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Appendix C

Appendix to Chapter 4

C.1 Dataset — Reforms

Table C.1: Reform events

Country	Year	Area	Score
Australia	2006	procedural inconvenience	1
Australia	2010	notice for individual dismissal procedural inconvenience	-1
Austria	2003	severance pay	1
Belgium	1970	notice for individual dismissal	-1
Belgium	1971	notice for individual dismissal	1
Belgium	1985	severance pay	1
Czech Republic	2007	procedural inconvenience	1
Czech Republic	2012	notice period, severance pay	1
Finland	1989	notice for individual dismissal	-1
Finland	1997	notice for individual dismissal	1
France	1987	procedural inconvenience	1
France	2003	collective dismissal	-1

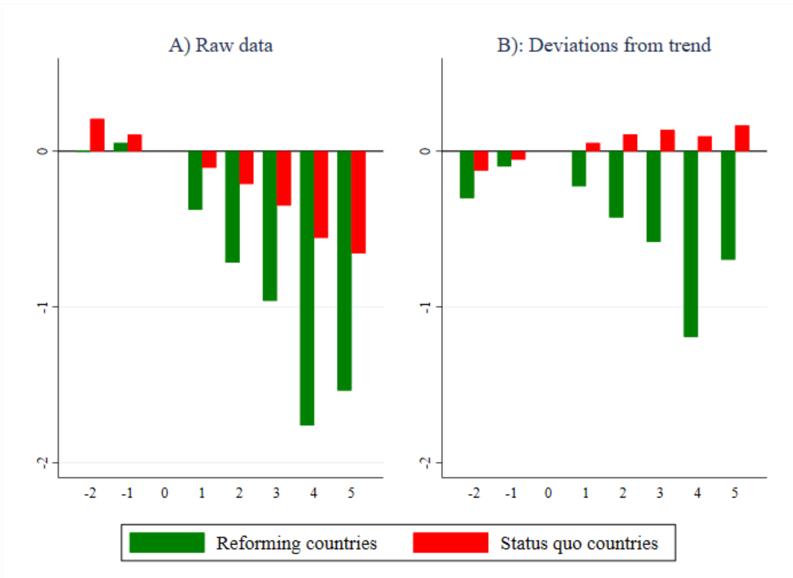
France	2009	procedural inconvenience	1
Germany	1994	notice for individual dismissal	-1
Germany	1997	procedural inconvenience	1
Germany	2004	procedural inconvenience	-1
Greece	2011	notice for individual dismissal severance pay collective dismissal	1
Greece	2012	severance pay	1
Ireland	1973	notice for individual dismissal	-1
Ireland	1977	procedural inconvenience notice for individual dismissal	-1
Ireland	2006	notice for individual dismissal	1
Ireland	2012	severance pay	-1
Italy	1970	procedural inconvenience	-1
Italy	1991	procedural inconvenience	1
Italy	2013	procedural inconvenience	1
Korea	1998	procedural inconvenience notice for individual dismissal collective dismissal	1
Japan	2007	procedural inconvenience	1
Netherlands	1976	collective dismissal	-1
Netherlands	1996	procedural inconvenience	1
New Zealand	2001	procedural inconvenience	-1
New Zealand	2012	trial period	1

Norway	1977	procedural inconvenience	-1
Portugal	1975	collective dismissal	-1
Portugal	1976	procedural inconvenience	-1
Portugal	1978	procedural inconvenience	1
Portugal	1990	procedural inconvenience	1
Portugal	1992	procedural inconvenience	1
Portugal	2004	procedural inconvenience	1
Portugal	2010	notice for individual dismissal severance pay procedural inconvenience	1
Slovak Republic	2004	notice period, severance pay	1
Slovak Republic	2012	notice period, severance pay	1
Spain	1978	procedural inconvenience collective dismissal	1
Spain	1981	procedural inconvenience collective dismissal	1
Spain	1995	procedural inconvenience collective dismissal	1
Spain	1998	severance pay	1
Spain	2001	procedural inconvenience severance pay	1
Spain	2011	severance pay	1
Spain	2013	procedural inconvenience collective dismissal severance pay	1
Sweden	1975	notice for individual dismissal	-1

Sweden	1997	notice for individual dismissal	1
United Kingdom	2000	severance pay	-1

Source: Duval et al., 2018

Figure C.1: Major employment protection reforms over time



Notes: the figure reports the total number (y-axis) of reforms to employment protection legislation implemented across all countries in the sample by year (x-axis).
Sources: Duval et al., 2018 and own calculations

C.2 Dataset — Layoff Rates

We use data contained in the 2014 Displaced Workers Survey (DWS), conducted in the context of the IPUMS-CPS (Flood et al. (2017)). The survey covers around ninety thousand individuals and provides information about (i) whether the individual held at least one job in the last three years, (ii) the industry of the current or last job, (iii) whether the individual was displaced in the last three years, (iv) the reason for the displacement, and (v) the industry in which the worker was employed when she/he was displaced. Using this information, for each industry we compute the total number of workers that were displaced for either of the following three reasons: (a) the plant or company closed or moved, (b) work was insufficient, (c) the position or shift was abolished. We do so for each of the three years covered by the survey (2011, 2012 and 2013). Since individuals were only asked in which industry they were employed in January 2014, we use data from the Current Population Survey (BLS) to compute industry-level employment changes in 2014, relative to 2011, 2012 and 2013, and multiply them by the employment level in 2014 to obtain employment levels for each year covered by the survey. Table C.2 below reports the layoff rates we computed in this way.

Table C.2: Layoff rates

	2011	2012	2013	Average	Industry code
Food, Beverages & Tobacco	3.04	1.99	4.07	3.03	10t12
Textiles	2.18	3.1	5.92	3.73	13t15
Wood, Paper & Reproduction	4.31	3.21	3.9	3.81	16t18
Coke & Refined Petroleum	0	0	3.21	1.07	19
Chemicals	3.43	2.11	2.18	2.58	20t21
Rubber & Plastics	2.82	2.22	2.17	2.41	22t23
Basic Metals	2.44	3.35	3.92	3.24	24t25
Electrical & Optical	4.67	5.96	6.25	5.62	26t27
Machinery & Equipment	3.04	2.39	3.15	2.86	28
Transport Equipment	2.94	2	3.37	2.77	29t30
Others Manufacturing	8.54	7.48	5.92	7.31	31t33
Wholesale & Retail, Motor vehicles	2.3	2.18	2.48	2.32	45
Wholesale ex. Motor Vehicles	1.85	2.84	3.39	2.69	46
Retail ex. Motor Vehicles	2.04	2.46	3.22	2.57	47
Transport & Storage	2.48	2.92	3.41	2.94	49t52
Postal & Courier	1.58	1.4	1.34	1.44	53
Publishing & Audiovisual	2.7	2.56	4.36	3.21	58t60
Telecommunications	2.08	1.81	2.05	1.98	61
IT & Others	2.47	3.14	3.69	3.1	62t63
Agriculture	0	5.2	5.62	3.61	A
Mining & Quarrying	/	/	/	/	B
Utilities	1.14	2.21	1.43	1.59	DtE
Construction	4.51	5.63	8.98	6.37	F
Accommodation & Food Services	1.96	2.86	4.43	3.08	I
Financial & Insurance	2.51	1.93	2.59	2.34	K
Real Estate	1.28	1.53	2.91	1.9	L
Professional & Support Activities	2.62	3.59	4.84	3.68	MtN
PA, Defense & SS	/	/	/	/	O
Education	0.9	1.43	1.72	1.35	P
Health & Social	1.31	1.5	2.54	1.78	Q
Arts & Recreation	2.06	2.81	5.33	3.4	R
Other Service Activities	1.85	2.61	3.72	2.73	S
Average	2.5	2.81	3.74	3.02	/

Notes: Layoff rates for the years 2011, 2012 and 2013 are calculated as the ratio of displaced workers for (i) company/plant closing, (ii) insufficient work, (iii) position or shift abolished over wage and salary employment, computed using individual-level data contained in the 2014 Displaced Workers Survey of the IPUMS-CPS (Flood et al. (2017)).

C.3 Dataset — Elasticities of Substitution

Let there be an aggregate production function under which gross output is produced using, among others, labor and capital as inputs. That is, $Y = H(K, L, X_i, A)$, where K and L stand respectively for the flow of capital and labor services, X_i other inputs and A is an index denoting technical efficiency. Assuming further that the change in technical efficiency is Hicks-neutral and capital and labor are weakly separable from other inputs, we can rewrite the production function as $Y = AJ(X_i, F(K, L))$, where $F(K, L)$ denotes the aggregate input. Next, we characterize F as a constant elasticity of substitution production function:

$$Y = F(K, L) = (\alpha(K)^{\varepsilon} + (1 - \alpha)(L)^{\varepsilon})^{1/\varepsilon}$$

Profit maximization implies the familiar condition equating the price of capital to its marginal product expressed in similar units:

$$P^K = PF_K(K, L)$$

where P^K is the price of capital services and P is the price of the aggregate input $F(K, L)$ Using $F_K(K, L) = \alpha K^{\varepsilon-1} F(K, L)^{1-\varepsilon}$ this equation can be rewritten as:

$$\frac{P^K}{P} = \alpha \left(\frac{F(K, L)}{K} \right)^{1-\varepsilon}$$

Notice that $1 - \varepsilon$ is the inverse of the EOS (that is, $1 - \varepsilon = 1/\sigma$). Taking logs and adding a disturbance term that captures potential errors in the firm optimization process, the EOS can be estimated from the following equation:

$$Ln \left(\frac{P^K_{j,t}}{P_{j,t}} \right) = ln(\alpha_j) + \frac{1}{\sigma} ln \left(\frac{F_{j,t}(K_{j,t}, L_{j,t})}{K_{j,t}} \right) + \epsilon_{j,t} \qquad \text{(C.1)}$$

where we added the subscripts j and t to indicate country and time. We estimate Equation C.1 separately for each industry using OLS. For the data, we rely on the EU KLEMS 2017 database (Jäger, 2017). This readily provides estimates of the flow of capital services, which is computed applying geometric depreciation rates (different by capital asset and industry) to the capital stock data (taken from Eurostat). For a sensitivity analysis, we also estimate a set of EOS using data on the real capital stock to proxy for the flow of capital services. Ideally, for the aggregate input we would need some measure of value added deflated by technical change. Lacking a measure of technical change, we use data on value added (volumes and prices) as proxies. These are contained in Jäger, 2017 and are consistent with Eurostat. To obtain an estimate of the rental price of capital services we follow two alternative approaches. One assumes that the rental rate is proportional to the price of capital services; this is the approach followed, among others, by Baccianti, 2013. In this case, we simply divide the nominal capital stock by the volume of capital services and use that as the rental rate. Our second, and preferred concept, is the 'Jorgensonian' rental rate, which also accounts for the depreciation of capital and the opportunity cost of the investment. Following Jorgenson, 1963, we assume that in equilibrium an investor is indifferent between (i) buying a unit of capital at price q^k_{t-1}, earning a rental fee P^k_t, and selling the depreciated end of period capital to get $q^k_t(1-\delta^k)$, or (ii) earning a nominal interest rate i_{t-1} on a different investment opportunity.[1] Hence, we calculate the rental price of capital, for each industry-country-year observation, as: [2]

$$P^k_{i,j,t} = q^k_{i,j,t-1} i_{j,t-1} + \delta^k_i q^k_{i,j,t} - (q^k_{i,j,t} - q^k_{i,j,t-1})$$

For the nominal interest rate, $i_{j,t}$, we follow O'Mahony and Timmer (2009) to derive an internal rate of return of capital as a residual of capital compensation, depreciation and capital gains. In practice, we calculate $i_{i,j,t}$ as:

$$i_{i,j,t} = \frac{P^K_{i,t} K_{i,j,t} + \sum_k (q^k_{i,j,t} - q^k_{i,j,t-1}) A^k_{i,j,t} - \sum_k \delta^k_i q^k_{i,j,t} A^k_{i,j,t}}{\sum_k q^k_{i,j,t-1} A^k_{i,j,t}}$$

where $A^k_{i,j,t}$ is the capital stock for asset k, in country j, industry i, at time t, and $P^K_{i,t} K_{i,j,t}$ is total capital compensation (calculated as value added minus labor compensation).[3] Due to the limited availability of capital stock and services data in the EU KLEMS database (Jäger, 2017), the estimation is restricted to a sample of 13 countries. [4] One potential concern in estimating Equation C.1 through OLS is that the variables might be non-stationary. If this were to be the case, the estimation would yield biased and inconsistent estimates. To deal with potential non-stationarity, we estimate Equation C.1 in first differences.[5] As observed by Antras, 2004, EOS

1 We do not account for the impact of taxation.

2 $P^k_{i,j,t}$ is calculated for each different type of capital asset k covered in Jäger, 2017: (i) residential structures, (ii) total non-residential investment, (iii) transport equipment, (iv) computing equipment, (v) communications equipment, (vi) other machinery and equipment, (vii) cultivated assets, (viii) other intellectual property products, (ix) research and development, and (x) computer and software database. To obtain a measure of the industry-wide price of capital, $P^K_{i,j,t}$ the price of each asset is multiplied its relative share in capital services and the sum is used as the aggregate price of capital.

3 An alternative (*ex-ante*) approach would be to use an exogenous measure for the rate of return, such as government bond interest rates plus a default risk premium. The (*ex-post*) approach we use does not require us to estimate risk premia and has the further advantage of ensuring consistency between income and production accounts and allows us to obtain country-industry-specific measures of the interest rate. See O'Mahony and Timmer (2009) for more details.

4 These countries are Austria, Czech Republic, Denmark, Finland, France, Germany, Italy, Luxembourg, the Netherlands, Slovak Republic, Spain, Sweden, and the United Kingdom.

5 Another concern is that the regressor in Equation C.1 might be endogenous, as it represents the firms' demand for capital. To deal with potential endogeneity Antras, 2004, who estimates

estimates derived from Equation C.1 might be biased if the assumption of Hicks-neutral technical change does not hold in practice. Therefore, we also relax this assumption and estimate a set of EOS from a production function allowing for labor- (A^l) and capital- (A^k) augmenting technical change. Following the literature, we assume those to grow at constant rates (τ^l) and (τ^k) respectively. The aggregate input is then produced according to:

$$Y = F(K, L, A^k, A^l) = \left(\alpha(A_0^k e^{\tau^k t} K)^{\varepsilon} + (1-\alpha)(A_0^l e^{\tau^l t} L)^{\varepsilon}\right)^{1/\varepsilon}$$

Taking the first-order condition equating the price of capital to its marginal product and after simple manipulations, we can estimate the EOS, σ, from the following equation:

$$ln\left(\frac{P_{j,t}^K}{P_{j,t}}\right) = ln(\alpha_j) + \left(\frac{1-\sigma}{\sigma}\right) ln(A_0^k) + \frac{1}{\sigma} ln\left(\frac{F_{j,t}(K_{j,t}, L_{j,t})}{K_{j,t}}\right) + \left(\frac{1-\sigma}{\sigma}\right)\tau^k t + \epsilon_{j,t} \tag{C.2}$$

Practically, this amounts to adding a linear trend to Equation C.1. These various approaches, which rely on different assumptions regarding the capital stock, the user cost of capital and the form of technical change, yield four alternative sets of EOS that are reported in Table C.3 below. The correlation among them ranges from 0.4 to 0.9. On average, our estimated EOS are below one in all four cases, going from 0.68 (when we allow for labor- and capital-augmenting technical change) to 0.85 (when we divide the nominal capital stock by capital services to obtain the rental rate of capital). The EOS is estimated to exceed 1 for just 4 to 6 industries. Our baseline set of EOS (EOS1) are those that assume Hicks-neutral technical change, use capital services data and calculate the rental rate following Jorgenson (1963). The other sets of EOS are used for sensitivity analyses.

an EOS for the aggregate U.S. economy, employs an IV strategy, using the stock of capital owned by the government as an instrument for capital services. Formulating an IV strategy is more problematic in our context since we estimate industry-specific EOS in a panel of countries. We proceed using OLS.

Table C.3: Elasticities of substitution

	EOS1	EOS2	EOS3	EOS4	Industry code
Food, Beverages & Tobacco	0.69	0.74	0.67	0.69	10t12
Textiles	0.38	0.45	0.4	0.36	13t15
Wood, Paper & Reproduction	0.49	0.54	0.49	0.46	16t18
Coke & Refined Petroleum	0.88	0.88	0.89	0.87	19
Chemicals	0.9	0.81	0.88	0.91	20t21
Rubber & Plastics	0.53	0.58	0.52	0.55	22t23
Basic Metals	0.45	0.47	0.94	0.45	24t25
Electrical & Optical	0.58	0.65	0.62	0.57	26t27
Machinery & Equipment	0.49	0.53	0.51	0.49	28
Transport Equipment	0.47	0.52	0.48	0.47	29t30
Others Manufacturing	0.44	0.51	0.4	0.42	31t33
Wholesale & Retail, Motor vehicles	0.47	0.46	0.57	0.47	45
Wholesale ex. Motor Vehicles	0.52	0.65	0.52	0.51	46
Retail ex. Motor Vehicles	0.39	0.36	0.36	0.35	47
Transport & Storage	1.36	0.54	1.55	1.8	49t52
Postal & Courier	0.73	0.6	1.1	0.66	53
Publishing & Audiovisual	0.54	0.47	0.64	0.51	58t60
Telecommunications	1.48	1.05	2.32	1.52	61
IT & Others	0.37	0.47	0.36	0.34	62t63
Agriculture	0.9	0.57	0.7	0.71	A
Mining & Quarrying	0.79	0.69	0.8	0.81	B
Utilities	0.95	0.94	0.87	0.94	DtE
Construction	0.3	0.31	0.35	0.31	F
Accommodation & Food Services	0.47	0.8	0.4	0.43	I
Financial & Insurance	0.88	1.09	1.16	0.83	K
Real Estate	1.2	1.29	1.04	1.2	L
Professional & Support Activities	0.56	0.68	0.67	0.49	MtN
PA, Defense & SS	0.86	1.53	1.39	0.8	O
Education	0.58	1.22	3.08	0.6	P
Health & Social	0.63	0.98	0.98	0.54	Q
Arts & Recreation	1.11	0.82	0.8	1.09	R
Other Service Activities	1.31	1.48	0.74	0.62	S
Average	0.71	0.74	0.85	0.68	/

Notes: Column "EOS1" reports elasticities of substitution (EOS) estimated according to Equation C.1 and using data on capital services and capital rental rates calculated as in Jorgenson (1963), and assuming Hicks-neutral technical change. Column "EOS2" report estimates obtained using capital stock rather than services data. Column "EOS3" report estimates obtained using data on nominal capital stock divided by capital services to proxy for the rental rate. Column "EOS4" report estimates obtained based on Equation C.2.

C.4 Dataset — Summary Statistics of Industry Data

Table C.4: Summary statistics of industry data

	VA share	Labor share	EOS	Layoff rate	Industry code
Food, Beverages & Tobacco	2.66	57.25	0.69	3.03	10t12
Textiles	1.25	77.51	0.38	3.73	13t15
Wood, Paper & Reproduction	1.86	69.14	0.49	3.81	16t18
Coke & Refined Petroleum	0.44	41.42	0.88	1.07	19
Chemicals	2.19	47.82	0.9	2.58	20t21
Rubber & Plastics	1.75	65.16	0.53	2.41	22t23
Basic Metals	2.84	68.34	0.45	3.24	24t25
Electrical & Optical	2.33	62.48	0.58	5.62	26t27
Machinery & Equipment	1.67	71.09	0.49	2.86	28
Transport Equipment	1.85	68.92	0.47	2.77	29t30
Others Manufacturing	1.34	77.38	0.44	7.31	31t33
Wholesale & Retail, Motor vehicles	1.43	69.2	0.47	2.32	45
Wholesale ex. Motor Vehicles	5.69	62.13	0.52	2.69	46
Retail ex. Motor Vehicles	5	76.44	0.39	2.57	47
Transport & Storage	4.75	67.43	1.36	2.94	49t52
Postal & Courier	0.89	82.18	0.73	1.44	53
Publishing & Audiovisual	1.36	65.86	0.54	3.21	58t60
Telecommunications	1.73	39.35	1.48	1.98	61
IT & Others	1.3	78.76	0.37	3.1	62t63
Agriculture	3.35	79.65	0.9	3.61	A
Mining & Quarrying	1.53	41.27	0.79	/	B
Utilities	2.84	34.35	0.95	1.59	DtE
Construction	6.71	78.85	0.3	6.37	F
Accommodation & Food Services	2.69	76.86	0.47	3.08	I
Financial & Insurance	5.95	57.42	0.88	2.34	K
Real Estate	8.95	6.83	1.2	1.9	L
Professional & Support Activities	7.2	72.87	0.56	3.68	MtN
PA, Defense & SS	7.21	76.15	0.86	/	O
Education	4.9	90.2	0.58	1.35	P
Health & Social	6.01	84.21	0.63	1.78	Q
Arts & Recreation	1.12	72.34	1.11	3.4	R
Other Service Activities	1.55	84.49	1.31	2.73	S
Average	3.2	65.73	0.71	3.02	/

Notes: "VA" stands for value added; "EOS" for elasticities of substitution. Shares in value added and labor shares are averages across countries and years, computed in Jäger, 2017. Elasticities of substitution are estimated according to Equation C.1. The natural layoff rate is calculated as the average ratio of displaced over wage and salary employment across the years 2011-2013, computed using individual-level data contained in the 2014 Displaced Workers Survey of the IPUMS-CPS.

C.5 Sylized Facts

In this appendix, we discuss in more detail the stylized facts summarized in Section 4.3.5. Figure C.2 plots the coefficients of year fixed effects from a regression of country-industry labor shares on country-industry fixed effects, year fixed effects and a constant. We observe that the labor share has been on a declining trend since the mid-1970s, with the magnitude of such decline somewhat accelerating in the 1990s. Two peculiar periods are the global recessions of the early 1990s and 2009, during which the labor share increased due to a minimal decline in labor compensation relative to value added. This is in line with the finding of Kehrig and Vincent, 2017 that the labor share tends to modestly increase in recessions, as well as with the presence of sluggish wages as in the model of Rios-Rull and Santaeulalia-Llopis, 2010. By including country-time fixed effects, we ensure that this feature is controlled for in our econometric analysis. We now explore cross-country and cross-industry heterogeneity in the decline of the labor share. In Figure C.3, we plot estimated linear trends in country labor shares for the 22 countries in our sample; the trend is negative and significant in 15 countries.[6] Next, we perform a similar exercise for industry labor shares (Figure C.4).[7] Of the 32 industries considered, 23 display a negative and statistically significant coefficient, whereas only 4 have a significant positive coefficient. We find some differences in the magnitude of the estimated time trends, but no industry emerges as an outlier. Overall, this exercise confirms that the trend decline in the labor share was rather broad-based, taking place both within countries and within industries, while at the same time displaying significant heterogeneity to be explained.[8] Changes in industrial composition could be important drivers of aggregate country labor share trends. Since our analysis focuses mostly on explaining within-industry changes in the labor share, it is important to quantify how much of the overall time-series variation at the country level is explained by within as opposed to between (shifts in industrial composition) changes. To do so, we decompose overall changes according to the following formula (see e.g. Karabarbounis and Neiman,

[6] In Figure C.6 we show linear trends of within-industry labor shares by country. For only two countries (Spain and the United Kingdom) does the sign of the estimated linear trend flip (and is significant) when moving from aggregate country to within-industry labor shares. Importantly, in 13 out of 22 countries we estimate a negative and significant trend, regardless of whether we consider within-industry or aggregate country shares. In Figure C.7 we plot the median, 25th and 75th percentile of industry labor shares for each country in our sample.

[7] Figure C.9 reports estimated linear trends in (global) labor shares for each of the 31 industries. Figure A5.8 shows the median, 25th and 75th percentiles of country-specific labor shares for each industry.

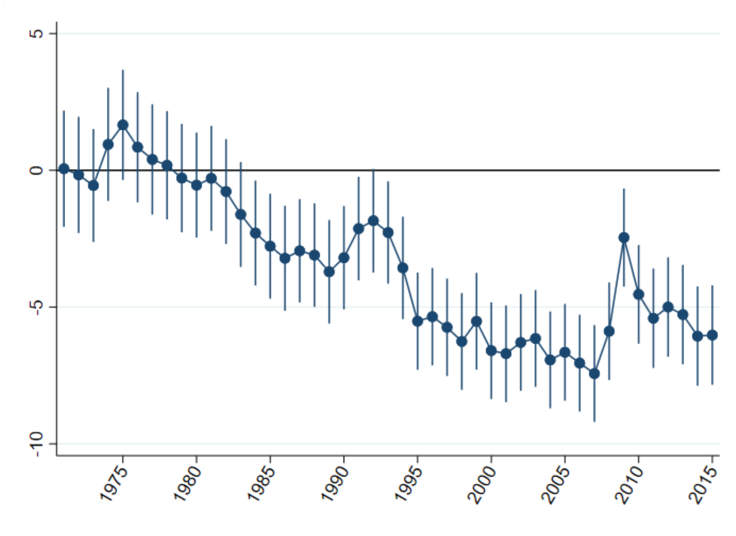
[8] Linear trends are more precisely estimated (lower standard errors) across different countries for specific sectors and industries, rather than across industries for specific countries. This provides further rationale for an econometric specification that, like ours, also considers industry-specific deterministic components.

2013):

$$\Delta LS^j = \sum_i \overline{\omega}_i^j \Delta LS_i^j + \sum_i \overline{LS}_i^j \Delta_i^j \tag{C.3}$$

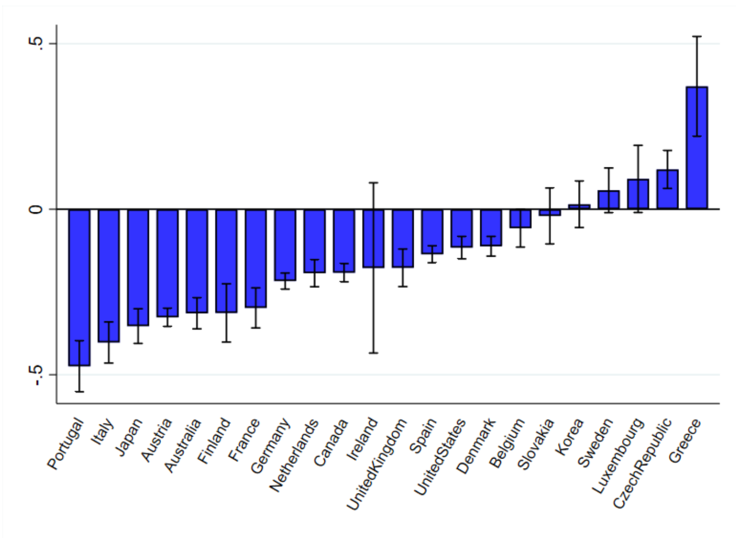
where Δx denotes the estimated linear trend and $\overline{x}$ the mean of variable x. LS refers to the labor share, ω is the share of added value, while superscript j and subscript i denote respectively country and industry. The first and second terms of the right-hand side of Equation C.3 represent the within- and between-industry components of changes in the aggregate country labor share, respectively. Figure C.5 plots the estimated aggregate country trends in the labor share (y-axis) against the within-industry component (x-axis). The linear regression explains about 70 percent of the country variation. This indicates that within-industry changes are more important than changes in industrial composition in explaining movements at the country level, which supports our country-industry-level analysis.

Figure C.2: The global decline in the labor share of income - 1970-2015



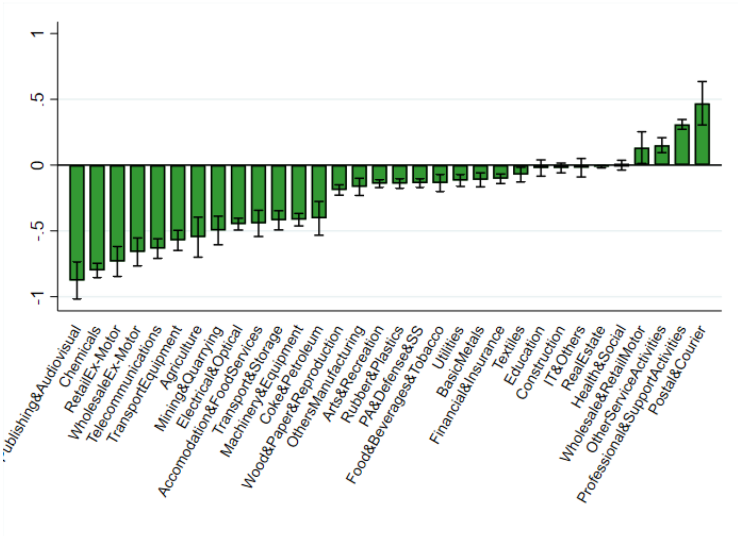
Notes: the figure shows the coefficients of the year fixed effect from the following regression: $LS_{i,j,t} = \alpha + \tau_t + \gamma_{i,j} + \epsilon_{i,j,t}$, where the subscripts i, j and t denote, respectively, industry, country and year. LS is the labor share, α is a constant term, τ are year fixed effects, γ are country-industry fixed effects, and ϵ is an error term. The (blue) red line show estimates from a regression in which industries are (un-)weighted by their relative share. Vertical lines show 1.645 standard errors. Estimates can be interpreted as the average labor share change in percentage points relative to 1970, the base year.
Sources: Jäger, 2017 and own calculations

Figure C.3: Time trends in country labor shares



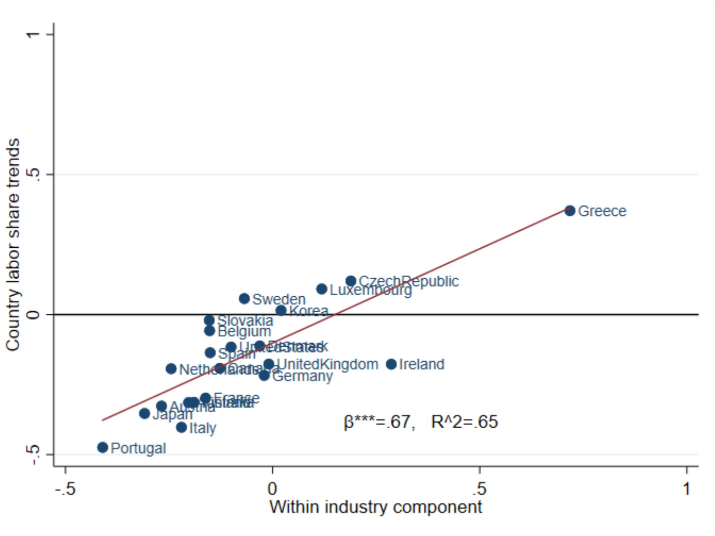
Notes: the figure shows estimated linear trends in industry labor shares (y-axis) for each country. Trends are estimated from the following regressions: $LS^j_t = \alpha^j + \tau^j_t + \epsilon^j_t$ where the subscript t and superscript j denote respectively year and country. LS is the labor share, α is a constant term, τ is the linear trend, and ϵ is an error term. Capped spikes denote 90 percent confidence intervals. Estimates should be interpreted as the average yearly change in country labor shares over the period considered. The period considered is country-specific and depends on the availability of labor income data in the EU KLEMS database, but is 1970-2015 in most cases.
Sources: Jäger, 2017 and own calculations

Figure C.4: Time trends in industry labor shares



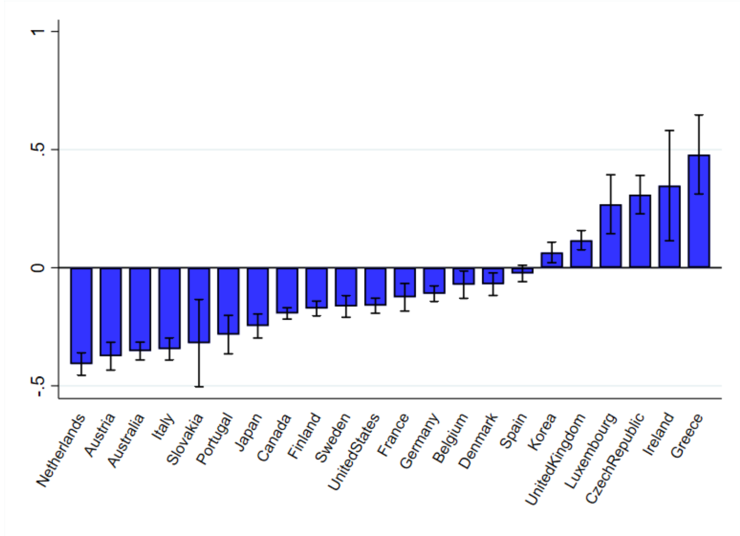
Notes: the figure shows estimated linear trends in aggregate labor shares (y-axis) for each industry. Trends are estimated from the following regressions: $LS_t^i = \alpha^i + \tau_t^i + \epsilon_t^i$, where the subscript t and superscript i denote, respectively, year and industry. LS is the labor share, α is a constant term, τ is the linear trend, and ϵ is an error term. Capped spikes denote 90 percent confidence intervals. Estimates should be interpreted as the average yearly change in industry labor shares over the period considered. The period considered is country- and industry-specific and depends on the availability of labor income data in the EU KLEMS database, but is 1970-2015 in most cases. *Sources:* Jäger, 2017 and own calculations

Figure C.5: Within vs. between industry decomposition of changes in labor shares



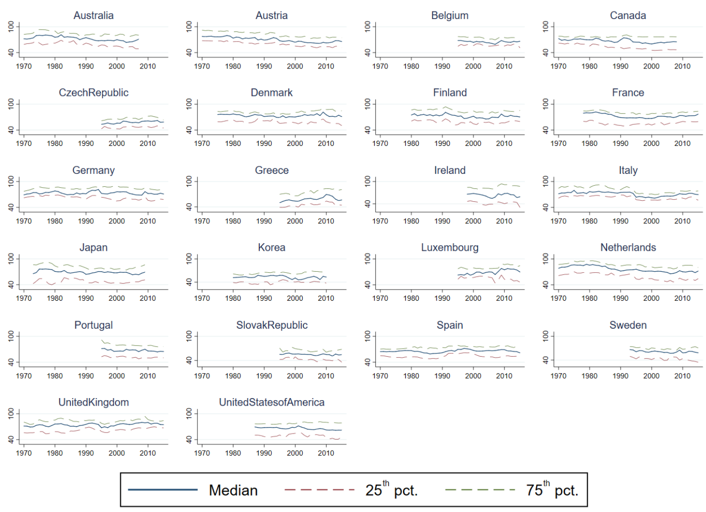
Notes: the figure plots country aggregate labor share trends (y-axis) over the within industry component in labor share trends (x-axis). Country trends are estimated from the following regression: $LS_t^j = \alpha^j + \tau_t^j + \epsilon_t^j$ where the subscript t and superscript j denote respectively year and country. LS is the labor share, α is a constant term, τ is the linear trend, and ϵ is an error term. Within industry components are estimated according to the following expression: $y^j = \sum_i \overline{\omega}_i^j \Delta LS_i^j$, where the superscript j and subscript i denote respectively country and industry, ΔLS denotes the estimated linear trend in the labor share, $\overline{\omega}$ refer to the mean of the share of added value. *Sources:* Jäger, 2017 and own calculations

Figure C.6: Time trends in country-industry labor shares by country



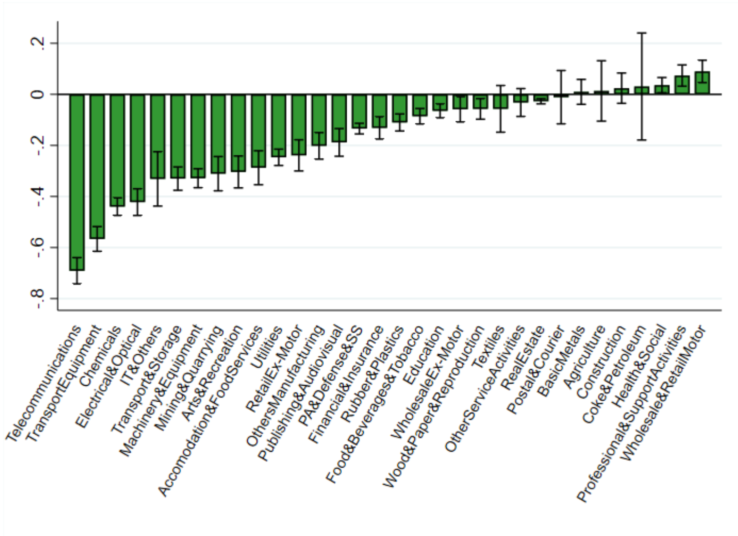
Notes: the figure shows estimated linear trends in industry labor shares (y-axis) for each country. Trends are estimated from the following regressions: $LS^{j}_{i,t} = \alpha^{j} + \gamma^{j}_{i} + \tau^{j}_{t} + \epsilon^{j}_{i,t}$, where the subscripts i and t denote, respectively, industry and year, while the superscript j denotes country. LS is the labor share, α is a constant term, γ are industry fixed effects, τ is the linear trend, and ϵ is an error term. Capped spikes denote 90 percent confidence intervals. Estimates should be interpreted as the average yearly change in country-industry labor shares over the period considered. The period considered is country-specific and depends on the availability of labor income data in the EU KLEMS database, but is 1970-2015 in most cases. *Sources:* Jäger, 2017 and own calculations

Figure C.7: Country-industry labor shares



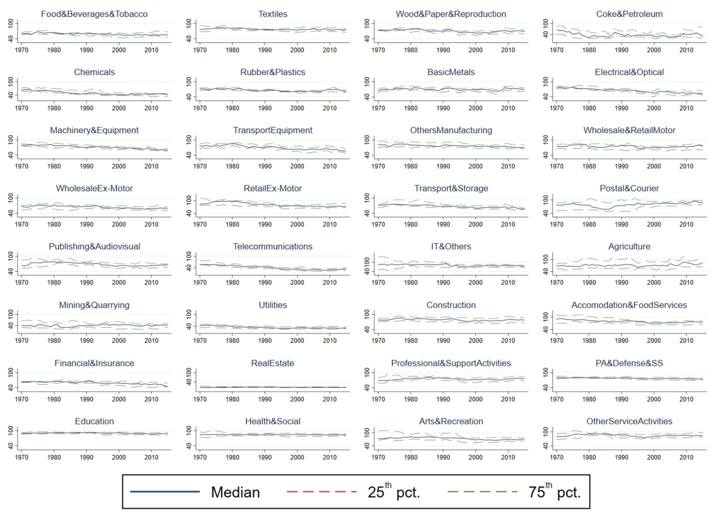
Notes: the figure shows the median (solid blue line), 25th percentile (dashed red line) and 75th percentile (dashed green line) of industry labor shares (x-axis) over time (y-axis), for each country in the sample, from 1970 to 2010. *Sources:* Jäger, 2017

Figure C.8: Time trends in country-industry labor shares by industry



Notes: the figure shows estimated linear trends in country-specific labor shares (y-axis) for each sector. Trends are estimated from the following regressions: $LS^{j}_{j,t} = \alpha^{i} + \gamma^{i}_{j} + \tau^{i}_{t} + \epsilon^{i}_{j,t}$, where the subscripts i and t denote, respectively, industry and year, while the superscript j denotes country. LS is the labor share, α is a constant term, γ are industry fixed effects, τ is the linear trend, and ϵ is an error term. Capped spikes denote 90 percent confidence intervals. Estimates should be interpreted as the average yearly change in country labor shares over the period considered. The period considered is country- and industry-specific and depends on the availability of labor income data in the EU KLEMS database, but is 1970-2015 in most cases. *Sources:* Jäger, 2017 and own calculations

Figure C.9: Industry-country labor shares



Notes: the figure shows the median (solid blue line), 25th percentile (dashed red line) and 75th percentile (dashed green line) of industry labor shares (x-axis) over time (y-axis), for each industry in the sample, from 1970 to 2010. *Sources:* Jäger, 2017

C.6 Robustness Checks on the Industry-country Analysis

Table C.5: Sample composition

	Impact	**1y**	**2y**	**3y**	**4y**	**5y**
Panel A) Identification through layoff rates						
Baseline	0.01	**-0.5**	-0.42	-0.76	**-0.83**	**-0.93**
All manufacturing	-0.06	**-0.33**	-0.22	-0.31	-0.3	**-0.49**
Control group	**-0.25**	**-0.56**	**-0.54**	**-1.04**	**-0.97**	**-0.62**
KLEMS 2017 database	0.06	-0.44	-0.48	**-0.94**	**-0.89**	**-0.96**
Panel B) Identification through elasticities of substitution						
Baseline	**-0.44**	**-0.86**	**-1.28**	-0.93	**-1.24**	**-1.51**
All manufacturing	-0.46	**-0.89**	**-1.25**	-0.86	**-1.15**	**-1.5**
Control group	**-0.73**	**-1.15**	**-1.53**	**-1.64**	**-1.74**	**-1.52**
KLEMS 2017 database	-0.35	-0.66	**-1.2**	**-1.08**	**-1.29**	**-1.51**
Panel C) Identification through layoff rates and elasticities of substitution						
Baseline	-0.47	**-1.22**	**-1.56**	**-1.35**	**-1.42**	**-1.7**
All manufacturing	-0.39	**-0.96**	**-1.05**	-0.8	-0.77	**-1.21**
Control group	**-0.77**	**-1.5**	**-1.75**	**-2.02**	**-1.95**	**-1.66**
KLEMS 2017 database	-0.4	**-1.02**	**-1.57**	**-1.59**	**-1.52**	**-1.77**

Notes: estimates based on Equation 4.10. The row "Baseline" reports estimates obtained from the baseline specification, which includes 22 countries and excludes the (i) Coke, Refined Petroleum and Nuclear Fuel, (ii) Other Manufacturing, (iii) Public Administration, Defense and Social Security, (iv) Education, (v) Health and Social Work, (vi) Agriculture, and (vii) Construction industries. The row "All manufacturing" reports estimates obtained also including industries (i) and (ii). The row "Control group" reports estimates obtained using industries (iii)-to-(vii) as control group. The row "KLEMS 2017 database" report estimates obtained using only the 18 countries covered in Jäger, 2017. Coefficients are in percentage points. Bold numbers indicate significance at the 90 percent confidence interval, based on clustered standard errors at the country-industry level. For Panels B and C standard errors are obtained through bootstrapping (500 replications). For a definition of Panels A, B, C, see notes to Figure 4.4.
Sources: Jäger, 2017, Duval et al., 2018, Flood et al. (2017) and own calculations

Table C.6: Layoff rates

	Impact	1y	2y	3y	4y	5y
Panel A) Identification through layoff rates						
Baseline	0.01	**-0.5**	-0.42	-0.76	**-0.83**	**-0.93**
Qualitative measure	0.01	-0.34	-0.61	**-1.48**	-1.05	-1.46
2013 layoff rate	0.11	**-0.74**	-0.46	-0.68	-0.69	-0.77
Panel B) Identification through layoff rates and elasticities of substitution						
Baseline	-0.47	**-1.22**	**-1.56**	**-1.35**	**-1.42**	**-1.7**
Qualitative measure	0.02	-0.07	-0.1	**-0.2**	**-0.22**	**-0.26**
2013 layoff rate	-0.4	**-1.17**	**-1.37**	**-1.09**	**-1.13**	**-1.27**

Notes: estimates based on Equation 4.10. The row "Baseline" reports estimates obtained from the baseline specification, relying on the average layoff rate calculated using the 2014 Displaced Workers Survey (covering the 2011-2013 period). The row "Qualitative measure" relies on a binary variable that takes value 1 (0) in industries whose layoff rate was above (below) the median for all the three years covered by the 2014 Displaced Workers Survey. The row "2013 layoff rate" report estimates obtained using the layoff rate calculated for the year 2013. Coefficients are in percentage points. Bold numbers indicate significance at the 90 percent confidence interval, based on clustered standard errors at the country-industry level. For Panel B standard errors are obtained through bootstrapping (500 replications).
Sources: Jäger, 2017, Duval et al., 2018, Flood et al. (2017) and own calculations

Table C.7: Elasticities of substitution

	Impact	1y	2y	3y	4y	5y
Panel A) Identification through elasticities of substitution						
Baseline	**-0.44**	**-0.86**	**-1.28**	-0.93	**-1.24**	**-1.51**
Stock	-0.53	-0.52	**-1.49**	-0.78	-0.93	-1.45
Rental rate	-0.3	**-0.83**	-0.82	-0.7	-0.99	**-1.28**
Technical change	-0.38	**-0.72**	**-0.86**	-0.65	**-1.1**	**-1.19**
Panel B) Identification through layoff rates and elasticities of substitution						
Baseline	-0.47	**-1.22**	**-1.56**	**-1.35**	**-1.42**	**-1.7**
Stock	-0.5	-1.05	**-1.92**	**-1.43**	-1.41	**-1.86**
Rental rate	-0.38	**-1.19**	**-1.11**	-1.08	-1.17	**-1.53**
Technical change	-0.41	**-1.09**	**-1.17**	**-1.1**	**-1.26**	**-1.4**

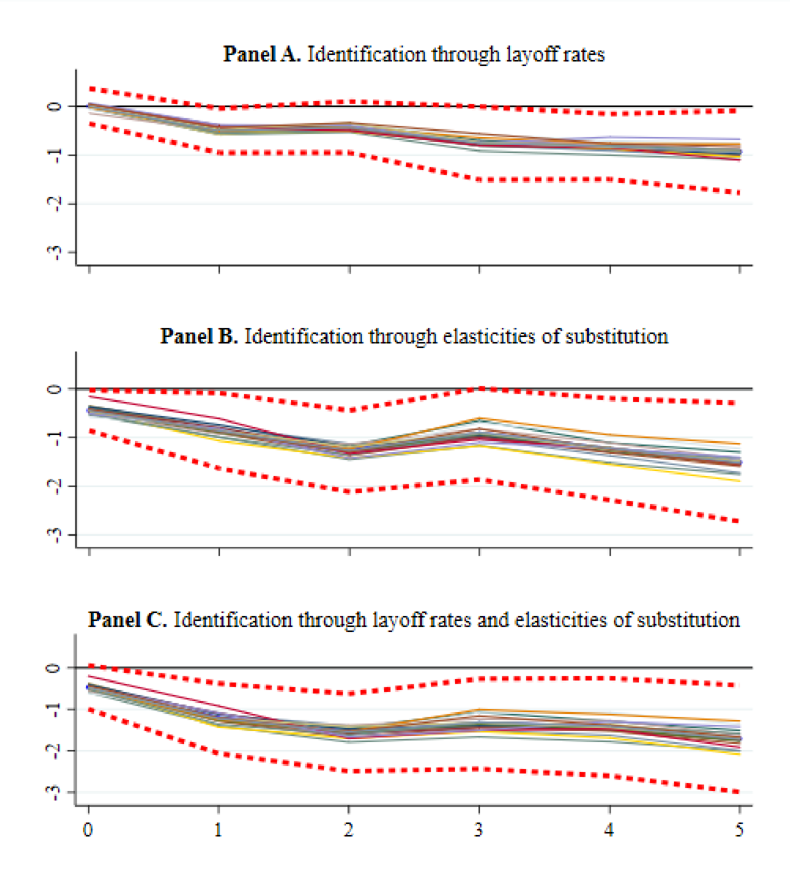
Notes: estimates based on Equation 4.10. The row "Baseline" reports estimates obtained from the baseline specification, relying on elasticities of substitution (EOS) estimated using data on capital services and capital rental rates calculated as in Jorgenson, 1963, and (iii) assuming Hicks-neutral technical change. The row "Stock" report estimates obtained using real capital stock rather than capital services data. The row "Rental rate" report estimates obtained using data on nominal capital stock divided by capital services to proxy for the rental rate of capital. The row "Technical change" report estimates obtained when relaxing the assumption of Hicks-neutral technical change. Bold numbers indicate significance at the 90 percent confidence interval, based on bootstrapped standard errors (500 replications), clustered at the country-industry level.
Sources: Jäger, 2017, Duval et al., 2018, Flood et al. (2017) and own calculations

Table C.8: Omitted variables

	Impact	**1y**	**2y**	**3y**	**4y**	**5y**
Panel A) Identification through layoff rates						
Baseline	0.01	**-0.5**	-0.42	-0.76	**-0.83**	**-0.93**
Relative investment price	0.03	-0.42	-0.48	**-0.79**	**-0.84**	**-1.1**
Trade openness	0.01	-0.45	-0.5	**-0.83**	**-0.88**	**-1.13**
Trade union density	0.02	-0.43	-0.48	**-0.81**	**-0.78**	**-1**
Panel B) Identification through elasticities of substitution						
Baseline	**-0.44**	**-0.86**	**-1.28**	-0.93	**-1.24**	**-1.51**
Relative investment price	-0.15	-0.6	**-1.34**	**-1.04**	**-1.24**	**-1.57**
Trade openness	-0.18	-0.63	**-1.36**	**-1.08**	**-1.31**	**-1.67**
Trade union density	-0.16	-0.6	**-1.39**	**-1.11**	**-1.19**	**-1.47**
Panel C) Identification through layoff rates and elasticities of substitution						
Baseline	-0.47	**-1.22**	**-1.56**	**-1.35**	**-1.42**	**-1.7**
Relative investment price	-0.19	**-0.9**	**-1.7**	**-1.51**	**-1.48**	**-1.93**
Trade openness	-0.23	**-0.94**	**-1.72**	**-1.56**	**-1.56**	**-2.02**
Trade union density	-0.2	**-0.91**	**-1.73**	**-1.59**	**-1.41**	**-1.75**

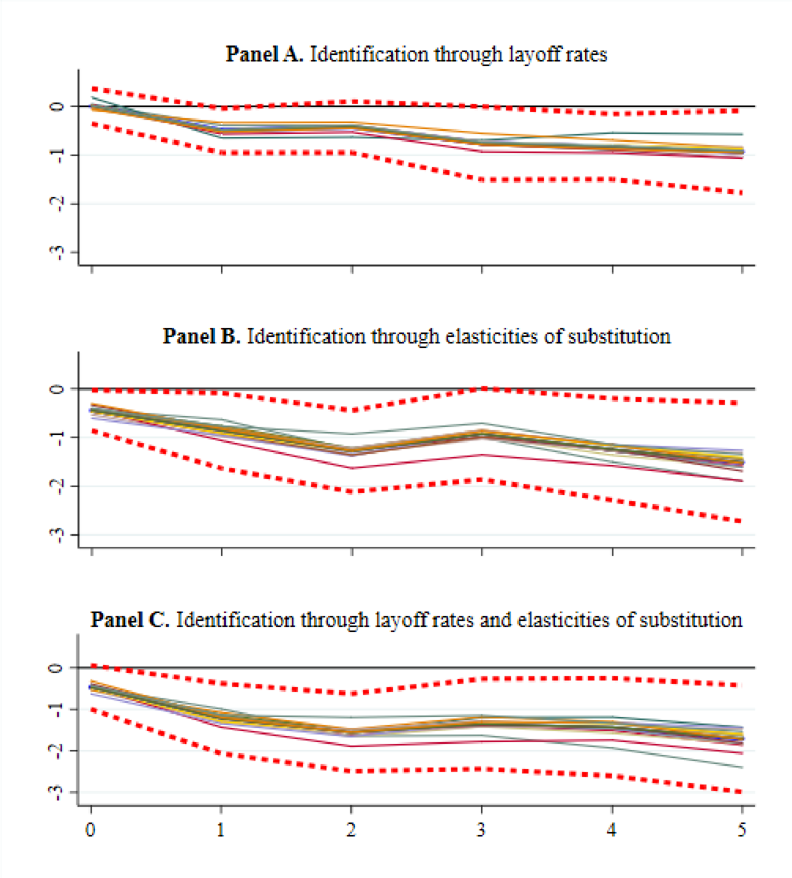
Notes: estimates based on Equation 4.10. The row "Baseline" reports estimates obtained from the baseline specification, relying on elasticities of substitution (EOS) estimated using data on capital services and capital rental rates calculated as in Jorgenson, 1963, and (iii) assuming Hicks-neutral technical change. The row "Stock" report estimates obtained using real capital stock rather than capital services data. The row "Rental rate" report estimates obtained using data on nominal capital stock divided by capital services to proxy for the rental rate of capital. The row "Technical change" report estimates obtained when relaxing the assumption of Hicks-neutral technical change. Bold numbers indicate significance at the 90 percent confidence interval, based on bootstrapped standard errors (500 replications), clustered at the country-industry level.
Sources: Jäger, 2017, Duval et al., 2018, Flood et al. (2017), Visser, 2016, Feenstra, Inklaar, and Timmer, 2015 and own calculations

Figure C.10: Country sample stability



Notes: estimates based on Equation 4.10. Each solid line represents estimates obtained excluding one country at a time. Red dotted lines indicate the 90 percent confidence interval based on standard errors clustered at the country-industry level obtained from the baseline specification, including all countries. For Panels B and C standard errors are obtained through bootstrapping (500 replications). The Y-axis reports the magnitude of the estimated coefficients (in percentage points), while the X-axis reports the response horizon (in years). For a definition of Panels A, B, C, see notes to 4.4.
Sources: Jäger, 2017, Duval et al., 2018, Flood et al. (2017) and own calculations

Figure C.11: Industry sample stability



Notes: estimates based on Equation 4.10. Each solid line represents estimates obtained excluding one industry at a time. Red dotted lines indicate the 90 percent confidence interval based on standard errors clustered at the country-industry level obtained from the baseline specification, including all countries. For Panels B and C standard errors are obtained through bootstrapping (500 replications). The Y-axis reports the magnitude of the estimated coefficients (in percentage points), while the X-axis reports the response horizon (in years). For a definition of Panels A, B, C, see notes to 4.4.
Sources: Jäger, 2017, Duval et al., 2018, Flood et al. (2017) and own calculations

C.7 Back-of-the-envelope Calculations

Let us start by writing the labor share in country j at time t as the weighted sum of industry labor shares, with the weight on each industry i given by its value-added share. That is:

$$LS_t^i \equiv \frac{w_t^j L_t^j}{p_t^j Y_t^j} = \sum_i LS_{i,t}^j \theta_{i,t}^j$$

where $\theta_{i,t}^j$ denotes the added value share of industry i. Assuming for simplicity that EPL does not affect the value-added shares of different industries in the economy, the marginal impact of an EPL reform can be written as:

$$\frac{\partial LS_t^i}{\partial EPL_t} = \sum_i \frac{\partial LS_{i,t}^j}{\partial EPL_t} \theta_{i,t}^j$$

Dividing all industries into two groups, denoted by superscripts 1 and 2, and further considering the impact of EPL reform to be the same within each of these groups, one obtains:

$$\frac{\partial LS_t}{\partial EPL_t} = \frac{\partial (LS_{i,t}^1 - LS_{i,t}^2)}{\partial EPL_t} \theta_{i,t}^1 + \frac{\partial LS_{i,t}^2}{\partial EPL_t}$$

using the fact that $\theta_{i,t}^2 = 1 - \theta_{i,t}^1$ by construction. If we can further assume that EPL reform has a negligible effect on the labor share in group 2 industries, then the impact of EPL reform on the aggregate labor share becomes:

$$\frac{\partial LS_t}{\partial EPL_t} = \frac{\partial (LS_{i,t}^1 - LS_{i,t}^2)}{\partial EPL_t} \theta_{i,t}^1$$

We apply this simple formula in the following way. We split industries into two groups, with the first group having a natural layoff rate above the median and an EOS below 1, and the other one consisting of all remaining industries. We then estimate Equation 4.10 using, as the industry identification variable θ_i a dummy taking value 1/0 for industries belonging to the first/second group. Results are reported in Table C.9. We then further assume that EPL reforms do not have effects in the second group, in line with the statistically insignificant coefficient at the five-year horizon reported in Table 4.3. Applying the five-year-ahead coefficient estimate to the number of net liberalizing reforms in each country over the period considered, we find that changes in EPL may explain about 15 percent of the overall labor share decline. This is roughly similar to the figure obtained using our country-level estimates. [9]

[9] As noted above, this simple back-of-the-envelope calculation assumes that EPL reforms have no reallocation effects across the two groups of industries. This assumption appears to hold in our data. When re-running Equation 4.10 with (log) value added as a dependent variable, we do not find any significant effects of EPL reform. Since this specification controls for aggregate

Table C.9: Extensions on the back-of-the-envelope calculation of aggregate effects

	Impact	1y	2y	3y	4y	5y
Identification through qualitative 0/1 dummy variable						
Labor share	-0.22	**-1.39**	**-1.54**	**-1.58**	**-1.33**	**-1.48**
Value added	0.1	0.64	0.79	1.55	1.38	1.26

Notes: estimates based on Equation 4.10 and using for identification a dummy taking value 1 for industries with an elasticity of substitution below 1 and layoff rate above the median, and 0 otherwise. The rows "Labor share" and "Value added" report estimates obtained using, respectively, the labor share and value added as dependent variables. Bold numbers indicate significance at the 90 percent confidence interval, based on clustered standard errors at the country-industry level.
Sources: Jäger, 2017, Duval et al., 2018 and own calculations

effects by including country-time dummies, the estimated coefficient can be interpreted as the effect of deregulation on the change in value-added shares.