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On Finance's Disparate Labor Share Dynamics: A Neoclassical Perspective

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On Finance's Disparate Labor Share Dynamics: A Neoclassical Perspective*

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Abstract

Labor's income share experiences a much lower decline in finance than in the remainder of the market economy. We find that the neoclassical model of income distribution can explain these heterogeneous sectoral dynamics. Finance's lower labor share decline is a reflection of its weaker net labor-augmenting productivity growth, as driven by unskilled labor. This counters the stronger skill-induced capital-labor synergies and capital intensity in the sector, which act to inflate the absolute size of labor share changes. Jointly, relative skilled labor supply, capital growth, and technical change channels generate relative skilled labor share changes that coincide exactly with the data.

Keywords: finance, labor share, income, capital-labor substitution, technical change

JEL: G2, O3, O4

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1 Introduction

Labor's declining share in income across the developed world has been attributed to many factors. These include the outsourcing of labor-intensive tasks in the presence of heightened globalization (Elsby *et al.*, 2013), the declining price of investment goods (Karabarbounis and Neiman, 2014), the global productivity slowdown (Grossman *et al.*, 2017b), automation (Acemoglu and Restrepo, 2018, 2020; Guimarães and Gil, 2022; Basso and Rachedi, 2025), and the rise of superstar firms (Autor *et al.*, 2020).[1] However, at the sectoral level, we find that the fall in the finance industry's labor share is not remotely close to that of the non-finance market economy. Since the mid-nineties, the non-finance sector has observed a 6.4 percent drop in its labor share compared to only 1 percent in finance.

This heterogeneity is consistent with the higher labor compensation in finance relative to other parts of the economy, which according to the literature is driven by the sector's deregulation (Philippon and Reshef, 2012, 2013), socially inefficient risk taking (Philippon and Reshef, 2012; Cheng *et al.*, 2015), and exorbitant rents arising from asymmetric information and complex opaque activities (Korinek and Kreamer, 2014; Axelson and Bond, 2015; Bolton *et al.*, 2016; Biais and Landier, 2020). At the same time, Greenwood and Scharfstein (2013) document that the financial sector has grown substantially in importance since the 1980s. While the authors illustrate this for the U.S. up until the early 2000s, Figure 1 shows that the growth applies more generally to advanced economies and continues in more recent times, with the exception of the dip during the global financial crisis.

In our paper, we adopt a different approach and examine whether an economic growth perspective can offer insight into the disparate evolution of finance's labor share. Across a panel of thirty advanced economies, we find that the neoclassical model of production and income distribution is able to predict the direction of and, moreover, the discrepancy in labor share

[1] See Grossman and Oberfield (2022) for a comprehensive review of the literature.

changes across finance and non-finance. In both sectors, our supply-side framework indicates that the fall in the labor share is generated by a combination of capital-labor complementarity and net labor-augmenting technical change. Although physical capital deepening takes place over time, net labor-augmenting productivity growth is generally sufficiently strong in both sectors such that it yields a declining effective capital-labor ratio. Given complementarity across factor inputs, the wage-to-rental ratio falls disproportionately to produce a weaker labor share.

Our underlying supply-side decomposition reveals that while finance's stronger capital-labor synergies and capital intensity act to inflate the absolute size of labor share changes, the sector's weaker net labor-augmenting productivity growth counters these effects to produce a smaller labor share change. As non-finance is relatively labor-intensive, productivity growth will be more skewed toward labor-augmenting productivity in the sector. This falls in line with the idea that technical change is directed toward scarce factor inputs (Acemoglu, 2002).[2]

Compared to non-finance, capital- and labor-biased productivity growth both tend to be higher in finance. If profitability is higher in financial activities as the literature suggests, then more investment will be diverted toward innovation in the finance industry, thus increasing the relative productivity of its factor inputs. More pronounced transitions down the occupational ladder in non-finance (Beaudry *et al.*, 2016), furthermore, may have diminished its productivity growth due to a misallocation of resources. Such labor movements could also be reflected in the heterogeneous sectoral labor share dynamics. Overall, our focus on sectoral outcomes contributes more widely to the relatively nascent literature emphasizing the importance of more micro-level data (Herrendorf *et al.*, 2015; Comin *et al.*, 2021; Oberfield and Raval, 2021).

Extending our analysis by studying the distributional effects within labor, we find that the decline in the labor share in both sectors is led by unskilled labor. Skilled labor on the other hand produces an opposing force, which is stronger in finance. Skilled labor is what drives the

[2] i.e. Labor is accumulated through population growth and education, and so does not develop in the same way as capital.

complementarity between capital and labor at the aggregate level according to our estimates, and this complementarity is significantly stronger in finance. Unskilled labor meanwhile exhibits weaker substitution possibilities with skilled labor and capital in the non-financial sector. These cross-sectoral differences in substitution elasticities imply that capital growth benefits the skilled relative to unskilled labor share in finance to a greater extent than in non-finance. This occurs due to the differential impacts on sectoral ratios of marginal products of labor, which lead to a larger increase in the relative demand for skilled labor in finance compared to that in non-finance at given relative supplies of skilled labor. Although economywide capital-skill complementarity is well documented in the literature and particularly so for the U.S. (Autor *et al.*, 1998, 2003; Ohanian *et al.*, 2023), potential heterogeneity in trends across sectors using international data is less well-explored (Lawrence, 2015).

Finally, we obtain evidence that the weaker net labor-augmenting productivity growth in finance is predominantly accounted for by a much sharper decline in "unskilled labor"-augmenting productivity in the sector. Technical change, taken as the weighted average of factor-augmenting productivity growth rates, ultimately displays a bias toward skilled labor in each sector with the tilt being more pronounced in finance. Together, relative supply of skilled labor, capital growth, and technical change channels project sectoral skilled relative to unskilled labor share changes that coincide exactly with those found in the data.

The rest of the paper is organized as follows. Section 2 presents a supply-side paradigm of how factor substitution, factor intensities, and technical change affect the labor share. Section 3 then briefly describes the data and estimation strategies employed. In turn, we discuss our findings in section 4. In section 5, we offer additional insights into sectoral labor share changes by examining distributional effects across skill types. Finally, section 6 concludes.

2 Theoretical Framework

The decomposition of the market-wide labor share over the financial sector (F) and the non-financial market economy (NF) can be written as

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

where $\tau \in \{F, NF\}$ 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 $1 - \delta_F = \delta_{NF}$. The degree of complementarity between sectoral outputs in Y_t is captured by ϵ. Cobb-Douglas sectoral production functions imply that sectoral factor shares are constant. As a result, in the presence of heterogeneous production technologies across sectors (i.e. capital intensity differences), aggregate factor share dynamics will be driven by sectoral output shares. If factor substitution elasticities differ from unity through a more general constant elasticity of substitution (CES) production structure, aggregate factor share changes are also influenced by sectoral factor shares. Differences in factor substitution possibilities across sectors further mean that the shape of structural change, in terms of factor reallocations, is affected. The latter approach therefore enhances flexibility.

Given labor and capital inputs L and K respectively, production in each sector is defined by the following CES function

$$Y_{\tau,t} = \left[\delta_{L,\tau}(A_{L,\tau,t} L_{\tau,t})^{\frac{\sigma_\tau - 1}{\sigma_\tau}} + \delta_{K,\tau}(A_{K,\tau,t} K_{\tau,t})^{\frac{\sigma_\tau - 1}{\sigma_\tau}}\right]^{\frac{\sigma_\tau}{\sigma_\tau - 1}} \qquad \forall \tau \in \{F, NF\}.^{3,4} \tag{2}$$

The distribution parameter $1 - \delta_{K,\tau} = \delta_{L,\tau} \in (0,1)$ reflects overall labor intensity in sectoral production. The elasticity of substitution between factors inputs in sector τ is gauged by σ_τ.

[3] The use of similar production technologies across financial and non-financial sectors is in line with the literature (Philippon, 2014, 2015). For example, Philippon (2014) explores both CES and Cobb-Douglas functions.

[4] Employing a linear Kmenta approximation of the CES function (a constrained translog function) instead would act to bias estimates of σ toward unity.

$A_{L,\tau}$ and $A_{K,\tau}$ are labor-augmenting and capital-augmenting productivity respectively in sector τ. These factor-biased productivities evolve according to exponential functions. Their respective constant growth rates, $\lambda_{L,\tau}$ and $\lambda_{K,\tau}$, are permitted to differ across sectors along with initial productivity levels.[5] Omitting subscript τ for brevity, the normalized version of equation (2) is written as

$$Y_t = \psi Y_0 \left[\delta_{L0} \left(e^{\lambda_L (t-t_0)} \frac{L_t}{L_0} \right)^{\frac{\sigma-1}{\sigma}} + \delta_{K0} \left(e^{\lambda_K (t-t_0)} \frac{K_t}{K_0} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}. \tag{3}$$

The distribution parameters δ_{j0} are interpreted as factor income shares at the point of normalization. The latter point (denoted by "0") 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. Using sample averages as base variable values attenuates the size of cyclical and stochastic components in the point of normalization. With all variables in indexed form, estimates are invariant to a change in measurement units. 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.[6]

Competitive factor markets imply that real factor returns, namely the real wage r_L and the real user cost of capital r_K, equal their respective marginal products. Taking logarithms of the normalized production function and optimality conditions yields the system of equations

$$\ln \frac{Y_t}{Y_0} = \ln \psi + \frac{\sigma}{\sigma - 1} \ln \left(\delta_{L0} \left(e^{\lambda_L (t-t_0)} \frac{L_t}{L_0} \right)^{\frac{\sigma-1}{\sigma}} + \delta_{K0} \left(e^{\lambda_K (t-t_0)} \frac{K_t}{K_0} \right)^{\frac{\sigma-1}{\sigma}} \right) \tag{4}$$

[5]Imposing Hicks-neutral technical change (i.e. factor-neutral productivity growth such that $\lambda_L = \lambda_K$), like in Karabarbounis and Neiman (2014), would limit the explanation of labor share changes to just the magnitude of σ in response to capital deepening in the sector.

[6]Normalization helps to alleviate the problem of estimating the deep parameters in the production function, namely the elasticity of substitution and the growth rates of factor augmenting technical progress. In the non-normalized framework, the distribution and efficiency parameters have no clear theoretical or empirical meaning. Normalization on the other hand affords these parameters meaningful interpretations in terms of the data. This provides the option of pre-setting these parameters prior to estimation, effectively reducing the number of freely estimated parameters by two in equation (3). Normalization is also important when biases in the direction of technical progress are to be empirically determined, as it fixes a baseline value for factor shares. If technical change is biased in the sense that factor income shares are changing over time, then the nature of this bias can only be classified with respect to a given benchmark value.

$$\ln \frac{r_{L,t}}{r_{L,0}} = \frac{\sigma - 1}{\sigma} \ln \psi + \frac{\sigma - 1}{\sigma} \lambda_L (t - t_0) + \frac{1}{\sigma}\left(\ln \frac{Y_t}{Y_0} - \ln \frac{L_t}{L_0} \right) \tag{5}$$

$$\ln \frac{r_{K,t}}{r_{K,0}} = \frac{\sigma - 1}{\sigma} \ln \psi + \frac{\sigma - 1}{\sigma} \lambda_K (t - t_0) + \frac{1}{\sigma}\left(\ln \frac{Y_t}{Y_0} - \ln \frac{K_t}{K_0} \right), \tag{6}$$

where $r_{L0} = \frac{\delta_{L0} Y_0}{L_0}$ and $r_{K0} = \frac{\delta_{K0} Y_0}{K_0}$. Subtracting equation (6) from equation (5) gives

$$\ln \frac{r_{L,t}/r_{L,0}}{r_{K,t}/r_{K,0}} = -\frac{1 - \sigma}{\sigma} (\lambda_L - \lambda_K)(t - t_0) + \frac{1}{\sigma} \ln \frac{K_t/K_0}{L_t/L_0}.^{7} \tag{7}$$

From equation (7), it is evident that growth in the relative wage is related to growth in the capital-labor ratio and technical change: $g^{r_L/r_K} = \frac{1}{\sigma}(g^K - g^L) + \frac{\sigma-1}{\sigma}(\lambda_L - \lambda_K)$. Employing equation (7), the expression for relative factor shares is

$$\underbrace{\ln \frac{\omega_{L,t}/\omega_{L,0}}{\omega_{K,t}/\omega_{K,0}}}_{\ln \frac{\omega_{L,t}}{\omega_{K,t}} - \ln \frac{\delta_{L0}}{\delta_{K0}}} = \frac{\sigma - 1}{\sigma} (\lambda_L - \lambda_K)(t - t_0) + \frac{1 - \sigma}{\sigma} \ln \frac{K_t/K_0}{L_t/L_0}. \tag{8}$$

Therefore, changes in the labor share (ω_L) with respect to changes in the effective capital-labor ratio $\tilde{k} = A_K K / A_L L$ are obtained from the following pair of equations

$$d \ln \omega_{L,t} = -(1 - \omega_{L,t}) \frac{\sigma - 1}{\sigma} d \ln \tilde{k} \tag{9}$$

$$d \ln \tilde{k} = (\lambda_K - \lambda_L) + d \ln \frac{K_t}{L_t}. \tag{10}$$

Analogously, growth in the relative labor share is $g^{\omega_L/\omega_K} = \frac{\sigma-1}{\sigma}(g^L - g^K + \lambda_L - \lambda_K) = \frac{1-\sigma}{\sigma} g^{\tilde{k}}$.

The global decline in labor's income share alongside growing wealth and income inequality has reinvigorated interest in estimates of σ given its implication for relative factor shares.

[7] Equation (7) continues to be valid in the presence of imperfect competition in the product market. More generally, allowing for a mark-up term in our analysis, where the representative firm in each sector faces an isoelastic demand, does not alter the findings.

Namely, as implied by equation (9), gross substitutability between capital and labor ($\sigma > 1$) means an increase in the labor share in response to a decrease in the effective capital-labor ratio. Gross complementarity ($\sigma < 1$) on the other hand yields the opposite as a disproportionately larger decline in the relative labor return is required to accommodate the rise in the relative effective supply of labor. A plethora of studies offer insights based on a single equation estimation approach, focusing on linear regressions of the form of (7) or (8) for example (Antràs, 2004; Lawrence, 2015; Chirinko and Mallick, 2017; Glover and Short, 2020; Grossman and Oberfield, 2022).[8] According to the Monte Carlo analysis of León-Ledesma *et al.* (2010), however, jointly modeling the production function and first-order conditions in a "systems" setup containing cross-equation restrictions is superior to single-equation approaches, especially when combined with "normalization". The systems approach merged with normalization, in addition to specifying functional forms for growth rates of efficiency levels, most notably is able to circumvent the famous impossibility theorem of Diamond *et al.* (1978).[9]

3 Data and Estimation

Annual data on output, capital, and labor are collated from the EU KLEMS repository. Quality-adjusted series for factor inputs are included in the data. Coverage of the market economy and 1-digit level finance sector (labeled as "financial and insurance activities") is available for 30 nations over the period 1995-2017.[10,11] The data are aligned with the ISIC 4 (NACE 2) industry classification scheme and the new European System of National Accounts (ESA 2010).

[8]In the single linear equation estimation strategy, normalization does not play an empirical role with time series or fixed effects panel regressions as the normalization points are absorbed by the constant terms.

[9]Klump *et al.* (2012) contend that Diamond-McFadden-prompted scepticism about the proper identification of the substitution elasticity and technical change largely loses its practical relevance in the context of normalization and system estimation.

[10]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).

[11]A further decomposition of the financial sector for each country is unavailable.

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. Quality-adjusted capital, given by the capital services volume index, takes into account the age-efficiency (marginal products) of the various asset types. Quality-adjusted labor, given by the labor services volume index, weights the raw labor input by skill type and experience as proxied by age. Thus input quality or composition effects can be calculated as the difference between growth rates in factor input services and the raw factor input. The nominal rental price of capital services is calculated as the ratio of total nominal capital income to the real capital stock. Similarly, the nominal wage rate for labor services is computed as total nominal labor compensation divided by the total labor input. Nominal returns divided by the GDP deflator give real factor returns. EU KLEMS accordingly adjusts the remuneration of labor by changes in labor quality and the number of self-employed (proprietors).[12] The sum of factor shares in value added equals unity.[13]

The production function and corresponding optimality conditions in equations (4)-(6) form our supply-side system of equations for estimation. Systems of pooled normalized panel specifications with cross-equation restrictions are estimated by applying the procedures of nonlinear seemingly unrelated regressions (NLSUR) and general method of moments (GMM).[14] An iterated feasible generalized nonlinear least squares estimator is employed for NLSUR while a two-step estimator is used for GMM. Country-specific normalization points are adopted. The likelihood of cross-equation correlations in residuals, the potential to maximize information and improve efficiency, and possible endogeneity issues drive the selection of estimators. Lags of employed variables act as instruments in GMM estimation of the normalized system.

[12]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. This formula assumes the same hourly wage across employees and the self-employed.

[13]EU KLEMS treats production as homogeneous of degree one in the inputs. To account for a mark-up, one would discount value added accordingly before substracting labor compensation to obtain capital compensation.

[14]A panel analysis, as opposed to a country-by-country time series approach, is appropriate given i) the relative homogeneity of countries in terms of economic status and ii) the length of the sample time period with an annual frequency.

4 Empirical Analysis

In addition to the weighted-average evolution of financial sector size in Figure 1, Table 1 reveals that 25 out of 30 countries display non-negative growth in the sector over the sample period. Furthermore, the financial sector expands by more than 20 percent in 14 countries (column (3)). The table, from a broader viewpoint, conveys a degree of synchronization in the national growth trajectories of financial services. By 2017, around half of countries possess a financial sector that constitutes close to 10 percent or more of the market economy. These statistics reflect the growing role of the financial industry in aggregate economic activity.

Tables 2 and 3 report the model parameter estimates for finance and non-finance sectors respectively. *GFCF* and *EMP* indicate the use of quality-unadjusted capital and labor data. *CAPQ* and *LABQ* meanwhile refer to quality-adjusted capital and labor inputs. For each set of specification estimates in columns (1)-(4), we report i) average annual changes in physical and effective capital-labor ratios over the period in columns (5) and (6) as per equation (10), ii) predicted and actual average annual labor share changes in columns (7) and (8) as per equation (9), and iii) the corresponding prediction error in column (9). Our assessment of residual diagnostics points to weak cross-sectional dependence and stationarity.[15]

Column (1) across tables indicates that the elasticity of substitution between capital and labor is less than unity in both sectors. In particular, the null hypothesis of $\sigma = 1$ can be rejected at conventional significance levels and thus the Cobb-Douglas form for the production function. Second, we find that complementarity between the two factor inputs is stronger in the financial sector than the non-financial market economy i.e. $\sigma_F < \sigma_{NF}$. Across system estimates, the average substitution elasticity in finance is approximately 0.2, while that in non-finance is

[15] Test results available upon request. Cross-section dependence tests of Pesaran (2004, 2015) are employed, 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). Pesaran (2021) highlights that the assumption of independence can be adopted in finite samples if cross-section correlations are low. First generation panel unit root tests of Choi (2001) (Phillips-Perron Fisher) and Im *et al.* (2003) are executed on both the original and cross-sectionally demeaned residual series. Taking the possibility of cross-sectional dependence into account directly, the second generation panel unit root test examined is that of Pesaran (2007).

around 0.4.[16] While the difference is notable, complementarity in both sectors is still strong.

As estimates of $\lambda_L - \lambda_K$ are positive and predominantly statistically significant, Tables 2 and 3 (column (4)) emphasize that technical change in both sectors is net labor augmenting. Although labor-augmenting and capital-augmenting productivity growth, λ_L and λ_K respectively, tend to be greater in finance, labor-biased technical change appears to be more pronounced in non-finance. First, higher factor-augmenting productivity growth in finance can be explained by higher rents and profits in the sector.[17] This pushes more investment toward innovation in finance, thus ultimately raising the relative productivity of its inputs. Figure 2(a) indeed shows that real output per worker is higher in finance over time, with it rising more sharply in finance relative to non-finance. On average, the productivity measure in finance is about twice that of the non-financial sector. Using quality-adjusted labor that accounts for skill type and experience, Figure 2(b) meanwhile indicates that cumulative growth in finance's real output per effective worker is markedly stronger. Second, as non-finance is more labor intensive[18], its productivity growth will exhibit a heavier tilt toward labor-augmenting productivity, relative to that observed in finance. This trend aligns with the notion that technical change is directed toward scarce goods and inputs.

Column (5) shows positive average growth in the physical capital-labor ratio for both sectors, with non-finance exhibiting higher growth. However, as column (6) demonstrates, net labor-augmenting productivity growth in both sectors is generally sufficiently strong to more than offset the rising physical capital-labor ratio, such that the effective capital-labor ratio declines over time. The latter decline is weaker in finance. The combination of capital-labor complementarity and adequately labor-biased technical change in our model produces an intertemporally diminishing labor share in column (7). This is exactly what we observe in the

[16] This result makes sense as our data show that finance is more skilled labor intensive than non-finance.

[17] In the class of models that we examine, following Acemoglu and Guerrieri (2008), it is possible to endogenize technical change in each sector so that it depends on research expenditure by a continuum of monopolistically competitive firms.

[18] We find $\delta_{L0}^{NF} = 0.65$ compared to $\delta_{L0}^{F} = 0.55$ on average across countries.

data for both sectors as evidenced in column (8).

According to Beaudry *et al.* (2016), labor began to move down the occupational ladder into less skill-intensive roles after the dot com bubble burst in the early 2000s. The strength of this trend may have varied across sectors, with labor share dynamics correspondingly reflecting such compositional adjustments. We find that the fall in the share of labor in income in the financial sector is markedly smaller than that of the non-financial sector over the sample period. The cross-country average total decline in non-finance is 6.4 percent and about 1 percent in finance. The sectoral discrepancy in annual figures is quite often reflected in the predicted sectoral labor share changes (columns (7)-(8)). As column (8) reports, the labor share of income in non-finance has been decreasing on average across countries by around 0.3 percent per annum, and correspondingly by less than 0.1 percent in the financial sector (0.05 percent to be exact). We find in columns (7)-(8) that the annual labor share change across sectors is predicted in the right direction. While results tend to be generally consistent across i) quality-adjusted and quality-unadjusted data, and ii) NLSUR and GMM estimates, the lowest prediction errors are obtained in the case of GMM when all factor inputs are either quality adjusted ($CAPQ$, $LABQ$) or quality unadjusted ($GFCF$, EMP). Examining the latter set of estimates, we can in fact see that the predicted annual decline is almost perfectly in line with the actual decline in each sector. In the face of a falling effective capital-labor ratio, stronger capital-labor synergies and capital intensity, as found in finance, act to increase the absolute magnitude of the labor share change. What counters these effects in finance to produce a relatively smaller decline in its labor share is the sector's weaker net labor-augmenting productivity growth.

In summary, our results indicate that the canonical neoclassical model provides a useful first-order approximation of the functional distribution of income across finance and non-finance sectors in advanced economies. So far, our analysis has stressed the interaction of capital deepening and factor productivity dynamics in explaining sectoral labor share patterns, given factor intensities and substitution possibilities. Labor compositions across finance and non-finance, however, very likely play an important role in understanding the story. To gain a better appreciation of our benchmark findings, we next investigate how workforce skills shape trends in each sector.

5 Distributional Effects Within Labor

A decomposition of labor's share in income by skill type reveals that unskilled labor (L_U) is responsible for the decline in the overall labor share in each sector. Conversely, skilled labor (L_S) exacts an opposing force in sectoral shares, with a more pronounced impact in finance as demonstrated by Figure 3. The graph indicates that the cross-country weighted average skilled labor share in finance has increased by around 10 percentage points cumulatively over the sample period, in comparison to about 3 percentage points in non-finance. Skilled labor comprises workers that have a university degree and above, while unskilled labor represents workers below that threshold including those with some years of college.[19] In particular, we find that finance's skilled relative to unskilled labor share is increasing at a rate of around 6 percent per annum (p.a.) on average compared to only 2 percent p.a. in non-finance. A few factors drive this asymmetry across sectors and thus finance's growing relative aggregate labor share. At the more granular level, these include i) greater complementarity between skilled labor and capital in finance relative to non-finance; ii) weaker substitutability between unskilled labor and capital in non-finance relative to finance; and iii) a much stronger deterioration in "unskilled labor"-augmenting productivity in finance.

To obtain the deeper insights, we expand our framework to the following normalized nested CES model

$$Y_t = \psi Y_0 \left[\delta_{LU0} \left(e^{\lambda_{LU}(t-t_0)} \frac{L_{U,t}}{L_{U,0}} \right)^{\frac{\sigma-1}{\sigma}} + \delta_{X0} X_t^{\frac{(\sigma-1)\nu}{(\nu-1)\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{11}$$

[19] Data on labor by level of education are obtained from EU KLEMS and WIOD's Socio Economic Accounts. The reason why we do not differentiate between medium and low skilled labor in the unskilled cohort is because of significant differences in national education systems below the university grade which ultimately impair cross-country comparability.

where

$$X_t = \left[\delta_{LS0}\left(e^{\lambda_{LS}(t-t_0)}\frac{L_{S,t}}{L_{S,0}}\right)^{\frac{\nu-1}{\nu}} + \delta_{K0}\left(e^{\lambda_K(t-t_0)}\frac{K_t}{K_0}\right)^{\frac{\nu-1}{\nu}}\right]. \tag{12}$$

σ is the elasticity of substitution between unskilled labor and skilled labor or capital, while ν is the elasticity of substitution between skilled labor and capital. As before, λ_i is the rate of "factor i"-augmenting productivity growth and δ_{i0} is the average intensity of input i in the given level of production.[20] We do not nest skilled and unskilled labor in X as this would equate to the previously analyzed two factor model by not allowing capital growth to impart differential effects on the aforementioned labor types. Similarly, we do not nest unskilled labor with capital in the bottom level of the model as this would, counter-intuitively, equate substitutability between skilled labor and unskilled labor with substitutability between skilled labor and capital.[21]

The corresponding system of equations for estimation, in logarithmic form, is made up of the output function and three first-order conditions

$$\ln\frac{Y_t}{Y_0} = \ln\psi + \frac{\sigma}{\sigma-1}\ln\left(\delta_{LU0}\left(e^{\lambda_{LU}(t-t_0)}\frac{L_{U,t}}{L_{U,0}}\right)^{\frac{\sigma-1}{\sigma}} + \delta_{X0}X_t^{\frac{(\sigma-1)\nu}{(\nu-1)\sigma}}\right) \tag{13}$$

$$\ln r_{LU,t} = \frac{\sigma-1}{\sigma}\ln\psi + \ln\underbrace{\left(\frac{\delta_{LU0}Y_0}{L_{U,0}}\right)}_{r_{LU0}} + \frac{\sigma-1}{\sigma}\lambda_{LU}(t-t_0) + \frac{1}{\sigma}\left(\ln\frac{Y_t}{Y_0} - \ln\frac{L_{U,t}}{L_{U,0}}\right) \tag{14}$$

$$\ln r_{LS,t} = \frac{\sigma-1}{\sigma}\ln\psi + \ln\underbrace{\left(\frac{\delta_{X0}\delta_{LS0}Y_0}{L_{S,0}}\right)}_{r_{LS0}} + \frac{\nu-1}{\nu}\lambda_{LS}(t-t_0) + \frac{\sigma-\nu}{\sigma(\nu-1)}\ln X_t + \frac{1}{\sigma}\ln\frac{Y_t}{Y_0} - \frac{1}{\nu}\ln\frac{L_{S,t}}{L_{S,0}} \tag{15}$$

$$\ln r_{K,t} = \frac{\sigma-1}{\sigma}\ln\psi + \ln\underbrace{\left(\frac{\delta_{X0}\delta_{K0}Y_0}{K_0}\right)}_{r_{K0}} + \frac{\nu-1}{\nu}\lambda_K(t-t_0) + \frac{\sigma-\nu}{\sigma(\nu-1)}\ln X_t + \frac{1}{\sigma}\ln\frac{Y_t}{Y_0} - \frac{1}{\nu}\ln\frac{K_t}{K_0}. \tag{16}$$

[20] δ_{LS0} and δ_{K0} are the skilled labor and capital intensities in the production of compound input X, while $\delta_{X0}\delta_{LS0}$ and $\delta_{X0}\delta_{K0}$ are the skilled labor and capital intensities in the production of output Y.

[21] More generally, the $L_S(L_U, K)$ configuration of inputs yields slow parameter convergence in estimation and unrealistic model parameter estimates thus suggesting misspecification.

Subtracting equation (14) from equation (15) to obtain $\ln \frac{r_{LS,t}/r_{LS0}}{r_{LU,t}/r_{LU0}}$ and adding $\ln \frac{L_{S,t}/L_{S,0}}{L_{U,t}/L_{U,0}}$ on both sides of the log skill premium equation gives the skilled relative to unskilled labor share

$$\ln \frac{\omega_{LS,t}}{\omega_{LU,t}} = \left(\frac{\nu - 1}{\nu} \lambda_{LS} - \frac{\sigma - 1}{\sigma} \lambda_{LU} \right) (t - t_0) + \frac{\sigma - \nu}{\sigma(\nu - 1)} \ln X_t + \frac{1 - \sigma}{\sigma} \ln \frac{L_{U,t}}{L_{U,0}} - \frac{1 - \nu}{\nu} \ln \frac{L_{S,t}}{L_{S,0}}. \quad (17)$$

Differentiating equation (17) with respect to time at the point of normalization $t = t_0$, where $Z = X = F_{i,t}/F_{i,0} = 1$, and defining $g^N = \dot{N}/N \approx \ln N_{t_0+1} - \ln N_{t_0}$, the corresponding growth expression for the relative skilled labor share is

$$g^{\omega_{LS}/\omega_{LU}} = \underbrace{\frac{1 - \sigma}{\sigma} g^{L_U} - \left[\frac{\delta_{K0}}{\nu} + \frac{\delta_{LS0}}{\sigma} - 1 \right] g^{L_S}}_{relative\ \ supply} + \underbrace{\left[\frac{\delta_{K0}(\sigma - \nu)}{\sigma\nu} \right] g^K}_{capital\ \ growth} +$$

$$\underbrace{+ \left[\frac{1 - \sigma}{\sigma} \right] \lambda_{LU} + \left[\frac{\nu - 1}{\nu} + \frac{\delta_{LS0}(\sigma - \nu)}{\sigma\nu} \right] \lambda_{LS} + \left[\frac{\delta_{K0}(\sigma - \nu)}{\sigma\nu} \right] \lambda_K}_{technical\ \ change} . \quad (18)$$

Table 4 reports average model parameter values across estimators for finance and non-finance. We find in column (1) that $\sigma_F > 1 > \sigma_{NF}$ meaning that unskilled labor exhibits greater substitutability with skilled labor and capital in finance relative to non-finance. On the other hand, we find in column (2) that $\nu_F < \nu_{NF} < 1$ implying that complementarity between skilled labor and capital is stronger in the financial sector. Together, the results suggest that skilled labor drives complementarity between aggregate labor and capital in each sector, with unskilled labor imparting opposing effects. In particular, the former is more pronounced in finance where the skilled labor intensity is higher ($\delta^F_{X0}\delta^F_{LS0} = 0.29 > 0.20 = \delta^{NF}_{X0}\delta^{NF}_{LS0}$) while the latter effect is more pronounced in non-finance where the unskilled labor intensity is greater ($\delta^F_{LU} = 0.26 < 0.45 = \delta^{NF}_{LU}$). Column (3) in Table 4 also shows that finance's notably stronger deterioration in "unskilled labor"-augmenting productivity ($\lambda^F_{LU} < \lambda^{NF}_{LU}$) is responsible for the sector's weaker net labor-augmenting technical change in the two-factor framework.

To understand the implications of the estimates in Table 4 for the composition of sectoral labor shares, we turn to equation (18). For each sector, the equation links the evolution of the relative skilled labor share to the relative supply of skilled labor, capital growth, and technical change. The relations, as shown, are mediated by factor substitution elasticities, factor intensities, and rates of factor-augmenting productivity growth. Starting with the relative supply effect, we note that higher values of σ and ν raise the likelihood of relative (physical) skilled labor supply growth inducing increases in the relative skilled labor share. From the perspective of skilled labor, the higher estimates of σ make it more likely that increases in the input ($g^{L_S} > 0$) dominate corresponding decreases in the relative skilled wage due to easier substitution between labor types. At the same time, the lower estimates of ν make it less probable that a higher skilled labor supply more than offsets corresponding declines in skilled wages due to substitution between skilled labor and capital being more difficult. From the perspective of unskilled labor, gross substitutability between unskilled labor and remaining factor inputs ($\sigma > 1$) coupled with a falling supply of unskilled labor ($g^{L_U} < 0$) unequivocally implies a deterioration in the unskilled labor share. Using our estimates of the underlying model parameters, as scrutinized in Table 4, Table 5 computes average estimates of the effects highlighted in equation (18). For comparability across sectors, column (1) in Table 5 shows the relative supply impact for approximately equal increases in L_S and L_U of 1 percent. Thus, for marginal increases in the relative supply of skilled labor in the local neighborhood of $g^{L_U} \approx g^{L_S} \approx 0.01$, we find that the relative skilled labor share declines more strongly in finance. This reflects the larger disproportionate decrease in finance's relative skilled wage, driven by cross-sectoral differences in σ and ν.

For $g^K > 0$, the second term on the right-hand side of equation (18) highlights how physical capital deepening can impart heterogeneous effects across skilled and unskilled labor shares. The sign of the partial effect of g^K on the relative skilled labor share relies on the difference $\sigma - \nu$. Growth in the real stock of capital results in a positive effect if its use is more complementary with skilled compared to unskilled labor i.e. $\sigma > \nu$.[22] In this case, at a given relative supply of skills, the demand for skilled relative to unskilled labor rises and leads to an increase in relative skilled compensation. Despite similar real capital growth rates of around 2 percent p.a. across the two sectors, we would expect the associated effects to be notably stronger in finance given our sectoral estimates of σ and ν in Table 4. Based on these estimates, we find in column (2) of Table 5 that 1 percent growth in the real capital stock yields approximately 2 percent growth in finance's relative skilled compensation in contrast to 1 percent in the non-financial sector. The differential developments in sectoral labor returns are therefore partly attributable to the capital-skill complementarity channel. Intuitively, $\sigma_F > \sigma_{NF}$ implies that the sensitivity of the marginal product of unskilled labor (MPL_U) to capital growth is stronger in the non-financial sector. $\nu_F < \nu_{NF}$ meanwhile suggests that the marginal product of skilled labor (MPL_S) is more sensitive to capital growth in the financial sector. When each sector faces capital growth of the same magnitude, $\frac{MPL_S}{MPL_U}$ shows a larger increase in finance than non-finance, and thus we observe a higher relative finance demand for skilled labor.

Focusing on the third term of equation (18), we can see that the technical change effect is a model-parameters-weighted average of rates of factor-augmenting productivity growth. Examining the composition of technical change, we see that the stronger rate of capital-augmenting productivity growth in finance relative to non-finance ($\lambda_K^F > \lambda_K^{NF}$) increases more strongly the relative skilled labor share of finance. This occurs for the same reasons as for the relatively stronger effects of physical capital growth in finance. Overall, effective capital growth and its impact are more pronounced in the financial sector as can be gauged from the term $\left[\frac{\delta_{K0}(\sigma-\nu)}{\sigma\nu}\right](g^K + \lambda_K)$ after factorization in equation (18). The biggest cross-sectoral discrepancy in factor-augmenting productivity growth rates is found for unskilled labor (λ_{LU}). The relatively strong deterioration in finance's "unskilled labor"-augmenting productivity combined with the sector's more notable

[22] Grossman *et al.* (2017a) 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.

unskilled labor substitution possibilities ($\sigma_F > \sigma_{NF}$) imposes a strong reduction in finance's unskilled labor share. While $\lambda_{LU} < 0$ induces weaker unskilled labor productivity, implying a decline in its effective volume, and thus its return as factor demand weakens, a higher σ acts to make skilled labor productivity more resistant to such developments in unskilled labor. The net result therefore is an increase in relative skilled labor compensation. "Skilled labor"-augmenting productivity growth (λ_{LS}) moreover is stronger in finance. This, together with unskilled labor's lower sensitivity to productivity developments in other inputs in the sector, enhances finance's relative skilled labor share more strongly than in non-finance. Collectively, technical change increases the relative skilled labor share in finance by more than twice as much as in non-finance on average, as can be seen from column (3) in Table 5.

What about the cumulative impact of relative supply, capital growth, and technical change in each sector for observed factor input growth rates? When we numerically evaluate the full growth expression for relative skilled labor shares in equation (18) using actual average annual factor growth rates (g^i are given in Table 5 note), we find that our results are incredibly consistent with the data. More precisely, for given $\{\hat{\sigma}, \hat{\nu}, \hat{\lambda}_i, \delta_{i0}, g^i\}^\tau$, equation (18) projects an average annual increase of approximately 6 percent in finance's relative skilled labor share, while the corresponding p.a. growth rate is about 2 percent for non-finance. These predicted values fall exactly in line with the actual average growth rates of relative skilled labor shares across sectors, as seen in the data.

6 Conclusions

Labor share dynamics in the developed world have exhibited significant heterogeneity across the financial sector and non-financial market economy over the past two decades. Using a panel of thirty advanced economies and the neoclassical model of income distribution, we find that finance's attenuated labor share decline is consistent with the following characteristics of the sector: i) stronger capital-labor synergies and capital intensity and ii) a relatively weaker rate of net labor-augmenting technical change. Feature i) acts to inflate the absolute size of labor share changes while feature ii) counters the former effects by limiting decreases in the effective capital-labor ratio. Taken together, this configuration yields the smaller labor share decline in finance. Notably, we are able to predict both the direction and sizes of annual labor share changes across both sectors.

Studying the distributional effects within labor, we find that unskilled labor accounts for declining sectoral labor shares while skilled labor alleviates this downward pressure more notably in finance. Stronger synergies between skilled labor and capital in finance drive the more pronounced complementarity between overall labor and capital in the sector. This contributes to the stronger capital growth effects on the relative skilled labor share in finance. In relation to technical change, unskilled labor is found to be the principal reason underlying finance's weaker net labor-augmenting productivity growth. Jointly, *relative skilled labor supply*, *capital growth*, and *technical change* channels project skilled relative to unskilled labor share changes across sectors that are completely in line with those observed in the data.

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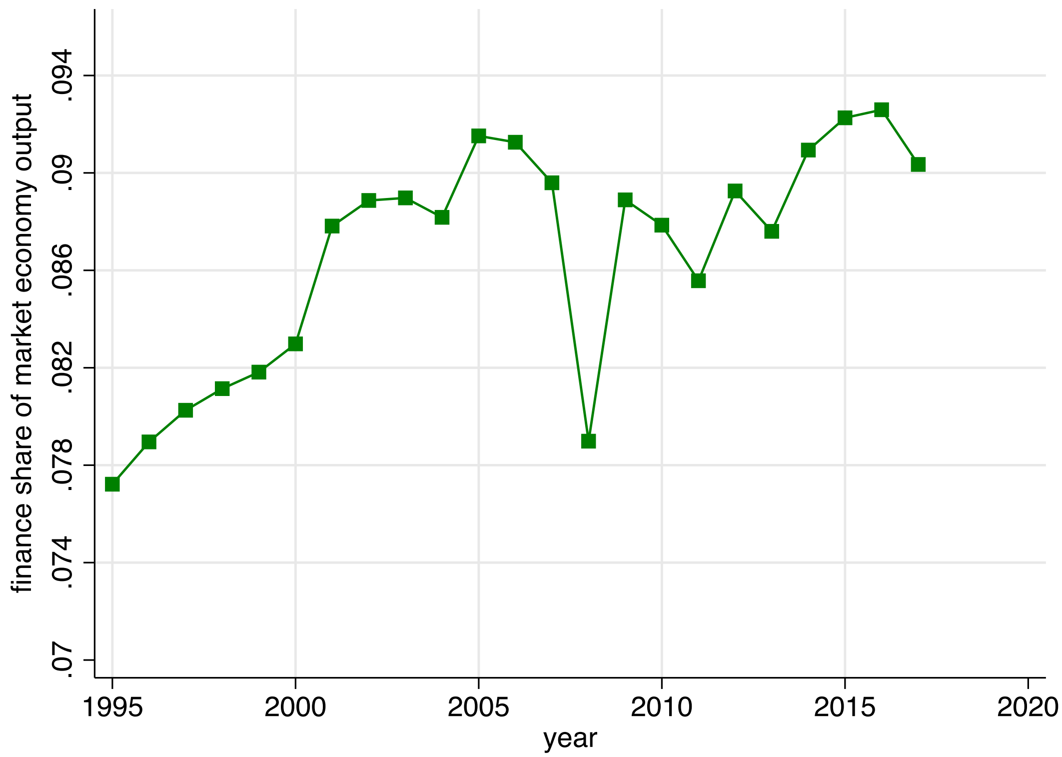
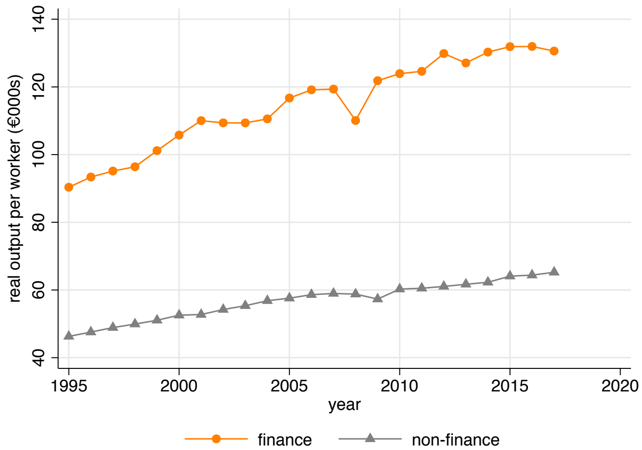
Figure 1: Financial Sector Growth

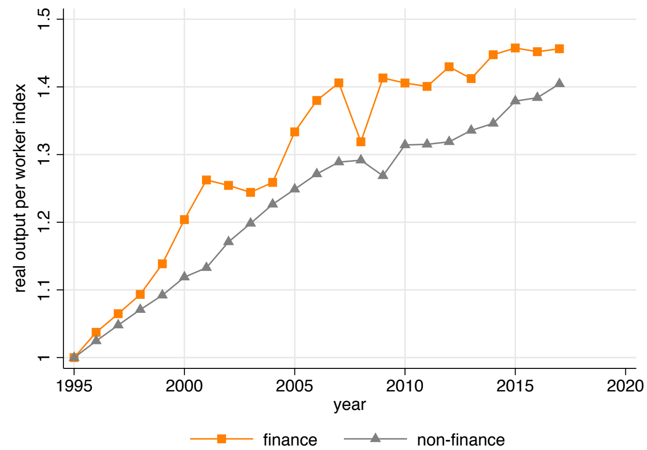


Notes: The plot gives the cross-country weighted average share of finance in market economy euro-denominated valued added. Finance includes insurance, securities, and credit intermediation related activities. The sample of countries comprises the EU28, U.S. and Japan. Author calculations based on EU KLEMS statistical database.

Figure 2: Sectoral Labor Productivities



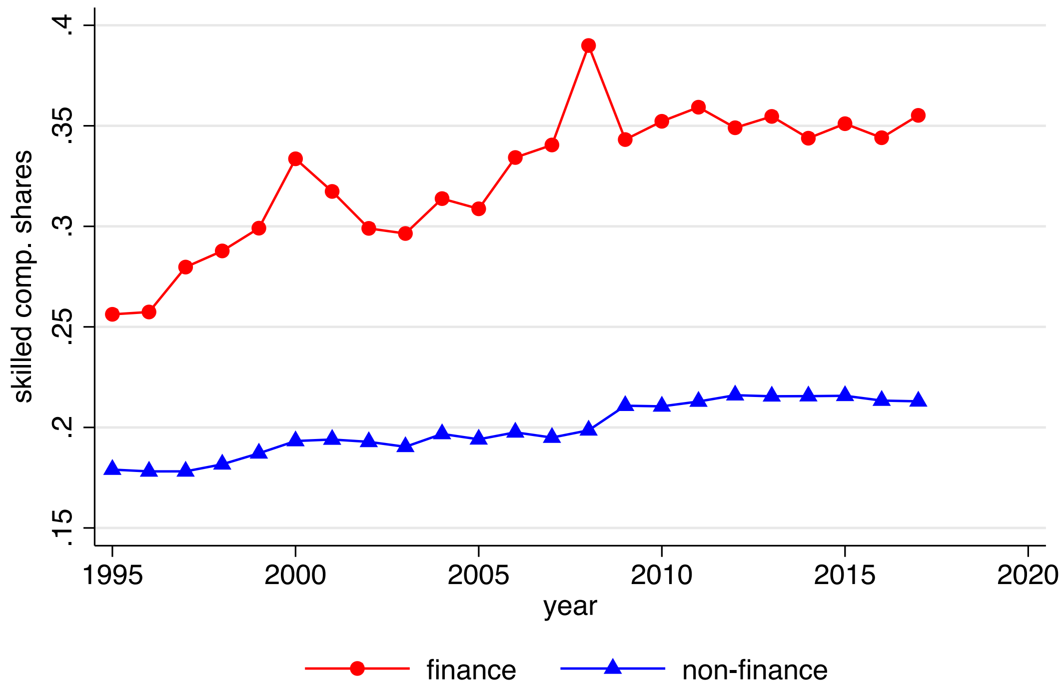
(a)



(b)

Notes: Plots give cross-country weighted average ratios. In a given year each country's weight is its share in cross-section full sample finance or non-finance euro-denominated value added. Real output per effective worker employs quality-adjusted labor data, which takes into account skill type and experience. Author calculations based on EU KLEMS statistical database.

Figure 3: Sectoral Skilled Compensation Shares



Notes: "Skilled compensation share" measures the cross-country weighted average share of skilled labor in value added in either the financial or non-financial sector. In a given year each country's weight is its share in cross-section full sample finance or non-finance euro-denominated value added. Author calculations based on EU KLEMS statistical database.

Table 1: Financial Sector Size and Growth By Country

Country	(1) $\frac{Y^F_{1995}}{Y_{1995}}$	(2) $\frac{Y^F_{2017}}{Y_{2017}}$	(3) $\%\Delta\left(\frac{Y^F}{Y}\right)$
Austria	0.043	0.058	34.9
Belgium	0.086	0.089	3.5
Bulgaria	0.031	0.095	206.5
Croatia	0.054	0.084	55.6
Cyprus	0.069	0.159	130.4
Czech Republic	0.048	0.069	43.8
Denmark	0.081	0.086	6.2
Estonia	0.038	0.052	36.9
Finland	0.060	0.044	-26.7
France	0.064	0.073	14.1
Germany	0.066	0.054	-18.2
Greece	0.060	0.070	16.7
Hungary	0.064	0.049	-23.4
Ireland	0.116	0.133	15.3
Italy	0.064	0.080	25.0
Japan	0.080	0.080	0.0
Latvia	0.047	0.054	14.9
Lithuania	0.028	0.028	0.0
Luxembourg	0.320	0.370	15.6
Malta	0.037	0.078	110.8
Netherlands	0.100	0.103	3.0
Poland	0.030	0.060	100.0
Portugal	0.049	0.067	36.7
Romania	0.086	0.040	-53.5
Slovakia	0.077	0.040	-48.1
Slovenia	0.046	0.056	21.7
Spain	0.040	0.050	25.0
Sweden	0.056	0.062	10.7
United Kingdom	0.091	0.112	23.1
United States	0.094	0.115	22.4
average	*0.071*	*0.084*	*26.8*
median	*0.060*	*0.070*	*17.0*

Notes: $\frac{Y^F_t}{Y_t}$ is the share of finance in market economy output at time t. $\%\Delta\left(\frac{Y^F}{Y}\right)$ is the percentage change in share between 1995 and 2017. Cross-country medians and unweighted cross-country averages reported.

Table 2: System Estimates for Financial Sector

Regression	**Parameter Estimates**				**Capital-Labor Ratio Changes**		**Labor Share Changes**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	σ	λ_L	λ_K	$\lambda_L - \lambda_K$	$d\ln k$	$d\ln\tilde{k}$	$(d\ln\omega_L)^P$	$(d\ln\omega_L)^A$	(8) - (7)
System: NLSUR									
L^{EMP}, K^{GFCF}	0.238***	0.025***	0.010**	0.015***	0.013	-0.002	-0.003	-0.001	0.002
	(0.048)	(0.004)	(0.005)	(0.005)					
L^{EMP}, K^{CAPQ}	0.162***	0.023***	0.017***	0.007	0.008	0.001	0.002	-0.001	-0.003
	(0.048)	(0.004)	(0.006)	(0.005)					
L^{LABQ}, K^{GFCF}	0.277***	0.027***	0.009*	0.018***	0.011	-0.007	-0.008	-0.001	0.007
	(0.054)	(0.005)	(0.005)	(0.006)					
L^{LABQ}, K^{CAPQ}	0.210***	0.026***	0.016***	0.010**	0.011	0.001	0.002	-0.001	-0.003
	(0.056)	(0.005)	(0.006)	(0.005)					
System: GMM									
L^{EMP}, K^{GFCF}	0.281***	0.024***	0.011***	0.013***	0.013	-0.000	-0.000	-0.001	-0.001
	(0.057)	(0.004)	(0.004)	(0.005)					
L^{EMP}, K^{CAPQ}	0.256***	0.023***	0.012**	0.011**	0.008	-0.003	-0.004	-0.001	0.003
	(0.040)	(0.004)	(0.005)	(0.005)					
L^{LABQ}, K^{GFCF}	0.327***	0.027***	0.008**	0.019***	0.011	-0.008	-0.007	-0.001	0.006
	(0.057)	(0.004)	(0.004)	(0.006)					
L^{LABQ}, K^{CAPQ}	0.233***	0.028***	0.016***	0.012***	0.011	-0.001	-0.001	-0.001	0.000
	(0.045)	(0.005)	(0.006)	(0.004)					

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Pooled normalized panel regressions employed. Using pooled averages, distribution parameters at the point of normalization are $\{\delta_{L0} = 0.55, \delta_{K0} = 0.45\}^F$. Robust standard errors in parentheses. Average annual changes reported. One to three years of lags are considered as instruments in GMM estimation. Sargan-Hansen test post GMM estimation is unable to reject the null hypothesis of valid overidentifying restrictions. Instrument proliferation is not an issue in our estimation with GMM. Statistical database of EU KLEMS employed.

Table 3: System Estimates for Non-Financial Market Economy

Regression	**Parameter Estimates**				**Capital-Labor Ratio Changes**		**Labor Share Changes**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	σ	λ_L	λ_K	$\lambda_L - \lambda_K$	$d\ln k$	$d\ln \tilde{k}$	$(d\ln \omega_L)^P$	$(d\ln \omega_L)^A$	(8) - (7)
System: NLSUR									
L^{EMP}, K^{GFCF}	0.418***	0.021***	−0.004	0.025***	0.017	-0.008	-0.004	-0.003	0.001
	(0.167)	(0.004)	(0.005)	(0.007)					
L^{EMP}, K^{CAPQ}	0.442***	0.024***	−0.011*	0.035***	0.016	-0.019	-0.008	-0.003	0.005
	(0.140)	(0.004)	(0.006)	(0.009)					
L^{LABQ}, K^{GFCF}	0.404***	0.020***	−0.004	0.024***	0.015	-0.009	-0.005	-0.003	0.002
	(0.153)	(0.003)	(0.005)	(0.006)					
L^{LABQ}, K^{CAPQ}	0.418***	0.022***	−0.011*	0.033***	0.020	-0.013	-0.006	-0.003	0.003
	(0.128)	(0.004)	(0.006)	(0.008)					
System: GMM									
L^{EMP}, K^{GFCF}	0.365***	0.019***	−0.002	0.021***	0.017	-0.004	-0.003	-0.003	-0.000
	(0.143)	(0.003)	(0.004)	(0.005)					
L^{EMP}, K^{CAPQ}	0.435***	0.021***	−0.006	0.027***	0.016	-0.011	-0.005	-0.003	0.002
	(0.142)	(0.003)	(0.005)	(0.007)					
L^{LABQ}, K^{GFCF}	0.369***	0.018***	−0.002	0.020***	0.015	-0.005	-0.003	-0.003	0.000
	(0.119)	(0.003)	(0.004)	(0.005)					
L^{LABQ}, K^{CAPQ}	0.408***	0.020***	−0.007	0.027***	0.020	-0.007	-0.004	-0.003	0.001
	(0.122)	(0.003)	(0.005)	(0.006)					

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Pooled normalized panel regressions employed. Using pooled averages, distribution parameters at the point of normalization are $\{\delta_{L0} = 0.65, \delta_{K0} = 0.35\}^{NF}$. Robust standard errors in parentheses. Average annual changes reported. One to three years of lags are considered as instruments in GMM estimation. Sargan-Hansen test post GMM estimation is unable to reject the null hypothesis of valid overidentifying restrictions. Instrument proliferation is not an issue in our estimation with GMM. Statistical database of EU KLEMS employed.

Table 4: Three-Factor Average System Estimates

Regression	**Parameter Estimates**				
	(1)	(2)	(3)	(4)	(5)
	σ	ν	λ_{LU}	λ_{LS}	λ_K
Finance					
$L_U;\sigma;(L_S;\nu;K)$	1.350***	0.252***	−0.108**	0.039***	0.066***
	(0.114)	(0.027)	(0.038)	(0.011)	(0.011)
Non-Finance					
$L_U;\sigma;(L_S;\nu;K)$	0.949***	0.350***	0.004	0.006	0.016**
	(0.051)	(0.117)	(0.010)	(0.009)	(0.008)

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Average model parameter estimates across NLSUR and GMM systems (using pooled normalized panel equations) are reported for each sector. Robust standard errors employed. The null hypotheses $\sigma = \nu$; $\sigma = 1$; $\nu = 1$; and $\lambda_{LU} = \lambda_{LS} = \lambda_K$ are rejected at conventional significance levels in both NLSUR and GMM system results. 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. Using pooled averages, distribution parameters at point of normalization are $\{\delta_{LU0} = 0.26, \delta_{X0} = 0.74, \delta_{LS0} = 0.39, \delta_{K0} = 0.61\}^F$ and $\{\delta_{LU0} = 0.45, \delta_{X0} = 0.55, \delta_{LS0} = 0.36, \delta_{K0} = 0.64\}^{NF}$. Statistical database of EU KLEMS employed.

Table 5: Average Relative Supply, Capital Growth, and Technical Change Effects

Sector	(1) RS	(2) KLC	(3) TC
Finance	-2.231^{***}	2.231^{***}	0.095^{***}
	(0.317)	(0.317)	(0.015)
Non-Finance	-1.320^{*}	1.320^{*}	0.036^{***}
	(0.714)	(0.714)	(0.011)

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Effects are on relative skilled labor share and are computed using equation (18). Average effects across NLSUR and GMM system based estimates are reported. Standard errors constructed via delta method in parentheses. "RS" is the relative supply of skilled labor effect in the baseline lower bound case of approximately equal growth rates of around 1% across skilled and unskilled labor i.e. $g^{L_U} \approx g^{L_S} \approx 0.01$ for comparability across sectors. "KLC" is the capital growth effect for $g^K = 0.01$ (1%), as mediated by the degree of complementarity between aggregate capital and skilled/unskilled labor. "TC" is the constant annual technical change effect. Pooled average (over countries and time) annual factor growth rates, $g^f = d\ln f \ \forall f \in \{L_U, L_S, K\}$, in finance (F) and non-finance (NF) are $\{g^{L_U} = -0.020, g^{L_S} = 0.044, g^K = 0.019\}^F$ and $\{g^{L_U} = -0.000, g^{L_S} = 0.031, g^K = 0.023\}^{NF}$ respectively.