Trade Union Decline, Deindustrialization, and Rising Income Inequality in the United States, 1947 to 2015

by

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Abstract

The steady rise of income inequality in the United States coincides with trade union decline and structural changes to the economy, but prior studies do not consider whether these phenomena interact in ways that magnify inequality. Drawing on institutional and market accounts of inequality, the author develops the argument that trade union decline, occurring within the context of deindustrialization and the offshoring of routine-manufacturing jobs, creates more profound distributional effects than these factors would create in isolation. This argument is tested (net of other important determinants of income inequality) using time-series regression models and national-level data from 1947 to 2015. Results support the proposed interaction effects, suggesting that a thorough understanding of inequality and social stratification must consider not only institutions and markets, but how they interact. The results also suggest that inequality is driven by financialization, public sector retrenchment, and unemployment, but not necessarily by technological change.

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1. INTRODUCTION

This study examines rising income inequality in the United States within the context of trade union decline and structural changes to the economy. During the post-war era, the distribution of income in the United States was relatively stable and egalitarian. The Gini coefficient of income inequality, estimated by the US Census Bureau (2017a) annually since 1947, changed little during this period, reaching a nadir of 34.8 in 1968. Since then, it has moved steadily upward, breaking an all-time high of 45.5 in 2013 (see Figure 1). These aggregate distributional changes clearly affect core sociological concerns, especially those regarding social stratification and mobility.

How can we explain these pronounced distributional changes? Institutional accounts undertaken by sociologists emphasize the demise of organized labor (Jacobs & Myers 2014; Kristal 2013; Volscho 2007; Wallace, Leicht, & Raffalovich 1999; Western & Rosenfeld 2011). Indeed, over the period in question, the US labor movement weakened considerably from its post-war peak, with the unionized portion of the US workforce declining by more than one half (Rosenfeld 2014; Chapter 1). Additionally, trade unions lost power due to the breakdown of the labor-capital accord (Rosenfeld 2014), the rise of neoliberalism and the curtailment of public sector employment (Jacobs & Myers 2014; Volscho 2007), and the onset of the Information Revolution (Kristal 2013; Kristal & Cohen 2015; Nelson 2001). Yet, despite being the focus of early accounts of rising inequality (Bluestone & Harrison 1982), the ongoing contraction of the industrial sector and the related phenomenon of heightened capital mobility receive less attention.

By contrast, market accounts of rising inequality (especially those favored by economists) emphasize technological change associated with the Information Revolution and how it favors the pecuniary interests of high-skilled workers (Autor 2014; Autor, Katz, & Krueger 1998; Autor, Levy, Murnane 2003; Goldin & Katz 2008). Sociologists make similar claims, arguing that recent technological change widens wage dispersion among workers with different skills (Liu & Grusky 2013)

and heightens the remuneration of capital over labor more generally (Kristal 2013). Sociologists also argue that deindustrialization, corporate restructuring, and flexible employment practices harm those toward the bottom of the income distribution (Kalleberg, Reskin, & Hudson 2000; Massey & Hirst 1998). Of particular concern is growth in "precarious" employment (Kalleberg 2009, 2011) characterized by low pay, temporary or part-time contracts, and the absence of clear paths for career advancement (Massey & Hirst 1998).

In this article, I draw on both institutional and market accounts of inequality to explain trends in the US income distribution since 1947. My general argument is that trade union decline, occurring within the context of deindustrialization and the offshoring of routine manufacturing jobs, creates larger distributional effects than these factors would in isolation. More specifically, I stress that employment opportunities for less-skilled Americans have shifted away from unionized jobs in the industrial sector (high-wage, secure employment) toward non-unionized jobs in the service sector (low-wage, insecure employment). However, this economic transformation not only reduces the prevalence of good unionized jobs, but weakens the bargaining power of trade unions more generally. The combined effect, I contend, drives income inequality substantially upward. To test such an argument requires the use of an interaction term between trade union density and measures of structural economic change. To my knowledge, this has not been done.

In what follows, I review the literature on institutional and market accounts of income inequality and develop my argument about how trade union decline interacts with deindustrialization and the offshoring of routine-production jobs to push inequality higher. Next, I advance arguments about how neoliberalism alters macroeconomic policy in ways that heighten inequality, how financialization widens inequality, and how the distributional effects of technological change may be overstated. Then, using time-series data on the US political economy from 1947 to 2015, I test these arguments with first-difference regression models assessing change in the Gini coefficient as well as change in the income ratios between various percentiles of the income distribution—namely the 95th/20th, the 95th/50th, and the 50th/20th. The results support my argument about the proposed interaction effects between deunionization and structural economic change, but

highlight important differences in how structural change affects different parts of the income distribution. The study concludes by discussing whether these results might hold in other advanced capitalist countries.

[Insert Figure 1 about here.]

2. TRADE UNION DECLINE, DEINDUSTRIALIZATION, AND RISING INCOME INEQUALITY

2. 1. Trade Union Decline

A prominent sociological perspective on distributional conflicts emphasizes the importance of organized labor for generating outcomes favorable to workers. As articulated by Korpi (1983, 2006), firms and workers possess different types of "power resources," which they use to bend market allocations of income in their favor. In labor markets, dominant firms are structurally advantaged by their strict control over enormous economic assets. This constitutes their key power resource, because it gives them bargaining power over lone workers when setting wages and working conditions. Workers, however, can redress this power imbalance through collective action. This constitutes their main power resource.

Trade unions are notable in this regard. The lone worker must accept the prevailing wage, even if that wage is depressed by the considerable bargaining power of dominant firms. But large groups of workers, acting in a coordinated fashion, generate their own bargaining power, which can be used to improve wages and working conditions. This is accomplished through collective bargaining and other forms of collective action.

The positive effects of trade unions for workers are well documented. Studies suggest that unions help workers to earn higher wages (Rosenfeld 2014: 68-73) and to reduce wage inequality among unionized and nonunionized workers alike (Rosenfeld 2014: 74-79; Western & Rosenfeld 2011). Other studies show that unions accelerate real wage growth (Kollmeyer 2017), boost labor's share of national income (Kristal 2013; Wallace, Leicht, Raffalovich 1999), and reduce general levels of income inequality (Jacobs & Myers 2014; Kwon 2016; Moller, Alderson, & Nielsen 2009). They also lessen incidences of working poverty (Brady, Baker, & Finnigan 2013). However, in terms of wages, it appears that middle-

income workers benefit more from unionization than lower-income workers (Firpo, Fortin, & Lemieux 2009: 962-966).

Despite the well-documented ways trade unions benefit workers, the American labor movement has been losing strength for decades (Rosenfeld 2014; Chapter 1). Even at its peak, organized labor in the United States was relatively weak compared to its counterparts in other affluent democracies, although union membership and collective bargaining in the industrial sector were always widespread. Now, after decades of decline, the American labor movement is particularly feeble, with only 10 percent of the US workforce being unionized (US Bureau of Labor Statistics 2016). In a wide-ranging study of deunionization and its effect on American society, Rosenfeld (2014) concludes that the weakened state of US trade unions prevents them from functioning as a power resource for American workers. The United States, in his words, lost one of its key "equalizing institutions." Importantly, for my study, I expect the decline of organized labor to play a key role in rising income inequality in the United States.

By contrast, there is a less sanguine view of trade unionism, which is influential in economics and political economy but not in sociology. Sometimes called insider-outsider theory or monopoly-union model, this view depicts trade unions as special interest groups seeking to advance the narrow interests of their members (Carruth & Oswald 1987; Freeman & Medoff 1984; Rueda 2007). More specifically, trade unions are conceptualized as "rent-seeking" cartels, which use collective action to push wages above equilibrium rates. This clearly benefits unionized workers via higher wages, but may harm other members of society by spurring inflation, slowing job creation, and reducing economic growth. If this occurs, trade union members are immune to these externalities (since they enjoy relatively secure employment with above-market wages), but non-unionized workers and people outside of the labor market are not. Consequently, trade unionism can create an insider-outsider distributional logic, which according to Rueda (2007), often cuts across the working class, separating the political interests of working-class insiders from working-class outsiders.

Interestingly, this view of trade unionism resonates with the dual labor market perspective developed in sociology. This perspective conceptualizes the US economy (especially during the post-war era) as comprising primary and

secondary labor markets (e.g. Tolbert 1978; Sakamoto & Chen 1991). Workers in the primary labor market presumably enjoy stable employment, high pay, internal job ladders, and unionization (especially for blue-collar workers), but these advantages are reinforced by social and institutional barriers that impede workers in the secondary labor market from competing for available jobs.

For my study, both the insider-outsider perspective and dual labor-market perspective suggest that trade unions may widen inequality between those in the middle and bottom of the income distribution. If this is true, organized labor may (inadvertently) reproduce or even exacerbate inequality. I test this idea in Section 5 by examining how changes in trade union density affect changes in the ratio between the median and 20th percentile of the income distribution.

2. 2. Deindustrialization

Affecting blue-collar workers in particular, deindustrialization and the concomitant rise of the service sector are thought to heighten income inequality. In the latter half of the 20th century, social scientists began predicting the arrival of a post-industrial society, in which economic activity would center on the provision of services rather than the production of physical goods (Clark 1957; Bell 1973). Indeed, as these scholars predicted, employment in the industrial sector fell from around 40 percent of the US workforce during the post-war era to just over 13 percent today (US Bureau of Labor Statistics 2017a). This phenomenon—generally known as deindustrialization—is linked to internal changes typically experienced by advanced economies and to the business practice of offshoring routine-manufacturing jobs to less developed countries (LDCs) (Kollmeyer 2009).

Regarding its distributional effects, the main contention is that deindustrialization systematically degrades the labor market opportunities of less-skilled workers (Bluestone & Harrison 1982). During the post-war era, a thriving industrial economy provided relatively high-paying jobs for less-skilled workers. This was made possible due to the US industrial sector's high productivity levels, heavily unionized workforce, and dominant position within international markets. However, for less-skilled workers, the onset of deindustrialization upended this advantageous situation by shifting employment opportunities away from well-paid

unionized jobs in the industrial sector toward low-paid non-unionized jobs in the service sector.

As Kalleberg and his colleagues (2000) note, many jobs created in the wake of deindustrialization and corporate restructuring of the 1980s and 1990s were "bad jobs." These are jobs with temporary or part-time contracts and low-pay and few fringe benefits, making them poor substitutes for erstwhile industrial employment (see also Kalleberg 2009, 2011). Indeed, research shows that deindustrialization and service sector expansion are associated with falling median earnings (Lorence 1991) and rising earnings inequality (Lorence & Nelson 1993; Wallace, Gauchat & Fullerton 2011). However, the proliferation of "bad jobs" is only part of the story, because service sector expansion creates a post-industrial dualism, characterized by bifurcation between high-wage producer services and low-wage personal services (see Kwon 2016; Moller & Rubin 2008).

A related phenomenon is the global reorganization of basic manufacturing activities. Starting in 1970s, US manufacturing firms and their competitors in other advanced economies began offshoring the bulk of their routine-production tasks to LDCs (see Harrison & Bluestone, 1988: Chapter 2; Kollmeyer 2009; Wood 1994). This process fundamentally changed the longstanding international division of labor and clearly contributed to the deindustrialization of advanced economies. In terms of its distributional effects, offshoring heightens inequality not only by substituting American workers for foreign workers, but also by yielding substantial labor-cost savings, which then manifest as higher incomes for corporations and their elite workers. This latter effect boosts top incomes but the former effect depresses middle and lower incomes. Indeed, studies of advanced capitalist countries link offshoring with rising income inequality (Alderson & Nielsen, 2002; Kollmeyer 2015) and with sluggish wage growth for the working class (Kollmeyer 2017).

2. 3. Interaction Effect

This study's main argument is that trade union decline, occurring within the context of deindustrialization and enhanced capital mobility, creates more profound distributional effects than these factors would create in isolation. In this sense, the steady upswing in US income inequality can be understood as arising

not just from institutional change and not just from structural economic change, but from the combination of the two. Conceptually, this implies that deunionization and structural economic change shape the income distribution through an interaction effect. In making this claim, I portray the distributional effects of trade unionism as arising from a moderated causal process, in which an otherwise straightforward bivariate relationship (trade unionism's effect on income inequality) is altered by a third variable (structural economic change).

The hypothesized interaction effect starts from a dualism between unionized industrial workers and non-unionized service-sector workers. On the topic of labor market dualism, Kuznets (1955) famously argued that industrialization initially pushes inequality higher because it shifts employment out of the traditional sector (where wages are uniformly low) into the modern sector (where wages are typically higher). At first, this process exacerbates inequality due to pronounced earnings differences between the traditional and modern sectors. But as the transformation continues and most people become employed in the modern sector, inequality stabilizes and eventually falls as the process continues toward completion. Related to my study, Kuznets' theory highlights how shifting employment patterns can alter the national income distribution, especially when the sectors have different earnings dynamics.

Extending this idea, contemporary sociologists argue that recent employment shifts from the industrial sector (with low wage dispersion) to the service sector (with high wage dispersion) heighten income inequality (Kwon 2014, 2016; Rohrback 2009). For example, Kwon (2016) maintains that a Kuznetsian dynamic is increasing inequality in the United States, because the expanding service sector exhibits substantial wage dispersion, arising from the diverging fortunes of high-earning knowledge workers and low-earning personal service workers (see also Moller & Rubin 2008). I agree with this account of income inequality, but additionally I ask whether changing employment patterns are intertwined with declining unionization rates in ways that exacerbate inequality.

Indeed, I believe this to be the case. Over recent decades, the fortunes of less-skilled workers have deteriorated as their employment opportunities shift from unionized jobs in the industrial sector (high-wage, secure employment) toward non-unionized jobs in the service sector (low-wage, insecure employment).

This transformation should widen inequality between the working class and the affluent, but its distributional effects may be more complex than they appear. This is the case, I argue, because deindustrialization and the offshoring of routine production processes not only eliminate good unionized jobs, but they weaken the bargaining power of organized labor more generally. This latter outcome suggests the presence of an interaction effect.

Several factors underpin the proposed interaction effect. One factor is that deindustrialization upended the structural conditions upon which successful trade unionism developed (Bluestone & Harrison 1982; Craver 1995; Troy 1986; Rosenfeld 2014). Historically, the American labor movement predominated in the Northeast and Midwest, where leading industrial firms used Fordist production techniques and employed sizeable workforces in large factory settings. These structural conditions proved conducive to labor organizing. But as deindustrialization proceeded and the remaining manufacturing firms substituted advanced equipment for less-skilled labor, American industry not only shrank in size but changed qualitatively (Whitford 2005). Especially in manufacturing, worksites became smaller, production techniques more flexible, and workforces more skilled. Manufacturing firms also gravitated toward the South and West, where unions typically enjoy less political and public support. Indeed, empirical research links these structural changes to the declining ability of trade unions to organize new workplaces (Wallace, Fullerton, & Gurbuz 2009).

Moreover, deindustrialization and offshoring leave trade unions in the industrial sector with less bargaining power. This occurs because industrial sector retrenchment undermines the ability of trade unions to confront their employers and collectively bargain for better wages and working conditions (Bluestone & Harrisons 1982). If industrial workers are plentiful but industrial jobs are scarce, and if manufacturing firms can relocate their production activities to LDCs, the balance of bargaining power clearly shifts away from organized labor. Under such conditions, trade unions struggle to secure wage increases, but sometimes even acquiesce to wage concessions or targeted job losses as a means of retaining scarce capital investment (Herod 1994; Sallaz 2004). In other words, the shrinking pool of capital investment puts industrial-sector trade unions on the back foot, causing them to prioritize saving jobs over increasing wages. In this way, industrial

restructuring and its related processes weaken the bargaining power of trade unions and lessen their ability to redistribute income and lower inequality.

Notably, this trend is reinforced by the inability of trade unions to gain a substantial foothold in the expanding service sector. As Lipset & Katchanovski (2001) point out, the service sector presents trade unions with difficult conditions for organizing and collectively bargaining (Dølvik & Waddington 2004). Unlike the industrial sector of the post-war period, service sector worksites are typically small and geographically dispersed, and workforces are fragmented by high turnover rates and non-standard employment practices (Weil 2014). Under such conditions, trade unions struggle to build solidarity, unite workers, and engage in collective action. This outcome not only lowers union densities, but it also hinders the ability of trade unions to function on behalf of their members. In sum, I contend that deindustrialization and the related process of offshoring intensify the distributional consequences of trade union decline, creating a situation in which the combined effect of these phenomena is greater than their individual effects would otherwise be.

3. OTHER DISTRIBUTIONAL FACTORS
3. 1. Neoliberalism and Macroeconomic Factors

Although my analysis focuses on the interplay between deindustrialization, offshoring, and trade union decline, I control for other factors that may affect the nation income distribution. Here, changes in macroeconomic conditions associated with the demise of Keynesianism and the rise of neoliberalism merit consideration. During the heyday of Keynesianism, pro-labor political forces pursued full employment as a key policy objective, because as Kalecki (1943) famously argued, full employment not only provides jobs for the unemployed, but shifts the entire balance of class power in favor of the working class (see also Glyn 1995). Inflation, however, is a different matter. Although high levels of inflation are problematic in many ways, incremental increases from modest levels may lessen inequality (Mocan 1999). This can happen because inflation is particularly harmful to the wealthy, especially those holding inflation-sensitive assets, but also

because inflation is positively associated with workers' bargaining power (Hung & Thompson 2016).

Crucially, US government policy toward unemployment and inflation changed significantly over the period examined in this study. Under Keynesianism, full employment was pursued and modest inflation tolerated, but under neoliberalism, the situation reversed. As Harvey (2007:23-25) notes, the "Volker shock" of 1979-80 signed a historic transformation in US monetary policy, essentially switching from a pursuit of low unemployment to a pursuit of low inflation. This policy transformation reflected and reinforced a change in the balance of class power, which moving it away from workers and toward capital (Hung & Thompson 2016). Hence, for my study, I expect unemployment to heighten inequality, but inflation to lower it. This expectation is in line with both Keynesian and neoliberal thinking.

3. 2. Technological Change and Education

Skill-biased technological change (SBTC) is the dominant explanation for rising income inequality in economics (Autor 2014; Autor, Katz, & Krueger 1998; Goldin & Katz 2008) and is attracting attention in sociology as well (see Fernandez 2001; Kristal 2013; Liu & Grusky 2013). Here the general idea is that technological change brought about by the Information Revolution typically benefits high-skilled workers who can use complex technologies, but disadvantages low-skilled workers whose jobs may be replaced by these technologies. In the early 1950s, US businesses invested about 10 percent of their capital outlays on information and communication technologies (ICT), but due to the Information Revolution, this figure steadily rose to over 50 percent today (US Bureau of Economic Analysis 2017a). This increase in ICT capital stocks coincides with rising inequality in the US.

However, for at least two reasons, the distributional effects of SBTC may be less pronounced than originally thought. First, as Autor and his colleagues (2003) note, computer-driven technologies often displace workers performing routine tasks, but routine tasks are not limited to working-class occupations. In fact, they are most concentrated in semi-skilled occupations. For example, computers cannot

(yet) perform the task of driving trucks or forklifts (lower-skilled, blue-collar work), but they can perform tasks previously undertaken by bank tellers, loan officers, bookkeepers, and tax preparers (semi-skilled, white-collar work). In fact, recent research suggests that middle-income jobs are the most susceptible to displacement by computerization (Autor, Katz, & Kearney 2008). This conclusion dovetails with sociological depictions of the "hourglass" economy, wherein job growth disproportionately occurs among low- and high-paying occupations (Massey & Hirst 1998). Given the diffuse distributional effects of SBTC, it is unsurprising that some studies find weak links between computerization and rising income inequality (Kim & Sakamoto 2010; Kristal & Cohen 2016; cf. Liu & Grusky 2013).

Second, the distributional effects of SBTC must be considered in tandem with educational outcomes. As described by Goldin and Katz (2008), US income inequality is shaped by a "race" between technological advancement on one hand and educational achievements on the other (see also Autor 2014). Technological change generally heightens inequality by creating shortages of high-skilled workers who can use emergent technologies, but such skill shortages can be overcome when workforces become better educated. Indeed, this has long happened in the United States. In the late 1940s, about four percent of American adults had university degrees, but that figure is nearly 30 percent today (US Census Bureau 2017b.) Importantly, improved educational outcomes should offset the disequalizing effect on SBTC. In sum, I expect that computerization plays only a modest role in explaining changes in the national income distribution.

3. 3. Financialization

Financialization is another factor to consider. On this subject, Tomaskovic-Devey & Lin (2011) document the sizeable "rents" collected by the US financial sector since the 1980s. Rents can be gained in a number of ways, including wielding political power to restructure regulatory regimes to the rent-seeker's advantage. Drawing on this concept, Tomaskovic-Devey and Lin argue that rents generated by the financial sector pushed US income inequality higher by creating over-sized profits and incomes in the financial sector (see also Lin & Tomaskovic-Devey 2013; Jacobs & Myers 2014).

This literature links financialization with the rising incomes of financial firms and their elite workers, but financialization may affect the bottom half of the income distribution as well. During the post-war era, firms typically viewed their workforces as junior partners in the pursuit of mutual goals. But financialization replaced cooperative capital-labor relations with more antagonistic management strategies (Jung 2015; Lazonick & O'Sullivan 2000). In particular, Lazonick & O'Sullivan (2000) claim that financialization encouraged a shift in the prevailing corporate business model, changing it from what they call "retain and reinvest" (using profits to fund business expansion) to "downsize and distribute" (cutting jobs to free income for shareholders). To implement this strategy, effected firms downsized their workforces, ridding themselves especially of lower-skilled workers whose jobs could be off-shored, outsourced, or automated (Peters 2011). In sum, I expect financialization to affect both the top and bottom portions of the income distribution.

3. 4. Other Structural Factors

Public sector retrenchment should push inequality higher. On this subject, sociologists show that public sector employment typically reduces income inequality (Lee, Kim, & Shim 2011; Kim & Sakamoto 2010; see also Moller, Alderson, & Nielsen 2009), ostensibly by providing good job opportunities for labor market "outsiders" and by curtailing wage dispersion between high- and low-skilled workers. During the post-war era, employment in local, state, and federal branches of government expanded for decades, climbing from 12 percent to 19 percent of all employment between 1947 and 1975 (US Bureau of Labor Statistics 2017a). Since this time, it has slowly ebbed downward, falling to 15 percent of the workforce today.

This trend should heighten inequality, but not through an interaction effect with trade union decline. Public sector retrenchment should only marginally weaken trade unions in the public sector, in part because public sector retrenchment has been less pronounced than deindustrialization, but also because public sector jobs cannot easily be offshored. Hence, I expect that the decline of public sector employment heightens inequality directly (by eliminating good jobs),

but not indirectly by undermining the organizational power of trade unions. I test this idea in Section 5.

Finally, demographic changes related pooling incomes within families should be considered. This factor is especially important since my dependent variable is derived from the family income distribution. In general, sociologists demonstrate that families headed by single mothers are positively associated with income inequality because single parents cannot pool incomes and because single mothers face unique obstacles in the labor market (Kollmeyer 2012; Moller, Alderson, & Nielsen 2009; Western, Bloome & Percheski 2008). In the late 1940s, about three percent of US families were headed by single mothers. This figure reached 12 percent in the mid-1990s, but changed little since (US Census Bureau 2018). My regression models control for this demographic factor.

4. DATA AND METHODS

To test my explanations for rising income inequality in the United States, I collect annual observations on various aspects of US society and political economy from 1947 to 2015. The data come from the Bureau of Economic Analysis, the Bureau of Labor Statistics, and the Census Bureau. I note that researchers studying the distributional effects of structural economic change must adopt a spatially broad unit of analysis, which adequately capture aggregate measures inherent to the study of distributional processes (e.g. income inequality, unemployment rate, etc.). Hence, prior studies of US income inequality use areal units ranging from metropolitan statistical areas (Lorence 1991; Lorence & Nelson 1993; Moller & Rubin 2008; Volscho 2007; Wallace, Michael, Gauchat, & Fullerton 2011) to counties and states (Brady, Baker, & Finnigan 2013; Moller, Alderson, & Nielsen 2009), to the country as a whole (Jacobs & Myers 2014; Kwon 2016; Volscho & Kelly 2012; Wallace, Leicht & Raffalovich 1999.) My research uses the latter as its unit of analysis, because I am interested in understanding broad changes, but also because national-level data extend back far enough to encompass historical periods in which unionization and industrialization generally trended upwards (post-war decades) and then generally trended downwards (1970s onward). Furthermore,

national-level data avoid thorny methodologically issues associated with the "modifiable areal unit problem."

4. 1. Dependent Variables

My study uses four measures of income inequality. Since 1947, the Census Bureau uses micro data from the March supplement of the *Current Population Survey* (CPS) to estimate the inflation-adjusted incomes of families at various percentiles of the US income distribution. From these point estimates, I calculate the ratio of incomes between families at the $95^{th}/20^{th}$, the $95^{th}/50^{th}$, and the $50^{th}/20^{th}$ percentiles of the US income distribution (US Census Bureau 2017a). I also use the Gini coefficient, as calculated by the Census Bureau, to capture inequality across the whole of American society. These estimates are based on pre-tax income, with income including salaries and wages, but also other earned sources, such as interest, rents, dividends, and business profits. They also include cash transfers (such as social security, disability, and unemployment provisions), but not in-kind transfers (such as food-stamps, medical reimbursements, and housing subsidies).

My measures of income inequality reflect several trade-offs. Since most of my data are only available annually, the study's time-span must be long enough to yield sufficient observations for statistical estimation. In this regard, the family income series is preferable to the household income series because the former starts in 1947 but the latter in 1968. Similarly, some researchers customize inequality measures using the micro data in the CPS files, but the required data start no earlier than 1964 (see National Bureau of Economic Research 2016). Again, this leads me to use the Census Bureau's pre-existing measures rather than customize my own. For similar reasons, Jacobs and Myers (2014) use the Census Bureau's Gini coefficient of family income inequality in their study of rising inequality. I use the same measure, but also including estimates of inequality between affluent and working-class families (the $95^{th}/20^{th}$ ratio), between affluent and median families (the $95^{th}/50^{th}$ ratio), and between median and working-class families (the $50^{th}/20^{th}$ ratio).

Admittedly, my use of family income data is not ideal. Using these data create a disjuncture between my theoretical ideas about the distributional effects

of market and institutional change and my measures of income inequality, which include cash transfers and pooled incomes for families with multiple breadwinners. However, to account for these aspects of my data, I control for government expenditures on social transfers and family demography related to pooling incomes. These control variables, discussed below, should absorb much of the statistical effects associated with my use of family income data.

4. 2. Independent Variables

My main independent variables capture deindustrialization, deunionization, and the offshoring of routine-production jobs. In particular, *union density* measures the percentage of the US workforce belonging to trade union. Data come from the *Statistical Abstracts of the United States* (US Census Bureau various years). *Industrial employment* measures the percentage of the US workforce employed in the industrial sector, with the industrial sector including manufacturing, mining, construction, oil and gas extraction, and similar activities. Data come from the US Bureau of Labor Statistics (2017a). *Imports from LDCs* captures the offshoring of routine production jobs to low-wage regions of the global economy. It equals the value of manufactured goods imported from LDCs as a percentage of the US GDP. The data come from OECD (2017)[1]. From these variables, I generate multiplicative interaction terms (*union density* x *industrial employment* and *union density* x *imports from LDCs)*. This allows me to test whether deindustrialization and offshoring intensify the distributional effects of trade union decline.

My models include several control variables. *Unemployment* and *inflation* control for macroeconomic factors associated with the shift from Keynesianism to neoliberalism. Data come from the US Bureau of Labor Statistics (2017b & 2017c). *Public sector employment* accounts for trends in government employment. It equals the percentage of the US workforce employed by local, state and federal government. Data come from U.S. Bureau of Labor Statistics (2017a). *Financial sector value added* accounts for the financialization of the US economy. It equals the value added in finance and real estate as a percentage of value added in the whole economy. Calculations made by author using data from the US Bureau of Economic Analysis (2017b).

I also control for technological change, but this more difficult to measure. Corrado and Hulten (2010) ask "how do you measure a technological revolution" when its effects are multi-facetted and diffuse? Their question is apt, but they offer little practical advice for researchers. Acknowledging these difficulties, I note that the distributional effects of SBTC not only reflect technological change (which heightens demand for high-skilled workers), but also improvements in educational outcomes (which heightens the supply of high-skilled workers) (see Goldin & Katz 2008). Consequently, I calculate *ICT stock / university educated* as the ratio of capital deepening in the economy's stock of ICT equipment to the percentage of Americans (25 years or older) with university degrees. For this variable, increasing values indicate that growth in ICT stock per worker is outpacing the supply of university graduates, which should push inequality higher. I try including ICT stock and university educated as separate variables, but the aforementioned ratio works better, in part because it overcomes a significant multicollinearity problem.[2] Data come from US Bureau of Economic Analysis (2017a) and from US Census Bureau (2017b).

Lastly, I control for two factors related to my use of family income data. First, *single-mother families* should increase inequality because single parents cannot pool income and because single mothers face entrenched obstacles in the labor market. This variable equals the percentage of all American families headed by single mothers. Data from the US Census Bureau (2018). Additionally, *social transfers* accounts for the inclusion of government cash payments in the Census Bureau's family income series. This variable measures aggregate cash payments, across all levels of US government, linked to social welfare programs. Figures are adjusted for inflation and population. Calculations by author using data come from the US Bureau of Economic Analysis (2018) and the US Bureau of Labor Statistics (2017c).

4. 3. Statistical Estimation

Using the time-series data described above, I use first-difference regression techniques to model change in US income inequality as a function of change in union strength, industrial employment, imports from LDCS, interaction effects, and relevant control variables. Shown in simplified form below, my model uses

Prais-Winsten estimation with robust standard errors to account for serial correlation and heteroscedasticity.

$$\Delta income\ inequality_t = b_1(\Delta union\ density_t) +$$
$$b_2(\Delta industrial\ employment_t) + b_3(\Delta union\ density_t *$$
$$\Delta industrial\ employment_t) + b_4(\Delta controls) + \varepsilon_t$$

This modelling strategy accounts for several complications associated with time-series data. One complication arises from nonstationarity (De Boef & Keele 2008; Wooldridge 2012: Chapters 11 & 18). Especially for data with a long time-series such as mine, annual observations can trend over time rather than vary randomly. When this occurs, statistically significant findings can reflect shared time trends among variables rather than underlying causal relationships (i.e. spurious regression). To examine whether my data exhibit this characteristic, I employ Dickey-Fuller tests for nonstationarity. Results suggest that my dependent variable and three independent variables are nonstationary in levels, but stationary in first differences.[3]

Given that my nonstationary variables are integrated of order one I(1), estimating my model in first differences offers an effective safeguard against spurious results. This technique entails first differencing each variable—e.g. change-score format—and then estimating the model as normal. First differencing yields conservative estimates, since information about the levels of variables is lost, but trends that may generate spurious results are removed. Additionally, first differencing mitigates against multicollinearity, which can be problem with time-series regression.

A second complication is the possibility of "non-i.i.d. errors" (Wooldridge 2012: Chapter 12). Estimation by ordinary least squares (OLS) assumes the model's errors are independent and identically distributed (i.i.d.), but models using time-series data often violate this assumption. If this occurs, OLS will yield biased standard errors, possibly leading to overly optimistic assumptions about statistical significance. To assess whether my error structure violates OLS assumptions, I run two post-estimation tests on the baseline model. The results suggest that my errors are serially correlated and heteroscedastic, but the problem is not severe.[4]

Nonetheless, to deal with these issues, I use the Prais-Winsten estimation procedure with Huber–White standard errors.

Lastly, given the time-series data, I consider whether the distributional effects of my independent variables unfold over multiple years or occur contemporaneously (Beck 1991; Wooldridge 2012: Chapter 18). The former outcome can be modelled with a "finite distributed-lag" specification, in which independent variables appear in both contemporaneous and lagged forms. I experiment with this technique, but I find no evidence of lagged effects. Hence, I use contemporaneous specification for all of my variables. Finally, to aid interpret of relative effects, I convert my variables to z-scores. This facilitates direct comparison of the parameter estimates, because now all variables share the same unit of measure (i.e. standard deviations from the mean).

5. RESULTS

5. 1 Main effects model

Table 1 begins by developing the main effects model of change in the US Gini coefficient between 1947 and 2015. To highlight the hypothesized interaction effects, I develop the main effects model in a stepwise fashion but exclude the control variables for now. To start the analysis, Model 1 shows the isolated effect of union density on income inequality, which is found to be negative, strong and highly significant. This finding is consistent with the power resource theory of trade unionism. Yet, when industrial employment and imports from LDCs are added to this bivariate model, the effect of union density declines by nearly two-thirds and becomes statistically insignificant (see Model 2). This reflects, I believe, the failure of this model to include the interaction effects I propose in Section 2.3.

Indeed, this appears to be the case. When an interaction term is added in Model 3, all the variables involved in the interaction effect become highly significant and exhibit the expected signs. In particular, the coefficient for the interaction between union density and industrial employment is negative and relatively large, suggesting that the distributional consequences of deindustrialization and deunionization primarily arise from a moderated effect. Likewise, Model 4 suggests a similar outcome with the offshoring of routine-production jobs. Here, as expected, the coefficient is positive rather than negative,

because unlike rising industrial employment, rising imports from LDCs should push inequality higher. Consequently, the expected sign is positive. Shown in the appendix, I also test whether similar interactions adhere between trade union decline and public sector retrenchment, but find no evidence to support this idea (see Table A1).

Figure 2 illustrates the importance of the interaction effects. Here, predicted and actual values of the Gini coefficient are compared after converting the variables from first differences to levels and re-estimating Models 2 and 4. Clearly, the model with interaction effects more accurately captures the steep upward rise of income inequality, which transpired over several decades even though the sharpest fall in union density occurred between the late 1970s and mid-1980s. Overall, the evidence presented in Figure 2 and Table 1 support the notion that deunionization, deindustrialization, and offshoring interact in ways that push inequality higher.

[Insert Table 1 and Figure 2 about here.]

Next, Table 2 introduces the full model and applies it to four measures of income inequality. Model 5 examines change in the Gini coefficient. Despite the introduction of the control variables, the parameter estimates for the main effects variables remain largely unchanged (cf. Model 4), suggesting that the proposed interaction effects are robust to different model specifications. Looking at the control variables, each exhibits the expected sign but many have high variances, leaving them short of statistical significance. Furthermore, the evidence points to public sector employment, financialization, and unemployment as statistically important determinants of inequality. Overall, these findings are consistent with my theoretical expectations.

Since all variables are measured in z-scores, parameter estimates can be directly compared, with the largest estimates (in absolute terms) representing the largest effects. In this regard, the largest effects are associated with my interaction terms, and the smallest effect with the *ICT stock / university educated* variable. This latter variable captures the distributional consequences of the "race between technology and education," although proponents of this argument claim it is difficult to measure (Corrado & Hulten 2010). While my findings contradict the

original SBTC framework and may reflect measurement error, they resonate with sociological research questioning the degree to which recent technological change drives inequality (see Kim & Sakamoto 2010; Kristal & Cohen 2016). Indeed, none of my models support the SBTC argument.

[Insert Table 2 about here.]

Now, I use my full model to explain income inequality between families at various points along the US income distribution. In particular, I examine inequality between affluent and working class families (via the 95th/20th ratio), between affluent and median families (via the 95th/50th ratio), and between median and working class families (via the 50th/20th ratio). Overall, the findings continue to support my argument, but highlight important differences in the ways economic change affects different parts of the income distribution.

When trade union decline occurs alongside deindustrialization and offshoring, income inequality rises substantially between affluent and working class families (Model 6) and between affluent and median families (Model 7). For these two models, the interaction effects continue to be important determinants of income inequality, highlighting the centrality of my theoretical argument for understanding change across various parts of the income distribution. However, for the 95th/20th ratio (Model 6), the interaction effect between trade union decline and rising imports from LDCs is lower in magnitude than the other relevant models (see Model 5 and 7). One interpretation of this finding is that many families at the 20th percentile are labor-market "outsiders," who are less affected by trade union decline and offshoring than families higher up the income distribution. Indeed, this explanation is consistent with Model 7, which shows that the interaction effect between declining union density and rising imports from LDCs substantially widens inequality between affluent and median families (95th/50th ratio). Note that public sector employment, financialization, and unemployment continue to be important determinants of inequality across these parts of the income distribution.

Next, I examine inequality between 50th and 20th percentiles of the income distribution (Model 8). If trade union decline, deindustrialization, and offshoring are transforming the remaining unionized portion of the US workforce into "privileged insiders" relative to their working-class counterparts, then this model

should provide some evidence of this outcome. The results, however, suggest something different. The interaction between trade union decline and falling industrial employment is now insignificant, but the interaction between trade union decline and rising imports from LDCs has reversed signs, indicating that these intertwined factors are forcing median and bottom-quintile incomes closer together. This finding suggests that recent economic change, far from creating "privileged insiders," puts downward pressure on the incomes of median earners. This idea is consistent with sociological research describing the emergence of an "hourglass economy" (Massey & Hirst 1998) fuelled by the proliferation of "bad jobs" (Kalleberg 2009, 2011) as well as economic research finding that middle-income earners are the greatest beneficiaries of unionization (Firpo, Fortin, & Lemieux 2009: 962-966).

Lastly, several findings related to the control variables are worth noting. Interestingly, unemployment and inflation become even more important determinants of inequality for this part of the income distribution. This implies that the Keynesian full-employment economy, in which low unemployment took precedence over low inflation, particularly benefited the less prosperous members of the working class (i.e. the bottom quintile), and that its demise has expanded inequality between the median and bottom-quintile of the national income distribution. Also, financialization heightens inequality more the lower part of the distribution (Model 8) than others parts of the distribution (Models 5-7). This finding is consistent with the argument that financialization not only increases top incomes, but adversely affects low-wage workers whose jobs are threatened by new management strategies associated finance-driven capitalism (Lazonick & O'Sullivan 2000; Peters 2011).

6. DISCUSSION AND CONCLUSION

The upsurge of income inequality in the United States coincides with the demise of organized labor and deep-seated changes to the US economy. Although these changes occurred contemporaneously, prior studies do not consider whether they interact in ways that magnify inequality. To fill this gap in the literature, I

theoretically develop and empirically test the argument that trade union decline, occurring along with deindustrialization and offshoring, is a significant but overlooked cause of rising income inequality in the United States. In particular, I emphasize the ways in which structural economic change not only reduces good unionized jobs, but also undermines the bargaining power of organized labor more generally. The combined effect, I argue, pushes income inequality upwards. To test this argument, I develop models of US income inequality that include interaction effects between trade union density and industrial employment and between trade union density and imports from LDCs. Based on US data from 1947 to 2015, I test my interaction effect model against four measures of income inequality. The results generally support my argument that interactions between deunionization and structural economic change decisively shape the income distribution.

My findings can be placed within the broader context of social scientific accounts of income inequality and social stratification. The literature reveals a fairly pronounced division between institutional and market accounts of inequality. By contrast, my analysis reveals that markets and institutions can intertwine in complex ways, yielding important distributional effects. This argument suggests that future research on inequality and social stratification should consider the possibility of such interactions, and how they may magnify or blunt distributional outcomes. Some scholars have moved the literature in this direction (see Kollmeyer 2015; Kristal & Cohen 2015), but more scholarship in this vein is in order.

In addition to power-resource theory, this study considers the "insider-outsider" perspective of trade unionism (see Rueda 2007). It is possible that, as technological change and outsourcing whittle away routine production jobs, the loss of unionized industrial employment disproportionately affects low- and semi-skilled workers. If this occurs, contemporary trade unions should represent more skilled workers, potentially transforming them into a social force for inequality among the working class. To examine this idea, I model change in the 50th/20th income ratio, but find little evidence of an "insider-outsider" dynamic altering this part of the income distribution. Instead, the market-institutional factors examined here seem to erode "insider-outsider" dynamics. This likely occurs because

deindustrialization, and especially the threat of offshoring, reduces the ability of unionized industrial workers to bargain for higher wages, causing their incomes to fall toward those of labor-market "outsiders." This finding is consistent with sociological conceptions of an "hourglass economy" (Massey & Hirst 1998), brought about by the proliferation of "bad jobs" (Kalleberg 2009, 2011), and with economic research showing unionization benefiting middle-income earners the most (Firpo, Fortin, & Lemieux 2009: 962-966).

I raise three more issues. My study highlights the importance of the full-employment economy as a policy mechanism for reducing inequality. The demise of Keynesianism and the rise of neoliberalism changed the macroeconomic priorities of US policymakers, moving them away from a concern with unemployment toward a concern with inflation. This policy shift partially reflects the exigencies of globalization, in particular the growing power of mobile capital, which cares greatly about sound money but much less about joblessness. By linking neoliberalism with changing macroeconomic outcomes, my study illustrates useful ways to gain analytical leverage on questions concerning neoliberalism and inequality. This could create fruitful lines of enquiry for those interested in melding economic, political, and sociological accounts of inequality.

My study also contributes to debates on skill-biased technological change. Clearly, the Information Revolution altered the American workplace, and clearly many of these changes have distributional consequences, but it does not necessarily follow that technological change altered inequality at the aggregate level. It is my contention that the lack of support for the SBTC theory, both here and elsewhere, reflects the fact that computer-driven technological change often generates offsetting and cross-cutting distributional effects, because it reduces demand for workers across a broad range of occupational categories. When these disparate effects are aggregated, the cumulative effect is attenuated. Furthermore, it is important to note that technological change can reduce labor's share of national income, as Kristal (2013) shows, even though its overall effect among American workers is modest.

Lastly, I consider whether my findings would hold in other advanced capitalist countries. To assess this question, one must recall that the proposed

interaction effects arise when structural economic change deunionizes large swaths of the workforce, and undermines the power of remaining trade unions. While deindustrialization, capital mobility, and service sector expansion complicate matters for trade unions everywhere (Dølvik & Waddington 2004), trade unions in Western Europe have more effectively navigated this new economic environment. This is the case partially because trade unions in Europe benefit from structural features absent from the US political economy—for example, centralized wage bargaining, policy concertation, left-labor party support, and codetermination. These supports help them to retain bargaining and organizational power, even when their membership rolls decline. Hence, I suspect that my argument is most applicable to the United States, but more research could help settle this question.

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END NOTES

1. Manufactured imports from LDCs are defined as follows. LDCs are non-OECD countries plus Mexico and Turkey. Manufactured goods are categories five through nine of the international standard industrial classification (ISIC) scheme, revision.

2. Data on imports come from OECD (2017), but only go back to 1960. Consistent with globalization literature, values are close to zero in the early 1960s. Hence, I extend the series back to 1947 by replacing missing data with zero values.

2. Measured in levels, the variable *ICT stock* and *% university educated* are correlated at .975.

3. The *dfuller* command in Stata assesses a null hypothesis that a variable contains a unit-root (i. e. a nonstationary series). Based on this test, the variables *income inequality, union density, industrial employment,* and *ICT stock / university educated* are deemed nonstationary.

4. Using the *estat dwaston* command in Stata, I run a Durbin-Watson test on the null hypothesis of uncorrelated errors for Model 5. This null hypothesis cannot be rejected (p=. 23). Next, using the *estat hettest* command, I run a Breusch-Pagan test on the null hypothesis that the errors have a common variance for Model. This null hypothesis cannot be rejected (p=. 52).

Figure 1. Gini Coefficient of Income Inequality in the United States, 1947 to 2015
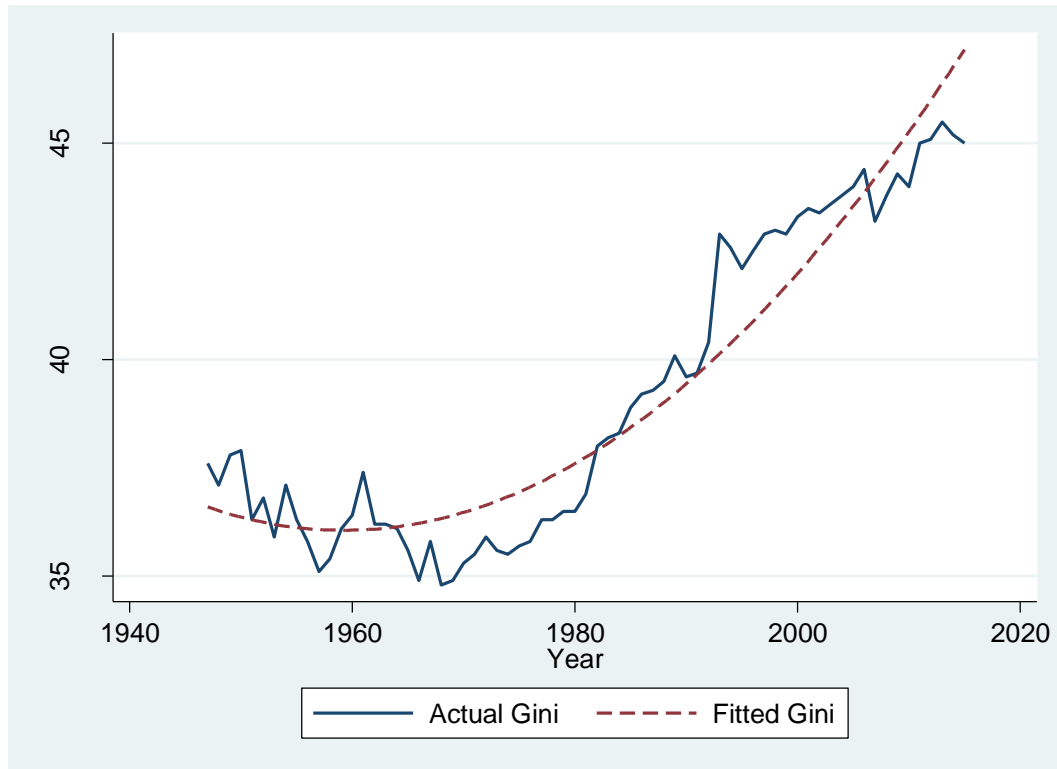
Note: Data from the historical tables of the *Current Population Survey* (US Census Bureau 2017a). Fitted curve based on fractional polynomial regression.

Figure 2. Predicted versus Actual Income Inequality
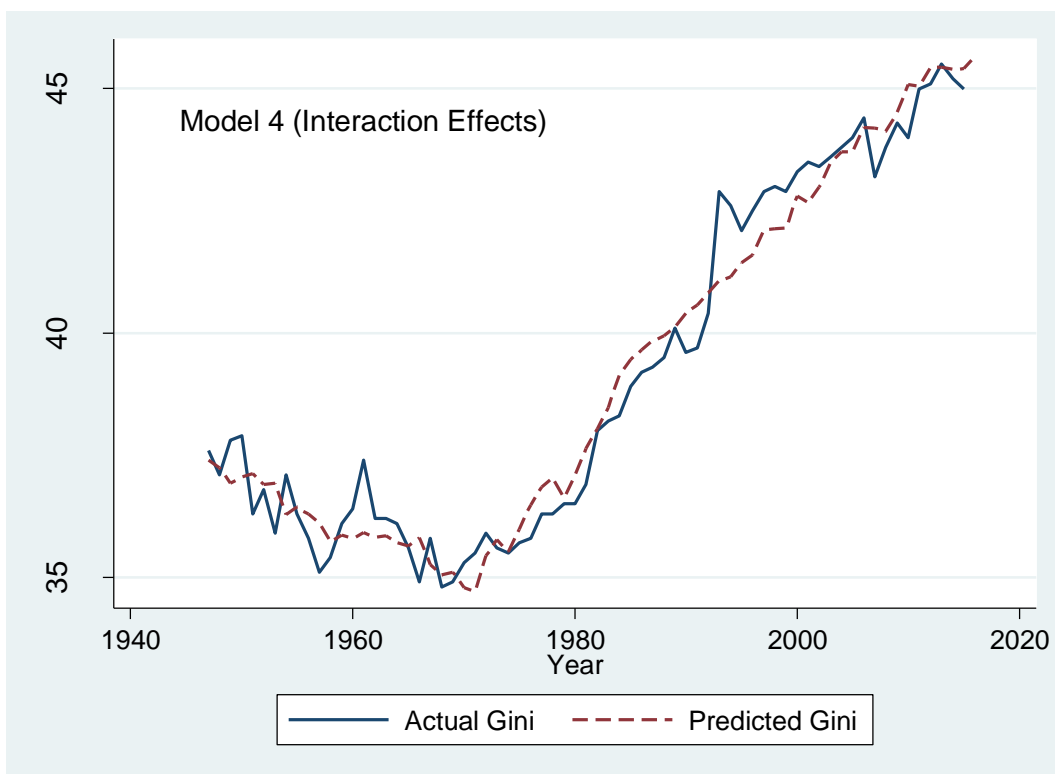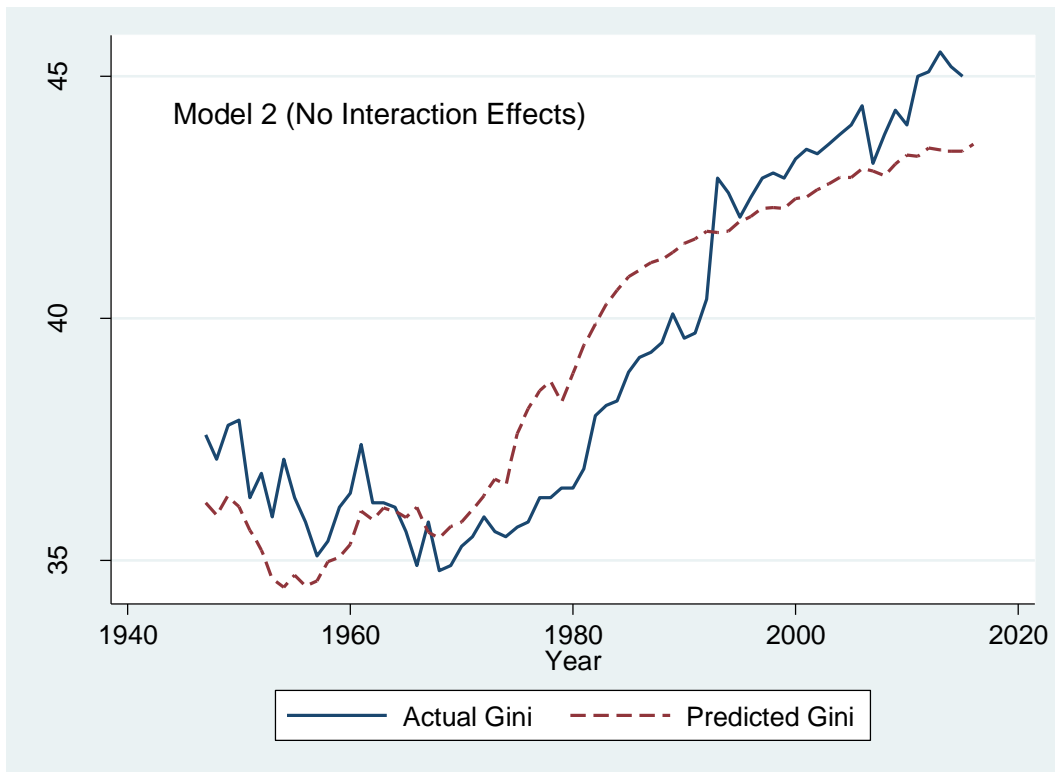
Table 1. Main Effects: First-Difference Regression Estimates of Income Inequality: 1947 to 2015.

	Δ Gini Coefficient			
	(1)	(2)	(3)	(4)
Δ Union density	-.633***	-.227	-.428*	-.586**
	(.178)	(.252)	(.255)	(.227)
Δ Industrial employment		-669**	-.916***	-.823***
		(.293)	(.311)	(.305)
Δ Imports from LDCs		.242	.214	.731*
		(.169)	(.174)	(.388)
Δ Union density x Δ Industrial employment			**-3.979****	**-4.381****
			(1.792)	**(1.707)**
Δ Union density x Δ Imports from LDCs				**9.569***
				(5.852)
N	68	68	68	68
R-squared	.13	.22	.26	.35
Durbin-Watson stat. (original)	2.46	2.34	2.27	2.35
Durbin-Watson stat. (transformed)	2.03	2.02	2.01	1.99

Note: Numbers in parentheses are robust standard errors. All variables converted to z-scores.

*= p < .10; ** = p < .05; *** = p < .01.

Table 2. Full Model: First-Difference Regression Estimates of Four Measures of Income Inequality: 1947 to 2015.

	Δ Inequality Measure			
	(5) Gini	(6) 95/20	(7) 95/50	(8) 50/20
Main Effects				
Δ Union density	-. 505*	-.213	-. 390	.377
	(. 271)	(.290)	(. 325)	(.460)
Δ Industrial employment	-. 419	-.110	-.107	.054
	(.545)	(.482)	(. 547)	(.984)
Δ Imports from LDCs	.839*	.387	.605**	-.252
	(.421)	(.254)	(.238)	(.283)
Δ Union density x Δ Industrial employment	**-4.431****	**-3.251***	**-3.541****	**-1. 228**
	(1. 950)	**(1.703)**	**(1. 696)**	**(3.137)**
Δ Union density x Δ Imports from LDCs	**9.047***	**3.245**	**8.465****	**-9.572***
	(5.109)	**(3.815)**	**(3.375)**	**(5.121)**
Other Factors				
Δ Unemployment	. 118***	.154***	. 092**	. 222**
	(. 038)	(.038)	(. 044)	(.106)
Δ Inflation	-.018	-.031	-. 018	-. 187***
	(. 023)	(.020)	(. 022)	(. 047)
Δ Public sector employment	-. 237*	-.285**	-. 302**	-.347
	(.132)	(.111)	(. 149)	(. 289)
Δ Financial sector value added	. 227	.391**	.467***	. 575*
	(. 190)	(.164)	(. 166)	(. 317)
Δ ICT stock to university graduates	. 073	.029	. 016	.211
	(.059)	(.039)	(.066)	(.160)
Δ Single-mother families	. 202	.231	.109	.206
	(. 185)	(.183)	(. 072)	(.380)
Δ Social transfers	-.204	-.263	-.215	-.842**
	(.107)	(.162)	(.169)	(.365)
N	68	68	68	68
R-squared	.50	.56	.42	. 54
Durbin-Watson stat. (original)	2. 41	2.20	2.11	2. 29
Durbin-Watson stat. (transformed)	2. 04	2.03	2.03	2. 02

Note: Numbers in parentheses are robust standard errors. All variables converted to z-scores.

*= p < .10; ** = p < .05; *** = p < .01.

Table A1. Public Sector Employment: First-Difference Regression Estimates of Four Measures
of Income Inequality: 1947 to 2015.

	Δ Gini Coefficient			
	(9)	(10)	(11)	(12)
	Gini	95/20	95/50	50/20
Δ Union density	-.089	-.020	.007	.217
	(.300)	(. 240)	(.307)	(.401)
Δ Public sector employment	-.277*	-.323**	-.377**	-.417*
	(.148)	(.121)	(.157)	(.248)
Δ Union density x Δ Public sector employment	.716	.622	.564	-.087
	(.715)	(.551)	(.571)	(1.051)
N	68	68	68	68
R-squared	.39	.53	.26	.51
Durbin-Watson stat. (original)	2.31	2.13	2.27	2. 38
Durbin-Watson stat. (transformed)	2.01	2.01	2.01	2.11

Note: Numbers in parentheses are robust standard errors. All variables converted to z-scores. Full battery of control variables included but not reported.
*= $p < .10$; ** = $p < .05$; *** = $p < .01$.