Online Appendix of "Trade Liberalization and Labor Market Institutions"

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Appendix A

Preferential Tariff Cuts

We build our tariff cut variable ($\Delta\tau$) following the steps below:

1. We have data on preferential tariffs at the HS 6-digit level for all the PTAs signed by the EU post-1995. For each product, we know preferential tariffs for time zero, i.e., year of ratification, and for all subsequent years until preferential tariffs go to zero (up to 22 years). In other words, we know the phase-out tariff period for each product for each PTA.

2. For each product at the 6-digit level, we know the MFN tariff, which we use as baseline to calculate the tariff cut.

3. We create a variable PRF that captures the level of PRF tariff for each product for each PTA in each year. This variable takes into account the phase-out tariff period. For instance, if a PTA is ratified in 2000, PRF of product i includes the level of PRF tariff from 2000 to 2021.

4. We create a tariff cut variable for each product and for each PTA. Tariff cut is the difference between MFN and PRF in the year of ratification and it is the inverse of the first difference of PRF, i.e., *PRF lagged-PRF*, in subsequent years. In other words, to calculate the tariff cut, we use MFN as baseline for the first year in which PRF tariffs kick in and the PRF tariffs of the previous year in subsequent years in which a PTA is in force.

5. We create a variable capturing proportional tariff cuts, i.e., $\frac{MFN-PRF}{MFN}$, in the first year and $\frac{PRF\ lagged-PRF}{PRF\ lagged}$, following the same procedure as in 4.

6. We create weighted tariff cuts and weighted proportional tariff cuts dividing tariffs by import value. We then follow the same procedures as in 4 and 5.

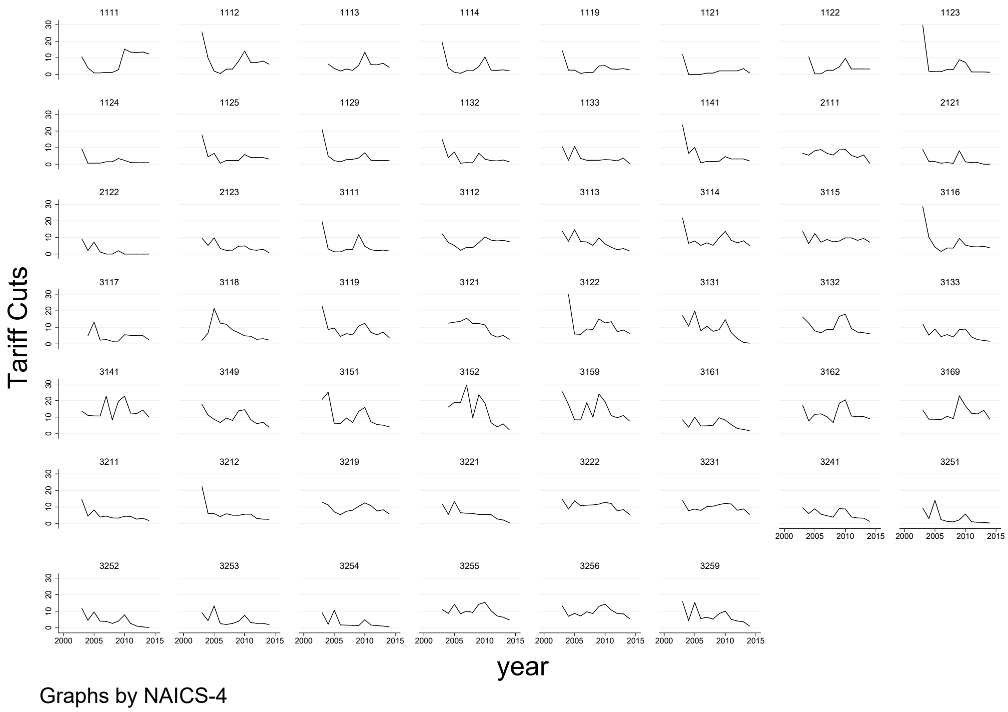
7. We sum all the tariff cuts (weighted and not) across all EU PTAs for a given product i in a given year t. That gives us our measure of preferential trade liberalization.

8. We take the average value of proportional tariff cuts (weighted and not) across all EU PTAs for a given product i in a given year t.

9. We merge the dataset with an NAICS 4-digit variable to merge the tariff data with the Amadeus database.

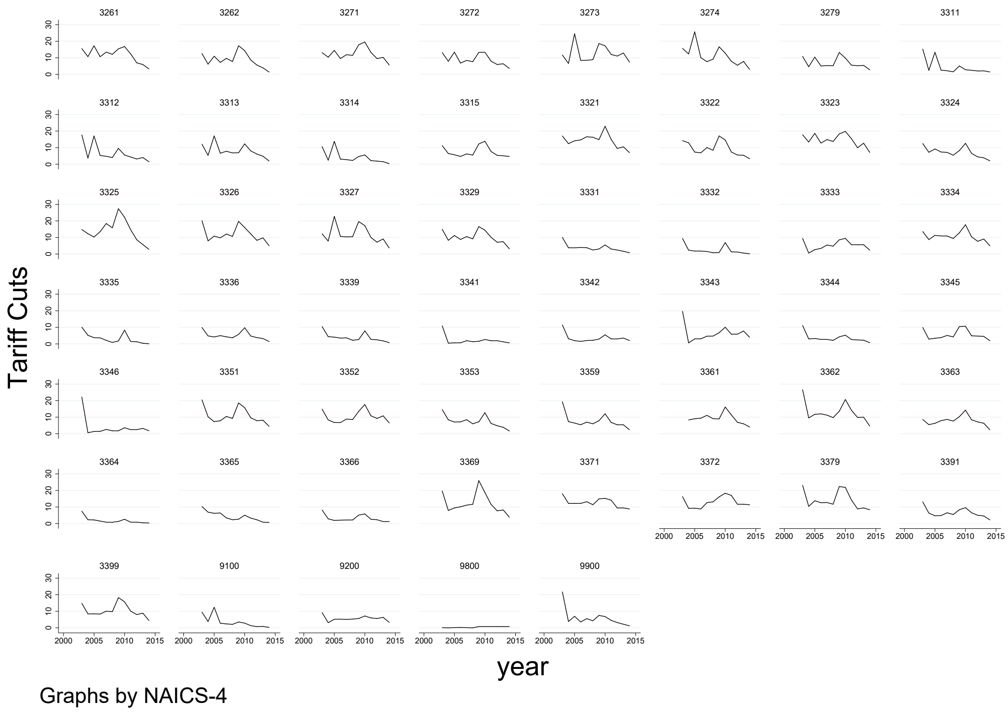
10. We take the average value of all our measures of tariff cuts (proportional and not, weighted and not) in each year to move from HS 6-digit to NAICS 4-digit. Note that we did not sum the tariff cut in this case because there are different numbers of 6-digit products in 4-digit industries.

Figure A1: Tariff cuts by industry and time (part 1)



Note: Source: Baccini et al. (2018).

Figure A2: Tariff cuts by industry and time (part 2)

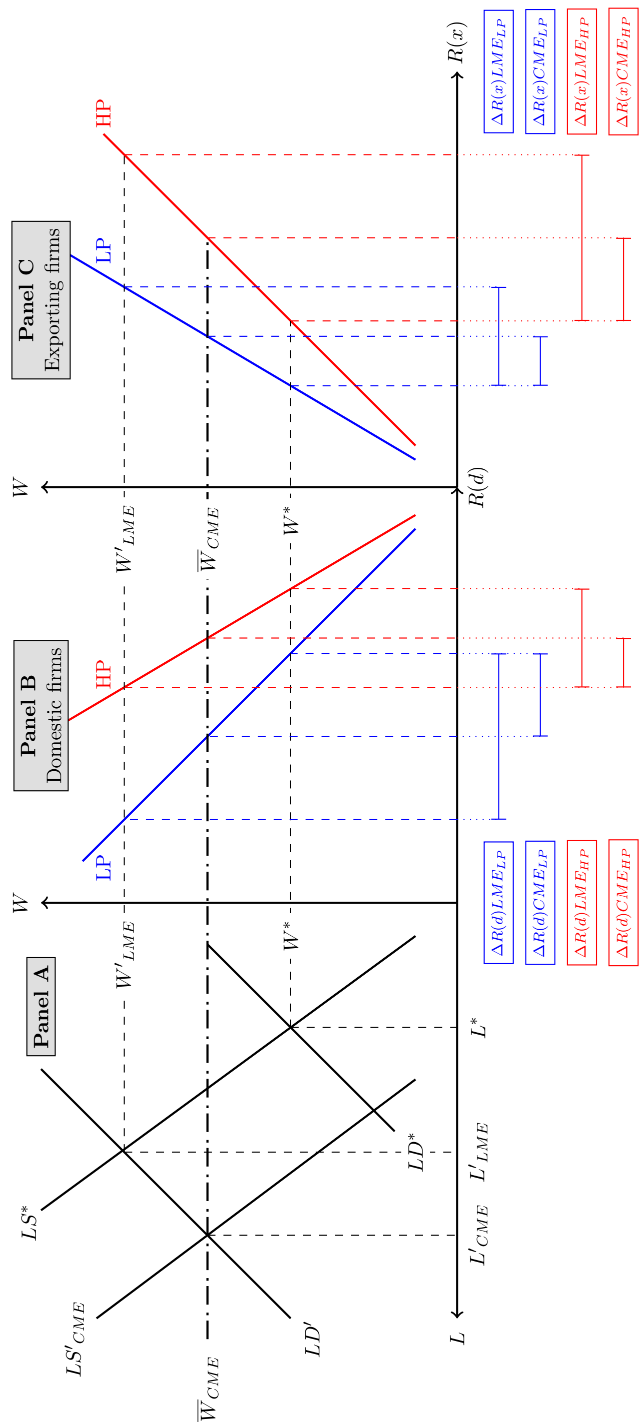


Note: Source: Baccini et al. (2018).

Appendix B

Figure Supporting the Theory

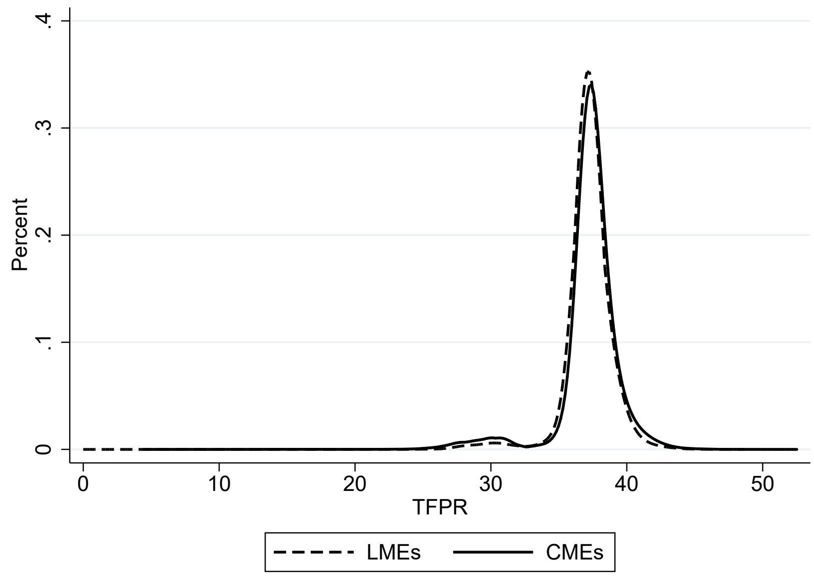
Figure B1: The effect of trade liberalization in CMEs and LMEs: domestic vs. exporting firms



Note: Blue curves refer to firms with lower productivity (LP), red ones to firms with higher productivity (HP).

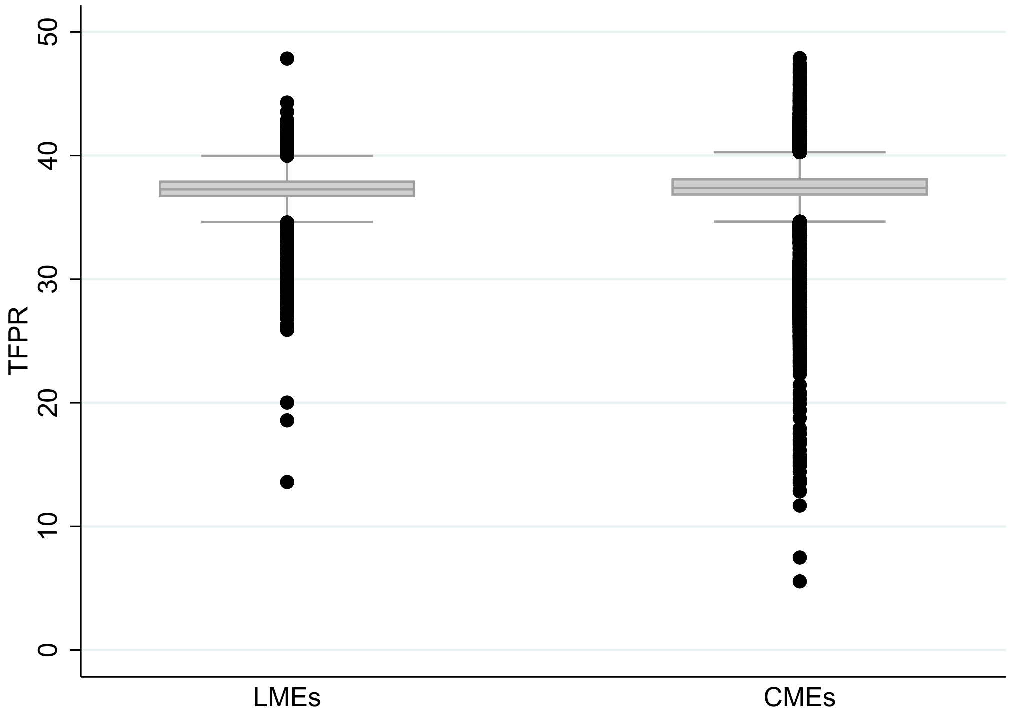
Descriptive Statistics (firm-level analysis)

Figure B2: Kernel Density Estimate of TFPR by Labor Institutions



Note: Sources: Amadeus dataset and Visser (2016).

Figure B3: Box Plot of TFPR by Labor Institutions



Note: Sources: Amadeus dataset and Visser (2016).

Table B1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	Source
Ln(Revenue)	4,053,929	13.70	2.87	-19.57	29.35	Amadeus
TFPR	4,053,929	37.37	1.84	0	49.67	Amadeus
CME	4,053,929	0.90	0.30	0	1	Visser
MFN	4,053,929	3.84	3.88	0	47.26	Baccini et al
HHI	4,053,929	0.06	0.10	0	1	Amadeus
K/L	4,053,929	11.72	1.82	-17.74	26.07	Amadeus
Firm Age	4,053,929	9.09	1.84	1	10	Amadeus
Firm Age2	4,053,929	85.97	26.43	1	100	Amadeus
ln(Labour)	4,053,929	2.27	1.34	0.69	13.25	Amadeus
Labour Flexibility	2,846,018	2.54	0.62	1.10	4.42	OECD
Union Density	2,897,046	26.47	16.69	6.53	77.71	Visser
Centralization	2,470,583	0.35	0.10	0.10	0.88	Visser
Government Intervention	4,032,150	2.97	0.95	1.50	5.00	Visser
Ext	4,042,895	1.49	1.26	0	3	Visser
Sector	3,956,669	1.34	0.73	0	2	Visser
Unauthority	3,934,890	0.34	0.14	0	0.80	Visser
Cfauthority	3,934,890	0.37	0.16	0	0.70	Visser
Corruption	4,053,929	0.81	0.79	-0.58	2.23	WB
PR	4,053,929	0.90	0.30	0	1	WB
Migration	4,029,283	8.10	4.60	0.70	18.00	UN
Social Expenditure	3,218,385	25.07	3.68	11.00	31.90	WDI
Service	4,053,929	62.44	8.67	42.48	77.81	WDI
Tax/GDP	4,053,929	19.51	4.43	1.50	51.11	WDI
FDI	4,053,129	0.95	1.28	-0.06	7.68	WDI
Euro	4,053,929	0.61	0.49	0	1	Authors
Private Credit	4,044,630	96.22	44.64	0.19	253.26	WDI
Bank Credit	4,044,630	96.16	44.62	0.19	253.15	WDI
Financial Credit	4,044,630	136.10	63.26	0.23	316.61	WDI
Unemployment	4,053,929	12.28	5.50	2.92	22.67	WDI
Export Tariff	4,053,929	7.16	14.56	0	1764.91	Baccini et al
Wage ceiling	4,032,150	0.05	0.21	0	1	Visser
Subsidies for VT	3,918,518	0.07	0.25	0	1	Visser
Import Tariff	4,053,929	11.61	67.84	0	1764.91	Baccini et al
Input Tariff	4,032,150	0.35	0.49	0	8.04	Baccini et al
Automation	3,211,758	11.94	14.62	0	56.03	Acemoglu & Restrepo

Appendix C

Confounders

The variables that we analyze as possible confounders in the empirical analysis are the following.

Innovation The logic is that innovation may help productive firms to navigate trade liberalization more than unproductive firms. If innovation is significantly higher in LMEs, this could be a potential alternative channel that explains our results. We rely on number of patents (by residents) to measure innovation, as well as on share of firms that spend on R&D, researchers in R&D (per million people), and technicians in R&D (per million people). Data come from the WDI. The time span is between 1960 and 2016.

Corruption The logic is that corruption may create additional fixed or variable costs for firms, especially when competition increases due to trade liberalization. These additional costs are more likely to be supported by productive firms rather than unproductive firms. In turn, this creates uneven gains from trade. If corruption correlates with labor market frictions, it may be a confounder. We rely on a measure of control of corruption by the Worldwide Governance Indicators (WGI) of the World Bank (Kaufmann et al. 2010). The time span is between 1996 and 2016.[1]

Electoral system The logic is that different types of electoral systems provide different incentives from politicians to support different types of firms. For instance, it may be that majoritarian systems raise incentives to remunerate large, productive firms more than proportional systems do. If this also happens during episodes of trade liberalization, electoral systems may be a confounder. Data on electoral systems come from the Database of Political Institutions 2017 (Cruz, Keefer, and Scartascini 2018).

Migration If migrants, especially economic migrants, move to CMEs from LMEs in the case of trade liberalization, the supply of labor would increase in CMEs more than in LMEs. This may reduce the increase of wages in ways that have nothing to do with labor market institutions. We use the international migrant stock as a percentage of the total population (both sexes). Data are available for all the countries in the sample, 2003 to 2016. Data come from the United Nations and are available at `http://www.un.org/en/development/desa/population/migration/data/index.shtml`.

Unemployment The logic is that (pre-trade-liberalization) high-level unemployment reduces the increase of wages after trade liberalization. In turn, this may help unproductive firms in the case of increasing competition due to tariff cuts. If unemployment correlates with labor market frictions, it may be a confounder. We rely on a measure of unemployment collected by the ILO and available through the WDI. The time span is between 1960 and 2016.

[1] Results are similar if we use other variables capturing the quality of governance, e.g., rule of law and regulatory quality.

Market structure We include social expenditure and government expenditure. Data are from the OECD and the WDI respectively, and are available from 1990 to 2016. Moreover, we include the size of the service sector, amount of taxes over GDP, and amount of FDI outflows. Data are from the WDI and are available from 1960 to 2016. Finally, we include a dummy for countries that adopted the Euro. Data come from `https://europa.eu/european-union/about-eu/money/euro_en`. All these variables can mitigate (e.g., social expenditure) or magnify (Euro) the reallocation effect. Therefore, they are all potential confounders.

Access to credit In countries in which access to credit is easy, firms can weather the increasing competition triggered by trade liberalization better than in countries in which firms face credit constraints. In particular, easy access to credit can help small, unproductive firms.[2] To capture access to credit we rely on the following variables: (1) domestic credit to private sector by banks (% of GDP); (2) domestic credit provided by financial sector (% of GDP); and (3) domestic credit to private sector (% of GDP). Data come from the WDI and are available from 1960 to 2016.[3]

[2] For a review of the literature on trade liberalization and access to credit, see Foley and Manova (2015).

[3] Results are similar if we use variables capturing access to credit from the Enterprise Survey of the World Bank. We do not rely on these variables in the main analysis because data start from 2006.

Table C1: Correlations of confounders

	CME
CME	1
Corruption	**0.48**
Unemployment	**0.11**
Electoral system	**0.34**
Migration	**0.17**
Innovation	**0.13**
Social expenditure	**0.33**
Services (%GDP)	**0.25**
Tax (%GDP)	**0.20**
FDI outflows	**0.65**
Euro	**0.17**
Private credit	**0.21**
Bank credit	**0.21**
Financial credit	**0.30**

Note: Sources: WGI (WB 2018), Database of Political Institutions (2017), UN (2018), ILO (2018), WDI (2018), OECD (2018).

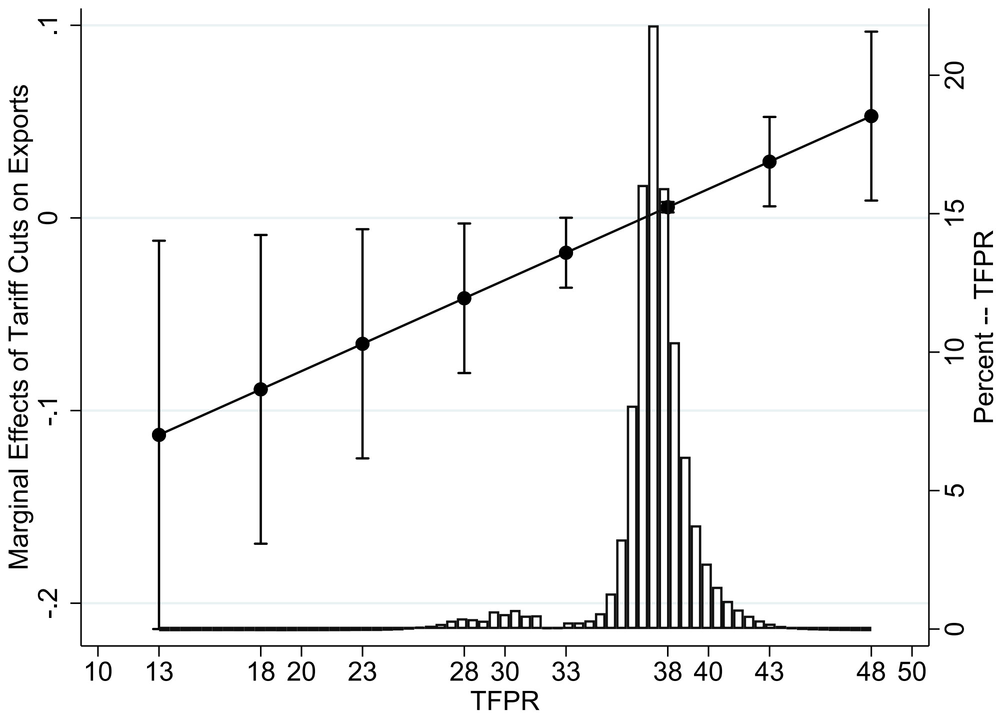
Appendix D

Mechanisms

Table D2 reports another test at the firm level, indicating that the cost of labor increases more for LMEs than CMEs after trade liberalization. We use firm-level data capturing the cost of employees over revenue as the dependent variable. We are unable to use the first differences of variable capturing the cost of employees over revenue, since our data are repeated cross-sectionally. Assuming that workers' (other-than-wage) benefits do not change differentially between CMEs and LMEs as a result of tariff reduction, this should be a good proxy for wages. We run models with this variable as outcome and the interaction among *CME*, $\Delta\tau$, and *TFPR* as key independent variables. Results are shown in Table D2. Model 1 shows the results of the baseline model, whereas Model 2 includes industry-specific trends. The coefficient of the main interaction is negative and significant in both models, as expected. All in all, these findings validate the claims that the cost of labor increases differentially more in LMEs than CMEs after trade liberalization.

Moreover, we show that the reallocation effect is indeed triggered by increasing trade activities from the most productive firms. In particular, we regress firms' exports over revenue on the interaction between *TFPR* and $\Delta\tau$. We also include all the controls as in the main models as well as country-year and industry fixed effects. Figure D1 shows that exports over revenue increases after trade liberalization only for the most productive firms. This finding validates the claim that a reduction in preferential tariffs increases the intensive margins of trade for the most productive firms. We also find no effect of PTAs on the extensive margin of trade (see Table D1, Model 1, in Appendix D).

Figure D1: The effect of tariff cuts on exports for different levels of firm productivity



Note: The outcome variable is exports over revenue. The graph shows the marginal effect of export tariff cuts on exports for different levels of firm productivity. The model includes country-year and industry fixed effects. OLS regression with robust standard errors are clustered at the industry-year level. The histogram shows the distribution of *TFPR*. 90% C.I.

Table D1: Mechanisms: Trade, Wages, and Employment

	(1)	(2)	(3)	(4)
	OLS			FracReg
	Extensive Margins	Intensive Margins	Hourly Wages	Labor Share
CME			1.178***	-0.259
			(0.323)	(0.447)
Δτ	-0.004	-0.174*	0.090***	-0.027***
	(0.002)	(0.094)	(0.027)	(0.008)
TFPR	0.019***	0.096*		
	(0.001)	(0.056)		
Δτ*CME			**-0.095****	**0.026*****
			(0.035)	**(0.008)**
Δτ*TFPR	**0.000**	**0.005***		
	(0.000)	**(0.003)**		
Constant	-0.929	-51.682***	-0.118	-4.401***
	(7.467)	(3.562)	(0.443)	(0.745)
Observations	537,291	535,334	354	22,157
R-squared	0.470	0.360	0.412	0.109
Controls	Yes	Yes	No	Yes
CountryYear FE	Yes	Yes	No	No
Industry FE	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes
Year FE	No	No	Yes	Yes

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: OLS regressions (Models 1, 2, and 3) and fractional response model (Model 4). Robust standard errors are clustered at the industry-year level (Models 1 and 2), at the country level (Model 3), and at the country-year level (Model 4). Unit of observation is firm-industry (4-digit NAICS)-country-year in Models 1 and 2 and industry-country-year in Models 3 and 4. The outcome variable is the log of revenue in Models 1 and 2, hourly wages in Model 3, and labor share in Model 4. Sources: Amadeus dataset, Baccini et al. (2018), ILO (2016), and Visser (2016).

Table D2: Wages and Cost of Labor

	(1)	(2)
	OLS	
	Cost of Labour	
$\Delta\tau$	-2.735**	-2.757**
	(1.185)	(1.197)
TFPR	-1.527***	-1.535***
	(0.454)	(0.458)
TFPR*$\Delta\tau$	0.067**	0.068**
	(0.031)	(0.031)
$\Delta\tau$*CME	2.692**	2.715**
	(1.181)	(1.192)
TFPR*CME	1.506***	1.515***
	(0.467)	(0.471)
TFPR*$\Delta\tau$*CME	**-0.066****	**-0.066****
	(0.031)	**(0.031)**
Constant	-22.429***	-3,463.642***
	(6.261)	(990.747)
Controls	Yes	Yes
CountryYear FE	Yes	Yes
Industry FE	Yes	Yes
Trends	No	Yes
Observations	3,735,589	3,735,589
R-squared	0.015	0.015

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: OLS with robust standard errors clustered at the country-year level in parentheses. Unit of observation is firm-industry (4-digit NAICS)-country-year. The outcome variable is the cost of employees. Sources: ILO, Amadeus dataset, Baccini et al. (2018), and Visser (2016).

Appendix E

Additional Evidence

Instrumenting tariffs To further dissipate concerns that endogeneity of wage bargaining institutions is responsible for our findings, we implement an instrumental variable (IV) approach. Let us explain the logic of our IV strategy. Let's assume that wage bargaining institutions are endogenous to globalization. In other words, it may be that governments implement a set of policies that are related to one another under the pressure of globalization. Hence, when governments implement trade liberalization, they are also likely to reform the labor market in a more liberal way. In other words, let G be government. We may be worried that $G \rightarrow \Delta\tau \rightarrow CME$. Thus, if we find an instrument I, which is orthogonal to G, we can then claim that $I \rightarrow G \nrightarrow \Delta\tau \nrightarrow CME$.

To instrument EU tariff cuts, we rely on tariff cuts implemented by trade competitors of the EU. Indeed, it is well-known that major trade entities compete with each other for preferential market access (Manger 2009, Baccini and Dür 2012). Thus, preferential tariff cuts in the same industries are similar among trade competitors. Since governments of EU countries have little to say on trade policies implemented by trade competitors, preferential tariff cuts implemented by EU trade competitors should prune the endogeneity from EU preferential tariff cuts, at least the endogeneity coming from the role of G.

We use preferential tariff cuts implemented by Australia, Canada, China, Japan, South Korea, and the US. More specifically, we build a synthetic measure of tariffs cuts implemented by these trading partners to minimize the difference with EU tariff cuts. By building a synthetic measure across different trading partners, we avoid the risk of relying on only one trading partner to instrument EU tariff cuts. This should further reduce concerns about a possible violation of the exclusion restriction. We label this variable *Z*. To instrument each double interaction with $\Delta\tau$ and the triple interaction term, we interact *Z* with *TFPR* and *CME*. Armed with these instruments, we estimate the following models in the first stage:

$$\begin{aligned}\Delta\tau_{ict} = \gamma_0 + \gamma_1 TFPR_{fic} + \gamma_2 Z_{it-1} + \gamma_3 TFPR_{fic} \times Z_{it-1} + \gamma_4 TFPR_{fic} \times CME_{ct} + \\ \gamma_5 Z_{it-1} \times CME_{ct} + \gamma_6 TFPR_{fic} \times Z_{it-1} \times CME_{ct} + \mathbf{X_{fict}}\gamma' + \mathbf{W_{ict}}\eta' + \delta_{\mathbf{ct}} + \delta_{\mathbf{i}} + \epsilon_{\mathbf{fict}},\end{aligned} \tag{1}$$

$$\begin{aligned}\Delta\tau_{ict} \times TFPR_{fic} = \gamma_0 &+ \gamma_1 TFPR_{fic} + \gamma_2 Z_{it-1} + \gamma_3 TFPR_{fic} \times Z_{it-1} \\ &+ \gamma_4 TFPR_{fic} \times CME_{ct} + \gamma_5 Z_{it-1} \times CME_{ct} \\ &+ \gamma_6 TFPR_{fic} \times Z_{it-1} \times CME_{ct} + \mathbf{X_{fict}}\gamma' + \mathbf{W_{ict}}\eta' \\ &+ \delta_{ct} + \delta_i + \epsilon_{fict},\end{aligned} \tag{2}$$

$$
\begin{aligned}
\Delta\tau_{ict} \times CME_{ct} = \gamma_0 + \gamma_1 TFPR_{fic} + \gamma_2 Z_{it-1} + \gamma_3 TFPR_{fic} \times Z_{it-1} + \gamma_4 TFPR_{fic} \times CME_{ct} + \\
\gamma_5 Z_{it-1} \times CME_{ct} + \gamma_6 TFPR_{fic} \times Z_{it-1} \times CME_{ct} + \mathbf{X_{fict}}\gamma^{'} + \mathbf{W_{ict}}\eta^{'} \\
+ \delta_{ct} + \delta_i + \epsilon_{fict},
\end{aligned} \tag{3}
$$

$$
\begin{aligned}
\Delta\tau_{ict} \times TFPR_{fic} \times CME_{ct} = {} & \gamma_0 + \gamma_1 TFPR_{fic} + \gamma_2 Z_{it-1} + \gamma_3 TFPR_{fic} \times Z_{it-1} \\
& + \gamma_4 TFPR_{fic} \times CME_{ct} + \gamma_5 Z_{it-1} \times CME_{ct} \\
& + \gamma_6 TFPR_{fic} \times Z_{it-1} \times CME_{ct} + \mathbf{X_{fict}}\gamma^{'} + \mathbf{W_{ict}}\eta^{'} \\
& + \delta_{ct} + \delta_i + \epsilon_{fict},
\end{aligned} \tag{4}
$$

We then plug each of the instrumented variable into our main equation 1 and estimate the following model in the second stage:

$$
\begin{aligned}
Revenue_{fict} = \beta_0 + \beta_1 TFPR_{fic} + \beta_2 \widehat{\Delta\tau_{it-1}} + \beta_3 TFP\widehat{R_{fic} \times} \Delta\tau_{it-1} + \beta_4 TFPR_{fic} \times CME_{ct} + \\
\beta_5 \Delta\tau_{it-1} \widehat{\times C} ME_{ct} + \beta_6 TFPR_{fic} \times \widehat{\Delta\tau_{it-1}} \times CME_{ct} + \mathbf{X_{fict}}\gamma^{'} + \mathbf{W_{ict}}\eta^{'} \\
+ \delta_{ct} + \delta_i + \epsilon_{fict},
\end{aligned} \tag{5}
$$

Our results hold with the IV estimates and diagnostics show no concerns about weak instruments or under-identification (Table E1, Model 1). In Model 2, we rely on two synthetic instruments: (1) one including the minimum distance between EU tariff cuts and tariff cuts implemented by Australia, Canada, and the US (Z_1); (2) one including the minimum distance between EU tariff cuts and tariff cuts implemented by China, Japan, and South Korea (Z_2). Even in this case, we interact Z_1 and Z_2 with *TFPR* and *CME.* Since we have more instruments than instrumented variables, we can test the over-identification assumption as a necessary (but not sufficient) validation of the exclusion restriction. The Hansen J statistic is not significant, i.e. there is no concern about over-identification, and our main results remain unchanged.

Labor flexibility We use measures of labor flexibility pertaining to the strictness of regulation of both individual dismissals and collective dismissals, as well as the strictness of regulation of the use of fixed-term and temporary work agency contracts. High values imply a flexible labor market, i.e., it is easy to dismiss workers and to rely on temporary contracts. Data come from the OECD (2016) and are available for all OECD countries over time. We interact these measures of flexibility with $\Delta\tau$ and *TFPR.* While this triple interaction is never significant, the coefficients of our main variables are unchanged (Table E2).

Automation We use the data on automation from Acemoglu and Restrepo (2019). The data are from the US, since we are concerned about automation being a function of trade liberalization, which would make automation a bad control. The data are from 1993 and do not vary over time. We use a crosswalk to match SIC industries, which are in the original automation data, to NAICS 4-digit industries, which are in our firm-level dataset. While the coefficient of automation alone is absorbed by industry fixed effects, we are able to estimate the effect of automation by interacting it with firm productivity and labor market institutions (double and triple interaction terms). The triple interaction term among automation, firm productivity, and labor market institutions is positive and significant (Table E3). Importantly, our main results hold even when we include this alternative channel.

Other labor market institutions While wage coordination is among the most important institutional features of varieties of capitalism (see Hall and Gingerich 2009; Guardiancich and Guidi 2016), there are other characteristics of the labor market that may be relevant to mediating the distributional consequences of trade liberalization. To address these concerns, we identify other variables from the ICTWSS database: government intervention, authority of unions over affiliates, mandatory extension of collective agreements, sectoral organization of employment relations, authority of unions over local branches, union density, measure of centralization of wage bargaining, and minimum wage. The variables that we analyze as alternative measures of labor market frictions follow. All of them are taken from the ICTWSS database (Visser 2016).

Government intervention in wage bargaining An ordinal variable ranging from 1 to 5, measuring the degree to which the government influences wage bargaining, where 1 means no intervention whatsoever and 5 means that the government "imposes private sector wage settlements, places a ceiling on bargaining outcomes or suspends bargaining" (Visser 2015).

Authority of unions over their affiliates A proxy measuring the authority of confederations over sectoral or local branches. This variable combines information on whether the confederation is routinely involved in consultation with the government, controls the appointment of affiliates' leaders, is involved in negotiation of the affiliates' wage agreements, has a fund for official strikes, and can veto strikes by affiliates.

Mandatory extension of collective agreements Mandatory extension of collective agreements to non-organized employers.

Sectoral organization of employment relations An ordinal variable measuring how institutionalized are the relationships between employers and unions at the sectoral level. The possible values are 0 (no institutionalization), 1 (medium institutionalization), and 2 (strong institutionalization).

Authority of unions over their local branches Authority of unions over local branches. Additive measure.

Union density The percentage of union members out of the total number of employed and salaried workers.

Centralization of wage bargaining A composite index that combines information about the predominant level at which wage bargaining takes place, the frequency or scope of additional enterprise bargaining, the possibility of renegotiation of contractual provisions at lower levels, the articulation of enterprise bargaining, and the possibility to derogate to national- or sector-level agreements.

Minimum wage National minimum wage is set by agreement.

We interact each of the aforementioned variables with $TFPR$ and $\Delta\tau$. Because these variables tend to be highly colinear, we do not include all of them at the same time and we do not include them together with our main triple interaction term. Including these variables leaves our results unchanged (Table E4). Three out of seven triple interactions are significant and have the expected negative sign. More specifically, government intervention in wage bargaining weakens the reallocation effect as well as the authority of confederation over its affiliates and mandatory extension of collective agreements to non-organized employers. These results confirm that labor market frictions help unproductive firms to reduce uneven distributional consequences of trade liberalization through imposing a wage ceiling.

Different tariff cuts In the main analysis, we have mostly focused on export tariff cuts. However, there are two other types of tariff cuts, which may be exploited. First, import tariff cuts, i.e., tariff cuts implemented by the EU, increase imports and, in turn, raise competition for domestic firms. In turn, this may reduce prices and so real wages. We build import tariff cuts in the same way as we build export tariff cuts (see Appendix B). Second, input tariff cuts reduce firms' costs of production and, in turn, increase their sales due to cheaper, more competitive goods. In turn, this increases the demand for labor and so wages. To build our measure of input tariffs, we follow Topalova and Khandelwal (2011). Formally, input tariff cuts are given by the following:

$$\text{Input Tariff Cut}_{jt} = \sum_s \text{a}_{js} \times \text{ Import Tariff Cuts}_{st}$$

where a_{js} is the share of input s in the value of output j. Data of share of input come from Input-Output (I-O) tables of EU countries. We use baseline values in 2000, which are available at the 4-digit level.[4]

The effect of other types of tariffs, i.e. import tariff cuts and input tariff cuts. In particular, we rerun the model described in equation 1, replacing export tariff cuts with import tariff cuts and input tariff cuts. Table E5 reports the results of this test. It turns out that import tariff cuts generate no differential reallocation effect between CMEs and LMEs, whereas the coefficient of the triple interaction term is significant in the case of input tariffs, which benefit disproportionally large,

[4]I-O tables are available at `https://www.exiobase.eu/index.php/data-download/exiobase1-year-2000-sample-files`.

productive firms. When foreign inputs become cheaper, multinationals reduce their production costs and therefore expand their sales. This increase in economic activities generates a demand for labor and so an upward pressure on wages. CMEs tame this upward pressure better than LMEs, giving relief to smaller, less productive firms. These findings confirm that in the case of trade policies giving advantages to exports and multinationals, gains from trade among firms are even more in CMEs than in LMEs.

Table E1: Instrumenting preferential tariff cuts

	(1)	(2)
	2SLS	
	ln(Revenue)	
$\Delta\tau$	-0.492***	-0.475***
	(0.114)	(0.134)
TFPR	0.400	0.402***
	(0.029)	(0.026)
TFPR*$\Delta\tau$	0.013***	0.013***
	(0.003)	(0.004)
$\Delta\tau$*CME	0.477***	0.459***
	(0.114)	(0.135)
TFPR*CME	-0.043	-0.046
	(0.038)	(0.035)
TFPR*$\Delta\tau$*CME	**-0.013*** **	**-0.012*** **
	(0.003)	**(0.004)**
Controls	Yes	Yes
CountryYear FE	Yes	Yes
Industry FE	Yes	Yes
Underidentification test	16.571***	29.639***
Weak identification test	45.365***	45.973***
Hansen J statistic		0.845
Observations	4,053,929	4,053,929
R-squared	0.631	0.631

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: OLS with robust standard errors clustered at the country-year level in parentheses. Unit of observation is firm-industry (4-digit NAICS)-country-year. The outcome variable is the log of revenue. Sources: ILO, Amadeus dataset, Baccini et al. (2018), and Visser (2016).

Table E2: Including Labor Flexibility

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS					
	ln(Revenue)					
Δτ	-0.272***	-0.277***	-0.275***	-0.269***	-0.274***	-0.273***
	(0.100)	(0.101)	(0.101)	(0.100)	(0.101)	(0.100)
TFPR	0.540***	0.527***	0.521***	0.541***	0.528***	0.522***
	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)
TFPR*Δτ	0.007***		0.008***	0.007***		0.008***
	(0.003)		(0.003)	(0.003)		(0.003)
Δτ*CME	0.145*	0.137*	0.135*	0.140*	0.132*	0.131*
	(0.080)	(0.079)	(0.079)	(0.079)	(0.079)	(0.078)
TFPR*CME	0.028	0.018	0.011	0.027	0.017	0.010
	(0.031)	(0.032)	(0.033)	(0.031)	(0.031)	(0.033)
TFPR*Δτ*CME	**-0.004***	**-0.004***	**-0.004***	**-0.004***	**-0.004***	**-0.004***
	(0.002)	**(0.002)**	**(0.002)**	**(0.002)**	**(0.002)**	**(0.002)**
Δτ*Wage Ceiling		0.266***	0.266***		0.267***	0.267***
		(0.035)	(0.034)		(0.035)	(0.035)
TFPR*Wage Ceiling		0.194***	0.201***		0.194***	0.201***
		(0.037)	(0.038)		(0.037)	(0.038)
Δτ*TFPR*Wage Ceiling		**-0.007*****	**-0.007*****		**-0.007*****	**-0.007*****
		(0.001)	**(0.001)**		**(0.001)**	**(0.001)**
Δτ*Subsidies for CVT			0.092***			0.089***
			(0.025)			(0.024)
TFPR*Subsidies for VT			0.096**			0.096**
			(0.047)			(0.047)
Δτ*TFPR*Subsidies for VT			**-0.002*****			**-0.002*****
			(0.001)			**(0.001)**
Δτ*Labour Flexibility	0.045	0.050	0.051	0.046	0.051	0.051
	(0.042)	(0.043)	(0.043)	(0.042)	(0.043)	(0.043)
TFPR*Labour Flexibility	-0.059**	-0.052*	-0.048*	-0.058**	-0.052*	-0.048*
	(0.028)	(0.028)	(0.029)	(0.028)	(0.028)	(0.029)
Δτ*TFPR*Labour Flexibility	**-0.001**	**-0.001**	**-0.001**	**-0.001**	**-0.001**	**-0.001**
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Constant	-10.564***	-10.309***	-10.099***	-287.449*	-285.299*	-285.953*
	(0.786)	(0.809)	(0.858)	(164.788)	(164.778)	(164.320)
Observations	2,846,018	2,846,018	2,846,018	2,846,018	2,846,018	2,846,018
R-squared	0.809	0.809	0.809	0.809	0.810	0.810
Controls	Yes	Yes	Yes	Yes	Yes	Yes
CountryYear FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Trends	No	No	No	Yes	Yes	Yes

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: OLS with robust standard errors clustered at the country-year level in parentheses. Unit of observation is firm-industry (4-digit NAICS)-country-year. The outcome variable is the log of revenue. Sources: ILO, Amadeus dataset, Baccini et al. (2018), and Visser (2016).

Table E3: Including Automation

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS					
	ln(Revenue)					
Δτ	-0.366***	-0.365***	-0.368***	-0.361**	-0.361**	-0.364**
	(0.139)	(0.139)	(0.139)	(0.141)	(0.140)	(0.140)
TFPR	0.434***	0.435***	0.433***	0.435***	0.436***	0.434***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
TFPR*Δτ	0.010***	0.010***	0.010***	0.010**	0.010***	0.010***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Δτ*CME	0.347**	0.344**	0.355**	0.343**	0.340**	0.351**
	(0.140)	(0.140)	(0.139)	(0.141)	(0.141)	(0.140)
TFPR*CME	-0.075**	-0.072**	-0.053	-0.076**	-0.073**	-0.054
	(0.034)	(0.036)	(0.036)	(0.033)	(0.035)	(0.035)
TFPR*Δτ*CME	**-0.009****	**-0.009****	**-0.010****	**-0.009****	**-0.009****	**-0.009****
	(0.004)	**(0.004)**	**(0.004)**	**(0.004)**	**(0.004)**	**(0.004)**
Δτ*Wage Ceiling		0.106**	0.093**		0.103**	0.090**
		(0.045)	(0.045)		(0.046)	(0.045)
TFPR*Wage Ceiling		-0.034	-0.049		-0.036	-0.051
		(0.052)	(0.053)		(0.052)	(0.053)
Δτ*TFPR*Wage Ceiling		**-0.003****	**-0.003****		**-0.003****	**-0.002****
		(0.001)	**(0.001)**		**(0.001)**	**(0.001)**
Δτ*Subsidies for CVT			0.095***			0.088***
			(0.020)			(0.021)
TFPR*Subsidies for VT			0.122***			0.120***
			(0.036)			(0.036)
Δτ*TFPR*Subsidies for VT			**-0.002*****			**-0.002*****
			(0.001)			**(0.001)**
TFPR*Automation	-0.003***	-0.004***	-0.003**	-0.003***	-0.004***	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Automation*CME	-0.039**	-0.043**	-0.032*	-0.039**	-0.043**	-0.032*
	(0.018)	(0.017)	(0.017)	(0.018)	(0.017)	(0.017)
TFPR*Automation*CME	**0.001****	**0.001****	**0.001***	**0.001****	**0.001****	**0.001***
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Constant	-8.542***	-8.700***	-9.117***	-162.247***	103.448**	204.364***
	(0.883)	(0.969)	(1.041)	(54.833)	(50.959)	(66.292)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
CountryYear FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Trends	No	No	No	Yes	Yes	Yes
Observations	4,053,929	4,032,150	3,918,518	4,053,929	4,032,150	3,918,518
R-squared	0.766	0.767	0.775	0.766	0.767	0.775

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: OLS with robust standard errors clustered at the country-year level in parentheses. Unit of observation is firm-industry (4-digit NAICS)-country-year. The outcome variable is the log of revenue. Sources: ILO, Amadeus dataset, Baccini et al. (2018), and Visser (2016).

Table E4: Including other labor market institutions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS							
	ln(Revenue)							
TFPR*Δτ*CME	**-0.010****	**-0.008****	**-0.009****	**-0.009****	**-0.010*****	**-0.011*****	**-0.009*****	**-0.010*****
	(0.004)	**(0.004)**	**(0.004)**	**(0.004)**	**(0.004)**	**(0.003)**	**(0.003)**	**(0.004)**
TFPR*Δτ*Govt. Intervention	-0.001							
	(0.001)							
TFPR*Δτ*Authority over Affliates		-0.001						
		(0.004)						
TFPR*Δτ*Mandatory Extension of Collective Agreements			-0.0003**					
			(0.000)					
TFPR*Δτ*Sectoral Organiz.				-0.000				
				(0.001)				
TFPR*Δτ*Authority over Local Branches					0.003			
					(0.004)			
TFPR*Δτ*Union Density						0.000		
						(0.000)		
TFPR*Δτ*Centralization							0.012	
							(0.010)	
TFPR*Δτ*Minimum Wage								-0.000
								(0.000)
Constant	-9.275***	-9.600***	-9.367***	-9.414***	-9.157***	-10.917***	-10.431***	-9.563***
	(0.818)	(0.687)	(0.661)	(0.783)	(0.786)	(0.963)	(0.844)	(0.741)
Observations	4,032,144	3,934,884	4,042,889	3,956,663	3,934,884	2,897,040	2,470,577	3,933,830
R-squared	0.767	0.770	0.768	0.769	0.770	0.784	0.781	0.774
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryYear FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trends	No	No	No	No	No	No	No	No

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: OLS with robust standard errors clustered at the country-year level in parentheses. Unit of observation is firm-industry (4-digit NAICS)-country-year. The outcome variable is the log of revenue. Sources: ILO, Amadeus dataset, Baccini et al. (2018), and Visser (2016).

Table E5: Including other Types of Tariffs

	(1)	(2)
	OLS	
	ln(Revenue)	
Δτ (import)	-0.544**	
	(0.238)	
Δτ (input)		1.416
		(1.019)
TFPR	0.469***	0.494***
	(0.039)	(0.030)
CME*TFPR	-0.120***	-0.149***
	(0.046)	(0.039)
Δτ (import)*TFPR	0.015**	
	(0.006)	
Δτ (input)*TFPR		0.037
		(0.027)
CME*Δτ (import)	0.040	
	(0.314)	
CME*Δτ (input)		2.739**
		(1.118)
CME*Δτ (import)*TFPR	**-0.001**	
	(0.008)	
CME*Δτ (inpu)*TFPR		**-0.073****
		(0.029)
Constant	-9.083***	-8.959***
	(0.773)	(0.760)
Observations	4,053,923	4,032,144
R-squared	0.766	0.767
Controls	Yes	Yes
CountryYear FE	Yes	Yes
Industry FE	Yes	Yes

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: OLS with robust standard errors clustered at the country-year level in parentheses. Unit of observation is firm-industry (4-digit NAICS)-country-year. The outcome variable is the log of revenue. Sources: ILO, Amadeus dataset, Baccini et al. (2018), and Visser (2016).

Appendix F

Robustness Checks

Interaction term diagnostics Regarding the interaction term, we follow best practices as recommended by Hainmueller et al. (2019). In particular, we show that our results are not sensitive to nonlinearity issues and there is no concern of lack of common support of our moderating variable, i.e., *TFPR*. Note that we are unable to use the command "interflex" developed by Hainmueller and colleagues (2019), since the command does not extend to triple interaction terms like ours. Thus, in performing these checks, we modify Hainmueller et al.'s tests and extend them to a design like ours including triple interaction terms (rather than double interaction terms). In particular, we implement the following checks:

- We recoded *TFPR* in an ordinal variable with eight values. We recoded the original variable in a eight-value ordinal variable, using the command "binsregselect," which implements a data-driven number of bins selectors using either quantile-spaced or evenly-spaced binning. The command has been recently developed by Cattaneo and colleagues. Using an ordinal variable reduces the probability of lack of common support of the moderator, since there are several observations for both CMEs and LMEs in each category. Results are very similar to the estimates with a continuous *TFPR* (Figure F1).

- We run a binning estimator as suggested by Hainmueller et al (2019: 170-71). To avoid estimating a quadruple interaction terms, which would be difficult to interpret, we estimate two regressions for a bin with low-productivity firms and a bin with high-productivity firms. We avoid estimating a medium category, since there is limited variation in the middle of the distribution of *TFPR*. Using two bins has also the advantage of very conservative test of the lack of common support of the moderator, since two bins include a very large number of observations for both CMEs and LMEs. Crucially, the triple interaction term is negative and significant in both bins. The effect of the triple interaction is larger in the low-productivity bin compared to the high-productivity bin (Table F1). This is in line with Figure 3, in which the largest difference in the linear estimates is for low-productivity firms. In short, the binning estimator shows no concern about nonlinearity or lack of common support of the moderator.

- We re-run our main model using the kernel-based regularized least squares (KRLS), developed by Hainmueller and Hazlett (2014). KRLS allows researchers to tackle regression and classification problems without strong functional form assumptions or a specification search. For our purpose, this estimation technique allows us to check whether nonlinearity issues of the triple interactions are driving our results. Put simply, leaving out an important function of the interaction can result in the same type of omitted variable bias as failing to include an important unobserved confounding variable. Results are shown in Table F2 and are similar to the results of the OLS regressions, reported in Table 1 and Figure 3.[5] In sum, there is no

[5]For computational reasons, we run the KRLS model on a small subsample of the data. Even with this relatively

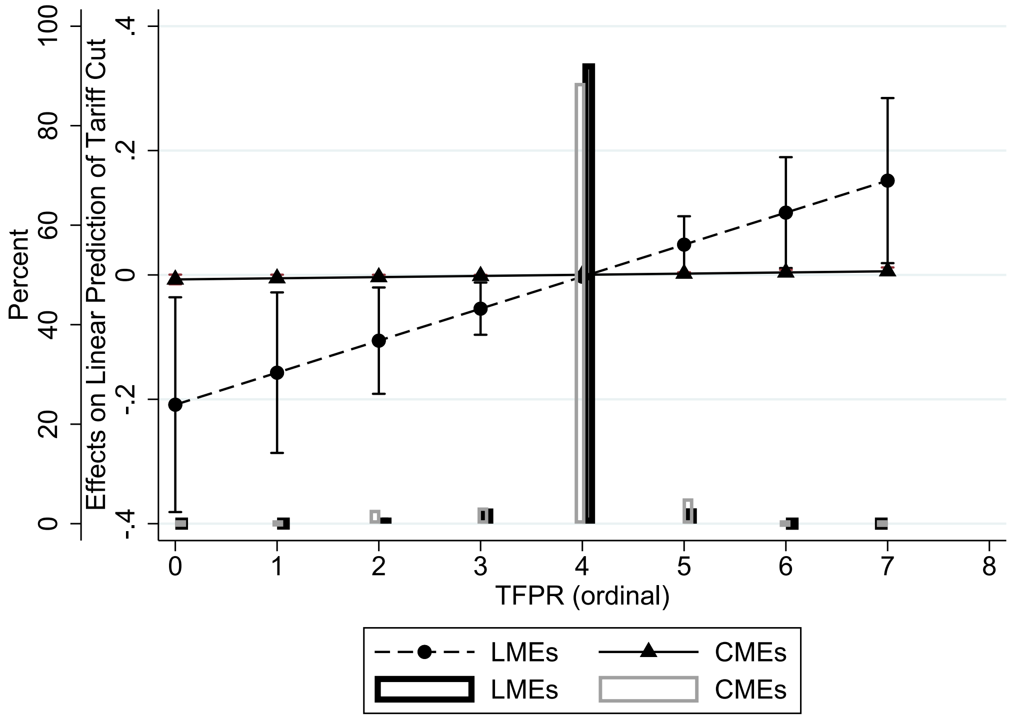
evidence that a nonlinear interaction effect is responsible for our results.

Sample issues Regarding sample issues, we show that our results are similar if we run our main models with the aforementioned weights in Kalemli-Ozcan et al. (2017). Moreover, our results hold if we run our main model, dropping one LME at a time. All these tests are reported in Tables F3 and F4.

Additional model specifications Regarding model specifications, we show that our results are robust to the inclusion of firm fixed effects. We do not include firm fixed effects in the main model, because our data are repeated cross-sectionally. Note that by including firm fixed effects, we are unable to estimate *TFPR*, which does not change across firms over time. In addition, we show that results are similar when we include preferential tariff cuts prior to 2003 together with $\Delta\tau$. In particular, we use 1995-2003 preferential tariff cuts in interaction with *TFPR* and *CME*. All these tests are reported in Tables F5, and F6.

low number of observations, the model takes more than 24 hours to run on a powerful computer.

Figure F1: The effect of tariff cuts on firm revenue for different levels of firm productivity (ordinal measure) in CMEs and LMEs



Note: LME includes countries with "fragmented wage bargaining, confined largely to individual firms or plants." CME includes countries with "mixed industry and firm-level bargaining, weak government coordination through MW setting or wage indexation," "negotiation guidelines based on centralized bargaining," "wage norms based on centralized bargaining by peak associations with or without government involvement," and "maximum or minimum wage rates/increases based on centralized bargaining." The histogram shows the distribution of *TFPR* (ordinal measure) for both CMEs and LMEs. 99% C.I.

Table F1: Binning estimator

	(1)	(2)
	OLS	
	ln(Revenue)	
	Bin 1 (low TFPR)	Bin 2 (high TFPR)
Δτ	0.008**	0.003
	(0.004)	(0.002)
TFPR X1	0.422***	
	(0.037)	
TFPR X1*Δτ	0.011**	
	(0.005)	
Δτ*CME	-0.008*	-0.003
	(0.004)	(0.002)
TFPR X1*CME	-0.047	
	(0.049)	
TFPR X1*Δτ*CME	**-0.010****	
	(0.005)	
TFPR X2		0.297***
		(0.015)
TFPR X2*Δτ		0.006***
		(0.002)
TFPR X2*CME		-0.073***
		(0.022)
TFPR X2*Δτ*CME		**-0.005*****
		(0.002)
Constant	4.528***	5.205***
	(0.307)	(0.129)
Controls	Yes	Yes
CountryYear FE	Yes	Yes
Industry FE	Yes	Yes
Trends	No	No
Observations	2,021,591	2,032,338
R-squared	0.777	0.762

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: Binning estimator with standard errors clustered at the country-year level in parentheses. Unit of observation is firm-industry (4-digit NAICS)-country-year. The outcome variable in all models is the log of revenue. Sources: Amadeus dataset, Baccini et al. (2018), and Visser (2016).

Table F2: Kernel-Based Regularized Least Squares

	(1)
	KRLS
	ln(Revenue)
$\Delta\tau$	-0.0004
	-0.001
TFPR	0.075***
	-0.011
TFPR*$\Delta\tau$	0.00003
	(0.00003)
$\Delta\tau$*CME	-0.004***
	(0.001)
TFPR*CME	0.0003***
	(0.0001)
TFPR*$\Delta\tau$*CME	**-0.00009*** **
	(0.00003)
Controls	Yes
CountryYear FE	Yes
Industry FE	Yes
Observations	4,053,923
Lambda	0.054
Tolerance	0.407
Sigma	215
Looloss	509.8
R-squared	0.985

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: KRLS regression. Unit of observation is firm-industry (4-digit NAICS)-country-year. The outcome variable in all models is the log of revenue. Sources: Amadeus dataset, Baccini et al. (2018), and Visser (2016).

Table F3: Reallocation effect with weighted estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS					
	ln(Revenue)					
Δτ	-0.384**	-0.384**	-0.385**	-0.380**	-0.379**	-0.381**
	(0.152)	(0.152)	(0.152)	(0.154)	(0.154)	(0.154)
TFPR	0.413***	0.413***	0.413***	0.414***	0.415***	0.414***
	(0.020)	(0.021)	(0.020)	(0.021)	(0.021)	(0.020)
TFPR*Δτ	0.010**		0.010**	0.010**		0.010**
	(0.004)		(0.004)	(0.004)		(0.004)
Δτ*CME	0.367**	0.364**	0.374**	0.363**	0.360**	0.371**
	(0.153)	(0.153)	(0.152)	(0.154)	(0.154)	(0.154)
TFPR*CME	-0.070**	-0.066*	-0.050	-0.070**	-0.067*	-0.051
	(0.034)	(0.036)	(0.037)	(0.033)	(0.035)	(0.036)
TFPR*Δτ*CME	**-0.010****	**-0.010****	**-0.010****	**-0.010****	**-0.010****	**-0.010****
	(0.004)	**(0.004)**	**(0.004)**	**(0.004)**	**(0.004)**	**(0.004)**
Δτ*Wage Ceiling		0.091**	0.083**		0.087**	0.080**
		(0.041)	(0.040)		(0.041)	(0.041)
TFPR*Wage Ceiling		-0.023	-0.039		-0.025	-0.041
		(0.051)	(0.051)		(0.050)	(0.051)
Δτ*TFPR*Wage Ceiling		**-0.003****	**-0.002****		**-0.002****	**-0.002****
		(0.001)	**(0.001)**		**(0.001)**	**(0.001)**
Δτ*Subsidies for CVT			0.077***			0.070***
			(0.022)			(0.024)
TFPR*Subsidies for VT			0.131***			0.129***
			(0.039)			(0.039)
Δτ*TFPR*Subsidies for VT			**-0.002*****			**-0.002*****
			(0.001)			**(0.001)**
Constant	-7.987***	-8.110***	-8.478***	489.891***	556.793***	18.745***
	(0.873)	(0.970)	(1.057)	(30.975)	(94.609)	(42.355)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
CountryYear FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Trends	No	No	No	Yes	Yes	Yes
Weight	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,051,865	4,030,086	3,916,454	4,051,865	4,030,086	3,916,454
R-squared	0.761	0.762	0.771	0.762	0.763	0.772

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: OLS with standard errors clustered at the country-year level in parentheses and weights from Kalemli-Ozcan et al. (2017). Unit of observation is firm-industry (4-digit NAICS)-country-year. The outcome variable in all models is the log of revenue. Sources: Amadeus dataset, Visser (2016), and Kalemli-Ozcan et al. (2017).

Table F4: Reallocation effect (dropping one LME at the time)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS							
	ln(Revenue)							
$\Delta\tau$	-0.367**	-0.402***	-0.416***	-0.372***	-0.373***	-0.210***	-0.372**	-0.373***
	(0.145)	(0.155)	(0.132)	(0.141)	(0.144)	(0.067)	(0.173)	(0.144)
TFPR	0.428***	0.403***	0.432***	0.418***	0.418***	0.438***	0.407***	0.418***
	(0.023)	(0.022)	(0.025)	(0.020)	(0.020)	(0.022)	(0.018)	(0.020)
$\Delta\tau$*TFPR	0.010**	0.011***	0.011***	0.010***	0.010***	0.006***	0.010**	0.010***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.005)	(0.004)
$\Delta\tau$*CME	0.348**	0.384**	0.398***	0.354**	0.355**	0.192***	0.354**	0.355**
	(0.146)	(0.155)	(0.133)	(0.142)	(0.144)	(0.068)	(0.173)	(0.144)
CME*TFPR	-0.072**	-0.047	-0.077**	-0.063*	-0.062*	-0.082**	-0.051	-0.062*
	(0.034)	(0.033)	(0.036)	(0.032)	(0.032)	(0.034)	(0.031)	(0.032)
CME*$\Delta\tau$*TFPR	**-0.009****	**-0.010****	**-0.011*****	**-0.010****	**-0.010****	**-0.005*****	**-0.010****	**-0.010****
	(0.004)	**(0.004)**	**(0.004)**	**(0.004)**	**(0.004)**	**(0.002)**	**(0.005)**	**(0.004)**
Constant	-9.031***	-9.014***	-9.075***	-9.019***	-9.011***	-8.944***	-8.954***	-9.011***
	(0.764)	(0.779)	(0.776)	(0.756)	(0.758)	(0.762)	(0.768)	(0.758)
Observations	3,994,419	3,940,839	3,877,552	4,049,459	4,039,509	3,993,449	3,991,567	4,039,509
R-squared	0.765	0.762	0.742	0.766	0.766	0.765	0.763	0.766
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: OLS with robust standard errors clustered at the country-year level in parentheses. Unit of observation is firm-industry (4-digit NAICS)-country-year. The outcome variable is the log of revenue. Sources: ILO, Amadeus dataset, Baccini et al. (2018), and Visser (2016).

Table F5: Reallocation effect with firm fixed effects

	(1) OLS ln(Revenue)
Δτ	-0.949***
	(0.228)
TFPR*Δτ	0.026***
	(0.006)
Δτ*CME	0.909***
	(0.229)
TFPR*CME	0.361***
	(0.068)
TFPR*Δτ*CME	**-0.024*** **
	(0.006)
Costant	-8.887***
	(2.313)
Observations	3,941,162
R-squared	0.881
Controls	Yes
CountryYear FE	Yes
Industry FE	Yes
Firm FE	Yes

Robust standard errors in parentheses *** p<0.01, ** p<0.05

Note: OLS with standard errors clustered at the country-year level in parentheses. Unit of observation is firm-industry (4-digit NAICS)-country-year. The outcome variable in all models is the log of revenue. Sources: Amadeus dataset and Visser (2016).

Table F6: Reallocation effect with pre-2003 tariff cuts

	(1)	(2)
	OLS	
	ln(Revenue)	
Δτ	-0.361**	-0.356**
	(0.140)	(0.141)
TFPR	0.418***	0.420***
	(0.020)	(0.020)
TFPR*Δτ	0.010**	0.010**
	(0.004)	(0.004)
Δτ*CME	0.343**	0.339**
	(0.140)	(0.141)
TFPR*CME	-0.063*	-0.064**
	(0.032)	(0.032)
TFPR*Δτ*CME	**-0.009****	**-0.009****
	(0.004)	**(0.004)**
Δτ (pre-2003)	-0.010**	-0.010**
	(0.005)	(0.005)
Δτ (pre-2003)*TFPR	0.000**	0.000**
	(0.000)	(0.000)
Δτ (pre-2003)*CME	0.007	0.007
	(0.005)	(0.005)
TFPR*Δτ (pre-2003)*CME	**-0.000**	**-0.000**
	(0.000)	**(0.000)**
Constant	-8.407***	-161.663***
	(0.824)	(54.665)
Controls	Yes	Yes
CountryYear FE	Yes	Yes
Industry FE	Yes	Yes
Trends	No	Yes
Observations	4,053,929	4,053,929
R-squared	0.766	0.766

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: OLS with standard errors clustered at the country-year level in parentheses. Unit of observation is firm-industry (4-digit NAICS)-country-year. The outcome variable in all models is the log of revenue. Sources: Amadeus dataset and Visser (2016).

Appendix G

Geocoding Amadeus

Geocoding Amadeus was performed differently for each country. There is no standardized method, as each Amadeus dataset had different values in terms of the geographic variables. First, we looked at the postal code (zip code) variable. Eurostat provides postal codes to NUTS region tables for each country in the European Union; however, in many cases the matches were geographically inaccurate. The postal code was still useful in some cases, especially in countries with relatively well-documented postal code systems. We then resorted to the region variable provided in Amadeus, which contains the general region in which a firm is located. The entries in the region variable often matched with a NUTS-2 or -3 level name. In most cases, if a country had NUTS-3 names within the region variable, a simple merge was performed. In other countries the region variable was finer in scale, corresponding to local administrative units, which are used by Eurostat to a lesser extent. Again, once the administrative level used in the region variable was identified, a merge was performed.

In the rare case where the region did not match any of the official Eurostat tables, we resorted to official country statistics websites to determine which administrative levels were used. Geocoding based on the region variable covered most of the Amadeus observations, and if a dataset was incomplete, we used a combination of the city and region variables to geocode. This combination was used to prevent any errors which may have arisen due to duplicate city names in certain countries. String matching based on city and region was performed with the help of data from Geonames, a free geographic database which covers all countries and place names (`https://www.geonames.org/`). These datasets contain the relevant administrative boundaries, which often matched Eurostat's NUTS-2 or -3 official names, and again a simple merge was performed.

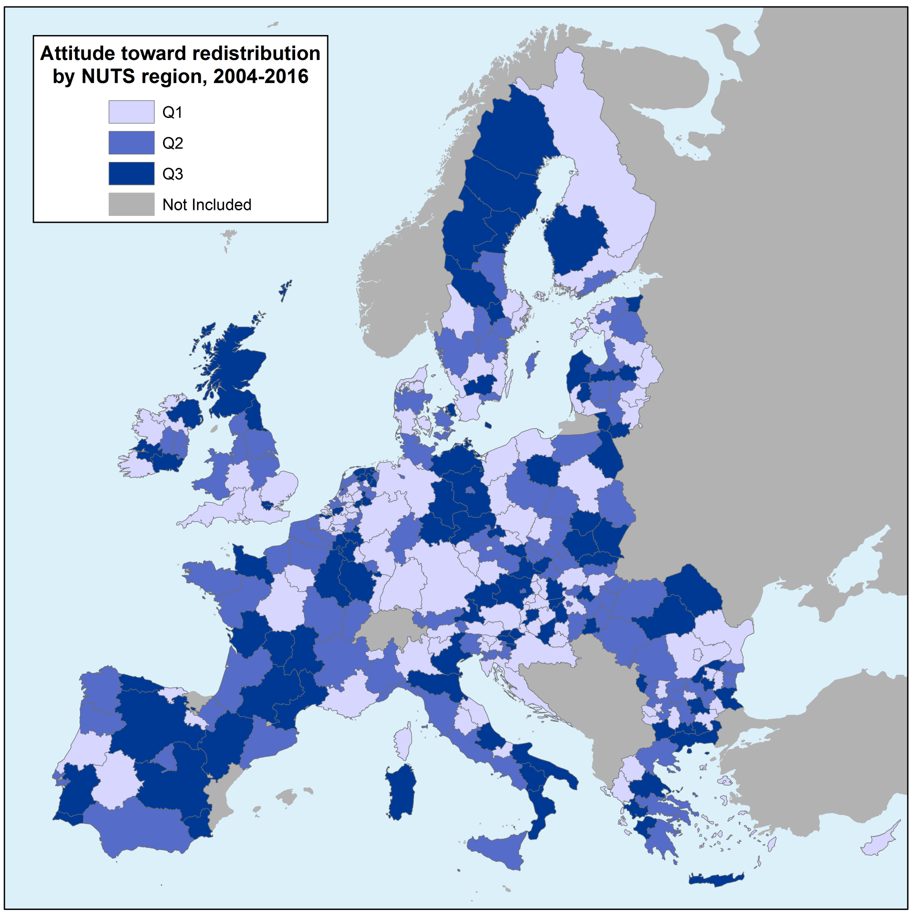
Appendix H

Measuring Skill Specificity

The variable *Skill Specificity* is constructed in a few steps. First, the share of lowest level ISCO units within the larger level unit is divided by the share of the surveyed population with that ISCO code. This is then divided by the ISCO skill classification for that ISCO code, which ranges between one and four. Then the measure is standardized. This is done at ISCO one-digit and ISCO two-digit separately, and these measures are then averaged.

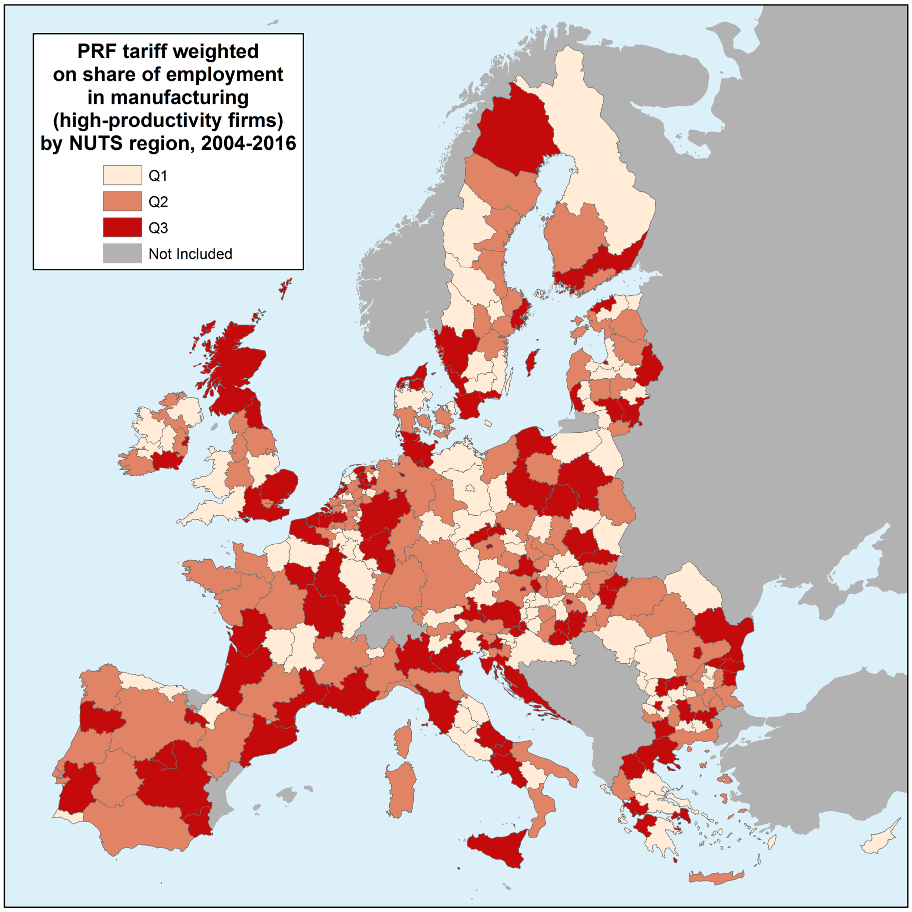
Additional Figures and Tables (individual-level analysis)

Figure H1: Support for redistribution



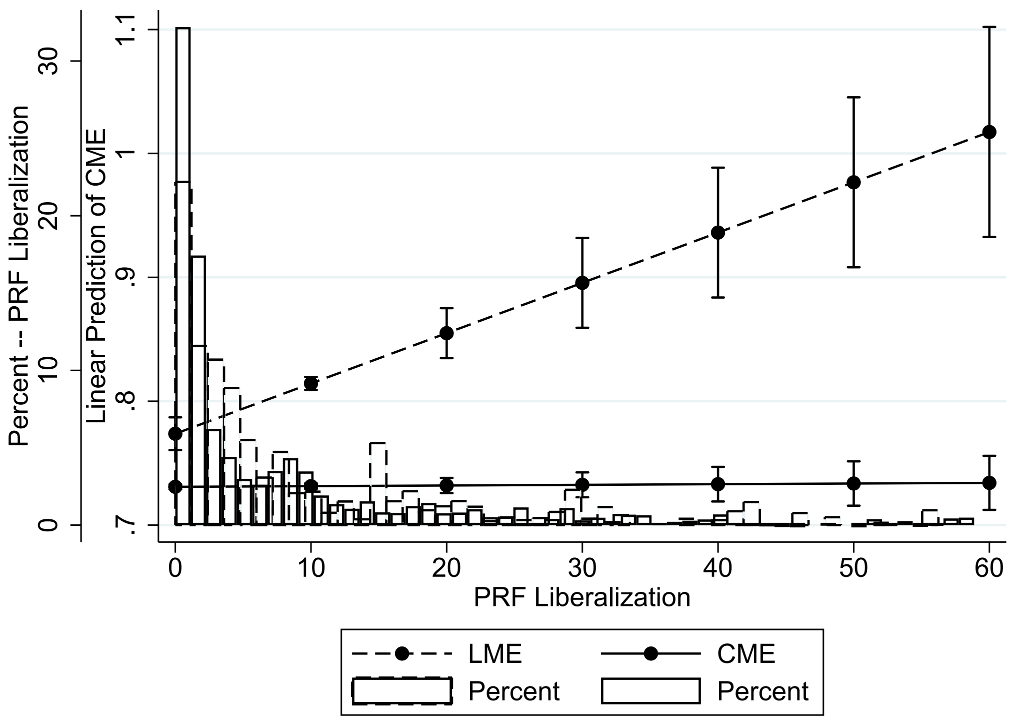
Note: The variable capturing individual attitudes towards redistribution is a dummy scoring one if respondents answer "strongly agree" or "agree" to the following sentence: *The government should take measures to reduce differences in income levels.* Data are unavailable for ES21, ES53, and ES70. Regions FRA1, FRA2, FRA3, FRA4, FRA5, ES63, ES64, PT20, and PT30 are not shown on the map.

Figure H2: PRF Liberalization



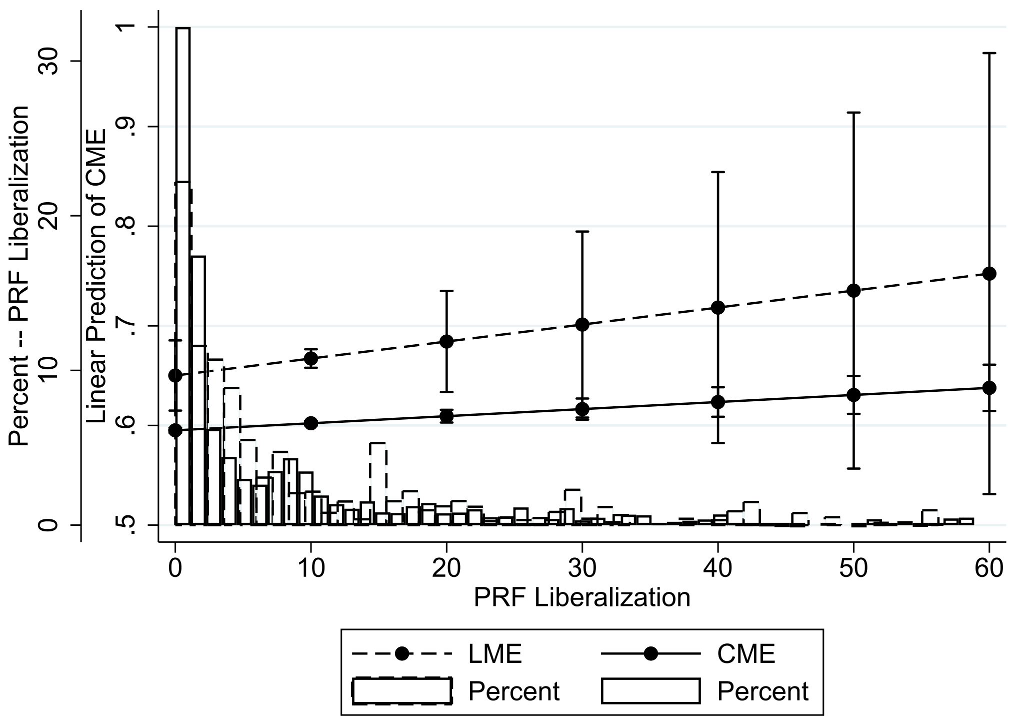
Note: The variable *Instrument for PRF Liberalization* measures preferential tariff cuts weighted on the share of manufacturing workers employed in very productive firms. Data are unavailable for ES21, ES53, and ES70. Regions FRA1, FRA2, FRA3, FRA4, FRA5, ES63, ES64, PT20, and PT30 are not shown on the map.

Figure H3: The effect of tariff cuts on support for redistribution in CMEs and LMEs (low-education)



Note: The predictions are plotted from Model 2 in Table 3. The outcome variable in all models is a dummy scoring one if respondents answer "strongly agree" or "agree" to the following sentence: *The government should take measures to reduce differences in income levels*. The graph shows the linear predictions of $\Delta\tau$ for CMEs and LMEs. The histogram shows the distribution of $\Delta\tau$ for both CMEs and LMEs. 90% C.I.

Figure H4: The effect of tariff cuts on support for redistribution in CMEs and LMEs (high-education)



Note: The predictions are plotted from Model 3 in Table 3. The outcome variable in all models is a dummy scoring one if respondents answer "strongly agree" or "agree" to the following sentence: *The government should take measures to reduce differences in income levels*. The graph shows the linear predictions of $\Delta\tau$ for CMEs and LMEs. The histogram shows the distribution of $\Delta\tau$ for both CMEs and LMEs. 90% C.I.

Table H1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Support of Redistribution	120,904	0.73	0.45	0	1
PRF Liberalization	120,904	9.55	15.11	0	110.32
Gender	120,904	1.51	0.50	1	2
CME	120,904	0.83	0.37	0	1
Years of Education	120,904	12.72	4.06	0	51
Ideology	120,904	5.01	2.19	0	10
Skill Specificity	120,904	1.19	0.61	0.40	4.90
Patents	120,904	75309.44	261793.70	0	2534918
Corruption	120,904	12.36	24.87	0	239.39
PR	120,904	8.69	14.71	0	110.32
Migration	120,904	99.74	183.33	0	1566.52
Unemployment	120,904	94.90	157.14	0	1264.10
Euro	120,904	6.34	12.39	0	96.66
Private Credit	120,904	987.45	1882.29	0	13721.83
Social Expenditure	120,904	224.17	379.80	0	2901.37
Tax/GDP	120,904	171.58	322.43	0	2962.35

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