Sectoral trends in earnings inequality and employment in international perspective
Globalisation, SBTC, or institutional change?[1]

Paper prepared for the 10th European Conference of the International Labour and Employment Relations Association (ILERA), 20-22 June 2013, Amsterdam

Contributed session 1.11: Wages and inequality

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Abstract

Current studies that address the rise in inequality are confined to country-level developments. This paper delineates trends in earnings inequality and employment at the sectoral level for eight countries between 1985-2005. Earnings inequality mainly manifests itself within rather than between sectors. In almost all sectors the inequality has risen. In addition, a clear shift from the manufacturing industry towards the financial sector is perceptible. There are few differences between countries. Multi-level empirical analyses indicate significant associations between the exposure to import and decreased employment within sectors, whilst no evidence is reported for relations between earnings inequality and international trade or SBTC.

[1] This study is part of the research programme 'Reforming Social Security' of Leiden University. Chen Wang is funded by the Chinese Scholarship Council. The usual disclaimer applies.

1. Introduction

A widely observed phenomenon in economic research is the gradual and widespread increase in income inequality in developed countries (*e.g.*, Brandolini and Smeeding, 2008; 2009; OECD, 2008; 2011a). In general this trend is attributed to widening market earnings (Förster, 2000; Immervoll and Richardson, 2011; Caminada *et al*., 2012).

Even though much attention has been given to trends in inequality at the country level, much less has been written on developments across different sectors. Questions that remain unanswered are whether these higher levels of inequality are a consequence of larger differences in average earnings between industries, or a higher earnings dispersion within industries. Another possible explanation is that there has been loss of employment within certain sectors. Furthermore, it is unclear if these tendencies in earnings and employment took place in all sectors, or whether there are differences between sectors, and lastly, in case there is heterogeneity across sectors, how these differences can be explained.

This study describes trends in earnings inequality and employment at the sectoral level in eight countries between 1985 and 2005 based on a new database (Wang *et al*., forthcoming). By means of a decomposition we depict that the bulk of earnings inequality at the country level is a consequence of inequality within rather than between sectors. Our calculations also denote a rise in sectoral earnings inequality that is widespread across sectors, corresponding to the rise of inequality at the country level. During the period under scrutiny a notable shift from the manufacturing industry towards the financial sectors took place. These sectoral trends do not differ much across countries.

Using multi-level panel analyses we investigate three possible explanations of these sectoral trends, namely, international trade, skill-biased technological change, and changes in labour market institutions. For the first two sets of factors sectoral data are available. In this way we investigate whether sectors that are more exposed to trade or technological change are associated with higher earnings inequality or job loss. We do not find positive associations between international trade or technological change and earnings inequality. Yet, there is robust evidence for a decrease in relative employment in import-competing industries. Lastly, we find a relation between decreased trade union influence at the country level and sectoral earnings inequality.

Our sectoral design is relatively new within the international inequality literature. The approach allows for heterogeneity between sectors due to imperfect labour mobility. Compared to the existing sectoral studies (Mahler *et al*., 1999; OECD, 2011a), this paper seeks to contribute to the literature by building a new database on inequality and employment

at the sectoral level that contains sectoral data over a larger period. This allows us to conduct cross-section panel regressions, in which we can control for certain unobserved and observed industry-specific and country-specific developments. Second, we update the analyses by including data from the early 1990s to 2005, a period in which trends persisted of rapidly increasing trade and technological change, and waning institutions. Third, we do not only explore earnings but also sectoral employment indicators. Fourth, as opposed to Mahler *et al*. (1999) we base our findings on individual rather than household earnings, so as to attribute earnings to sectors with less noise.

The remainder of the paper is structured as follows. Section 2 gives a description of the dataset and the used indicators. Then, in Section 3 the trends at the country and sectoral level are presented. In Section 4 we expound on three explanations for our sectoral trends, which are subsequently analysed in Section 5. Section 6 concludes.

2. Data section

2.1 Income definition, sector standardisation, and sample

To calculate the level of earnings inequality at the sectoral level this paper makes use of the *Leiden LIS Sectoral Income Inequality Dataset* (Wang *et al*., forthcoming).[2] This database is constructed on the basis of the Luxembourg Income Study (LIS) micro data.

Embroidering on the approach laid down by Mahler *et al*. (1999) we confine our sample to individuals aged between 25 and 54, which are those people most dependent on earnings as source of income. As we are interested in earnings inequality, we only include income from wages and salaries or self-employment. Income from other sources is omitted, such as interest and rent, and we do not adjust the wages for taxes or social contributions. For all calculations we correct for bias from extreme observations by complying with standard LIS top- and bottom coding conventions, with 1 per cent of mean earnings as the bottom, and ten times the median earnings as the top boundary.

We explicitly dissent from Mahler *et al*. (1999) by using individual earnings rather than summing and equivalising these earnings at the household level. The main problem with summing earnings at the household level is that in this manner earnings from the spouse or other relatives are attributed to the sector in which the household head is working, even though they might work in a different sector than the household head. As a sensitivity test, we

[2] This dataset will become available at www.hsz.leidenuniv.nl.

also show results for household-level earnings and for individual earnings in which we restrict our sample to household heads only.

We standardise all available waves based on the International Standard of Industrial Classification (ISIC) rev. 3.0 at the two and three digit level.[3] Table 1 provides the full set of included sectors. The two-digit level distinguishes between the main nine industries. We use the three-digit level to further break down the manufacturing and transport and telecommunication sector into 12 subsectors, as in Mahler *et al*. (1999) and OECD (2011a).[4]

Table 1 Industry classification

Two-digit ISIC sectors	Three-digit ISIC subsectors
1. Agriculture and fishing	(none)
2. Mining and quarrying	(none)
3. Manufacturing	31. Manufacturing of food products, beverages, and tobacco
	32. Manufacturing of textiles, textile products, leather, and footwear
	33. Manufacturing of wood and products of wood and cork
	34. Manufacturing of pulp, paper, paper products, printing, and publishing
	35. Manufacturing of chemical, rubber, plastics, and fuel products
	36. Manufacturing of other non-metallic mineral products
	37. Manufacturing of basic metals and fabricated metal products
	38. Manufacturing of machinery and equipment)
	39. Manufacturing of transport equipment
	30. Manufacturing n.e.c. and recycling
4. Electricity, gas, and water	(none)
5. Construction	(none)
6. Wholesale and retail trade, restaurants and hotels	(none)
7. Transport and telecommunications	71. Transport
	72. Telecommunications
8. Finance, insurance, real estate, and business	(none)
9. Community, social, and personal services	(none)

Sectoral information is available for eight OECD countries as listed in Table 2, on the basis of which we compose an unbalanced panel of five periods of five years each in between around 1985 up to and including around 2005.[5] In total we have 639 observations at the sectoral level.

[3] Sometimes this required some interpretation or the exclusion of some sectors (mainly manufacturing of transport equipment and recycling); the classification scheme is available upon request. Evidence that the classification scheme is reliable comes from the correlation between the relative employment size of the sectors based on our data and data available from OECD STAN. This correlation is for all countries around 0.93.

[4] Unfortunately no further breakdown in the community services sector is possible with LIS micro data for a sufficient number of country-period observations.

[5] For Spain in 1995 and 2000 information at the sectoral level is available as well, but the number of surveyed people is too low to calculate levels of inequality at a disaggregated level with sufficient confidence. Belgium is excluded as only data on net earnings are available. For Poland data are available, but not for our indicator for skill-biased technological change, thus we exclude it altogether.

Table 2 Country sample

Country	Waves
1. Czech Republic	1996, 2004
2. Denmark	1987, 1992, 1995, 2000, 2004
3. Finland	1987, 1991, 1995, 2000, 2004
4. Germany	1984, 1989, 1994, 2000, 2004
5. Ireland	1995[6], 2004
6. Sweden	1987, 1992, 2000, 2005
7. UK	1986, 1999, 2004
8. US	1986, 1991, 1994, 2000, 2004

2.2 Earnings inequality at the country level

We make use of two indicators to calculate the earnings inequality. The mean log deviation (MLD) or GE(0) is more sensitive to fluctuations at the bottom end of the distribution, whereas the Gini is more sensitive to changes across the mean of the distribution. We start by calculating the earnings inequality based on our earnings definition at the country level for both indicators. We subsequently decompose the MLD into a part within and a part between sectors, as this indicator does not leave a residual. This decomposition is defined as follows, with sectors indexed $\{k = 1, \dots, g\}$ weighted by their share of employed individuals v_k, where the sector includes the individuals indexed $\{j = 1, \dots, m\}$ with earnings y_i, weight w_i, and arithmetic mean earnings $\bar{y}$:

$$\text{MLD} = \sum_{k=1}^{g} v_k \sum_{j=1}^{m} \frac{w_{kj}}{\sum_{j=1}^{m} w_{kj}} \log\left(\frac{\overline{y_k}}{y_{kj}}\right) + \sum_{k=1}^{g} v_k \log\left(\frac{\overline{y_k}}{\bar{y}}\right)$$

The first element on the right-hand side denotes inequality within industries, calculated as the weighted sum of the MLD in all separate sectors. The second part summarises the between-sector part, which are the arithmetic mean earnings in sector k as a fraction of the mean earnings of the total population.

2.3 Earnings inequality at the sectoral level

Next, we investigate earnings inequality trends at the sectoral level. To this end we apply the MLD and the Gini. The MLD at the sectoral level is defined in the following fashion:

$$\text{MLD}_k = \sum_{j=1}^{m} \frac{w_j}{\sum_{j=1}^{m} w_j} \log\left(\frac{\bar{y}}{y_j}\right)$$

[6] We combine the 1994-1996 waves where we recalculate the earnings information to 1995 levels using information on inflation from the World Bank.

The Gini has the advantages of being the most frequently used inequality measure, and it can be corrected for underestimation bias in case of small sample sizes. Therefore, we use this indicator for the descriptive trends.[7] Deltas (2003) shows using Monte Carlo simulations for different cumulative distributions that the Gini can understate the 'true' inequality level when the sample size is relatively low (roughly from $m < 30$). By multiplying the Gini by $\frac{m}{m-1}$, which Deltas calls the first order correction, the underestimation bias is significantly reduced.[8] The first order corrected Gini at the sectoral level then becomes:

$$\text{F. o. c. Gini}_k = \frac{m}{m-1}\left\{\sum_{j=1}^{m}\frac{w_j}{\sum_{j=1}^{m} w_j}\,\frac{2\sum_{j=1}^{m} w_j - w_j + 1}{\bar{y}\sum_{j=1}^{m} w_j}\left(y_j - \bar{y}\right)\right\}$$

2.4 Employment measures at the sectoral level

It might be the increased inequality at country level is not so much a consequence of widening earnings distribution, but rather of employment loss at the bottom end of the earnings distribution (Gottschalk and Smeeding, 1997; Atkinson, 2003). Even though the LIS database allows for the standardised calculation of sectoral earnings inequality for multiple countries over time, unfortunately, it is not possible to track individual employment shifts over time. This is due to the fact that the LIS database is a time series rather than a panel at the individual level.

Using a number of proxies we try to depict employment effects at the sectoral level in an indirect fashion. First, we use own data based on LIS (Wang *et al*., forthcoming) and OECD STAN data (2011b) on relative employment size to investigate total labour shifts between sectors. The relative employment size is defined as the number of persons engaged per industry divided by the total number of persons engaged.[9] We show our own data for the descriptives[10] Second, following Mahler *et al*. (1999), we also calculate the relative median sectoral wage, defined as the sectoral median earnings divided by the national median earnings. The relative median earnings in a sector will increase when job loss mainly occurs at the lower end of the earnings distribution.[11]

[7] The correlation between the first-order corrected Gini and the MLD at the sectoral level is 0.88.
[8] We also conduct the regressions leaving out the sectors with $m < 30$ which does not affect the results.
[9] This indicator is only sensitive to net changes at the extensive rather than intensive margin.
[10] The correlation between the two is 0.96.
[11] Both employment indicators are amended for the person weight as provided by LIS.

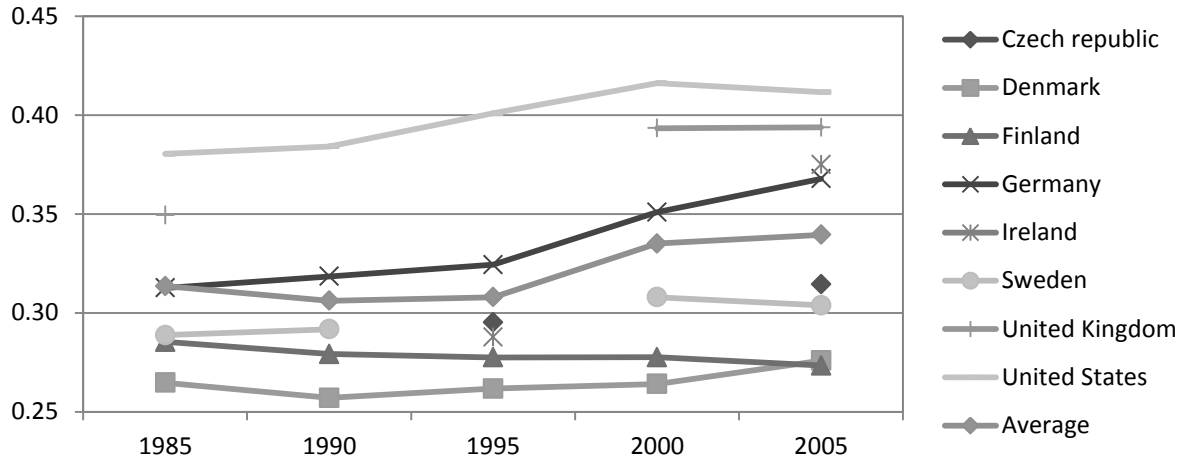
3. Trends in inequality over time, across countries, and across industries

3.1 Trends at the country level

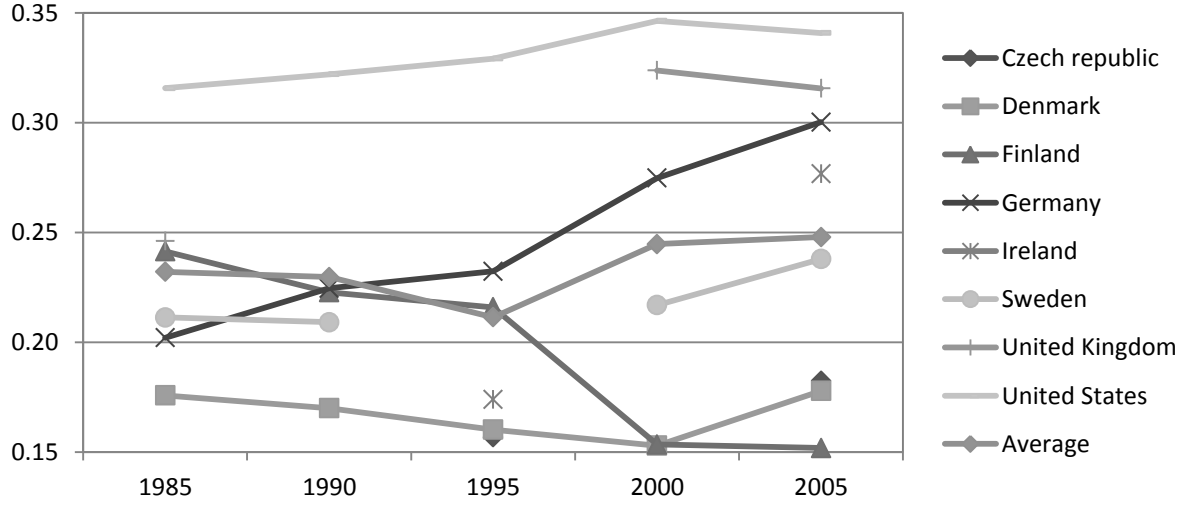
Figure 1 shows the trends in inequality at the country level using our Leiden LIS Sectoral Income Inequality dataset. The calculations are based on the same sample as used in the regressions, thus, all employed individuals with heads aged 25-54 excluding those not classified in a sector. Basically, Figure 1 shows the trends across countries over time when all sectors are pooled.

Figure 1 Earnings inequality at the country level 1985-2005

1a Gini



1b MLD



Source: Leiden LIS Sectoral Income Inequality Dataset

Inequality is the highest in the Anglo-Saxon countries, and significantly lower in the Northern countries. As is widely documented in the literature, earnings are growing wider apart within countries over time (OECD, 2008; 2011a; Brandolini and Smeeding, 2008; 2009; Immervoll and Richardson, 2011; Caminada *et al*., 2012). The strongest increase took place between 1995 and 2000. In addition, we see a strong upsurge in especially the MLD of Germany; up to around 1990 the earnings inequality was still below average, rising up to a level just below the United Kingdom around 2005.

The Gini and the MLD display a by and large comparable trend, although the MLD is characterised by a more erratic course. A noticeable exception is Finland, where the Gini shows a gradual descent whilst the MLD drops rather abruptly from 1995 to 2000. Apparently during this period the earnings inequality at the bottom end of the distribution decreased more rapidly than around the middle. If we calculate the Atkinson index (0.5), which is inclined towards shifts around the centre of the distribution, and the Theil index which is equally sensitive to fluctuations, we can see a distribution diminution that is in between the ones displayed by the Gini and the MLD. Cowell and Fiorio (2011) report for this period an increase in inequality at the top-end of the distribution in Finland, even though they base their analysis on disposable household income from LIS data. This could explain why the Gini decreases less rapidly than the MLD.

Table 3 presents the decomposition of the MLD. Columns 1-3 show the level of earnings inequality at the country level and the fourth one denotes the increase over time. Columns 5-7 summarise the percentage of the MLD at the country level due to inequality within industries. The table clearly indicates that the lion's share of inequality is a result of earnings dispersion within industries, rather than differences in average earnings between industries.[12] On average, within-industry inequality became an even larger share of the inequality at the country level. The differences between countries are small.

[12] For this calculation we differentiate between 19 industries, namely, all two-digit sectors apart from the manufacturing and transport and telecommunications sectors, for which we utilise the subsectors. Of course, the share of inequality between groups depends on the number of distinguished groups. As an extreme case, the share of between-group inequality becomes 100 per cent when every individual is defined as a separate group. Yet, for our study with a relatively small number of sectors in comparison to the number of households, the results are not that sensitive to the number of sectors that are defined. The share of within-sector inequality for the United States in 2005 increases from 96.0 to 96.8 per cent if we take the manufacturing and transport and telecommunication sector at the aggregated rather than at the disaggregated level.

Table 3 Inequality within and between sectors over time

	MLD at country level			Difference	Share of MLD due to within-sector inequality (%)			Difference
	1985	1995	2005	85-05	1985	1995	2005	85-05
Czech Republic	.	0.157	0.182	.	.	93.4%	96.1%	.
Denmark	0.176	0.160	0.178	0.002	95.4%	95.4%	96.5%	1.1%
Finland	0.241	0.216	0.152	-0.090	87.6%	91.8%	93.7%	6.0%
Germany	0.202	0.232	0.300	0.098	95.0%	94.9%	94.1%	-0.9%
Ireland	.	0.174	0.277	.	.	93.8%	93.3%	.
Sweden	0.211	.	0.238	0.027	95.3%	.	96.1%	0.8%
United Kingdom	0.246	.	0.316	0.070	94.5%	.	92.8%	-1.7%
United States	0.316	0.329	0.341	0.025	95.1%	95.3%	96.0%	0.9%
Average	0.232	0.211	0.248	0.022	93.8%	94.1%	94.8%	1.0%

Source: Leiden LIS Sectoral Income Inequality Dataset

3.2 Trends in inequality within industries

We now turn to the earnings inequality at the sectoral level, which according to our decomposition comprises the main part of country-level earnings dispersion. Here we employ the first order corrected Gini. We first pool data from all available periods to compare the levels of earnings inequality across industries and countries in Table 4.

Notwithstanding a number of deviations there are few differences in earnings inequality between countries. Agriculture, wholesale, and the financial sector ubiquitously stand out as sectors with a higher inequality than the country average, calculated as the average of sectoral earnings inequality per country. The opposite holds for mining, utilities, and the manufacturing of metals and transport. The earnings dispersion in Ireland within construction and the manufacturing of minerals and machinery is larger than its country mean, whilst in the other countries these sectors have a relatively lower inequality. To a lesser degree this also goes for the transport and telecommunication sector in the UK and the manufacturing of wood in the US.

Table 4 Pooled earnings inequality across sectors and countries

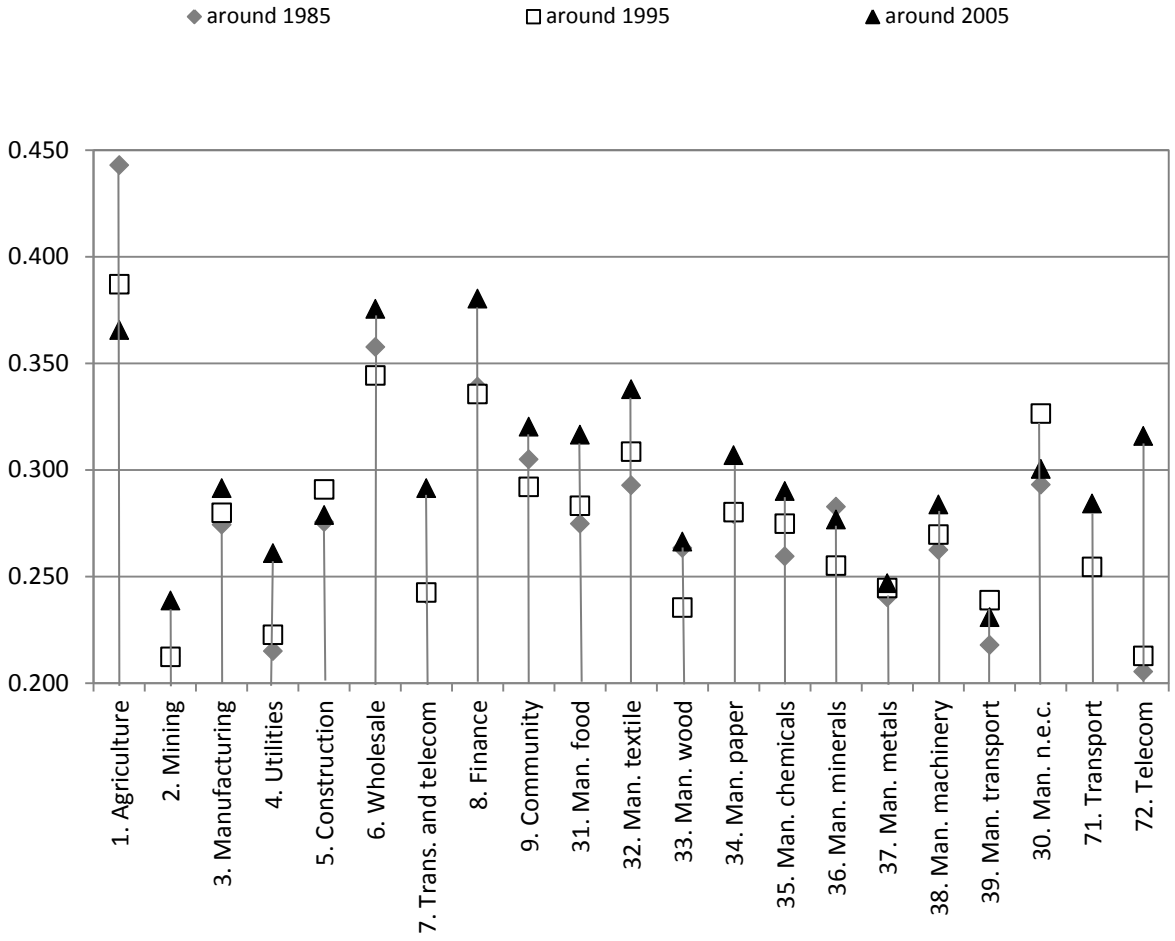
Industry	CZE	DNK	FIN	DEU	IRL	SWE	GBR	USA	Industry mean
1. Agriculture	0.292	0.356	0.493	0.353	0.383	0.402	0.381	0.463	0.391
2. Mining	0.216	0.211	0.225	0.191	0.164	0.169	0.293	0.326	0.225
3. Manufacturing	0.299	0.230	0.236	0.292	0.284	0.255	0.316	0.358	0.284
4. Utilities	0.257	0.190	0.219	0.231	0.239	0.202	0.274	0.288	0.237
5. Construction	0.276	0.227	0.263	0.269	0.307	0.221	0.332	0.357	0.282
6. Wholesale	0.362	0.293	0.292	0.393	0.368	0.330	0.420	0.433	0.361
7. Trans. and telecom	0.263	0.223	0.233	0.267	0.245	0.253	0.336	0.317	0.267
8. Finance	0.341	0.298	0.300	0.381	0.360	0.334	0.401	0.425	0.355
9. Community	0.275	0.249	0.257	0.320	0.314	0.289	0.375	0.393	0.309
31. Man. food	0.338	0.228	0.231	0.320	0.263	0.277	0.336	0.359	0.294
32. Man. textile	0.345	0.254	0.284	0.320	0.288	0.259	0.356	0.386	0.312
33. Man. wood	0.268	0.189	0.222	0.246	0.271	0.217	0.297	0.369	0.260
34. Man. paper	0.326	0.228	0.221	0.342	0.277	0.253	0.328	0.343	0.290
35. Man. chemicals	0.306	0.238	0.231	0.265	0.273	0.266	0.299	0.346	0.278
36. Man. minerals	0.272	0.228	0.195	0.293	0.307	0.217	0.262	0.322	0.262
37. Man. metals	0.280	0.196	0.208	0.251	0.220	0.211	0.271	0.319	0.245
38. Man. machinery	0.267	0.223	0.227	0.288	0.299	0.257	0.314	0.345	0.278
39. Man. transport	0.249	0.199	0.172	0.251	0.214	0.218	0.242	0.302	0.231
30. Man. n.e.c.	0.272	0.225	0.219	0.372	0.306	0.279	0.338	0.385	0.300
71. Transport	0.253	0.236	0.239	0.272	0.253	0.257	0.333	0.336	0.272
72. Telecom	0.294	0.198	0.215	0.244	0.223	0.245	0.340	0.303	0.258
Country mean	0.288	0.234	0.247	0.294	0.279	0.258	0.326	0.356	0.285

Note: First order corrected Gini, full sample
Source: Leiden LIS Sectoral Income Inequality Dataset

Now we turn to the developments of sectoral inequality over time, pooled for all countries.[13] Figure 2 shows the levels of sectoral earnings inequality in 1985, 1995, and 2005. Mirroring the trend at the country level, sectoral earnings in general have become more dispersed over time. Only in agriculture and the manufacturing of minerals inequality reached its top around 1985. In five sectors, next to the two aforementioned also construction, manufacturing of transport and manufacturing n.e.c., were earnings more dispersed in 1985 or 1995 than in 2005.

[13] The results barely change if we restrict the sample to the four countries for which we have observations in all periods. The differences in earnings inequality within wholesale between the three first periods decreases, and inequality within manufacturing of minerals in 1985 becomes even higher.

Figure 2 Trends of sectoral earnings inequality over time



Note: First order corrected Gini, full sample
Source: Leiden LIS Sectoral Income Inequality Dataset

3.3 Trends in sectoral levels of employment

Now we inspect trends for our two sectoral employment indicators. First, we investigate the relative employment size of sectors based on LIS data. We again first pool all sectoral observations over time per country, as shown in Table 5.

Table 5 Pooled relative employment size across sectors and countries

Industry	CZE	DNK	FIN	DEU	IRL	SWE	GBR	USA	Industry mean
1. Agriculture	0.048	0.022	0.051	0.014	0.035	0.017	0.014	0.015	0.027
2. Mining	0.017	0.001	0.002	0.004	0.003	0.003	0.010	0.007	0.006
3. Manufacturing	0.267	0.179	0.222	0.297	0.160	0.195	0.212	0.175	0.213
4. Utilities	0.020	0.006	0.012	0.011	0.009	0.008	0.011	0.014	0.011
5. Construction	0.079	0.059	0.071	0.077	0.070	0.058	0.065	0.063	0.068
6. Wholesale	0.133	0.141	0.134	0.143	0.155	0.123	0.158	0.201	0.149
7. Trans. and telecom.	0.076	0.071	0.077	0.047	0.082	0.072	0.071	0.066	0.070
8. Finance	0.078	0.118	0.115	0.110	0.141	0.121	0.143	0.136	0.120
9. Community	0.282	0.402	0.315	0.286	0.345	0.405	0.340	0.323	0.337
31. Man. food	0.025	0.031	0.023	0.023	0.039	0.018	0.026	0.016	0.025
32. Man. textile	0.030	0.008	0.014	0.017	0.014	0.005	0.018	0.014	0.015
33. Man. wood	0.013	0.008	0.016	0.004	0.004	0.012	0.005	0.006	0.008
34. Man. paper	0.011	0.019	0.042	0.024	0.011	0.025	0.023	0.021	0.022
35. Man. chemicals	0.029	0.021	0.017	0.041	0.025	0.016	0.028	0.020	0.025
36. Man. minerals	0.014	0.008	0.009	0.007	0.006	0.004	0.008	0.005	0.008
37. Man. metals	0.049	0.013	0.029	0.060	0.013	0.017	0.014	0.017	0.027
38. Man. machinery	0.063	0.058	0.055	0.074	0.037	0.078	0.057	0.046	0.059
39. Man. transport	0.018	0.007	0.009	0.037	0.005	0.029	0.027	0.021	0.019
30. Man. n.e.c.	0.014	0.013	0.007	0.010	0.006	0.008	0.009	0.009	0.009
71. Transport	0.058	0.051	0.055	0.041	0.054	0.049	0.047	0.040	0.049
72. Telecom	0.018	0.021	0.022	0.016	0.028	0.023	0.024	0.026	0.022
Country mean	0.064	0.060	0.062	0.064	0.059	0.061	0.062	0.059	0.061

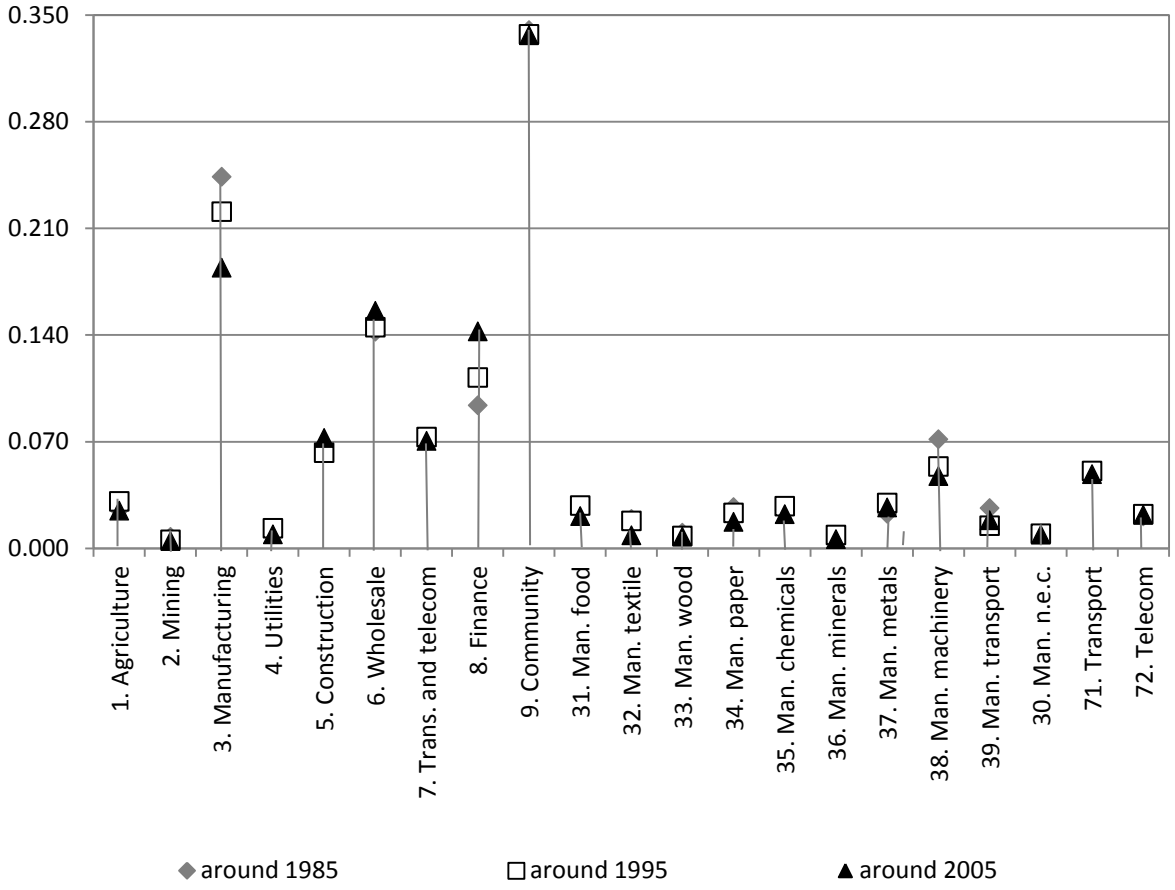
Note: Relative employment size, full sample
Source: Leiden LIS Sectoral Income Inequality Dataset

Again, the differences between countries are small. In Czech Republic still one in three persons is employed in agriculture, mining, or manufacturing, compared to one in four in the other countries. The community sector is relatively large in Finland and Denmark (around 40.0 compared to 33.7%). The Anglo-Saxon countries are characterised by a comparatively large financial sector (around 14.0 compared to 12.0%). The manufacturing industry, in particular the manufacturing of transport, metal, and chemicals, is relatively large in Germany (29.7 versus 21.3%).

The sectoral employment sizes appear to be relatively stable over time, as shown in Figure 3.[14] Most clearly perceptible is the drift in employment from manufacturing towards the financial sector. We can also discern a minor reduction in employment in agriculture and mining, whereas a small increase is observable in construction and wholesale. There is hardly any fluctuation in the largest sector, the community sector.

[14] For 1985 data are missing for a number of sectors, causing the sum of all relative employment sizes to differ from 1 for this period. This overestimation has been corrected for. Restricting the graph to the four countries for which all observations are available does not affects the results.

Figure 3 Trends of relative employment size over time



Note: Relative employment size, full sample
Source: Leiden LIS Sectoral Income Inequality Dataset

As Table 6 shows, the differences between countries are also relatively limited for the sectoral relative median earnings. Mining, utilities, transport and telecommunications, and finance pay relatively well in all countries. On the contrary, earnings are uniformly low in agriculture, followed by the manufacturing of textile and wholesale. The sectoral median earnings are below its country counterpart for the manufacturing industry in all countries except for Czech Republic and Ireland, whilst only in these two countries the median earnings are relatively high in the community sector. Principally in Finland the relative median earnings the relative median earnings are low in agriculture (0.45 to 0.68 on average), whilst earnings are higher than average for mining in the UK (1.60 to 1.29) and utilities in Ireland (1.72 to 1.33). Within the manufacturing industry the differences between countries are even smaller.

Table 6 Pooled relative median earnings across sectors and countries

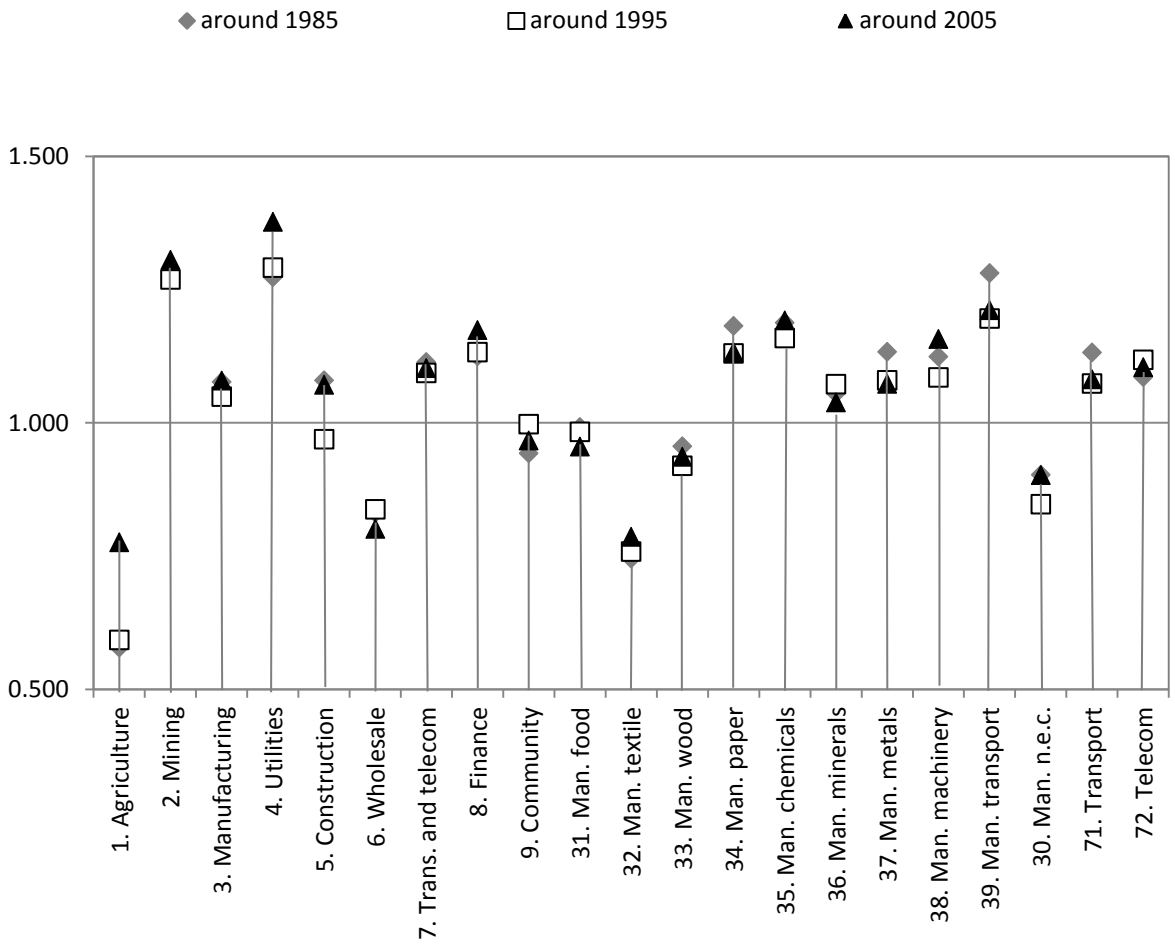
Industry	CZE	DNK	FIN	DEU	IRL	SWE	GBR	USA	Industry mean
1. Agriculture	0.818	0.745	0.453	0.697	0.623	0.710	0.779	0.603	0.679
2. Mining	1.235	1.283	1.106	1.300	1.029	1.264	1.602	1.481	1.287
3. Manufacturing	0.945	1.047	1.108	1.108	0.969	1.098	1.102	1.125	1.063
4. Utilities	1.159	1.188	1.245	1.295	1.715	1.313	1.309	1.430	1.332
5. Construction	1.079	1.051	1.002	1.018	0.993	1.140	1.118	1.008	1.051
6. Wholesale	0.850	0.962	0.889	0.698	0.755	0.959	0.684	0.754	0.819
7. Trans. and telecom.	1.081	1.058	1.092	1.017	1.133	1.068	1.101	1.281	1.104
8. Finance	1.299	1.161	1.083	1.126	1.107	1.153	1.237	1.094	1.158
9. Community	1.040	0.943	0.968	0.964	1.068	0.899	0.919	0.981	0.973
31. Man. food	0.866	1.045	1.019	0.916	0.936	1.011	0.969	0.945	0.963
32. Man. textile	0.683	0.823	0.733	0.820	0.829	0.888	0.689	0.660	0.766
33. Man. wood	0.860	0.968	0.958	0.933	0.875	1.036	0.991	0.851	0.934
34. Man. paper	1.045	1.208	1.318	1.013	1.083	1.180	1.184	1.093	1.140
35. Man. chemicals	0.986	1.124	1.205	1.190	1.125	1.142	1.239	1.369	1.173
36. Man. minerals	0.925	1.048	1.090	1.116	1.003	1.112	1.045	1.053	1.049
37. Man. metals	1.048	1.018	1.122	1.097	0.979	1.100	1.165	1.118	1.081
38. Man. machinery	0.999	1.046	1.170	1.149	0.972	1.105	1.165	1.275	1.110
39. Man. transport	1.132	1.087	1.132	1.224	1.172	1.188	1.241	1.462	1.205
30. Man. n.e.c.	0.818	0.922	0.886	0.968	0.783	0.973	0.931	0.863	0.893
71. Transport	1.122	1.092	1.107	1.014	1.050	1.067	1.081	1.170	1.088
72. Telecom	1.000	0.986	1.052	0.990	1.259	1.062	1.124	1.384	1.107
Country mean	0.999	1.038	1.035	1.031	1.022	1.070	1.080	1.095	1.046

Note: Relative median earnings, full sample
Source: Leiden LIS Sectoral Income Inequality Dataset

There are few fluctuations over time, as shown in Figure 4. The largest change took place in agriculture, where the (low) earnings went up significantly between 1995 and 2005.[15] Also within the homogeneous mining and utilities industry, sectors with low earnings dispersion and a decreasing employment size, we can see increasing median earnings.

[15] If we only look at the four countries for which all observations are available, then the absolute levels hardly change. For the manufacturing of wood the median wage becomes the highest around 1985.

Figure 4 Trends of relative median earnings over time



Note: Relative median earnings, full sample
Source: Leiden LIS Sectoral Income Inequality Dataset

4. Possible explanations for sectoral levels of inequality and employment

From the previous section we can conclude that there are differences in levels and trends of inequality within sectors, the relative employment size and median earnings. Here we expound on possible explanations for these sectoral trends from the inequality literature. Three possible causes of rising earnings inequality at the country level are most frequently put forward, namely, increased trade or globalisation, skill-biased technological change, and waning institutions.

4.1 Trade integration

The amount of international trade increased substantially during the last decades, in particular between developed and developing countries (Harrison *et al*., 2011). The Stolper-Samuelson theorem and the factor price equalisation hypothesis predict distributional consequences of

these phenomena (Kremer and Maskin, 2006; Davis and Mishra, 2007). Individuals owning production factors intensively used in the production of the exportable good profit from trade engagements, whilst the opposite holds for the people owning the production factors predominantly used in the import-competing industry. For trade between developed and developing countries, where the advanced economies have a relative abundance of highly skilled workers and where in developing countries lowly skilled workers are relatively abundant, trade will induce a higher skill demand in developed countries. Earnings or employment opportunities for lowly skilled labour in developed countries will then be compressed. The factor price equalisation argument predicts that trade equalises factor prices throughout the world, leading to wage cuts for the lowly skilled in developed countries (Freeman, 1995).

Mahler (2004) and Mahler *et al*. (1999) differentiate between effects of import and export on the earnings distribution. Import might impair the wages or employment possibilities of domestic workers by putting them into direct competition with foreign workers. When mainly the lowly skilled jobs are prone to outsourcing to low wage countries, then import has a direct effect on the earnings distribution. For export, the opposite might hold as it could give room for higher earnings or job creation.

The empirical evidence for widening incomes due to trade integration is ambiguous. Generally, country-level studies report largely insignificant effects (OECD, 2011a; Harrison *et al*., 2011; Mahler, 2004). The same holds for the sectoral studies of Mahler *et al*. (1999) and OECD (2011a). More recent studies, however, do not only incorporate trade flows, but also financial flows (FDI) and outsourcing or trade in intermediates (Hellier and Chusseau, 2013), for which some inequality-enhancing effects are presented (Alderson and Nielsen, 2002; Dreher and Gaston, 2008; Bergh and Nillson, 2010). Unfortunately, only a very limited number of observations are available on sectoral FDI.[16]

4.2 Skill-biased technological change

A prevalent theory is that rapid technological innovation complements the highly skilled, whilst it substitutes routine labour by capital (Van Reenen, 2011; see for a formal model that also includes trade Acemoglu, 2003a). Empirical evidence for skill-biased technological change (SBTC) is relatively robust (Acemoglu, 2003b; Autor *et al*., 2003; 2006; 2013; Goos

[16] The results (not shown here) do not provide evidence for inequality-enhancing effects of inward or outward FDI.

and Manning, 2007; Goos *et al*., 2009; OECD, 2011a; see for an overview *e.g.*, Hellier and Chusseau, 2013).

Regarding sectoral studies, the OECD (2011a) reports a positive correlation between changes in the hourly skill wage gap per sector and the share of ICT from EU-KLEMS. Michaels *et al*. (forthcoming) calculate the wage bill for three education groups (high, middle, and low) and find that in industries with the greatest growth in ICT intensity from EU-KLEMS data were also the ones with the strongest growth in wages for the highly educated workers. The lowly educated were largely unaffected by this rise in ICT, whilst demand for middle educated workers fell in industries with the greatest growth in ICT intensity. Trade openness is also associated with this sectoral polarisation, but becomes insignificant in their study when ICT intensity is added to the equation.

4.3 Institutions

Another branch of the literature addresses changes in labour market policies as the main cause of growing earnings dispersion in the developed world. In particular the weaker influence of trade unions and changes in employment protection legislation (EPL) are put forward in the empirical literature (Mahler, 2004; Koeniger *et al*., 2007; Checchi and Garcia-Penalosa, 2008; Dustmann *et al*., 2009; OECD, 2011a; Oesch and Menes, 2011). In general, it can be expected that the more centralised and coordinated the process of wage bargaining is, the more compressed wages are. With respect to the effects of EPL on wage inequality, generally two types of arguments are provided in the literature. On the one hand, strict EPL brings employees in a strong bargaining position for employees and therefore to less wage dispersion. However, this will mainly apply to employees with a permanent contract. Therefore, strict EPL can lead to a dual labour market with relatively high degrees of wage earnings inequality between the segments. Thus, the overall effect of EPL is rather ambiguous.

The strictness of EPL is set at the national level, and there is no sectoral information available for the influence of trade unions. Still, the institutions might provide an explanation for fluctuations in earnings inequality in all sectors per country.

5. Empirical analyses of sectoral trends

5.1 A sectoral approach to investigating earnings inequality

Thus far few studies investigate patterns of inequality by means of a sectoral design. Two examples of sectoral studies over time in multiple countries are Mahler *et al*. (1999) and OECD (2011a). Yet, both studies only calculate sectoral inequality at two moments in time, as a result of which the analyses are delimited to correlations without correction of confounding factors. Furthermore, the calculations of Mahler *et al*. (1999) are based on household rather than individual data, which introduces noise into the data as earnings are attributed to sectors in which people were not necessarily working.

A sectoral design has a number of advantages over a country-level study. Empirically, the number of observations increases and it becomes possible to correct for unobserved industry-specific next to country-specific developments. In addition to this, a sectoral design allows for heterogeneity between sectors. As shown later in this section (see Table 7) there are clear differences in the degree to which sectors are exposed to trade or technological change. These differences in exposure may render differences in effects on earnings or employment per sector if there is imperfect labour mobility between sectors. Evidence for imperfect labour mobility comes from persistent wage differences between sectors that cannot be explained by (observable) composition effects (Krueger and Summers, 1988; Dickens and Katz, 1987). These persistent differences may be a result of labour market frictions, such as search costs in looking for jobs (Mortensen and Pissarides, 1999), job and industry specific human capital (Estevez-Abe *et al*., 2001), or institutions such as employment protection legislation that depress labour mobility (Hellier and Chusseau, 2013). Artuc *et al*. (2008) and Artuc and McLaren (2010) for instance show that it takes around eight years before a wage effect in a liberalising sector of a trade shock spreads out across the economy.

Our sectoral design also has limitations. First, dependencies between industries are not taken into account as sectors are taken as independent units of analysis. In addition, certain confounding factors that might have an effect on both trade or technology and sectoral earnings and employment, are not included in the model, such as product market developments. Therefore, the empirical results should be seen as associations rather than causal evidence.

5.2 The multilevel econometric model

Our database consists of country-industry data, which allows us to exploit variation within countries across industries and over time. Following Bassanini *et al*. (2009), we estimate the following equation using OLS:

$$\text{inequality}_{ijt} = \beta_0 + \beta\ \text{trade}_{ijt} + \gamma\ \text{SBTC}_{ijt} + \text{instit}_{it}\delta\ + X_{it}\mu + \varphi_i\theta + \varphi_j\theta + \varepsilon_{ijt}$$

Our main dependent variable is earnings inequality within sector j, country i, and period t. We also explore employment effects using the relative employment size and relative median earnings at the sectoral level as dependent variables.[17]

For two independent variables data are available at the sectoral level. From our theoretical section we hypothesised that the degree to which sectors are exposed to international trade and technological progress might explain sectoral inequality and employment patterns. For the trade data ($\beta\ \text{trade}_{ijt}$) we use the OECD STAN database (2011b) where we calculate trade values in percentage of sectoral added value from the same year as the LIS waves. We differentiate between import and export, unfortunately no distinction is possible between trade among developed and trade between developed and developing countries.[18] For our sectoral indicator of technological progress ($\gamma\ \text{SBTC}_{ijt}$) we follow OECD (2011a) and Michaels *et al*. (forthcoming) and use the share of compensation of ICT capital in total capital compensation from EU-KLEMS.

To test the waning institutions hypothesis, we add a vector of institutional variables at the country level ($\text{instit}_{it}\delta$). We take a measure of overall EPL from OECD data. Visser (2011) provides us with data on union coverage and level of wage coordination, where a higher number indicates a more centralised level of wage bargaining.[19] The vector $X_{it}\mu$ contains two common control variables measured at the country level, namely, the unemployment rate and real GDP per capita divided by 100, from the OECD National Accounts. The relationship between GDP per capita and inequality is strongly contested in both causal directions (see *e.g.*, Thewissen, 2012) but it corrects for effects from possible

[17] All dependent variables are multiplied by 100 in the regressions to enhance readability.

[18] This is a common problem in the current literature (Bensidoun *et al*., 2011). As the largest increases in trade during the last two decades came from trade between developed and developing countries, in particular, from trade with China and India (OECD, 2011a), we conduct sensitivity tests in which only focus on the periods from 1995 onwards, which does not affect the main results, see Section 5.6.

[19] The variable WCoord from Visser (2011) is divided into: 5 = economy-wide bargaining, 4 = mixed industry- and economy-wide bargaining, 3 = industry-level bargaining with no (standard) pattern setting, 2 = mixed industry- and firm-level bargaining, 1 = fragmented or no bargaining.

differences in wealth development between countries. Inclusion of the country-level unemployment rate can be seen as a rough control for labour market efficiency and rigidity differences between countries.

We also implicitly control for unobserved industry-specific developments by including interactions of sector dummies and the trend ($\varphi_j\theta$), such as for the fact that industries might be exposed to different demand dynamics in their product markets. The set ($\varphi_i\theta$) includes interaction terms of the country dummies and the trend, to control for unobserved effects that have comparable effects on earnings within different industries at the country level.[20] Standard errors are clustered at the country level to allow for general forms of heteroskedasticity and autocorrelation within countries.

5.3 Descriptive statistics for the independent variables

Table 7 shows that the amount of import and export increased in every sector. The largest increase took place in the manufacturing of textile and manufacturing of transport; in mining import rose significantly while exports remained stable. The amount of international trade barely rose in the utility sector.

The sectoral share of ICT has increased over time as well, but not uniformly across all sectors. The starkest increases took place in manufacturing n.e.c., telecommunications, and mining. The share of ICT decreased significantly in agriculture, which is fully due to high values of the share of ICT in Germany around 1985.[21] Minor reductions occurred in the manufacturing of wood, minerals, and transport.

[20] As a sensitivity test we also exclude the sets of interaction variables. These results, prone to unobserved heterogeneity, change to some extent the results for the country-level institutions, export and the relative employment size, and import and relative median earnings, see Section 5.6.

[21] These extreme values for Germany drop out in the regressions as no data on export and import are available for 1985 and 1990.

Table 7 Trends in international trade and technological change at the sectoral level

	Import (% sectoral value added)		Export (% sectoral value added)		Share of ICT (%)	
	1985	2005	1985	2005	1985	2005
1 Agriculture	21.15[a]	47.85	22.57[a]	25.81	0.19	0.03
2 Mining	285.94[a]	459.81	46.72[a]	49.97	0.03	0.11
3 Manufacturing	91.63	144.40	88.25	167.30	0.10	0.12
4 Utilities	3.13[a]	3.79	1.06[a]	5.47	0.04	0.05
5 Construction	.	.	.	.	0.06	0.12
6 Wholesale	.	.	.	.	0.19	0.18
7 Transport and telecommunications	.	.	.	.	0.23	0.26
8 Finance	.	.	.	.	0.09	0.12
9 Community	.	.	.	.	0.14	0.18
31 Man. food	50.75	81.07	59.80	83.18	0.07	0.09
32 Man. textile	208.18	503.79	95.18	264.39	0.07	0.13
33 Man. wood	65.16	83.37	72.08	81.69	0.08	0.07
34 Man. paper	31.15	54.91	64.57	83.03	0.14	0.16
35 Man. chemicals	130.61	166.18	96.18	188.81	0.06	0.09
36 Man. minerals	41.20	65.52	30.37	63.09	0.09	0.07
37 Man. metals	87.43	123.94	72.77	111.63	0.07	0.13
38 Man. machinery	124.23	209.20	109.38	239.74	0.16	0.17
39 Man. transport	174.15	424.87	120.47	245.23	0.26	0.20
30 Man. n.e.c.	75.77	132.52	66.65	110.70	0.09	0.26
71 Transport	.	.	.	.	0.13	0.15
72 Telecommunications	.	.	.	.	0.30	0.40
Average	99.32	178.66	67.57	122.86	0.12	0.15

Note: Import and export are expressed in % of sectoral value added, pooled for countries for which data are available.
[a] Data from 1990
Source: Import and export from OECD STAN, share of ICT from EU-KLEMS.

As can also be seen in Table 7, for a number of sectors no data on international trade are available. Of particular importance are the community sector, which can be expected to be less exposed to international trade, and the financial sector, in which the relative employment size grew relatively fast. In Section 5.6 we impute zero's for international trade in the community sector, which does not affect the results.

Table 8 summarises the country-level data for the incorporated set of institutions per country. On average the union coverage rate decreased and EPL became less strict. Finland and Sweden are the only countries in which the union coverage rate increased over time. In the UK and Ireland EPL became more strict, but only marginally so. There is less fluctuation in the level of wage coordination within countries over time. In Sweden wage coordination became more decentralised whereas it became more centralised in Denmark.[22]

[22] In 1991 the Swedish Federation of Employers withdrew from the tripartite negotiations, so that the central collective wage negotiations came to a halt (Lindvall and Sebring, 2005).

Table 8 Trends in institutions at the country level

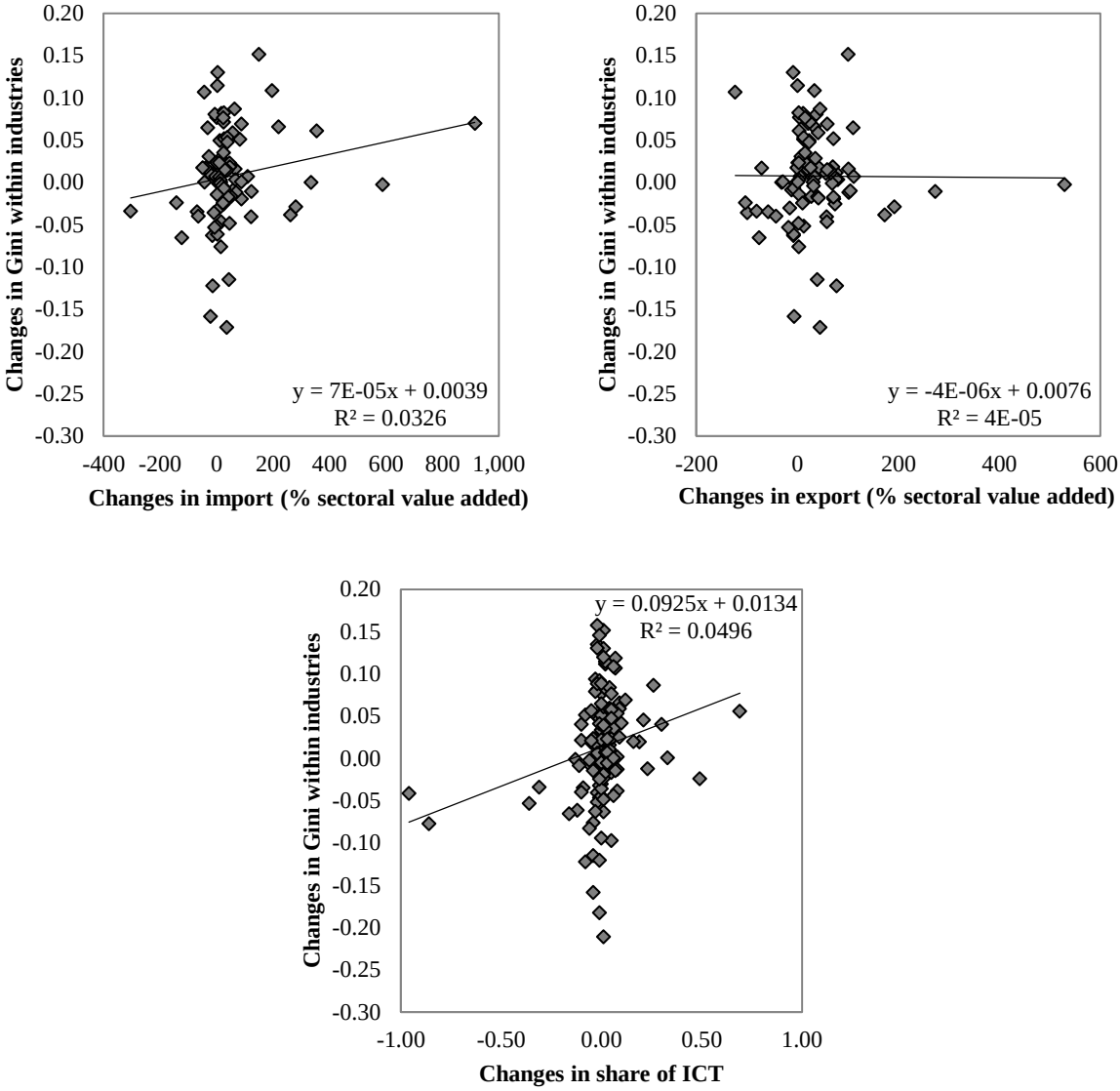
Country	Union coverage rate (%)		Level of wage coordination		EPL	
	1985	2005	1985	2005	1985	2005
Czech Republic	60.0[a]	43.5	2[a]	2	1.90[a]	1.90
Denmark	83.0	83.0	3	4	2.40	1.50
Finland	77.0	90.0	4	4	2.33	2.02
Germany	78.0	64.3	4	4	3.17	2.12
Ireland	60.0[a]	54.6	5[a]	5	0.93[a]	1.11
Sweden	85.0	94.0	4	3	3.49	2.24
UK	64.0	34.7	1	1	0.60	0.75
US	19.9	13.8	1	1	0.21	0.21
Average	65.9	59.7	3	3	1.88	1.48

Note: [a] Data from around 1995
Source: Union coverage and level of wage coordination from Visser (2011), EPL from OECD EPL.

5.4 Within-industry inequality

We start with simple scatterplots for the sectoral data to investigate the correlation between changes in the first order corrected Gini and sectoral levels of import, export, and the share of ICT. There is a weak positive relation between changes in import and the first order corrected Gini, as can be seen from Figure 5. For export the relationship is absent altogether. There is a somewhat stronger but still weak positive association for changes in the share of ICT, which is in line with the SBTC hypothesis.

Figure 5 OLS associations for import, share of ICT, and sectoral earnings inequality



Note: Changes in first order corrected Gini. Differences between 2005 and 1985 for sectoral observations, except for Czech Republic, Ireland, and Germany for import (between 2005 and 1995), and Sweden (between 2005 and 2000)
Source: First order corrected Gini from the Leiden LIS Sectoral Income Inequality Dataset, import from OECD STAN, share of ICT from EU-KLEMS

As shown in Table 9 no evidence is found in line with the hypothesis that international trade leads to earnings inequality at the sectoral level. The only borderline significant result is the negative association between export and the first order corrected Gini, which indicates that sectors more exposed to export actually have a more compressed earnings structure.

The sectoral share of ICT is insignificant in all regressions, thus, we do not find evidence for the SBTC hypothesis. The union coverage rate is consistently significant, however, and its sign corresponds to our hypothesis that a weaker trade union position goes hand-in-hand with a more dispersed earnings distribution. The level of wage coordination is

significant only for the Gini regressions, whereas EPL becomes significant in the regressions with the MLD as the dependent variable. Finally, the unemployment rate at country level has a negative association with sectoral inequality. A possible explanation for this is that when the unemployment rate is rampant, people with earnings at the lower end of the distribution are most prone to job loss. Another reason is that starters with relatively low earnings postpone entry into the labour market (*e.g.*, Elsby *et al*., 2010).

Table 9 Panel data regressions for earnings inequality within sectors

	First order corrected Gini		MLD	
Sectoral data	(1)	(2)	(3)	(4)
Import	-0.002		-0.000	
	(0.319)		(0.797)	
Export		-0.008*		-0.009
		(0.077)		(0.202)
Share of ICT	1.068	0.359	0.903	0.544
	(0.553)	(0.869)	(0.737)	(0.848)
Country level data				
Union coverage	-0.134***	-0.134***	-0.257***	-0.254***
rate	(0.001)	(0.001)	(0.004)	(0.003)
Level of wage	-1.884***	-1.784***	-1.391	-1.288
coordination	(0.001)	(0.002)	(0.126)	(0.156)
EPL	0.897	0.912	3.478**	3.447***
	(0.376)	(0.343)	(0.012)	(0.009)
Unemployment	-0.410***	-0.392***	-0.235*	-0.218*
rate	(0.000)	(0.001)	(0.071)	(0.097)
Real GDP per	-0.026**	-0.027**	-0.044	-0.045
capita/100	(0.045)	(0.035)	(0.124)	(0.122)
Constant	44.054***	44.071***	38.350***	38.261***
	(0.000)	(0.000)	(0.001)	(0.001)
*N*T*I*	334	334	334	334
Adjusted R^2	0.627	0.629	0.407	0.409

Note: OLS with country*period and sector*period fixed effects, full sample, 1985-2005, clustered standard errors. Significance levels are noted by *** (1 per cent), ** (5 per cent), or * (10 per cent)

Source: First order corrected Gini and MLD from the Leiden LIS Sectoral Income Inequality Dataset, import and export from OECD STAN, share of ICT from EU-KLEMS, union coverage and level of wage coordination from Visser (2011), all other data from OECD

5.5 Employment effects

It might be the increased inequality at country level is not so much a consequence of widening earnings distribution, but rather of employment loss at the bottom end of the earnings distribution (Gottschalk and Smeeding, 1997; Atkinson, 2003). As explained earlier, unfortunately the LIS database is a time series rather than a panel at the individual level. This makes it impossible to directly track employment shifts, such as transfers to less exposed sectors or to unemployment.

There are two indirect measures at our disposal to investigate employment effects. First, we can use data on the relative employment size of a sector. If our independent variables have caused job loss, we should expect a decrease in the relative employment size of the sector. Second, if this job loss mainly occurred for people at the lower end of the earnings distribution, we should expect higher relative median earnings in sectors that were more exposed to trade or that were more skill-intensive (see also Mahler *et al*., 1999, who coin this inequality between sectors).

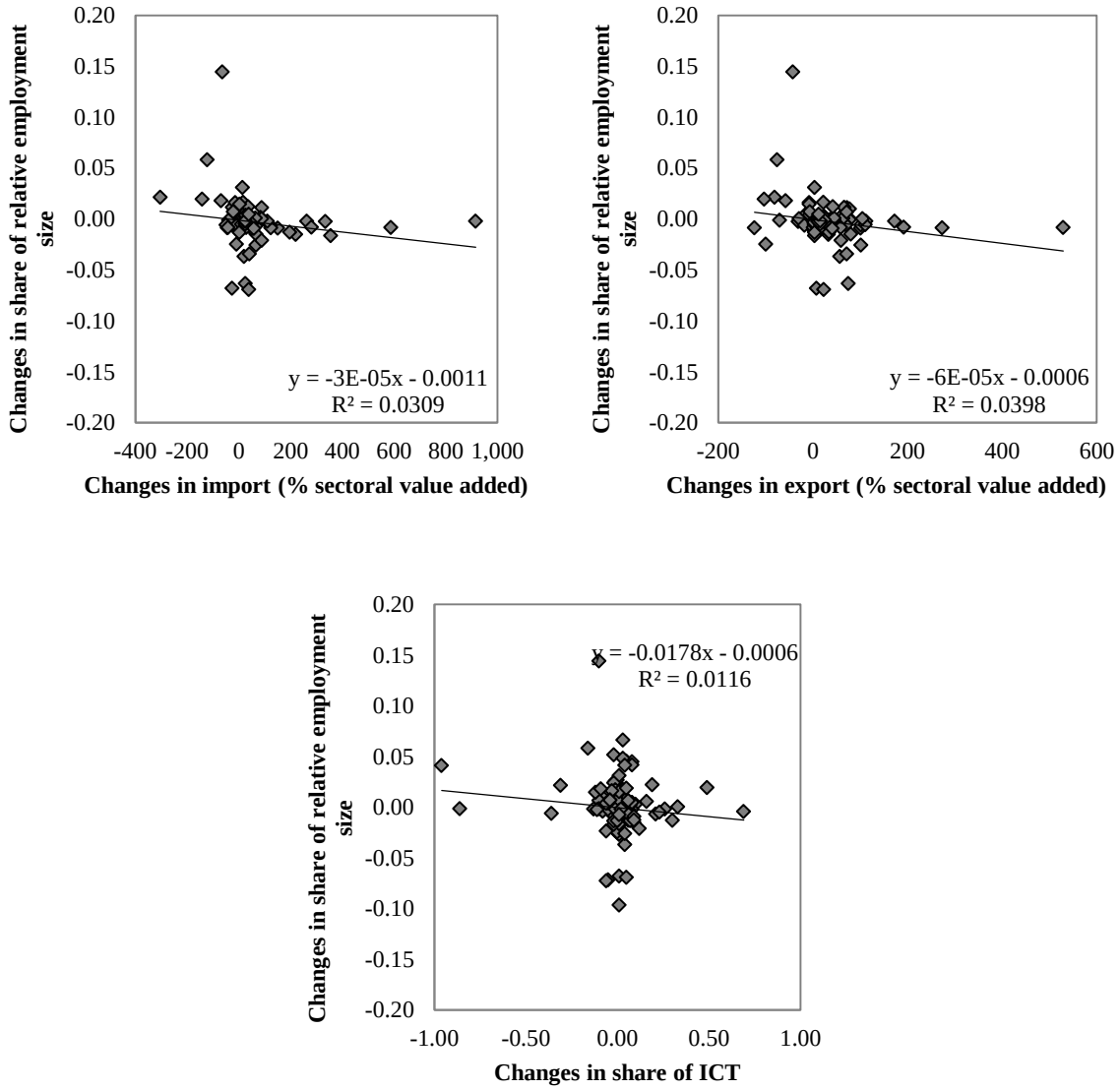
For the relative employment size we use our own LIS and the OECD STAN data, defined as the number of persons engaged per industry divided by the total number of persons engaged. This indicator only tells us something about the extensive margin; cuts in working hours are not incorporated. The indicators from the two data sources are highly correlated (0.96). For the relative median earnings we divide the sectoral median earnings by its country-level counterpart of the same period.

As both employment indicators are expressed in percentages relative to the national level, the institutional and control variables at the country level lose their interpretation. As the sectoral terms are expressed in ratios, they average out to around 100 at the country level. The country-level variables are therefore left out of the regressions, although the results are not affected by their inclusion.[23]

Figure 6 shows a weak negative association between changes in import, export, and the share of ICT on the one hand, and the relative employment size on the other. Yet, the explanatory power is limited as evident from the low R^2 value.

[23] The coefficients for the country-level indicators are still estimated as for some sectors data are missing, so that the problem of perfect collinearity does not arise.

Figure 6 OLS associations for import, share of ICT, and relative employment size



Note: Changes in relative employment size. Differences between 2005 and 1985 for sectoral observations, except for Czech Republic, Ireland, and Germany for import (between 2005 and 1995), and Sweden (between 2005 and 2000)
Source: Relative employment size from the Leiden LIS Sectoral Income Inequality Dataset, import from OECD STAN, share of ICT from EU-KLEMS

We can see from the results in Table 10 that import is significantly associated with the relative employment size of industries. We can infer from this that the relative number of jobs has decreased in sectors more exposed to import. This is in line with the hypothesis that trade leads to job loss in import-competing sectors. From the results we can conclude that for a given sector, an increase in import of 1 per cent of the sectoral value added is on average associated with an in between 0.001 and 0.002 lower relative employment size in a period, holding constant the control variables. There is no evidence for job creation in sectors with a large export fraction. For the ICT propensity we only find one borderline significant result; the positive direction is not in agreement with the SBTC job loss hypothesis.

Table 10 Panel data regressions for the relative employment size

	LIS data		OECD data	
Sectoral data	(1)	(2)	(3)	(4)
Import	-0.002***		-0.001***	
	(0.007)		(0.005)	
Export		0.001		-0.001
		(0.232)		(0.673)
Share of ICT	0.686*	0.386	0.434	0.125
	(0.097)	(0.377)	(0.207)	(0.730)
Constant	2.660***	2.611***	2.215***	2.224***
	(0.000)	(0.000)	(0.000)	(0.000)
*N*T*I*	334	334	339	339
Adjusted R^2	0.627	0.609	0.672	0.655

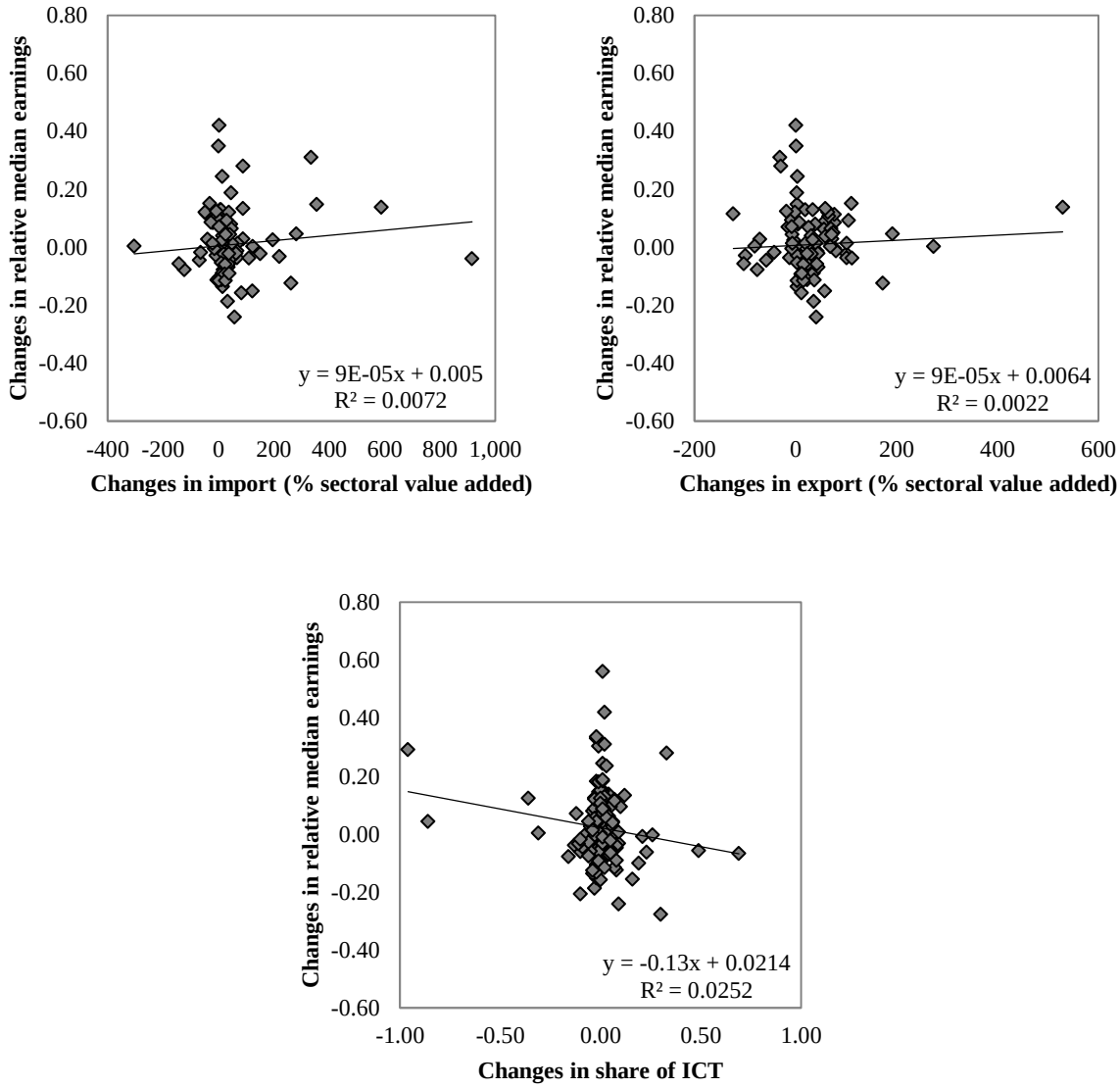
Note: OLS with country*period and sector*period fixed effects, full sample, 1985-2005, clustered standard errors. Significance levels are noted by *** (1 per cent), ** (5 per cent), or * (10 per cent)

Source: Relative employment size from OECD STAN and Leiden LIS Sectoral Income Inequality Dataset, import and export from OECD STAN, share of ICT from EU-KLEMS

Yet, the relative employment size does not necessarily tell us something about job loss for lowly skilled; it simply captures all relative job movements. Therefore, we also use the sectoral median earnings relative to the national median earnings. In case that low wage jobs for lowly skilled have disappeared we should expect higher relative median earnings in sectors that became more exposed to international trade or more skill intensive.

Figure 7 shows that the OLS associations are generally weak. Changes in both import and export have a marginal positive association with changes in the relative median earnings. This is not in line with the hypothesis that trade led to job loss at the lower end of the distribution, resulting in higher relative median earnings. For the share of ICT a somewhat stronger negative association is reported.

Figure 7 OLS associations for import, share of ICT, and relative median earnings



Note: Differences between 2005 and 1985 for sectoral observations, except for Czech Republic, Ireland, and Germany for import (between 2005 and 1995), and Sweden (between 2005 and 2000)

Source: Relative median earnings from the Leiden LIS Sectoral Income Inequality Dataset, import from OECD STAN, share of ICT from EU-KLEMS

The regressions presented in Table 11 actually show a negative association between import and the relative median earnings which is significant at the 10 per cent level. This finding indicates that the diminution of employment found in the former regressions is not associated with concomitant job loss for the lowly skilled, although the evidence is not particularly strong here. All things considered, we find that sectors more exposed to import are characterised by a lower number of jobs, potentially lower median earnings, but not a more dispersed earnings distribution. An explanation for this is that job loss in import-competing sectors is not only tailored to the low end of the earnings distribution, but rather that the whole distribution shifts down as a result of increased international competition. Other

explanations are feasible as well though, and in addition, the evidence for lower relative median earnings is weak. For export and ICT intensity no significant associations are reported.

Table 11 Panel data regressions for the relative median earnings

	Relative median earnings	
Sectoral data	(1)	(2)
Import	-0.016*	
	(0.054)	
Export		0.014
		(0.516)
Share of ICT	3.596	0.485
	(0.713)	(0.962)
Constant	103.335***	102.721***
	(0.000)	(0.000)
*N*T*I*	334	334
Adjusted R^2	0.660	0.650

Note: OLS with country*period and sector*period fixed effects, full sample, 1985-2005, clustered standard errors. Significance levels are noted by *** (1 per cent), ** (5 per cent), or * (10 per cent)

Source: Relative median earnings from the Leiden LIS Sectoral Income Inequality Dataset, import and export from OECD STAN, share of ICT from EU-KLEMS

5.6 Sensitivity tests

We perform a battery of additional tests to investigate the sensitivity of our results. First, we test whether the reported results are sensitive to the selected sample. We exclude the industries in which the number of included households in the LIS household data is below 30, causing the number of observations to decrease from 334 to 316. This does not affect the results. Second, we test for the possibility that trade only had an effect from around 1995 onwards, when the trade between developed and developing countries mainly increased (OECD, 2011a). This alters the regressions with sectoral earnings inequality as the dependent variable somewhat; export becomes insignificant and so does UCR for the MLD, whereas the level of wage coordination and EPL become significant in all regressions. In our original results the community sector was excluded as no data for international trade are available. If we impute zeros for the missing values and redo the estimations (the *N* increases to 363), then the only difference is that export becomes insignificant for the first order corrected Gini.

Next, we test more generally whether the reported results are robust to the exclusion of countries and sectors. The general picture is again confirmed; import remains significantly associated with the relative employment size, whilst the significant associations between export and the first order corrected Gini and between import and relative median earnings

disappear frequently. The results for the institutions and ICT intensity are not affected by this jackknifing procedure.

Subsequently, the fact that we do not find many significant results might be due to the conservative nature of our empirical specification. By including interactions of country dummies and the time trend, or sector dummies and the time trend, we remove patterns over time in sectors and countries from the data which reduces the variation. Therefore we also estimate the models without the dummies. This comes at a high price though, as it makes the results more susceptible to unobserved heterogeneity bias. There are still no signs of inequality-enhancing effects of international trade. Without the country and time trend interactions the institutions become significant in all four inequality regressions. There are some signs for a significant positive association between export and the relative employment size, entailing that export could lead to job creation, when the sector and time trend interactions are removed. The initially found significant association between import and the relative median earnings disappears regularly.

It could be that parts of the changes in earnings or employment are caused by people shifting from unemployment to part-time unemployment or from part-time to fulltime jobs. Especially spouses and other relatives are prone to make these labour shifts. We recalculate all indicators where we include household heads only and redo the regressions; correlations are above 0.94 for the sectoral earnings inequality and employment size, and 0.85 for the relative median earnings. There are still no signs of inequality-enhancing effects of international trade, while EPL becomes significant for the first order corrected Gini. The association between the relative sectoral size and import remains firm, whereas the significance between import and the relative median earnings disappears.

Last, we explore possible consequences of the fact that we base our estimations on individual rather than household earnings, as Mahler *et al*. (1999) did. Employing household earnings introduces noise into the dataset as earnings are attributed to sectors in which they were not necessarily made. However, if labour supply decisions are made at the household level and when earnings are shared between household members, it might be preferable to base the regressions on household data. The correlations between the individual and household data indicators are high for the relative employment size (above 0.93), but lower for the inequality indicators (0.82 for the first order corrected Gini and 0.67 for the MLD) and the relative median earnings (0.68). We still do not find evidence for inequality-enhancing effects from international trade, whilst the level of wage coordination becomes comfortably significant for all regressions. The most salient finding is the robustly significant positive

association between the share of ICT and within-sector inequality. Thus, based on household level data we do find evidence for SBTC. The employment regressions correspond to the ones based on individual data, except the consistently insignificant association between trade and relative median earnings that was already apparent from the other sensitivity tests.

6. Conclusions

This paper describes trends in sectoral earnings inequality and employment using a new database containing information for eight countries between 1985 and 2005. In addition, using multilevel tests possible explanations for variations in sectoral inequality and employment are scrutinised. Our decomposition depicts that earnings inequality at the country level is by and large a consequence of dispersion within sectors rather than large differences in mean earnings between sectors. This share of within-sector inequality has increased further over time.

Mirroring the developments at the country-level, earnings inequality has increased within the lion's share of sectors. The level itself differs per sector, where inequality is the highest in agriculture, although this is one of the few sectors which shows a trend towards equalisation over time. In particular the mining and utilities industries are characterised by a relatively even earnings distribution, combined with relatively high median earnings. Therefore, these sectors comprise a relatively homogeneous workforce. The median earnings are relatively low in the classically labour-intensive industries, namely, agriculture, wholesale, and the manufacturing of textile, although median earnings are rising fast in the agricultural sector. Our comparison of the relative employment sizes of industries over time imparts a notable employment shift from the manufacturing industry towards the financial sector. For all these trends the differences across countries are limited.

By means of multilevel panel regressions we do not find evidence for associations between trade and earnings inequality. Yet, the reported results denote that the employment size has decreased in sectors that are more exposed to import. No further evidence is found that this job loss has occurred at the bottom end of the earnings distribution. In addition, the union coverage rate at the country level is found to be negatively associated with sectoral earnings inequality, which corresponds to the hypothesis that waning trade union power is an explanation for rising inequality. These results are robust to a set of sensitivity analyses. Further inspection using sectoral data for trade union influence can provide more insight.

The regression results are not in line with the predictions from the SBTC hypothesis, as we do not find significant associations between the sectoral ICT intensity and any of the

dependent variables. This comes somewhat as a surprise as at the country level the evidence for SBTC is relatively robust. It is therefore relevant to further investigate in the future how our results can be consonant with the previous findings on SBTC.

The conducted regressions do not provide causal evidence. Other confounding factors, in particular in product markets, can be expected to affect both the earnings and employment, as well as the trade and technology. In addition, individual labour market transitions cannot be tracked directly by means of the used database. Still, the analyses instigate a sectoral approach in investigating inequality, in which heterogeneity between sectors is accounted for.

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