The Fall of the Labor Share and the Rise of Superstar Firms*

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Abstract

The fall of labor's share of GDP in the United States and many other countries in recent decades is well documented but its causes remain uncertain. Existing empirical assessments of trends in labor's share typically have relied on industry or macro data, obscuring heterogeneity among firms. In this paper, we analyze micro panel data from the U.S. Economic Census since 1982 and international sources and document empirical patterns to assess a new interpretation of the fall in the labor share based on the rise of "superstar firms." If globalization or technological changes advantage the most productive firms in each industry, product market concentration will rise as industries become increasingly dominated by superstar firms with high profits and a low share of labor in firm value-added and sales. As the importance of superstar firms increases, the aggregate labor share will tend to fall. Our hypothesis offers several testable predictions: industry sales will increasingly concentrate in a small number of firms; industries where concentration rises most will have the largest declines in the labor share; the fall in the labor share will be driven largely by between-firm reallocation rather than (primarily) a fall in the unweighted mean labor share within firms; the between-firm reallocation component of the fall in the labor share will be greatest in the sectors with the largest increases in market concentration; and finally, such patterns will be observed not only in U.S. firms, but also internationally. We find support for all of these predictions.

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I Introduction

Much research has documented a decline in the share of GDP going to labor in many nations over recent decades (e.g., Blanchard, 1997; Elsby, Hobjin and Sahin, 2013; Karabarbounis and Neiman, 2013; Piketty 2014). Dao et al. (2017) point to a decline in the labor share between 1991 and 2014 in 29 large countries that account for about two-thirds of world GDP in 2014. Figure 1 illustrates this general decline in labor's share with the fall in the United States particularly evident since 2000. The erstwhile stability of the labor share of GDP throughout much of the twentieth century was one of the famous Kaldor (1961) "stylized facts" of growth. Macro-level stability of labor's share was always, as Keynes remarked, "something of a miracle," and indeed disguised a lot of instability at the industry level (Elsby, Hobijn and Sahin, 2013; Jones, 2003). Karabarbounis and Neiman (2013) emphasize that the decline in labor's share both in the U.S. and overseas represents primarily a within-industry rather than a between-industry phenomenon. Although there is controversy over the degree to which the fall in the labor share of GDP is due to measurement issues such as the treatment of capital depreciation (Bridgman, 2014), housing (Rognlie, 2015), self-employment and proprietor's income (Elsby, Hobjin, and Sahin, 2013; Gollin, 2002) and intangible capital (Koh, Santaeulalia-Lopis and Zheng, 2016), there is a general consensus that the fall is real and significant.

There is less consensus, however, on what are the *causes* of the recent decline in the labor share. Karabarbounis and Neiman (2013) put forward the argument that the cost of capital relative to labor has fallen, driven by rapid declines in quality-adjusted equipment prices especially of Information and Communication Technologies (ICT). Although such a relative capital price decline should have no effect on factor shares if production technologies are Cobb-Douglas, there will be a decline in the labor share if the capital-labor elasticity of substitution is greater than one. Karabarbounis and Neiman provide some evidence that the elasticity is greater than one, but the bulk of the empirical literature suggests an elasticity of below one (e.g., Lawrence, 2015; Oberfield and Raval, 2014; Antras, 2004; Hamermesh, 1990), casting some doubt on this explanation.[1] Another implication of models based on representative firms (even at the industry level) is that the fall in labor's share should primarily occur *within* firms as the fall in relative factor prices is something that all firms face simultaneously. We will show, by contrast, that the fall in the aggregate labor share has a large element of reallocation *between* firms with shifts in output toward firms with low

[1] Piketty (2014) also argues for a high capital-labor elasticity in his $r > g$ formulation, but again evidence for this view is limited.

(and declining) labor shares.

Elsby, Hobjin and Sahin (2013) argue for the importance of trade and international outsourcing, and they present evidence indicating that the labor share declines the most in U.S. industries that were strongly affected by increasing imports (e.g., from China). We explore the role of trade as well, but do not find that manufacturing industries with greater exposure to exogenous trade shocks differentially lose labor share relative to other manufacturing industries (although they do decline in terms of employment). Additionally, we observe similar patterns of a decline in labor's share in largely non-traded sectors such as wholesale trade, retail trade, and utilities. Elsby, Hobjin and Sahin (2013) and Piketty (2014) also stress the role of social norms and labor market institutions, such as unions and the real value of the minimum wage. The common experience of a decline in labor shares across countries with different levels and evolution of unionization and other labor market institutions somewhat vitiates against this argument.[2]

Our contribution is threefold. First, we provide microeconomic evidence on the evolution of labor shares at the firm and establishment level. The existing empirical evidence is largely based on macroeconomic and industry-level variation which makes it harder to shed light on the distinctive implications of competing theories, particularly the contrasts between theories implying heterogeneous vs. homogeneous changes in the labor share across firms in an industry.[3] Second, we present a new "superstar firm" model of the labor share change. The model is based on the idea that industries are increasingly characterized by a "winner take most" feature where a small number of firms gain a very large share of the market. A possible explanation for this phenomenon is that consumers have become more sensitive to price and quality due to greater product market competition (e.g., through globalization) or new technologies (e.g., if consumers or corporate buyers become more sensitive to price due to greater availability of price comparisons on the Internet, as in Akerman, Leuven and Mogstad, 2017). Stronger network effects are a related explanation for the increasing dominance of companies such as Google, Facebook, Apple, Amazon, Uber, AirBNB, Walmart, and Federal Express in their sectors. The superstar firm model emphasizes firm heterogeneity in the evolution of industry-level and aggregate labor share. Third, we present an array of evidence consistent with the superstar firm model over the last 30 years using a variety of datasets, including firm- and establishment-level U.S. Census panel data covering the six major sectors of

[2] Blanchard (1997) and Blanchard and Giavazzi (2003) stress labor market institutions. Azmat, Manning and Van Reenen (2012) put more weight on privatization at least in the network industries.

[3] An exception is Bockerman and Maliranta (2012) who use longitudinal plant-level data to decompose changes in the labor share in Finnish manufacturing into between and within plant components.

manufacturing, retail trade, wholesale trade, services, utilities and transportation, and finance.

We establish the following facts that are broadly consistent with our model's predictions for how the rise of superstar firms can lead to a fall of labor's share: (i) there has been a rise in sales concentration within four-digit industries across the vast bulk of the U.S. private sector; (ii) industries with larger increases in product market concentration have experienced larger declines in the labor share; (iii) the fall in the labor share is largely due to the reallocation of sales between firms rather than a general fall in the labor share within incumbent firms; (iv) the reallocation-driven fall in the labor share is most pronounced in precisely the industries which had the largest increase in sales concentration; and (v) these patterns are also present in firm- and industry-level datasets from other OECD countries. Although we do not provide clean causal identification of our superstar firm model, the facts we document push us towards a somewhat neglected firm-level perspective on the changes in the labor share (Furman and Orszag, 2015).[4]

Our paper is closest to Barkai (2016), who independently discovered a negative industry-level relationship between changes in labor share and changes in concentration for the United States. Barkai also presents evidence at the aggregate level that profits appear to have risen as a share of GDP and that the pure capital share of income (defined as the value of the capital stock times the required rate of return on capital over GDP) has fallen, a pattern consistent with our superstar firm model.[5] His analysis uses exclusively industry and macro data. A major difference is that we can delve in depth into the firm-level reasons for these patterns and link it to our model, particularly the implications and evidence on between-firm (output reallocation) versus within-firm contributors to falling industry- and aggregate-level labor share. We thus view our contribution and that of Barkai (2016) as complementary.[6]

The structure of the paper is as follows. Section II sketches our model. Section III presents the data and Section IV the results. Section V provides concluding remarks. More details on the model and data are in Appendices A and B respectively.

[4] Berkowitz, Ma and Nishioka (2017) also stress how an increase in market power could generate a decline in the labor share and find some evidence in support of this in Chinese micro-data.

[5] In this paper we focus on the labor share of value added as it is empirically difficult to separate out the non-labor share into the part due to profits (Π) and the part due to to capital costs evaluated at the competitive return (rK). Similarly, it is challenging to map profits in company accounts to economic profits. Nevertheless, in a large sample of firms across many countries, Dobbs et al. (2015) do find that accounting profits rose as a share of GDP risen from 7.6% to 9.8% between 1980 and 2013.

[6] Barkai (2016) finds an even larger role for rising concentration in accounting for the fall in the aggregate labor share. This is likely because his data covers only the latter half of our sample period (omitting the 1982-1997 period) and pools across all sectors (while we allow the effects of concentration on the labor share to be industry specific).

II An Illustrative Model of Superstar Firms

To provide intuition for why the fall in labor share may be linked to the rise of superstar firms, we consider a production function $Y_i = A_i V_i^{1-\alpha} K_i^{\alpha}$ where Y_i is value-added, V_i is variable labor, K_i is capital and A_i is Hicks-neutral efficiency (TFPQ) in firm i.[7] Consistent with a wealth of evidence, we assume that A_i is heterogeneous across firms (Melitz, 2003; Hopenhayn, 1992). More productive, higher A_i firms will have higher levels of factor inputs and greater sales. We follow Bartelsman, Haltiwanger and Scarpetta (2013) in assuming that there is a fixed amount of overhead labor F needed for production,[8] so total labor is given by $L = V + F$. Factor markets are assumed to be competitive (with wage w and cost of capital r), but we allow for imperfect competition in the product market. From the static first order condition for labor we can write the share of labor costs (wL_i) in nominal value-added ($P_i Y_i$) as:

$$S_i \equiv \left(\frac{wL_i}{P_i Y_i}\right) = \frac{1-\alpha}{\mu_i} + \frac{wF}{P_i Y_i} \tag{1}$$

where $\mu_i = (P_i/c_i)$ is the mark-up, the ratio of product price P_i to marginal cost c_i. The firm i subscripts indicate that for given economy-wide values of (α, w, F), a firm will have a lower labor share if (i) its mark-up is higher and/or (ii) its share of fixed labor costs in total value-added is lower. Superstar firms (those with high A_i) will be larger as they produce more efficiently and capture a higher share of industry output. They will also therefore tend to have lower labor shares.

In some models of imperfect competition, there are larger price-cost mark-ups for firms with a higher market share $\omega_i = P_i Y_i / \sum_i (P_i Y_i)$. For example, the homogeneous product Cournot model generates a mark-up $\mu_i = \frac{\rho}{\rho - \omega_i}$, where ρ is the absolute value of price elasticity of demand. In monopolistically competitive models the mark-up is the same across firms in an industry, $\mu = \frac{\rho}{\rho-1}$, but because high A_i firms are larger, they will have a lower share of fixed costs in value-added $\frac{wF}{P_i Y_i}$, and so their overall labor share will be lower. In either case, when there is an exogenous shock that favors more productive firms and thereby in equilibrium allocates more market share to superstar firms, the aggregate labor share will fall from a reallocation effect between firms as the weight of the economy shifts to the larger, low labor share firms.

[7] We treat output and value-added interchangeably here as we are abstracting away from intermediate inputs. We distinguish intermediate inputs in the empirical application. We model firm heterogeneity in terms of efficiency, but our model is broadly isomorphic to ones where firms are exogenously heterogeneous in firm specific quality. In such an alternative interpretation, superstar firms would have a particularly high product quality draw.

[8] Adding in a fixed cost in capital makes no qualitative difference to any of the results below. Aggregate capital costs (evaluated at the competitive rate of return) as a share of value added will also fall alongside the labor share as the profit share rises (see Barkai, 2016).

Appendix A formalizes this idea in a simple example of a superstar firm model in a monopolistically competitive setting. Entrepreneurs enter an industry and are *ex ante* uncertain of their productivity A_i. They can pay a sunk cost of entry κ and then take a draw from a known productivity distribution. Since there is a fixed cost of production, some low productivity firms will then choose to exit. If they choose to remain in the industry and produce, the high productivity firms will employ more inputs and enjoy a higher market share. In the presence of fixed overhead labor costs the more productive firms will also have higher revenue-based TFP (TFPR), as shown in Bartelsman, Haltiwanger and Scarpetta (2013). The implication is that more productive firms will have a higher share of profits in value-added and hence a lower labor share. The degree of concentration in the industry will depend, inter alia, on the degree of competition as measured by consumer sensitivity to prices. If consumers or corporate buyers become more sensitive to price, relatively more output will be allocated to the more productive firms. This reallocation of market share will increase the degree of sales concentration and will be a force decreasing the labor share because a larger fraction of output is being produced by more productive "superstar" firms.[9]

An increase in product market competition (i.e. ρ up) will lead the high productivity superstar firms to capture a larger share of the market. Several predictions follow from a rise in ρ that we can take to the data: (i) within-industry concentration rates of firm sales will rise; (ii) in those industries where concentration rises the most, labor shares will fall the most; (iii) the fall in the labor share will have a substantial reallocation component between firms, rather than being a purely within-firm phenomenon; (iv) in those industries where concentration rises the most, the reallocation from firms with high to low labor shares will be the greatest; (v) similar patterns of changes in concentration and labor's share should be found across countries (to the extent that the shock that benefits superstar firms is global). We take these predictions to a series of newly constructed micro-datasets in the United States and around the world.

Our stylized model is meant to illustrate our intuition about the connection of the rise of superstar firms and decline in labor's share. Similar results could occur from any force that makes the industry more concentrated—more "winner take most"—such as an increased importance of

[9] Note that for an individual firm the change in labor share is actually likely to be positive, as increased competition will put downward pressure on the profit margins of firms (and therefore increase the labor share) as in equation (1). Indeed, employer market power was emphasized by Kalecki (1938) as the reason for variations in labor shares over the business cycle. Our key difference is that we have a heterogeneous (rather than representative) firm model, as in Demsetz (1973). Indeed, we show below that for five of our six sectors, there is actually a *rise* in incumbent firm's labor share over time which is consistent with an increase in competition. Appendix A discusses conditions under which the aggregate labor share will fall after an increase in competition.

network effects, as long as high market share firms have lower labor shares.[10] A high level of concentration does not necessarily mean that there is persistent dominance—one dominant firm could swiftly replace another as in standard neo-Schumpeterian models of creative destruction (Aghion and Howitt, 1992). But dynamic models could create incumbent advantages for high market share firms. Such a phenomenon could occur through innovation incentives—as in the Gilbert and Newbery (1982) model, where incumbents are more likely to innovate than entrants. A more sophisticated version of these ideas is found in Acemoglu and Hildebrand (2017), who develop a Klette and Kortum (2004) style model that generates persistent dominance through innovation incentives. A more worrying explanation of growing concentration would be if incumbent advantage were enhanced through erecting barriers to entry (e.g., the growth of occupational licensing highlighted by Kleiner and Krueger, 2013, or a weakening of anti-trust enforcement). Explanations for growing concentration from regulatory entry barriers have starkly different welfare implications than explanations based on stronger enhanced competition or innovation. We partially assess these alternative explanations of growing sales concentration by examining whether changes in concentration are larger in dynamic industries (where innovation is increasing) or in declining sectors.

Finally, one could imagine that the increase in concentration does not arise from an increase in competition, but rather from an increase in the sunk costs of entry, κ. Increased entry barriers would mean that there are fewer firms in the industry, profit mark-ups are larger, and the labor share declines as average margins rise.[11] However, in this case, we would predict that the fall in the labor share is a *within*-firm phenomenon as all incumbent firms benefit from higher equilibrium prices deriving from greater entry barriers. We shall see below that, instead, the reallocation component between firms is a central factor in the fall of the labor share.

III Data

We next describe the main features of our data. Further details on the datasets are contained in Appendix B.

[10] If, for example, the underlying distribution of entrepreneurial ability becomes more skewed, the industry will also become more concentrated.

[11] The interpretation of the relationship between profit margins and the concentration level is a classic issue in industrial organization. In the Bain (1951) "Structure-Conduct-Performance" tradition, higher concentration reflected greater entry barriers which led to an increased risk of explicit or implicit collusion. Demsetz (1973), by contrast, posited a "Differential Efficiency" model closer to ours, where increases in competition allocated more output to more productive firms. In either case, however, concentration would be associated with higher profit shares of revenue and, in our context, a lower labor share. See Schmalensee (1987) for an effort to empirically distinguish these hypotheses.

III.A Data Construction

The data for our main analysis come from the U.S. Economic Census, which is conducted every five years and surveys all establishments in selected sectors based on their current economic activity. Specifically, we focus on the Economic Census for the three decade interval of 1982 - 2012 for six large sectors: manufacturing, retail trade, wholesale trade, services, finance, and utilities and transportation.[12] The covered establishments in these six sectors comprise approximately 80 percent of total private sector employment. To implement our industry-level analysis, we assign each establishment in each year to a 1987 SIC-based time-consistent industry code, the details of which are described in Appendix B. We are able to observe 676 industries, 388 of which are in manufacturing.

For each of the six sectors, the Census reports each establishment's total annual payroll, total output, total employment, and, importantly for our purposes, an identifier for the firm to which the establishment belongs. Annual payroll includes all forms of paid compensation, such as salaries, wages, commissions, sick leave, and also employer contributions to pension plans, all reported in pre-tax dollars. The Census of Manufacturing also includes a wider definition of compensation that includes all fringe benefits, the most important of which is employer contributions to health insurance, and we also present results using this broader measure of labor costs.[13] The exact definition of output differs based on the nature of the industry, but the measure intends to capture total sales, shipments, receipts, revenue, or business done by the establishment.

In addition to payroll and sales which are reported for all sectors, the Census of Manufacturing further includes information on value-added at the establishment level. Value-added is calculated by subtracting the total cost of materials, supplies, fuel, purchased electricity and contract work from the total value of shipments, and then adjusting for changes in inventories over that year. Thus, we can present a more in-depth analysis of key variables in manufacturing.

Because industry definitions have changed over time, we construct a consistent set of industry definitions for the full 1982-2012 period (as is documented in Appendix B). We build all of our industry-level measures using these time-consistent industry definitions, and thus our measures

[12] Within these six sectors, several industries are excluded from the Economic Census: rail transportation is excluded from transportation; postal service is excluded from wholesale trade; funds, trusts and other financial vehicles are excluded from finance; and schools (elementary, secondary, and colleges), religious organizations, political organizations, labor unions and private households are excluded from services. The Census also does not cover government-owned establishments within the covered industries. We also drop some industries in Finance, Services, and Manufacturing that are not consistently covered across these 6 sectors. See Appendix B for details.

[13] Additional compensation costs are only collected for the subset of Census establishments in the Annual Survey of Manufacturers (ASM), but are imputed by the Census Bureau for the remainder.

of industry concentration differ slightly from published statistics. The correlation between our calculated measures and those based on published data is almost perfect, however, when using the native but time-varying industry definitions.[14]

We supplement the U.S. Census-based measures of industry labor share and industry concentration with additional international datasets. First, we draw on KLEMS (see O'Mahony and Timmer, 2009, http://www.euklems.net/), an industry level panel dataset covering OECD countries since 1980. We use the KLEMS to measure international trends in the labor share and also to augment the measurement of the labor share in the Census by exploiting KLEMS data on intermediate service inputs (see Appendix B).

Second, we use data on industry imports from the UN Comtrade Database from 1992-2012 to construct adjusted measures of industry concentration that account for changes in the size of the domestic market. To compare these data to the industry data in the Census, we convert six-digit HS product codes to 1987 SIC codes using a crosswalk from Autor, Dorn and Hanson (2013), and slightly aggregate industries to obtain our time-consistent 1987 SIC-based codes. Our approach yields for each industry a time series of the dollar value of imports from six country groups.[15]

Third, to examine the relationship between sales concentration and the labor share internationally, we turn to a database of firm-level balance sheets from 14 European countries that covers the 2000-2012 period. The data, compiled by the European Central Bank's Competitiveness Research Network (CompNet), draws on various administrative and public sources across countries, and aims at collecting information for all non-financial corporations.[16] This source aggregates data from all firms and provides aggregate information on the labor share and industry concentration for various two-digit industries. Although great effort was made to make these measures comparable across countries, there are some important differences that affect the reliability of cross-country comparisons.[17] Consequently, we estimate specifications separately for each country.

Finally, to implement firm level decompositions internationally, we use the BVD Orbis database to obtain panel data on firm-level labor shares in the manufacturing sectors of six European coun-

[14] One minor difference emerges because we drop a handful of establishments that do not have the LBDNUM identifier variable, which is needed to track establishments over time.

[15] The six country groups are Canada, eight other developed countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland), Mexico and CAFTA, China, all low income countries other than China, and rest of the world.

[16] See Lopez-Garcia, di Mauro and CompNet Task Force (2015) for details.

[17] Most importantly, for our purposes, countries use different reporting thresholds in the definition of their sampling frames. For example, the Belgian data cover all firms, while French data include only firms with high sales, and the Polish data cover only firms with more than five employees. Consequently, countries differ in the fraction of employment or value-added included in the sample.

tries for private and publicly listed firms. BVD Orbis is the best publicly available database for comparing firm panels across countries (Kalemli-Ozcan, Sorensen, Villegas-Sanchez, Volosovych and Yesiltas, 2015).[18]

III.B Initial Data Description

Figure 1 plots labor's share of value-added since the 1970s in 12 developed countries. A decline in the labor share is evident in almost all countries, especially in the later part of the sample period.[19] Focusing in on the United States, Figure 2 presents labor's share of value-added in U.S. manufacturing. The figure includes three measures of labor's share. We first construct the labor share using payroll, which is the standard labor cost measure that is available for all sectors, as the numerator and value-added in the denominator. We modify this baseline measure to include a broader measure of compensation that includes non-wage labor costs (such as employer health insurance contributions), which are only provided in the Census of Manufacturing and not the other parts of the Economic Census. Lastly, we also plot payroll normalized by sales, rather than value-added, as this is the measure that can be constructed beyond manufacturing. Figure 2 shows the levels vary across these three measures, but all three series show a clear downward trend.

To what extent is manufacturing different from other sectors? We do not have firm-level measures of value-added data from the Census outside of manufacturing, so we have to use the cruder measure of the ratio of payroll to sales. The benefit of this measure is that it can be computed for all six broad sectors covered in the Census. The ratio of payroll to sales is plotted separately for each sector in the panels of Figure 3. Finance stands out as the only sector where there is a clear upwards trend in the labor share. In all non-financial sectors, there has been a fall in the labor share since 2002—indeed the labor share is lower at the end of the sample than at the beginning in all sectors except wholesale (where there is a rise followed by a fall). One other feature is that the 1997-2002 period stands out as a notable deviation from the overall downward trend, as the labor share rose in all sectors except manufacturing, and even here the secular downward trend temporarily stabilized. One possible explanation for this temporary deviation is that the late 1990s was an unusually strong period for the labor market with high wage and employment growth.

[18] Unfortunately BVD Orbis does not contain data that can readily be used to comprehensively construct reliable sales concentration measures due to partial reporting of revenues.

[19] Of the 12 countries, Sweden and the UK seem the exceptions with no clear trend. Bell (2015) suggests that the UK does have a downward trend in the labor share when the data is corrected for the accounting treatment of payments into (under-funded) private pension schemes for retirees. Payments into these schemes, which benefit only those workers who have already retired, are counted as current labor compensation in the national accounts data, therefore overstating the non-wage compensation of current employees.

We next turn to concentration in the product market, which in the superstar firm model should be connected with the decline in the labor share. We measure industry concentration as (i) the fraction of total sales that is accrued by the four largest firms in an industry (denoted CR4), (ii) the fraction of sales accrued by the 20 largest firms (CR20), and (iii) the industry's Herfindahl-Hirschman Index (HHI).[20] In addition, we also compute the CR4 and CR20 concentration measures based on employment rather than sales. Following Autor, Dorn, Katz, Patterson and Van Reenen (2017), Figure 4 plots the average sales- and employment-based CR4 and CR20 measures of concentration across four-digit industries for each of the six major sectors. Appendix Figure A.1 shows a corresponding plot for the Herfindahl-Hirschman Index (denoted HHI). Figure 4 shows a remarkably consistent pattern. First, there is a clear upward trend over time—according to all measures, industries have become more concentrated on average. Second, the trend is much stronger when measuring concentration in sales rather than employment. This suggests that firms may attain large market shares with relatively few workers - what Brynjolfsson, McAfee, Sorrell and Zhou (2008) term "scale without mass." Third, a comparison of Figure 4 and Figure A.1 shows that the upward trend is slightly weaker for the HHI, presumably because this metric is giving some weight to concentration among firms outside the top 20 where concentration has risen less. Table 1 provides descriptive statistics for sample size, labor share, and sales concentration in each of the six sectors.

Finally, before more formally exploring the implications of the model, we present preliminary evidence of the cross-sectional relationship between firm size and labor share. As discussed in Section II, superstar firms produce more efficiently and therefore are both larger and have lower labor shares. Figure 5 shows the relationship between a firm's labor share, defined as the ratio of payroll to sales, and the firm's share of their industry's annual sales. The figure shows that across most sectors, there is a negative relationship between labor share and firm size, supporting the model's prediction that large firms have lower labor shares.

[20] Since we calculate concentration at the industry level, we define a firm as the sum of all establishments that belong to the the same parent company and industry. If a company has establishments in three industries, it will be counted as three different firms in this analysis. About 20% of manufacturing companies span multiple industries.

IV Results

IV.A Concentration and the Fall of the Labor Share

Manufacturing

Table 2 presents the results of regressing the change in the labor share on the change in industrial concentration for our sample window of 1982 through 2012. We begin with the manufacturing sector as these data are richest, but then move on to results from the other sectors. We estimate OLS regressions for each of the six sectors separately of the form:

$$\Delta S_{jt} = \alpha \Delta CONC_{jt} + \tau_t + u_{jt} \tag{2}$$

where S_{jt} is the labor share of industry j at time t , $CONC_{jt}$ is a measure of sales concentration, τ_t is a full set of time dummies and u_{jt} is an error term. We allow for the standard errors to be correlated over time by clustering at the industry level.

All cells in Table 2 show estimates of α from equation (2). The first three columns present five-year long differences (Δ) and the last three columns present ten-year long-differences. The coefficients are comparable across the two blocks of results as both sides are scaled in the same way.

Our baseline specification in row 1 indicates the relationship between changes in concentration and changes in the share of payroll in value-added. The results are striking: across all specifications, industries where concentration rose the most were also those where the labor share fell by the most. These correlations are statistically significant at the 10% level or greater in all columns.[21]

The other rows of Table 2 present various robustness tests of this basic association. In row 2, we use a broader measure of labor compensation that includes employer contributions to fringe benefits such as private health insurance. Non-wage costs such as employer contributions to health insurance and private pensions account for a growing fraction of labor costs (Pessoa and Van Reenen, 2013). Row 3 uses an adjusted value-added measure. While the value-added measure in the Census deducts materials from gross output, it does not reflect all intermediate service inputs. We use information from the KLEMS data to correct our value-added measure for use of intermediate services (see Appendix B for details), and again find robust results. We present a stringent robustness test of the model in row 4 by including a full set of four-digit industry dummies, thus allowing for

[21] The HHI results are the most imprecise, presumably because, as noted above, they give some weight to concentration levels of the firms outside the top 20, which are unlikely to have "superstar" characteristics.

different trends in concentration by industry and therefore obtaining identification exclusively from acceleration or deceleration of labor shares and concentration over and above these trends. The coefficients on concentration remain significant with larger point estimates than row 1.

A concern with our core measure of concentration is that it captures exclusively domestic U.S. concentration levels and thereby overstates effective concentration for traded-goods industries, particularly in the manufacturing sector, where there is substantial international market penetration (this is not a big concern in services where there are comparatively few imports). If firms operate in global markets and the trends in U.S. concentration do not follow the trends in global concentration, then our results may be misleading. We address this issue in various ways. Since import penetration data are not available on a consistent basis across our whole time period, we focus on 1992-2012. Row 5 of Table 2 re-estimates our baseline model for the shortened period and finds a slightly stronger relationship. Row 6 controls for the growth in imports over value-added in each five year period, and redefines industry concentration to include imports. In augmenting our concentration measures, we treat each block of source countries for U.S. imports as its own firm, and calculate industry concentration including imports both in the numerator (if an industry receives a large volume of imports from a country group) and in the denominator, reflecting the total domestic market. Using this augmented concentration measure, the coefficients on all concentration measures remain negative and are all significant except for the HHI.[22]

Our measure of concentration is based on firm sales, but it is also possible to construct concentration indices based on employment. The relationship of the labor share with these alternative measures of concentration is presented in the seventh row of Table 2. Interestingly, the coefficients switch sign and are positive (although with one exception, insignificant). This is not a problematic result from the perspective of our conceptual framework; sales are the appropriate measure of concentration, not employment. Indeed, many of the canonical superstar firms such as Google and Facebook employ relatively few workers compared to revenue, as their market value is based on intellectual property and a cadre of highly-skilled workers. Measuring concentration using employment rather than sales fails to capture this revenue-based concentration among IP and human capital-intensive firms.

[22] The Census data enumerate shipments and value-added from each firm's U.S. establishments, which may include exports. We do not believe that an analogous adjustment is appropriate for exports, however. Since the labor used at the firm goes into the production of output destined for exports as well as domestic consumption, it seems natural to use total sales (including exports) when creating concentration measures. The concentration measures published by the U.S. Census Bureau also follow this convention. If we wanted a purely domestic measure of market concentration, we would want to deduct exports as well as incorporating imports.

All Sectors

We next broaden our focus to include a larger range of Census sectors than just manufacturing: Retail, Wholesale, Utilities and Transportation, Finance, and Services. We repeat our baseline specification on these sectors, although the sample window is shorter for Finance (1992-2012) and Utilities and Transportation (1992-2007). Further, we do not have value-added available for industries outside of manufacturing, and thus instead present results for payroll over sales. To assess whether this change in definition affects our results, we repeat the manufacturing sector analysis from Table 2 in Table 3 using payroll normalized by sales rather than value-added, the results of which are reported in row 1. All the coefficients remain negative, statistically significant and quantitatively similar.[23]

Figure 6 plots the coefficients that result from the estimation of equation (2) separately for each sector, using the CR20 as the measure of concentration and looking at changes over 5 year periods (column (2) of Table 3). It is clear that rising concentration is uniformly associated with a fall in the labor share, both outside of manufacturing as well as within it. The coefficient on the concentration measure is negative and significant at the 5% level in each sector. Additionally, the final row of Table 3 pools all six sectors and estimates equation (2) with sector-specific fixed effects. The pooled specification shows a strong negative association between changes in the labor share and concentration. Table 3 also shows additional variants of this regression using alternate measures of concentration as well as stacked 10-year changes rather than five-year changes. The negative relationship is extremely robust across specifications: it is negative in all 30 specifications in rows 2 to 6 of Table 3, and significantly so at the 10% or greater level in 26 cases. Since most employment and output is produced outside of manufacturing, these results underscore the pervasiveness and relevance of the concentration-labor-share relationship for almost the entire U.S. economy.[24]

Period-specific Estimates

We have implemented a large number of robustness tests on these regressions and discuss a few of them here. Our main estimating equation (2) imposes a common coefficient over time on the con-

[23] Figure 3 shows that the mean fall in payroll as a share of sales in manufacturing is 7 percentage points, which is less than half of the 16.5 percentage point fall for payroll normalized on value-added (Figure 2). Similarly, the coefficient on concentration in the share of value-added equation is just over twice as large as the that in the share of sales equation (e.g. -0.148 for the CR4 in column (1) of Table 2 compared to -0.064 in Table 3).

[24] To see whether the results are driven by just the number of firms in the industry, we included this as a separate control variable in changes and/or initial levels. Although the coefficient on concentration tends to fall slightly in such specifications, it remains generally significant, suggesting that it is the distribution of market shares that matters and not just the number or average size of firms.

centration measures and only takes heterogeneity between years into account through the inclusion of time dummies. Figure 7 shows the regression coefficients that result from separate period-by-period estimates of equation (2), again using CR20 as the measure of industry concentration as an illustration. Focus first on manufacturing, shown in Panels A and B. Using either definition of the labor share denominator (value-added or sales), we find that the relationship between the change in the labor share and the change in concentration is significantly negative in all periods (except in 1982-1987), and generally strengthens over the sample period. Although the numbers of individual industries within each of the the five non-manufacturing sectors are fewer than in the manufacturing sector and therefore provide noisier measurement, the same broad patterns emerge: a negative relationship is evident across most years, and tends to become stronger over time. Appendix Figures A.2 through A.7 present scatterplots of the data underlying the coefficient estimates presented in Figure 7. Figure A.2 contains the results for manufacturing, for example, presenting the scatterplot of the change in the payroll share of sales on the $y-$axis and the change in the CR20 on the $x-$axis. The size of each industry is represented by its initial 1982 level of sales. Looking across all 31 panels in different time periods and sectors, there is a clear negative relationship between concentration and labor share in 28 of them.

Magnitudes

We perform a simple exercise to illustrate the quantitative importance of concentration changes in accounting for the fall in the labor share. We recover the time dummies from our estimates of equation (2), which condition on the change in concentration, and compare these dummies to the "unconditional" time dummies obtained from estimates that exclude the concentration variable. Figure 8 plots the unconditional and conditional time dummies, both cumulated over time. The difference between the two lines illustrates the proximate contribution of concentration to the falling labor share, i.e., what the regression estimates imply would have been the change in the labor share had concentration not risen. Observed measures of concentration can account for some of the fall of the labor share, but not the majority. In services for example, the labor share of sales fell from 37% to 34.5% (2.5 percentage points). We predict that this fall would counterfactually have been to 35.2% in the absence of the rise in concentration, i.e. a 1.7 percentage point decline, implying that about a third of the reduction in labor share is proximately explained by rising concentration—a non-trivial fraction. Similarly, rising concentration accounts for 10% of the decline in the labor share in manufacturing, 25% percent in utilities and transportation, and more than 100% in retail trade. While the labor share actually rose in both wholesale trade and finance, our regressions imply that it would have risen by an additional 50% and 150% in these two sectors, respectively, had concentration not increased.

Although the magnitude of the effects is modest when looking over the entire period, Figure 7 shows, consistent with earlier results, that the importance of concentration has risen over time. For example, if we restrict attention to the second half the sample (1997-2012), where the relationship between concentration and labor share strengthened and where the rise in concentration was more dramatic, we calculate that rising CR20 concentration in manufacturing accounts for a third of the fall in the labor share.[25]

IV.B Decomposing Changes in the Labor Share Within and Between Firms

Methodology

An implication of the superstar firm model is that the growth of the labor share should have an important between-firm (reallocation) component, as firms with low labor share (or firms with declining labor shares) capture a rising fraction of industry sales or value-added. To explore this implication, we implement the Melitz and Polanec (2015) decomposition, which generalizes the Olley and Pakes (1996) method to allow for entry and exit. While these tools were originally developed for productivity decompositions, they can be applied straightforwardly to labor shares. We write the level of the aggregate labor share as:

$$S = \sum \omega_i S_i = \bar{S} + \sum \left(\omega_i - \bar{\omega}\right)\left(S_i - \bar{S}\right) \tag{3}$$

where the size-weight, ω_i, is firm i's share of value-added in an industry, $\omega_i = \frac{P_i Y_i}{\sum_i P_i Y_i}$, $\bar{S}$ is the unweighted mean labor share of the firms in the industry and $\bar{\omega}$ is the unweighted mean value-added share.[26]

Consider the change (Δ) in the aggregate labor share from the the base year ($t = 1$) to the current period ($t = 2$).[27]

[25] The fraction of the overall decline in the labor share that is explained by rising concentration comes from a simple back of the envelope calculation. From 1997-2012, the CR20 in manufacturing went up by around 6 percentage points and the labor share fell by around 6 percentage points. From Figure 7, the average coefficient relating the change in concentration to the change in labor share in manufacturing over this period was -0.345, implying that concentration explained $\frac{-0.345\times 6}{6} \times 100 = 34.5\%$ of the fall in the labor share in manufacturing over this period.

[26] The weight ω_i used in these calculations is the denominator of the relevant labor share measure. Thus, within manufacturing, when we consider decompositions of the payroll-to-value-added ratio, we use the value-added share as the firm's weight. In all other decompositions, we use the payroll-to-sales ratio, and use the firm's share of total sales as the firm's weight.

[27] Note that 5 year changes in the Census data form the bulk of our analysis.

$$\Delta S = S_2 - S_1 = \Delta\bar{S} + \Delta\left[\sum(\omega_i - \bar{\omega})(S_i - \bar{S})\right] \tag{4}$$

Melitz and Polanec (2015) generalize this Olley-Pakes decomposition to account for exit and entry:

$$\Delta S = \Delta\bar{S}_S + \Delta\left[\sum\left(\omega_i - \bar{\omega}\right)\left(S_i - \bar{S}\right)\right]_S + \omega_{X,1}\left(S_{S,1} - S_{X,1}\right) + \omega_{E,2}\left(S_{E,2} - S_{S,2}\right) \tag{5}$$

where subscript S denotes *survivors*, subscript X denotes *exiters* and subscript E denotes *entrants*. The variable $\omega_{X,1}$ is the value-added weighted mean labor share of exiters (by definition all measured in period 1) and $\omega_{E,2}$ is the value-added weighted mean labor share of entrants (measured in period 2). The term $S_{S,t}$ is the aggregate labor share of survivors in period t (i.e. firms that survived between periods 2 and 1), $S_{E,2}$ is the aggregate value-added share of entrants in period 2, and $S_{X,1}$ is the value-added share of exiters in period 1. One can think of the first two terms as splitting the change in the labor share among survivors into a within-firm component, $\Delta\bar{S}_S$, and a reallocation component, $\Delta\left[\sum\left(\omega_i - \bar{\omega}\right)\left(S_i - \bar{S}\right)\right]_S$, which reflects the change in the covariance between firm size and firm labor shares for surviving incumbents. The last two terms account for contributions from exiting and entering firms, respectively.

Main Decomposition Results

In Figure 9, we show an illustrative plot for the Melitz-Polanec decomposition calculated for adjacent five-year periods for manufacturing payroll over value-added and then cumulated over two 15-year periods, 1982-1997 and 1997-2012. The labor share declined substantially in both periods: -10.35 percentage points between 1982 and 1997 and -6.15 percentage points between 1997 and 2012. Importantly, the reallocation among incumbents ("between") was the main component of the fall (-7.85 percentage points in the early period and -4.92 percentage points in the later period). While the within-firm component is negative over both periods, the reallocation component among incumbents is three (1982-1997) to seven (1997-2012) times as large as the within-firm component. For example, the fact that the within-incumbent contribution to the falling labor share is only 0.7 percentage points 1997-2012 indicates that for the unweighted average firm, the labor share fell by under a percentage point over the entire 15 year period.

The reallocation term captures changes in activity among incumbent firms, but there is an additional reallocation effect coming from entry and exit. Exiting firms contribute to the fall in the labor share over both periods (-2.2 and -2.8 percentage points in the early and later period respectively). High labor share firms are disproportionately likely to exit, which makes sense as these firms are generally the less profitable. Conversely, the contribution from firm entry is positive in both periods (2.3 percentage points); new firms also tend to have elevated labor shares, presumably because they set relatively low output prices and endure low margins in a bid to build market share (see Foster, Haltiwanger and Syverson (2008, 2016) for supporting evidence from the Census of Manufacturers). Since the contribution of entry and exit is broadly similar, these two terms approximately cancel each other out in our decomposition exercise.

Table 4 reports the decompositions of labor share change in manufacturing for each of the individual five-year periods covered by the data. In the first five columns we detail the payroll to value-added results. Reallocation among incumbent firms contributes negatively to the labor share in every five-year period whereas within-firm movements contribute *positively* in two of the six time periods (1987-92 and 2007-12). The right panel of Table 4 repeats the decompositions using the broader measure of compensation over value-added, and shows that the patterns are even stronger for this metric: almost all of the fall in the labor share can be explained by a between-incumbent reallocation of value-added. For example, the last row shows that the compensation share fell by 18.9 percentage points between 1982 and 2012 and 96% of this change (= 18.21/18.9) is accounted for by a reallocation amongst incumbent firms. The unweighted labor share for incumbents fell by only 0.69 percentage points.

The finding that the reallocation of market share among incumbent firms contributes negatively to the overall labor share generalizes to all of the six sectors that we consider.[28] Figure 10 plots the Melitz-Polanec decomposition for each sector cumulated now over the entire sample period for which data is available (e.g., 1982-2012 for manufacturing, but only 1992-2012 for finance). Recall that we do not have firm-level value-added data outside of manufacturing, so this analysis decomposes payroll over sales, using a firm's sales share as its weight. As in Figure 9 for payroll over value added, within manufacturing the total contribution of market share reallocation among incumbent firms (5 percentage points) is about four times as large as the within-firm component (1.2 percentage points) for payroll over sales. Echoing the findings in manufacturing, we find that the between-incumbent reallocation effect contributes strongly to the decline in the payroll share in each of the other five sectors except services where the entry component dominates. By contrast, the within-incumbent contribution is *positive* in all sectors except for manufacturing. Table 5

[28] The level of the payroll to sales ratio differs substantially across sectors due in part to differences in intermediate input costs (see Figure 3), and we thus implement decompositions separately by sector. Using the more aggregate NIPA data on payroll to value-added ratio, Elsby, Hobjin and Sahin (2013) show that the overall decline in the labor share is driven primarily by within rather than between sector movements.

reports the decompositions over five-year periods underlying the sample totals plotted in Figure 10. The table shows that the between incumbent reallocation component is the dominant term. For example, the reallocation term contributes to the fall in the labor share in 25 of the 31 potential 5 year differences, whereas the within incumbent component only contributes to a fall in the labor share in 5 out of the 31 possible 5 year differences.[29]

Robustness of the decomposition analysis

We have subjected the decomposition findings to a large number of robustness tests, some of which are reported below. For example, the above analysis is performed at the firm rather than establishment level. While this is appealing because it closely aligns with the model, there is a potential complication as entry and exit can occur through merger and acquisition activity rather than start-up or bankruptcy. In Appendix Table A.1, we conduct the decomposition analysis at the establishment level (Panel A) and find qualitatively similar patterns, reflecting the fact that the overwhelming number of firms only have a single establishment. We also perform the analysis using firm-by-industry cells (Panel B) in place of firms that can overlap multiple industries (the definition used in the previous analysis linking changes in labor shares to changes in industry-level concentration). Again, the results that are quite similar. Finally, in Panel C, we perform the decomposition at 15-year intervals rather than five-year intervals. Although the definition of an incumbent firm is thus changed to comprise only firms that survived 15 years, the pattern of findings persists.[30]

Compustat Data

We also implemented our decomposition analysis using U.S. publicly listed firms in the Compustat database. There are several data issues in implementing these analyses. First, labor costs are not a mandatory reporting item for publicly listed U.S. firms. Only about 13 percent of firms report "staff expenses," and those reporting are mainly larger firms. Second, value-added is not reported in Compustat as there is no consistent definition of intermediate inputs. We considered decompositions based on both sales and value-added as measured by the wage bill plus gross profits. Third, firms report their consolidated global value which includes the wage bill of workers who are employed

[29]The general increase in the within-firm component of the labor share is consistent with our simple model in Appendix A where an increase in competition reduces margins for individual firms, even though it reallocates more market share to the low labor share firms.

[30]Kehrig and Vincent (2017) similarly find that the between-firm reallocation term dominates in accounting for the aggregate fall in the labor share using a variety of other decomposition analyses.

overseas; hence, this concept is not directly comparable to Census data which record activities within the United States. Finally, as is well known, Compustat does not cover privately-held firms so the sample is much smaller than the Census. Despite these multiple caveats, we obtain broadly similar patterns of results when examining Compustat data for manufacturing (which is likely to be most comparably reported to representative datasets by Compustat). There is a clear decline in the labor share and it is dominated by between-firm (rather than within-firm) movements using the Melitz-Polanec decomposition (see Table A.5).[31] Compustat data also enable us to examine Tobin's average Q (the ratio of stock market value to capital stock), which may proxy for expected future rents and/or a firms's intangible capital. We would expect to see a negative relationship between the change in the labor share and the change in Tobin's Q at the firm level and a positive relationship between changes in Q and sales concentration at the industry level. This is indeed what we observe.[32]

IV.C The Between-Firm Component of the Fall in the Labor Share is Related to Rising Concentration

We have established that, across most of the U.S. private economy, there has been a fall in the labor share and a rise in sales concentration; that the fall in the labor share is greatest in the four digit sub-industries of these sectors where concentration rose the most; and that the fall in labor share is primarily a between-firm reallocation story rather than a within-firm phenomenon. Figure 11 examines another prediction of the superstar firm model, which is that the industries where concentration rose the most were those that experienced the largest fall in the reallocation component of the labor share. If, contrary to our hypothesis, the rise in concentration weakened competition and thereby allowed firms to raise prices across the board (e.g. through explicit or implicit price coordination), the higher mark-ups would tend to spur a rising profit share/falling labor share among all firms within an industry. Our superstar firm hypothesis, by contrast, focuses on rises in size of the most profitable firms.

In Figure 11, the dark grey bars show the coefficient estimates and standard errors from regressions of the reallocation component of the fall in the labor share (recovered from Table 5), on the

[31] Hartman-Glaser, Lustig and Zhang (2016) find a somewhat different overall trend from us, but they impute missing values by using industry averages and they use non-manufacturing data.

[32] For example, regressing the five year change in firm labor shares on the five year change in Tobin's Q and time dummies in all Census years 1982-2007 generates a coefficient (standard error) on Q of $-0.085(0.013)$ with 3,533 observations. An industry regression of the change in Tobin's Q on the change in the CR20 for industries where we have consistent industry definitions (Census years 1992-2007) has a coefficient (standard error) on concentration of 0.411(0.224) with 32 observations.

change in the CR20. The lighter bars directly underneath report the estimates that result from regressions of the within-incumbent component of the change in the labor share on concentration, and the white and black bars show the estimates for the firm entry and exit components, respectively. Appendix Table A.2 (column (2)) shows the corresponding regressions underlying Figure 11 alongside results using the other measures of concentration. The pattern of results in Figure 11 is consistent across all sectors: the tight correlations between changes in concentration and changes in labor shares reported in Figure 6 are driven by the reallocation component. The between-incumbent reallocation component shows up as negative and significant in all sectors, while the coefficients on the within-firm component are small, generally insignificant, and occasionally positive. Firm entry and exit correlate with concentration differently across sectors, but these components always play a small role compared to the between-incumbent reallocation component. The results provide further evidence, consistent with the superstar firm hypothesis, that concentrating industries experienced a differential reallocation of economic activity towards firms that had lower labor shares.

A further extension we considered was to implement our decompositions of changes in the labor share into between- and within-firm components using alternative techniques such as a traditional shift-share analysis (Bailey, Hulten and Campbell, 1992) or a modified shift-share approach where the covariance term is allocated equally to the within- and between-components as in Autor, Katz and Krueger (1998). We implemented a variety of such approaches and performed decompositions such as those underlying Figure 10. We continue to find a large role for the between-firm reallocation component of the fall in the labor share but the within-firm component becomes more important as well. In contrast to Figure 11, we also find for the shift-share decompositions that concentration loads significantly on the within-firm component. These shift-share decompositions give greater weight to the within-firm changes of *initially larger* firms than do the Olley-Pakes and Melitz-Polanec methodologies, where the within component is simply the unweighted mean of within-firm changes. The shift-share models therefore suggest that within-firm declines in labor share make some contribution to the aggregate decline in labor share, but this within-firm contribution primarily comes from larger firms. In short, increases in concentration are associated with decreases in labor share among the largest firms.[33]

[33] The covariance term in the shift-share analysis $\left(\sum [\Delta\omega_i \Delta S]_S\right)$ is a non-trivial component although it does not seem related to increases in concentration. This appears to be related to outliers to which the double difference in the covariance term is particularly sensitive.

IV.D International Evidence

Karabarbounis and Neiman (2013) and Piketty (2014) have documented that the fall in the labor share is an international phenomenon. We explore the international evidence further using industry and firm-level data from various OECD countries.

Industry labor shares: KLEMS

Figure 1 documented the pervasive decline in the labor share across several OECD countries. We begin our industry and firm-level analysis by exploring the correlation of the labor share (measured in levels) across the 32 industries that comprise the market sector. Figure 12 reports these correlations for each country over the 1997-2007 period (where the data are most abundant). Panel A reports, for each country, the average correlation of their labor share levels with each of the other 11 countries. The correlation is high in all cases, with average correlation coefficients between 0.7 and 0.9. Panel B correlates the *change* in labor shares by country pairs, and reports the average correlation for each country as well as the fraction of the country's pairwise correlations that are negative. The correlations in changes are weaker than those in levels, but the bulk of the evidence still indicates that declines in the labor share tend to occur in the same industries across countries: the average correlation is positive for each country, and there is a positive correlation across industries between country pairs in over three-quarters of all cases (51 of 66). The correlation matrices underlying these summary tables are reported in Table A.3.

Industry labor shares and concentration

We next examine the relationship between the change in the labor share and the change in concentration across countries. Although we do not have access to the equivalent of the Census Bureau firm-level data for all countries outside of the United States, we can draw on cross-national, industry-level data for a shorter period from the COMPNET database, developed by the European Central Bank. COMPNET is originally a firm-level data set constructed from a variety of country-specific sources through the Central Banks of the contributor nations. These data are collapsed to the industry-year level when made available to external researchers. The data set contains measures of the labor share and of concentration (defined as the fraction of industry sales produced by the top ten firms in the country). We estimate equation (2) in five-year (2011-2006) or ten-year (2011-2001) long differences separately across all of the 14 countries for which data are available. Table 6 has the results from this exercise, and shows that in the five-year difference specifications of column (1), 12 out of the 14 countries have the expected negative sign that is predicted by the superstar firm model, while all countries but Belgium have a negative sign in the longer differences in column 2 (for which fewer countries have available data). The coefficients are imprecise, however, and often insignificant. In the 10-year difference specification, five of the 10 coefficients are negative and significant at the 10% level or greater, while four additional countries have negative but insignificant coefficients.

Firm-level decompositions

In this subsection, we use data from BVD Orbis, which is currently the best available source for comparable, cross-national firm-level data to decompose changes in labor share into between- and within-firm components for 6 OECD countries. Orbis is a compilation of firm accounts in electronic form from essentially all countries in the world. Accounting regulations and Orbis coverage differ across countries, however, so we confine the analysis to a set of European countries where reasonable quality data are available for the 2000s. We use the earliest five-year periods available where Orbis has comprehensive data. These are 2003-2008 for the UK, Sweden and France, and 2005-2010 for Germany, Italy and Portugal. Firms in all six countries have seen a decline in the aggregate labor share of value-added over this period. Figure 13 presents this decomposition for the manufacturing sector for all six countries.[34] Just as in the more comprehensive U.S. data, it is the between-firm reallocation component that is the main contributor to the decline in the labor share in all countries. This reallocation component is always negative, whereas the within-firm component is positive in half of the countries.

Summary on international evidence

Although our international data are not as rich as those available for the United States, the pattern of findings for other countries mirrors the evidence from the more detailed U.S. data: (i) the decline in the labor share has occurred in broadly similar industries across countries; (ii) the industries with the greatest increases in concentration exhibited the sharpest falls in the labor share; and (iii) the fall in the labor share is primarily a between-firm (reallocation) rather than within-firm phenomenon. Thus, the international evidence is broadly consistent with the hypothesis that a rise in superstar firms has played a major role in the decline in labor's share throughout the OECD.

[34] We focus on manufacturing as measurement of the labor share is more reliable for this sector. Appendix Table A.4 shows the details of the data and the decomposition.

IV.E What Explains the Rise in Concentration?

Technology

The superstar firm model is most immediately applicable to high-tech industries, where we think that many sectors may have developed a "winner takes most" character. It is less obviously applicable to rapidly declining sectors. This observation leads us to explore whether rising concentration is more prevalent in dynamic industries exhibiting rapid technological advances, or if it is not specific to these industries. We employ two commonly used measures of technical change, patent-intensity and total factor productivity (TFP), as well as four ancillary proxies for output, costs, investment and expenditure: output per worker, material costs per worker, assets per worker, and payroll per hour. Figure 14 presents the coefficient estimates from regressions of growth in various industry characteristics on growth in CR20 measure of concentration in U.S. manufacturing industries.[35]

The rise in industry concentration is positively and significantly correlated with the growth of patenting intensity. The relationship is economically and statistically significant. As an alternative measure of technical progress we also show that concentration rates were rising faster in sectors where labor productivity (output per worker) rose faster (second row of Figure 14). Of course, this might be because of faster growth in material inputs or capital in these industries (third and fourth rows). Nevertheless, even when we control for output increases arising from five possible factor inputs (labor, structures capital, equipment capital, energy inputs and non-energy material inputs) in our TFP measure, we find a significantly positive correlation between concentration growth and TFP growth. These correlations suggest that the industries becoming more concentrated are those with faster technological progress. Interestingly, the final row of Figure 14 shows that we do not find any correlation of concentration growth with average wage (payroll per hour) changes. This suggests that concentrating sectors are not those where average wages are systematically falling, even though the share of labor is.

Recent work by the OECD (Andrews, Criscuolo and Gal, 2015) examines firm-level data in 24 OECD countries between 2001 and 2013 and finds that productivity differences have widened between the top 5 percent of firms and the rest of the distribution. They attribute the widening to a slowdown in technological diffusion between the frontier firms and the laggards, arising from the way that leading firms can better protect their advantages and contributing to a slowdown in aggregate productivity growth. They do not look directly at labor shares, but a slowdown in

[35] The independent variable in these regressions is the change in CR20 concentration and the dependent variable is the industry characteristic. All regressions include year dummies.

technological diffusion could be a reason for the growth of superstar firms. We investigate this idea by examining a measure of technology diffusion based on the speed of patent citations. Consistent with the hypothesis of Andrews et al. (2015), we find that in industries where the speed of diffusion had slowed (as indicated by a drop in the speed of citations), concentration had risen by more and labor shares had fallen by more. For example, in industries where the percent of total citations received in the first five years was 10 percentage points lower, concentration rose by an extra 3.3 percentage points.

Trade

Using data from both manufacturing and non-manufacturing industries, Elsby, Hobijn and Sahin (2013) find a negative industry-level association between the change in the labor share and growth of total import intensity.[36] They conclude that the offshoring of the labor-intensive components of U.S. manufacturing may have contributed to the falling domestic labor share during the 1990s and 2000s. Following their work, we explore the relationship between changes in labor's share and changes in Chinese import intensity. Appendix Table A.6 summarizes regressions of changes in industry-level outcomes in U.S. manufacturing on changes in Chinese imports intensity. We report both OLS regressions and 2SLS models using the Autor, Dorn and Hanson (2013) approach of instrumenting for import exposure using contemporaneous import growth in the same industries in eight other developed countries. As a sensitivity test, we report results both including and excluding the post-2007 Great Recession. The first three columns of Appendix Table A.6 corroborate the well-documented finding that industries that were more exposed to Chinese imports had greater falls in sales, payroll and value-added than other sectors (significantly so in almost all cases). The next three columns find a positive correlation between the growth of Chinese import penetration and the rise of industry concentration, although this relationship is imprecisely estimated. The last two columns find that an increase in Chinese imports predicts a *rise* in industry labor share (though this relationship is often insignificant). While this result is unexpected in light of Elsby, Hobijn and Sahin (2013), it is implied by the estimates in columns (1) through (3). Specifically, because the negative effect of rising Chinese import exposure on industry payroll is smaller in absolute magnitude than its negative effect on industry value-added and industry sales, the labor share of sales and value-added tends to rise with growth of industry import exposure.[37]

[36] They define total import intensity using the 1993-2010 input-output tables as the percentage increase in value-added needed to satisfy U.S. final demand were the U.S. to produce all goods domestically.

[37] In addition to using different measures of industry trade exposure, the analysis in Elsby, Hobijn and Sahin (2013) differs from ours in their use of data from both manufacturing and non-manufacturing industries. While we are able

Other factors

We also examined the correlation of the change in concentration with a large number of other candidate explanatory variables. These include measures of business dynamism, computer investment, and susceptibility to routine task-replacing technical change, among others. We do not find these variables to be systematically or robustly correlated with changes in concentration.

V Conclusions

In this paper we have considered a new "superstar firm" explanation for the widely remarked fall in the labor share of GDP. We hypothesize that markets have changed such that firms with superior quality, lower costs, or greater innovation reap disproportionate rewards relative to prior eras. Since these superstar firms have higher profit levels, they also tend to have a lower share of labor in sales and value-added. As superstar firms gain market share across a wide range of sectors, the aggregate share of labor falls. Our model, combined with technological or institutional changes advantaging the most productive firms in many industries, yields predictions that are supported by Census micro-data across the bulk of the U.S. private sector. First, sales concentration levels rise across large swathes of industries. Second, those industries where concentration rises the most have the sharpest falls in the labor share. Third, the fall in the labor share has an important reallocation component between firms—the unweighted mean of labor share has not fallen much. Fourth, this between-firm reallocation of the labor share is greatest in the sectors that are concentrating the most. Fifth, these broad patterns are observed not only in U.S. data, but also internationally in European OECD countries. Notably, the growth of concentration is disproportionately apparent in industries experiencing faster technical change as measured by the growth of patent-intensity or total factor productivity, suggesting that technological dynamism, rather than simply anti-competitive forces, is an important driver of this trend.

The work in this paper is of course descriptive and suggestive rather than the final word in this area. Future work needs to understand more precisely the shocks that lead to the emergence of superstar firms. We have presented our model as one where productivity (or quality) differences between firms are magnified when the competitive environment changes, turning leading firms into

to replicate their finding of a negative association between rising imports and falling labor share, we find that this negative relationship is eliminated when we include a dummy variable for the manufacturing sector. This pattern likely reflects the facts that (1) the fall in the labor share has been greater in manufacturing than in other sectors; and (2) manufacturing is more subject to import exposure then non-manufacturing. Import exposure variable has little explanatory power for within-manufacturing, cross-industry variation in the fall in the labor share, however, and it cannot readily explain why labor's share has fallen outside of manufacturing.

dominating superstars. One source for the change in the environment could be technological: high tech sectors and parts of retail and transportation as well have an increasingly "winner takes all" aspect. But an alternative story is that leading firms are now able to lobby better and create barriers to entry, making it more difficult for smaller firms to grow or for new firms to enter. In its pure form, this "rigged economy" view seems unlikely as a complete explanation. The industries where concentration has grown are those that have been increasing their innovation most rapidly as indicated by patents (Figure 14). One might be concerned that these patents are designed to thwart innovation and enshrine monopolies (e.g., Boldrin and Levine, 2008). However, we also observe similar relationships when measuring innovation by citation-weighted patents or TFP growth.

A more subtle story, however, is that firms initially gain high market shares by legitimately competing on the merits of their innovations or superior efficiency. Once they have gained a commanding position, however, they use their market power to erect various barriers to entry to protect their position. Nothing in our analysis rules out this mechanism, and we regard it as an important area for subsequent research.

The rise of superstar firms and decline in the labor share also appears to be related to changes in the boundaries of large dominant employers with such firms increasingly using domestic outsourcing to contracting firms, temporary help agencies, and independent contractors and freelancers for a wider range of activities previously done in-house, including janitorial work, food services, logistics, and clerical work (Weil, 2014; Katz and Krueger 2016). This fissuring of the workplace can directly reduce the labor share by saving on the wage premia (firm effects) typically paid by large high-wage employers to ordinary workers and by reducing the bargaining power of both in-house and outsourced workers in occupations subject to outsourcing threats and increased labor market competition (Dube and Kaplan, 2010; Goldschmidt and Schmieder, 2017). The increased fissuring of the workplace has been associated with a rising correlation of firm wage effects and person effects (skills) that accounts for a significant portion of the increase in U.S. wage inequality since 1980 (Song et al., 2016). Linking the rise of superstar firms and the fall of the labor share with the trends in inequality between employees should also be an important avenue of future research.

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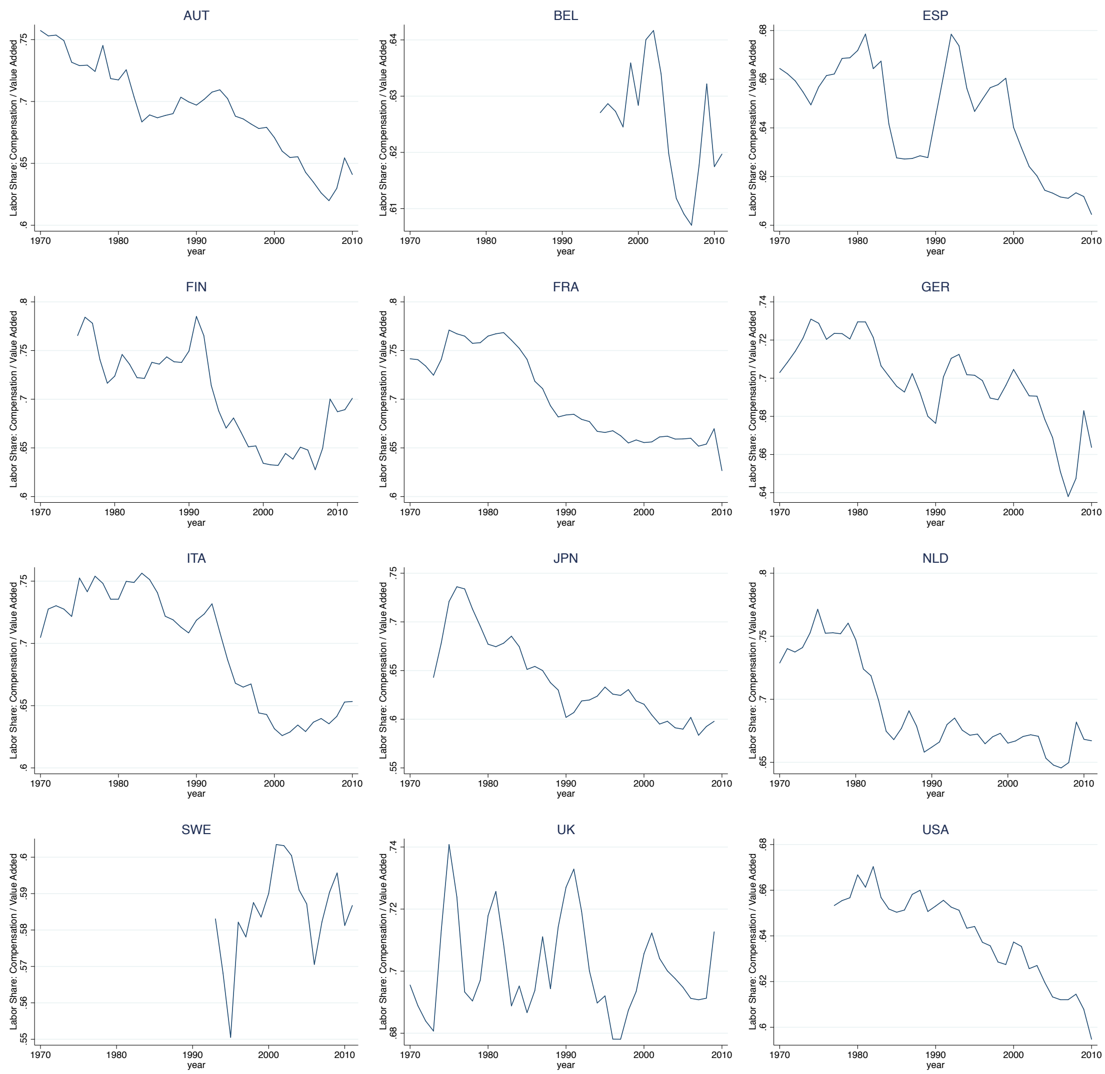
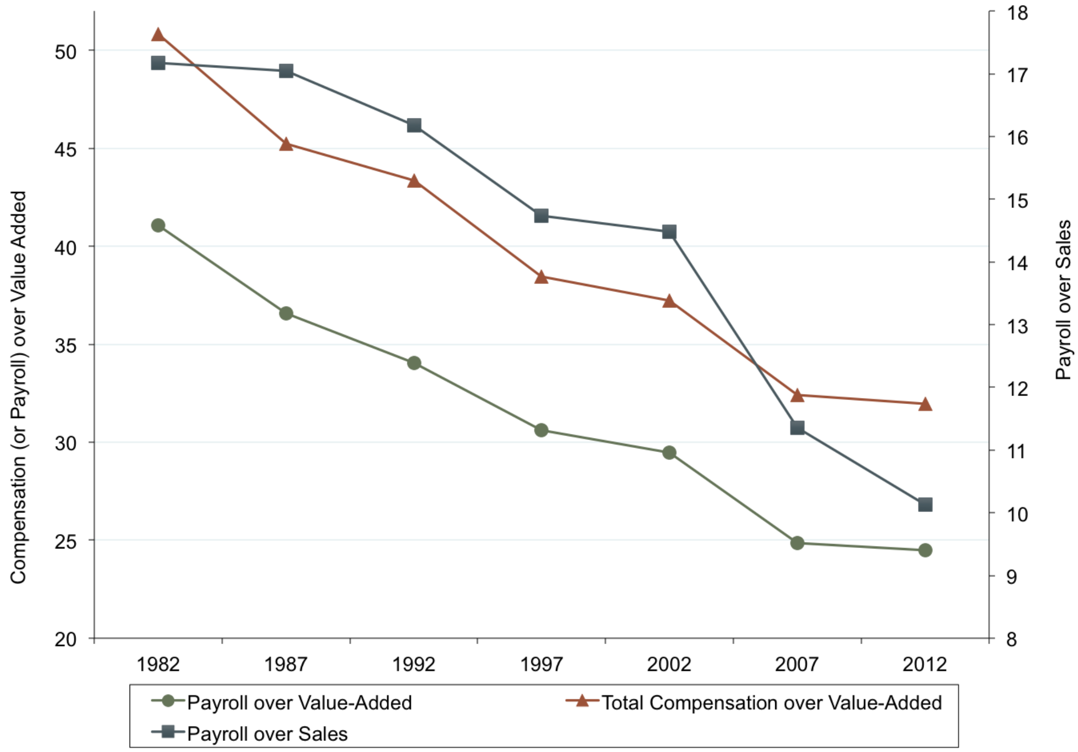
VII Figures

Figure 1: International Comparison: Labor Share by Country



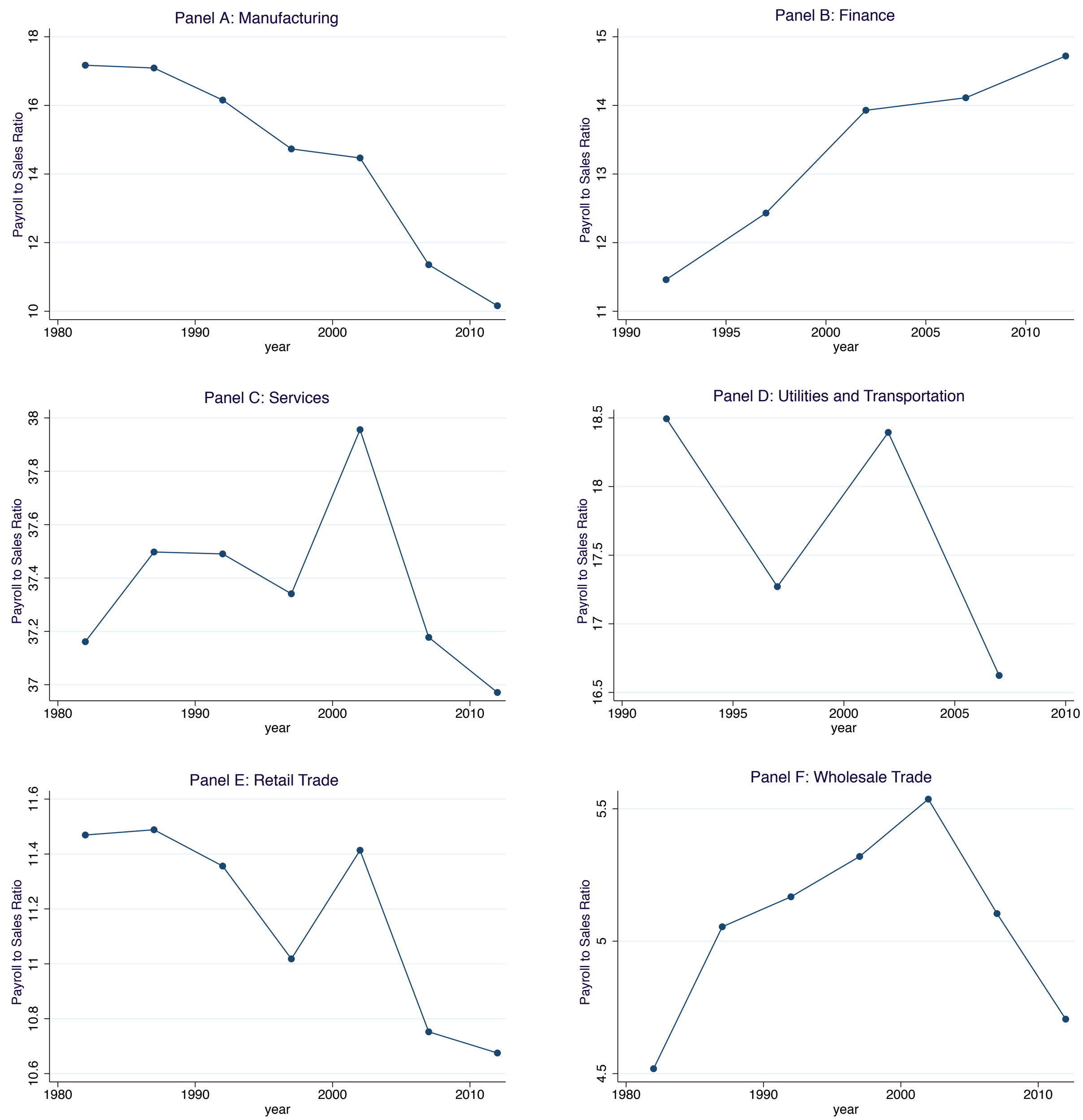
Notes: Each panel plots the ratio of aggregate compensation over value-added for all industries in a country based on KLEMS data.

Figure 2: The Labor Share in Manufacturing



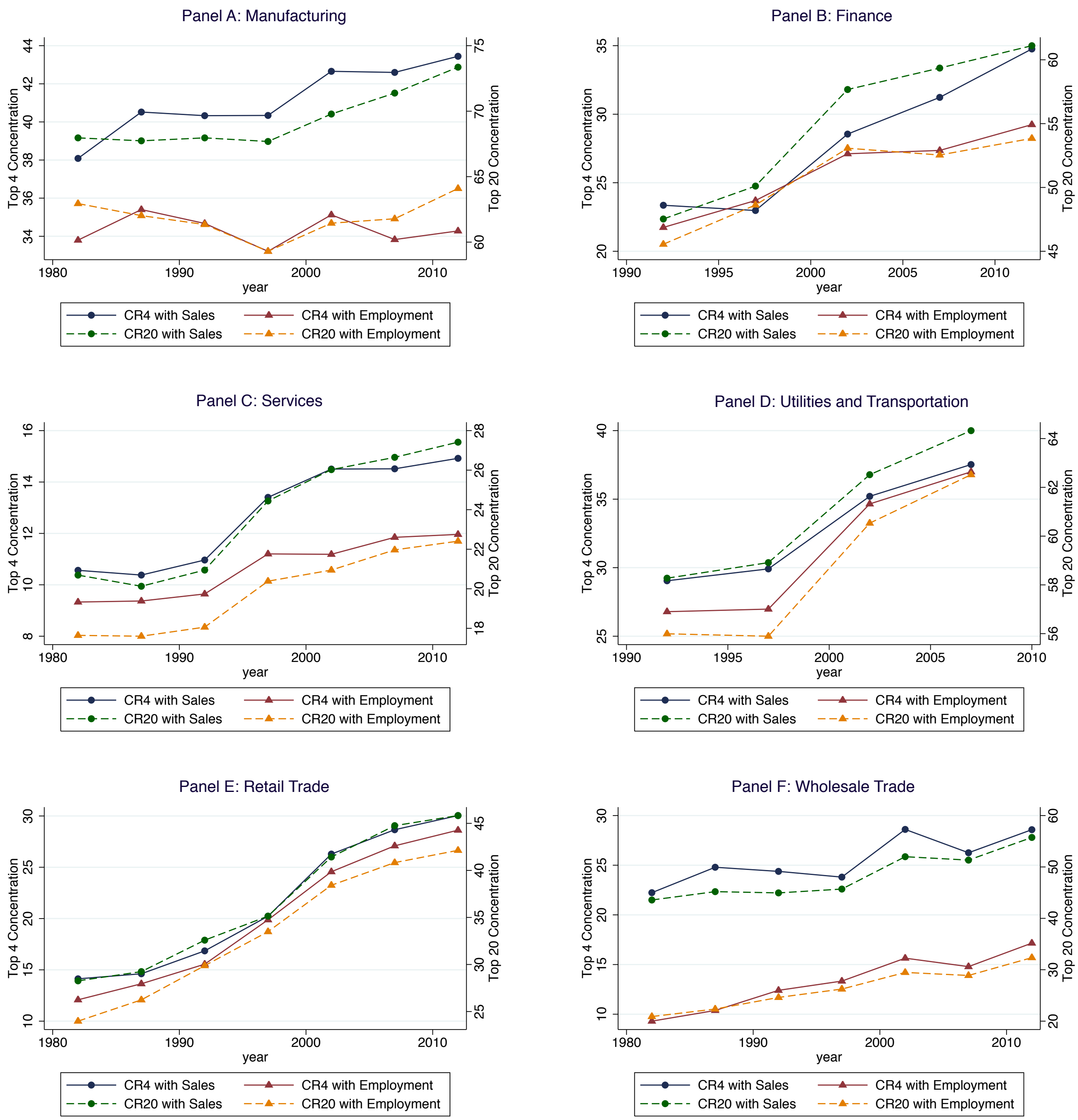
Notes: This figure plots the aggregate labor share in manufacturing from 1982-2012. The green circles (plotted on the left axis) represent the ratio of wages and salaries (payroll) to value-added. The red diamonds (also plotted on the left axis) include a broader definition of labor income and plots the ratio of wages, salaries and fringe benefits (compensation) to value-added. The blue squares (plotted on the right axis) show wages and salaries normalized by sales rather than value-added.

Figure 3: Average Payroll-to-Sales Ratio



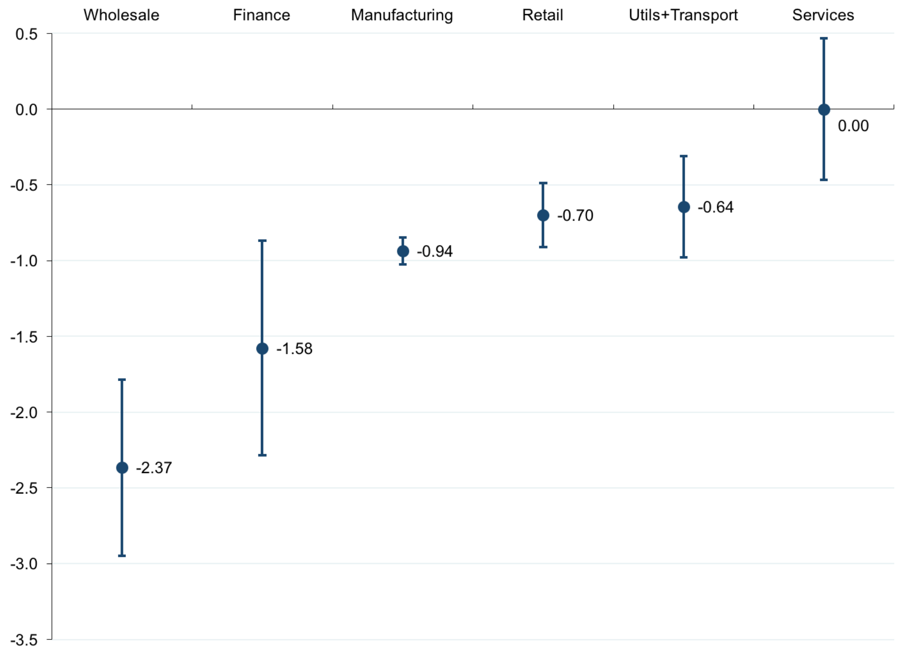
Notes: Each panel plots the overall payroll-to-sales ratio in one of the six major sectors covered by the U.S. Economic Census.

Figure 4: Average Concentration Across Four Digit Industries by Major Sector



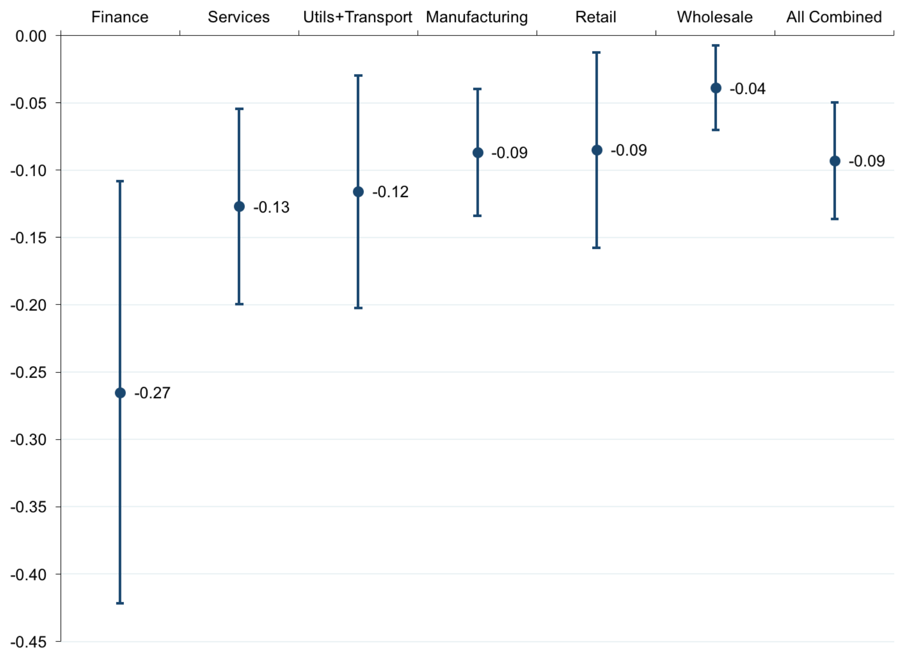
Notes: This figure plots the average concentration ratio in six major sectors of the U.S. economy. Industry concentration is calculated for each time-consistent four-digit industry code, and then averaged across all industries within each of the six sectors. The solid blue line (circles), plotted on the left axis, shows the average fraction of total industry sales that is accounted for by the largest four firms in that industry, and the solid red line (triangles), also plotted on the left axis, shows the average fraction of industry employment utilized in the four largest firms in the industry. Similarly, the dashed green line (circles), plotted on the right axis, shows the average fraction of total industry sales that is accounted for by the largest 20 firms in that industry, and the dashed orange line (triangles), also plotted on the right axis, shows the average fraction of industry employment utilized in the 20 largest firms in the industry.

Figure 5: The Relationship Between Firm Size and Labor Share



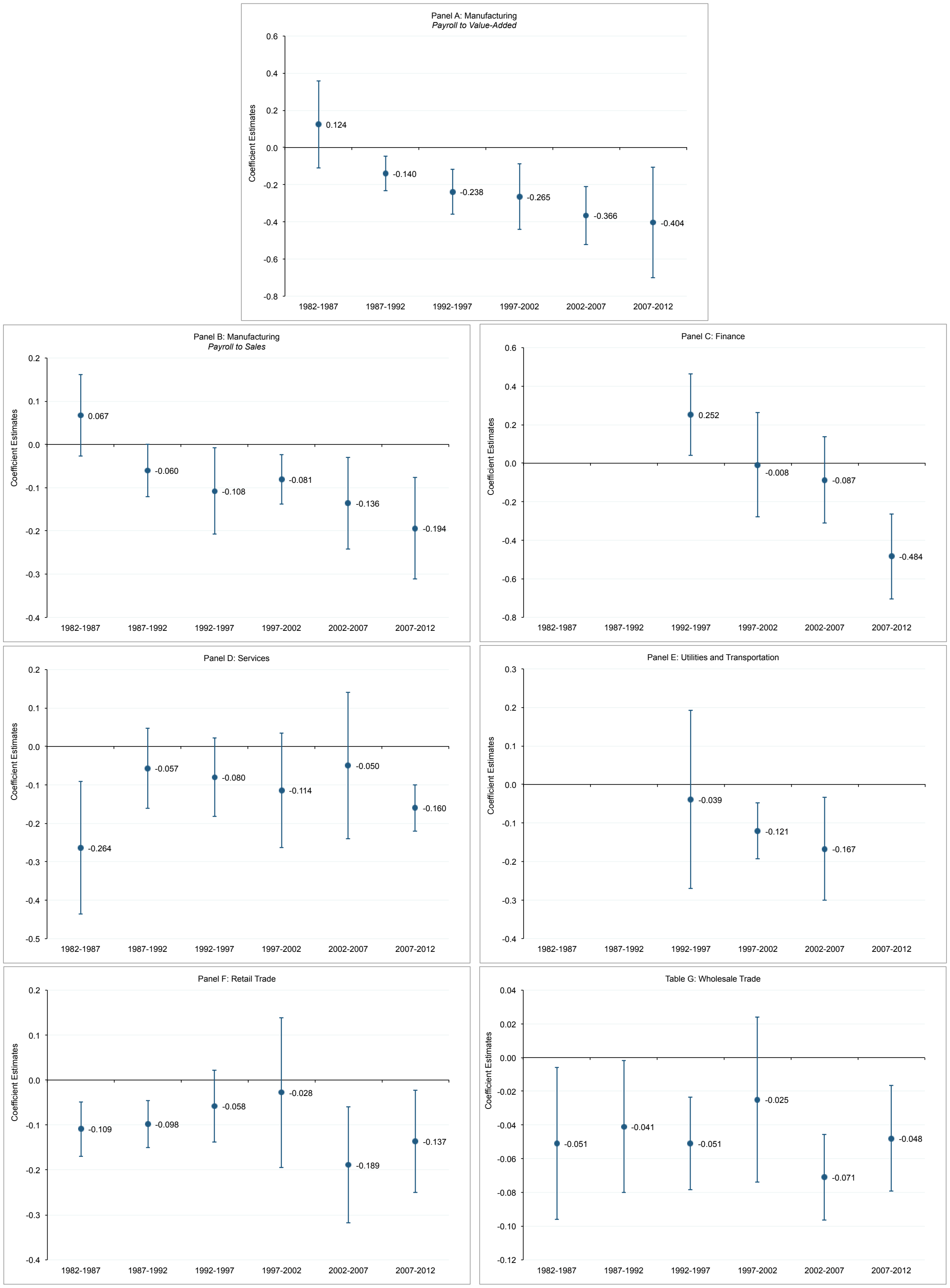
Notes: The dots indicate the coefficient estimates of a regression of a firm's labor share on its share of overall sales in its four-digit industry. The regressions include all years available for that sector, and year fixed effects. The labor share is defined as the payroll-to-sales ratio in each sector. The blue lines represent the 95% confidence intervals.

Figure 6: The Relationship Between the Change in Labor Share and the Change in Concentration Across Six Sectors



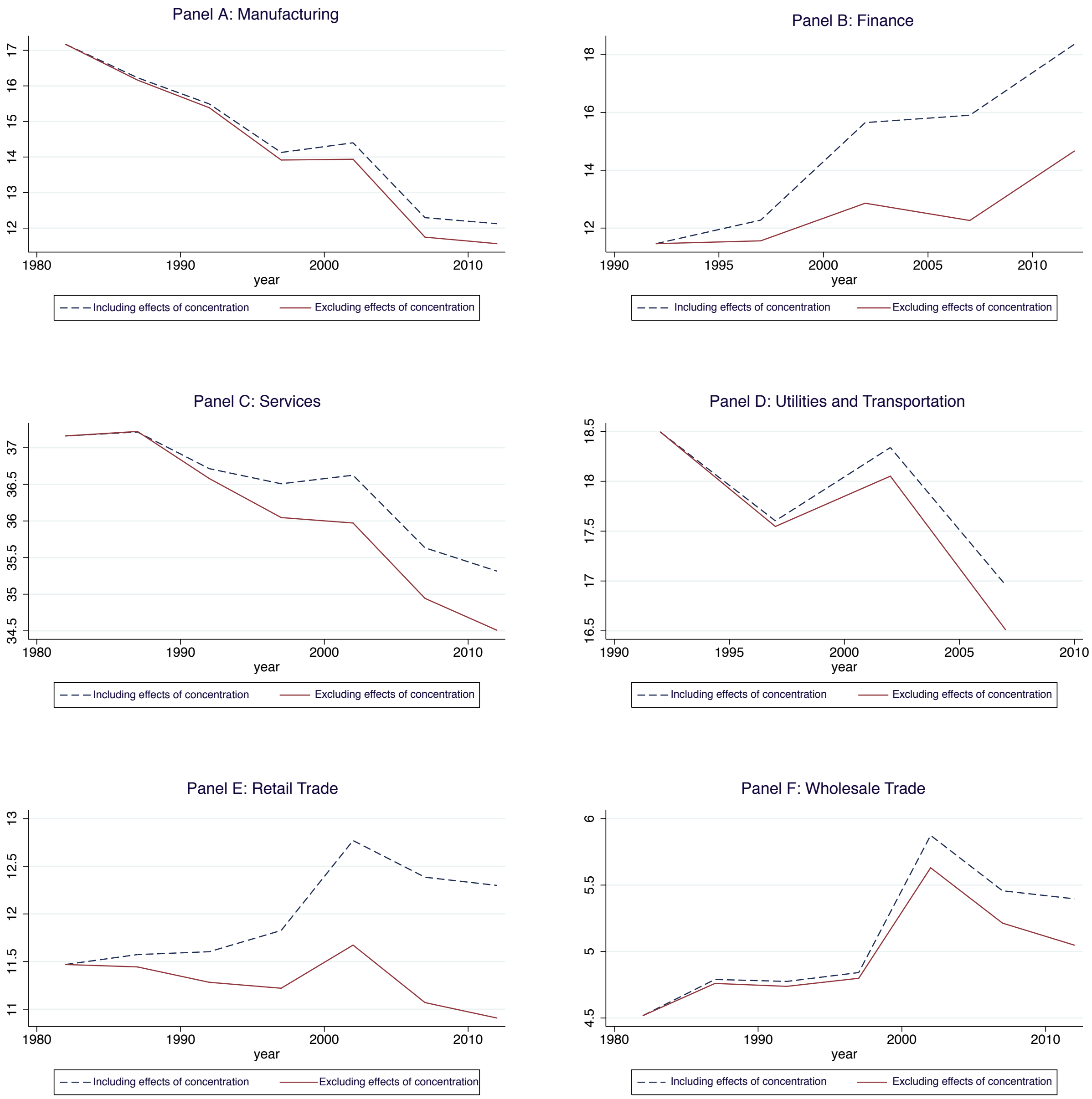
Notes: The figure indicates OLS regression estimates from ΔLabor Share (payroll over sales) on ΔCR20 (stacked five-year changes from 1982-2012 with dummies for each time period). Dots indicate coefficient estimates and lines indicate 95% confidence intervals. Table 3 tabulates the full regression results.

Figure 7: Correlation Between the Change in Labor Share and the Change in Concentration: Period Specific Estimates



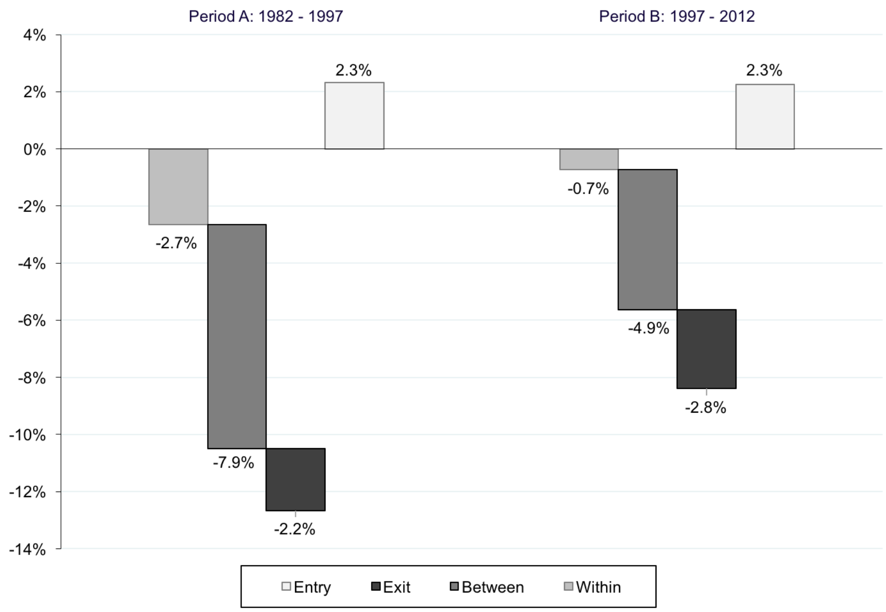
Notes: For manufacturing, the labor share is defined using the payroll to value-added ratio in panel A, and each industry is weighted by the industry's 1982 share of value-added. For all other panels, the labor share is defined as the ratio of payroll to sales, and each industry is weighted by its initial share of sales in 1982 (except for the finance and utilities and transportation sectors, where initial sales shares are based on 1992 data due to shorter sample periods). Concentration is measured using CR20. The lines represent the 95% confidence intervals.

Figure 8: The Role of Concentration in Explaining the Evolution of the Change in Labor Share



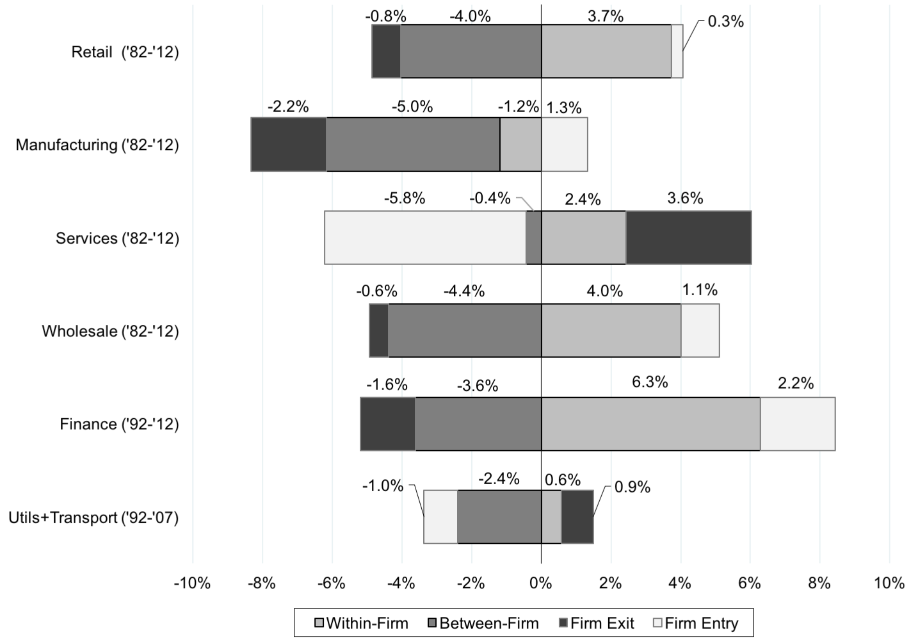
Notes: The red line plots the cumulated coefficients that result from a regression of the five-year change in the payroll-to-sales ratio within a four-digit industry on time dummies, with each industry weighted by its initial share of total sales. This corresponds to the weighted average payroll-to-sales ratio in each year. The dashed blue line plots the cumulated coefficients on the time dummies when the regression controls for the contemporaneous five-year change in sales-based CR20, and thus indicates a time trend that excludes the contribution of changing concentration to the evolution of the labor share.

Figure 9: Melitz-Polanec Decomposition of the Change in Labor Share in Manufacturing



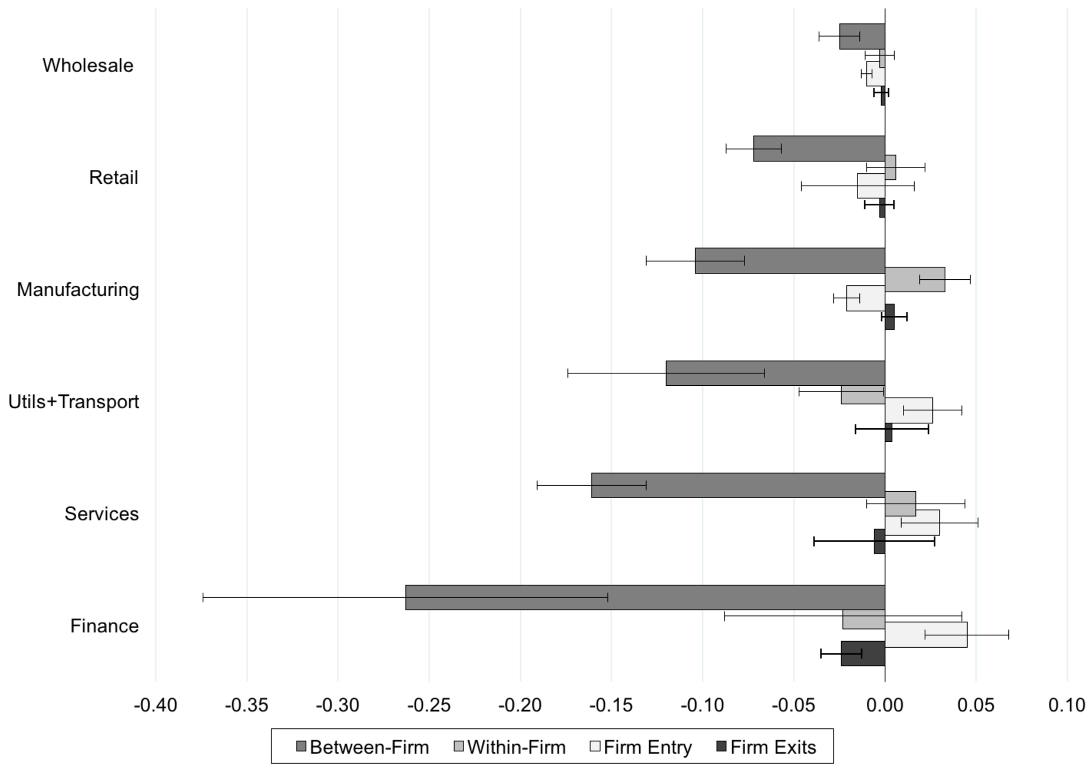
Notes: Each bar represents the cumulated sum of the Melitz-Polanec decomposition components calculated over adjacent five-year intervals. The left panel shows the sum of the decompositions from 1982-1987, 1987-1992 and 1992-1997 and the right panel shows the sum of the decompositions from 1997-2002, 2002-2007, and 2007-2012. Table 4 reports the underlying year-by-year estimates.

Figure 10: Melitz-Polanec Decomposition of the Change in Labor Share in Six Sectors



Notes: Each bar represents the cumulated sum of the Melitz-Polanec decomposition components calculated over adjacent five-year intervals. Table 5 reports the underlying year-by-year estimates.

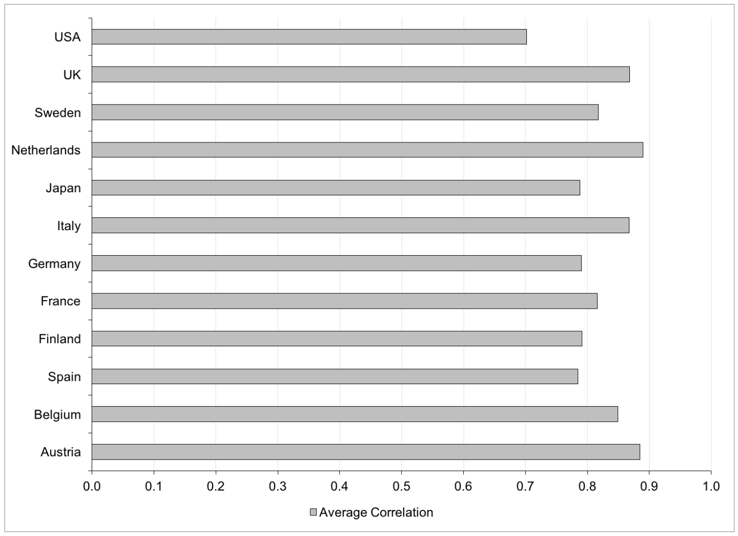
Figure 11: Regressions of the Components of the Change in Labor Share on the Change in Concentration



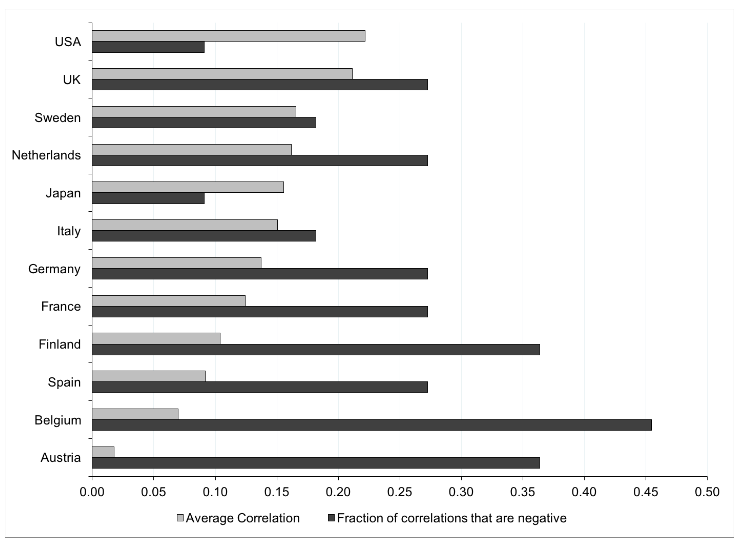
Notes: Each bar plots the regression coefficient resulting from regressions of the Melitz-Polanec decomposition components on the change in CR20 concentration. Regressions include year dummies and standard errors are clustered at the four-digit industry level. Each industry is weighted by its initial share of total sales. Whisker lines represent 95% confidence interval.

Figure 12: Industry-Level Cross-Country Comparisons of Labor Shares

Panel A: Levels

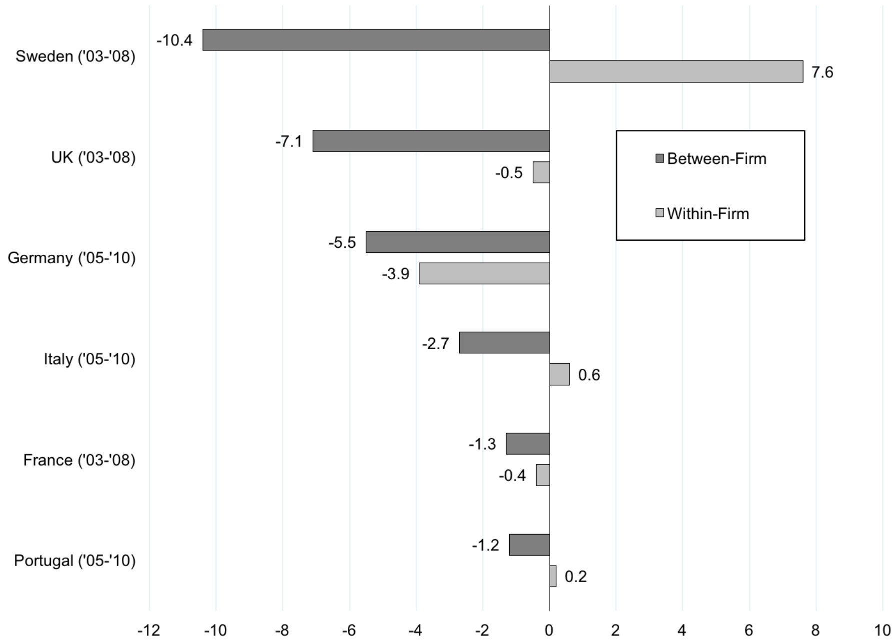


Panel B: Changes



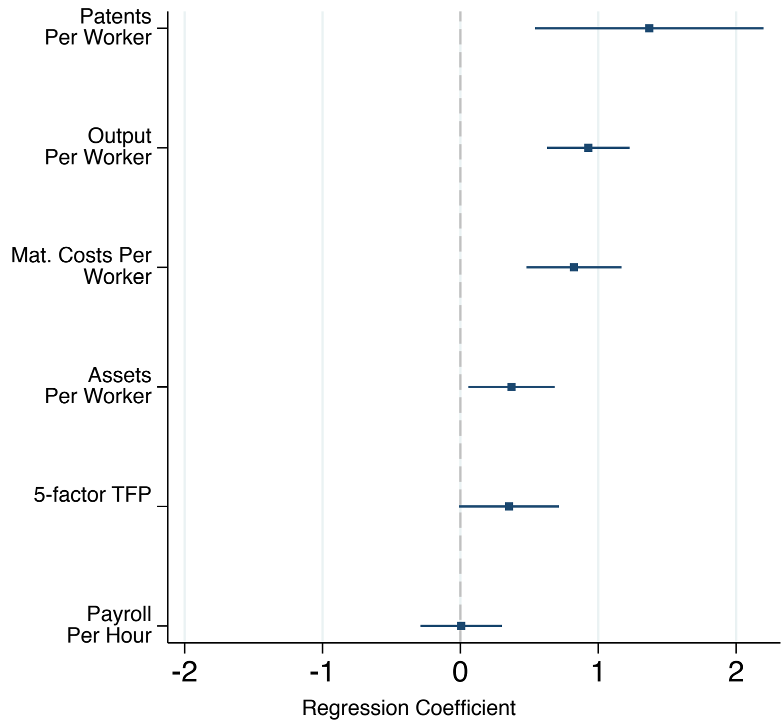
Notes: Panel A plots, for each country, the correlation of the levels of its labor shares in 32 industries with the corresponding industry-level labor shares in 11 other countries, averaged over the 11 pairwise correlations with each other country. Note that each cross-country correlation appears twice in the figure, as the correlation between the USA and the UK would enter the average correlation for the U.S. and the average correlation for the UK. The light grey bars in Panel B plot the industry-level correlation of the ten-year change in the labor share, averaged over 11 country pairs. The darker solid bars in panel B show the fraction of the country pair correlations that are negative. In each panel, the sample period is 1997-2007. Each industry in the correlation is weighted by the value-added share of that industry averaged over the two countries in comparison. In order to reduce measurement error, the correlations are calculated using centered five-year moving averages.

Figure 13: Decomposing the Payroll Share Using Firm Level Data from Different Countries



Notes: This figure plots Olley-Pakes decompositions of the change of the payroll share into between-firm and within-firm components (equation 4 in the text) using BVD Orbis Data. Between-firm refers to the reallocation component occurring between incumbent firms, while within-firm refers to the unweighted average change in the labor share. (BVD does not provide reliable data on entry and exit.) These calculations are performed over five-year periods within reliably-measured manufacturing data in indicated European countries. Labor share is payroll divided by value-added (equal to gross profits plus payroll). See Appendix for details of the firm-level panel data and exact numbers underlying the decompositions.

Figure 14: Change in Concentration in U.S. Manufacturing and Change in Industry Characteristics



Notes: The figure indicates coefficient estimates and 95% confidence intervals from six separate regressions of the change in CR 20 concentration ratio on the industry characteristic indicated in the figure and year fixed effects. The regressions are based on four-digit manufacturing industries and include pooled five-year changes for the full sample period 1982-2012. Standard errors are clustered at the four-digit industry level. Patents are the sum of all USPTO patents from a cross-walk between patent technology classes and industry codes. (We thank William Kerr for providing these data.) TFP is Total Factor Productivity constructed using five factors of production.

VIII Tables

Table 1: Summary Statistics

	Mean	SD	Minimum	Maximum
	(1)	(2)	(3)	(4)
Manufacturing (388 industries, 2,328 obs)				
Number of establishments	197,530	10,635	169,107	216,730
Number of Firms	151,936	10,386	129,080	171,233
Payroll to Sales Ratio	15.2386	8.3752	0.872	48.582
Change in Payroll to Sales Ratio	-0.9611	1.9821	-17.616	14.614
CR4	40.6642	22.5451	3.344041	100
Change in CR4	0.7476	6.4473	-39.725	39.505
CR20	68.7607	23.2561	8.376	100
Change in CR20	0.7566	4.3078	-32.526	24.002
Retail Trade (58 industries, 348 obs)				
Number of establishments	1,598,458	74,292	1,562,915	1,722,947
Number of Firms	1,115,863	17,814	1,104,697	1,152,079
Payroll to Sales Ratio	11.258	5.7401	2.748	29.112
Change in Payroll to Sales Ratio	-0.0588	0.9862	-11.703	10.259
CR4	19.9905	18.9734	0.635	79.133
Change in CR4	2.5071	4.8131	-23.844	32.407
CR20	35.0778	26.4192	1.824	99.983
Change in CR20	2.6928	4.2785	-35.006	49.889
Wholesale Trade (56 industries, 336 obs)				
Number of establishments	411,651	22,275	400,878	442,693
Number of Firms	324,899	20,452	306,174	355,052
Payroll to Sales Ratio	5.0694	3.1859	0.45	14.093
Change in Payroll to Sales Ratio	-0.1811	0.8854	-3.742	4.372
CR4	24.6336	13.4093	4.32	65.046
Change in CR4	0.3548	6.8544	-30.894	35.26
CR20	46.4094	17.3136	11.326	83.67
Change in CR20	1.0315	7.0595	-26.108	33.956

Services (95 industries, 570 obs)				
Number of establishments	2,039,671	412,831	1,769,458	2,698,102
Number of Firms	1,725,578	287,188	1,586,300	2,256,011
Payroll to Sales Ratio	37.4223	10.9437	5.489	74.268
Change in Payroll to Sales Ratio	-0.352	2.4102	-14.288	19.654
CR4	12.1406	11.4397	0.316	77.131
Change in CR4	0.7283	4.409	-32.727	35.399
CR20	22.7854	17.1222	0.848	100
Change in CR20	0.9533	4.7568	-27.768	31.461
Finance (31 industries, 124 obs)				
Number of establishments	676,357	101,246	637,839	842,694
Number of Firms	456,175	65,420	432,753	561,940
Payroll to Sales Ratio	12.8464	9.1203	1.152	39.701
Change in Payroll to Sales Ratio	-0.7437	3.5948	-20.704	17.068
CR4	26.0744	15.1231	2.634	97.387
Change in CR4	2.0704	6.2006	-21.075	34.552
CR20	53.0273	19.7478	6.102	100
Change in CR20	3.6006	5.8551	-25.22	31.261
Utilities and Transportation (48 industries, 144 obs)				
Number of establishments	286,939	30,476	292,474	345,951
Number of Firms	203,626	17,563	213,349	228,854
Payroll to Sales Ratio	18.0455	8.4094	4.484	53.536
Change in Payroll to Sales Ratio	-0.658	2.3697	-11.528	10.021
CR4	31.0864	19.7924	3.042	91.645
Change in CR4	1.9307	8.5871	-27.318	27.699
CR20	59.6948	24.2405	9.221	100
Change in CR20	1.203	6.4252	-25.247	25.538

Notes: The number of establishments and number of firms reflect totals for the entire sector. All other variables are the weighted averages of the underlying four-digit industries, where the weight is the industry's share of sales in the initial year. Changes refer to five year averages. Data period is 1982-2012 for maufacturing, services, wholesale trade and retail trade, 1992-2012 for finance and 1992-2007 for utilities and transportation. CR4 and CR20 are defined in terms of sales. In future drafts, this table will include summary statistics on the payroll to value-added share in manufacturing. Those summary stiatistics have not yet been disclosed by the census.

Table 2: Industry Regressions of Change in Share of Labor on Change in Concentration, Manufacturing

	5 year Change						10 year Change					
	CR4		CR20		HHI		CR4		CR20		HHI	
	(1)		(2)		(3)		(4)		(5)		(6)	
1 Baseline	-0.148	**	-0.234	**	-0.189	*	-0.135	**	-0.165	**	-0.173	~
	(0.036)		(0.047)		(0.096)		(0.043)		(0.058)		(0.096)	
2 Compensation Share of Value Added	-0.175	**	-0.264	**	-0.231	~	-0.143	*	-0.166	*	-0.193	
	(0.046)		(0.061)		(0.121)		(0.056)		(0.076)		(0.129)	
3 Deduct Service Intermediates from VA	-0.331	**	-0.517	**	-0.501	**	-0.269	**	-0.347	**	-0.313	
	(0.062)		(0.071)		(0.176)		(0.055)		(0.066)		(0.261)	
4 Industry Trends (Four-Digit Dummies)	-0.171	**	-0.307	**	-0.208	~	-0.198	**	-0.275	**	-0.219	~
	(0.042)		(0.053)		(0.118)		(0.065)		(0.093)		(0.129)	
5 1992 - 2012 Sub-Period	-0.181	**	-0.316	**	-0.230	*	---		---		---	
	(0.044)		(0.063)		(0.117)							
6 Including Imports (1992 - 2012)	-0.104	*	-0.327	**	-0.052		---		---		---	
	(0.045)		(0.060)		(0.174)							
7 Employment-Based Concentration Measure	0.048		0.039		0.195	*	0.024		0.032		0.081	
	(0.036)		(0.036)		(0.082)		(0.035)		(0.044)		(0.080)	
8 Average Change in Concentration	0.69		0.6		0.14		1.38		1.2		0.28	

Notes: ~ p ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01. obs=2,328 except in row 3 (obs=1,164) and rows 5 and 6 (obs=1,552). Each cell is the coefficient on a concentration measure from a separate OLS regression (standard errors in parentheses clustered by industry) of the change in the labor share on the change in concentration. "CR4" ("CR20") is the share of sales in the largest four (twenty) firms in the four digit industry. HHI is the Herfindahl Index. Time period is 1982-2012 using the Census of Manufacturing aggregated up to four-digit industry-level (except in rows 5 and 6 where we use 1992-2012) and regressions include dummies for each time period. Regressions are weighted by the share of value added of the four digit industry in total manufacturing value added in the initial year (1982). "Baseline" in row 1 defines the labor share as wages and salaries over value-added. "Compensation" in row 2 is wider definition of payroll including all fringe benefits. Service intermediates in row 3 from KLEMS. Row 4 adds four-digit industry dummies. Row 6 redefines concentration to include imports, and includes as an additional control the change in the ratio of imports to value-added. Row 7 defines concentration in terms of employment instead of our preferred sales-based measure. The weighted average 5 and 10 year change in labor share over our sample period is 2.2 and 4.4, respectively.

Table 3: Industry Regressions of the Change in the Payroll-to-Sales Ratio on the Change in Concentration, Different Sectors

		Stacked Five-Year Changes						Stacked Ten-Year Changes					
		CR4		CR20		HHI		CR4		CR20		HHI	
		(1)		(2)		(3)		(4)		(5)		(6)	
1	Manufacturing	-0.064	**	-0.087	**	-0.107	**	-0.044	*	-0.044		-0.096	**
	n = 2,328; 1,164	(0.013)		(0.024)		(0.027)		(0.022)		(0.034)		(0.037)	
2	Retail	-0.036	~	-0.085	*	-0.045	~	-0.045	*	-0.070	*	-0.075	**
	n = 348; 174	(0.021)		(0.037)		(0.026)		(0.018)		(0.029)		(0.023)	
3	Services	-0.090		-0.127	**	-0.354	**	-0.087		-0.129	**	-0.378	*
	n = 570; 285	(0.057)		(0.037)		(0.083)		(0.070)		(0.043)		(0.158)	
4	Wholesale	-0.035	**	-0.039	*	-0.079	*	-0.037	*	-0.036	*	-0.067	
	n = 336; 168	(0.012)		(0.016)		(0.039)		(0.018)		(0.018)		(0.050)	
5	Finance	-0.230	**	-0.265	**	-0.565	**	-0.252	**	-0.291	**	-0.740	*
	n = 124; 62	(0.083)		(0.080)		(0.204)		(0.091)		(0.070)		(0.294)	
6	Utilities + Transport	-0.118	**	-0.116	**	-0.434	**	-0.048		-0.122	*	-0.269	**
	n = 144; 48	(0.026)		(0.044)		(0.054)		(0.072)		(0.051)		(0.104)	
7	All combined	-0.076	**	-0.093	**	-0.144	**	-0.063	**	-0.083	**	-0.122	**
	n = 3,850; 1,901	(0.016)		(0.022)		(0.028)		(0.019)		(0.024)		(0.033)	

Notes: ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$. Number of observations ($n = x; y$) are indicated below each sector for the first 3 columns (x) and the last 3 columns (y). Each cell displays the coefficient on a concentration measure from a separate OLS regression (standard errors in parentheses clustered by industry). Data is aggregated up to time-consistent four digit industries. In manufacturing, retail, services and wholesale, we pool data from 1982-2012, in finance, we pool data from 1992-2012, and in Utilities + Transport, we pool data from 1992-2007. The combined regression in row 7 includes 6 sector fixed effects. Regressions are weighted by the share of sales of the four digit industry in total sector sales in the initial year and each regression includes fixed effects for each 5-year period.

Table 4: Decompositions of the Change in the Payroll-to-Value-Added Ratio, Manufacturing

	Wage Bill share of value added					Compensation share of value added				
	Total	Within	Between	Exit	Entry	*Total*	Within	Between	Exit	Entry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
5 yr period										
1982-1987	-4.47	-3.29	-1.28	-0.58	0.68	-5.75	-1.04	-5.05	-0.45	0.79
1987-1992	-2.43	2.66	-5.28	-0.75	0.94	-1.74	3.81	-5.73	-0.83	1.01
1992-1997	-3.47	-2.02	-1.30	-0.84	0.69	-4.81	-2.74	-1.94	-0.88	0.75
1997-2002	-1.09	-0.15	-0.70	-0.87	0.63	-1.27	-2.20	1.12	-0.92	0.73
2002-2007	-4.71	-2.90	-1.86	-1.09	1.14	-4.87	1.45	-6.59	-1.17	1.44
2007-2012	-0.36	2.33	-2.37	-0.80	0.48	-0.47	0.04	-0.03	-0.98	0.50
Mean		-0.56	-2.13	-0.82	0.76		-0.11	-3.03	-0.87	0.87
15 yr period										
1982-1997	-10.35	-2.65	-7.85	-2.16	2.31	-12.30	0.03	-12.71	-2.16	2.54
1997-2012	-6.15	-0.72	-4.92	-2.76	2.25	-6.63	-0.72	-5.50	-3.08	2.67
Overall										
1982-2012	-16.50	-3.37	-12.78	-4.92	4.56	-18.90	-0.69	-18.21	-5.24	5.21

Notes: This table shows the results of a decomposition of the change in the labor share using the dynamic Melitz-Polanec (2015) methodology as described in the text. We divide the change in the overall labor share (columns (1) and (6)) into four components. "Within" is the change in the labor share due to a general fall in the share across all incumbent firms. "Between" is incumbent reallocation from the change due to the growing relative size of low labor share incumbent firms (and the interaction of the growth in their size and the growth in their labor share). "Exit" is the contribution to the change from the exit of high labor share firms and "Entry" is the contribution from the entry of low labor share firms. These all use the micro-data from the five yearly Census of Manufacturing. "15 year period" is the cumulated sum of each 5 year change over two 15 year periods: e.g. -10.35% in column (1) for 1982-1997 is comprised of the sum of each 5 year period (-4.47% - 2.43% - 3.47%). "Overall" is the cumulated sum over the entire 1982-2012 period.

Table 5: Decompositions of the Change in the Payroll to Sales Ratio, All Sectors

Panel A	Manufacturing					Wholesale				
	Total	Within	Between	Exit	Entry	*Total*	Within	Between	Exit	Entry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
5 yr period										
1982-1987	-0.08	-0.48	0.47	-0.33	0.26	0.54	0.6	-0.29	-0.02	0.25
1987-1992	-0.93	1	-1.77	-0.38	0.22	0.12	0.57	-0.47	-0.12	0.14
1992-1997	-1.43	-0.74	-0.63	-0.31	0.25	0.15	1.02	-0.98	-0.06	0.17
1997-2002	-0.26	0.65	-0.63	-0.36	0.08	0.22	1.44	-1.43	-0.07	0.28
2002-2007	-3.11	-1.94	-1.02	-0.45	0.3	-0.44	-0.38	-0.18	-0.06	0.18
2007-2012	-1.2	0.33	-1.39	-0.35	0.21	-0.4	0.76	-1.04	-0.21	0.09
Mean		-0.2	-0.83	-0.36	0.22		0.67	-0.73	-0.09	0.19
15 yr period										
1982-1997	-2.43	-0.22	-1.92	-1.02	0.73	0.8	2.19	-1.74	-0.2	0.55
1997-2012	-4.57	-0.97	-3.05	-1.15	0.6	-0.62	1.82	-2.64	-0.35	0.55
Overall										
1982-2012	-7.01	-1.19	-4.97	-2.17	1.32	0.19	4.01	-4.38	-0.55	1.11

Panel B	Retail					Services				
	Total	Within	Between	Exit	Entry	*Total*	Within	Between	Exit	Entry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
5 yr period										
1982-1987	0.02	0.09	-0.02	-0.07	0.02	0.34	0.15	0.58	0.98	-1.37
1987-1992	-0.14	0.82	-0.71	-0.17	-0.08	-0.01	-0.23	0.82	1.02	-1.62
1992-1997	-0.34	1.26	-1.52	-0.21	0.13	-0.15	1.82	-2.05	1.14	-1.06
1997-2002	0.4	1.27	-0.8	-0.07	0	0.61	-2.02	2.86	0.12	-0.35
2002-2007	-0.67	0.11	-0.75	-0.21	0.18	-0.78	2.2	-2.69	0.34	-0.63
2007-2012	-0.07	0.19	-0.23	-0.1	0.07	-0.2	0.51	0.04	-0.01	-0.74
Mean		0.62	-0.67	-0.14	0.05		0.41	-0.07	0.6	-0.96
15 yr period										
1982-1997	-0.45	2.17	-2.25	-0.45	0.07	0.18	1.74	-0.65	3.14	-4.05
1997-2012	-0.34	1.57	-1.78	-0.38	0.25	-0.37	0.69	0.21	0.45	-1.72
Overall										
1982-2012	-0.79	3.74	-4.03	-0.83	0.32	-0.19	2.43	-0.44	3.59	-5.77

Panel C	Finance					Utilities & Transportation				
	Total	Within	Between	Exit	Entry	*Total*	Within	Between	Exit	Entry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
5 yr period										
1992-1997	0.97	1.43	-0.57	-0.2	0.31	-1.23	1.21	-1.67	0.17	-0.94
1997-2002	1.5	0.32	0.89	-0.4	0.69	1.12	0.25	0.53	0.75	-0.41
2002-2007	0.19	2.02	-1.99	-0.68	0.84	-1.78	-0.88	-1.25	-0.02	0.37
2007-2012	0.6	2.51	-1.94	-0.29	0.32					
Mean	0.82	1.57	-0.9	-0.39	0.54	-0.63	0.19	-0.8	0.3	-0.33
10 yr period										
1992-2002	2.46	1.75	0.32	-0.6	0.99					
2002-2012	0.8	4.54	-3.93	-0.97	1.16					
Overall										
1992-2012	3.25	6.29	-3.62	-1.57	2.15					
1992-2007						-1.89	0.58	-2.39	0.91	-0.98

Notes: This Table shows the results of a decomposition of the change in the labor share using the dynamic Melitz and Polanec (2015) methodology as described in the text and notes to the previous Table. These all use the micro-data from the five yearly Censuses in the relevant industry. "15 year period" is the same calculation over 15 year periods and "overall" is over the entire period 1982-2012.

Table 6: International COMPNET Regressions of the Change in Labor Share on the Change in Concentration (Industry level, all sectors)

	5 yr. Change		10 yr. Change		No. Obs.
Italy	-0.124	**	-0.200	**	53
	(0.052)		(0.095)		
Estonia	-0.140		-0.125		53
	(0.197)		(0.084)		
Portugal	-0.083		---		53
	(0.063)		---		
Slovenia	-0.106		-0.101		53
	(0.140)		(0.187)		
Slovakia	-0.153	**	-0.343	***	52
	(0.060)		(0.100)		
Finland	-0.208	***	-0.181	**	53
	(0.059)		(0.076)		
Belgium	-0.008		0.330	*	53
	(0.053)		(0.176)		
Germany	-0.091		-0.151		44
	(0.060)		(0.094)		
Poland	0.007		---		53
	(0.076)		---		
France	0.325		-0.183	**	53
	(0.255)		(0.087)		
Latvia	-0.039		---		52
	(0.108)		---		
Romania	-0.137		---		53
	(0.096)		---		
Austria	-0.297	***	-0.275	**	37
	(0.098)		(0.108)		
Lithuania	-0.124		-0.045		53
	(0.156)		(0.201)		

Notes: Concentration is defined at the fraction of output produced by the 10 largest firms. Regression includes 5-year changes from 2006-2011 and 10-year changes (when available) from 2001-2011. Observations are weighted by the sector's share of the country's total value added. Estimates by OLS with standard errors clustered at the sector level.

IX APPENDICES (NOT INTENDED FOR PUBLICATION UNLESS REQUESTED)

APPENDIX A: MODEL OF SUPERSTAR FIRMS

We present a simple model of an industry characterized by heterogeneous firms, imperfect competition in the product market and fixed costs of overhead labor. We then consider a change in the economic environment (such as increase in product market competition as indexed by consumers' sensitivity to price) that will generate more output being allocated to the more productive companies ("superstar firms"). Since these firms have higher labor shares and higher market shares, this will cause both an increase in concentration and a tendency for the industry's aggregate labor share to decline.

Firms enter an industry and obtain an idiosyncratic draw of productivity ($A_i = TFPQ_i$, quantity based Total Factor Productivity) from a known distribution.[38] We assume capital cannot be adjusted for one period, but then after this it is completely flexible (as in Olley and Pakes, 1996). There is overhead labor, F, needed to produce output.[39] We allow for potentially decreasing returns to scale γ in a Cobb-Douglas production function (we imposed $\gamma = 1$ in the main text for simplicity). Value-added, Y_i, for firm i is:

$$Y_i = A_i V_i^{\gamma-\alpha} K_i^{\alpha} = A_i \left(L_i - F\right)^{\gamma-\alpha} K_i^{\alpha} \tag{6}$$

where K is the capital stock and total labor is $L_i = V_i + F$, the sum of variable labor V plus fixed labor. Factor markets are competitive so that all firms face the same wage, w, and cost of capital, r. Each firm faces an inverse demand curve with elasticity ρ, $P_i = (b/Y_i)^{\frac{1}{\rho}}$ where b is a demand shifter and P_i is firm $i's$ price (each firm produces a single variety). There is a sunk cost of entry, κ, and potential firms will choose to enter an industry until the point where expected profits (i.e., net of the sunk cost) are zero, thereby pinning down the equilibrium number of firms.

We can define a threshold level of productivity, $\widetilde{A}^{\rho}$ such that if the productivity draw is below this threshold, the firm will immediately exit because it does not expect to be able to recover its fixed costs. The productivity threshold can be derived as:

$$\widetilde{A}^{\rho} = \frac{b^{\rho-1} r^{\alpha\rho} w^{1-\rho\alpha} F^{1-\rho\gamma}}{\alpha^{\rho\alpha} \left(\gamma-\alpha\right)^{\rho(\gamma-\alpha)} \rho^{\rho} \left(1-\gamma\rho\right)^{1-\gamma\rho}} \tag{7}$$

This productivity threshold is increasing in the level of fixed costs and the degree of product market competition. None of the terms on the right hand side of equation (7) vary across firms.

A firm's optimal capital stock is

$$K_i^* = A_i^{\frac{\rho}{1-\rho\gamma}} \Omega\left(w, r\right) \tag{8}$$

where $\Omega(w,r) > 0$ is a constant that does not vary across firms.[40] Optimal variable labor is:

$$V_i^* = L_i^* - F = A_i^{\frac{\rho}{1-\rho\gamma}} \frac{r\left(\gamma-\alpha\right)}{w\alpha} \Omega \tag{9}$$

[38] A heterogeneous initial draw of productivity is isomorphic to a draw in firm-specific quality in this class of models. We can think generically of A_i as the entrepreneurial-managerial quality of the founder.

[39] Allowing for fixed costs in capital would make no difference to the propositions below. The capital share evaluated at the competitive return also falls as the profit share rises (see Barkai, 2016).

[40] $\Omega\left(w,r\right) = [b^{1-\rho} \rho r^{(\gamma-\alpha)\rho-1} \alpha^{1-(\gamma-\alpha)\rho} w^{-(\gamma-\alpha)\rho} \left(\gamma-\alpha\right)^{(\gamma-\alpha)\rho}]^{1/(1-\rho\gamma)}$

For all operating firms, nominal value-added over variable labor is:

$$\frac{P_i Y_i}{V_i} = b^{1-\rho} \left(\frac{r(\gamma - \alpha)}{w\alpha} \right)^{\rho(\gamma-\alpha)-1} \Omega^{\rho\gamma - 1} \tag{10}$$

This ratio is constant across all firms, so there is no variation in the average revenue productivity of variable labor. However, what is observed in the data is value-added over all labor (empirical labor productivity) that includes both fixed and variable employment:

$$\frac{P_i Y_i}{L_i^*} = \frac{P_i Y_i}{F + V_i^*} = \left\{ \frac{F}{P_i Y_i} + b^{\rho-1} \left(\frac{r(\gamma - \alpha)}{w\alpha} \right)^{1-\rho(\gamma-\alpha)} \Omega^{1-\rho\gamma} \right\}^{-1} \tag{11}$$

In the absence of fixed costs ($F = 0$) labor productivity (equation (11)) is constant across all firms as the second term within the curly brackets is constant across firms in an industry (as in Hsieh and Klenow, 2009). However, as noted by Bartelsman, Haltiwanger and Scarpetta (2013), when there are fixed costs ($F > 0$), labor productivity is increasing in the size of the firm since the share of fixed overhead labor in revenue $\left(\frac{F}{P_i Y_i}\right)$ is decreasing in size. Since size increases in A_i , the high A firms will have higher nominal value-added to employment ratios. Intuitively, the share of fixed labor costs in total labor costs is declining as the firm grows larger. As this ratio falls so does the overall labor share, so for larger firms there is a smaller share of labor.

Proposition 1. ***Superstar firms have a lower labor share.***

Proof. Inverting equation (11) and multiplying each side by the wage gives:

$$S_i \equiv \frac{wL_i^*}{P_i Y_i} = \frac{wF}{P_i Y_i} + wb^{\rho-1} \left(\frac{r(\gamma - \alpha)}{w\alpha} \right)^{1-\rho(\gamma-\alpha)} \Omega^{1-\rho\gamma} \tag{12}$$

Superstar (high A) firms will have a lower $\frac{wL_i^*}{P_i Y_i}$ and therefore a lower labor share.

□

Proposition 2. ***An increase in product market competition (as measured by ρ) increases concentration.***

Proof. Consider two firms i and j with $A_i > A_j$. Given our functional forms we can write their relative market shares, $\omega_i/\omega_j = (A_i/A_j)^{(\rho-1)/\rho(1-\rho\gamma)} > 1$ where $\omega_i = \frac{P_i Y_i}{\sum_i P_i Y_i}$. The market share of high A firm i is increasing in its productivity advantage over the low A firm j. Furthermore, for any given productivity difference, an increase in product market competition (ρ rises) will increase the relative market share of the more productive firm. This follows since $sign\left\{\frac{\partial^2(\omega_i/\omega_j)}{\partial(A_i/A_j)\partial\rho}\right\} = sign\left\{1 + \rho\gamma(\rho - 2)\right\} > 0$ because $\rho > 1$ and $\gamma \leq 1$. Since the market share of the higher market share firms will rise when competition rises (and those of the low market share firms are falling), concentration will rise.

□

Proposition 3. ***An increase in product market competition reallocates output to the low labor share firms.***

Proof. Define the industry aggregate labor share as $S \equiv \sum_i \frac{wL_i}{P_i Y_i} = \sum_i \omega_i S_i$. Proposition 2 established that an increase in competition allocates more market share to the high A firms. Since these firms have a lower labor share, there is a reallocation effect towards lowering the aggregate labor share.

□

Proposition 4. ***An increase in product market competition will decrease the aggregate labor share, as long as the reallocation effect between firms effect dominate the within-firm effect.***

Proof. From proposition 3, there is a shift in market share towards the low labor share firms when ρ rises. This is reinforced by an effect on the extensive margin. An increase in competition raises the productivity threshold (equation (7)). This will cut off some of the tail of low A, high labor share firms. Note, however, that there is also an offsetting within-firm effect since an individual firm's price cost margins are declining in ρ: $\mu_i = \frac{P_i}{c_i} = \frac{\rho}{\rho-1}$. Since the labor share is declining in the price-cost margin, and so increasing in ρ, within firms the labor share will tend to rise with higher competition. Hence the overall effect of competition on the labor share is ambiguous and depends on the balance of the within and between-firm effects. In simplified cases of the general model we can characterize sufficient conditions under which there will be an unambiguous rise in the labor share following an increase in ρ.

□

APPENDIX B: DATA

Data Details

Our primary data are from the U.S. Economic Census conducted every 5 years by the Census Bureau.[41] We focus on six sectors for which we could access micro-data over a significant period of time: Manufacturing, Retail trade, Wholesale trade, Services, Finance and Utilities and Transportation. There is also a Census of Construction, but it does not provide a consistent firm identifier. Within these six sectors, several industries are excluded from the Economic Census: rail transportation from Transportation; postal service from Wholesale trade; funds, trusts and other financial vehicles are excluded from Finance; and schools (elementary, secondary, and colleges), religious organizations, political organizations, labor unions and private households are excluded from Services. The Economic Census also does not cover government-owned establishments within covered industries.

Our analysis includes only establishments that have at least one employee ("employer firms"), a positive value of annual sales, and are assigned a code that allows us to link them over time in the Census (LBDNUM). We exclude any observations that are drawn from administrative records, as these observations are largely imputed and are not included in official statistics published by the Census Bureau. We also Winsorize the establishment-level labor share at the 99^{th} percentile to account for outliers. As an establishment's value-added goes towards zero, the labor share

[41] More details on Economic Census are available at `https://factfinder.census.gov/faces/affhelp/jsf/pages/metadata.xhtml?lang=en&type=survey&id=survey.en.ECN_ECN_US`

can become arbitrarily large. While this has little effect on the industry-level analysis, where we weight observations by their share of value-added, these large outliers can affect the decompositions of changes in labor share into between-firm reallocation and within-firm components in Figure 9 and 10. We confirmed the robustness of our results to alternate treatments of outliers, including dropping them altogether or top-coding the labor share at one.

While each establishment is assigned to one primary industry, firms with multiple establishments are often active in several industries. In all of our industry-level analyses, we define firms separately by four-digit SIC industry, meaning that a firm with establishments in three different industries will be treated as three separate firms in our analysis. This definition of the firm is motivated by our focus on concentration ratios, where the relevant measure is not the total size of the firm but rather the importance of that firm in a given industry. In manufacturing, about 20 percent of firms are active in multiple industries, and on average, firms span 2.6 industries. These numbers are slightly lower in retail and wholesale trade and services, but are slightly higher in finance where about a quarter of firms span multiple industries. The only analysis in which we do not define a firm as a firm-by-industry pair is the overall within-between decompositions in Table 4 and 5. In this table, we define a firm using all establishments, regardless of industry. However, in Appendix Table A.1, we present decompositions in which we define a firm using the firm-by-industry pair.

Constructing Time-Consistent Industry Codes

Since we analyze cross-industry variation in concentration, accurate classification of industries is central to our analysis. In the raw data, each establishment is assigned an industry code that is based on the primary activity of the establishment. In 1982, the establishments are given a 1972 SIC code, from 1987-1997, the establishments are given a 1987 SIC code, and from 2002 to 2012, the establishments are given a NAICS code based on the classification corresponding to that year (i.e. 2002 is in 2002 NAICS codes). While most of our regressions are run at the industry level, the definition of industry concentration ratios and firm-level decompositions require that each establishment is assigned to a single industry, meaning that a weighed (i.e., fractional) crosswalk of NAICS to SIC codes is not suitable. To construct a one-to-one crosswalk, we utilize the panel structure of the Census data and the fact that in 1997, each establishment is given both a 1987 SIC code and a 1997 NAICS code. If the establishment has the same NAICS code in the following years, we assign the given 1987 SIC code that is reported for the year 1997 to the later years as well. Then, if either the establishment was not in the sample in 1997 or the NAICS code changed in the later years, we use a modal mapping from the NAICS codes to the 1987 SIC code, meaning that we assign each NAICS industry to the SIC code that is it most likely to map to in the probabilistic mappings provided by the Census.

There are, however, some 1987 SIC codes that are not the most likely industry for any NAICS code, meaning that those 1987 SIC industries would not exist in the post-1997 data ("orphaned SIC codes"). To avoid the creation of such an artifact in the data, we aggregate SIC codes so that each aggregate SIC codes is observed both before and after the SIC-NAICS seam. In deciding which industries to group, we find the 1997 NAICS codes that establishments from the orphaned SIC codes are most likely to be reclassified as, and then we combine that SIC code with the SIC codes that were the most likely 1987 SIC codes for that NAICS code. For example, establishments from 1987 SIC code 2259 "Knitting Mills, Not Elsewhere Classified"' are most likely to be re-classified as NAICS code 315191 "Outerwear Knitting Mills," but of all the establishments that were given code 315191, the most common 1987 SIC code was 2253 "Knit Outerwear Mills." Therefore, we aggregate the 1987 SIC codes 2253 and 2259. We follow the same procedure for bridging the

1972-1987 SIC reclassification.

Our final industry panel corresponds to a slight aggregation of four-digit SIC industries, and comprises 388 industries in manufacturing, 58 industries in retail trade, 95 industries in services, 31 industries in finance, 56 industries in wholesale trade, and 48 industries in utilities and transportation.

Correcting Census Value-Added for Service Intermediate Inputs using KLEMS

The measure of value-added in the Census adjusts for intermediate purchased goods but does not adjust for intermediate purchased services, meaning that an increase over time in intermediate purchased services will appear in the Census data as an increase in value-added (and possibly exaggerate the fall in the labor share). The KLEMS data allow us to roughly adjust value-added in the Census to account for any trends in intermediate purchased services over time. Since the KLEMS data are only available at the two- to three-digit industry level, we make the adjustment at the establishment level in two ways, both of which use the fact that the Census data include information on the value of material costs for each establishment. First, we calculate in KLEMS the ratio of intermediate purchased services to intermediate materials and assume that each establishment in a given two-digit industry utilizes purchased services in that proportion. This is the method we report in Row 3 in Table 2. As a second alternative, we calculate the fraction of total two-digit industry intermediate material costs that are accounted for by each four-digit industry, and assume that four-digit industries purchase the same fraction of total intermediate services. The level of the labor share is higher (as value-added is lower) when correcting for purchases of intermediate services, but the trends are similar across the original and adjusted data series, as well as across both methods of adjustment.

Comparing Census and NIPA/BEA data

In this section, we compare the Census data that we use throughout the analysis to the broad industry-level NIPA data produced by the Bureau of Economic Analysis (which is used by Elsby, Hobjin and Sahin, 2013, for example). The goal of this exercise is twofold. First, we aim to validate the construction of establishment-level data by showing that, when aggregated, it is similar to the aggregate trends discussed widely in the literature. Second, we use the NIPA data to benchmark the payroll-to-sales ratio outside of manufacturing to Census data. Since the Census does not collect sufficient information outside manufacturing to construct measures of value-added, our main analysis uses the payroll-to-sales ratio as a alternate measure.

The Census derives its estimates from mandatory report forms. The NIPA estimates are instead derived from a compilation of data sources. One of these sources is the Economic Census, but it also includes annual, quarterly and monthly surveys, financial reports, government budgets and IRS tax data. A reason for these additional data is that NIPA data are reported at a higher frequency (quarterly) than Census data. They are also reported at a higher level of industry aggregation than Census. For our purposes, this difference leads to two important distinctions between the Census and NIPA data. First, the industry definition varies across the two sources. The Census unit of analysis is an establishment whereas in NIPA it is the firm. Consider a firm whose primary industry is retail but that also has a manufacturing plant. In Census data, the employment of the manufacturing establishment is counted towards the manufacturing sector while the remainder of the firm's establishments are classified as retail. By contrast, NIPA could attribute all the firm's employment (including that of the manufacturing establishment) to retail. Additionally, the

BEA/NIPA includes some sub-industries that are not included in the Census, such as management and private households.

Second, and more importantly, the two agencies define the components of the labor share differently. Panel A of Figure A.8 displays the payroll-to-value-added ratio for manufacturing in NIPA and Census, and shows that while the trends are similar, the level of the series differs substantially across the two data sources. As is shown in Panel B of Figure A.8, this discrepancy stems from a small difference in the numerator (compensation) and a larger difference in the denominator (value-added). The left figure in Panel B plots the compensation series in the two datasets, which appear reasonably comparable. As discussed above, there is a narrow and broad definition of payroll in the Census. There is also a narrow and broad definition in NIPA, although the broad NIPA definition is even wider than in the Census. Indeed, the broader definition of compensation in the Census data closely tracks the narrower definition of compensation in the NIPA data.[42]

NIPA and Census data diverge more in their definition of value-added. The right figure in Panel B shows that value-added in the Census data is significantly higher than value-added in the NIPA data. While there are several differences in the two series, the largest difference is in their treatment of intermediate purchased services. Since the Census does not collect information on intermediate purchased services, it does not subtract these from value-added, and therefore measures value-added as the establishment's output less its material costs.[43] However, the BEA does collect information on intermediate purchased services and subtracts it from its value-added measure. In order to explore the importance of this mechanism, as discussed in the previous subsection we use industry-level estimates of intermediate purchased services from the KLEMS data. These data are reported annually beginning in 1997 at the three-digit NAICS level. As the red line in the right figure of Panel B shows, subtracting off the intermediate purchased services within manufacturing almost completely closes the gap in value-added across the two data sources. Indeed, using this modified value-added series results in aggregate labor shares that are much closer—near identical in fact when we use the broader measure of Census compensation (see Panel A of Figure A.8).

As discussed above, the Census does not collect detailed information on intermediate inputs outside manufacturing. Therefore we analyze the behavior of the payroll-to-sales ratio. Figure A.9 shows for each sector the payroll-to-sales ratio in the Census compared with its closest counterpart in NIPA: the payroll to gross output ratio. We also include the NIPA payroll to value-added ratio which is not available in the Census except for the manufacturing sector. Each series is normalized to one in 1987.

Starting with manufacturing in the top left panel, the series are relatively aligned in terms of trends, but diverge a bit, especially after 1997. This is mainly because the NIPA data are released in 1987 SIC codes pre-1997 and in 1997 NAICS codes post-1997, creating a discrepancy in the NIPA series.

Looking at the other five sectors, two patterns emerge. First, there is a general trend downwards in the labor share measured across almost all sectors. Second, the NIPA trends are more closely correlated with each other than they are with the Census trends, which is unsurprising as the denominator is identical. Third, the Census trends diverge from the NIPA more strongly outside

[42] The BEA also includes a more comprehensive measure of compensation that includes employer contributions to insurance plans as well as government social insurance programs. This is reported on an accrual basis, and reflects liabilities rather than actual payments.

[43] Note that the Census does collect information on the costs of contract work that is done by others on materials furnished by the reporting establishment. Since this cost is included in their measure of intermediate costs, it is subtracted from value-added. However, this does not include the costs of contracted services such as advertising, insurance, or professional consultants.

manufacturing, especially around the industry re-classification seam of 1997.

Disaggregating the numerator and denominator reveals that the payroll measures in Census and NIPA move much more in tandem than the sales and output measures. Apart from the industry reclassification, there may be several reasons for this divergence. First, Census sales differ from NIPA output primarily because of inventories, so output will exceed sales when inventories are rising as a fraction of output. This may particularly be an issue for wholesaling, which will plausibly be strongly affected by inventory behavior, and where we do see large divergences with labor shares rising in the 1987-2002 period in the Census while declining in NIPA. Second, we have excluded some industries that are not defined consistently over time in the Census but are unable to remove these industries from NIPA. So to the extent these sub-industries exhibit different growth trends, this will show up in the aggregates. These dropped industries are exclusively in Finance, Services and Manufacturing. From Finance, we drop SIC codes 6722 (Management Investment Offices), 6726 (Unit Investment Trusts), 6552 (Land Subdividers and Developers), 6712 (Offices of Bank Holding Companies) and 6719 (Offices of Holding Companies not elsewhere classified). From Services, we drop SIC codes 7338 (Secretarial and Court Reporting Services), 8734 (Testing Laboratories), 8062 (General Medical and Surgical Hospitals), 8063 (Psychiatric Hospitals), and 8069 (Specialty Hospitals, Except Psychiatric). Lastly, from Manufacturing, we drop industries the move outside manufacturing in the 1997 SIC-NAICS redefinition. These are 2411 (Logging), 2711 (Newspaper Publishing and Printing), 2721 (Periodical Publishing and Printing), 2731 (Book Publishing and Printing), 2741 (Miscellaneous Publishing), 2771 (Greeting Cards) and 3732 (Boat Building and Repair). This could be a reason for the large discrepancies we see in Finance where the labor share falls in NIPA after 1992 but rises in the Census data (at least until 2002). This is because the NIPA output series for Finance increases much more strongly, which could be due to how assets are valued during the financial boom. It is difficult to know what difference, if any, these would make to our results.

International Datasets

In addition to the KLEMS dataset discussed above, we draw on two other international datasets: BVD Orbis and COMPNET. Bureau Van Dijk (BVD) is a private sector aggregator of company accounting data. Orbis is its most comprehensive product covering in principle the population of all public and private company accounts in the world (Kalemli-Ozcan, Sorensen, Villegas-Sanchez, Volosovych and Yesiltas, 2015). Orbis is a panel data set. BVD seeks to harmonize the data in a common format focusing on a sub-set of the variables that are used for investment analysis. Orbis has been built up over time, so it is less comprehensive the further back in time one goes. Furthermore, the data are constrained by what firms report in their accounts. Accounting regulations differ across countries with some countries requiring more comprehensive reporting than others. For example, the U.S. requires private firms to report very little information in the public domain compared to European countries such as France. Across all countries, more information is demanded from larger firms than smaller firms.

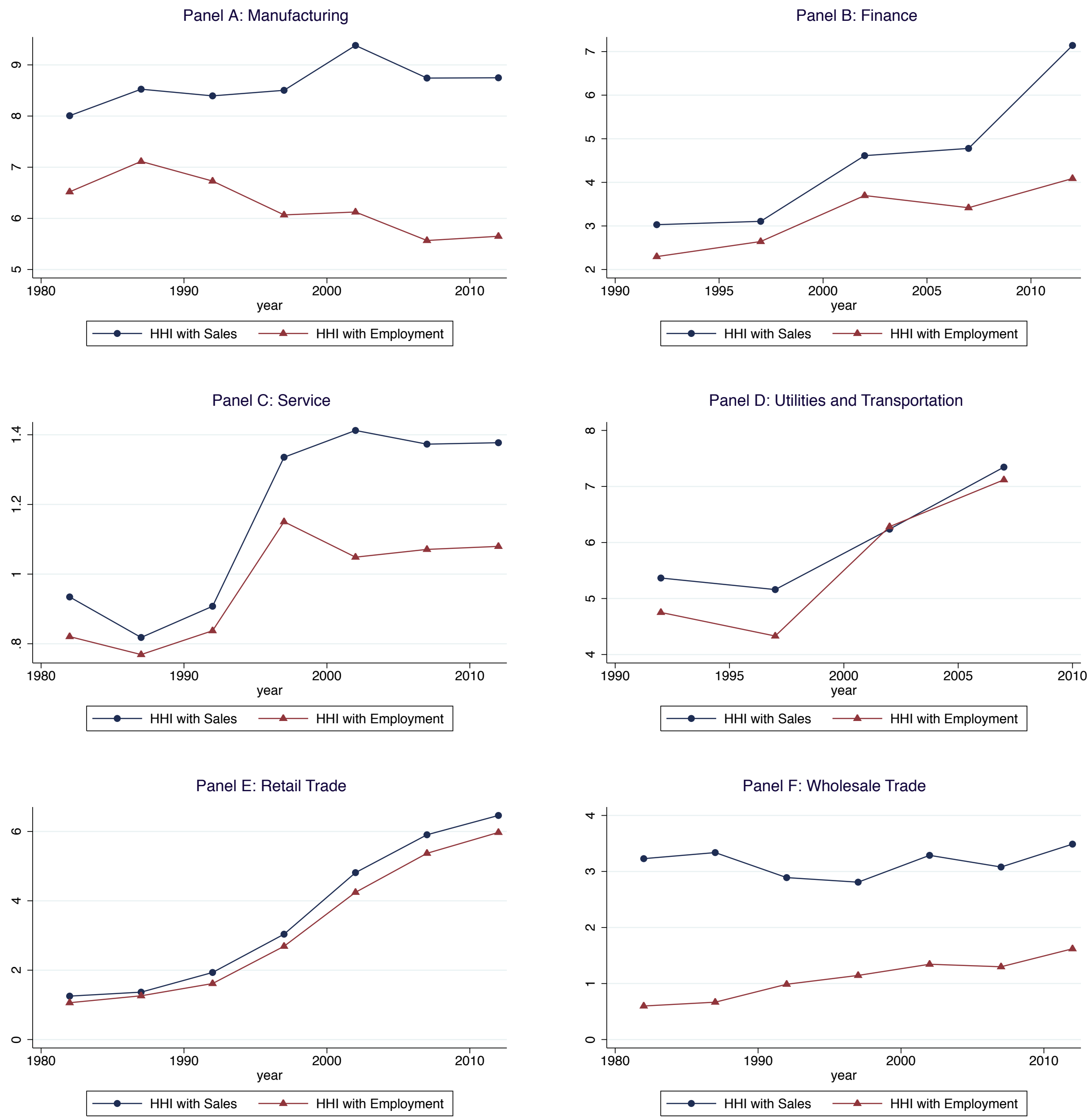
For our analysis we require firms have information on their primary industry and their payroll. To construct value-added, we sum payroll with gross profits (i.e. before tax, depreciation and interest have been deducted, sometimes known as EBITA, Earnings Before Interest Tax and Amortization). Intermediate inputs are rarely reported in company accounts, so deducting these from sales (as we do with the Census data) is not feasible. The labor share is then the ratio of payroll to this measure of value-added. We also do some robustness checks comparing this measure with the ratio of wage bill to sales. We focused on the sub-sample of countries where we could get reasonably comprehensive data which were the sub-set of European countries Table A.3. We used the 5 year period for which we could get the largest panel between 2003 and 2008.

The second international firm database is Compnet. This has balance sheet data from 14 European countries that cover the 2000-2012 period. These data, compiled by the European Central Bank's Competitiveness Research Network, draw on various administrative and public sources across countries, and aim to collect information for all non-financial corporations (see Lopez-Garcia, di Mauro and CompNet Task Force 2015 for details). This was an initiative led by the European Central Bank in a effort to obtain systematic micro-data to help inform its macro-economic modeling. It was able to coordinate with the Central Banks from different European Union member states to get access to micro-data that were not always in the public domain.

The version of Compnet made available to us (kindly through Erik Bartelsman) aggregates the firm level data to the industry level. It contains information on the labor share and industry concentration (both the fraction of sales produced by the largest ten firms and the Herfindahl-Hirschman Index for various two-digit industries. Although great effort was made to make these measures comparable across countries, there are some important differences that affect the reliability of cross-country comparisons. Most importantly for our purposes, countries use different reporting thresholds in the definition of their sampling frames. These data are weighted to try to account for different firm sizes and sample response probabilities.

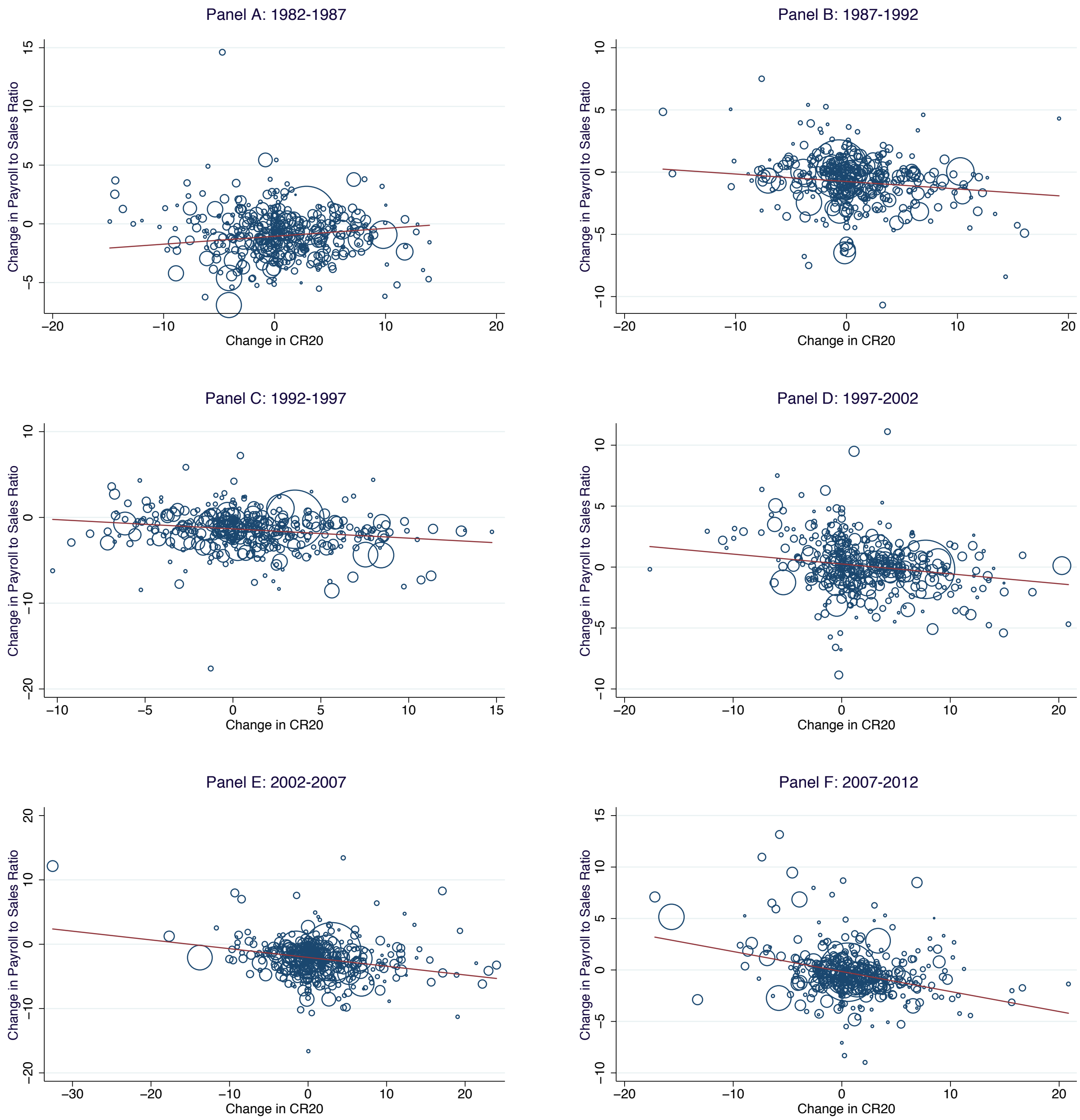
X Appendix Figures

Figure A.1: Average Herfindahl-Hirschman Index by Sector



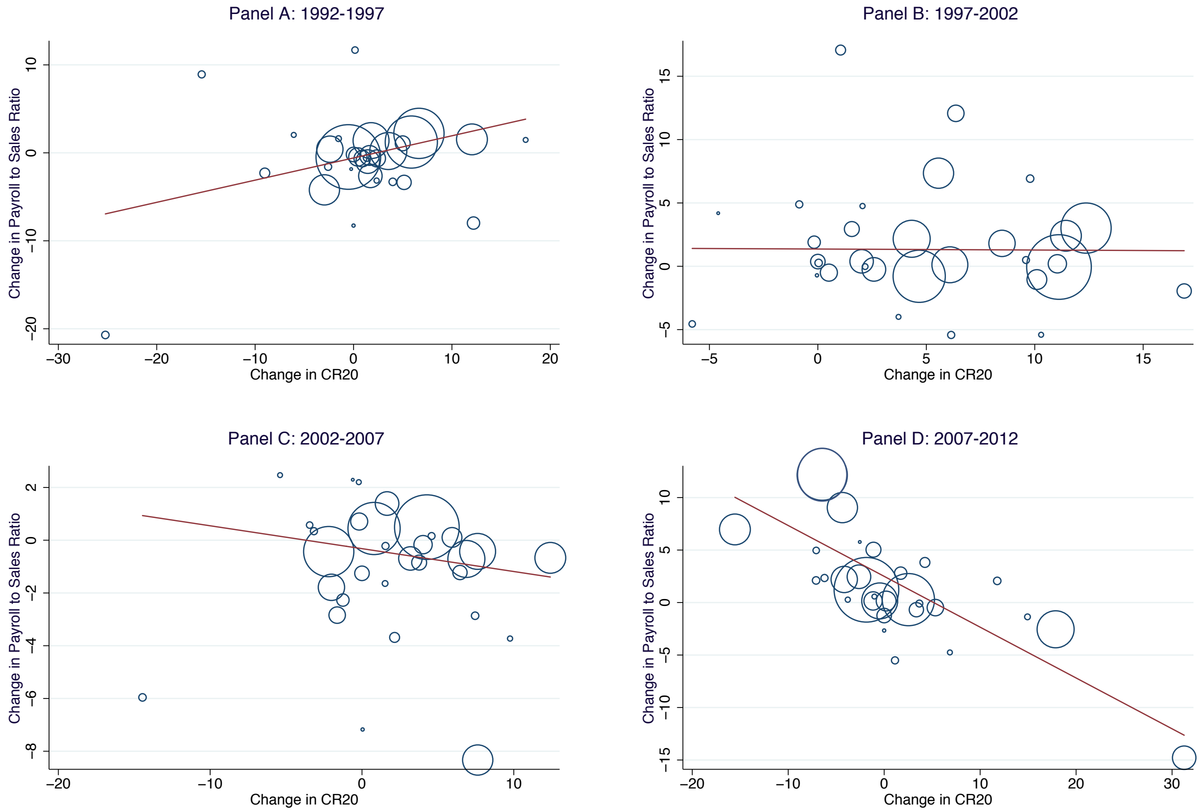
Notes: Each figure plots the average HHI calculated within four-digit industries. Industry concentration is calculated for each time-consistent four-digit industry code, and then averaged across all industries within each of the six sectors. The blue circles plot the HHI calculated using firm sales and the red triangles plot the HHI calculated using employment.

Figure A.2: The Change in Concentration Versus the Change in the Payroll-to-Sales Ratio in Each Five-Year Period: Manufacturing



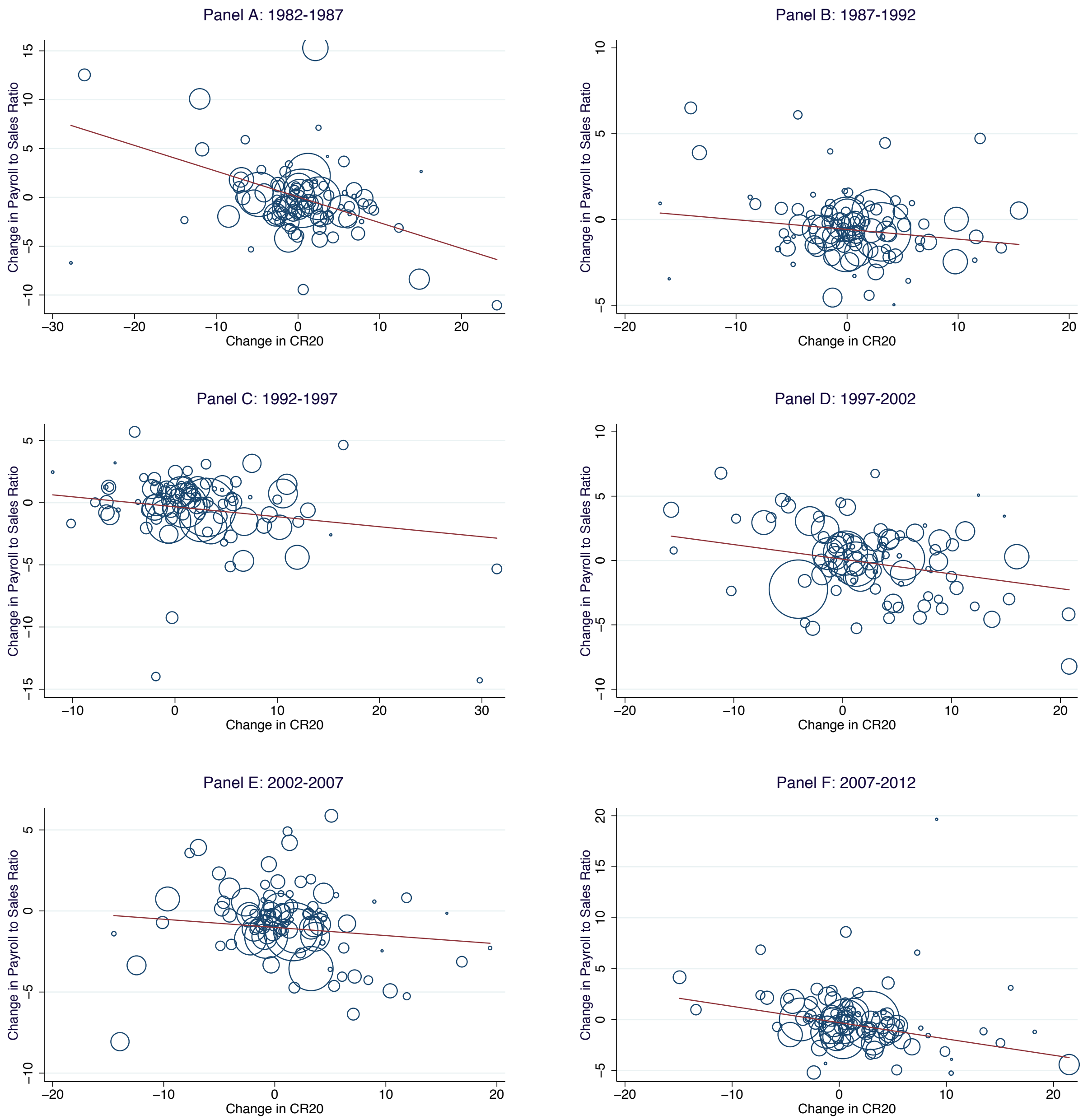
Notes: Each dot represents a four-digit industry, with its size reflecting the industry's 1982 share of sales. The red line shows the best-fit line, using the 1982 share of sales as the industry weight. Concentration is defined using CR20.

Figure A.3: The Change in Concentration Versus the Change in the Payroll-to-Sales Ratio in Each Five-Year Period: Finance



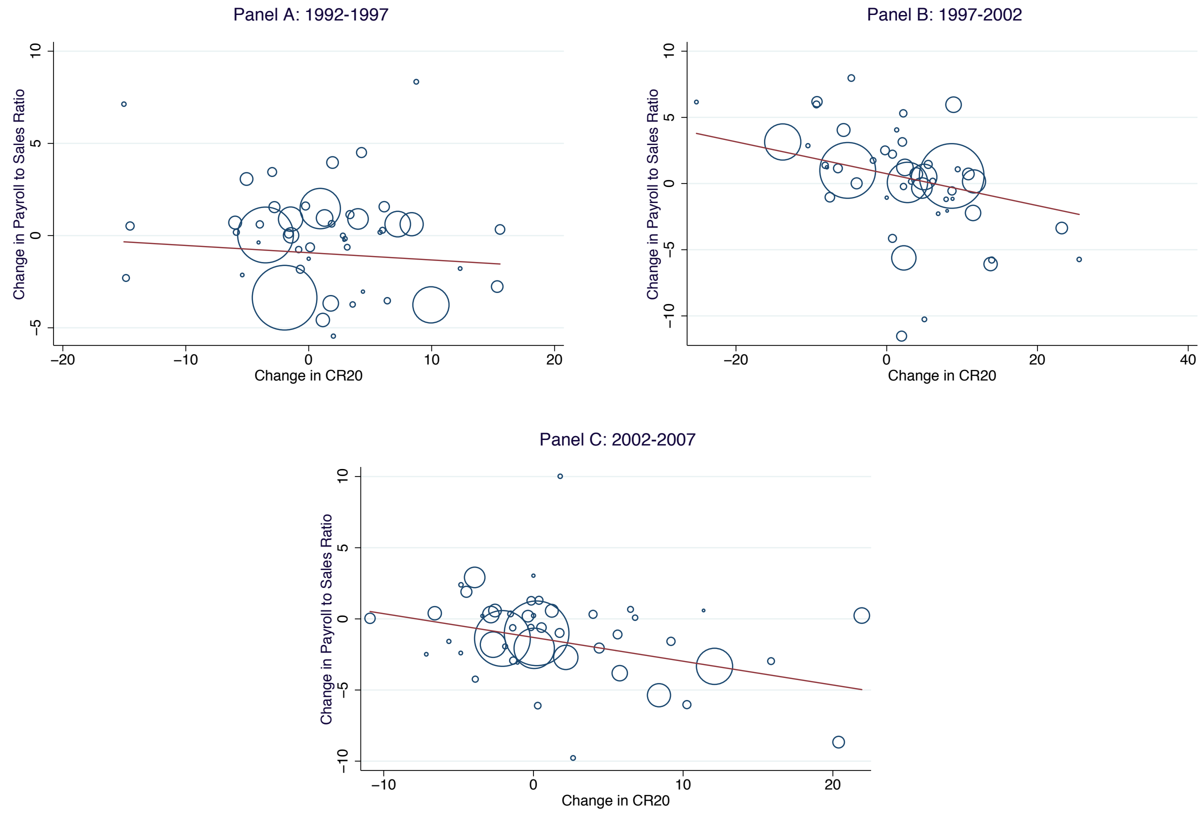
Notes: Each dot represents a four-digit industry, with its size reflecting the industry's 1992 share of sales. The red line shows the best-fit line, using the 1992 share of sales as the industry weight. Concentration is defined using CR20.

Figure A.4: The Change in Concentration Versus the Change in the Payroll-to-Sales Ratio in Each Five-Year Period: Services



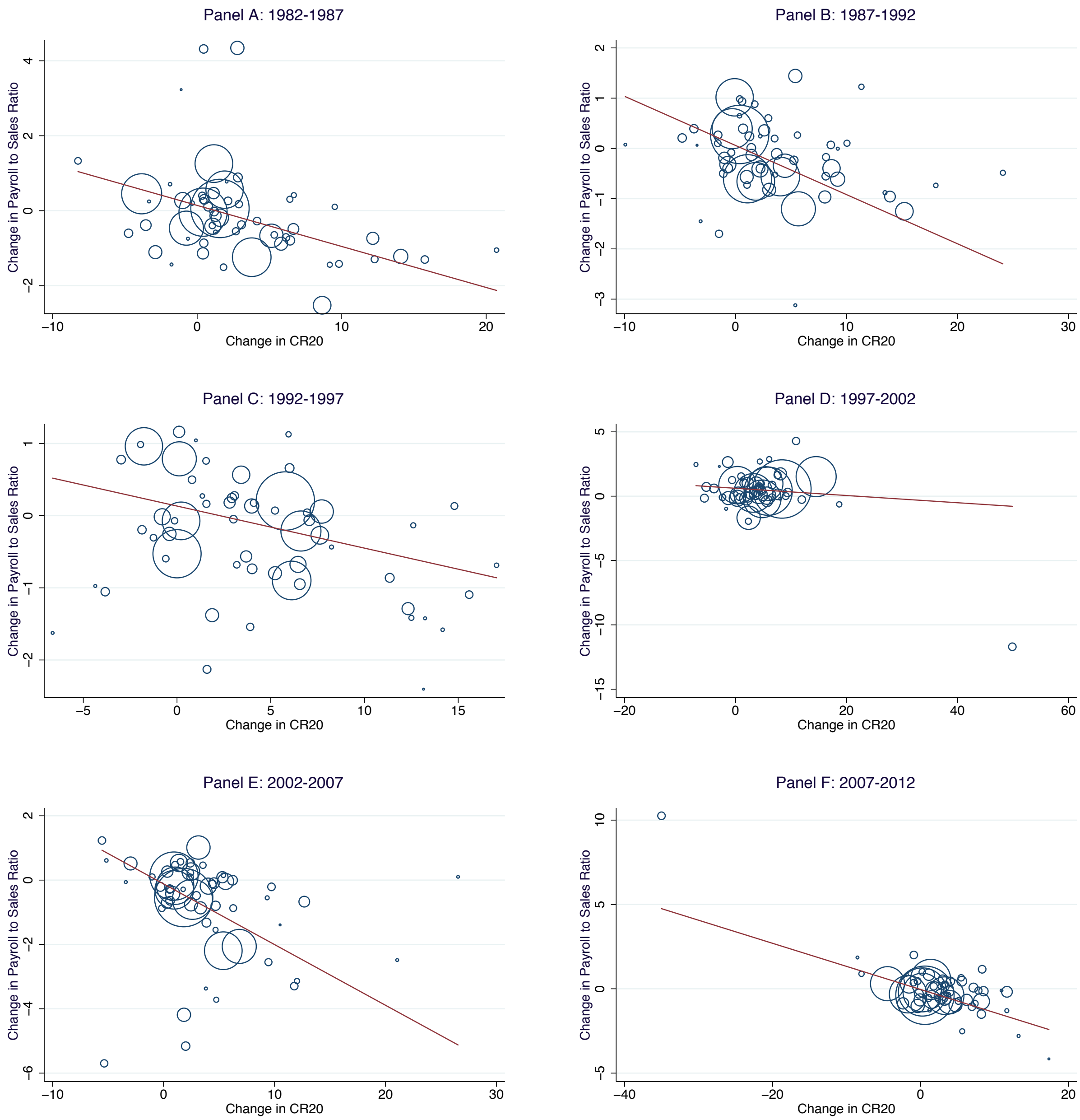
Notes: Each dot represents a four-digit industry, with its size reflecting the industry's 1982 share of sales. The red line shows the best-fit line, using the 1982 share of sales as the industry weight. Concentration is defined using CR20.

Figure A.5: The Change in Concentration Versus the Change in the Payroll-to-Sales Ratio in Each Five-Year Period: Utilities and Transportation



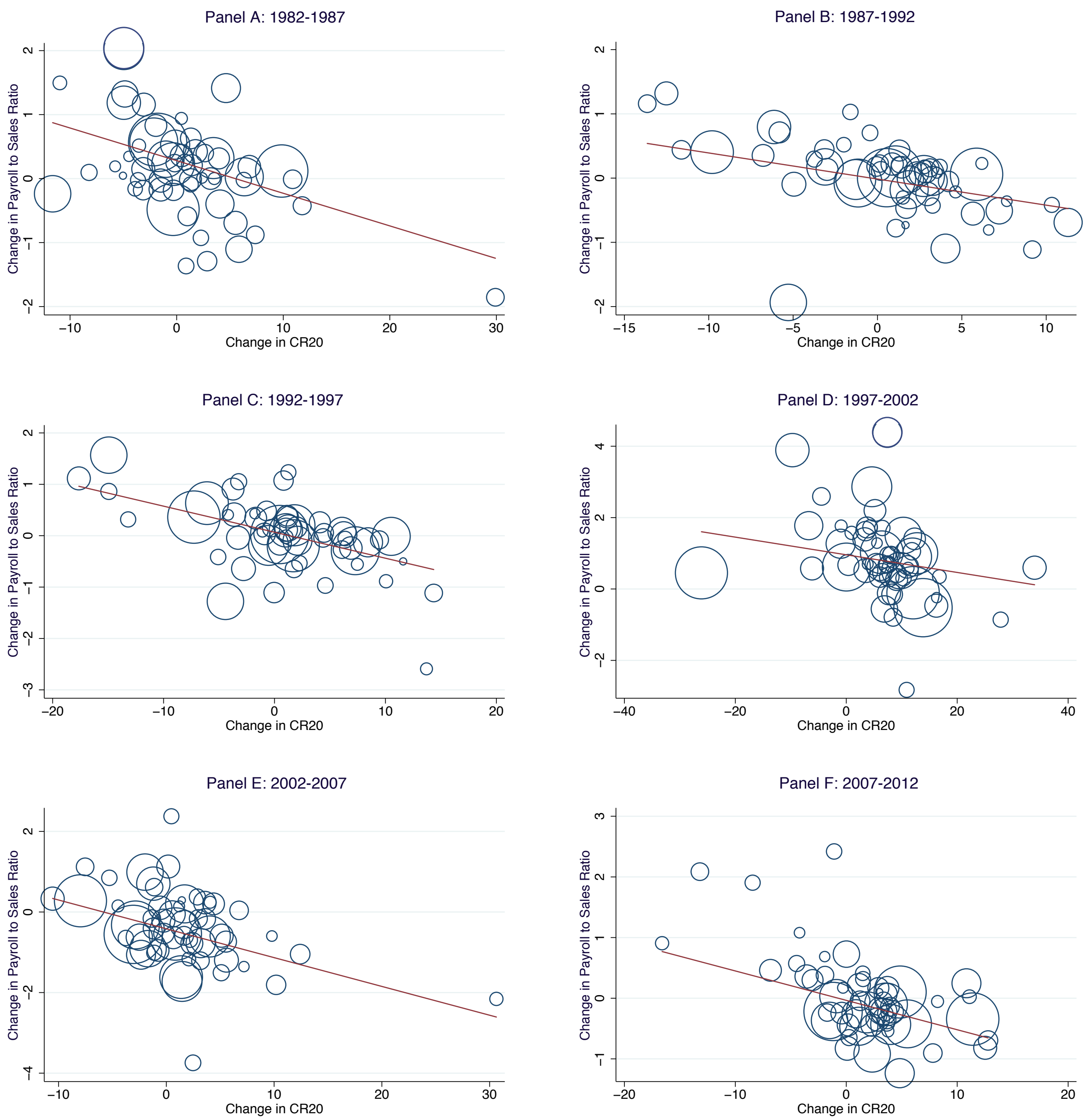
Notes: Each dot represents a four-digit industry, with its size reflecting the industry's 1992 share of sales. The red line shows the best-fit line, using the 1992 share of sales as the industry weight. Concentration is defined using CR20.

Figure A.6: The Change in Concentration Versus the Change in the Payroll-to-Sales Ratio in Each Five-Year Period: Retail Trade



Notes: Each dot represents a four-digit industry, with its size reflecting the industry's 1982 share of sales. The red line shows the best-fit line, using the 1982 share of sales as the industry weight. Concentration is defined using CR20.

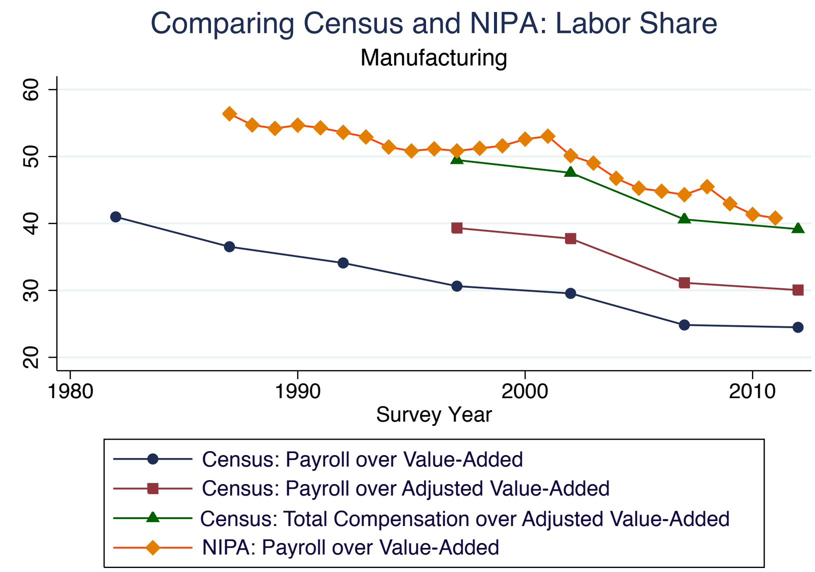
Figure A.7: The Change in Concentration Versus the Change in the Payroll-to-Sales Ratio in Each Five-Year Period: Wholesale Trade



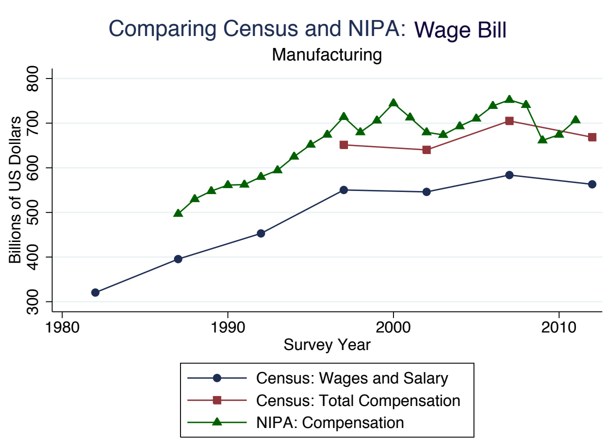
Notes: Each dot represents a four-digit industry, with its size reflecting the industry's 1982 share of sales. The red line shows the best-fit line, using the 1982 share of sales as the industry weight. Concentration is defined using CR20.

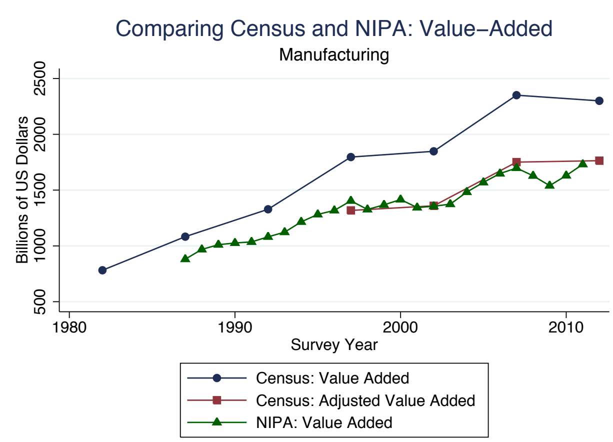
Figure A.8: Comparing Labor Share in NIPA and Census: Manufacturing Only

Panel A: The Labor Share



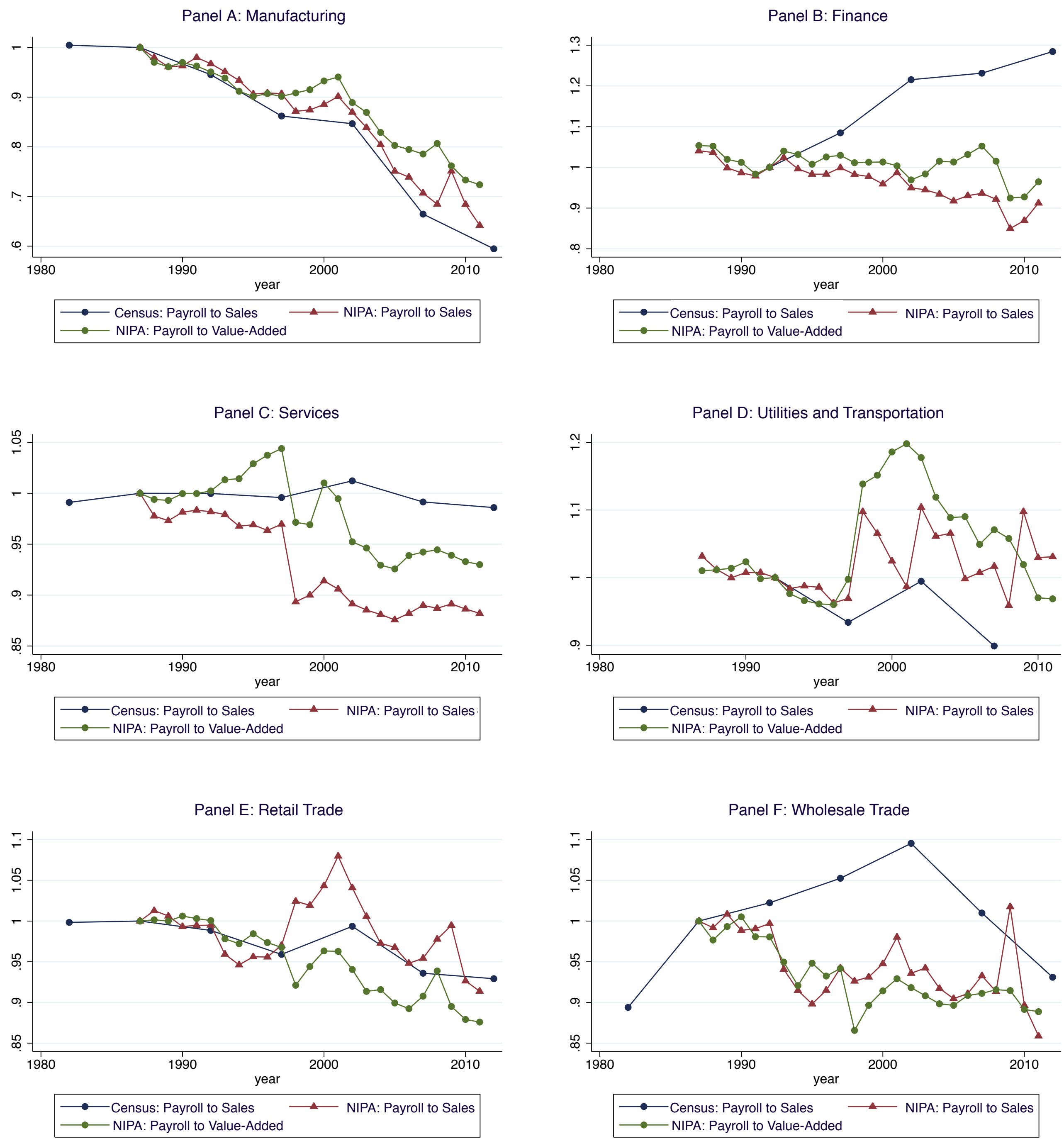
Panel B: Components of the Labor Share





Notes: Panel A plots the aggregate labor share in Manufacturing calculated from the Census and NIPA/BEA data. Blue circles show the labor share calculated in the Census as the ratio of payroll to value-added. Red squares show the same ratio, but here value-added is adjusted by subtracting intermediate purchased services as described in Appendix B. Green triangles further augment the labor share to include additional labor costs to payroll. Lastly, the yellow diamonds plot the payroll over value-added from the NIPA data. Panel B plots the various components of the labor share used in the construction of the labor shares in Panel A. In the left figure, we plot three measures of the wage bill and on the right, we plot 3 measures of value-added.

Figure A.9: Comparing the Payroll-to-Sales Ratio in the Census with the Labor Share in NIPA



Notes: Each panel shows the payroll to sales ratio in the Census, the payroll to gross-output ratio in the NIPA/BEA data, and the payroll to value-added ratio in the NIPA/BEA data. All series are normalized to one in 1987.

XI Appendix Tables

Table A.1: Decompositions of the Change in the Labor Share in Manufacturing: Alternative Aggregation Levels

	Panel A: Plant Level							
	Wage Bill share of value added				Compensation share of value added			
	Within	Between	Exit	Entry	Within	Between	Exit	Entry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
5 yr period								
1982-1987	-3.75	-0.30	-0.88	0.47	-2.16	-3.10	-1.02	0.52
1987-1992	2.36	-4.24	-0.78	0.24	3.71	-4.69	-0.92	0.17
1992-1997	-2.00	-1.40	-0.51	0.45	-2.72	-1.97	-0.57	0.46
1997-2002	0.27	-0.67	-0.69	0.01	-0.95	0.60	-0.78	-0.14
2002-2007	-2.58	-1.84	-0.78	0.48	0.86	-5.40	-0.90	0.56
2007-2012	1.98	-2.26	-0.46	0.38	0.34	-0.61	-0.57	0.35
Mean	-0.62	-1.79	-0.68	0.34	-0.15	-2.53	-0.79	0.32
15 yr Period								
1982-1997	-3.39	-5.94	-2.17	1.16	-1.17	-9.76	-2.51	1.15
1997-2012	-0.33	-4.77	-1.93	0.87	0.25	-5.41	-2.25	0.77
Overall								
1982-2012	-3.72	-10.71	-4.10	2.03	-0.92	-15.17	-4.76	1.92

	Panel B: Firm by Industry Level							
	Wage Bill share of value added				Compensation share of value added			
	Within	Between	Exit	Entry	Within	Between	Exit	Entry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
5 yr period								
1982-1987	-3.75	-0.65	-1.19	1.12	-1.84	-4.02	-1.18	1.30
1987-1992	2.29	-4.80	-1.40	1.48	3.46	-5.18	-1.63	1.60
1992-1997	-2.22	-1.14	-1.49	1.38	-3.01	-1.70	-1.63	1.54
1997-2002	-0.28	-0.68	-1.34	1.23	-2.05	0.95	-1.54	1.37
2002-2007	-2.81	-1.94	-1.80	1.84	1.22	-6.44	-1.98	2.32
2007-2012	2.10	-2.11	-1.43	1.08	0.00	0.11	-1.78	1.20
Mean	-0.78	-1.89	-1.44	1.35	-0.37	-2.71	-1.62	1.55
15 yr Period								
1982-1997	-3.67	-6.58	-4.08	3.98	-1.39	-10.90	-4.44	4.44
1997-2012	-0.99	-4.74	-4.57	4.14	-0.82	-5.38	-5.31	4.88
Overall								
1982-2012	-4.66	-11.32	-8.65	8.12	-2.21	-16.28	-9.75	9.32

	Panel C: 15-Year Decompositions, Firm Level							
	Wage Bill share of value added				Compensation share of value added			
	Within	Between	Exit	Entry	Within	Between	Exit	Entry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
15yr Period								
1982-1997	-3.79	-7.17	-1.58	2.18	-1.21	-12.07	-1.39	2.39
1997-2012	-2.29	-3.70	-2.08	1.91	-2.49	-4.03	-2.25	2.14

Notes: This Table shows the results of a decomposition of the change in the labor share using the dynamic Melitz-Polanec methodology as described in the text. Essentially we divide the change in the overall labor share into four components. "Within" is the change in the labor share due to a general fall in the share across all incumbent plants. "Between" is the change due to the growing relative size of low labor share incumbent plants. "Exit" is the contribution to the change from the exit of high labor share plants and "Entry" is contribution from the entry of low labor share plants. These all use the micro-data from the five yearly Censuses of Manufacturing. Panel A shows the decomposition at the plant level, panel B shows the decomposition at the firm-by-industry level, and Panel C does the decomposition with only adjacent 15-year periods.

Table A.2: Regressions of the Components of the Change in the Payroll-to-Sales Ratio on the Change in Concentration

	CR4		CR20		HHI	
	(1)		(2)		(3)	
Panel A. Between						
Retail	-0.039	*	-0.072	**	-0.044	
Wholesale	-0.01		-0.025	*	-0.029	
Services	-0.165	**	-0.161	**	-0.491	**
Manufacturing	-0.082	**	-0.104	**	-0.104	*
Utilities/Transportation	-0.128	**	-0.12	*	-0.453	**
Finance	-0.262	*	-0.263	*	-0.546	*
Combined	-0.086	**	-0.096	**	-0.136	**
Panel B. Within						
Retail	0.004		0.006		0.009	
Wholesale	-0.016	*	-0.003		-0.019	
Services	0.03		0.017		0.092	*
Manufacturing	0.02	*	0.033	*	0.006	
Utilities/Transportation	0.01		-0.024		0.011	
Finance	0.005		-0.023		-0.038	
Combined	0.009		0.006		-0.002	
Panel C. Entrants						
Retail	0.006		-0.015		0.018	
Wholesale	-0.007	*	-0.01	**	-0.016	
Services	0.012		0.03		0.018	
Manufacturing	-0.007		-0.021	**	-0.005	
Utilities/Transportation	0.016		0.026		0.014	
Finance	0.038	*	0.045	~	0.056	
Combined	0.002		0		0.005	
Panel D: Exiters						
Retail	-0.007		-0.003		-0.028	*
Wholesale	-0.002		-0.002		-0.014	
Services	0.041		-0.006		0.042	
Finance	0.005		0.005		-0.004	
Manufacturing	-0.015		0.004		-0.004	
Utilities/Transportation	-0.01		-0.024	*	-0.035	~
Combined	0		-0.002		-0.011	

Notes: ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$. Each cell is the coefficient on a concentration measure from a separate OLS regression (standard errors in parentheses clustered by four digit industry). Dependent variable is a component of the decomposition as in Table 5. Regressions are weighted by the share of sales of the four digit industry in total sector sales in the initial year.

Table A.3: Industry-Level Cross-Country Comparisons of Labor Shares

Panel A

	Av Level	Austria	Belgium	Spain	Finland	France	Germany	Italy	Japan	Netherlands	Sweden	UK	USA
Austria	65.47	1											
Belgium	64.95	0.731	1										
Spain	67.17	0.54	0.93	1									
Finland	65.79	0.731	0.814	0.747	1								
France	64.9	0.822	0.926	0.851	0.911	1							
Germany	64.52	0.753	0.867	0.713	0.801	0.894	1						
Italy	63.82	0.75	0.943	0.867	0.843	0.952	0.893	1					
Japan	62.89	0.631	0.805	0.799	0.814	0.815	0.749	0.821	1				
Netherlands	65.33	0.757	0.818	0.748	0.808	0.918	0.669	0.877	0.778	1			
Sweden	62.93	0.451	0.87	0.815	0.815	0.819	0.773	0.813	0.825	0.785	1		
UK	65.91	0.741	0.922	0.829	0.83	0.927	0.757	0.891	0.798	0.895	0.804	1	
USA	62.48	0.817	0.927	0.869	0.883	0.949	0.803	0.896	0.858	0.923	0.862	0.948	1

Panel B

	Change	Austria	Belgium	Spain	Finland	France	Germany	Italy	Japan	Netherlands	Sweden	UK	USA
Austria	-0.6	1											
Belgium	-0.61	-0.063	1										
Spain	-0.48	0.222	0.451	1									
Finland	-0.53	0.534	0.217	0.476	1								
France	-0.36	-0.232	0.432	0.399	0.11	1							
Germany	-0.88	0.517	-0.153	-0.198	0.231	-0.129	1						
Italy	-0.53	0.094	0.283	0.259	-0.163	0.132	-0.02	1					
Japan	-1.02	0.233	0.291	-0.089	0.152	0.035	0.274	0.083	1				
Netherlands	-1	0.112	0.236	0.012	0.227	0.29	0.238	0.093	0.227	1			
Sweden	-0.93	0.163	-0.017	-0.388	0.275	0.056	0.281	-0.338	0.294	0.106	1		
UK	-1.06	-0.138	0.438	0.525	0.058	0.508	-0.387	0.084	-0.083	-0.096	0.055	1	
USA	-1.02	0.069	0.208	0.112	0.321*	0.22	0.112	-0.313	-0.047	0.266	0.525	0.181	1

Notes: Correlations include 32 industries both within and outside manufacturing. In each correlation, industries are weighted by the value-added share of that industry averaged over the two countries in the comparison. Levels in panel A are averages between 1997 and 2007. Panel B correlations are 10-year changes from 1997-2007. In order to reduce measurement error, we run these correlations using the centered 5-year moving average.

Table A.4: Decomposing the Wage Bill Share Using Firm-Level Data from Different Countries

	Years	Observations	Base level of labor share	Change in aggregate share	Between firm component	Within firm component	Exit	Entry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UK	2003-2008	112,007	68%	-7.5%	-7.0	-0.1	-2.5	2.2
Sweden	2003-2008	154,741	74%	-2.7%	-10.4	0.1	7.1	0.2
France	2003-2008	704,276	76%	-1.7%	-1.3	1.3	-1.5	0.0
Germany	2005-2010	117,817	81%	-4.5%	-4.3	0.0	-0.2	0.1
Italy	2005-2010	697,939	74%	2.5%	-2.2	5.7	-0.9	0.0
Portugal	2005-2010	202,590	72%	-4.8%	-6.8	2.9	-1.9	1.0

Notes: This uses firm data from BVD Orbis. Value added is constructed by adding wage bill to pre-tax profits (EBIT). Sample includes firms whose primary three digit industry is in manufacturing. We use the MP method to break down the aggregate change into a between and within firm component.

Table A.5: Decomposition of the Change in the Wage-Bill Share in Manufacturing (using Compustat)

	Total fall in the labor share	Within	Between	Exit	Entry
	(1)	(2)	(3)	(4)	(5)
1993-1998	-6.0	-4.7	-2.0	0.8	-0.3
1998-2003	-5.4	2.1	-6.0	-0.1	-1.5
2003-2008	-14.2	-6.8	-7.4	-1.6	1.6
Mean		-3.1	-5.1	-0.3	-0.1

Note: Melitz-Polanec (2015) decomposition method. Value added measured as sum of wage bill and value added. There is a break in accounting treatment of wage bill in 1993 which is why we focus on the post 1993 period. Sample includes Compustat firms (US publicly listed) who report wage bill and profits.

Table A.6: The Labor Share and the Rise in Chinese Imports

	Sales	Wages	Value Added	CR4	CR20	HHI	Labor Share	Payroll-to-Sales
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OLS Estimates								
Sample 1: 1992-2012								
5 year Changes	-1.967 **	-0.485 ~	-0.805 *	0.563	0.234	1.630	7.070 *	2.034
	(0.76)	(0.28)	(0.36)	(4.66)	(5.11)	(2.12)	(3.16)	(1.85)
10 year Changes	-1.717 *	-0.487	-1.026	-12.514	-2.577	-4.780	13.634 **	5.506
	(0.75)	(0.67)	(0.89)	(10.48)	(11.80)	(4.20)	(3.16)	(3.54)
IV Estimates								
Sample 1: 1992-2012								
5 year Changes	-3.693 **	-0.855 *	-1.156 **	6.027	4.765	6.814 *	6.695 *	2.457
	(1.42)	(0.36)	(0.42)	(5.07)	(4.94)	(3.38)	(3.24)	(1.83)
10 year Changes	-4.553 **	-1.043	-1.788 ~	-1.973	11.178	4.962	16.375 **	8.067 *
	(1.75)	(0.80)	(0.98)	(13.60)	(13.76)	(7.49)	(3.24)	(3.72)
Sample 2: 1992-2007								
5 year Changes	-2.667 **	-1.125 **	-1.237 **	16.295 ~	10.442 *	12.681 *	0.321	-1.29
	(1.00)	(0.41)	(0.42)	(9.00)	(4.56)	(5.90)	(3.24)	(1.48)
10 year Changes	-3.024 **	-1.961 **	-2.314 **	20.47	11.974 ~	18.405 *	6.443	0.21
	(1.01)	(0.73)	(0.81)	(15.22)	(6.99)	(9.22)	(6.05)	(1.70)

Notes: ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$. Regressions reflect 2SLS estimates, using the growth in imports from China to 8 other developed countries as an instrument for the growth in Chinese imports to the U.S. (as in Autor et al. 2013) and various industry-level outcome measures, denoted by the column header. For example, column 1 shows estimates of the effect of Chinese imports on industy sales. Industries are weighted by their 1982 share of sales. Regressions include year dummies and standard errors are clustered at the slightly aggregated SIC codes, consistent with Autor, Dorn and Hanson (2013). The partial F-statistic for the first stage in sample 1 for 5 and 10 year change is 76.25 and 50.30, respectively. The partial F-statistic for the first stage in sample 2 for 5 and 10 year changes is 89.79 and 97.25, respectively.