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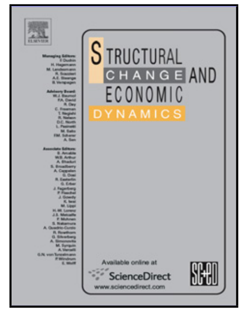

Title: Industrial employment and income inequality: Evidence from panel data

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- Is income inequality related to industrial employment shares?
- The paper uses a panel of 27 countries from 1991 to 2014.
- The results show that industrial employment significantly affects inequality.
- Moreover, the middle-earners have borne the largest burden of inequality increases.

Industrial employment and income inequality: Evidence from panel data

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Abstract

Over the last decades, the Western world has seen millions of relatively well-paid manufacturing jobs disappear. Some have shifted to low-income countries, while other have been permanently lost due the introduction of labor-saving technologies. Concurrently, many comparatively low-wage jobs have been created in services, for example in fast food and retailing. This paper uses a dynamic panel of 27 high and middle income countries from 1991 to 2014 to estimate the effects of declining industrial employment shares on income inequality. The analysis shows that industrial employment is significantly negatively associated with income inequality. Additionally, the results suggest that it is the middle-earners that have borne the largest burden in terms of inequality increases.

Keywords: income inequality; job market polarization; deindustrialization
JEL classifications: D63, O14, O25

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1 Introduction

In the wake of the recent financial and economic crisis, the topic of income inequality has again become prominent in the national political debate in many countries. The Occupy Wall Street movement and the presidential campaign of United States senator Bernie Sanders are two recent examples of this. Concurrently, there has been a lively debate on globalization and automation, and to what extent these are contributing to the relative decline in the importance of the manufacturing sector in the Western world. For example, only a tenth of the U.S. workforce is employed in manufacturing, down from a third in the 1970s.

Building a campaign on promises of revitalizing the manufacturing sector, chiefly through tariffs on Chinese and Mexican imports, Donald Trump became the first Republican candidate in decades to win the "Rust Belt" states of Michigan, Pennsylvania and Wisconsin. These states are characterized by decades of decline in the manufacturing sector. Similarly, in Europe, right- and left-wing populist parties have gained momentum in virtually every nation, drawing considerable support from the working class in these countries.

The literature tends to focus on two mechanisms behind the decline in Western manufacturing employment: trade and technology. The logic behind the first argument is that globalization, through free-trade agreements and removal of trade barriers, has created incentives for firms to shift production from high-wage countries to low-wage countries. The second hypothesis is essentially that skill-biased technological change, for instance through automation, leads to a higher relative demand for college-educated workers, and a decreased relative demand for low-skilled workers doing manual labor. This would, thus, increase the wage differential between these two groups of workers. Regardless of the underlying causes, the decline of the manufacturing sector in advanced economies is not merely a concern for displaced workers and their relatives. For instance, in Europe, some two-thirds of R&D spending is done in manufacturing (Rodrik 2016), highlighting the importance of this sector for the entire economy. Figure 1 shows the relationship between income inequality and the manufacturing share of nonfarm employment in the United States between 1970 and 2014. The nonfarm employment graph is the same as in Autor et al. (2016). This figure clearly shows that the manufacturing employment share has been in steady decline over the entire sample period, with an acceleration after the turn of the millennium, and a tendency to flatten out beginning around 2010. Income inequality has in-

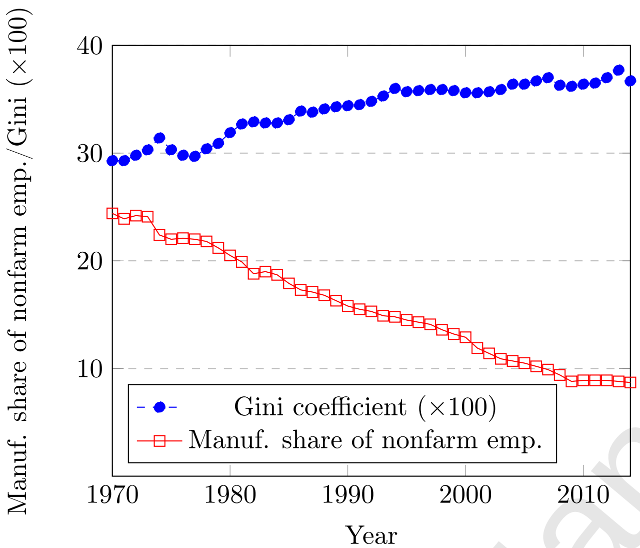

Figure 1: Graphical relationship between income inequality and the manufacturing share of nonfarm employment in the United States between 1970 and 2014.

creased considerably during this period. Similar conclusions can be reached for most Western countries. However, research has slightly neglected that during the early 21st century, income inequality has decreased in several newly industrialized countries, for instance in Turkey and in most Latin American countries (Pamuk 2008; Lustig et al. 2013). For example, the Gini coefficient of income inequality decreased by 13 % in Brazil and by 14% in Turkey between 2000 and 2014, while industry's share of employment increased in both countries during the same time period (ILO 2014; Solt 2016). This is a sharp contrast to the 1980s and 1990s, when income inequality increased virtually everywhere.

Additionally, when looking at the changes in real income over the last decades, the Western manufacturing worker is, again, the loser. During the two-decade period from 1988 to 2008, the working class of the Western countries, roughly corresponding to the 75th to 90th percentiles of the global income distribution, saw their real incomes decline. This is a sharp contrast to the incomes of the top five percent of the global income distribution, corresponding to the upper middle and upper classes in the developed world, who have experienced significant increases in real incomes (Milanovic 2012). Apart from the upper classes of the rich countries, the middle classes in newly industrialized countries have

Sector	*Average hourly wage*
Manufacturing (all)	£15.64
Call centers	£14.51
Event catering	£11.02
Social work for the elderly and disabled	£10.07
Hotels	£9.89
Child day-care activities	£9.42
Coffehouses	£8.82
Restaurants	£8.66

Table 1: Average gross hourly wages for a number of relatively low-skilled jobs in the United Kingdom, 2016. Data source: Office for National Statistics (2016).

seen large increases in real incomes. Many of these nations - Mexico, China, Brazil and former Eastern Bloc countries are not seldom accused of "stealing" Western manufacturing jobs.

Regardless of the cause of declining manufacturing employment rates in advanced countries, there is a particular mechanism - *job market polarization* associated with deindustrialization that is particularly appalling for explaining increased income inequality.

The term was first introduced by Goos and Manning (2007). In essence, it means that displaced manufacturing workers, who tend to be relatively well-paid, take low-paid jobs in services instead. The antecedent of the term is originally due to Autor et al. (2003), who argue that technology will replace human labor predominantly in routine tasks. Hence, the adverse effects of technological change will primarily be felt by those with relatively low-skilled jobs, chiefly, but not limited to, manufacturing. Table 1, which shows average hourly wages for a number of jobs in the U.K., helps to illustrate the point behind the job polarization hypothesis. Wages in manufacturing are considerably higher than those in fast-growing service sectors such as fast food, catering, and call centers. These sectors that have absorbed a sizable proportion of displaced manufacturing workers (cf. Goos and Manning 2007).

Concomitantly, wages at the rightmost tail of the income distribution have increased over the last decades. For the U.S, Goldin and Katz (2007) estimate the increase in the college wage premium between 1980 and 2005 to be in the region of 24 percentage points. Hence, both incomes and the top of the income distribution, as well as incomes at the bottom of the distribution contribute to job market polarization. However, most studies have tended to focus on the relative enrichment of the top decile, or the relative impoverishment of the bottom earners (cf. Piketty and Saez 2003; Meyer and Sullivan 2013). This paper will, instead, focus on the declining relative incomes of middle-earners.

Although the erosion of the middle class as explanation for increased inequality was not entirely neglected by the 1980s and 1990s literature, the distributional effects of deindustrialization were considered relatively minor (cf. Bluestone and Harrison 1988; Bound and Johnson 1992). Towards the turn of millennium, however, there were attempts to shed new light on this topic (cf. Galbraith and Berner 2001). This revival of interest in the relationship between manufacturing employment and inequality is not unexpected given that the early 21st century has seen an acceleration both in deindustrialization as well as in income inequality, further supported by increased trade liberalization and a greater degree of automation in production. Given that the political and scholarly debate in many Western countries is currently highly focused on trade liberalization and offshoring, deindustrialization and income inequality is even more relevant today than it was around the turn of the millennium, when NAFTA had recently been implemented, and the European Single Market was considerably smaller than it is today. For instance, Ebenstein et al. (2014) estimate that occupation switching due to trade in the U.S labor market results in wage losses of approximately 15 percentage points, and that this effect is particularly evident for manufacturing.

However, the role of the *share* of manufacturing employment has largely been neglected, as most previous studies have focused on wage inequality within manufacturing. Nevertheless, employment share is included in Galbraith and Kum (2005) and Jaumotte et al. (2008) as a control variable when estimating panel models with the Gini coefficient as the dependent variable. While both papers find that the employment share is significantly negatively related to inqequality, the dataset used by Jaumotte et al. (2008) ends in 2003, and the paper by Galbraith and Kum (2005) uses values from the University of Texas Inequality Project's *Estimated Household Income Inequality Data Set* (EHII), which is available until 2008. Hence, both these studies fail to take into account the period after the Great Recession. Also, since the early 21st century has seen an acceleration in both inequality and deindustrialization, the manufacturing employment share is even more relevant today as an alternative to the mainstream explanations of increased inequality based on rising skill-premia.

This paper tries to fill the research gap on manufacturing employment shares and inequality by using data on 27 high- and middle-income countries to fit a dynamic panel model stretching from 1991 to 2014. The industrial employment share is shown to have a significant effect on income inequality as measured by the Gini coefficient. More precisely, a decreasing industrial employment rate is associated with a significant increase in income inequality. However, deindustrialization does not significantly contribute to increasing the gap between the top and bottom earners, as measured by the Palma (2011) ratio of the income shares of top decile to the bottom 40%. This result suggests that the largest distributional changes as a result of lower manufacturing employment rates have taken place within the middle- and working classes. This notion gives support to the job market polarization hypothesis.

The rest of the paper is structured as follows. Section 2 provides a deeper insight into the existing research on the relationship between industrial employment and inequality. Section 3 descries the data and the econometric model, while Section 4 presents the results. The paper concludes with Section 5.

2 Deindustrialization and income inequality

Since the 1980s, income inequality has risen in virtually all advanced economies. Concurrently, relative demand for low-skilled workers, particularly production workers, has declined sharply. Both in Europe and in the United States and Canada, the share of manufacturing of total employment has been in decline. In the United States, the fall in relative demand for less skilled workers has resulted in declining real wages. In many Western European countries, where salaries are to a greater extent institutionally fixed (for instance, through collective bargaining), and thus more "sticky", unemployment rates among less-skilled workers have increased (Freeman 1995). That the relationship between deindustrialization and inequality is not a mere juxtaposition is well-established. Already in the late 1980s and early 1990s, wage polarization as a result of lower manufacturing employment rates were considered one of the major culprits behind the increase in wage inequality in the United States and increased unemployment in Western Europe (Bluestone and Harrison 1988; Freeman 1995). Indeed, the share of manufacturing employment is shown to have accounted for up to 55 percent of the change in wage inequality in the United States between 1970 and 1990 (Bernard and Jensen 1994).

In essence, there are two mechanisms through which lower manufacturing employment rates contribute to increased inequality. Firstly, through job losses in manufacturing leading to long-term unemployment amongst displaced workers. While it is fairly incontrovertible to claim that mass unemployment amongst displaced manufacturing workers will lead to earnings losses and increased income inequality, there is little empirical evidence of this phenomenon. Despite an increase in unemployment in OECD-Europe during the 1990s, U.S unemployment decreased during the same period (cf. Shimer 1998). And after all, most displaced workers both in Europe and in the U.S. and Canada, do find new jobs. However, a job loss in manufacturing is associated with persistent negative effects on earnings for the affected individual. Two recent studies using U.S. and Canadian data, respectively, have estimated the earnings losses for displaced manufacturing workers to be in the region of 15 percent five to six years after displacement (Couch and Placzek 2010; Morissette et al. 2013).

Concomitant with the decline of manufacturing, the importance of the service sectors has increased in virtually all advanced countries. Examples of fast-growing low-skilled service sectors include fast food and call centers, sometimes colloquially dubbed "McJobs". This has led some to argue in support of a mechanism where deindustrialization leads to downward pressure on wages as workers previously employed in manufacturing take low-paid jobs in services, leading to increased wage inequality. This mechanism is known in the literature as *job market polarization*. As mentioned in the Introduction, the term itself is due to Goos and Manning (2007), although several papers in the 1990s explored the idea. Most of them found that displaced manufacturing workers experienced wage losses if they transferred to the service sector (cf. Gibbons and Katz 1991; Jacobson et al. 1993; Juhn 1999). Moreover, a lack of low-skilled service jobs for displaced manufacturing workers has been put forward as one of the reasons for the increase in long-term unemployment in OECD-Europe during the 1990s (Ljungqvist and Sargent 1998). Others, however, have noted that the increase in inequality noted in advanced economies is primarily a consequence of increased inequality within, rather than between, sectors (cf. Faggio et al. 2007). Hence, if the latter is correct, intersectoral movements from manufacturing to services cannot not explain the increase in wage inequality.

What is more controversial is the *reason* behind the decline of the Western manufacturing industry. The 1990s literature focused extensively on the role of skill-biased technological change (cf. Mincer 1991; Bound and Johnson 1992; Krugman and Lawrence 1993; Berman et al. 1994). In short, automation and computerization decreased the relative demand for manual labor and increased the relative demand for highly-educated workers. At the same time, the wage premium for college-educated workers increased dramatically, particularly in the

U.S. (Goldin and Katz 2007). Other explanations include the decline of unions (Freeman 1991), movements in exchange rates (Rossi and Galbraith 2016), and increasing immigration resulting in greater supply of low-skilled workers, thus decreasing relative wages for these workers (Borjas et al. 1997). For the U.S., some studies noted that increasing trade deficits towards the late 1980s, causing a decline in manufacturing employment, could be an explanation to increased inequality (Murphy and Welch 1991; Katz and Murphy 1992). However, most studies failed to show any correlation between inequality and trade (cf. Krugman 2000). Also, by the Stolper-Samuelson theorem, North-South trade should lead to a change in relative prices. However, in the U.S, the relative prices of skilled to unskilled goods remained roughly constant, even though trade shares had increased (Lawrence and Slaughter 1993). Moreover, inequality increased in many developing countries in the 1980s and 1990s, which clearly contradicts the predictions of the Stolper-Samuelson theorem (cf. Goldberg and Pavcnik 2007). This seemed to rule out trade as an explanation for increased inequality.

At the turn of the 21st century, the general consensus among economists was that the slump in industrial employment and increase in inequality was caused primarily by technological change causing a shift in relative demand towards highly-educated workers (see Autor et al. 2016 for a summary). Some studies even claimed that the increase in inequality noted in the 1980s was a one-time event, which was not likely to re-occur (Card and DiNardo 2002; Lemieux 2006). Moreover, trade did not significantly contribute to inequality, and the aggregate gains from trade were positive, as predicted by standard trade theory.

However, a number of events in the late 20th and early 21th centuries have made the link between deindustrialization and inequality worth reconsidering. Firstly, the decrease in manufacturing employment rate accelerated during the early 21st century. U.S manufacturing employment decreased from 17.1 million to 11.4 million in 2011. Up to 2.4 million U.S. jobs were lost between 1999 and 2011 solely due to Chinese import competition, primarily in manufacturing (Acemoğlu et al. 2016). Data from other countries support the notion of an acceleration in deindustrialization. In France, for instance, while manufacturing employment decreased by 36% between 1980 and 2007, the decline was particularly sharp post-2000. What is more, the proportion of this decline attributed to foreign competition was more than twice as high over the sub-period 2000 to 2007, relative to the entire period of 1980 to 2007 (Trésor-Economics 2010). Data from the U.S. reveals that two out of three displaced manufacturing workers who were rehired in 2012 experienced wage cuts, a majority of these in excess of 20% (Beachy 2012). Moreover, the 1990s saw a clear change in job growth in the U.S labor market, where the growth of employment was considerably larger in professions at the upper and lower tails of the wage distribution relative to middle-income jobs (Autor et al. 2006). A similar development took place in the United Kingdom (Goos and Manning 2007). Although, again, far from everyone agrees that offshoring is the main culprit behind this development, the relative importance of trade in explaining job market polarization is greater in manufacturing than in other sectors (cf. Harrigan et al. 2016).

Concomitant with empirical studies, the last two decades have seen the development of a number of new theoretical trade-inequality models as an alternative to conventional Stolper-Samuelson wisdom. Dinopoulos and Segerstrom (1999) propose a theoretical North-North trade model, according to which trade liberalization causes decreases manufacturing employment and increases inequality in both trading nations without affecting relative prices. Other recent trade models exploring the relationship between trade and inequality have focused on labor-market imperfections and intersectoral movements of labor to demonstrate how trade can contribute to increased inequality (cf. Helpman et al. 2010; Fajgelbaum and Khandelwal 2016; Antràs et al. 2017).

Another major change in the global macroeconomic context in recent years is the increasing level of economic integration, chiefly, but not limited to, the removal of trade barriers. In the case of Europe, the clearest example is the expansion of the European Union and the Common Market. For the U.S., trade agreements such as the North American Free Trade Agreement (NAFTA) and Trans-Pacific Partnership (TPP) have frequently been scapegoated for the loss of manufacturing jobs, at least in the political debate. Whether or not tariff liberalization increases inequality is an open question. If a reduction in tariffs leads to increased competition from countries with a larger supply of low-skilled labor, wage inequality is likely to increase (Hanson and Harrison 1999). However, other studies indicate that the adverse effects on inequality of trade liberalization are relatively minor, if not non-existent, for developed countries (cf. Haskel and Slaughter 2003; Milanovic and Squire 2005).

Moreover, the last decade has seen a revival in the interest in skill-biased technological change, primarily as a result of automation and robotization. A highly controversial paper by Frey and Osborne (2013) estimates the share of U.S. employment at risk due to automation at almost fifty percent. Although this figure was deemed to high by other studies (cf. Arntz et al. 2016), there has been considerable debate in most countries on the if a large share of jobs

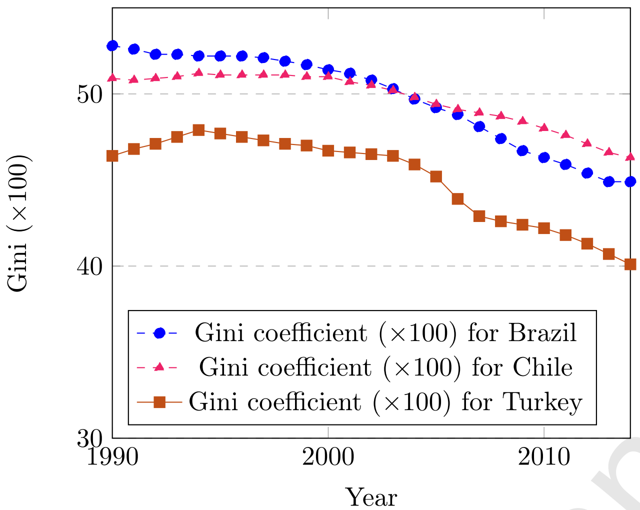

Figure 2: The evolution of the Gini coefficient of income inequality for Brazil, Chile and Turkey between 1990 and 2014.

disappear. The most widely discussed solution is some kind of basic income (cf. Pulkka 2017). Most economists, however, argue that the populist debate tends to over-focus on the negative aspects of technological progress, and ignoring positive aspects, such as higher productivity increasing demand for labor (cf. Autor 2015). Still, some recent studies have found support to the notion that skill-biased technological change continues to be one of the main drivers behind increased wage inequality in advanced economies (Goos et al 2009; Kristal 2013; Kristal and Cohen 2017). However, others have argued that computerization and automation have little effect on the wage distribution (Handel 2007; King et al. 2017), or that the polarization effects of automation are likely to level off in the future (Autor 2015).

Finally, there is the peculiarity of decreasing income inequality in developing countries. During the 1980s and 1990s, inequality increased in virtually all countries. Since, there has been a decrease in inequality in several newly industrialized countries, contradicting the Stolper-Samuelson predictions. For instance, the Gini coefficient decreased in 13 out of 17 countries in Latin America between 2010 and 2017 (Lustig et al. 2013). Another newly industrialized country that has experienced falling inequality in the early 21st century is Turkey (Pamuk 2008). Figure 2 highlights this trend for three countries.

Clearly, this is a significant contrast to the development of the 1980s and

	Mean	Std dev	Min	Max
Dependent variable				
Gini coefficient ($\times 100$)	31.79	7.81	18.67	52.58
Palma ratio ($\times 100$)	138.77	76.13	69.0	456.0
Independent variables				
Industrial employment share	26.28	5.64	16.53	44.29
Government expenditure-to-GDP	19.28	3.76	9.08	29.67
GNI per capita	31,948.04	11,365.63	9,385.27	65,638.37
Trade-to-GDP	71.33	36.30	15.64	209.66

Table 2: Mean, standard deviation, minimum and maximum for the dependent and independent variables.

1990s. The reasons behind this trend are generally considered to be falling skills premia, an increase in thew wage-setting power of trade unions and institutional reforms (Lustig et al. 2013; Tsounta and Osueke 2014); more or less the same mechanisms that have resulted in higher inequality in advanced economies, only acting in the opposite direction. However, what has been neglected by research is that several of these countries, including Latin American countries, as well as Turkey, have seen an increase in the share of manufacturing employment during the late 1990s and early 2000s (ILO 2014). Assuming a Lewis-style two-sectoral model with a relatively large rural or urban informal sector and a relatively small manufacturing sector, intersectoral migration in such a labor market is determined by the expected wage differential between the two sectors (cf. Harris and Todaro 1970). This wage differential depends both on the relative wage difference between the two sectors and the supply of manufacturing jobs. Hence, workers migrate from low-paying jobs in agriculture and in the urban informal sector to higher-paid manufacturing jobs, thus contributing to a decease in aggregate income inequality. Again, this can be seen as the reverse mechanism vis-à-vis the "migration" from manufacturing to services in implied by the job polarization hypothesis for advanced economies.

3 Data and model

3.1 Data

The dataset covers 27 high-and middle-income countries from 1991 to 2014. The countries included are Australia, Austria, Belgium, Brazil, Canada, Chile, Czech Republic, Denmark, Finland, France, Germany, Ireland, Israel, Italy,

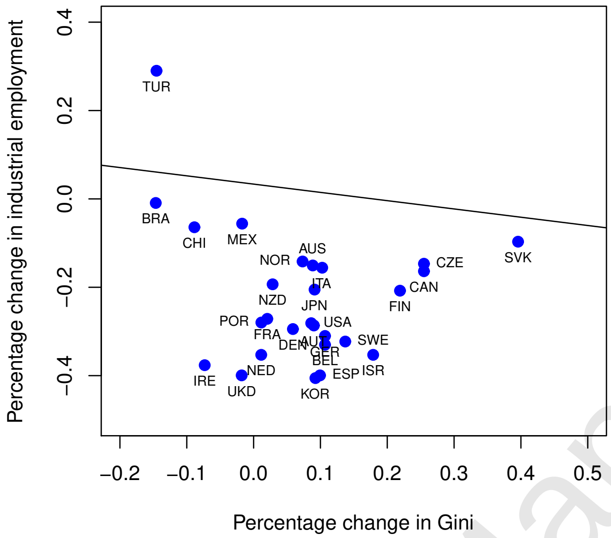

Figure 3: On the horizontal axis the percentage change between 1991 and 2014 in Gini for the 27 countries in the dataset, and on the vertical axis the corresponding percentage change in industrial employment.

Japan, Mexico, Netherlands, New Zealand, Norway, Portugal, Slovakia, South Korea, Spain, Sweden, Turkey, the United Kingdom and the United States.

Income inequality is measured by the Gini coefficient, which takes the value zero in the case of perfect inequality of incomes, and unity in the limiting case when all income is held by one person and the reminder of the population has zero income. As data source for the dependent variable, this paper uses net of tax Gini data from the *Standardized World Income Inequality Database* (SWIID), developed by Solt (2016) with the purpose of standardizing Gini observations from different data sources. To briefly summarize the SWIID approach, it uses data from several databases, wherein one of the databases, namely the Luxembourg Income Study (LIS), is chosen as the "reference" data, to which all other series are harmonized. However, the LIS has relatively few data points, and hence, requires imputation. By using loess regression on the data points of each of the other series used in constructing the harmonization, it is possible to predict the missing points using the coefficients from those regressions. For each point estimate, the SWIID uses five-year moving average smoothing, with twice as much weight on the estimate for the current year. To further account for the uncertainty associated with the imputation, each of the predicted variables is re-generated 1,000 times using Monte Carlo simulations, of which 100 are reported in the database. Then, it is possible to calculate the mean of these 100 observations, in order to obtain point estimates and the corresponding confidence intervals for each year.

For robustness, the parameter estimates are compared to the ones obtained when using the Palma ratio as a measure of income inequality in lieu of the Gini coefficient. The Palma ratio is the ratio between the income share of the richest ten percent to the income share of the poorest forty percent (Palma 2011). Whereas the Gini puts the same weight on changes to the income distribution regardless where on the distribution these changes are occurring, the Palma ratio emphasizes the relative difference between those at the very top of the distribution and the bottom 40 %. However, the Gini coefficient is still dominating empirical research, and is as such the preferred measure of this paper. Both the Gini coefficient and the Palma ratio are multiplied by 100 to avoid negative numbers when taking logs.

The explanatory variable of interest is the industrial employment share, which is the ratio of the number of employees in industry divided by the total labor force. The data on industrial employment is taken from the International Labour Organization (ILO 2014). This definition includes, besides manufacturing, workers in mining and construction, where the latter is not the focus of this paper. However, the inclusion of construction in the measure is only a minor issue, since the relative importance of the construction sector is similar across most advanced countries, typically around five percent of GDP.

The control variables are the ratio of government expenditure to GDP, the per capita gross national income (GNI), and the trade-to-GDP-ratio. To summarize briefly the motivation behind each of the control variables, starting with government expenditure, state-funded social programs usually target the bottom earners in a society. Thus, higher government spending should, to some extent, equalize income distribution (Dabla-Norris et al. 2015; Jauch and Watzka 2016). However, other studies have shown that increased government expenditure can in fact exacerbate inequality, particularly if government funds are directed at certain income groups only (cf. Clements 1997). For instance, in many countries, access to tertiary education is limited to those at the top of the income distribution only, and hence, government spending on higher education could worsen inequality. Additionally, having government spending as a control variable makes it easier to isolate the effects of domestic redistribute policies, such as transfers aimed to mitigate inequality. Increased transfers to households

	Gini coef.	*Palma ratio*	*Ind.emp. share*	*Gov.exp-to-GDP*	*Trade-to-GDP*	*GNI (capita)*
Dependent variables						
Gini coef. (×100)	1	0.93	-0.28	-0.51	-0.43	-0.65
Palma ratio (×100)	0.93	1	-0.26	-0.43	-0.38	-0.66
Independent variables						
Ind.emp.share	-0.28	-0.26	1	-0.11	0.16	-0.27
Gov.exp-to-GDP	-0.51	-0.43	-0.11	1	0.28	0.41
Trade-to-GDP	-0.43	-0.38	0.16	0.28	1	0.60
GNI (capita)	-0.65	-0.66	-0.27	0.41	0.23	1

Table 3: Correlation matrix.

is considered to be one of the main reasons behind the flattening of the Gini curve noticed in the U.K during the late 1990s and early 2000s (cf. Belfield et al. 2017). Similar policies have been implemented in several Latin American countries that have seen fallen inequality levels, notably in Argentina and Brazil (Lustig et al. 2014).

Regarding the relationship between per capita income and inequality, the well-known Kuznets hypothesis predicts an inverted U relationship (Kuznets 1955). Hence, for high-income countries, an increase in income should give a decrease in income inequality. The possible existence of a Kuznets curve has been widely discussed in the literature (cf. Gallup 2012 for a summary on the empirical research on the area), with no clear evidence pointing in either direction. Nevertheless, either GNI or GDP per capita is often included as an independent variable in empirical research on income inequality (cf. Reuveny and Li 2003). This paper uses GNI instead of GDP, since the former includes income earned overseas. The motivation behind this is fairly straightforward - for high-income countries, foreign assets are often a considerable source of income, particularly for individuals at the top of the income distributions. GNI is measured using constant Geary-Khamis dollars, so as to dampen the effects of inflation, exchange rate fluctuations and differences in between-country purchasing power parities.

As mentioned in Section 2 of this paper, the distributional effects of higher trade volumes are subject to considerable debate (for other empirical studies on trade and inequality, see e.g. Edwards 1997; Chakrabarti 2000; Anderson 2005; Harrison 2010). In the analysis in Section 4, the trade volume, measured as the sum of imports and exports divided by GDP, is included as the third and final control variable.

The World Bank's World Development Indicators (World Bank 2017) are used as data source for all independent variables except for the industrial employment share. Table 1 provides the descriptive statistics, both for the dependent the independent variables, while Table 2 gives the correlation matrix. Appendix A summarizes the variables and data sources.

3.2 Model

The econometric model is

$$y_{it} = \phi y_{i,t-1} + \gamma z_{it} + \boldsymbol{\beta}' \boldsymbol{x}_{it} + u_{it} \tag{1}$$

for individuals $i = 1, \ldots, N$ and time periods $t = 1, \ldots, T$, where y_{it} denotes the logarithm of income inequality of country i at time t as measured by the Gini coefficient, z_{it} is the logarithm of the percentage of the workforce employed in the industry sector, $\boldsymbol{x}_{it}$ is a vector of log-transformed control variables, and u_{it} is an error term with $\mathbb{E}(u_{it}) = 0$ for all i and t.

In the model described by (1), the error term u_{it} can be decomposed into a country-specific error that does not vary with t, and an idiosyncratic error that varies both time and among countries. Since the country-specific error is the same for all time periods, there is correlation between the lagged dependent variable used as an explanatory variable and the error. Applying the standard fixed-effects least squares estimator to an endogenous model like the one above would give biased coefficient estimates (Nickell 1981). Instead, the difference GMM of Arellano and Bond (1991) utilizing first differences of lags of the dependent variable as instruments is commonly used for parameter estimation. However, this estimator suffers from small-sample bias when the number of time periods is low and when the value of the autoregressive parameter ϕ is close to unity (Blundell and Bond 1998). Moreover, this bias is higher when the sample size N is low (Soto 2009), which is the case in this paper. Hence, Section 4 provides the estimates from the system GMM of Arellano and Bover (1995) and Blundell and Bond (1998) in addition to those of the difference GMM. The system GMM estimator utilizes more moment conditions than the difference GMM, and tends to perform better in nearly non-stationary data (Blundell and Bond 1998). Another advantage of the system GMM is that the consistency of that estimator, unlike the difference GMM, does not hinge on the assumption of no second-order serial correlation, i.e that $\mathbb{E}\left(\Delta u_{it} \Delta u_{i,t-2}\right) = 0$.

It is important to note that having too many moment conditions may cause biased parameter estimates, a problem known as *instrument proliferation* (Roodman 2009a). The problem of instrument proliferation can be remedied by collapsing the instrument matrix, which essentially means using fewer lags as instruments. This can be done in two ways: either by reducing the number of lags used as instruments, or to "squeeze" horizontally the instrument matrix, so as to reduce the number of zeroes in the matrix (cf. Roodman 2009a). Since the latter method reduces the number of instruments without dropping lags, it will convey more information. Also, the small-sample bias has been shown to be lower than when the former method is applied (Roodman 2009a). Hence, this method is used in Section 4 when analyzing the GMM results. In addition to the difference and system GMM, Section 4 presents the results of the biased fixed-effects estimator for comparison.

4 Results

4.1 Main results

Table 2 presents the results. Column (1) gives the estimates and robust standard errors, clustered by country, of the fixed effects ordinary least squares (OLS). Column (2) gives the parameter values and robust standard errors when using the twostep difference GMM, while columns (3) and (4) correspond to the one- and twostep system GMM, using robust standard errors. The difference between the onestep and twostep estimator lies in which GMM weighting matrix is used, the twostep weighting matrix being "optimal" in the sense that is maximizes asymptotic efficiency (cf. Hwang and Sun 2015).

In addition to the logarithm of Gini lagged one year and the logarithm of the industrial employment share, all four models use the control variables described in Section 3, that is, the logarithm of government expenditures to GDP, the logarithm of per capita GNI, as well as the logarithm of the trade-to-GDP-ratio. Since the focus of this paper is the industrial employment share, these estimates are provided in the Appendix.

The industrial employment share is highly significant according to three of the four estimators, the exception being the difference GMM. The numerical value of the coefficient ranges from -0.028 using the fixed-effects OLS estimator to -0.044 using the twostep system GMM. Note that the effect, albeit highly significant, is numerically relatively small. *Ceteris paribus*, a one-percent

	(1)	(2)	(3)	(4)
log *Gini coefficient* (-1)	0.901***	0.823***	0.869***	0.889***
	(0.022)	(0.077)	(0.023)	(0.027)
log *Industrial employment share*	−0.028***	−0.0032	−0.044***	−0.034**
	(0.0092)	(0.0089)	(0.012)	(0.013)
Control variables included	Yes	Yes	Yes	Yes
Number of observations	596	569	596	596
Number of countries	27	27	27	27
Number of instruments		26	26	28
Method	FE OLS	diff. GMM, twostep	sys. GMM, twostep	sys. GMM, twostep
AB test of second order serial correlation		[0.18]		
Hansen J test		[0.36]	[0.43]	[0.43]

Table 4: Results from the regressions. The dependent variable is the Gini coefficient. The main independent variable is the industrial employment share. Robust standard errors in parentheses, where *, ** and *** denote statistical significance at the 10, 5, and 1% level, respectively. Values in squared brackets are p-values. All calculations were performed in *Stata*, using the xtabond2 package (Roodman 2009b).

increase in the industrial employment share decreases income inequality by less than a twentieth of a percent. The numerical value is approximately one-half of that found in Jaumotte et al. (2008), but considerably higher than in Galbraith and Kum (2005). As always, it is difficult to compare parameter estimates with those found in other studies, given that the countries included, time periods and control variables are different.

Using the biased fixed-effects OLS estimator severely underestimates the effect of industrial employment share on income inequality, as shown by the results in column (1). The effect is almost twice as large when using the onestep system GMM in lieu of the fixed-effects estimator, and fifty percent higher when using the twostep estimator.

The estimates of the autoregressive parameter ϕ, corresponding to the lagged logarithm of the Gini coefficient, range from 0.823 to 0.901, depending on which estimator is utilized. Additionally, Table 1 presents the p-values of the Arellano-Bond test of second-order serial correlation (Arellano and Bond 1991) for specification (2), as well as the Hansen J test of overidentifying restrictions (Sargan 1958; Hansen 1982) for specifications (2)-(4). The null hypothesis of the latter is that the instruments used in the model are valid, that is, uncorrelated with

	(1)	(2)	(3)	(4)
log *Palma ratio* (-1)	0.939^{***}	0.798^{***}	0.935^{***}	0.939^{***}
	(0.020)	(0.177)	(0.033)	(0.036)
log *Industrial employment share*	-0.024	-0.099^{***}	-0.041^{*}	-0.027
	(0.020)	(0.036)	(0.025)	(0.047)
Control variables included	Yes	Yes	Yes	Yes
Number of observations	596	569	596	596
Number of countries	27	27	27	27
Number of instruments		26	28	28
Method	FE OLS twostep	diff. GMM, onestep	sys. GMM, twostep	sys. GMM,
AB test of second order serial correlation		[0.18]		
Hansen J test		[0.48]	[0.34]	[0.34]

Table 5: Results from the regressions. The dependent variable is the Palma ratio. Robust standard errors in parentheses, where *, ** and *** denote statistical significance at the 10, 5, and 1% level, respectively. Values in squared brackets are p-values. All calculations were performed in *Stata*, using the xtabond2 package (Roodman 2009b).

the error term. It is not possible to reject the null hypothesis of instrument validity for specifications (2)-(4). The same conclusion regarding the null hypothesis of no second-order serial correlation holds for the Arellano-Bond test for specification (2).

4.2 Robustness checks

For robustness, Table 5 presents the results of the re-runned regressions with the Palma ratio (multiplied by 100) as the dependent variable. Considering first the onestep system GMM estimator, the industrial manufacturing share coefficient is now significant at the 10% level, and the estimate is -0.041. This is similar in magnitude to the onestep system GMM estimates when using the Gini coefficient as the dependent variable. The two-step system GMM estimator gives a lower estimate in absolute terms, -0.027, which is insignificant. This estimate is very close in magnitude to the likewise insignificant fixed-effects estimator. However, the twostep difference GMM estimator is now highly significant with a parameter estimate equal to -0.099. The instability of the parameter estimates of the difference GMM puts further doubt regarding its validity in highly persistent small N, small T panels, although discussions of this type are beyond the scope of this paper.

To summarize, when using the Palma ratio instead of the Gini coefficient, there is a weaker relationship between inequality and the industrial employment according to three out of four estimators, in terms of parameter significance. The most robust estimators in this setting with highly persistent data, the onestep and twostep system GMM, indicate lower parameter estimates in absolute value. The decline is from -0.044 to -0.041 with the onestep estimator and from -0.034 to -0.027 when using the twostep estimator.

5 Concluding remarks

Using a panel of 27 high-and middle income-countries from 1991 to 2014, the purpose of this paper has been to investigate the effect of deindustrialization on income inequality.

The results indicate a strong negative relationship between industrial employment and inequality. This means that the decline of the manufacturing sector is an important explanation behind the increased inequality noted in most advanced economies. Similarly, for newly industrialized countries, a growing manufacturing sector may contribute to ameliorating societal income disparity. However, the numerical effect is relatively minor. Holding other variables constant, a one-percent decrease in industrial employment increases inequality by less than a twentieth of a percent. This coefficient estimate is approximately half of that reported by Jaumotte et al. (2008), but higher than the one in Galbraith and Kum (2005).

When using the ratio of the top 10% to the bottom 40% income percentiles, the Palma ratio, as the dependent variable instead of the Gini coefficient, the results were slightly weaker. This indicates that it is, in relative terms, the middle of the income distribution that has borne the largest burden of increased inequality, and not the top and bottom earners. This gives support to the job polarization hypothesis among middle earners. However, because of the relatively small numerical effect, the notion that large amounts of displaced manufacturing workers have been forced to take low-paid fast food jobs is somewhat exaggerated. Notwithstanding numerical values, the increase in inequality due to the erosion of traditional working- and middle-class jobs in manufacturing should be of significant concern for policymakers.

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Appendix A: Data summary and data sources

Variable	*Description*	*Data source*
Gini coefficient	Measure of income inequality, $0 \leq \text{Gini} \leq 1$	SWIID (2016)
Palma ratio	Ratio of top decile incomes and bottom 40% incomes	OECD (2017)
Industrial employment share	Ratio of industrial employment and total employment	ILO (2014)
Government expenditure-to-GDP	Ratio of general government final consumption expenditure and GDP	World Bank (2017)
GNI per capita	Ratio of gross national income and population (2011 intl. dollars)	World Bank (2017)
Trade-to-GDP	Ratio of imports plus exports and GDP	World Bank (2017)

Table 6: Data summary with description and data sources.

Appendix B: Results tables including control variables

	(1)	(2)	(3)	(4)
log *Gini coefficient* (-1)	0.901^{***}	0.823^{***}	0.869^{***}	0.889^{***}
	(0.022)	(0.077)	(0.023)	(0.027)
log *Industrial employment share*	-0.028^{***}	-0.0032	-0.044^{***}	-0.034^{**}
	(0.0092)	(0.0089)	(0.012)	(0.013)
log *Gov. expenditure-to-GDP*	-0.0041	-0.00071	-0.029	-0.023
	(0.0091)	(0.0085)	(0.018)	(0.016)
log *Trade-to-GDP*	-0.0080	$-0.010^{\star}$	-0.013^{***}	-0.010^{**}
	(0.0058)	(0.0055)	(0.0043)	(0.0046)
log *GNI per capita*	$-0.015^{\star}$	-0.00043	-0.038^{***}	-0.034^{***}
	(0.0091)	(0.011)	(0.0076)	(0.0078)
Number of observations	596	569	596	596
Number of countries	27	27	27	27
Number of instruments		26	26	28
Method	FE OLS	diff. GMM, twostep	sys. GMM, onestep	sys. GMM, twostep
AB test of second order serial correlation		[0.18]		
Hansen J test		[0.36]	[0.43]	[0.43]

Table 7: Full results from the regressions. The dependent variable is the Gini coefficient. The main independent variable is the industrial employment share. Robust standard errors in parentheses, where *, ** and *** denote statistical significance at the 10, 5, and 1% level, respectively. Values in squared brackets are p-values. All calculations were performed in *Stata*, using the xtabond2 package (Roodman 2009b).

	(1)	(2)	(3)	(4)
log *Palma ratio* (-1)	0.939***	0.798***	0.935***	0.939***
	(0.020)	(0.177)	(0.033)	(0.036)
log *Industrial employment share*	−0.024***	−0.099	−0.041***	−0.027
	(0.020)	(0.036)	(0.025)	(0.047)
log *Gov. expenditure-to-GDP*	−0.016	−0.067	−0.025	−0.0035
	(0.029)	(0.065)	(0.018)	(0.025)
log *Trade-to-GDP*	0.0028	−0.0073	−0.014***	−0.014***
	(0.0092)	(0.020)	(0.0054)	(0.0052)
log *GNI per capita*	−0.016	−0.0043	−0.030	−0.027
	(0.014)	(0.031)	(0.022)	(0.035)
Number of observations	596	569	596	596
Number of countries	27	27	27	27
Number of instruments		26	26	28
Method	FE OLS	diff. GMM, twostep	sys. GMM, onestep	sys. GMM, twostep
AB test of second order serial correlation		[0.18]		
Hansen J test		[0.48]	[0.34]	[0.34]

Table 8: Full results from the regressions. The dependent variable is the Palma ratio. The main independent variable is the industrial employment share. Robust standard errors in parentheses, where *, ** and *** denote statistical significance at the 10, 5, and 1% level, respectively. Values in squared brackets are p-values. All calculations were performed in *Stata*, using the xtabond2 package (Roodman 2009b).