Adverse Trade Shocks and Inequality in American Manufacturing†

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Abstract

Both trade and inequality in the US and other major economies have increased markedly since 1980, as the working class in rich countries has experienced relatively slow income growth while the Chinese middle class has prospered. In this study, we test the impact of rising trade integration on inequality using disaggregated sectoral data for 359 US manufacturing sectors over the period 1972-2009. We test whether sectors with greater initial exposure to international trade experienced greater increases in inequality and more severe declines in unit labor costs when US relative prices were high and imports surged relative to exports. We also test whether sectors with more initial exposure to Chinese import competion experienced rising inequality once the flood of imports came from China. Surprisingly, we find no evidence that these adverse trade shocks had any differential impact on measured inequality or on labor's share of income in more exposed manufacturing sectors over this period. We also document facts inconsistent with the thesis that skill-biased technological change was the cause of the rise in inequality in the manufacturing sector since the 1980s.

JEL Classification: F10, F16, F41, N60, L60

Keywords: Inequality, Globalization, Skill-Biased Technological Change, American Manufacturing

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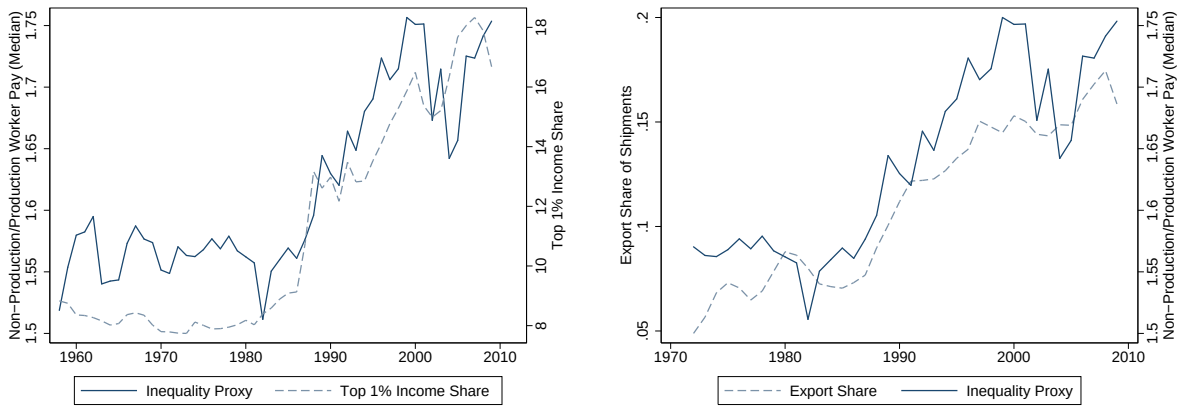
1 Introduction

The US has experienced a dramatic rise in inequality since 1980. Figure 1(a) shows that the share of income in the US going to the top 1% has increased from roughly 8% in 1980 to 18% by 2008. Meanwhile, labor's share of income in US manufacturing has fallen steadily while the US has experienced a dramatic increase in trade, particularly with developing countries such as China. Figure 1(b) displays a striking similarity between the export share of manufacturing shipments, and the ratio of non-production-worker pay to production worker pay, a commonly-used proxy for inequality in the manufacturing sector.[1] Milanovic *et al.* (2013) has shown that since 1988, working class incomes in rich countries have stagnated, while the middle classes in countries such as China and India have prospered.[2] At the same time, recent research, including Autor *et al.* (2013), Pierce and Schott (2014), and Campbell (2014b), indicates that the rise of China and relative price movements are responsible for the sudden collapse in manufacturing employment in the early 2000s, a decade in which Acemoglu *et al.* (2014) argue that the "sag" in *overall* U.S. employment was partly caused by the collateral damage from Chinese import competition. Thus it seems natural to ask whether rising trade integration, including with China, has contributed to the rise in inequality. This question is especially relevant as the sharp increase in overall inequality in the US and other countries since 1980 has become the subject of a major research agenda in economics and the object of a public debate over the causes, consequences, and potential solutions to rising inequality. Studying the manufacturing sector using disaggregated industry data is a natural choice since these sectors have widely varying degrees of exposure to international trade, but are otherwise broadly similar.

While there is a large literature on *globalization* and inequality, including Feenstra and Hanson (1999, 2003), Krugman (1993, 2008), Leamer (1993, 1994), Van Reenen (2011), Williamson (1997), Sachs *et al.* (1994), Jaumotte *et al.* (2013) among many others, this paper differentiates itself both in the specific question asked and in the data and methodology used to answer it. One difficulty with answering the question of what impact "globalization" has had on US inequality is that in the US case, sharp RER movements have led to several periods of import booms and export busts (see Figure 2). Since the end of Bretton Woods, there have been two periods of sharp dollar appreciation, and both periods were associated with increases in import penetration and

[1] For example, Feenstra and Hanson (2003) used the non-production worker share of the wage bill. The only difference is that we use pay per worker.

[2] See Figure 15 in the online appendix. This graph was recently highlighted by Paul Krugman on his blog.



(a) Inequality in Manufacturing vs. Overall

(b) Inequality in Manufacturing vs. Export Share

Figure 1: Trade and Inequality

Notes: Inequality here is proxied by the ratio of non-production to production worker wages. The export share of shipments is simply defined as exports divided by shipments, where shipment data come from the BEA's ASM and export data are from WITS, using the SIC classification. The income share of the 1% (for the economy as a whole) are from Piketty and Saez (2007).

stagnating exports as a share of shipments. Figure 2 plots the relationship between a measure of the real exchange rate, Weighted Average Relative Unit Labor Costs (called WARULC, developed in Campbell 2014a), and the evolution of the ratio between import penetration and export share for manufacturing.[3]

Given this reality, our strategy is to use disaggregated data on 359 manufacturing sectors over the period 1958 to 2009 and a difference-in-difference methodology, and ask whether manufacturing sectors which are more exposed to international trade experience differential increases in inequality and unit labor costs during periods when the US unit labor costs are high relative to trading partners.[4] In addition, we ask how much of the increase in inequality is concentrated in sectors and time periods with outsized growth in output per production worker and TFP.

We generally find little to no role for trade shocks in the rise in inequality or the decline in unit labor costs, and we also find at best mixed support for the thesis of skill-biased technological change. Note that our results do not necessarily imply that the collapse in US manufacturing employment in the early 2000s had no impact on overall inequality, as workers who lost their manufacturing jobs during this period dropped out of our sample and may have impacted overall inequality (even as they reduced

[3]Import penetration is defined as: IP = imports/(shipments+imports-exports).

[4]As there were precisely two episodes when US relative prices appreciated sharply relative to trading partners, this is effectively a "repeated difference-in-difference" research design, which we believe is preferable to a single difference-in-difference.

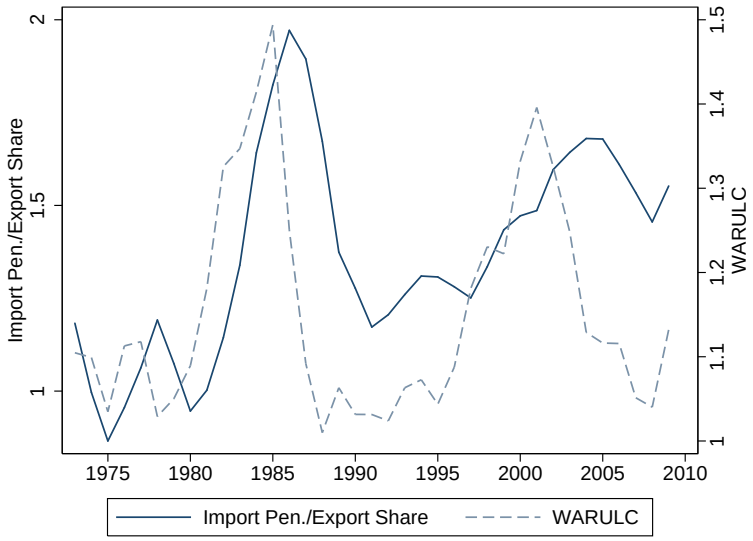


Figure 2: Adverse Trade Shocks: RER Movements

measured inequality in the manufacturing sector). However, the evidence does indicate that neither trade nor productivity growth were directly responsible for much of the measured increase in inequality in the manufacturing sector. This finding at minimum presents a challenge and puzzle for those who believe that globalization is the main or even a major factor behind the increase in inequality in the US overall since 1980, and suggests that other factors, such as those highlighted by Levy and Temin (2007) and Alvaredo, Atkinson, Piketty and Saez (2013), must also be at work.

The waves of rising relative import penetration displayed in Figure 2 should already raise doubts about the idea that adverse trade shocks, such as from the rise of China, are responsible for the dramatic rise in inequality in manufacturing or in the overall economy. This is because the largest movement in inequality in manufacturing happened starting in the mid-1980s and continued steadily through 2000 (starting earlier and continuing through 2008 in the case of the share of income going to the top 1%), while for much of this period, such as in the late 1980s, the export share of shipments was actually growing faster than import penetration. Thus, even in the aggregate, there appears to be scant correlation between periods of rising import penetration and increases in inequality. Even so, there is a relatively close correlation between the export share of trade and inequality in the US (Figure 1(b)).[5] There is a possibility that periods of fast growth in exports raised inequality in export sectors, which could intuitively

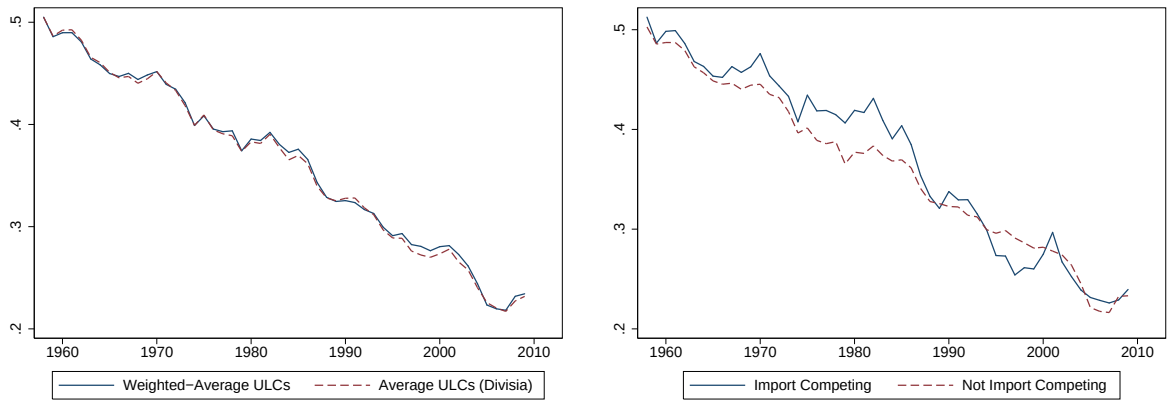
[5]Admittedly, the correlation here is imperfect, as the export share of shipments increased in the 1970s, and yet there was no trend in inequality in that decade. Also, although SIC data do not extend back to the 1960s, if we were to plot HS data instead from 1962, we would see that the export share of trade also increased in the 1960s, and yet with no increase in inequality.

happen if, as exports rose, managers in these sectors kept more of the gains. Thus, it is an open question whether the sectors that increased exports also experienced a rise in inequality compared to sectors which did not, just as it is important to ask whether sectors more exposed to imports experienced larger increases in inequality than those which are less exposed. Although this is admittedly not necessarily a definitive test of whether globalization has lead to a rise in inequality, if trade were the cause of the rise in inequality in pay in the manufacturing sector, you would expect the impact to be concentrated in the sectors which trade a lot rather than those sectors which trade little.

We also research the impact of trade shocks on Unit Labor Costs in manufacturing. In a seminal contribution, Ellsby *et al.* (2013) find a correlation between declines in the labor's share of income and trade, and argue that rising trade integration, particularly with China, was the cause of the decline in the labor's share of income in manufacturing over the past several decades. We repeat this exercise using 359 sectors instead of 45, and find that the correlation disappears. Indeed, even the aggregate data do not necessarily point to any link between unit labor costs and trade. Figure 2(a) shows that average unit labor costs in manufacturing (averaging over disaggregated sectors) have fallen steadily since 1960 at a relatively constant pace, even though both import and export growth has happened in waves depending on US relative prices. This conclusion holds up when creating a "Divisia" index (alternatively called a Tornquist index) of ULCs, or when computing a simple weighted-average of ULCs by sector (weighted by sector size), which indicates that the decline was not caused by outsized growth in sectors with low ULCs, but was rather a broad-based decline.[6] This conclusion also remains when we compare sectors which are relatively more import-competing to sectors that are relatively less import-competing. In this case we see that the early 1980s, when there was a flood of imports associated with the dollar's strength, was a time when ULCs for import-competing sectors seem to have overperformed, and the same trend is apparent during the 1995-2002 period.

Lastly, we also test how much of the rise in inequality can be explained by either rising capital-labor ratios or rising productivity, as might be implied by a theory of skill-biased technological change in which workers are replaced by machines. However, we find that rising labor productivity is actually associated with *declining* sectoral inequality, we find no relation between growing capital-labor ratios and inequality, and while we

[6]The "Divisia" index is only affected by changes within each sector, while the geometric weighted average will also be impacted by compositional shifts between sectors with different magnitudes of unit labor costs. Thus, these two indices plotted together show us that the decline in ULCs in manufacturing was not caused by compositional shifts, *i.e.*, by outsized declines in sectors with relatively higher ULCs.



(a) Divisia vs. WAULC

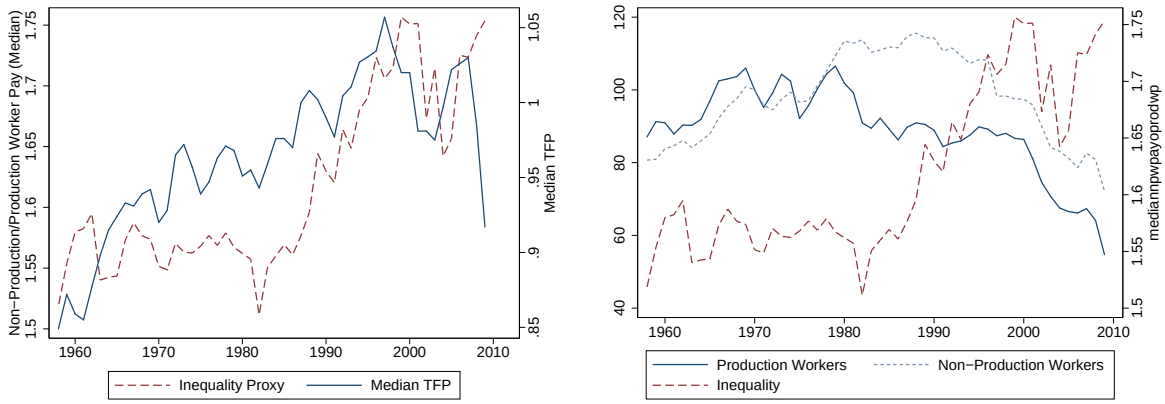
(b) ULCs by Import Share of Trade, 1975

Figure 3: Unit Labor Costs

Notes: In Panel (a), the "divisia" index of ULCs is an index of indices (also called a Tornquist index), whereas the Weighted-Average ULCs (WAULC) are a simple geometric weighted average (with sectoral value added as the weights). The divisia index is only impacted by changes within sectors while the WAULC index is also impacted by compositional changes in sectors. In Panel (b), the cutoff is sectors with import penetration of at least .1 in 1975, which is roughly the top 20% of sectors.

do find a correlation between total factor productivity and inequality, the impact is not enough to explain much of the increase in inequality. Once again, the aggregate data also do not seem to point clearly toward the thesis of skill-biased technological change. Median 5-factor TFP growth (provided by the NBER-CES data provide by Becker, Gray, and Morvakov) rose sharply in the 1960s (Figure 4a), and then continued to grow streadily through 1999 after which it declined (quite contrary to the popular believe that productivity growth boomed in the 2000s, causing the employment decline). Inequality in the median sector, by contrast, was declining gradually until the mid-1980s before increasing sharply. In addition, Figure 4(b) shows that other than the period 1980 to 1985, when there was not much change in inequality in manufacturing, the demand for non-production workers seemed to fluctuate closely with the demand for production workers. Note that while it is be possible to tell a more sophisticated SBTC story that does not necessarily depend on either productivity growth or increased relative hiring of non-production workers, the point here is that the basic fingerprints of a crude SBTC thesis which is popular in the theoretical literature (for example, see Acemoglu 2015, "How the Machines Replace Labor") are not readily apparent in manufacturing data.[7]

[7]See Card and DiNardo (2002) for a nice general discussion of other problems with the SBTC thesis.



(a) TFP Growth and Inequality

(b) Skilled vs. Unskilled Labor

Figure 4: Skill-Biased Technological Change?

Notes: Data from the BEA's Annual Survey of Manufacturing. The Employment indices in Panel (b) are indexed to 100 in 1979. Non-production workers were on average 28% of all manufacturing workers, with employment of 5.1 million in 1996.

2 Estimation

2.1 Data

We use manufacturing data from the Annual Survey of Manufactures (ASM) provided by the Bureau of Economic Analysis, trade data from the World Bank (WITS), and data on imported intermediate inputs from the BEA's Input-Output table for the year 1997. Sectoral tariff data come from Schott (2008) via Feenstra, Romalis, and Schott (2002), as does data on difference between schedule one and schedule two tariffs China would have faced had MFN status been revoked (the key control in Pierce and Schott, 2014). The classification of broad industrial sectors by markups is borrowed from Campa and Goldberg (2001). As an alternative measure of inequality, we also use data on the distribution of earnings from the BLS's Occupational Employment Statistics for the years 2002 to 2010.

The chief measure of the real exchange rate used in this paper is the Weighted-Average Relative Unit Labor Cost (WARULC) index, introduced by Campbell (2014b) to address index numbers problems which afflict the RULC indexes created by the IMF, and which also afflict other commonly used RER indices such as those created by the Federal Reserve.[8]

[8] According to Campbell (2014a), the four key problems with the IMF's index are that it (1) is computed as an index-of-indices, and thus does not reflect compositional changes in trade toward countries that have lower unit labor costs, (2) does not include China, (3) uses fixed trade weights,

2.2 Empirical Approach

We identify the impact of trade competition caused by (large) movements in relative prices using a panel difference-in-difference approach for 359 disaggregated manufacturing sectors with balanced data over the period 1973 to 2009, comparing how inequality evolved in relatively more open sectors when US relative unit labor costs were high compared to when US unit labor costs were in line with US trading partners. The estimating equation is:

$$ln(I_{ht}/I_{h,t-1}) = \alpha_t + \beta_0 R.Openness_{h,t-1} + \beta_1 ln(RER_{t-1})) * R.Openness_{h,t-1} + \tag{2.1}$$

$$\beta_2 ln(D_{h,t}/D_{h,t-1}) + \beta_3 ln(TFP_{h,t}/TFP_{h,t-1}) + \sum_{i=4}^{n} \beta_i C_{i,t} + \alpha_h + \nu_t + \epsilon_{ht},$$

$$\forall h = 1, ..., 359, \ t = 1973, ..., 2009,$$

where I_{ht} is a measure of inequality (or unit labor costs) of industry h at time t, $R.Openness_{h,t-1}$ is relative openness in sector h at time t-1 (replaced with export share or import penetration in some regressions), RER is a measure of the real exchange rate, such as WARULC, $D_{h,t}$ is real sectoral demand, $TFP_{h,t}$ is a measure of TFP (we use 4 and 5-factor measures of productivity in addition to value-added and shipments divided by production worker or total employment), and the Cs are various other controls. Our baseline regression also includes sectoral fixed effects α_h, year fixed effects ν_t, and two-way clustered errors, by both industry and year, and all regressions are weighted by initial period value-added. The results do not appear to be sensitive to the choice of weights, as qualitatively similar results can be attained when weighting by average value-added, employment, or shipments. Additionally, one gets very similar results by simply using openness rather than relative openness, and when we separate import penetration from the share of exports in production.[9]

which have become outdated, and (4) uses country-specific deflators, which can become biased over time without the benefit of multiple benchmarks (this is the same problem that afflicted previous versions of the Penn World Tables). WARULC addresses all four of these problems explicitly, and so it is the key measure of the RER used in this paper. However, the results are robust to using other measures of the RER or to just using actual changes in trade flows as will be discussed.

[9]These robustness checks, and others, are contained in the Additional Appendix. For instance, the results would not change significantly using a geometric rather than an arithmetic average of export share and import penetration as a measure of openness. Additionally, the results are robust to omitting defense, and computer-related sectors, given that the periods of dollar appreciation are associated with large increases in defense-spending and also since the official productivity data for the computer sector has been called into question by Houseman *et al.* (2010). We also omit the publishing sector as this is marginally a manufacturing sector and was dropped from manufacturing in the NAICs classification, but our results are robust to including publishing. Changes in import penetration and export share are

Our core estimation strategy is displayed graphically in Figures 5 and 6. In Figure 5(a), we plot the evolution of inequality in more open sectors vs. less open sectors over time with two standard deviation error bounds, and show that, if anything, inequality worsened in more open sectors in the 2000s, although the difference was not statistically significant, and that there appears to have been no difference in the 1980s. In Figure 5(b), we divide the sample between sectors with at least 5% of consumption coming from China in 1995 and those with less than 3%. We find, surprisingly, that those sectors with relatively higher initial exposure to Chinese imports actually saw a decline in inequality in the 2000s, although the difference with the non-Chinese competing sectors was actually not significant.

We also want to be sure that our results are not an artifact of the particular measure of inequality we use in this dataset, the ratio of non-production worker to production worker wages from the ASM. Thus, in Figure 6, we plot the evolution of inequality using the ratio of workers wages at the 75th percentile of the distribution to wages at the 10th percentile from the BLS's Occupational Employment Statistics using NAICs data for the years 2002 to 2010.[10] The story here is a bit different, as China-competing sectors did exbihit increasing inequality relative to other sectors in this period, but the difference is not significant.

Note that while research (*e.g.*, Campbell 2014b, and see Klein *et al.* 2002 for an overview of literature to that point) has generally found that the episodes of dollar appreciation were the cause of the ensuing trade deficits, the actual cause of these adverse trade shocks (whether it is relative prices or another factor) is not a necessary condition for the validity of the identification strategy used in this paper. The research design is simply to compare the evolution of inequality in more open sectors compared to less open sectors in periods when import penetration grew quickly relative to export shares versus other periods. The critical assumption is that there was no other third factor that we have neglected to control for which may have caused (or prevented) a large movement in inequality in more tradable sectors and which also caused a large percentage increase in imports.

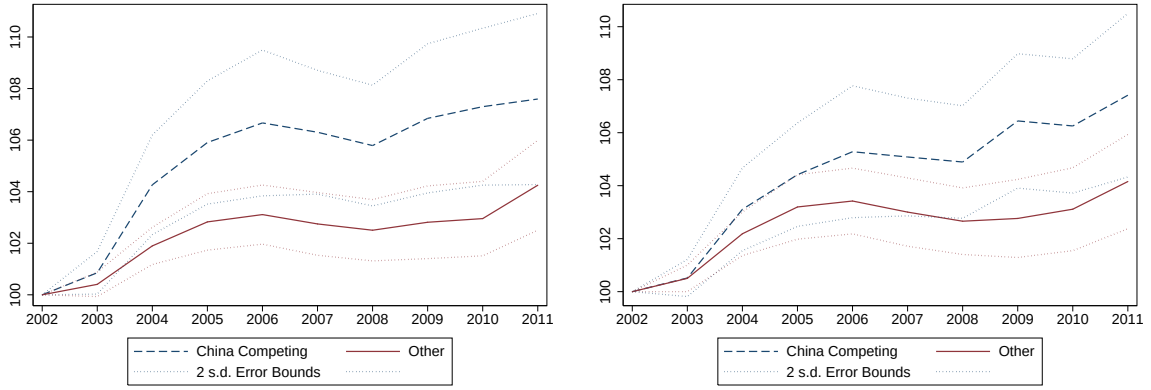
also highly correlated with changes in employment—a necessary condition for lagged relative openness interaction with the real exchange rate to predict innovations in employment.

[10]Unfortunately, this data is top-coded at a fairly low value making it unsuitable for gauging trends in inequality at the 90th percentile or higher as would clearly be preferable, as the largest changes in inequality in the US come much further up the distribution.

(a) By Degrees of Overall Openness

(b) By Exposure to Chinese Competition

Figure 5: Evolution of Inequality, Disaggregated (SIC)



(a) Based on Initial Exposure to China

(b) Based on Actual Increase in Chinese Imports

Figure 6: Changes in Inequality, China-Competing Sectors vs. Others (NAICs)

Notes: Inequality in Figure 5 here is proxied by the ratio of non-production to production worker wages (per worker), whereas in Figure 6, inequality is proxied by the ratio of wages of workers at the 75th percentile to workers at the 10th percentile of earnings by 4-digit NAICs sectors from the BLS's Occupational Employment Stastistics. Open sectors in 5(a) are defined by those with a share of openess of at least .15 (openness = average of import penetration the export share of shipments), and non-open sectors are defined as those with openess of less than .1. In 5(b), China-competing sectors are defined as those with at least 5% of domestic consumption originating in China in 1995, and other sectors are those with less than 3%. In 6(a) a cutoff of 5% of domestic consumption originating in China in 2002 was used, and in 6(b), the "China Competing" sectors are those in the top quarter of the distribution of increases in Chinese import penetration from 2002 to 2010.

2.3 Empirical Results

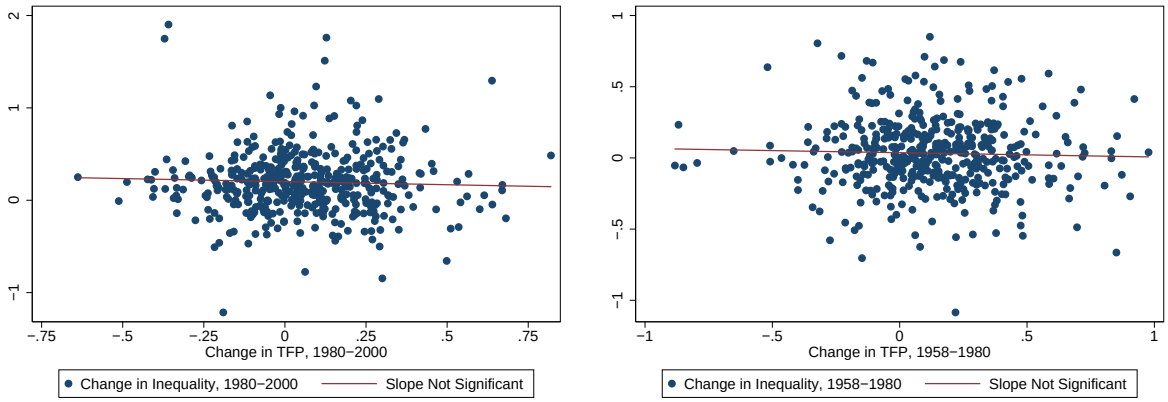
Estimating equation 2.1 in Table 1, column (1), we show that there appears to be no relation between appreciation in WARULCs and movements in the ratio between non-production worker wages and production worker wages in relatively more open sectors. This is a suprising result given the correlation in Figure (1), and given that Campbell (2014b) found that employment, investment, and output in relatively more open manufacturing sectors are all quite sensitive to movements in relative prices. We also find that lagged Chinese import penetration does not predict increases in inequality – in fact the point estimate is negative, although insignificant. Lastly, we find that labor productivity growth (value-added per production worker) is strongly associated with *declining* inequality. We also control for various other factors which may affect output or employment, and thus inequality. These include demand growth by sector (which is not consistently significant), the share of imported intermediate inputs, lagged capital-labor ratios, lagged capital-labor ratios interacted with the real interest rate, and the costs of inputs, and the costs of these inputs interacted with the share of these inputs at the sectoral level. None of these controls other than productivity are consistently significant (thus, in the robustness table which follows, we redo the results with these insignificant regressors removed).

However, in column (2) when we use a multi-factor measure of productivity growth instead of value-added per production worker, we do see a positive correlation significant at 95% confidence. These results are robust to using a quantile regression, as in column (3). In column (4), we separate openness into import penetration (defined as imports divided by domestic consumption, where domestic consumption is shipments plus imports minus exports) and the export share of shipments. Additionally, we interact import penetration with an import Weighted Relative Unit Labor Cost index and the export share of shipments with an export-WARULC index. Again, we see no tendency of sectors which are more exposed to trade to have any trends in sectoral inequality when domestic unit labor costs are high relative to trading partners. In column (5), we use the actual changes in the export share of shipment and in import penetration, and in this case we find that changes in import penetration actually predict *declines* in inequality (albeit imprecisely), which runs counter to the thesis that import competition from developing countries caused the increase in inequality in the manufacturing sector.[11] In column (6), the dependent variable is sectoral unit labor costs. We find that RER appreciations (for

[11] Also note that export share and import penetration are highly correlated, especially in later years, and that separating these into separate regressions would render the coefficient on import penetration statistically insignificant.

the manufacturing sector as a whole) are not significantly associated with movements in ULCs (also commonly referred to as labor's share of value added). This would seemingly suggest that periods of adverse trade shocks are not the cause of the decline in ULCs.

In Table 2, we provide a number of robustness tests, by varying the inclusion of year and industry FEs, and other controls. In this table, each cell represents a separate regression, for 36 regressions total. What we find is that no variable is a consistent predictor of inequality or of ULCs across specifications with the possible exception of 5-factor TFP growth, which is significant in four out of six specifications. It should be noted that in both of these specifications, when a quantile regression is used instead statistical significance is achieved, indicating that the insignificance is likely due to statistical outliers. Even so, we do not believe that multi-factor TFP-growth was a major cause of the rise in inequality, as even the statistically signficant regression results imply that TFP growth was only responsible for 1-17% of the rise in inequality from 1980 to 1997.[12] Another check is to look at the overall change in inequality from 1980 to 2000 vs. the changes in TFP in Figure 7(a), in order to abstract from cylical concerns in favor of the big picture. However, even here there is also no correlation.[13]



(a) 1980-2000

(b) 1958-1980

Figure 7: TFP Growth vs. Changes in Inequality

Notes: Inequality here is proxied by the ratio of non-production to production worker wages in the manufacturing sector, from the ASM. Values above zero on the y-axis thus indicate an increase in inequality. Trade data come from WITS.

[12]This estimate uses the OLS estimate minus two standard deviations for the lower bound, and the quantile estimate plus two standard deviations for the upper bound.

[13]Nor was there a correlation in the period before 1980, and while we do not show the results, there also hasn't been a significant correlation since. Why, then, do we find a correlation in the regression results? We believe it may have to do with the cyclicality of the data.

Table 1: Relative Prices, Trade, Openness and Inequality

	(1)	(2)	(3)	(4)	(5)	(6)
	$ln\,\Delta$ Ineq.	$ln\,\Delta$ Ineq.	$ln\,\Delta$ Ineq.	$ln\,\Delta$ Ineq.	$ln\,\Delta$ Ineq.	$ln\Delta ULC$
L.Relative Openness	-0.00152	-0.00254	-0.000856		0.0000337	0.00335
	(0.00209)	(0.00228)	(0.00360)		(0.00102)	(0.00227)
$ln\,\Delta$ VA-per-Prod. Worker	-0.0961***			-0.0964***	-0.0981***	-0.755***
	(0.0124)			(0.0124)	(0.0135)	(0.0353)
$ln\,\Delta$ Demand	0.0225	-0.0349	-0.0329***	0.0229	0.0318*	0.0279
	(0.0194)	(0.0228)	(0.0120)	(0.0192)	(0.0181)	(0.0181)
Post-PNTR x NTR Gap_i	0.00149	-0.000359	-0.00312	0.00210	0.000467	-0.0187
	(0.0189)	(0.0182)	(0.0126)	(0.0195)	(0.0192)	(0.0219)
Imported Inputs*L.ln(WARULC)	-0.0703	-0.0685	0.0477	-0.0786	-0.0500	0.349***
	(0.0497)	(0.0638)	(0.109)	(0.0499)	(0.0371)	(0.0886)
L.(K/L)	0.00874	0.00796	0.0316**	0.00941	0.00782	-0.0410
	(0.0125)	(0.0108)	(0.0132)	(0.0128)	(0.0136)	(0.0303)
L.(K/L)*Real Interest Rate	0.239	-0.253	0.325	0.249	0.216	2.044
	(0.523)	(0.505)	(0.769)	(0.523)	(0.534)	(1.447)
L.Rel.Openness*RIR	-0.00439	-0.00567	-0.0104	-0.00383	-0.000646	-0.000536
	(0.00576)	(0.00622)	(0.00713)	(0.00615)	(0.00476)	(0.00455)
L.$ln\,\Delta$ Price of Materials	0.0156	0.0488	0.0692	0.0164	0.0157	-0.279***
	(0.0477)	(0.0465)	(0.0825)	(0.0477)	(0.0483)	(0.0701)
L.$ln\,\Delta$ Price of Investment	-0.0691	-0.0475	-0.0951	-0.0708	-0.0550	-0.217**
	(0.0613)	(0.0573)	(0.0634)	(0.0619)	(0.0588)	(0.107)
L.$ln\,\Delta$ Price of Energy	-0.00113	0.00372	-0.0310***	-0.000188	-0.00186	0.0121
	(0.0227)	(0.0237)	(0.0112)	(0.0231)	(0.0233)	(0.0232)
L.ln(WARULC)*Rel.Openness	0.0118	0.0174	0.0122			-0.00948
	(0.0107)	(0.0112)	(0.0138)			(0.0109)
L1.Chinese Import Penetration	-0.00485					
	(0.0110)					
$ln\Delta$ TFP		0.0662**	0.0945***			
		(0.0279)	(0.0283)			
L.Rel. Import Penetration				-0.00107		
				(0.00229)		
L.ln(iWARULC)*R.Import Pen.				0.00869		
				(0.00954)		
L.Rel. Export Share				-0.000645		
				(0.00223)		
L.ln(eWARULC)*R.Export Sh.				0.00197		
				(0.0120)		
Δ Export Share					0.0723	
					(0.0477)	
Δ Import Penetration					-0.0695*	
					(0.0416)	
Observations	12710	12710		12710	12710	12715

Two-way clustered standard errors in parentheses. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions weighted by initial sectoral value-added, and include 4-digit SIC industry and year fixed effects over the period 1973-2009. The dependent variables in the first 5 columns are the ratio of non-production worker pay to production worker pay, and in column (6) is unit labor costs. The variables of interest are in bold type. Column (3) is a quantile regression; the others are OLS.

Table 2: Robustness Exercises: Impact of Trade on Inequality and ULCs

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var: Log Change in Inequality						
L.ln(WARULC)*Rel.Openness	0.018	0.018	-0.0070	0.012	-0.014	0.019
	(0.011)	(0.011)	(0.015)	(0.011)	(0.016)	(0.014)
$ln\,\Delta$ TFP (5-factor)	0.070**	0.070**	0.044	0.062**	0.033	0.070**
	(0.028)	(0.028)	(0.033)	(0.030)	(0.028)	(0.032)
L.ln(iWARULC)*R.Import Pen.	0.012	0.012	0.0025	0.0083	-0.0099	0.012
	(0.0096)	(0.0096)	(0.013)	(0.0098)	(0.014)	(0.012)
L.ln(eWARULC)*R.Export Sh.	0.0057	0.0057	-0.0098	0.0043	-0.0042	0.0069
	(0.011)	(0.011)	(0.016)	(0.013)	(0.013)	(0.015)
Δ Export Share	0.041	0.041	0.054	0.034	0.072	0.036
	(0.048)	(0.048)	(0.055)	(0.050)	(0.050)	(0.053)
Δ Import Penetration	-0.0076	-0.0076	-0.039	-0.0033	-0.051	-0.0047
	(0.050)	(0.050)	(0.064)	(0.054)	(0.060)	(0.058)
Dep. Var: Log Change in Unit Labor Costs						
L.ln(WARULC)*Rel.Openness	-0.021	-0.021	-0.017	-0.0082	-0.022	-0.017
	(0.018)	(0.018)	(0.024)	(0.018)	(0.020)	(0.020)
L.ln(iWARULC)*R.Import Pen.	-0.013	-0.013	-0.0044	-0.013	-0.016	-0.016
	(0.019)	(0.019)	(0.021)	(0.017)	(0.019)	(0.020)
L.ln(eWARULC)*R.Export Sh.	-0.000078	-0.000078	-0.00053	0.0083	-0.0010	0.0057
	(0.018)	(0.018)	(0.020)	(0.021)	(0.019)	(0.019)
Δ Export Share	0.19**	0.19**	0.13	0.17*	0.17*	0.16
	(0.091)	(0.091)	(0.10)	(0.090)	(0.099)	(0.099)
Δ Import Penetration	-0.18	-0.18	-0.20	-0.20	-0.17	-0.21
	(0.12)	(0.12)	(0.14)	(0.12)	(0.14)	(0.13)
Year FE	No	Yes	No	Yes	No	Yes
Industry FE	No	No	Yes	Yes	No	Yes
Full Controls	Yes	Yes	Yes	No	No	Yes

Two-way Clustered standard errors in parenthesis, clustered by year and 4-digit SIC sectors. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. There are six sets of six regressions, for 36 regressions total. The first three rows of six regressions use the log change in the ratio of non-production to production worker wages as a proxy for inequality. Rows 4-6 use sectoral unit labor costs as the dependent variable. Each column contains different combinations of controls and fixed effects as indicated. For example, all of the regressions in column one include a full set of controls, but no year or sectoral fixed effects, while column (6) includes year and sectoral fixed effects and a full set of controls. All regressions are weighted by initial period value-added.

3 Conclusion and Interpretation

While we do not find any significant impact of trade shocks, such as from the rise of China, on inequality within manufacturing, we stress that it does not necessarily follow that the collapse in manufacturing employment, which many authors have traced to trade shocks, did not have an impact on overall inequality in the 2000s. Some authors (Campbell, 2014b) place the total collateral damage to the manufacturing sector from trade as high as three million jobs, which also would have devastated local labor markets (Autor *et al.* 2013) and affected other sectors via import-output linkages (Acemoglu *et al.* 2014), leaving a total death toll much higher than three million. The reason is that workers which lose their jobs drop out of the ASM, and thus if low-wage workers are disproportionately fired, and these workers were to either accept lower paying jobs or not find any jobs afterward, then the loss of jobs could affect overall inequality even while not impacting measured inequality within the manufacturing sector. The tangible implication of our results is that it is likely that factors outside of manufacturing led to the dramatic increase in inequality in manufacturing from the early 1980s to 2000, which also exclude skill-biased technological change. What factors might these be? We would suggest the institutional factors highlighted by Levy and Temin (2007) and Alvaredo *et al.* (2013), which include the sharp decline in top marginal tax rates in Anglo countries in the 1980s and other related institutional changes, and to a lesser extent the declining importance of the minimum wage and perhaps the long-term declining role of unions. These explanations have the potential to explain why the US and UK experienced sharp increases in inequality starting in 1980 while other technologically advanced countries which have also experienced rising trade integration, including Japan, Germany, and France, have not.

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4 Online Appendix

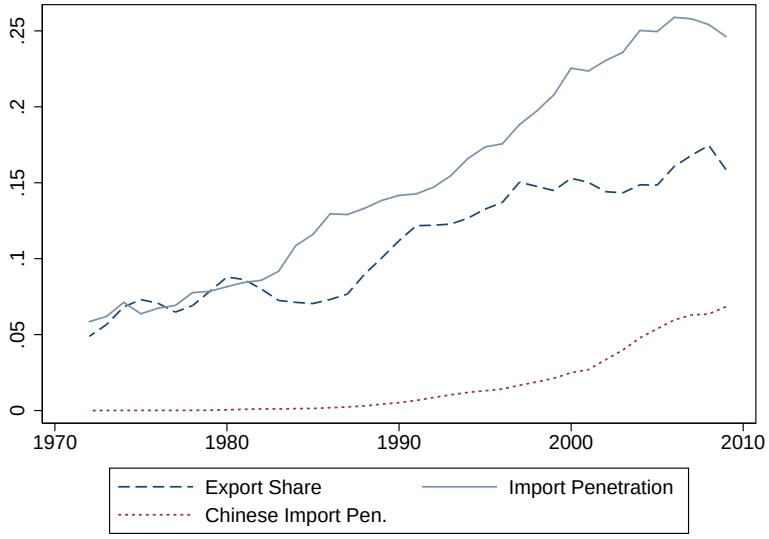


Figure 8: Export Share, Inequality, and Chinese Import Penetration

Table 3: Robustness Exercises: Non-Production Worker and Production Worker Wages

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var: Log Δ in Non-Prod. Worker Wages						
L.ln(WARULC)*Rel.Openness	-0.0035	-0.0035	-0.011	0.00051	-0.027	-0.0052
	(0.0076)	(0.0076)	(0.012)	(0.0085)	(0.017)	(0.010)
L.ln(iWARULC)*R.Import Pen.	-0.0018	-0.0018	-0.011	-0.00040	-0.039**	-0.0034
	(0.0089)	(0.0089)	(0.010)	(0.0070)	(0.016)	(0.0095)
L.ln(eWARULC)*R.Export Sh.	-0.0029	-0.0029	-0.0039	0.0020	0.0032	-0.0021
	(0.011)	(0.011)	(0.014)	(0.010)	(0.015)	(0.011)
Δ Export Share	0.042	0.042	0.072	0.039	0.050	0.044
	(0.043)	(0.043)	(0.054)	(0.036)	(0.046)	(0.041)
Δ Import Penetration	-0.047	-0.047	-0.044	-0.039	-0.073	-0.044
	(0.052)	(0.052)	(0.055)	(0.043)	(0.053)	(0.051)
Dep. Var: Log Change Prod. Worker Wages						
L.ln(WARULC)*Rel.Openness	-0.022***	-0.022***	-0.0037	-0.011	-0.013	-0.024***
	(0.0079)	(0.0079)	(0.010)	(0.0067)	(0.016)	(0.0083)
L.ln(iWARULC)*R.Import Pen.	-0.014**	-0.014**	-0.014	-0.0087	-0.030*	-0.015*
	(0.0065)	(0.0065)	(0.0099)	(0.0075)	(0.018)	(0.0080)
L.ln(eWARULC)*R.Export Sh.	-0.0085	-0.0085	0.0059	-0.0023	0.0074	-0.0090
	(0.0088)	(0.0088)	(0.012)	(0.0094)	(0.015)	(0.0100)
Δ Export Share	0.00085	0.00085	0.018	0.0051	-0.022	0.0087
	(0.035)	(0.035)	(0.035)	(0.037)	(0.045)	(0.035)
Δ Import Penetration	-0.039	-0.039	-0.0041	-0.036	-0.021	-0.039
	(0.046)	(0.046)	(0.059)	(0.052)	(0.055)	(0.051)
Year FE	No	Yes	No	Yes	No	Yes
Industry FE	No	No	Yes	Yes	No	Yes
Full Controls	Yes	Yes	Yes	No	No	Yes

Two-way Clustered standard errors in parenthesis, clustered by year and 4-digit SIC sectors. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. There are six sets of six regressions, for 36 regressions total. The first three rows of six regressions use the log change in the ratio of non-production to production worker wages as a proxy for inequality. Rows 4-6 use sectoral unit labor costs as the dependent variable. Each column contains different combinations of controls and fixed effects as indicated. For example, all of the regressions in column one include a full set of controls, but no year or sectoral fixed effects, while column (6) includes year and sectoral fixed effects and a full set of controls. All regressions are weighted by initial period value-added.

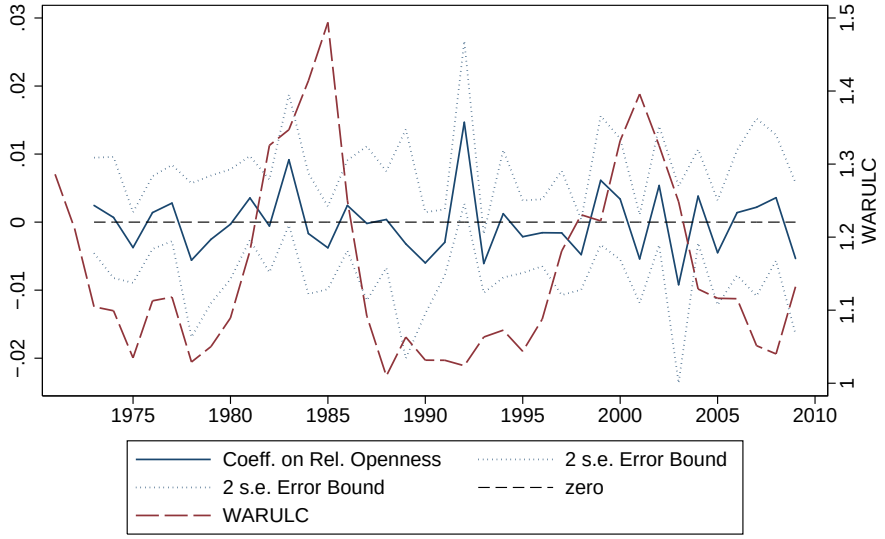
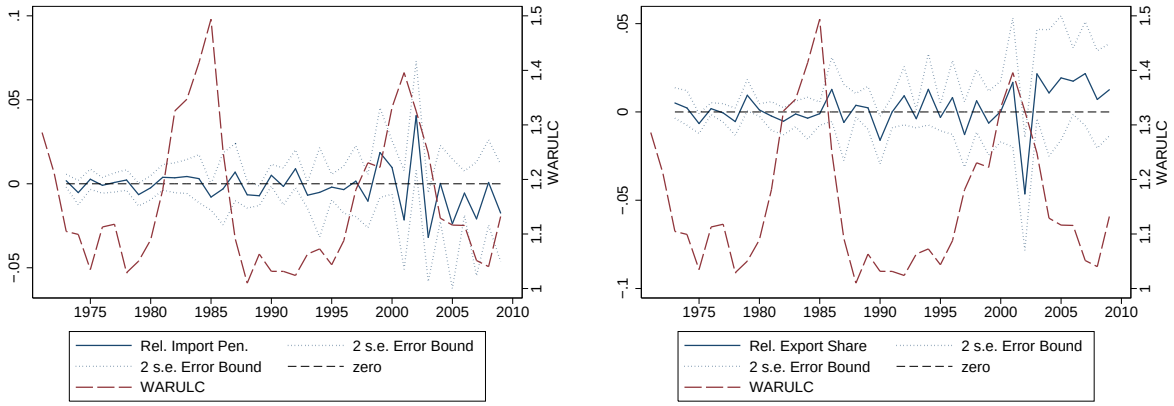


Figure 9: Impact of Relative Openness on Inequality by Year

Notes: These are the results from yearly regressions of relative openess on inequality by sector with controls for demand and TFP growth, with two standard deviation error bounds plotted in dotted dark blue, compared to the WARULC index in maroon.

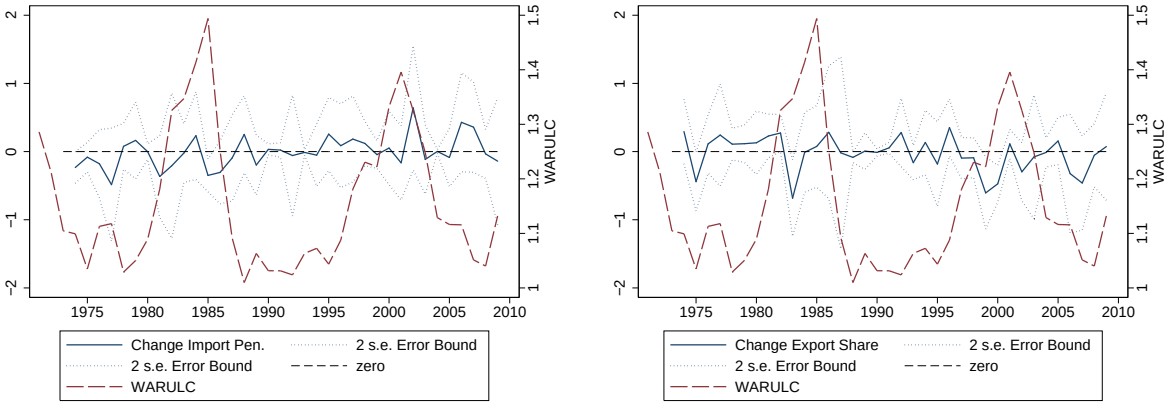


(a) Import Penetration

(b) Export Share

Figure 10: Trade Exposure and Changes in Inequality, 1973-2009

Notes: These are the results from yearly regressions of import penetration and export share on inequality by sector with controls for demand and TFP growth, with two standard deviation error bounds plotted in dotted dark blue, compared to the WARULC index in maroon.

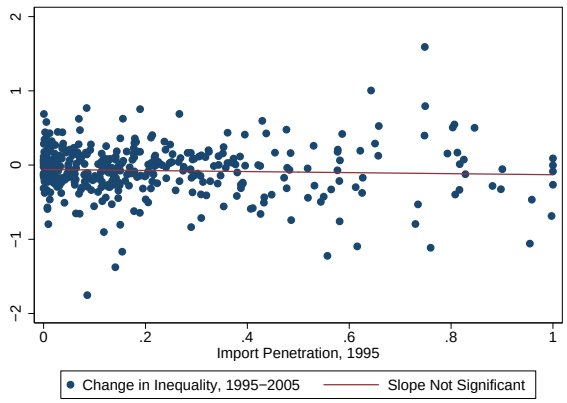


(a) Import Penetration

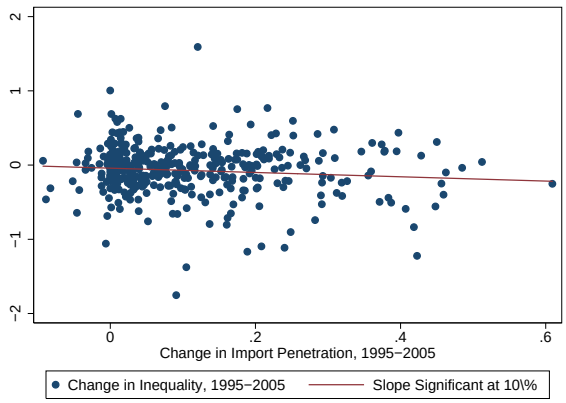
(b) Export Share

Figure 11: Change in Trade Exposure vs. Evolution in Inequality, 1973-2009

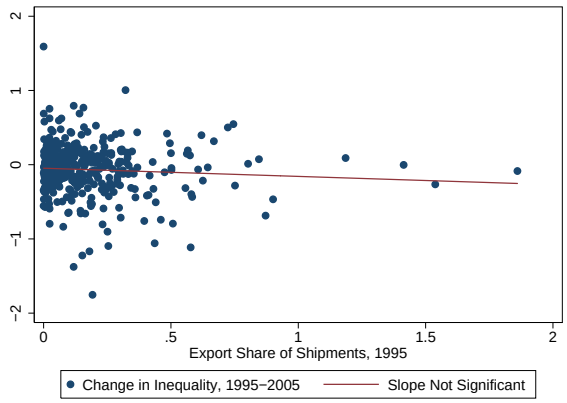
Notes: These are the results from yearly regressions of the change in import penetration and the change in export share on inequality by sector with controls for demand and TFP growth, with two standard deviation error bounds plotted in dotted dark blue, compared to the WARULC index in maroon.



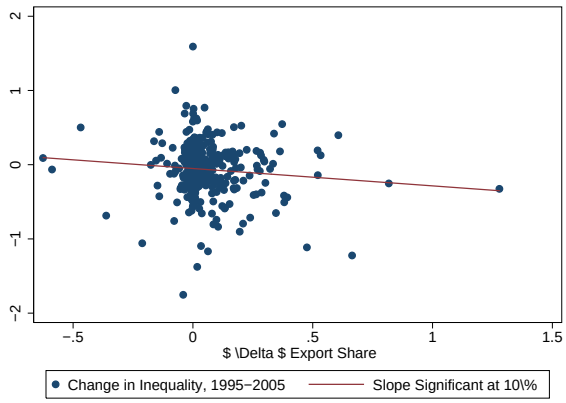
(a) Δ Inequality vs. Initial Import Penetration



(b) Δ Inequality vs. Δ Import Exposure



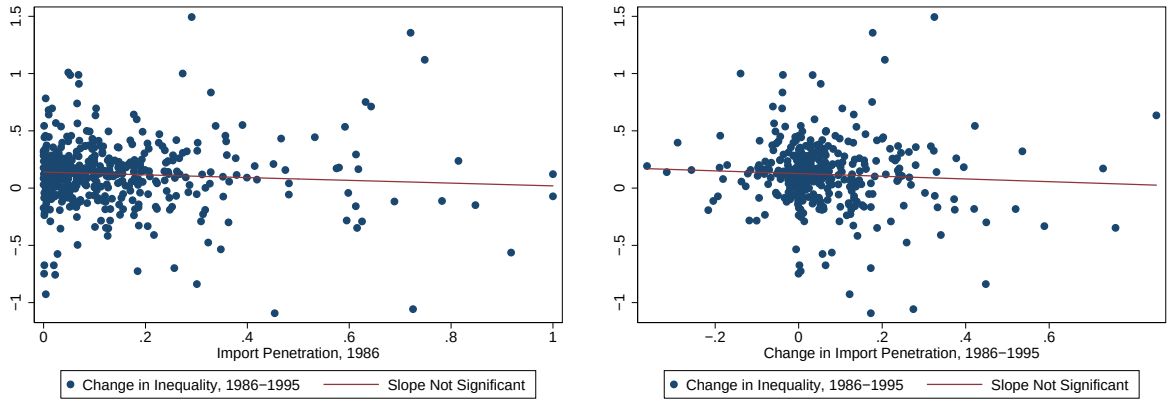
(c) Δ Inequality vs. Initial Export Share



(d) Δ Inequality vs. Δ Export Share

Figure 12: Trade Exposure and Inequality, 1995-2005

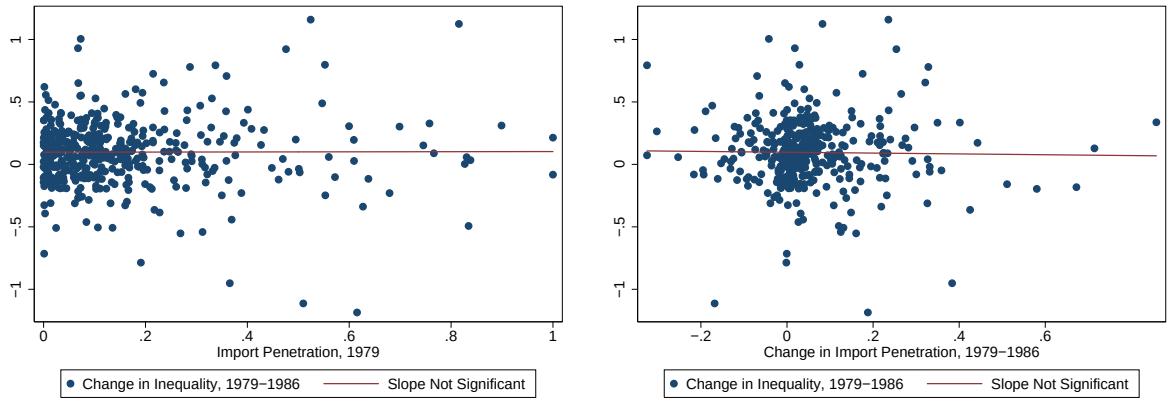
Notes: Each dot is a 4-digit SIC manufacturing sector. Inequality here is proxied by the ratio of non-production to production worker wages in the manufacturing sector, from the ASM. Values above zero on the y-axis thus indicate an increase in inequality. Trade data are from WITS.



(a) Δ Inequality vs. Initial Import Penetration (b) Δ Import Exposure vs. Δ Inequality

Figure 13: Trade Exposure and Inequality, 1986-1995

Notes: Inequality here is proxied by the ratio of non-production to production worker wages in the manufacturing sector, from the ASM. Values above zero on the y-axis thus indicate an increase in inequality. Trade data come from WITS.



(a) Δ Inequality vs. Initial Import Penetration (b) Δ Import Exposure vs. Δ Inequality

Figure 14: Trade Exposure and Inequality, 1979-1986

Notes: Inequality here is proxied by the ratio of non-production to production worker wages in the manufacturing sector, from the ASM. Values above zero on the y-axis thus indicate an increase in inequality. Trade data come from WITS.

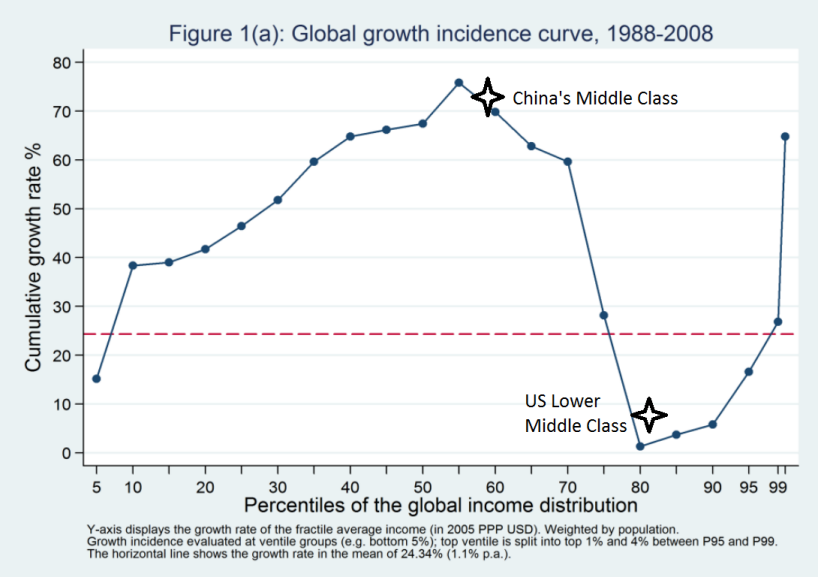


Figure 15: Changes in Global Income Distribution

Notes: This chart is taken from Lakner and Milanovic 2013, with the stars for China's middle class and the US lower middle class added in.