On the Principle of Second Best in Labor Markets

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Abstract

This paper presents an integrated framework to identify the determinants of growth in jobs, wages, and wage inequality using harmonized firm-level data for 13 European and Central Asian countries during the period 2006-2024. The paper shows that policies that increase firms' revenues are more effective than those that reduce labor costs to generate new jobs. Reducing sales taxes, rather than labor taxes is more effective to raise employment. A 1 p.p reduction in sales taxes increases jobs by 0.07% percent. Allowing imperfect competition in labor and product markets also increase jobs. But the effect of markups on employment is 14.3 times larger than that of markdowns. The paper also shows that imperfect competition both in labor and product markets are relevant to explain jobs, wages, and wage dispersion. The results show that if imperfect competition in labor markets cannot be addressed, then it's better to have imperfect competition in product markets, as the positive effect of markdowns on jobs is *exacerbated* by markups, while the negative effect on wages is *attenuated* by them. Equity-wise, allowing imperfect competition in *both* markets is a better policy choice than allowing monopolistic or oligopolist market structures only in the labor market.

Keywords: jobs, wages, wage inequality.

JEL Codes: J21, J23, J31, L12, L13.

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1 Introduction

Europe and Central Asia's (ECA hereafter) major structural challenges are still indelible, despite a decade of worldwide progress. Creating more and better jobs are still at the cornerstone of improving living standards, as some economies are failing to do so or to reallocate workers to high-wage jobs (Donovan et al., 2023). The employment rate today, 55%, is slightly higher than that in 2014, 52% (Arias et al., 2014; Criscuolo et al., 2014), while the wage gap with the U.S has worsened since the global financial crisis. Wage inequality has increased, with skill differentiation not being enough to fully explain wage dispersion. What has kept ECA trapped in a low-number-of-good-jobs state compared to its potential? While this question remains still unanswered, research aimed at rationalizing related findings has shifted focus from skills upgrading aspects to industrial organization factors[1] including the role of labor market power, imperfect pass-through of productivity shocks to employment and wages, and unbalanced rent-sharing between employees and employers.

Productivity shocks can be a key driver of labor demand and wage changes in highly responsive environments. When positive, they increase the value of the marginal product of labor and encourage firms to hire more workers and pay them more. Firms in ECA have recently been exposed to several productivity shocks of more persistent nature than originally anticipated (e.g., Covid-19). They have also been affected by global trends. Some of them are productivity enhancing (e.g.,digitization), while others not so much (e.g., climate change). To take advantage of the employment-related growing opportunities that productivity-enhancing shocks and trends provide, firms in the region must operate in frictionless environments, where they can quickly adjust the labor demand, scale up output, and maximize profits (Hopenhayn and Rogerson, 1993; Ljungqvist and Sargent, 1998; Kuhn and Jung, 2015; Engbom, 2022). How responsive ECA employment and wages are to productivity shocks is, however, still unknown. Several factors can affect the pass-through of productivity gains to employment and wage gains. Sales and factor taxes are one of them. They can also alter rent-sharing and tunneling problems. That is, how these gains are distributed between managers and workers.

Distributional concerns also include preoccupation for increased wage inequality and the drivers behind it. While evidence for the U.S shows that this is a between more than a within sectorial phenomenon (Haltiwanger et al., 2013; Caselli, 2005; Lagakos, 2020), indirect evidence for Europe suggests the opposite (cite Andrew et al.,). More importantly, there is currently a debate about the potential drivers rationalizing this finding, as evidence for ECA shows a lot of wage dispersion, even within very narrowly defined labor markets, where skills are not enough to explain wage inequality (cite WB).

The objective of this paper is threefold. Fist, we analyze the determinants of the pass-through of productivity gains to jobs and wage growth in an integrated framework that takes into consideration labor and product markets, bringing industrial organization factors, as well as policies such as sales and factor taxes into it. We also study if the findings align with the predictions of standard monopolistic

[1]See Card et al. (2018) for a literature review).

competition models and if not, what are the policy insights from it. Second, we present evidence for a large sample of European and Central Asian countries, while most of the literature is U.S-centric. This allows us to provide a broader characterization of the topic and understand if and how the results vary along the development path. Third, we estimate what factors matter most to explain wage inequality and analyze if rents are equally shared between managers and workers or if tunneling problems, potentially exacerbated by the effect of taxes, unbalance their distribution. In doing so, we use harmonized micro data (cite) covering 936,333 firms on average per year from 13 countries during the period 2006-2024.

Our findings shows that industrial organization aspects are relevant to explain jobs, wages, and wage inequality. The latter includes productivity shocks, idiosyncratic demand shocks, markups and markdowns as well as sales and factor taxes. The paper shows that productivity growth in ECA is labor saving, the tfp-wage pass-through is incomplete, and tfp differences across firms is the most relevant variable to explain wage inequality. Policy-wise, the paper shows that reducing sales taxes is more effective than declining labor costs to foster jobs growth, although firms pass part of the tax burden to workers. Thus, increasing income inequality. The findings render support to the principle of the second best (Bhagwati, 1962; Lipsey and Lancaster, 1956) in labor markets, as allowing imperfect competition in *both* labor and product markets is a better policy choice to create jobs, increase wages, and reduce inequality than allowing monopolistic or oligopolistic market structures *only* in labor markets.

Our paper relates to several strands of research. The first one focuses on the creation (or destruction) of jobs that technological change brought about. It is related to the debate about the effects of digitization and robotization on job destruction and skill-biased labor demand (Autor, 2015; Autor et al., 2020; Autor and Salomons, 2018; Acemoglu and Restrepo, 2018, 2019, 2020; World Bank, 2019). The evidence shows that while technological change can be labor saving in the short run, general equilibrium effects, which operate through wage reductions can increase labor demand in the long run.

A second strand of research focus on the effect of imperfect competition in labor markets on employment and wages. Using data for Brazil, Carvalho et al. (2023) rely on quasi-experimental variation through random auction design to infer imperfect competition in labor markets. Using information on random-stop auctions, they identify idiosyncratic demand shocks and estimate the pass-through to wages and employment. They also study how rival firms react to winners' behavior. The author shows that bid winners increase wages and employment, while rival firms react by increasing wages but not their size. In the same line of research, Garin and Silvério (2023) study wage responses to demand shocks to explain heterogeneity of wages across firms in Portugal. They show that firms pass idiosyncratic shocks to wage growth, implying a dependence of workers' compensation on non-competitive quasi-rents.

Baker et al. (2023) extend classical settings of imperfect competition in labor markets to incorporate imperfect competition in product markets aiming to analyze how the interaction between them affects the degree of market power. The authors show that market power in one market is attenuated by the presence of market power in another market. Therefore, limiting firms' ability to set large markdowns and increasing rent-sharing. Berger et al., (2022) presents a model of oligopolistic competition in labor markets to rationalize the finding that few firms in the U.S concentrate most of the employment. In their model, firms set wages and compete for workers. Labor market power is a function of labor shares and two parameters that govern the easiness of workers' reallocation across and within sectors. The authors show that in settings like this one, there is imperfect productivity-wage pass-through, which causes welfare losses of 7.6 percent. Lamadon et al. (2022) present a model, where heterogeneous workers' preferences and firms' amenities, create through sorting, vertical and horizontal differentiation, imperfect competition in labor markets, and thus wage-setting power and rents.

A third strand of research analyzes the determinants of wage dispersion. Recent work for 20 OECD countries (OECD 2021) shows, using matched employer-employee data, a minor role for skills to explain wage dispersion. The paper shows that one half of wage inequality is explained by differences in wages between firms, with one third due to firms' wage-setting practices that vary across countries, depending on the type of collective bargaining process (decentralized or not) and the cost of job mobility. Decker et al. (2020) shows that the increase in wage dispersion in the U.S is a between sectorial phenomenon more than a within one, with the ICT sector contributing the most to enlarge the wage gap. In addition, correlated wedges have also increased productivity dispersion and wage inequality in the U.S.

Previous work by Autor et al. (2003) emphasizes the role of technological progress in rationalizing the increase of inequality in the U.S. The authors argue that technological change replace workers that perform routine tasks and bias the labor demand towards high-skilled workers. As a result, there is job polarization and wage inequality increases. Piketty and Saez (2003) shows that the share of top income display a U-shaped pattern, opposing Kuznets' predictions that inequality should exhibit an inverse U-shaped relationship with the development process because of industrialization. The authors shows that the increase in top income shares is the direct consequence of the surge in top wages, as capital owners, who have been hit hardly with shocks (Great depression and World War II), were not able to recover their income partly due to estate taxation. This paper adds to the literature by providing a broader characterization of how jobs, wages, and wage inequality respond to industrial organization factors using an integrated framework and data for 13 European and Central Asian countries.

The paper is organized as follows. Section II discusses the data and the variables we calculate to conduct the analysis. Section III presents the main findings. The last section concludes.

2 Data

To conduct the analysis, we work with a harmonized firm-level panel dataset (Iacovone et al., 2025), which contains information for 13 countries (see Table 1) and an average of 936,333 firms per year (see Table 2) during the period 2006-2024. Given that the contribution of this paper is empirical, we rely on well established theories and methodologies to construct the variables of interest.

We estimate total factor productivity (TFP hereafter) following the Levinsohn and Petrin (2003) methodology, which uses materials as the proxy variable to identify the production function elasticities and thus estimate unbiasely TFP. We recover from Hsieh and Klenow (2009) theory the wedges, specifically sales tax and relative factor taxes. We follow Syverson (2024) to calculate markups as the inverse of one minus profits' share of revenue times the scale elasticity that we assume is equal to 1. Then, we use the production function approach by Asker et al. (2014) to calculate markdowns as the ratio between the output-labor elasticity to the share of labor costs on total production cost. Table 3 presents summary statistics of the main variables. To identify the effects on jobs, wages, and wage inequality we lagged the explanatory variables and employ three ways fixed effects to control for country, sector, and regional trends. We also include firm fixed effects to control for time invariant wage-setting practices, determinants of internal labor markets, firms' bargaining power, amenity differentiation across firms, firms' anti-competitive conduct in labor markets, and sorting. The three estimated specifications are as follows:

$$\begin{aligned}\log(\text{Employment}_t) \quad = \quad & \alpha + \beta_1 \log(\text{Wage}_{t-1}) + \beta_2 \log(\text{TFP}_{t-1}) + \beta_3 \log(\text{TFP}_{t-1}) \times \log(\text{tax}^K_{t-1}/\text{tax}^L_{t-1}) \\ & + \beta_4 \log(\text{TFP}_{t-1}) \times \log(1 - \text{tax}^S_{t-1}) + \beta_5 \log(\text{tax}^K_{t-1}/\text{tax}^L_{t-1}) + \beta_6 \log(1 - \text{tax}^S_{t-1}) \\ & + \beta_7 \log(\text{Markdown}_{t-1}) + \beta_8 \log(\text{Markup}_{t-1}) + \beta_9 \log(\text{Markdown}_{t-1}) \times \log(\text{Markup}_{t-1})\end{aligned} \tag{1}$$

$$\begin{aligned}\log(\text{Wage}_t) \quad = \quad & \alpha + \beta_1 \log(\text{TFP}_{t-1}) + \beta_2 \log(\text{TFP}_{t-1}) \times \log(\text{tax}^K_{t-1}/\text{tax}^L_{t-1}) + \beta_3 \log(\text{TFP}_{t-1}) \times \log(1 - \text{tax}^S_{t-1}) \\ & + \beta_4 \log(\text{tax}^K_{t-1}/\text{tax}^L_{t-1}) + \beta_5 \log(1 - \text{tax}^S_{t-1}) + \beta_6 \log(\text{Sales}_{t-1}) + \beta_7 \log(\text{Markdown}_{t-1}) \\ & + \beta_8 \log(\text{Markup}_{t-1}) + \beta_9 \log(\text{Markdown}_{t-1}) \times \log(\text{Markup}_{t-1})\end{aligned} \tag{2}$$

$$\begin{aligned}\text{SD}(\log(\text{Wage}_t)) \quad = \quad & \alpha + \beta_1 \text{SD}(\log(\text{TFP}_{t-1})) + \beta_2 \text{SD}(\log(\text{TFP}_{t-1})) \times \text{SD}(\log(\text{tax}^K_{t-1}/\text{tax}^L_{t-1})) \\ & + \beta_3 \text{SD}(\log(\text{TFP}_{t-1})) \times \text{SD}(\log(1 - \text{tax}^S_{t-1})) + \beta_4 \text{SD}(\log(\text{tax}^K_{t-1}/\text{tax}^L_{t-1})) \\ & + \beta_5 \text{SD}(\log(1 - \text{tax}^S_{t-1})) + \beta_6 \text{SD}(\log(\text{Sales}_{t-1})) + \beta_7 \text{SD}(\log(\text{Markdown}_{t-1})) \\ & + \beta_8 \text{SD}(\log(\text{Markup}_{t-1})) + \beta_9 \text{SD}(\log(\text{Markdown}_{t-1})) \times \text{SD}(\log(\text{Markup}_{t-1}))\end{aligned} \tag{3}$$

where SD stands for wage dispersion.

3 Results

This section starts with the analysis of jobs determinants. It follows with the study of wage drivers. It concludes by exploring wage inequality.

3.1 Explaining job growth

We start this section by analyzing the determinants of employment growth. Table 4 presents the results and Table 5 displays the marginal effect for the average firm. Some of the findings go along the lines of what is expected according to labor market theory, while others like wages do not. Without taking into account the effect of sales and factor taxes, productivity growth is labor saving due to workers-substitutable technological progress. Increases in sales taxes, exacerbate the negative effect of productivity growth on employment, suggesting an underlying theory with labor demand in equilibrium given as in equation (4), where sales and factor wedges tax disproportionately more high productivity (A_{it}) firms. For the average firm, the tfp-jobs pass-through elasticity is -0.95%. More importantly, reducing sales taxes rather than labor taxes is most effective to increase jobs. A 1 p.p reduction in sales taxes increases jobs by 0.07% percent.

$$L^*_{it} = f(A_{it}, (1 - tax^S)^{ln(A_{it})}, (\frac{tax^K}{tax^L})^{ln(A_{it})}, \mu, \eta, \mu * \eta, w, r, \alpha, \beta) \tag{4}$$

Table 5 shows that despite the relevance of markdowns, η , and markups, μ, to create jobs–as they raise the value of the marginal product of labor and labor demand–the effect of markups on employment is 14.3 times larger than that of markdowns. A finding somehow related to our previous result, which shows that policies that increase firms' revenues are more effective than those that reduce labor costs to generate new jobs. There is also a welfare-jobs trade-off, as market power in one market *exacerbates* the effect of market power in the other market. Jobs-wise, it is better to have imperfect competition in labor and product markets than have it only in the labor market.

Jobs responds to the analyzed drivers in the manufacturing and low-skill service sectors as in the whole sample. There are, however, important differences between high skill sectors. The tfp-jobs pass-through is 4.15 times higher in the global innovator sector than in the high skill social service one. Markups and markdowns increase jobs in the first sector but they reduce it in the second one. Wages decline in both sectors with imperfect competition in labor and product markets. However, joint market power attenuates the wage decline in the global innovator sector, while it has no effect on the social service one. There is no sector for which a reduction in labor taxes translate into more jobs. Reductions in sales taxes increases jobs in non-service sectors and low-skill domestic service one. This type of taxes are not a relevant source of job creation in the global innovator sector. Their reductions destroy jobs in the social service one.

Results also vary along the development path. There are relevant differences in the direction and magnitude of the estimated effects between the most and the least advanced cluster of countries.[2] Higher wages reduce the labor in equilibrium for less developed economies, but it has the opposite effect in most advanced clusters. While markdowns have a positive effect on employment growth for the most developed cluster, it has a negative effect for the rest. Imperfect competition in product markets is irrelevant to affect job growth in the group of less advanced economies.

3.2 Explaining wage growth

Analyzing how jobs and wages respond to imperfect competition is key to understand the joint effect of market power on labor dynamics. Markups increase the value of workers' marginal product and wages, while markdowns reduce their cost. As a result, wages increase. However, due to imperfect competition in labor markets, wages decline (Table 6). But this decline is lower when firms operate in imperfectly competitive markets, as firms need to retain workers to exploit their advantage in product markets. Consequently, contrary to what we observe with jobs, market power in the product market *attenuates* the declining wage effect of market power in the labor market. The impact of markups on wages is 2.1 larger than that of markdowns. A 1 percentage point increase in markups reduces wages by 38.1%, while the elasticity is 18.2% for markdowns. Distributional-wise, the results highlight the need to prioritize reforms in product markets first instead of labor market ones to pave the road for complete pass-through of tfp-gains to workers.

Another important question when analyzing labor market dynamics is that related to distributional aspects. That is, what percentage of the productivity gains are passed-through to workers and does the degree of rent-sharing. Table 6 and 7 show that there is incomplete pass-through, as only half of the productivity gains are passed-through to wages. In other words, managers retain 50% of the gains from making the firm more efficient and pass only half of those gains to their workers. Labor taxes, however, reduce the tfp-wage pass-through by roughly 1.4%; while sales taxes increase it by 3.2%. Sales taxes have a regressive effect on wages with elasticity of 0.06%. In other words, employers pass-through part of the tax government imposes on firms' revenues to employees by reducing their wages. By contrast, labor taxes are progressive, as they increase wages by 0.08%. As mentioned before, imperfect competition in labor and product markets reduce wages, while their interaction attenuates the effect.

Highly dynamic sectors like global innovator and social services display the highest pass-through of tfp and demand shocks to wages. But they also exhibit the highest sales tax-wage pass-through. The global innovator and social service sector display almost perfect tfp-wage pass-through due to talent retention, 0.862 and 0.932, respectively. The pass-through is 2.45 times larger in the social service sector than that in the non-service one, the least equitable. Wages also respond to demand shocks. And this response is again high in the most dynamic sectors, with elasticities of the 20%

[2]Countries are clustered in 4 groups. Cluster 1 includes Bulgaria, Georgia, Montenegro, North Macedonia, Kosovo, and Serbia. Cluster 2 groups Romania and Croatia. Cluster 3 involves Moldova and Armenia. The last cluster includes Kazakhstan and Kyrgyzstan.

and 16.9%, respectively. However, firms in these sectors also pass part of revenue sales taxes to their employees. A 1 p.p increase in sales taxes decreases wages in these sectors by 1.6% and 1%, respectively. Wages are not immune to the effect of imperfect competition. The negative impact of markups on wages is, for all the sectors, 2 times larger than that of markdowns. Highlighting the importance of fostering competition in product markets. An argument that could rationalize this finding is that highly specialized employees working in those sectors may have less good outside options than less qualified ones. As a result, they are subject to hold up problems.

The positive though incomplete pass-through of tfp gains to wages is high for cluster 4–Kazakhstan and Krgyzstan–and cluster 3–Moldova and Armenia, with elasticities of 72% and 67%, respectively. The lowest pass-through, 45.3%, is observed for cluster 1, which includes several Western Balkan economies. There is an ubiquitous adjustment of wages to demand shocks. The elasticity ranges from 1.6% for the most advanced cluster to 1.87% for the second least developed one.

3.3 Explaining wage inequality

One of the current concerns for policymakers is the increase in wage inequality. While studies for the U.S describe it as a between sectorial phenomenon, where the ICT sector accounts for a large part of it, recent evidence for OECD countries (cite OECD) refers to a within event. From a research point of view, the attention has shifted from skills as the primary driver of wage dispersion to industrial organization factors such as productivity differences across firms, idiosyncratic demand shocks, and other policy-related aspects that shape firms' behavior, like market power in labor and product markets, sales and factor taxes.

Table 8 shows the relative contribution of each factor, controlling for firm fixed effects as a proxy of labor composition by skill type. The table shows that 17% of the standard deviation in wages is explained by tfp, while 6.3% comes from idiosyncratic demand dispersion. While markups have a higher effect than markdowns on wage reductions, their relative importance to explain wage dispersion reverses. A 1 p.p increase in markdown dispersion increases wage dispersion by 9%, while the effect is 6% for markdowns. Thus, showing that imperfect competition both in labor and product markets tax disproportionately more workers located at the bottom of the income distribution. One interesting finding is that the estimated elasticities for markdowns and the interaction term with markups have different signs. The results thus show that labor and product markets shouldn't be analyzed in isolation as policy-wise, the inferred reforms maybe misleading when it comes to reducing inequality. Equity-wise, allowing imperfect competition in both markets is a better policy choice than allowing monopolistic or oligopolist market structures only in labor markets.

4 Conclusions

Policymakers have put jobs and wages at the center of their governmental agendas. Not only because good jobs are key to improving living standards, but also because the foundational paradigms to secure good jobs are currently challenged. Technological progress is eroding part of the comparative advantages that allowed economies, specialized in the production of labor-intensive products, to assure good jobs, while friendshoring is limiting even more the original jobs promises of the export-led growth model. Let alone that deindustrialization in some countries is reallocating labor towards low-paying jobs, while the increase in markups and markdowns is raising important distributional concerns.

While the gains from the first wave of structural reforms are exhausted, a new wave of reforms is needed to create good jobs, specifically in a context where several of the barriers lifted decades ago have been reinstated, while new ones like anticompetitive conduct, taxes, regulations, and trade restrictions have been imposed to protect new vested interests. Therefore, what can governments do to create more and better jobs when the first-best policy choice may not be available due to such constraints?

Lipsey and Lancaster (1956) introduced the *principle of the second best* and Bhagwati (1962) applied it to trade theory by showing that when one optimal equilibrium condition is not satisfied and the first-best policy choice cannot be achieved, then a second-best policy may require intervention or inefficiency. We examine this issue in the context of labor markets using an integrated framework that empirically brings into consideration industrial organization aspects to explain jobs, wages, and wage inequality. The paper shows that policies that increase firms' benefits are more effective than those that reduce labor costs to create good jobs. The results also render support to the principle of second best in labor markets as they show that jobs-, wages-, and equity-wise imperfect competition in labor markets justifies imperfect competition in product markets.

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Table 1
Number of Firms by Country

	Number of Firms	Number of Observations
Armenia	175,799	432,368
Bulgaria	363,507	1,724,544
Croatia	222,727	1,500,704
Georgia	51,436	139,800
Kazakhstan	228,011	651,277
Kosovo	126,909	815,798
Kyrgyzstan	26,405	129,810
Moldova	50,892	196,343
Montenegro	53,838	252,221
North Macedonia	98,304	584,646
Romania	1,317,035	7,683,273
Serbia	161,392	1,165,326
Ukraine	494,901	2,514,211

Table 2
Number of Firms by Year

	Number of Firms
2006	57,993
2007	70,067
2008	163,274
2009	168,038
2010	220,284
2011	902,406
2012	919,048
2013	1,190,335
2014	1,205,338
2015	1,248,112
2016	1,280,670
2017	1,375,899
2018	1,530,008
2019	1,608,652
2020	1,587,464
2021	1,627,245
2022	1,479,986
2023	1,079,967
2024	75,535

Table 3
Main Statistics

	Number of Observations	Mean	Standard Deviation	Minimum	Median	Maximum
Log(Employment)	17,361,901	0.977	1.214	0.000	0.693	12.529
Log(Wage)	10,065,047	9.095	1.028	-3.164	9.262	19.082
Log(TFP)	6,215,727	1.793	0.251	0.293	1.815	2.323
Log(1 - Sales tax)	8,393,614	1.301	2.236	-13.285	1.109	13.340
Log(K tax / L tax)	8,279,644	-0.321	1.453	-15.746	-0.311	24.265
Log(Sales)	15,732,562	12.890	2.763	2.398	12.644	33.335
Log(Markdown)	5,262,082	0.784	2.625	-9.743	0.483	28.635
Log(Markup)	7,482,400	0.334	1.442	-15.549	0.347	9.314

Table 4
Specification 1

	Log(Employment$_t$)	
	(1)	(2)
Log(Wage$_t$)	0.009***	
	(0.001)	
Log(Wage$_{t-1}$)		0.147***
		(0.001)
Log(TFP$_t$)	-1.249***	
	(0.007)	
Log(TFP$_{t-1}$)		-0.922***
		(0.008)
Log(TFP$_t$) $\times$ Log(tax$_t^K$/tax$_t^L$)	-0.041***	
	(0.001)	
Log(TFP$_{t-1}$) $\times$ Log(tax$_{t-1}^K$/tax$_{t-1}^L$)		-0.004***
		(0.001)
Log(TFP$_t$) $\times$ Log($1-$ tax$_t^S$)	0.172***	
	(0.001)	
Log(TFP$_{t-1}$) $\times$ Log($1-$ tax$_{t-1}^S$)		0.089***
		(0.002)
Log(tax$_t^K$/tax$_t^L$)	0.082***	
	(0.002)	
Log(tax$_{t-1}^K$/tax$_{t-1}^L$)		-0.005**
		(0.002)
Log($1-$ tax$_t^S$)	-0.289***	
	(0.002)	
Log($1-$ tax$_{t-1}^S$)		-0.153***
		(0.003)
Log(Markdown$_t$)	-0.110***	
	(0.001)	
Log(Markdown$_{t-1}$)		0.012***
		(0.001)
Log(Markup$_t$)	0.024***	
	(0.002)	
Log(Markup$_{t-1}$)		0.184***
		(0.003)
Log(Markdown$_t$) $\times$ Log(Markup$_t$)	0.004***	
	(0.000)	
Log(Markdown$_{t-1}$) $\times$ Log(Markup$_{t-1}$)		0.003***
		(0.000)
Dependent Variable Mean	1.892	1.843
Dependent Std. Dev.	1.187	1.251
N Firms	773,262	707,278
N Observations	4,923,866	4,359,971
R^2	0.924	0.894
Firm FE	Yes	Yes
Country $\times$ Year FE	Yes	Yes
Industry $\times$ Year FE	Yes	Yes
Regional $\times$ Year FE	Yes	Yes

This table reports ...

Table 5
Specification 1: Marginal Effects

	Log(Employment$_t$)	
	(1)	(2)
Log(Wage$_t$)	0.009***	
	(0.001)	
Log(Wage$_{t-1}$)		0.147***
		(0.001)
Log(TFP$_t$)	-1.345***	
	(0.007)	
Log(TFP$_{t-1}$)		-0.950***
		(0.008)
Log($\text{tax}_t^K/\text{tax}_t^L$)	0.009***	
	(0.000)	
Log($\text{tax}_{t-1}^K/\text{tax}_{t-1}^L$)		-0.013***
		(0.000)
Log($1-\text{tax}_t^S$)	0.023***	
	(0.001)	
Log($1-\text{tax}_{t-1}^S$)		0.007***
		(0.001)
Log(Markdown$_t$)	-0.108***	
	(0.001)	
Log(Markdown$_{t-1}$)		0.013***
		(0.001)
Log(Markup$_t$)	0.026***	
	(0.002)	
Log(Markup$_{t-1}$)		0.186***
		(0.003)
Dependent Variable Mean	1.892	1.843
Dependent Std. Dev.	1.187	1.251
N Firms	773,262	707,278
N Observations	4,923,866	4,359,971
R^2	0.924	0.894
Firm FE	Yes	Yes
Country × Year FE	Yes	Yes
Industry × Year FE	Yes	Yes
Regional × Year FE	Yes	Yes

This table reports ...

Table 6
Specification 2

	Log(Wage$_t$)	
	(1)	(2)
Log(TFP$_t$)	2.580***	
	(0.005)	
Log(TFP$_{t-1}$)		0.493***
		(0.005)
Log(TFP$_t$) $\times$ Log(tax$_t^K$/tax$_t^L$)	0.000	
	(0.001)	
Log(TFP$_{t-1}$) $\times$ Log(tax$_{t-1}^K$/tax$_{t-1}^L$)		0.014***
		(0.001)
Log(TFP$_t$) $\times$ Log($1-$ tax$_t^S$)	-0.056***	
	(0.001)	
Log(TFP$_{t-1}$) $\times$ Log($1-$ tax$_{t-1}^S$)		-0.025***
		(0.001)
Log(tax$_t^K$/tax$_t^L$)	-0.004***	
	(0.001)	
Log(tax$_{t-1}^K$/tax$_{t-1}^L$)		-0.032***
		(0.002)
Log($1-$ tax$_t^S$)	0.192***	
	(0.002)	
Log($1-$ tax$_{t-1}^S$)		0.053***
		(0.002)
Log(Sales$_t$)	0.373***	
	(0.000)	
Log(Sales$_{t-1}$)		0.167***
		(0.001)
Log(Markdown$_t$)	-0.554***	
	(0.001)	
Log(Markdown$_{t-1}$)		-0.183***
		(0.001)
Log(Markup$_t$)	-1.184***	
	(0.002)	
Log(Markup$_{t-1}$)		-0.382***
		(0.002)
Log(Markdown$_t$) $\times$ Log(Markup$_t$)	0.004***	
	(0.000)	
Log(Markdown$_{t-1}$) $\times$ Log(Markup$_{t-1}$)		0.001***
		(0.000)
Dependent Variable Mean	9.376	9.474
Dependent Std. Dev.	0.756	0.716
N Firms	773,262	690,959
N Observations	4,923,866	4,242,038
R^2	0.931	0.818
Firm FE	Yes	Yes
Country $\times$ Year FE	Yes	Yes
Industry $\times$ Year FE	Yes	Yes
Regional $\times$ Year FE	Yes	Yes

This table reports ...

Table 7
Specification 2: Marginal Effects

	Log(Wage_t)	
	(1)	(2)
Log(Sales_t)	0.373***	
	(0.000)	
Log(Sales_{t-1})		0.167***
		(0.001)
Log(TFP_t)	2.594***	
	(0.005)	
Log(TFP_{t-1})		0.518***
		(0.005)
Log($\text{tax}_t^K/\text{tax}_t^L$)	-0.003***	
	(0.000)	
Log($\text{tax}_{t-1}^K/\text{tax}_{t-1}^L$)		-0.008***
		(0.000)
Log($1 - \text{tax}_t^S$)	0.090***	
	(0.001)	
Log($1 - \text{tax}_{t-1}^S$)		0.006***
		(0.001)
Log(Markdown_t)	-0.552***	
	(0.001)	
Log(Markdown_{t-1})		-0.182***
		(0.001)
Log(Markup_t)	-1.181***	
	(0.002)	
Log(Markup_{t-1})		-0.381***
		(0.002)
Dependent Variable Mean	9.376	9.474
Dependent Std. Dev.	0.756	0.716
N Firms	773,262	690,959
N Observations	4,923,866	4,242,038
R^2	0.931	0.818
Firm FE	Yes	Yes
Country × Year FE	Yes	Yes
Industry × Year FE	Yes	Yes
Regional × Year FE	Yes	Yes

This table reports ...

Table 8
Specification 3

	SD(Log(Wage_t))	
	(1)	(2)
SD(Log(TFP_t))	0.189***	
	(0.017)	
SD(Log(TFP_{t-1}))		0.170***
		(0.017)
SD(Log(TFP_t) $\times$ Log($\text{tax}_t^K/\text{tax}_t^L$))	-0.032***	
	(0.001)	
SD(Log(TFP_{t-1}) $\times$ Log($\text{tax}_{t-1}^K/\text{tax}_{t-1}^L$))		-0.009***
		(0.001)
SD(Log(TFP_t) $\times$ Log($1-\text{tax}_t^S$))	-0.038***	
	(0.002)	
SD(Log(TFP_{t-1}) $\times$ Log($1-\text{tax}_{t-1}^S$))		-0.013***
		(0.002)
SD(Log($\text{tax}_t^K/\text{tax}_t^L$))	0.097***	
	(0.002)	
SD(Log($\text{tax}_{t-1}^K/\text{tax}_{t-1}^L$))		0.038***
		(0.002)
SD(Log($1-\text{tax}_t^S$))	0.175***	
	(0.003)	
SD(Log($1-\text{tax}_{t-1}^S$))		0.066***
		(0.003)
SD(Log(Sales_t))	0.083***	
	(0.001)	
SD(Log(Sales_{t-1}))		0.063***
		(0.002)
SD(Log(Markdown_t))	0.042***	
	(0.002)	
SD(Log(Markdown_{t-1}))		0.013***
		(0.002)
SD(Log(Markup_t))	-0.043***	
	(0.003)	
SD(Log(Markup_{t-1}))		-0.004
		(0.003)
SD(Log(Markdown_t) $\times$ Log(Markup_t))	-0.002***	
	(0.000)	
SD(Log(Markdown_{t-1}) $\times$ Log(Markup_{t-1}))		-0.001***
		(0.000)
Dependent Variable Mean	0.699	0.704
Dependent Std. Dev.	0.396	0.393
N Clusters	25,671	24,429
R^2	0.456	0.417
Country $\times$ Year FE	Yes	Yes
Industry $\times$ Year FE	Yes	Yes
Regional $\times$ Year FE	Yes	Yes

This table reports ...

Table 9
Specification 3: Marginal Effects

	SD(Log(Wage_t))	
	(1)	(2)
SD(Log(Sales_t))	0.083***	
	(0.001)	
SD(Log(Sales_{t-1}))		0.063***
		(0.002)
SD(Log(TFP_t))	0.186***	
	(0.016)	
SD(Log(TFP_{t-1}))		0.171***
		(0.016)
SD(Log($\text{tax}_t^K/\text{tax}_t^L$))	0.050***	
	(0.001)	
SD(Log($\text{tax}_{t-1}^K/\text{tax}_{t-1}^L$))		0.024***
		(0.001)
SD(Log($1-\text{tax}_t^S$))	0.132***	
	(0.003)	
SD(Log($1-\text{tax}_{t-1}^S$))		0.052***
		(0.003)
SD(Log(Markdown_t))	0.019***	
	(0.002)	
SD(Log(Markdown_{t-1}))		0.009***
		(0.002)
SD(Log(Markup_t))	-0.015***	
	(0.003)	
SD(Log(Markup_{t-1}))		-0.006**
		(0.003)
Dependent Variable Mean	0.699	0.704
Dependent Std. Dev.	0.396	0.393
N Clusters	25,762	24,524
R^2	0.452	0.416
Country × Year FE	Yes	Yes
Industry × Year FE	Yes	Yes
Regional × Year FE	Yes	Yes

This table reports ...

Table 10

Main Specifications Log(Employment) by Service Sector

	Log(Employment$_t$)				
	Non-Service	Global Innovator	Low-skill Tradable	Low-skill Domestic	Skill-intensive Social
	(1)	(2)	(3)	(4)	(5)
Log(Wage$_{t-1}$)	0.138***	0.171***	0.170***	0.135***	0.054***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.006)
Log(TFP$_{t-1}$)	-0.892***	-1.024***	-1.031***	-0.944***	-0.266***
	(0.014)	(0.025)	(0.016)	(0.015)	(0.046)
Log(TFP$_{t-1}$) $\times$ Log(tax$^K_{t-1}$/tax$^L_{t-1}$)	0.010***	0.007*	0.012***	-0.003	0.012
	(0.003)	(0.004)	(0.003)	(0.003)	(0.009)
Log(TFP$_{t-1}$) $\times$ Log($1 - tax^S_{t-1}$)	0.097***	0.098***	0.103***	0.081***	0.023*
	(0.003)	(0.006)	(0.004)	(0.004)	(0.013)
Log(tax$^K_{t-1}$/tax$^L_{t-1}$)	-0.028***	-0.023***	-0.043***	-0.004	-0.041**
	(0.004)	(0.008)	(0.006)	(0.005)	(0.019)
Log($1 - tax^S_{t-1}$)	-0.143***	-0.197***	-0.198***	-0.143***	-0.068***
	(0.005)	(0.011)	(0.007)	(0.007)	(0.025)
Log(Markdown$_{t-1}$)	-0.001	0.022***	0.033***	0.001	-0.088***
	(0.002)	(0.004)	(0.003)	(0.003)	(0.009)
Log(Markup$_{t-1}$)	0.206***	0.151***	0.222***	0.162***	-0.111***
	(0.005)	(0.009)	(0.005)	(0.006)	(0.017)
Log(Markdown$_{t-1}$) $\times$ Log(Markup$_{t-1}$)	0.003***	0.002***	0.004***	0.002***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Dependent Variable Mean	2.221	1.566	1.809	1.614	1.669
Dependent Std. Dev.	1.416	1.105	1.173	1.102	1.114
N Firms	210,114	95,493	182,221	194,258	24,683
N Observations	1,308,396	579,427	1,114,083	1,199,409	155,674
R^2	0.902	0.884	0.882	0.877	0.906
Firm FE	Yes	Yes	Yes	Yes	Yes
Country $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
Regional $\times$ Year FE	Yes	Yes	Yes	Yes	Yes

This table reports ...

Table 11

Main Specifications Log(Employment) by Service Sector: Marginal Effects

	Log(Employment$_t$)				
	Non-Service	Global Innovator	Low-skill Tradable	Low-skill Domestic	Skill-intensive Social
	(1)	(2)	(3)	(4)	(5)
Log(Wage$_{t-1}$)	0.138***	0.171***	0.170***	0.135***	0.054***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.006)
Log(TFP$_{t-1}$)	-0.872***	-1.038***	-1.069***	-0.982***	-0.251***
	(0.013)	(0.025)	(0.016)	(0.015)	(0.044)
Log(tax$^K_{t-1}$/tax$^L_{t-1}$)	-0.011***	-0.009***	-0.022***	-0.010***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Log($1 - tax^S_{t-1}$)	0.015***	-0.005	-0.013***	0.011***	-0.023***
	(0.002)	(0.004)	(0.002)	(0.002)	(0.007)
Log(Markdown$_{t-1}$)	-0.001	0.023***	0.034***	0.002	-0.085***
	(0.002)	(0.004)	(0.003)	(0.003)	(0.009)
Log(Markup$_{t-1}$)	0.210***	0.152***	0.225***	0.163***	-0.109***
	(0.005)	(0.009)	(0.005)	(0.006)	(0.017)
Dependent Variable Mean	2.221	1.566	1.809	1.614	1.669
Dependent Std. Dev.	1.416	1.105	1.173	1.102	1.114
N Firms	210,114	95,493	182,221	194,258	24,683
N Observations	1,308,396	579,427	1,114,083	1,199,409	155,674
R^2	0.902	0.884	0.882	0.877	0.906
Firm FE	Yes	Yes	Yes	Yes	Yes
Country $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
Regional $\times$ Year FE	Yes	Yes	Yes	Yes	Yes

This table reports ...

Table 12
Main Specifications Log(Wage) by Service Sector

	Log(Wage$_t$)				
	Non-Service	Global Innovator	Low-skill Tradable	Low-skill Domestic	Skill-intensive Social
	(1)	(2)	(3)	(4)	(5)
Log(TFP$_{t-1}$)	0.384***	0.821***	0.464***	0.485***	0.879***
	(0.009)	(0.017)	(0.011)	(0.010)	(0.036)
Log(TFP$_{t-1}$) × Log(tax$^K_{t-1}$/tax$^L_{t-1}$)	-0.002	0.019***	0.021***	0.016***	0.036***
	(0.002)	(0.004)	(0.002)	(0.002)	(0.008)
Log(TFP$_{t-1}$) × Log($1-$tax$^S_{t-1}$)	-0.025***	-0.064***	-0.027***	-0.032***	-0.074***
	(0.002)	(0.005)	(0.003)	(0.003)	(0.013)
Log(tax$^K_{t-1}$/tax$^L_{t-1}$)	-0.002	-0.047***	-0.046***	-0.039***	-0.077***
	(0.003)	(0.007)	(0.005)	(0.004)	(0.017)
Log($1-$tax$^S_{t-1}$)	0.049***	0.136***	0.051***	0.067***	0.159***
	(0.003)	(0.010)	(0.006)	(0.006)	(0.023)
Log(Sales$_{t-1}$)	0.155***	0.200***	0.163***	0.160***	0.169***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.004)
Log(Markdown$_{t-1}$)	-0.155***	-0.237***	-0.181***	-0.188***	-0.227***
	(0.002)	(0.004)	(0.002)	(0.002)	(0.008)
Log(Markup$_{t-1}$)	-0.324***	-0.486***	-0.378***	-0.386***	-0.481***
	(0.004)	(0.007)	(0.004)	(0.005)	(0.015)
Log(Markdown$_{t-1}$) × Log(Markup$_{t-1}$)	0.001***	0.001***	0.001***	0.001***	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Dependent Variable Mean	9.499	9.646	9.462	9.377	9.465
Dependent Std. Dev.	0.702	0.781	0.709	0.677	0.746
N Firms	205,155	93,217	177,769	190,070	24,268
N Observations	1,270,362	563,396	1,081,232	1,171,365	152,847
R^2	0.818	0.829	0.816	0.802	0.836
Firm FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Regional × Year FE	Yes	Yes	Yes	Yes	Yes

This table reports ...

Table 13
Main Specifications Log(Wage) by Service Sector: Marginal Effects

	Log(Wage$_t$)				
	Non-Service	Global Innovator	Low-skill Tradable	Low-skill Domestic	Skill-intensive Social
	(1)	(2)	(3)	(4)	(5)
Log(Sales$_{t-1}$)	0.155***	0.200***	0.163***	0.160***	0.169***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.004)
Log(TFP$_{t-1}$)	0.379***	0.862***	0.504***	0.523***	0.923***
	(0.008)	(0.017)	(0.010)	(0.010)	(0.035)
Log(tax$^K_{t-1}$/tax$^L_{t-1}$)	-0.006***	-0.010***	-0.009***	-0.009***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Log($1-$tax$^S_{t-1}$)	0.007***	0.010***	0.002	0.005***	0.016**
	(0.001)	(0.003)	(0.001)	(0.002)	(0.007)
Log(Markdown$_{t-1}$)	-0.155***	-0.236***	-0.180***	-0.187***	-0.227***
	(0.002)	(0.004)	(0.002)	(0.002)	(0.008)
Log(Markup$_{t-1}$)	-0.323***	-0.486***	-0.377***	-0.385***	-0.481***
	(0.003)	(0.007)	(0.004)	(0.005)	(0.015)
Dependent Variable Mean	9.499	9.646	9.462	9.377	9.465
Dependent Std. Dev.	0.702	0.781	0.709	0.677	0.746
N Firms	205,155	93,217	177,769	190,070	24,268
N Observations	1,270,362	563,396	1,081,232	1,171,365	152,847
R^2	0.818	0.829	0.816	0.802	0.836
Firm FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Regional × Year FE	Yes	Yes	Yes	Yes	Yes

This table reports ...

Table 14

Main Specifications Log(Employment) by Country Cluster

	Log(Employment$_t$)			
	Cluster=1	Cluster=2	Cluster=3	Cluster=4
	(1)	(2)	(3)	(4)
Log(Wage$_{t-1}$)	0.092***	0.152***	0.106***	0.001
	(0.002)	(0.001)	(0.010)	(0.011)
Log(TFP$_{t-1}$)	-0.679***	-1.004***	-1.203***	-0.746***
	(0.014)	(0.009)	(0.091)	(0.067)
Log(TFP$_{t-1}$) $\times$ Log(tax$^K_{t-1}$/tax$^L_{t-1}$)	0.021***	0.034***	0.038***	-0.011
	(0.003)	(0.002)	(0.013)	(0.013)
Log(TFP$_{t-1}$) $\times$ Log($1-$ tax$^S_{t-1}$)	0.047***	0.079***	-0.017*	0.043***
	(0.003)	(0.002)	(0.010)	(0.010)
Log(tax$^K_{t-1}$/tax$^L_{t-1}$)	-0.037***	-0.086***	-0.050*	0.117***
	(0.005)	(0.003)	(0.026)	(0.024)
Log($1-$ tax$^S_{t-1}$)	-0.063***	-0.133***	-0.029	-0.063***
	(0.005)	(0.004)	(0.019)	(0.017)
Log(Markdown$_{t-1}$)	-0.015***	0.002	0.036***	0.014*
	(0.002)	(0.002)	(0.011)	(0.008)
Log(Markup$_{t-1}$)	0.112***	0.192***	-0.127***	0.200***
	(0.004)	(0.004)	(0.020)	(0.018)
Log(Markdown$_{t-1}$) $\times$ Log(Markup$_{t-1}$)	0.013***	0.013***	0.014***	-0.002
	(0.000)	(0.000)	(0.001)	(0.001)
Dependent Variable Mean	1.873	1.702	2.892	3.145
Dependent Std. Dev.	1.185	1.142	1.315	1.660
N Firms	187,556	476,460	16,264	13,278
N Observations	1,059,326	3,052,931	88,508	79,764
R^2	0.924	0.861	0.908	0.933
Firm FE	Yes	Yes	Yes	Yes
Country $\times$ Year FE	Yes	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes	Yes
Regional $\times$ Year FE	Yes	Yes	Yes	Yes

This table reports ...

Table 15

Main Specifications Log(Employment) by Country Cluster: Marginal Effects

	Log(Employment$_t$)			
	Cluster=1	Cluster=2	Cluster=3	Cluster=4
	(1)	(2)	(3)	(4)
Log(Wage$_{t-1}$)	0.092***	0.152***	0.106***	0.001
	(0.002)	(0.001)	(0.010)	(0.011)
Log(TFP$_{t-1}$)	-0.664***	-0.987***	-1.225***	-0.744***
	(0.014)	(0.009)	(0.080)	(0.066)
Log(tax$^K_{t-1}$/tax$^L_{t-1}$)	0.000	-0.024***	0.018**	0.098***
	(0.001)	(0.000)	(0.007)	(0.005)
Log($1-$ tax$^S_{t-1}$)	0.022***	0.011***	-0.059***	0.011***
	(0.002)	(0.002)	(0.005)	(0.004)
Log(Markdown$_{t-1}$)	-0.013***	0.010***	-0.025**	0.014*
	(0.002)	(0.002)	(0.011)	(0.008)
Log(Markup$_{t-1}$)	0.127***	0.195***	0.024	0.197***
	(0.004)	(0.004)	(0.018)	(0.017)
Dependent Variable Mean	1.873	1.702	2.892	3.145
Dependent Std. Dev.	1.185	1.142	1.315	1.660
N Firms	187,556	476,460	16,264	13,278
N Observations	1,059,326	3,052,931	88,508	79,764
R^2	0.924	0.861	0.908	0.933
Firm FE	Yes	Yes	Yes	Yes
Country $\times$ Year FE	Yes	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes	Yes
Regional $\times$ Year FE	Yes	Yes	Yes	Yes

This table reports ...

Table 16
Main Specifications Log(Wage) by Country Cluster

	Log(Wage_t)			
	Cluster=1	Cluster=2	Cluster=3	Cluster=4
	(1)	(2)	(3)	(4)
Log(TFP_{t-1})	0.410***	0.507***	0.839***	0.665***
	(0.012)	(0.006)	(0.079)	(0.045)
Log(TFP_{t-1}) × Log($\text{tax}^K_{t-1}/\text{tax}^L_{t-1}$)	0.034***	0.011***	-0.006	0.002
	(0.003)	(0.001)	(0.013)	(0.009)
Log(TFP_{t-1}) × Log($1-\text{tax}^S_{t-1}$)	-0.018***	-0.033***	-0.032***	0.006
	(0.003)	(0.002)	(0.010)	(0.007)
Log($\text{tax}^K_{t-1}/\text{tax}^L_{t-1}$)	-0.068***	-0.029***	-0.032	-0.004
	(0.005)	(0.002)	(0.029)	(0.017)
Log($1-\text{tax}^S_{t-1}$)	0.037***	0.071***	0.066***	-0.009
	(0.005)	(0.003)	(0.019)	(0.011)
Log(Sales_{t-1})	0.187***	0.160***	0.168***	0.179***
	(0.001)	(0.001)	(0.005)	(0.005)
Log(Markdown_{t-1})	-0.197***	-0.173***	-0.194***	-0.185***
	(0.002)	(0.001)	(0.020)	(0.006)
Log(Markup_{t-1})	-0.434***	-0.357***	-0.366***	-0.410***
	(0.004)	(0.003)	(0.021)	(0.014)
Log(Markdown_{t-1}) × Log(Markup_{t-1})	0.003***	0.001***	0.001	0.001*
	(0.000)	(0.000)	(0.000)	(0.001)
Dependent Variable Mean	9.308	9.562	8.692	8.786
Dependent Std. Dev.	0.726	0.661	0.983	0.920
N Firms	180,422	469,984	15,035	13,054
N Observations	994,081	3,015,261	83,957	76,332
R^2	0.841	0.779	0.902	0.886
Firm FE	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
Regional × Year FE	Yes	Yes	Yes	Yes

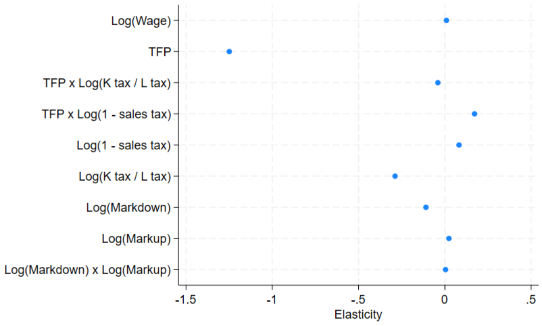
This table reports ...

Table 17
Main Specifications Log(Wage) by Country Cluster: Marginal Effects

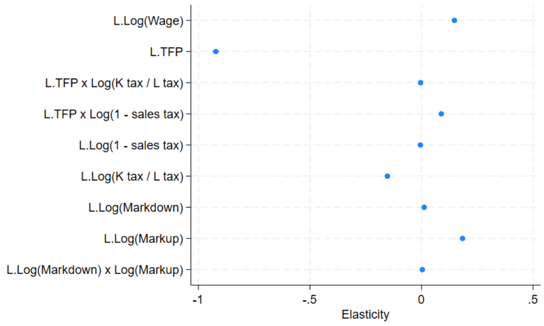
	Log(Wage_t)			
	Cluster=1	Cluster=2	Cluster=3	Cluster=4
	(1)	(2)	(3)	(4)
Log(Sales_{t-1})	0.187***	0.160***	0.168***	0.179***
	(0.001)	(0.001)	(0.005)	(0.005)
Log(TFP_{t-1})	0.453***	0.536***	0.720***	0.668***
	(0.012)	(0.006)	(0.055)	(0.043)
Log($\text{tax}^K_{t-1}/\text{tax}^L_{t-1}$)	-0.007***	-0.008***	-0.042**	-0.001
	(0.001)	(0.000)	(0.017)	(0.003)
Log($1-\text{tax}^S_{t-1}$)	0.004***	0.012***	0.008**	0.002
	(0.001)	(0.001)	(0.003)	(0.003)
Log(Markdown_{t-1})	-0.197***	-0.172***	-0.197***	-0.185***
	(0.002)	(0.001)	(0.019)	(0.006)
Log(Markup_{t-1})	-0.430***	-0.356***	-0.359***	-0.407***
	(0.004)	(0.003)	(0.023)	(0.013)
Dependent Variable Mean	9.308	9.562	8.692	8.786
Dependent Std. Dev.	0.726	0.661	0.983	0.920
N Firms	180,422	469,984	15,035	13,054
N Observations	994,081	3,015,261	83,957	76,332
R^2	0.841	0.779	0.902	0.886
Firm FE	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
Regional × Year FE	Yes	Yes	Yes	Yes

This table reports ...

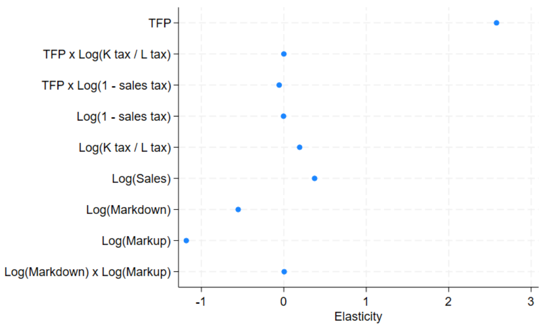
Figure 1
Main Specifications: Graphs



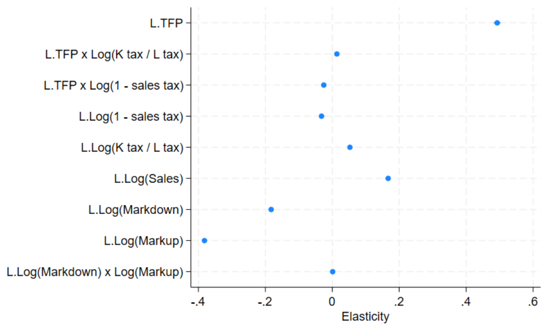
(a) Respect to Employment in t



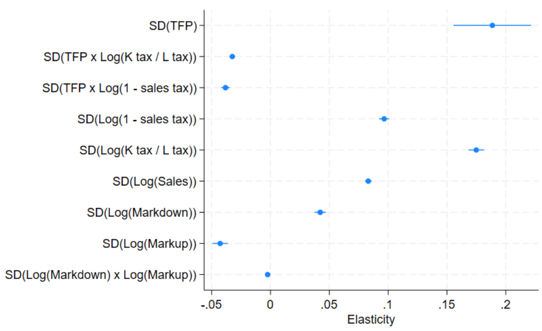
(b) Respect to Employment in t-1



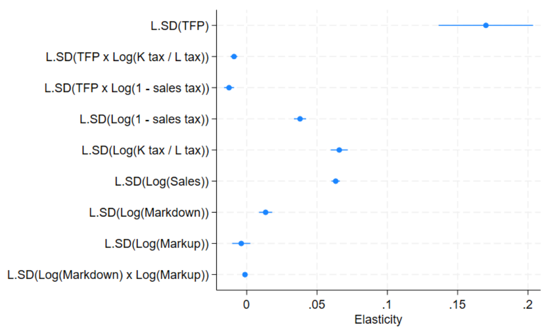
(c) Respect to Wage in t



(d) Respect to Wage in t-1



(e) Respect to SD(Wage) in t



(f) Respect to SD(Wage) in t-1

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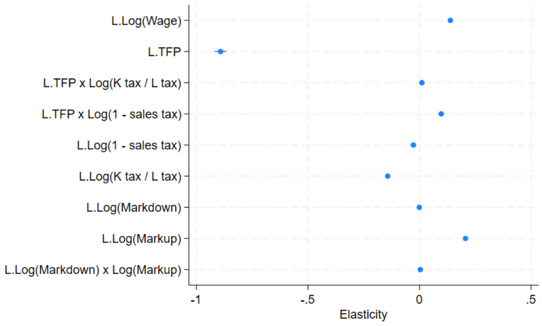
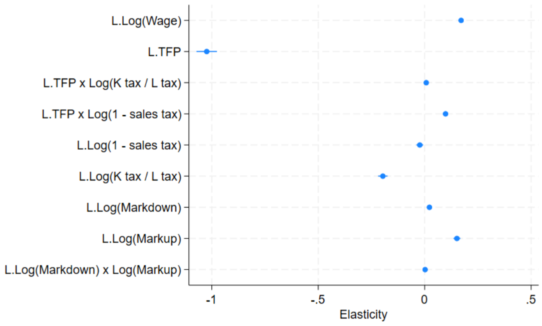
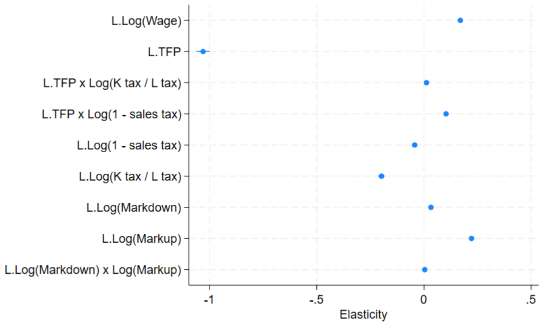
Figure 2
Graphs by Service Sector: Log(Employment$_{t-1}$)



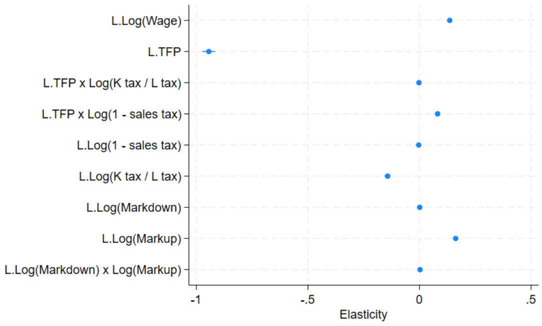
(a) Non-Service



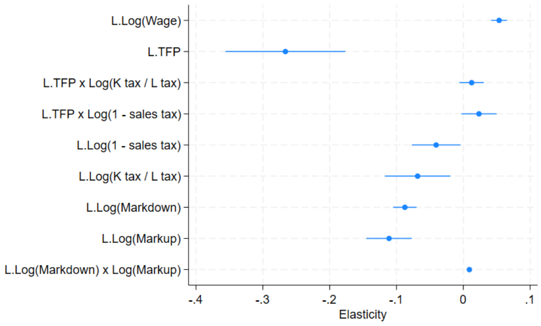
(b) Global Innovator



(c) Low-skill Tradable



(d) Low-skill Domestic



(e) Skill-intensive Social

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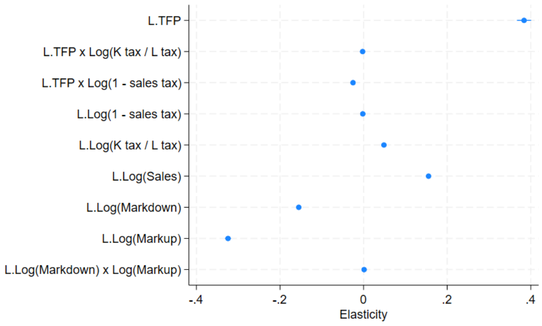
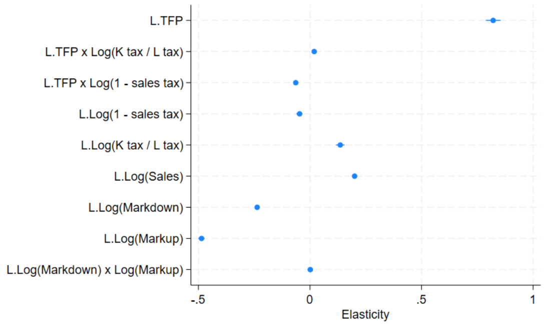
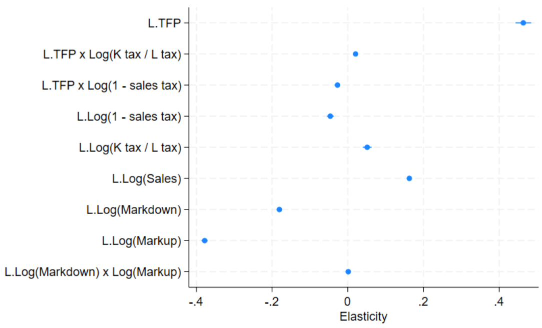
Figure 3
Graphs by Service: $\text{Log}(\text{Wage}_{t-1})$



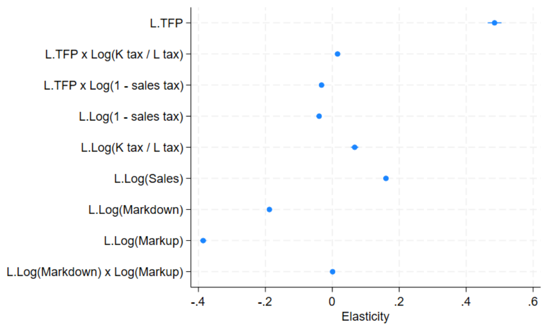
(a) Non-Service



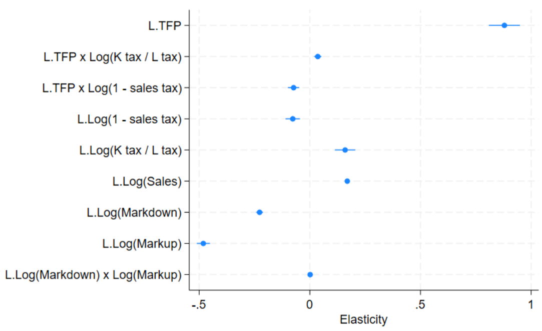
(b) Global Innovator



(c) Low-skill Tradable



(d) Low-skill Domestic



(e) Skill-intensive Social

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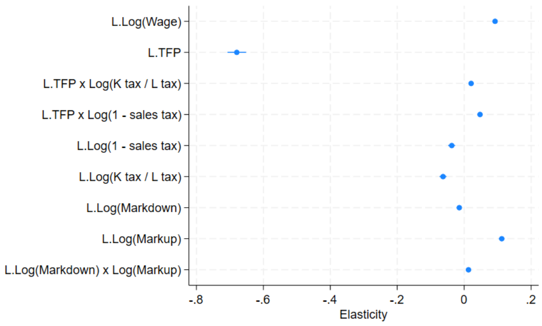
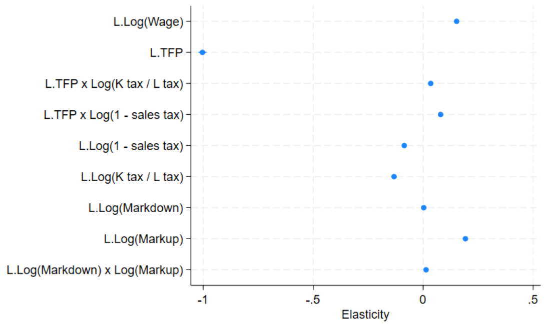
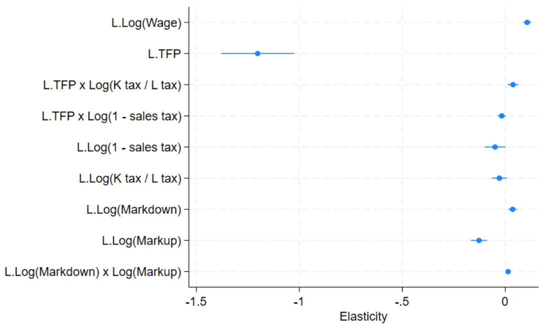
Figure 4
Graphs by Country Cluster: Log(Employment$_{t-1}$)



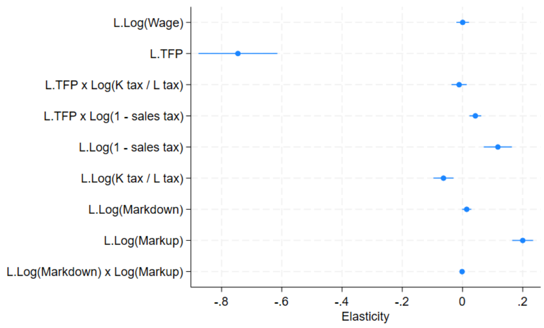
(a) Cluster=1



(b) Cluster=2



(c) Cluster=3



(d) Cluster=4

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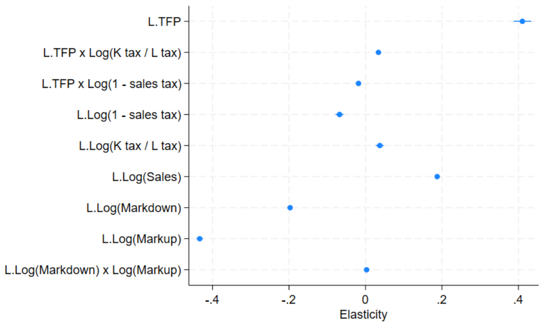
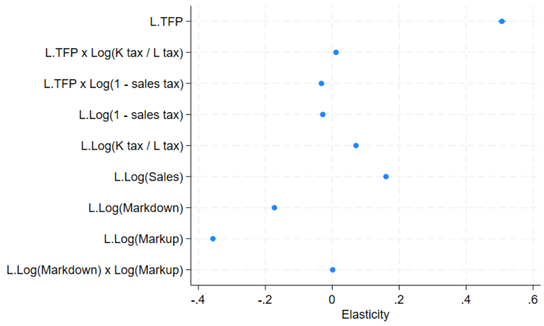
Figure 5

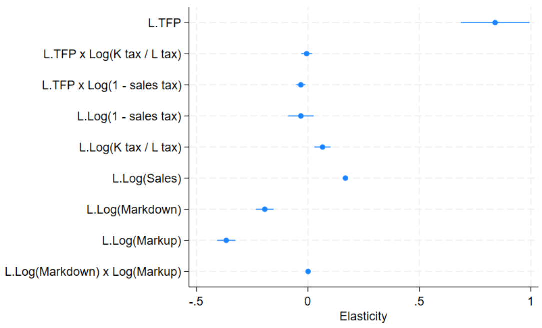
Graphs by Country Cluster: Log(Wage_{t-1})



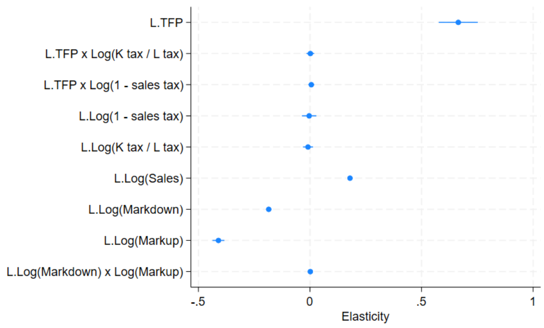
(a) Cluster=1



(b) Cluster=2



(c) Cluster=3



(d) Cluster=4

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