	7.522	9.049**	−6.703**		1.483***	5.220**	0.039
	(238.492)	(175.557)		(5.935)	(172.864)	(7.107)	(3.704)	(3.034)		(0.496)	(2.668)	(0.045)
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	305.250	-214.274		25.899	188.375	1.683	9.298***	−6.884***		2.554***	4.330***	0.017
	(303.703)	(220.124)		(22.685)	(199.140)	(1.622)	(1.518)	(1.269)		(0.569)	(1.020)	(0.039)
$L_U;\sigma;[K^n_{ict};\rho;(K^y_{ict};\nu;L_S)]$	11.130**	−7.110**		3.664**	3.446***	0.144**	3.917**	−2.426**		1.347*	1.079***	−0.000
	(4.466)	(2.999)		(1.884)	(1.249)	(0.074)	(1.336)	(1.063)		(0.744)	(0.359)	(0.016)
C. System: GMM												
$L_U;\sigma;[K_I;\rho;(K_T;\nu;L_S)]$	10.048***	−6.171***		1.734***	4.437***	0.194***	7.506***	−5.395***		1.146***	4.249***	0.056***
	(1.332)	(0.923)		(0.196)	(0.961)	(0.038)	(0.227)	(0.224)		(0.120)	(0.322)	(0.005)
$L_U;\sigma;[K_T;\rho;(K_I;\nu;L_S)]$	8.774***	−5.556***		2.220***	3.336***	0.122***	4.829***	−3.188***		0.910***	2.278***	0.027***
	(0.790)	(0.647)		(0.134)	(0.664)	(0.015)	(0.139)	(0.093)		(0.067)	(0.060)	(0.004)
$L_U;\sigma;[K^n_{ict};\rho;(K^y_{ict};\nu;L_S)]$	6.236***	−3.648***		0.833**	2.814***	0.061***	3.617***	−3.621***		0.091	3.531***	−0.042*
	(1.313)	(0.843)		(0.414)	(0.716)	(0.022)	(0.622)	(0.814)		(0.202)	(0.759)	(0.026)
Source: Table 5												

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors constructed via delta method in parentheses. Asterisks in bold in columns (1) and (7) indicate statistical significance in test of null hypothesis of coefficient equaling unity. "RSC" is the relative supply of skilled labor condition with values greater than unity ensuring a negative relative supply effect in all cases but the second and third configurations of panel A where less than unity and less than zero ($g^{L_U} - g^{L_S} < 0$) respectively are required. Except for the third configuration in panel A where sample g^{L_U} and g^{L_S} are used, "RS" is the relative supply of skilled labor effect in the baseline lower bound case of equal growth rates across skilled and unskilled labor i.e. $g^{L_U} = g^{L_S}$ for comparability across sectors. "KLC" is the aggregate capital - skilled/unskilled labor complementarity effect in the three-factor models of panel A. "KLC_2" is the F_2-skilled/unskilled labor complementarity effect in the four-factor models of panels B and C where F_2 is intangible or tangible or non-ICT capital in order of given model configurations. "KLC_3" is the F_3-skilled/unskilled labor complementarity effect in the four-factor models of panels B and C where F_3 is tangible or intangible or ICT capital in order of given model configurations. "TC" is the constant annual technical change effect. Excluding the third configuration in panel A, division of RS, KLC, KLC_2, and KLC_3 coefficients by 100 gives the effect at a 1 percent (0.01) growth rate in the corresponding factor input i.e. $(\partial g^{r_{LS}/r_{LU}}/\partial g^{F_j})/100$. Pooled average (over countries and time) annual factor growth rates, $g^f = d\ln f \ \forall f \in \{L_U, L_S, K, K_T, K_I, K_{NICT}, K_{ICT}, K^{ad}_T, K^{ad}_I, K^{ad}_{NICT}, K^{ad}_{ICT}\}$, in finance (F) and non-finance (NF) are $\{g^{L_U} = -0.020, g^{L_S} = 0.044, g^K = 0.019, g^{K_T} = 0.010, g^{K_I} = 0.074, g^{K_{NICT}} = 0.008, g^{K_{ICT}} = 0.053, g^{K^{ad}_T} = 0.010, g^{K^{ad}_I} = 0.042, g^{K^{ad}_{NICT}} = 0.010, g^{K^{ad}_{ICT}} = 0.053\}^F$ and $\{g^{L_U} = -0.000, g^{L_S} = 0.031, g^K = 0.023, g^{K_T} = 0.018, g^{K_I} = 0.042, g^{K_{NICT}} = 0.017, g^{K_{ICT}} = 0.072, g^{K^{ad}_T} = 0.018, g^{K^{ad}_I} = 0.035, g^{K^{ad}_{NICT}} = 0.020, g^{K^{ad}_{ICT}} = 0.072\}^{NF}$ respectively. Pooled mean annual factor growth rates are similar to corresponding median rates. Statistical database of EU KLEMS underlies analysis of panels A and B. Analytical database (ad) of EU KLEMS underlies analysis of panel C.

Table 8: Drivers of Relative Finance Wages I: Panel Regressions with Annual Data

dependent variable:	(1) $\frac{w_F^T}{w_{NF}^T}$	(2) $\frac{w_F^S}{w_{NF}^S}$	(3) $\frac{w_F^S/w_F^T}{w_{NF}^S/w_{NF}^T}$	(4) $\frac{w_F^S/w_F^U}{w_{NF}^S/w_{NF}^U}$	(5) $\frac{w_F^T}{w_{NF}^T}$	(6) $\frac{w_F^S}{w_{NF}^S}$	(7) $\frac{w_F^S/w_F^T}{w_{NF}^S/w_{NF}^T}$	(8) $\frac{w_F^S/w_F^U}{w_{NF}^S/w_{NF}^U}$
A. Pooled OLS								
Rel. Intangible Cap.	0.096***	0.123***	0.029*	0.054*	0.100***	0.124***	0.028*	0.050*
	(0.036)	(0.038)	(0.017)	(0.030)	(0.036)	(0.038)	(0.017)	(0.030)
Rel. Skilled Lab.	0.117**	−0.019	−0.135***	−0.007	0.166**	−0.006	−0.134***	−0.012
	(0.058)	(0.042)	(0.047)	(0.067)	(0.077)	(0.042)	(0.048)	(0.069)
Fin. Deregulation	−0.434	−0.304	0.254**	0.586**	−0.371	−0.299	0.241*	0.524**
	(0.308)	(0.313)	(0.125)	(0.242)	(0.306)	(0.310)	(0.126)	(0.242)
Fin. Globalization	0.023*	0.038*	−0.003	−0.055	0.030**	0.043**	−0.002	−0.059
	(0.013)	(0.021)	(0.022)	(0.036)	(0.014)	(0.021)	(0.023)	(0.037)
Banking Comp.	−0.836***	−1.213***	−0.325**	−0.765***	−0.784***	−1.205***	−0.316**	−0.739***
	(0.215)	(0.255)	(0.161)	(0.257)	(0.223)	(0.256)	(0.162)	(0.261)
Lab. Mark. Flex.	−0.078	−0.204**	−0.134***	−0.260***	−0.071	−0.201**	−0.133***	−0.262***
	(0.049)	(0.080)	(0.044)	(0.089)	(0.049)	(0.080)	(0.045)	(0.090)
BankComp*LMFlex	0.270***	0.427***	0.160**	0.319***	0.251***	0.420***	0.157**	0.315**
	(0.080)	(0.106)	(0.072)	(0.122)	(0.080)	(0.107)	(0.072)	(0.125)
Domestic Credit	0.078***	0.098***	0.003	0.003	0.085***	0.100***	0.005	0.007
	(0.027)	(0.028)	(0.018)	(0.037)	(0.027)	(0.028)	(0.019)	(0.036)
Time dummies	no	no	no	no	yes	yes	yes	yes
R-squared	0.50	0.50	0.41	0.31	0.51	0.51	0.42	0.34
$\overline{\rho}_u$	0.02	0.02	0.04	0.06	-0.02	0.01	0.00	-0.01
$\overline{\lvert\rho\rvert}_u$	0.26	0.26	0.29	0.30	0.29	0.26	0.30	0.35
CSD_u	0.02	0.13	0.00	0.00	0.11	0.58	0.66	0.33
CIPS_u	0.06	0.07	0.00	0.00	0.00	0.01	0.00	0.03
B. Pooled GMM								
Rel. Intangible Cap.	0.083***	0.154***	0.027***	0.070***	0.102***	0.136***	0.035**	0.066***
	(0.021)	(0.020)	(0.009)	(0.024)	(0.027)	(0.027)	(0.016)	(0.025)
Rel. Skilled Lab.	0.125***	−0.078***	−0.129***	−0.005	0.144***	−0.058**	−0.145***	−0.050
	(0.044)	(0.026)	(0.023)	(0.048)	(0.044)	(0.030)	(0.022)	(0.051)
Fin. Deregulation	−0.538***	−0.298	0.354***	0.685***	−0.440**	−0.131	0.371***	0.608**
	(0.182)	(0.203)	(0.050)	(0.270)	(0.206)	(0.226)	(0.095)	(0.276)
Fin. Globalization	0.019***	0.054***	−0.002	−0.062***	0.023***	0.047***	−0.007	−0.066***
	(0.007)	(0.018)	(0.008)	(0.021)	(0.009)	(0.014)	(0.010)	(0.019)
Banking Comp.	−0.798***	−1.454***	−0.414***	−0.818***	−0.672***	−1.330***	−0.347***	−0.926***
	(0.107)	(0.201)	(0.082)	(0.230)	(0.162)	(0.218)	(0.070)	(0.183)
Lab. Mark. Flex.	−0.064**	−0.259***	−0.165***	−0.307***	−0.068*	−0.286***	−0.155***	−0.348***
	(0.032)	(0.048)	(0.019)	(0.045)	(0.038)	(0.060)	(0.022)	(0.041)
BankComp*LMFlex	0.229***	0.526***	0.206***	0.373***	0.228***	0.539***	0.188***	0.428***
	(0.048)	(0.069)	(0.027)	(0.080)	(0.056)	(0.085)	(0.024)	(0.072)
Domestic Credit	0.120***	0.025	0.014*	0.040	0.114***	0.031	0.019*	0.026
	(0.018)	(0.021)	(0.008)	(0.036)	(0.026)	(0.028)	(0.011)	(0.031)
Time dummies	no	no	no	no	yes	yes	yes	yes
SH	0.27	0.32	0.42	0.23	0.46	0.49	0.41	0.18
$\overline{\rho}_u$	0.01	0.01	0.00	0.02	0.00	-0.01	0.00	-0.00
$\overline{\lvert\rho\rvert}_u$	0.27	0.29	0.26	0.28	0.27	0.29	0.31	0.29
CSD_u	0.44	0.38	0.74	0.02	0.76	0.55	0.75	0.43
CIPS_u	0.01	0.00	0.03	0.05	0.02	0.05	0.08	0.01

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in parentheses. Real intangible capital and skilled labor intensities (i.e. shares in total real capital and labor respectively) in finance relative to non-finance employed. Apart from banking competition, labor market flexibility, and their interaction (BankComp*LMFlex), all variables are in logarithmic form. P-values reported for SH, CSD_u, and CIPS_u tests. SH is the Sargan/Hansen test of valid overidentifying restrictions (null hypothesis). u denotes corresponding panel regression residuals. CSD_u refers to the cross section dependence test of Pesaran (2004, 2015) applied to u 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). $\overline{\rho}_u$ and $\overline{\lvert\rho\rvert}_u$ are the average and average absolute cross-section correlation coefficients (off-diagonal elements) obtained from the Pesaran CSD test for u. Null hypothesis of Pesaran (2007) test, CIPS_u, is that all panel residual series are non-stationary.

Table 9: Drivers of Relative Finance Wages II: Panel Regressions with Annual Data

dependent variable:	(1) $\frac{w_F^T}{w_{NF}^T}$	(2) $\frac{w_F^S}{w_{NF}^S}$	(3) $\frac{w_F^S/w_F^T}{w_{NF}^S/w_{NF}^T}$	(4) $\frac{w_F^S/w_F^U}{w_{NF}^S/w_{NF}^U}$	(5) $\frac{w_F^T}{w_{NF}^T}$	(6) $\frac{w_F^S}{w_{NF}^S}$	(7) $\frac{w_F^S/w_F^T}{w_{NF}^S/w_{NF}^T}$	(8) $\frac{w_F^S/w_F^U}{w_{NF}^S/w_{NF}^U}$
A. Pooled OLS								
Rel. ICT Cap.	0.023	0.042	0.046*	0.087*	0.023	0.043	0.046*	0.081*
	(0.039)	(0.036)	(0.028)	(0.046)	(0.039)	(0.038)	(0.028)	(0.047)
Rel. Skilled Lab.	0.170***	−0.013	−0.196***	−0.081	0.199***	−0.010	−0.198***	−0.091
	(0.051)	(0.056)	(0.047)	(0.066)	(0.063)	(0.052)	(0.047)	(0.066)
Fin. Deregulation	−0.541	−0.351	0.206*	0.361	−0.540	−0.374	0.188	0.319
	(0.345)	(0.354)	(0.121)	(0.260)	(0.363)	(0.386)	(0.123)	(0.264)
Fin. Globalization	0.028**	0.048**	0.020	0.010	0.033**	0.051**	0.020	0.004
	(0.014)	(0.023)	(0.020)	(0.035)	(0.014)	(0.026)	(0.020)	(0.036)
Banking Comp.	−0.542***	−1.122***	−0.493**	−1.112***	−0.491***	−1.121***	−0.491**	−1.100***
	(0.149)	(0.213)	(0.211)	(0.335)	(0.171)	(0.216)	(0.213)	(0.342)
Lab. Mark. Flex.	−0.058	−0.165**	−0.142***	−0.275***	−0.051	−0.164**	−0.143***	−0.279***
	(0.059)	(0.073)	(0.053)	(0.101)	(0.061)	(0.078)	(0.054)	(0.103)
BankComp*LMFlex	0.197**	0.374***	0.216**	0.414***	0.179*	0.372***	0.215**	0.414***
	(0.093)	(0.094)	(0.086)	(0.151)	(0.099)	(0.098)	(0.088)	(0.154)
Domestic Credit	0.082**	0.134***	0.040**	0.038	0.088**	0.136***	0.039**	0.032
	(0.035)	(0.037)	(0.017)	(0.032)	(0.035)	(0.038)	(0.017)	(0.034)
Time dummies	no	no	no	no	yes	yes	yes	yes
R-squared	0.43	0.43	0.50	0.32	0.44	0.44	0.51	0.34
$\overline{\rho}_u$	0.02	0.02	0.03	0.06	-0.01	-0.02	-0.01	0.00
$\overline{\lvert\rho\rvert}_u$	0.24	0.23	0.24	0.25	0.27	0.24	0.27	0.28
CSD_u	0.01	0.11	0.00	0.00	0.16	0.05	0.31	0.60
CIPS_u	0.10	0.04	0.01	0.07	0.00	0.03	0.05	0.10
B. Pooled GMM								
Rel. ICT Cap.	0.033**	0.036**	0.049***	0.137***	0.042*	0.036*	0.054***	0.125***
	(0.015)	(0.016)	(0.013)	(0.037)	(0.022)	(0.021)	(0.017)	(0.041)
Rel. Skilled Lab.	0.210***	0.014	−0.217***	−0.114**	0.219***	0.010	−0.189***	−0.089*
	(0.036)	(0.048)	(0.027)	(0.048)	(0.036)	(0.047)	(0.032)	(0.048)
Fin. Deregulation	−0.582***	−0.496**	0.232***	0.516***	−0.703**	−0.587***	0.266***	0.496***
	(0.159)	(0.196)	(0.068)	(0.179)	(0.293)	(0.192)	(0.095)	(0.187)
Fin. Globalization	0.028***	0.042***	0.032***	0.012	0.033***	0.051***	0.023*	0.008
	(0.004)	(0.015)	(0.008)	(0.023)	(0.005)	(0.014)	(0.012)	(0.024)
Banking Comp.	−0.522***	−0.911***	−0.649***	−1.353***	−0.539***	−0.960***	−0.584***	−1.314***
	(0.106)	(0.148)	(0.075)	(0.231)	(0.127)	(0.157)	(0.123)	(0.249)
Lab. Mark. Flex.	−0.059***	−0.124***	−0.182***	−0.370***	−0.072***	−0.140***	−0.187***	−0.380***
	(0.024)	(0.032)	(0.018)	(0.032)	(0.027)	(0.025)	(0.023)	(0.043)
BankComp*LMFlex	0.186***	0.280***	0.277***	0.543***	0.200***	0.292***	0.275***	0.535***
	(0.052)	(0.053)	(0.024)	(0.071)	(0.056)	(0.045)	(0.039)	(0.081)
Domestic Credit	0.115***	0.172***	0.023***	0.023	0.129***	0.179***	0.032***	0.003
	(0.017)	(0.024)	(0.009)	(0.029)	(0.021)	(0.023)	(0.012)	(0.024)
Time dummies	no	no	no	no	yes	yes	yes	yes
SH	0.55	0.28	0.34	0.31	0.53	0.47	0.57	0.44
$\overline{\rho}_u$	0.01	0.01	-0.00	0.03	0.00	0.00	-0.02	-0.01
$\overline{\lvert\rho\rvert}_u$	0.23	0.23	0.19	0.22	0.25	0.22	0.25	0.26
CSD_u	0.15	0.38	0.76	0.00	0.92	0.87	0.06	0.36
CIPS_u	0.03	0.00	0.09	0.07	0.02	0.00	0.00	0.00

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in parentheses. Real ICT capital and skilled labor intensities (i.e. shares in total real capital and labor respectively) in finance relative to non-finance employed. Apart from banking competition, labor market flexibility, and their interaction (BankComp*LMFlex), all variables are in logarithmic form. P-values reported for SH, CSD_u, and CIPS_u tests. SH is the Sargan/Hansen test of valid overidentifying restrictions (null hypothesis). u denotes corresponding panel regression residuals. CSD_u refers to the cross section dependence test of Pesaran (2004, 2015) applied to u 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). $\overline{\rho}_u$ and $\overline{\lvert\rho\rvert}_u$ are the average and average absolute cross-section correlation coefficients (off-diagonal elements) obtained from the Pesaran CSD test for u. Null hypothesis of Pesaran (2007) test, CIPS_u, is that all panel residual series are non-stationary.

Table 10: Drivers of Relative Finance Wages I: Panel Regressions with 4-Year Averages

dependent variable:	(1) $\frac{w_F^T}{w_{NF}^T}$	(2) $\frac{w_F^S}{w_{NF}^S}$	(3) $\frac{w_F^S/w_F^T}{w_{NF}^S/w_{NF}^T}$	(4) $\frac{w_F^S/w_F^U}{w_{NF}^S/w_{NF}^U}$	(5) $\frac{w_F^T}{w_{NF}^T}$	(6) $\frac{w_F^S}{w_{NF}^S}$	(7) $\frac{w_F^S/w_F^T}{w_{NF}^S/w_{NF}^T}$	(8) $\frac{w_F^S/w_F^U}{w_{NF}^S/w_{NF}^U}$
A. Pooled OLS								
Rel. Intangible Cap.	0.102***	0.118**	0.037*	0.070**	0.105***	0.120**	0.036*	0.066*
	(0.039)	(0.050)	(0.022)	(0.034)	(0.039)	(0.050)	(0.022)	(0.035)
Rel. Skilled Lab.	0.118**	−0.101*	−0.135***	−0.020	0.181**	−0.091	−0.142***	−0.029
	(0.060)	(0.060)	(0.048)	(0.077)	(0.081)	(0.061)	(0.051)	(0.082)
Fin. Deregulation	−0.390	−0.192	0.274*	0.698**	−0.340	−0.191	0.238	0.617*
	(0.380)	(0.302)	(0.164)	(0.306)	(0.370)	(0.309)	(0.168)	(0.319)
Fin. Globalization	0.021*	0.062*	−0.007	−0.062	0.029**	0.066*	−0.009	−0.065
	(0.013)	(0.033)	(0.023)	(0.038)	(0.014)	(0.036)	(0.024)	(0.039)
Banking Comp.	−0.921***	−1.507***	−0.361**	−0.930***	−0.812***	−1.490***	−0.366**	−0.903***
	(0.225)	(0.340)	(0.167)	(0.296)	(0.239)	(0.348)	(0.169)	(0.308)
Lab. Mark. Flex.	−0.114*	−0.271***	−0.154***	−0.308***	−0.097	−0.265***	−0.161***	−0.310***
	(0.065)	(0.094)	(0.042)	(0.109)	(0.063)	(0.100)	(0.044)	(0.112)
BankComp*LMFlex	0.325***	0.546***	0.198***	0.403***	0.284***	0.534***	0.205***	0.398**
	(0.107)	(0.131)	(0.073)	(0.151)	(0.105)	(0.137)	(0.076)	(0.157)
Domestic Credit	0.086**	−0.012	0.002	−0.011	0.099***	−0.008	0.002	−0.007
	(0.036)	(0.049)	(0.026)	(0.051)	(0.036)	(0.051)	(0.027)	(0.052)
Time dummies	no	no	no	no	yes	yes	yes	yes
R-squared	0.52	0.35	0.45	0.33	0.54	0.36	0.46	0.35
$\overline{\rho}_u$	0.01	-0.01	-0.00	-0.00	-0.00	-0.02	-0.00	-0.01
$\overline{\lvert\rho\rvert}_u$	0.25	0.35	0.25	0.28	0.28	0.35	0.24	0.28
CSD_u	0.57	0.69	0.74	0.69	0.80	0.22	0.42	0.24
F-PP_u^d	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
B. Pooled GMM								
Rel. Intangible Cap.	0.103***	0.168***	0.036*	0.097***	0.107***	0.167***	0.034*	0.093***
	(0.034)	(0.052)	(0.021)	(0.039)	(0.034)	(0.052)	(0.021)	(0.038)
Rel. Skilled Lab.	0.144**	−0.120*	−0.147***	−0.015	0.175**	−0.127**	−0.152***	−0.039
	(0.070)	(0.073)	(0.059)	(0.110)	(0.080)	(0.060)	(0.059)	(0.112)
Fin. Deregulation	−0.689	−0.032	0.373**	1.093**	−0.577	−0.075	0.324*	0.943*
	(0.437)	(0.417)	(0.193)	(0.497)	(0.415)	(0.426)	(0.199)	(0.498)
Fin. Globalization	0.025*	0.065**	−0.006	−0.049	0.028*	0.066*	−0.006	−0.054
	(0.015)	(0.032)	(0.024)	(0.038)	(0.015)	(0.036)	(0.023)	(0.038)
Banking Comp.	−0.870***	−1.933***	−0.377*	−1.318***	−0.863***	−1.930***	−0.362*	−1.325***
	(0.260)	(0.394)	(0.219)	(0.395)	(0.260)	(0.388)	(0.224)	(0.383)
Lab. Mark. Flex.	−0.067	−0.375***	−0.162**	−0.422***	−0.069	−0.372***	−0.159**	−0.436***
	(0.076)	(0.089)	(0.068)	(0.129)	(0.072)	(0.093)	(0.070)	(0.128)
BankComp*LMFlex	0.259**	0.723***	0.200*	0.578***	0.261**	0.718***	0.193*	0.593***
	(0.124)	(0.134)	(0.110)	(0.189)	(0.119)	(0.136)	(0.113)	(0.184)
Domestic Credit	0.141***	−0.027	0.005	−0.023	0.145***	−0.029	0.007	−0.024
	(0.052)	(0.056)	(0.045)	(0.086)	(0.049)	(0.054)	(0.044)	(0.085)
Time dummies	no	no	no	no	yes	yes	yes	yes
SH	NA	NA	NA	NA	NA	NA	NA	NA
$\overline{\rho}_u$	0.01	-0.01	0.00	0.00	0.01	-0.02	-0.00	-0.01
$\overline{\lvert\rho\rvert}_u$	0.28	0.35	0.27	0.27	0.28	0.35	0.26	0.26
CSD_u	0.35	0.41	0.86	0.78	0.57	0.18	0.72	0.45
F-PP_u^d	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in parentheses. 4-year averages are non-overlapping. Real intangible capital and skilled labor intensities (i.e. shares in total real capital and labor respectively) in finance relative to non-finance employed. Apart from banking competition, labor market flexibility, and their interaction (BankComp*LMFlex), all variables are in logarithmic form. GMM model is exactly identified when "NA" is reported for Sargan/Hansen (SH) test of overidentifying restrictions. u denotes corresponding panel regression residuals. P-values reported for CSD_u and F-PP_u^d tests. CSD_u refers to cross section dependence test of Pesaran (2004, 2015) applied to u where the null 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). $\overline{\rho}_u$ and $\overline{\lvert\rho\rvert}_u$ are average and average absolute cross-section correlation coefficients obtained from the Pesaran CSD test for u. Null hypothesis of Choi (2001)'s Phillips-Perron Fisher test, F-PP_u^d, is that all cross-sectionally demeaned residual series are non-stationary.

Table 11: Drivers of Relative Finance Wages II: Panel Regressions with 4-Year Averages

dependent variable:	(1) $\frac{w_F^T}{w_{NF}^T}$	(2) $\frac{w_F^S}{w_{NF}^S}$	(3) $\frac{w_F^S/w_F^T}{w_{NF}^S/w_{NF}^T}$	(4) $\frac{w_F^S/w_F^U}{w_{NF}^S/w_{NF}^U}$	(5) $\frac{w_F^T}{w_{NF}^T}$	(6) $\frac{w_F^S}{w_{NF}^S}$	(7) $\frac{w_F^S/w_F^T}{w_{NF}^S/w_{NF}^T}$	(8) $\frac{w_F^S/w_F^U}{w_{NF}^S/w_{NF}^U}$
A. Pooled OLS								
Rel. ICT Cap.	0.045	0.058	0.051*	0.121**	0.046	0.057	0.050*	0.115**
	(0.039)	(0.040)	(0.031)	(0.052)	(0.039)	(0.041)	(0.031)	(0.055)
Rel. Skilled Lab.	0.140***	−0.013	−0.175***	−0.133*	0.198***	−0.007	−0.182***	−0.149*
	(0.052)	(0.062)	(0.055)	(0.075)	(0.069)	(0.057)	(0.054)	(0.086)
Fin. Deregulation	−0.488	−0.404	0.287*	0.599*	−0.482	−0.431	0.276*	0.495
	(0.459)	(0.320)	(0.171)	(0.332)	(0.443)	(0.358)	(0.170)	(0.408)
Fin. Globalization	0.021*	0.062***	0.022	−0.010	0.032**	0.062**	0.019	−0.017
	(0.012)	(0.023)	(0.022)	(0.032)	(0.014)	(0.025)	(0.022)	(0.034)
Banking Comp.	−0.571***	−1.222***	−0.544**	−1.449***	−0.484***	−1.193***	−0.548**	−1.417***
	(0.158)	(0.223)	(0.223)	(0.341)	(0.173)	(0.222)	(0.227)	(0.361)
Lab. Mark. Flex.	−0.036	−0.195***	−0.168***	−0.373***	−0.033	−0.193**	−0.171***	−0.379***
	(0.055)	(0.074)	(0.045)	(0.100)	(0.055)	(0.079)	(0.046)	(0.110)
BankComp*LMFlex	0.189**	0.417***	0.249***	0.585***	0.168*	0.408***	0.254***	0.584***
	(0.094)	(0.100)	(0.080)	(0.146)	(0.096)	(0.103)	(0.081)	(0.158)
Domestic Credit	0.120***	0.155***	0.053**	0.024	0.132***	0.159***	0.051*	0.025
	(0.036)	(0.040)	(0.027)	(0.055)	(0.036)	(0.042)	(0.027)	(0.058)
Time dummies	no	no	no	no	yes	yes	yes	yes
R-squared	0.49	0.49	0.54	0.38	0.51	0.50	0.55	0.41
$\overline{\rho}_u$	0.01	-0.01	-0.00	-0.00	-0.00	-0.02	-0.00	-0.02
$\overline{\lvert\rho\rvert}_u$	0.27	0.29	0.33	0.19	0.27	0.28	0.32	0.23
CSD_u	0.20	0.52	0.55	0.69	0.91	0.12	0.40	0.12
F-PP_u^d	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
B. Pooled GMM								
Rel. ICT Cap.	0.059	0.075*	0.066*	0.143**	0.061	0.076*	0.065*	0.138**
	(0.049)	(0.040)	(0.036)	(0.059)	(0.050)	(0.040)	(0.036)	(0.060)
Rel. Skilled Lab.	0.227***	−0.011	−0.230***	−0.151	0.237***	−0.014	−0.238***	−0.196*
	(0.064)	(0.073)	(0.066)	(0.109)	(0.079)	(0.075)	(0.064)	(0.107)
Fin. Deregulation	−0.473	−0.543	0.309**	0.859*	−0.438	−0.533	0.294**	0.687
	(0.421)	(0.467)	(0.144)	(0.499)	(0.418)	(0.491)	(0.152)	(0.524)
Fin. Globalization	0.031**	0.055**	0.023	0.005	0.032**	0.054*	0.021	−0.007
	(0.015)	(0.026)	(0.020)	(0.031)	(0.014)	(0.029)	(0.022)	(0.034)
Banking Comp.	−0.562***	−1.232***	−0.658***	−1.783***	−0.571***	−1.238***	−0.663***	−1.801***
	(0.176)	(0.268)	(0.231)	(0.367)	(0.178)	(0.264)	(0.230)	(0.349)
Lab. Mark. Flex.	−0.027	−0.162*	−0.173***	−0.459***	−0.032	−0.159*	−0.177***	−0.477***
	(0.079)	(0.098)	(0.044)	(0.105)	(0.079)	(0.094)	(0.045)	(0.107)
BankComp*LMFlex	0.176	0.392***	0.283***	0.731***	0.185	0.391***	0.288***	0.755***
	(0.132)	(0.135)	(0.075)	(0.151)	(0.135)	(0.128)	(0.077)	(0.144)
Domestic Credit	0.193***	0.222***	0.049*	0.046	0.194***	0.224***	0.046*	0.038
	(0.049)	(0.063)	(0.026)	(0.084)	(0.048)	(0.065)	(0.026)	(0.086)
Time dummies	no	no	no	no	yes	yes	yes	yes
SH	NA	NA	NA	NA	NA	NA	NA	NA
$\overline{\rho}_u$	0.00	-0.01	-0.00	-0.00	-0.00	-0.01	-0.01	-0.02
$\overline{\lvert\rho\rvert}_u$	0.28	0.29	0.33	0.22	0.27	0.28	0.33	0.24
CSD_u	0.75	0.46	0.47	1.00	0.85	0.30	0.24	0.16
F-PP_u^d	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in parentheses. 4-year averages are non-overlapping. Real ICT capital and skilled labor intensities (i.e. shares in total real capital and labor respectively) in finance relative to non-finance employed. Apart from banking competition, labor market flexibility, and their interaction (BankComp*LMFlex), all variables are in logarithmic form. GMM model is exactly identified when "NA" is reported for Sargan/Hansen (SH) test of overidentifying restrictions. u denotes corresponding panel regression residuals. P-values reported for CSD_u and F-PP_u^d tests. CSD_u refers to cross section dependence test of Pesaran (2004, 2015) applied to u where the null 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). $\overline{\rho}_u$ and $\overline{\lvert\rho\rvert}_u$ are average and average absolute cross-section correlation coefficients obtained from the Pesaran CSD test for u. Null hypothesis of Choi (2001)'s Phillips-Perron Fisher test, F-PP_u^d, is that all cross-sectionally demeaned residual series are non-stationary.