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Abstract

Across the developed world, we find that labor's share of income at the sectoral level has experienced a much lower decline in finance than in the remainder of the market economy. We examine how well these heterogeneous sectoral dynamics can be explained by the neoclassical growth model. The framework is able to predict the direction and magnitude of labor share changes in both finance and non-finance through a combination of capital-labor complementarity and net labor-augmenting technical change. The underlying supply-side decomposition reveals that the lower labor share decline in finance is a reflection of its weaker net labor-augmenting productivity growth. The latter counters the stronger capital-labor synergies and capital intensity in the sector, which act to inflate the absolute size of labor share changes. Labor- and capital-biased productivity growth both tend to be higher in finance consistent with higher profitability in the industry.

Keywords: finance, labor share, 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), automation (Acemoglu and Restrepo, 2018, 2020), and the rise of superstar firms (Autor *et al.*, 2020). 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 disparity 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).

In our paper, we adopt a different approach and examine whether an economic growth perspective can offer insight into finance's heterogeneous evolution of the labor share. Across a panel of thirty advanced economies, we find that the neoclassical growth model is able to predict the direction of and, moreover, the discrepancy in labor share 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).[1] 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

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

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.

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. Finally, section 5 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

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

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

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

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. $A_{L,\tau}$ 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 are permitted to differ across sectors along with initial productivity levels. 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 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.[2]

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

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

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

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

[2] 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.

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

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

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 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 $g^{\omega_L/\omega_K} = \frac{\sigma-1}{\sigma}(g^L - g^K + \lambda_L - \lambda_K) = \frac{1-\sigma}{\sigma} g^{\tilde{k}}$.

According to the Monte Carlo analysis of León-Ledesma *et al.* (2010), 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).[3]

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

[3] 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.

nations over the period 1995-2017.[4] The data are aligned with the ISIC 4 (NACE 2) industry classification scheme and the new European System of National Accounts (ESA 2010).

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 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).[5] The sum of factor shares in value added equals unity.

The production function and corresponding optimality conditions 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). 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.

4 Empirical Analysis

Tables 1 and 2 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 specifi-

[4] 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).

[5] 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.

cation 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.[6]

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 around 0.4.[7] 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 1 and 2 (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. This pushes more investment toward innovation in finance, thus ultimately raising the relative productivity of its inputs. Second, as non-finance is more labor intensive[8], 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 data for both sectors as evidenced in column (8).

According to Beaudry *et al.* (2016), labor began to move down the occupational ladder into

[6]Test results available upon request.

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

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

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.

5 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 growth framework, 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.

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Table 1: 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. Statistical database of EU KLEMS employed.

Table 2: 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. Statistical database of EU KLEMS employed.