The Rise in Inequality: Technology and Trade, or History and Taxes?†

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Abstract

Both trade and inequality in the US, Europe, 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. Personal computing was also effectively born at this time, which coincided with large cuts in top marginal tax rates. In this study, we test between these theories – trade, taxes, or technology – using two different methodologies. First, we study 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, or faster TFP growth, 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. Secondly, using aggregate data for 18 countries internationally, we test whether trade shocks and marginal tax rates are generally correlated with rising inequality. We find little role for trade or technology, but we do find that the level of top marginal tax rates appears to impact *changes* in the top 1% share of income, implying that top income shares are a function of history.

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, which roughly coincides with the advent of personal computing and the Reagan tax cuts. 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. Ellsby *et al.* (2013) 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.

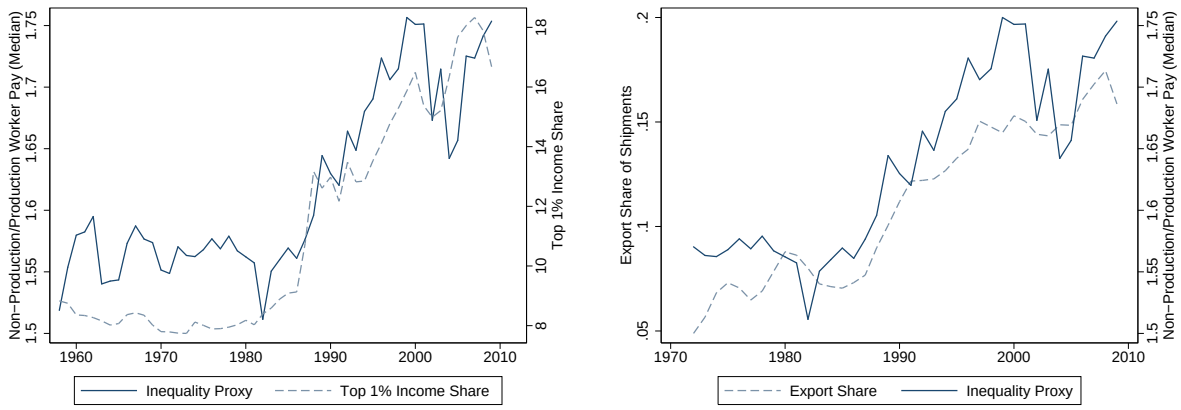
Thus it seems natural to ask whether rising trade integration, including with China, has contributed to the rise in inequality, even when controlling for other factors, such as top marginal tax rates (Alvaredo *et al.* 2013 and Piketty *et al.* 2014), which appear to have explanatory power. This question 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.

There is, of course, already a large literature on the cause of the rise in inequality. The early debate from the 1980s and 1990s centered around whether the cause was trade or skill-biased technological change.[3] A comprehensive survery of the trade and inequality literature by Cline (1997) concluded that trade was responsible for a sizeable 20% of the rise in wage inequality in the 1980s, while, for a long time, many economists

[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 7. This graph was recently highlighted by Paul Krugman on his blog.

[3] Early papers analyzing the role of trade in inequality include Feenstra and Hanson (1999, 2003), Krugman (1993, 2008), Leamer (1993, 1994), Williamson (1997), and Sachs *et al.* (1994). The classic SBTC literature includes, *e.g.* Berman *et al.* (1998), Kiley (1999), and tk.



(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" is for manufacturing shipments, 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).

took it for granted that SBTC was responsible for much of the rise in inequality. For example, for Acemoglu (1998, 2015), the complicity of SBTC in the rise of inequality was self-evident, and the key task was to explain theoretically "Why do new technologies complement skills?" (1998) and to explain "How Machines Replace Labor" (2015).[4] Yet, other research, including Card *et al.* (2002), has cast doubt on the role of skill-biased technological change.[5] The recent literature (Temin and Levy [2007], Alvaredo *et al.* [2013], and Piketty *et al.* [2014]) on labor market institutions and inequality includes further caution: top marginal tax rates were cut sharply in the US and several other Anglo countries in the 1980s, and these countries were precisely the ones which exhibited the largest increases in inequality, while other technologically advanced countries, including Japan, France, and Germany, did not.

While there is already a large literature on *globalization* and inequality (recent contributions include Kaplan and Rauh [2007], Lawrence [2008], and Haskel *et al.* [2012]), this paper differentiates itself from existing research 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

[4]Empirically, there are recent papers which still find support for SBTC, including Van Reenen (2011), and Jaumotte *et al.* (2013).

[5]For others, including Moore and Ranjan (2005), for whom the question was still "Globalization vs. SBTC", found a role for both trade and technology.

(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 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.[6]

Given this reality, our first of two strategies employed in this paper 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.[7] 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.

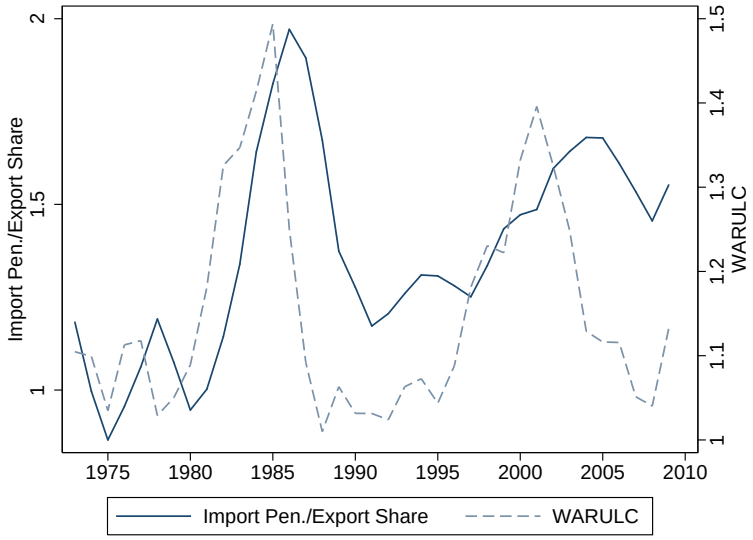


Figure 2: Adverse Trade Shocks: RER Movements

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.[8] 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

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

[7]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.

[8]Thus, our findings do not appear to be consistent with the findings of Ellsby . et al.

out of our sample and may have impacted overall inequality (even as they reduced 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 top marginal tax rates, must also be at work.

However, our first approach does assume to a certain extent that labor is segmented by industry (or alternatively, since manufacturing industries are clustered, by geography). To the extent you believe that labor can flow freely between sectors, then a trade shock could possibly impact aggregate inequality even if the sectors which trade the most did not experience outsized increases in inequality. To address this problem, the second approach we take in this paper is to use aggregate data for 18 countries, and test the theory that marginal tax rates led to the rise in the 1% share of income vs. an alternative theory that trade shocks were the cause. Secondly, using an international dataset of 18 countries, we subject the theory that changes in top marginal tax rates explain the evolution of the top 1% share of income to a battery of additional robustness checks, including adding additional fixed effects, additional controls, and more conservative error assumptions. Thirdly, we test this theory "out-of-sample", using newly collected historical data on top marginal tax rates. Fourth, and most importantly, this literature has found that the current level of the top marginal tax rate determines the level of top 1% share of income. We find, first, that this specification is not robust to a full battery of robustness checks, but that an alternative dynamic specification fits the data better and does appear to be robust to a battery of robustness checks. In our dynamic specification, the level of the top marginal tax rate impacts the rate of change of the income share of the top 1%. This implies that the level of the top income share is also a function of lagged values of the top marginal tax rate. This is, of course, a general insight from the field of economic history – that history matters. This result also provides additional support for the argument of Piketty *et al.* (2013, 2014) that top marginal tax rates affect top income shares via bargaining.

In what follows, first we present evidence from the disaggregated approach, and after that we examine the international evidence using aggregate data.

2 First Estimation Approach: Disaggregated Data

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).[9] 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.[10]

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

[9]The Campa-Goldberg classification of low markup industries at the 2-digit SIC level includes primary metal products, fabricated metal products, transportation equipment, food and kindred products, textile mill products, apparel and mill products, lumber and wood products, furniture and fixtures, paper and allied products, petroleum and coal products, and leather and leather products.

[10]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, 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.

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.[11] 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.[12]

Our core estimation strategy is displayed graphically in Figures 3 and 4. In Figure 3(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 3(b), we divide the sample between sectors with at least 5% of consumption coming

[11] These controls include sectoral input prices (labor, materials, energy, and investment), sectoral input prices interacted with sectoral input shares, capital-labor ratios, capital-labor ratios interacted with real interest rates, openness interacted with the real interest rate, and the Campa-Goldberg measure of markups by sector interacted with the real exchange rate.

[12] 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 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.

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 4, 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.[13] 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.

2.3 Empirical Results

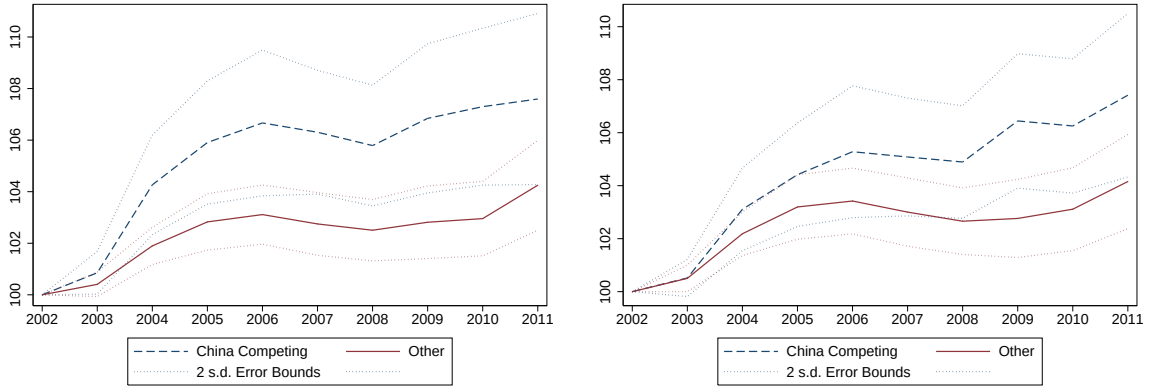
Estimating equation 2.1 in Table 2, column (1), we show that there appears to be no relation between appreciation in WARULCs and movements in the ratio between non-production worker wages and production worker wages in relatively more open sectors. This is a suprising result given the correlation in 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 produc-

[13] 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 3: Evolution of Inequality, Disaggregated (SIC)



(a) Based on Initial Exposure to China

(b) Based on Actual Increase in Chinese Imports

Figure 4: Changes in Inequality, China-Competing Sectors vs. Others (NAICs)

Notes: Inequality in Figure 3 here is proxied by the ratio of non-production to production worker wages (per worker), whereas in Figure 4, 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 3(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 3(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 4(a) a cutoff of 5% of domestic consumption originating in China in 2002 was used, and in 4(b), the "China Competing" sectors are those in the top quarter of the distribution of increases in Chinese import penetration from 2002 to 2010.

tivity 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 shipments 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.[14] Thus, this column is a striking reversal of the apparent trend in Figure 1(b). This is essentially because the rise in inequality by sector was relatively broad-based, and there is no correlation between the sectors that experienced the largest rise in exports, and those that experienced the largest rise in inequality. In column (6), the dependent variable is sectoral unit labor costs. We find that RER appreciations (for 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

[14] 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.

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

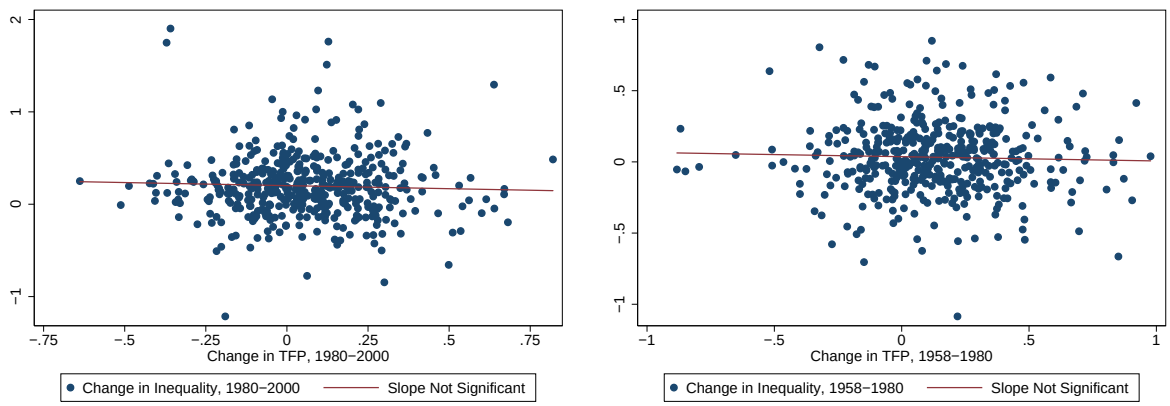
Two-way clustered standard errors in parentheses. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions weighted by initial sectoral value-added, and include 4-digit SIC industry and year fixed effects over the period 1973-2009. The dependent variables in the first 5 columns are the ratio of non-production 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.

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.[15] Another check is to look at the overall change in inequality from 1980 to 2000 vs. the changes in TFP in Figure 5(a), in order to abstract from cylical concerns in favor of the big picture. However, even here there is also no correlation.[16]



(a) 1980-2000

(b) 1958-1980

Figure 5: 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.

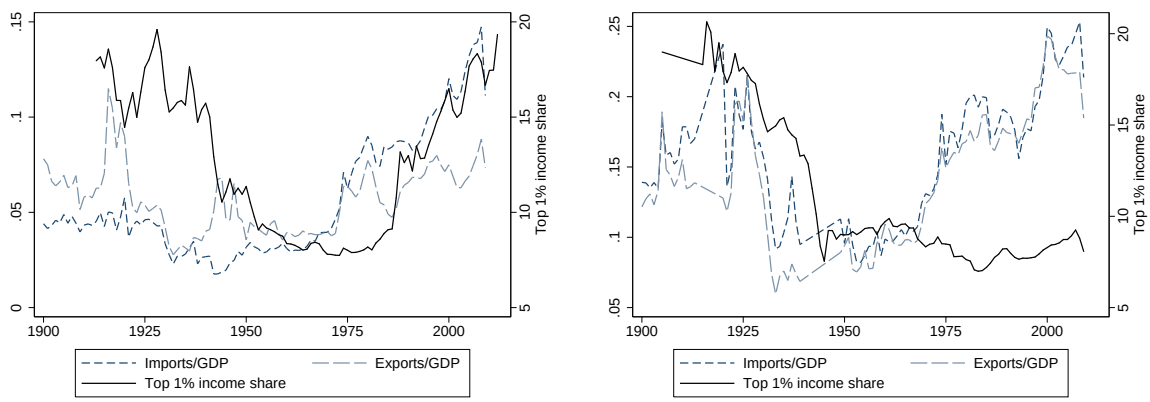
3 International Evidence

Given the weaknesses of using disaggregate data, a useful second strategy is to use aggregate, international data. To the extent one believes that workers can move flexibly

[15]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.

[16]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.

between sectors and thus that trade could have an impact on aggregate inequality even if there is no evidence of outsized gains in inequality in the sectors most exposed to trade, then if trade causes inequality, one should find a correlation between trade shocks and aggregate inequality. However, internationally, there appears to be little correlation between trade shocks and inequality. Figure 6 demonstrates this lack of correlation comparing trade and inequality data for the US and France. For the US, there appears to be a correlation between trade and inequality only for the period since 1980. Trade rose considerably in the 1970s, a period a when there was no trend in the income share of the top 1%, and the interwar period was a time of less trade and more inequality than the immediate postwar period. And while France has also experienced a similar rise in trade since 1970 as the US, the richest 1% in France actually saw their shares of total income decline during this time.



(a) US

(b) France

Figure 6: Trade vs. 1% Share of Income

Piketty *et al.* (2014) explain the dramatic rise in the income share of the top 1% in the US and other Anglo countries as a result of the sharp decline in top marginal tax rates that these countries had in the 1980s (see Figure 8). Other major economies, including France, Japan, and Germany, did not see either large reductions in top marginal tax rates or in increases in the income shares of the top 1% over this period. Using data for 18 countries over the period 1960 to 2010, they run the regression:

$$ln(1\%IncomeShare_{it}) = \alpha + \beta ln(1 - TopMTR_{it}) + c * t + \epsilon_{it}, \tag{3.1}$$

where t is a time trend and "Top MTR" is the top marginal tax rate, and where the errors are robust.

First, we benchmark the Piketty *et al.* (2014) results in the first row of Table 6, only we report errors clustered at the country level rather than robust, to correct for autocorrelation. In columns 2-6, we include different combinations of year trends, year FE, country FEs, and country-specific year trends. However, we find that the apparent impact of top marginal tax rates on the income share of the top 1% is not robust to the inclusion of country-specific trends and clustered standard errors. In Column (5), with country FEs and country-specific year trends, the coefficient shrinks to .17 vs. a standard error of .13, and in Column (6), when year FEs are also included, the coefficient falls to .091, although this remains significant at 90%.

When we also include the log of the trade share of GDP, or the trade balance as a share of GDP (in the second and third rows of Table 6), we find that trade is generally not significantly correlated with income shares of the top 1%.[17]

However, we also do not believe this particular setup is justified by the dynamic nature of how people respond to tax changes in reality. What we actually observe is that when goverments cut their top marginal tax rates, in the US case from .72 to .53 in 1980, and then to .32 in 1988, the trajectory of the income share of the top 1% changes (see Figure 8). Although there does appear to be a large short-run change based on tax avoidance and reporting, the trend in the *growth* of top income shares clearly changes. We believe that this is consistent with the theoretical rationale provided by Piketty *et al.* (2014), in which the top marginal tax rate plays a role in bargaining for CEO salaries and other executives. When income over a certain cutoff is taxed at a very high rate (such as 72%), a person may be naturally likely to bargain harder for a salary increase, most of which will be paid to the government. Yet, the other factor in wage bargaining has always been the current level of wages (see, for example, Bewley 1999), as workers are resentful of pay cuts. Thus, the natural outcome of an interaction in bargaining outcomes should be that CEOs and other executives would bid up their salaries relative to their own starting point. Of the other mechanisms for how the top 1% share could respond to marginal tax rates mentioned by Piketty *et al.* (2014), through either labor supply or tax avoidance, both could also conceivably have a dynamic response, for example if individual's labor supply decisions were persistent, or if learning were important for tax avoidance. However, intuitively, we would suspect that the bulk of these adjustments should happen relatively quickly, so that if the dynamic specification is more accurate, this would seemingly imply that the impact of top marginal tax rates in bargaining is the more critical mechanism over long periods.

[17] We also tried the import and the export shares of trade, and find similar results in both cases and thus have saved those results for the Online Appendix.

Table 3: Taxes, Trade, and the Top 1% Share of Income

	(1)	(2)	(3)	(4)	(5)	(6)
1. Dep. Var.: ln(Top 1% Share)						
ln(1-Top MTR)	0.32***	0.38***	0.33***	0.28***	0.17	0.095*
	(0.075)	(0.13)	(0.086)	(0.060)	(0.13)	(0.048)
ln(1-Top MTR)	0.38***	0.40***	0.32***	0.28***	0.17	0.076
	(0.089)	(0.12)	(0.090)	(0.053)	(0.13)	(0.047)
Log Trade over GDP	-0.18***	-0.17**	-0.053	0.085	-0.11	0.15
	(0.061)	(0.061)	(0.15)	(0.18)	(0.15)	(0.091)
ln(1-Top MTR)	0.33***	0.38***	0.33***	0.28***	0.18	0.091*
	(0.076)	(0.13)	(0.086)	(0.058)	(0.13)	(0.049)
Trade Balance, Share of GDP	-0.32	-0.18	0.054	-0.23	-0.24	-0.13
	(0.56)	(0.56)	(0.54)	(0.51)	(0.38)	(0.38)
2. Dep. Var.: ln Δ Top 1% Share						
Top Marginal Tax Rate	-0.12***	-0.092***	-0.14***	-0.12***	-0.22***	-0.21***
	(0.014)	(0.022)	(0.032)	(0.027)	(0.043)	(0.041)
Top Marginal Tax Rate	-0.12***	-0.093***	-0.13***	-0.12***	-0.21***	-0.19***
	(0.014)	(0.021)	(0.033)	(0.029)	(0.043)	(0.043)
Log Trade over GDP	-0.0041	-0.0070**	-0.0043	0.029	-0.0087	0.037*
	(0.0033)	(0.0027)	(0.016)	(0.017)	(0.024)	(0.019)
Top Marginal Tax Rate	-0.12***	-0.093***	-0.14***	-0.12***	-0.21***	-0.20***
	(0.014)	(0.023)	(0.032)	(0.028)	(0.043)	(0.044)
ln Δ (Exports/GDP)	0.031	0.030	0.036	0.046	0.031	0.046
	(0.032)	(0.032)	(0.031)	(0.046)	(0.031)	(0.046)
Top Marginal Tax Rate	-0.12***	-0.093***	-0.13***	-0.12***	-0.21***	-0.20***
	(0.014)	(0.022)	(0.032)	(0.028)	(0.043)	(0.042)
ln Δ (Imports/GDP)	0.0045	0.0019	0.0030	0.016	-0.0047	0.010
	(0.020)	(0.021)	(0.022)	(0.041)	(0.021)	(0.041)
Top Marginal Tax Rate	-0.12***	-0.096***	-0.13***	-0.12***	-0.20***	-0.20***
	(0.014)	(0.023)	(0.032)	(0.027)	(0.043)	(0.042)
Trade Balance, as Share of GDP	0.069	0.049	0.043	0.024	0.097	0.0064
	(0.054)	(0.053)	(0.084)	(0.077)	(0.13)	(0.15)
Year Trend	No	Yes	Yes	No	No	No
Year FE	No	No	No	Yes	No	Yes
Country FE	No	No	Yes	Yes	Yes	Yes
Country-Specific Year Trend	No	No	No	No	Yes	Yes

Standard errors clustered by country in parenthesis. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. There are eight sets of six regressions, for 48 regressions total. The first three rows of six regressions use the log of the top 1% share of income as the dependent variable. The regressions featured in rows 4-8 use the log change in the top 1% share of income as the dependent variable. Each column then includes a different combination of year trends and fixed effects. Top MTR = Top Marginal Tax Rate. Log Trade over GDP is the sum of the import and export share of GDP. The regressions in the second specification also include a control for the log change in per capita GDP; the results are suppressed for space. There are 18 countries in sample over the period 1960-2010, for a total of 781-813 observations depending on the regression.

An intuitive alternative dynamic specification is:

$$ln\Delta(1\%IncomeShare_{it}) = \alpha + \beta_1 TopMTR_{it} + \beta_2 ln\Delta GDP_{it} + c * t + \epsilon_{it}, \qquad (3.2)$$

where we now have the log change in the top income share on the left-hand side, and the level of top marginal tax rates on the right-hand side. We also control for log changes in GDP, as the top 1%'s share of income is observed to be strongly procyclical, and will include varying fixed effects and country-specific trends as before.

In the second set of regressions, beginning with the fourth row of Table 6, we find that the top marginal tax rate impacts log changes in the Top 1%'s share of income significantly in all specifications, regardless of which combinations of year or country fixed effects, and country-specific trends are included as controls. We also believe this better reflects the reality that when top marginal tax rates were lowered for the US and several other Anglo countries in the 1980s, the top 1% share of income began to increase and, on a cyclically-adjusted basis, appears to have been increasing ever since.

4 Conclusion and Interpretation

We did not find any significant impact of trade shocks, such as from the rise of China, on inequality within the US manufacturing sector, or internationally using aggregate data. While we do not find any significant impact of trade shocks, on inequality within manufacturing, we stress that the disaggregate evidence for US manufacturing does not necessarily imply 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. The reason is that workers who 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.

However, the evidence from using aggregate, international evidence also points to the conclusion that the impact of trade shocks on overall inequality is at best modest. Rising trade and trade deficits do not appear to be correlated with inequality. Both the disaggrated data for the US and the aggregate international evidence also suggest that there is little support for the thesis that skill-biased technological change is at the heart of the recent rise in inequality in many countries.

While little support is found for trade or technology, in this paper we find additional support for the thesis that it was changes in the top marginal tax rates, and perhaps

other institutional changes as discussed by Levy and Temin (2007), that led to the large rise in inequality in the US and other countries since 1980. Our finding that the level of top marginal tax rates affects changes in top 1% share of income indicates that "history matters" for the top 1% share, and provides further evidence that this operates via bargaining.

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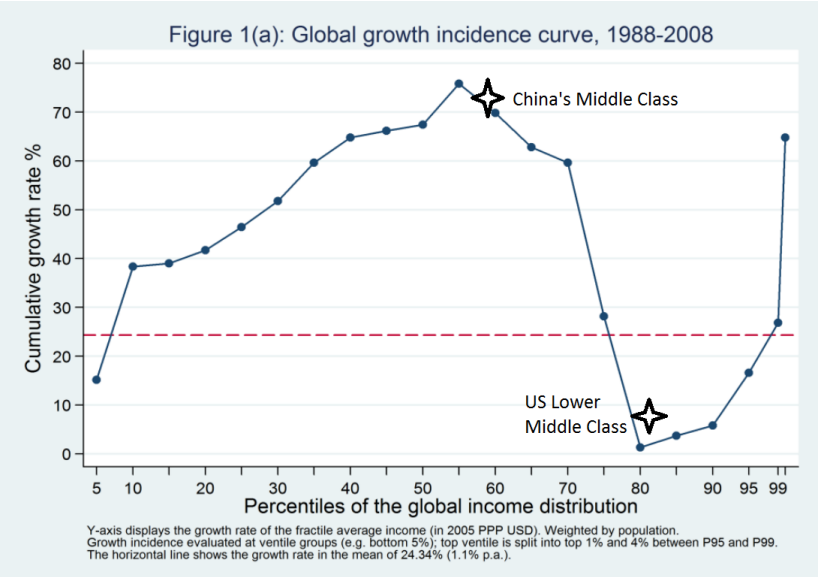
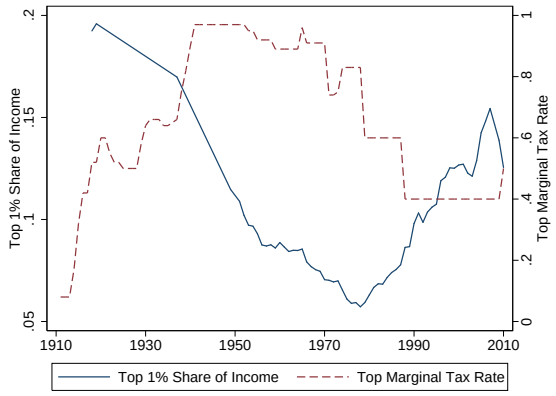
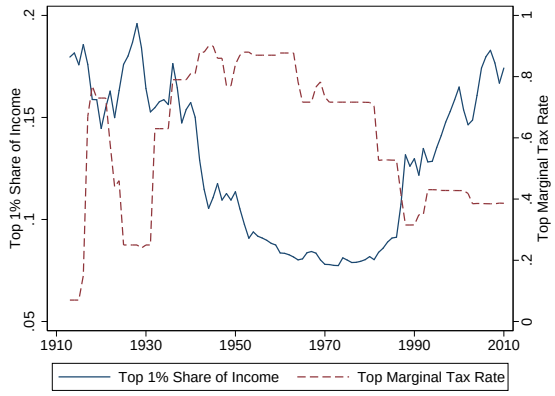


Figure 7: Changes in Global Income Distribution

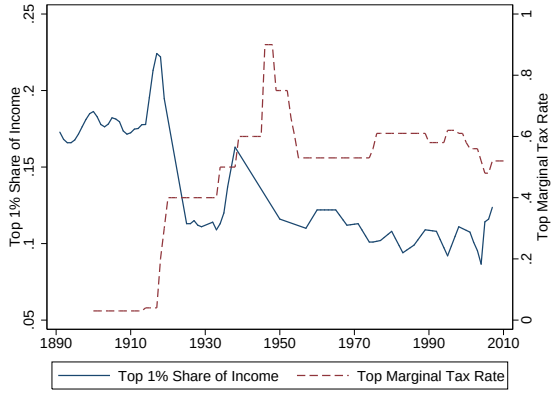
Notes: This chart is taken from Lakner and Milanovic 2013, with the stars for China's middle class and the US lower middle class added in.



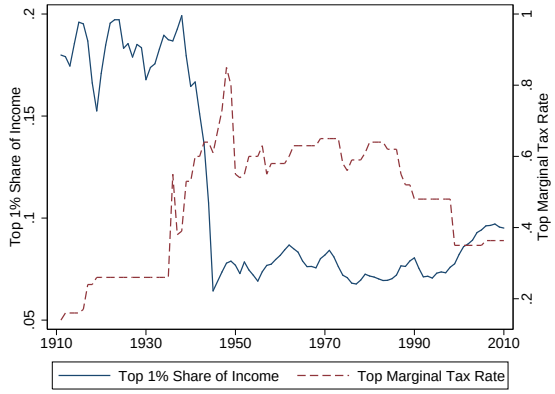
(a) UK



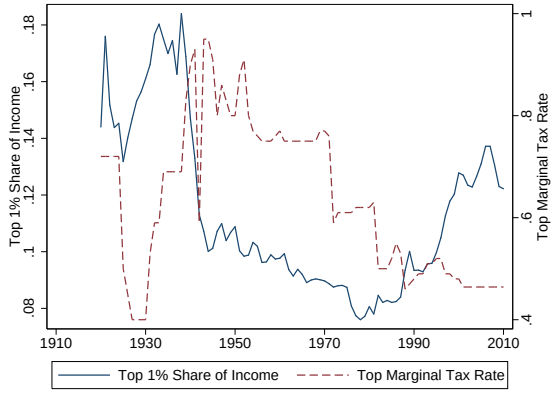
(b) USA



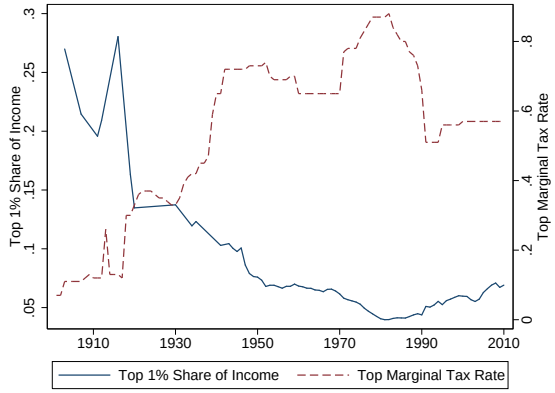
(c) Germany



(d) Japan



(e) Canada



(f) Sweden

Figure 8: Top Marginal Tax Rate vs. 1% Share of Income

5 Online Appendix

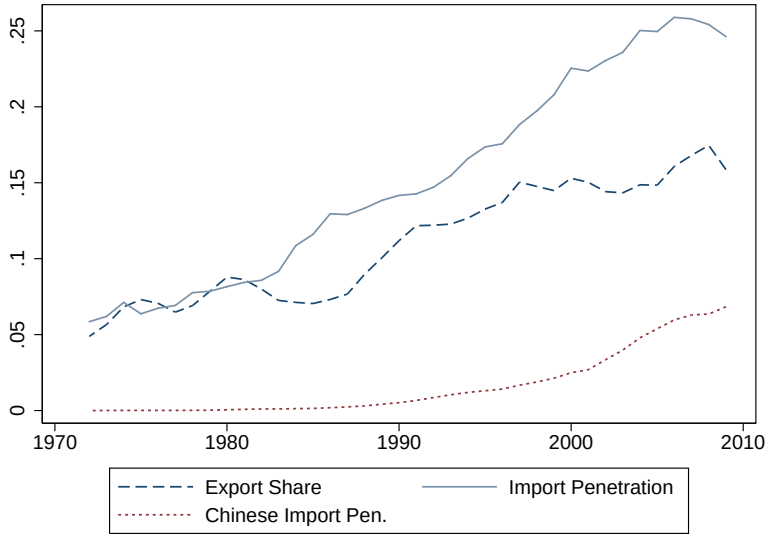


Figure 9: Export Share, Inequality, and Chinese Import Penetration

Table 4: 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.

Table 5: Trade and the Production Worker Share of Wage Bill

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var: Log Δ in Non-Prod. Worker Wages						
L.ln(WARULC)*Rel.Openness	-0.0070*	-0.0070*	-0.016***	-0.0019	-0.0076	-0.0077
	(0.0041)	(0.0041)	(0.0060)	(0.0050)	(0.0061)	(0.0049)
L.ln(iWARULC)*R.Import Pen.	-0.0074	-0.0074	-0.010*	-0.0033	-0.0066	-0.0076
	(0.0053)	(0.0053)	(0.0062)	(0.0046)	(0.0052)	(0.0057)
L.ln(eWARULC)*R.Export Sh.	-0.0018	-0.0018	-0.0082	-0.00037	-0.0028	-0.0022
	(0.0056)	(0.0056)	(0.0076)	(0.0061)	(0.0074)	(0.0058)
Δ Export Share	0.062***	0.062***	0.088***	0.071***	0.074***	0.069***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.017)	(0.023)
Δ Import Penetration	0.028	0.028	0.042	0.032	0.023	0.034
	(0.023)	(0.023)	(0.032)	(0.023)	(0.024)	(0.026)
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 three sets of six regressions, for 18 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.

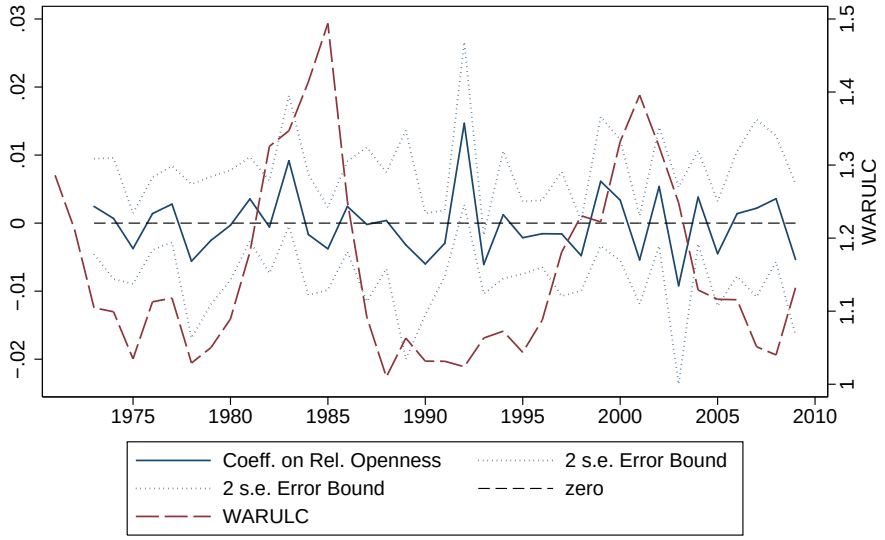


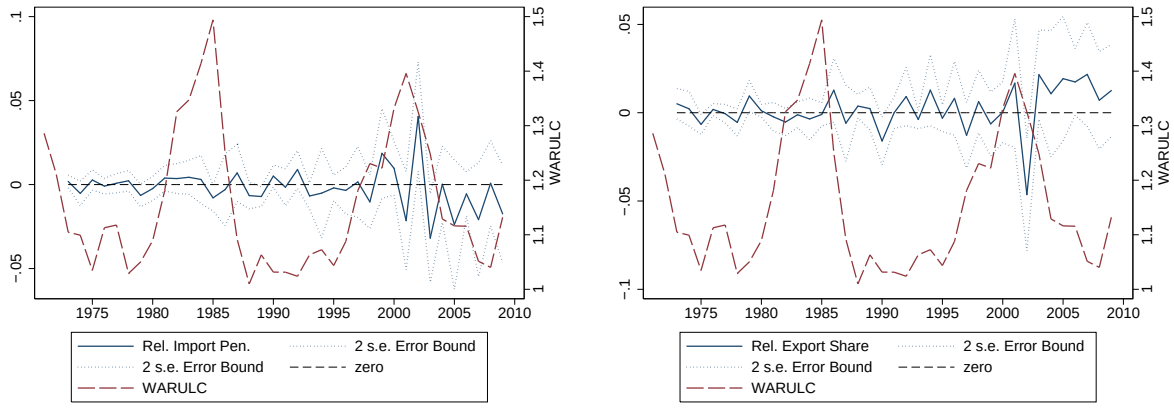
Figure 10: Impact of Relative Openness on Inequality by Year

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.

Table 6: Trade and the Top 1%: Alternative Functional Forms

	(1)	(2)	(3)	(4)	(5)	(6)
1. Dep. Var.: ln(Top 1% Share)						
ln(1-MTR)	0.37***	0.40***	0.33***	0.28***	0.17	0.078
	(0.091)	(0.13)	(0.087)	(0.049)	(0.13)	(0.047)
ln Imports over GDP	-0.17**	-0.16**	-0.0021	0.099	-0.061	0.13*
	(0.058)	(0.057)	(0.11)	(0.15)	(0.13)	(0.071)
ln(1-MTR)	0.38***	0.39***	0.32***	0.28***	0.18	0.081
	(0.085)	(0.12)	(0.094)	(0.062)	(0.12)	(0.048)
ln Exports over GDP	-0.17**	-0.17**	-0.15	-0.046	-0.17	0.091
	(0.060)	(0.062)	(0.13)	(0.11)	(0.13)	(0.087)
ln(1-MTR)	0.32***	0.38***	0.33***	0.28***	0.17	0.089*
	(0.075)	(0.12)	(0.086)	(0.060)	(0.13)	(0.049)
Δ (Trade Balance/GDP)	-1.11***	-1.09***	-0.62*	-0.13	-0.57*	-0.16
	(0.36)	(0.36)	(0.31)	(0.26)	(0.30)	(0.26)
ln Δ GDPpc	0.46***	0.51***	0.50***	0.16	0.52***	0.18
	(0.063)	(0.062)	(0.081)	(0.12)	(0.091)	(0.14)
2. Dep. Var.: ln Δ Top 1% Share						
ln Marginal Tax Rate	-0.069***	-0.052***	-0.076***	-0.070***	-0.12***	-0.12***
	(0.0073)	(0.011)	(0.020)	(0.019)	(0.023)	(0.027)
ln Trade over GDP	-0.0032	-0.0063**	-0.0039	0.029	-0.0075	0.036*
	(0.0031)	(0.0027)	(0.017)	(0.018)	(0.025)	(0.019)
ln Marginal Tax Rate	-0.068***	-0.053***	-0.077***	-0.071***	-0.12***	-0.12***
	(0.0077)	(0.012)	(0.019)	(0.017)	(0.023)	(0.027)
ln Δ (Exports/GDP)	0.031	0.031	0.036	0.046	0.030	0.046
	(0.032)	(0.032)	(0.030)	(0.045)	(0.031)	(0.046)
ln Marginal Tax Rate	-0.068***	-0.053***	-0.077***	-0.070***	-0.12***	-0.12***
	(0.0077)	(0.012)	(0.019)	(0.018)	(0.023)	(0.026)
ln Δ (imports/GDP)	0.0051	0.0022	0.0040	0.018	-0.0054	0.0095
	(0.020)	(0.021)	(0.022)	(0.041)	(0.021)	(0.040)
ln Marginal Tax Rate	-0.068***	-0.053***	-0.077***	-0.070***	-0.12***	-0.12***
	(0.0079)	(0.012)	(0.019)	(0.017)	(0.023)	(0.026)
Δ (Trade Balance/GDP)	0.080	0.091	0.096	0.029	0.095	0.036
	(0.15)	(0.16)	(0.17)	(0.17)	(0.17)	(0.18)
Year Trend	No	Yes	Yes	No	No	No
Year FE	No	No	No	Yes	No	Yes
Country FE	No	No	Yes	Yes	Yes	Yes
Country-Specific Year Trend	No	No	No	No	Yes	Yes

Standard errors clustered by country in parenthesis. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. There are eight sets of six regressions, for 48 regressions total. The first three rows of six regressions use the log of the top 1% share of income as the dependent variable. The regressions featured in rows 4-8 use the log change in the top 1% share of income as the dependent variable. Each column then includes a different combination of year trends and fixed effects. MTR = Marginal Tax Rate. Log Trade over GDP is the sum of the import and export share of GDP. The regressions in the second specification also include a control for the log change in per capita GDP; the results are suppressed for space. There are 18 countries in the sample, over the period 1960 to 2010, for a total of 780-801 observations depending on the regression.

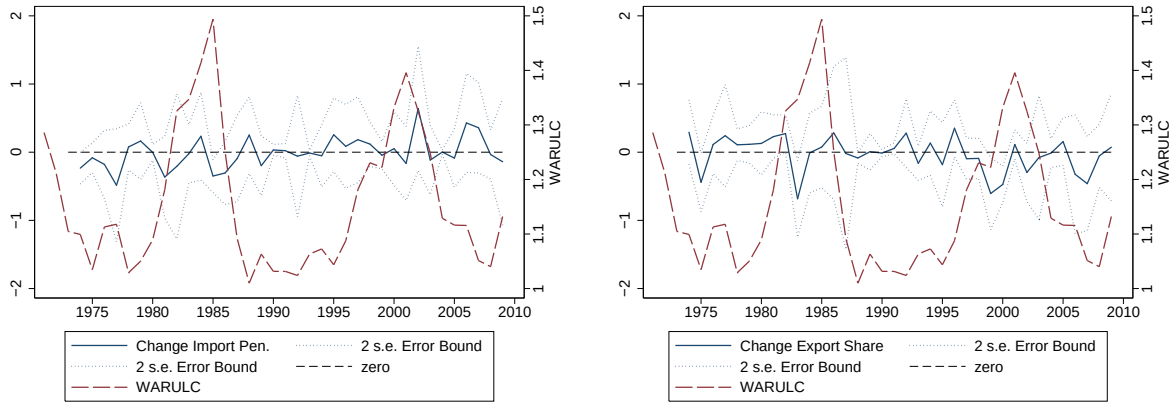


(a) Import Penetration

(b) Export Share

Figure 11: 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.

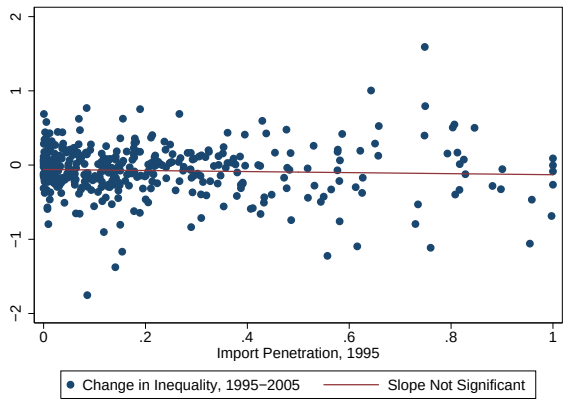


(a) Import Penetration

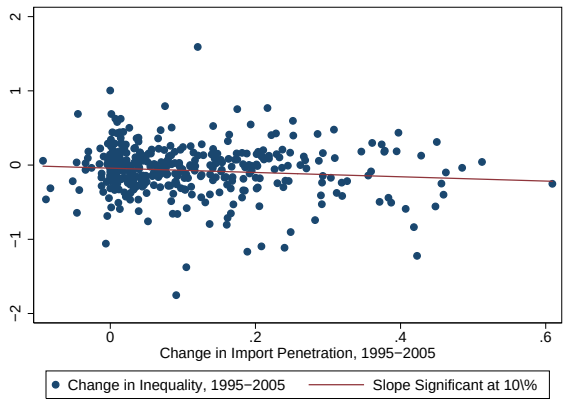
(b) Export Share

Figure 12: Change in Trade Exposure vs. Evolution in Inequality, 1973-2009

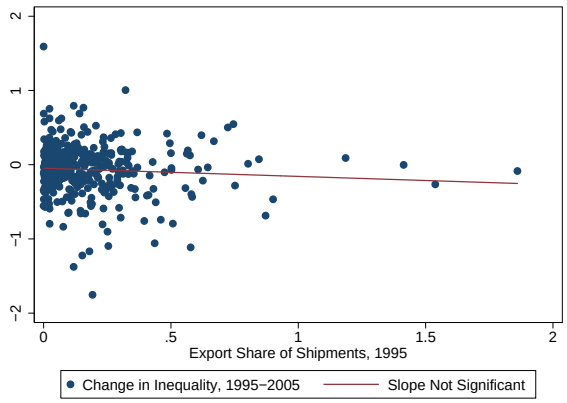
Notes: These are the results from yearly regressions of the change in import penetration and the change in export share on inequality by sector with controls for demand and TFP growth, with two standard deviation error bounds plotted in dotted dark blue, compared to the WARULC index in maroon.



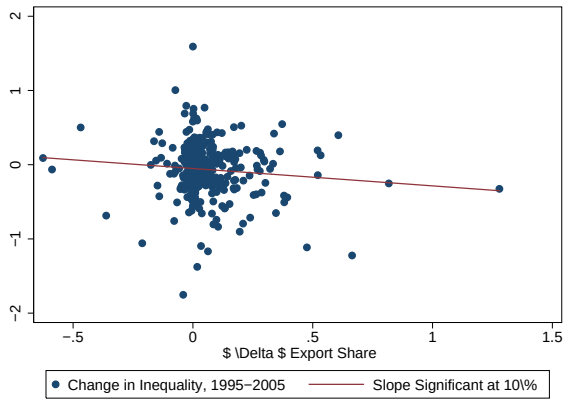
(a) Δ Inequality vs. Initial Import Penetration



(b) Δ Inequality vs. Δ Import Exposure



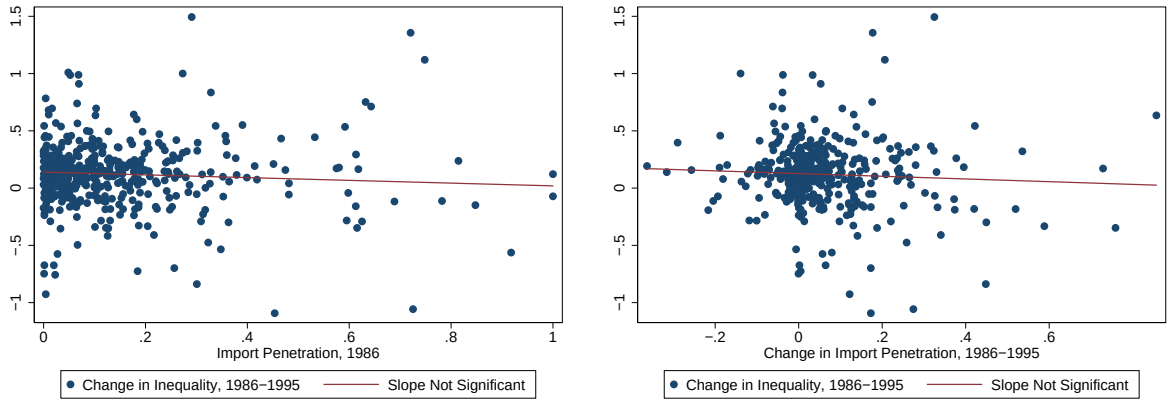
(c) Δ Inequality vs. Initial Export Share



(d) Δ Inequality vs. Δ Export Share

Figure 13: Trade Exposure and Inequality, 1995-2005

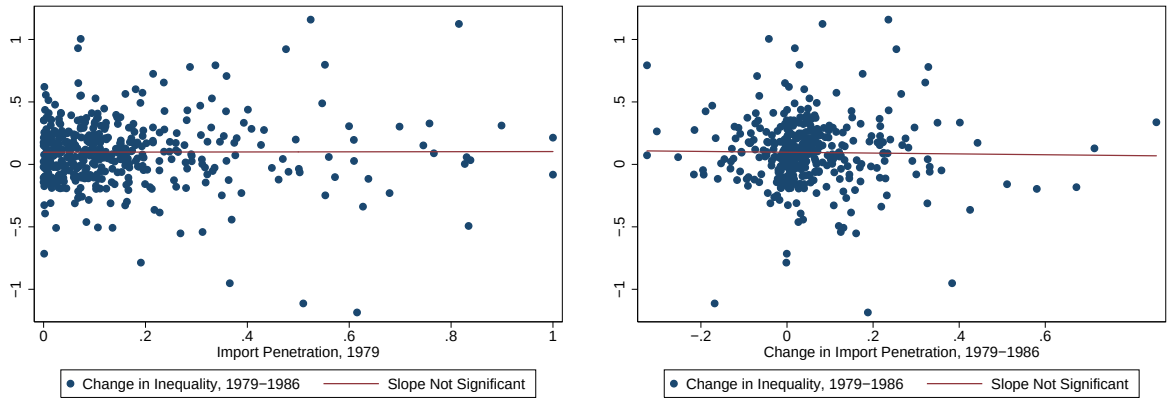
Notes: Each dot is a 4-digit SIC manufacturing sector. Inequality here is proxied by the ratio of non-production to production worker wages in the manufacturing sector, from the ASM. Values above zero on the y-axis thus indicate an increase in inequality. Trade data are from WITS.



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

Figure 14: Trade Exposure and Inequality, 1986-1995

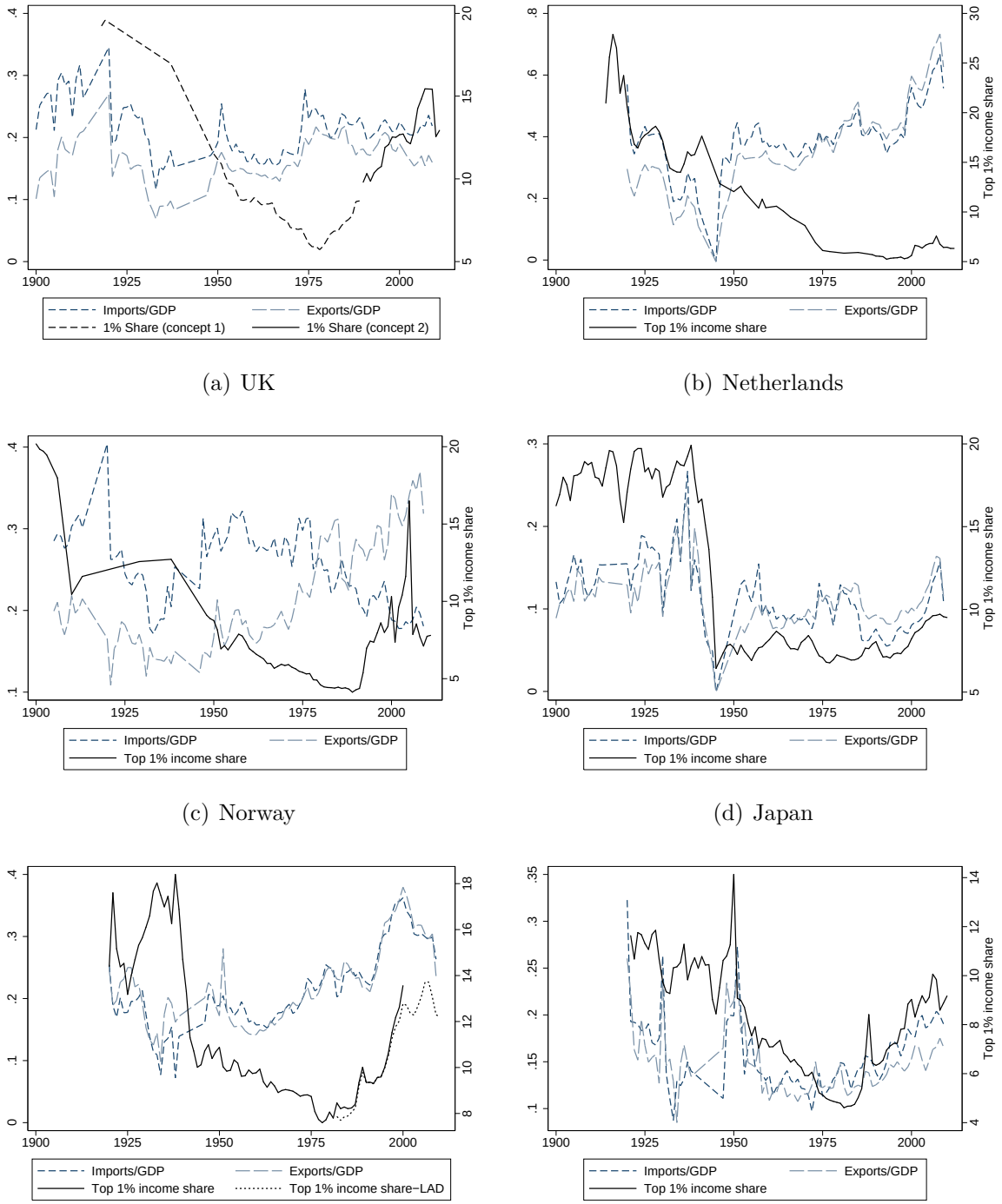
Notes: Inequality here is proxied by the ratio of non-production to production worker wages in the manufacturing sector, from the ASM. Values above zero on the y-axis thus indicate an increase in inequality. Trade data come from WITS.



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

Figure 15: 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.



(a) UK

(b) Netherlands

(c) Norway

(d) Japan

(e) Canada

(f) Australia

Figure 16: Trade vs. 1% Share of Income