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 typically rely 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 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. Since these firms have high markups and a low labor share of firm value-added and sales, this depresses the aggregate labor share. We empirically assess seven predictions of this hypothesis: (i) industry sales will increasingly concentrate in a small number of firms; (ii) industries where concentration rises most will have the largest declines in the labor share; (iii) the fall in the labor share will be driven largely by reallocation rather than a fall in the unweighted mean labor share across all firms; (iv) 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; (v) the industries that are becoming more concentrated will exhibit faster growth of productivity and innovation; (vi) the aggregate markup will rise more than the unweighted firm markup; and (vii) these patterns should 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. The 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 (Elsby, Hobjin, and Sahin, 2013; Gollin, 2002), intangible capital (Koh, Santaeulalia-Lopis and Zheng, 2016) and business owners taking capital instead of labor income (Smith, Yagan, Zidar and Zwick, 2017), there is a general consensus that the fall is real and significant.[1]

There is less consensus, however, on what are the *causes* of the recent decline in the labor share. Karabarbounis and Neiman (2013) hypothesize 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), which could lower the labor share if the capital-labor elasticity of substitution is greater than one.[2] Elsby, Hobjin and Sahin (2013) argue for the importance of trade and international outsourcing especially with China. Like them, we will explore the role of trade, but we 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 a decline in labor's share in largely

[1] The main issue in terms of housing is the calculation of the contribution of owner-occupied housing to GDP which is affected by property price fluctuations. We sidestep this by focusing on the Economic Census which includes firms (the "corporate sector" of the NIPA), not households. Similarly, the Census enumerates only employer firms, so does not have the self-employed. There remains an issue of how business owners allocate income, but Smith Smith, Yagan, Zidar and Zwick (2017) show that this can account for only an eighth of the labor share decline. We discuss some of the other factors, such as intangible capital below.

[2] Karabarbounis and Neiman (2013) argue for this, 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).

non-traded sectors such as wholesale trade, retail trade, and utilities, where trade exposure is more limited. Piketty (2014) stresses the role of social norms and labor market institutions, such as unions and the real value of the minimum wage. As we will show, the broadly common experience of a decline in labor shares across countries with different levels and evolution of unionization and other labor market institutions somewhat vitiates this argument.[3]

In this paper, we propose and empirically explore an alternative hypothesis for the decline in the labor share that is based on the rise of "superstar firms". If a change in the economic environment advantages the most productive firms in an industry, product market concentration will rise and the labor share will fall as the economy becomes dominated by superstar firms with high markups and lower labor shares. This would occur if consumers have become more sensitive to price and quality due to greater product market competition (e.g., through globalization) or improved search 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). Our "winner take most" mechanism could also arise due to the growth of platform competition in many industries or scale advantages related to the growth of intangible capital (e.g. Walmart's massive investment in proprietary software to manage their logistics and inventory control—see Bessen, 2017). Central to our empirical analysis, this superstar firm framework implies that the reallocation of economic activity among firms with differing heterogenous productivity and labor shares is key to understanding the fall in the aggregate labor share.

This paper's contribution is threefold. First, we provide microeconomic evidence on the evolution of labor shares at the firm and establishment level using U.S. Census panel data covering six major sectors: manufacturing, retail trade, wholesale trade, services, utilities and transportation, and finance. Our micro-level analysis is distinct from most existing empirical evidence that is largely based on macroeconomic and industry-level variation. Those aggregate approaches, while valuable in many dimensions, obscure the distinctive implications of competing theories, particularly the contrast between models implying heterogeneous changes (such as our superstar firm perspective) compared to homogeneous changes in the labor share across firms in an industry.[4] Second, we formalize a new "superstar firm" model of the labor share change. The model is based

[3] 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.

[4] Exceptions are 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. Focusing on U.S. manufacturing, Kehrig and Vincent (2017) also use US Census of Manufactures micro data to decompose labor share changes. We discuss their contribution below.

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. Third, we present a substantial body of evidence from the last 30 years using a variety of U.S. and international datasets that is broadly consistent with the superstar firm hypothesis.

Specifically, we establish the following seven facts that support 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. Part of this is due to increased specialization on core competencies and partly it is due to firms just getting bigger. For example, the share of US employment in firms with over 5,000 employees rose from 28.2% in 1987 to 33.8% in 2016.[5] ; (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 exhibited the largest increase in sales concentration; (v) the industries that are becoming more concentrated are those with faster growth of productivity and innovation; (vi) larger firms have higher markups and the size-weighted aggregate markup has risen more than the unweighted average markup; and (vii) these patterns are not unique to the United States but are also present in other OECD countries. Although we do not provide precise causal identification of our superstar firm model, the fact pattern presented here supports a firm-level perspective on the changes in the labor share.[6]

Our formal model, detailed below, generates superstar effects from increases in the toughness of product market competition, which raise the market share of the most productive firms in each sector at the expense of less productive competitors. Though our model formalizes the market toughness channel, we underscore that a number of closely related mechanisms can deliver similar superstar effects. First, strong network effects are a related explanation for the dominance of companies such as Google, Facebook, Apple, Amazon, AirBNB and Uber in their respective industries. Second, rapid falls in the quality-adjusted prices of intangible capital such as software could give

[5] Census Bureau Business Dynamics Statistics (e.g. https://www.census.gov/ces/dataproducts/bds/data_firm2016.html). As we show below, employment shares underestimate the growth in superstar firms which often have high sales with relatively few workers. And, because firms are increasingly specialized in their main industries, as we document below using Compustat data, total sales underestimates the growth of concentration in specific industries.

[6] See Furman and Orszag (2015) for an early discussion. 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.

large firms an advantage if there is a large overhead/fixed cost element.[7] For example, Walmart has made substantial technology investments to enable it to monitor supply chain logistics and manage inventory to an extent that, arguably, would be infeasible for smaller competitors (Bessen, 2017). An alternative perspective on the rise of superstar firms is that they reflect a diminution of competition, due to a weakening of US anti-trust enforcement (Dottling, Gutierrez and Philippon, 2018). Our findings on the similarity of trends in the U.S. and Europe, where antitrust authorities have acted more aggressively on large firms (Gutierrez and Philippon, 2018), combined with the fact that the concentrating sectors appear to be growing more productive and innovative, suggests that this is unlikely to be the primary explanation, although it may important in some specific industries (see Cooper et al, 2019, on healthcare for example).

Our paper is also closely related to Barkai (2016), who independently documented a negative industry-level relationship between changes in labor share and changes in concentration for the United States. Barkai presents evidence at the aggregate level that profits appear to have risen as a share of GDP, and that the pure capital share (capital stock multiplied by the required rate of return) of GDP has fallen, a pattern consistent with our superstar firm model and the empirical analysis we will present on rising aggregate markups. Barkai's analysis uses exclusively industry-level and macro data. A major contribution of our micro-level approach is that we can explore the firm-level contributions to these patterns and link them 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. Our work also corroborates (and helps to interpret) that of de Loecker, Eeckhout and Unger (2018) who argue that the (weighted average) markup of price over variable cost has been rising in the US (where, ceteris paribus, a rise in the markup means a fall in the labor share). As with these papers, our model also implies rises in aggregate markups due to a reallocation of market share towards superstar firms, which have both lower labor shares and high markups. We confirm these patterns in our Census data.

Compared to our earlier work in the *American Economic Review Papers and Proceedings* (Autor et al, 2017b), this paper formalizes the superstar theory, presents firm-level decompositions of the labor share; explores the correlation of the labor share with concentration on the one hand and the factors influencing concentration on the other; analyzes markups directly; and provides a

[7] See Bauer and Lashkari (2018); Crouzet and Eberly (2018), Karabarbounis and Neiman (2018), Koh et al (2016) and Unger (2019) for variants of this argument.

quantitative characterization of superstar firms using Compustat data.[8]

The structure of the paper proceeds as follows. Section II sketches our model. Section III presents the data and Section IV the empirical support for the model's predictions. Section V presents additional descriptive facts of superstar firms, and Section VI provides concluding remarks. Online Appendices detail the formal model (Appendix A), markup calculation (Appendix B), superstar firm characteristics (Appendix C) and data (Appendix D).

II A Model of Superstar Firms

To provide intuition for why the fall in labor share may be linked to the rise of superstar firms, consider a production function $Y_i = z_i L_i^{\alpha^L} K_i^{1-\alpha^L}$ where Y_i is value-added, L_i is variable labor, K_i is capital and z_i is Hicks-neutral efficiency (TFPQ) in firm i.[9] Consistent with a wealth of evidence, we assume that z_i is heterogeneous across firms (Melitz, 2003; Hopenhayn, 1992). More productive, higher z_i, firms will have higher levels of factor inputs and greater output.

Factor markets are assumed to be competitive (with wage w and cost of capital ρ), 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_iY_i) as:[10]

$$S_i \equiv \left(\frac{wL_i}{P_iY_i}\right) = \frac{\alpha^L}{m_i} \tag{1}$$

where $m_i = (P_i/c_i)$ 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^L, w, ρ), a firm will have a lower labor share if its mark-up is higher. Superstar firms (those with high z_i) will be larger as they produce more efficiently and capture a higher share of industry output. If they have have higher price-cost markups, they will also have lower labor shares. Indeed, a wide class of models of imperfect competition will generate larger price-cost mark-ups for firms with a higher market share, $\omega_i = P_iY_i/\sum_i (P_iY_i)$. This is because mark-ups (m_i) are generally falling in the absolute value of the elasticity of demand η_i, and according to Marshall's "Second Law of Demand", consumers will be more price-inelastic at higher levels of consumption and lower levels of price.[11] Most utility

[8] A point of overlap is that we again present concentration trends. Even here however, we have updated the earlier data in several ways, most importantly by incorporating the full 2012 Economic Census.

[9] We treat output and value-added interchangeably here as we are abstracting away from intermediate inputs. We distinguish intermediate inputs in the empirical application.

[10] Employer product market power was emphasized by Kalecki (1938) as the reason for variations in labor shares over the business cycle.

[11] Mrazova and Neary (2017) discuss the implications of a wide class of utility functions (generating "demand manifolds") including those which are not consistent with Marshall's Second Law.

functions will have this property, such as the Quadratic Utility Function which generates a linear demand curve. In this case $m_i = \eta_i/(\eta_i - 1)$. Another example is the homogeneous product Cournot model, which generates $m_i = \frac{\eta_i}{\eta_i - \omega_i}$. The empirical literature also tends to find higher mark-ups for larger, more productive firms.[12] A leading exception to this is when preferences are CES (the Dixit-Stiglitz form with a constant elasticity of substitution between varieties), in which case mark-ups are the same across all firms of whatever size and productivity ($m = \eta/(\eta - 1)$). In Autor et al (2017), we show that even in such a CES model, labor shares could be lower for larger firms if there are fixed costs of overhead labor that do not rise proportionately with firm size.[13]

Because labor shares are lower for larger firms in standard models, an exogenous shock that reallocates market share towards these firms will tend to depress the labor share in aggregate. Intuitively, as the weight of the economy shifts toward larger firms, this will lower the average labor share even with no fall in the labor share at any given firm. In Appendix A we formalize these ideas in an explicit model of monopolistic competition, which we use to illustrate some key results. The model is a generalization of Melitz and Ottaviano (2008), augmented with a more general demand structure and (most importantly) a more general productivity distribution. In the model, entrepreneurs entering an industry are *ex ante* uncertain of their productivity z_i. They pay a sunk entry cost κ and draw z_i from a known productivity distribution with density function, $\lambda(z)$. Firms that draw a larger value of z will employ more inputs and have a higher market share. Our demand functions obey Marshall's Second Law, so we obtain the first result that larger firms will have lower labor shares.

As is standard (e.g. Arakolis et al, 2018), we characterize the "toughness" of the market in terms of a marginal cost cut-off c^*. Firms with marginal costs exceeding this level will earn negative profits and exit. Globalization, which increases effective market size, or greater competition (meaning higher substitutability between varieties of goods) will tend to make markets tougher and reduce the cut-off, c^*, causing low productivity firms to shrink and exit. The reallocation of market share towards more productive firms will increase the degree of sales concentration and will be a force

[12] See the discussion in Arkolakis et al (2018). In the time series, the empirical trade literature finds incomplete pass through of marginal cost shocks to price with elasticities of less than unity, which implies higher mark-ups for low cost firms. A smaller literature estimating cross sectional mark-ups finds larger mark-ups for bigger firms (e.g. de Loecker and Warzynski, 2012). Below, we empirically confirm this is true on our US Census data.

[13] Denote fixed overhead costs of labor F and variable labor costs so V, $L = V + F$. In this case $S_i = \frac{\alpha^L}{m} + \frac{wF}{P_i Y_i}$. Since high z_i firms are larger, they will have a lower share of fixed costs in value-added (wF/P_iY_i) and lower observed labor shares (see Bartelsman, Haltiwanger and Scarpetta, 2013). We emphasized this mechanism in the original working paper version of this paper (Autor et al, 2017a), but we regard the broader model of Appendix A as more rigorous and more realistic.

decreasing the labor share because a larger fraction of output is produced by more productive ("superstar") firms. This is our second result.

Since the change in market toughness will also tend to reduce the mark-up for any individual firm, labor shares at the firm level will *rise*. In order to obtain an *aggregate decline* in the labor shares when markets get tougher, the "between firm" reallocation effect must dominate this "within firm" effect. Our third result is to show that the aggregate labor share will indeed fall following this change in the economic environment if the underlying productivity density is log-convex $\lambda(z)$, meaning that the productivity distribution is more skewed than the Pareto distribution. Conversely, the aggregate labor share will rise if the density is log-concave and will remain unchanged if the density is log-linear. Interestingly, the standard assumption (e.g. Melitz and Ottaviano, 2008) is that the pdf of productivity is Pareto. Since this is an example of a log-linear density function, it delivers the specialized result that the within and between effects of a change in the economic environment perfectly offset each other, so the aggregate labor share is invariant to changes in market toughness. Since the underlying distribution of productivity draws $\lambda(z)$ in unobservable, the impact of a change in market toughness on the aggregate labor share is an empirical issue. While the prediction that rising market toughness could generate an increase in concentration and the profit share is counterintuitive, the ambiguous relationship between concentration, profit shares, and the stringency of competition is well known in Industrial Organization.[14]

The model in Appendix A implies that after an increase in market toughness: (i) the market concentration of firm sales will rise, meaning that the market shares of the largest firms will rise; (ii) in those industries where concentration rises the most, labor shares will fall the most (assuming that the underlying distribution of productivity draws is log-convex); (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) the industries that are becoming more concentrated will be those with the largest productivity growth; (vi) due to high-markup firms expanding, the aggregate markup will rise ; and (vii) similar patterns of changes in concentration and labor's share will be found across countries (to the extent that the shock that benefits superstar

[14]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 the one in Appendix A, 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.

firms is global). We take these predictions to a series of newly constructed micro-datasets for the United States and around the world.

Our stylized model is meant to illustrate our intuition for the connection between 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 network effects, as long as high market share firms have lower labor shares.[15] 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 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 as argued by Gutierrez and Philippon, 2016 and 2018). Explanations for growing concentration from weakening antitrust enforcement have starkly different welfare implications than explanations based on innovation or toughening competition. We partially—though not definitively—assess these alternative explanations by examining whether changes in concentration are larger in dynamic industries (where innovation and productivity is increasing) or in declining sectors.

III Data

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

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. We analyze the Economic Census for the three decade interval of 1982 - 2012 for six large sectors: manufacturing, retail trade, wholesale trade, services, utilities and transportation and finance.[16]

[15] Another way of generating this would be if the underlying distribution of entrepreneurial ability become more skewed. As it is unclear why the primitives would change in this manner, we prefer to model a change in the economic environment as this offers more hope of empirically identifying the mechanisms at play.

[16] 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 ex-

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. 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 Manufactures 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.[17] 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 most sectors, in constructing the NIPA, the BEA uses the Economic Censuses to construct gross output and then works through data sources on materials use to construct value added. The finance sector is the most problematic in this regard.[18] Accordingly, we place finance at the end of all tables and figures and advise caution in interpreting the results in this sector.

In addition to payroll and sales which are reported for all sectors, the Economic Census for the manufacturing sector 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. This enables us to 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 D). We build all of our industry-level measures using these time-consistent industry definitions, and thus our measures of industry concentration differ slightly from published statistics. The correlation between our

cluded 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 six sectors. See Appendix D for details.

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

[18]For the banking sector, for example, BEA calculates value-added from interest rate spreads between lending and deposit rates.

calculated measures and those based on published data is almost perfect, however, when using the native but time-varying industry definitions.[19]

We supplement the U.S. Census-based measures with various international datasets. First, we draw on the 2012 release of the EU KLEMS database (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.[20]

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 we 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.[21]

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. This database, compiled by the European Central Bank's Competitiveness Research Network (CompNet), draws on various administrative and public sources across countries, and seeks to cover all non-financial corporations.[22] CompNet aggregates data from all firms to provide 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.[23] Consequently, we estimate specifications separately for each country and focus on a within-country analysis.

[19] 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. In Appendix D, we also compare our results with the alternative set of consistent industry definitions developed by Fort and Klimek (2016) who used a NAICS-based measure, obtaining similar results to our own.

[20] We choose the 2012 KLEMS release because subsequent versions of EU Klems are not fully backward compatible and provide shorter time series for many countries.

[21] 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 the rest of the world.

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

[23] 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.

Fourth, 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 countries 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).[24]

Finally, in order to describe the characteristics of 'superstar' firms and characterize their international scope, we supplement the analysis of Census data with the Standard & Poor's Compustat database. This database reports economic information for firms listed on a U.S. stock exchange. We focus on the largest 500 firms and explore the characteristics of the largest firms within that group. Further details on data construction are reported in Appendix Appendix D, and the Compustat analysis is found in Appendix Appendix C.

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.[25] 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 as 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 Manufactures 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 outside of Manufactures. Figure 2 shows that all three series show a clear downward trend, though of course their initial levels differ.

To what extent is manufacturing different from other sectors? Because robust firm-level measures of value-added are not available from the Economic Census outside of manufacturing, we use the cruder measure of the ratio of payroll to sales. This measure, which can be computed for all six broad sectors covered in the Census, is plotted by sector in the six panels of Figure 3.

[24]Unfortunately, due to partial reporting of revenues, BVD Orbis cannot be used to comprehensively construct sales concentration measures.

[25]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 are 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.

Finance stands out as the only sector where there is a clear upward trend in the labor share. As above, this is also the sector in which measures of inputs and outputs are most problematic. 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 services, where the labor share fell steeply between 2002 and 2008 then partly rebounded. 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 in this period, and even here the secular downward trend only temporarily stabilized. One 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. Appendix D compares Census data to NIPA. The fall in the labor share of value added is clearer in NIPA than Census payroll to sales ratios. Appendix Figure A.7 shows that all non-finance sectors saw a net fall in labor share over the full 1982 - 2012 time period, and even in finance, the labor share is stable from from the mid 1980s to the Great Recession (before then falling).

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).[26] For comparison, we also compute the CR4 and CR20 concentration measures based on employment rather than sales. Following Autor et al (2017b), 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 using updated data from the Census. Appendix Figure A.1 shows a corresponding plot for the Herfindahl-Hirschman Index (denoted HHI). Both figures show 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 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 more weight to firms outside the top 20 where concentration has risen by less.

[26]Since we calculate concentration at the industry level, we define a firm as the sum of all establishments that belong to 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 four-digit industries.

One interesting question is whether these increases in concentration are mainly due to superstar firms expanding their scope over multiple industries, as in the case of Amazon, or rather are due to a greater firm focus on core industries. We found that the largest firm (by sales) in the four digit industry in the Census operated on average in 13 other four digit industries in 1982, but this number fell to under 9 by 2012. Similarly, conditional on a firm being among the top four firms in a four-digit industry in 1982, it was on average among the top four in 0.37 other industries (i.e. statistically speaking, being the top firm in one industry gave a firm almost a 40% chance of being among the top four in another industry). By 2012, this fraction had fallen from 0.37 to 0.24. Thus, the data suggests that companies like Amazon, which are becoming increasingly dominant across multiple industries, are the exception. Overall, firms are becoming more concentrated in their leading line of business but less integrated across other activities. Table 1 provides further descriptive statistics for sample size, labor share, and sales concentration in each of the six sectors.

Before more formally exploring the implications of the model, we present evidence of the cross-sectional relationship between firm size and labor share. As discussed in Section II, our conceptual framework is predicated on the idea that because "superstar" firms produce more efficiently, they are both both larger and have lower labor shares. To check this implication, Figure 5 reports the bivariate correlation between firms' labor shares, defined as the ratio of payroll to sales, and firms' share of their respective industry's annual sales. Consistent with our reasoning, there is a negative relationship between labor share and firm size across all six sectors, and this relationship is statistically significant in five of the six sectors.

IV Empirical Tests of the Predictions of Superstar Firm Model

IV.A Rising Concentration Correlates with Falling Labor Shares

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. In each of the six sectors, we separately estimate OLS regressions in long differences (indicated by Δ) of the form

$$\Delta S_{jt} = \beta \Delta \text{CONC}_{jt} + \tau_t + u_{jt}, \tag{2}$$

where S_{jt} is the labor share of four-digit SIC 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 report estimates of β from equation (2). The first three columns present five-year long differences, and the last three columns present ten-year long-differences. Since the left- and right-hand side variables each cover the same time interval in each estimate, the coefficients have a comparable interpretation in the five-year and ten-year specifications.

Our baseline specification in row 1 detects a striking relationship between changes in concentration and changes in the share of payroll in value-added. Across all three measures of concentration (C4, C20, and HHI), industries where concentration rose the most were those where the labor share fell by the most. These correlations are statistically significant at the 5 percent level in all but the last column (where it is significant at the 10% level).[27] The subsequent rows of Table 2 present a variety of robustness tests of this basic association. In row 2, we use a broader measure of the labor share—using "compensation" instead of payroll—that includes employer contributions to fringe benefits such as private health insurance, which account for a growing fraction of labor costs (Pessoa and Van Reenen, 2013). Row 3 uses an adjusted value-added measure which uses KLEMS data to attempt to account for intermediate service inputs that are not included in the Census data (see Appendix D for details). In row 4, we define concentration based on value-added rather than sales. Row 5 presents a stringent robustness test by including a full set of four-digit industry dummies, thus obtaining identification exclusively from acceleration or deceleration of concentration and labor shares relative to industry-specific trends. The strong association between rising concentration and falling labor share is robust to all of these permutations.

Our core measure of concentration captures exclusively domestic U.S. concentration and hence may overstate effective concentration for traded-goods industries, particularly in manufacturing, where there is substantial international market penetration.[28] 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 several ways. Since import penetration data are not available on a consistent basis across our full time period, we focus on the 1992-2012 period where these data are available. For reference, row 6 of Table 2 re-estimates our baseline model for the shortened period and finds a slightly stronger relationship between labor share and concentration.

[27]The HHI estimates, which give weight to firms outside of the top 20, are least precise. Our superstar model focuses on the leading firms in each sector rather than the entire distribution of firms.

[28]This is a minor concern in non-manufacturing sectors, where there are comparatively few imports.

Row 7 next adds in the growth in imports over value-added in each five year period on the right hand side, and finds that the coefficient on concentration falls only slightly. In Section (V), we further investigate the role of trade in explaining the fall in the labor share.

Karabarbounis and Neiman (2014) stress the role of the falling cost of the prices of investment goods in driving down the labor share. To examine this idea, row 8 includes the start-of-period level of the capital to value-added ratio on the right hand side of the regression. Under the Karabarbounis and Neiman (2014) hypothesis, we would expect capital-intensive industries to have the largest falls in the labor share. Consistent with this logic, the coefficient on capital intensity is negative and significant. The coefficient on concentration is little changed from row 1, however, suggesting that the superstar mechanism linking rising concentration to falling industry-level average labor shares is not a simple manifestation of capital intensity or capital deepening.

Finally, note that our measure of concentration is based on firm sales (or value added), 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 final 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; measures based on outputs, reflecting a firm's position in the product market, is the appropriate measure of concentration, not employment. Indeed, many of the canonical superstar firms such as Google and Facebook employ relatively few workers relative to their market capitalization. Thus, 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.

All Sectors

We now broaden our focus to include the full set of Census sectors (alongside manufacturing): retail, wholesale, services, utilities and transportation, and finance. We apply our baseline specification to these sectors, with two modifications: first, the sample window is shorter for finance and utilities and transportation (1992-2012) because of lack of consistent data prior to 1992 in these sectors; second, because we do not have value-added outside of manufacturing, we use payroll over sales as our dependent variable. 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. In the first three columns, for example, All the coefficients remain negative, statistically significant, and quantitatively similar.[29]

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 five year periods (column 2 of Table 3). It is clear from both Figure 6 and Table 3 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 percent level or lower in each sector. When we pool all six sectors and estimate equation (2) with sector-specific fixed effects (final row of Table 3, labeled "combined"), we again find a strong negative association between rising concentration and falling labor share.

Table 3 also reports several variants of this regression using alternate measures of concentration as well as stacked ten-year changes rather than five-year changes. The negative relationship is robust across specifications: negative in all 36 specifications in rows 1 to 6 of Table 3 and significantly so at the 10 percent or greater level in 28 cases.[30] We also examined specifications using the change in the CR1 (that is, the market share of the single largest firm in the industry) as the concentration measure. As expected given the other results, we find that the change in the CR1 is negatively associated with changes in the labor share in all specifications in all six segments.[31] 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.

Further robustness tests

We have implemented a large number of robustness tests on these regressions and discuss several of them here. First, we repeated the robustness tests applied to manufacturing in Table 2 to the full set of six sectors to the extent that the data permit. For example, following the model of row 5 of

[29] 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 -0.062 in Table 3).

[30] To assess whether the results are driven by the number of firms in the industry rather than their concentration, we additionally included the count of firms as a separate control variable in changes and 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 simply the number of firms (though obviously these are correlated).

[31] For the five year difference specifications the coefficient (standard error) on the CR1 in manufacturing was -0.124 (0.041) for payroll over value added, -0.146 (0.054) for compensation over value added, and -0.060 (0.014) for payroll over sales. For payroll over sales it was -0.018 (0.019), -0.035 (0.016), -0.114 (0.064), -0.097 (0.043) and -0.252 (0.091) for retail, wholesale, services, utilities and transportation and finance respectively (the combined value pooled across all six sectors was -0.074 (0.016)).

Table 2, we added a full set of four-digit industry trends to the five-year first-difference by-sector estimates in Table 3. All coefficients were negative across the three measures of concentration and 14 of the 18 were significant at the 5 percent level.

Second, the superstar firm model is most immediately applicable to higher-tech industries, which may have developed a stronger "winner takes most" character, while it is less obviously applicable to declining sectors. To explore this heterogeneity, we divide our sample of industries into the high-tech versus other sectors. Consistent with expectations, we find that the coefficient on firm concentration predicts a larger fall in the labor-share in high-tech sectors (classified in a variety of ways) than in the complementary set of non high-tech sectors.[32]

Third, we note that our main estimating equation (2) imposes a common coefficient over time on the concentration measures and takes heterogeneity between years into account only through the inclusion of time dummies. Figure A.5 shows the regression coefficients that result from separate period-by-period estimates of equation (2) using CR20 as the measure of industry concentration as an illustration. Under either definition of the labor share denominator (value-added or sales) in manufacturing, the relationship between the change in the labor share and the change in concentration is significantly negative in all periods except for 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. In the working paper version of this paper, we present scatterplots of the data underlying the coefficient estimates presented in Figure A.5 that illustrate these points.

IV.B Between-Firm Reallocation Drives Fall in Labor Share

Methodology

The third implication of the superstar firm model is that the fall in the labor share should have an important between-firm (reallocation) component, as firms with a low labor share capture a rising

[32] We followed Decker, Haltiwanger, Jarmin and Miranda (2018) by using the definition of high-tech in Hecker (2005). Here, an industry is deemed high-tech if the industry-level employment share in technology-oriented occupations is at least twice the average for all industries. This occupation classification is based on the 2002 BLS National Employment Matrix that gives the occupational distribution across four-digit NAICS codes. We use the NAICS-SIC crosswalk and identify the SIC codes that map entirely to the high tech four-digit NAICS codes, yielding 109 four-digit "high tech" SIC codes. Re-running our primary model with this classification, we found that the coefficient on concentration is negative and significant in both sub-samples, but is almost twice as large in absolute magnitude in the high-tech sub-sample. In a pooled specification, the interaction between the high tech dummy and the CR20 is negative and significant (-0.067 with a standard error of 0.031).

fraction of industry sales or value-added. To explore this implication, we implement a variant of the Melitz and Polanec (2015) decomposition which was originally developed for productivity decompositions but it be applied readily to the labor share.[33] We write the level of the aggregate labor share as

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

where the size-weight, ω_i, is firm i's share of value-added in an industry, $\omega_i = P_i Y_i / \sum_i P_i Y_i$, $\bar{S}$ is the unweighted mean labor share of the firms in the industry, and $\bar{\omega}$ is the unweighted mean value-added share.[34]

Consider the change in the aggregate labor share between two time periods, $t = 0$ and $t = 1$. Abstracting from entry and exit, we write the Olley-Pakes decomposition as: [35]

$$\Delta S = S_1 - S_0 = \Delta \bar{S} + \Delta \left[\sum (\omega_i - \bar{\omega})(S_i - \bar{S})\right]. \tag{4}$$

Following Melitz and Polanec (2015), we augment this decomposition with terms that account for exit and entry:

$$\Delta S = \Delta \bar{S}_S + \Delta \left[\sum (\omega_i - \bar{\omega}) \left(S_i - \bar{S}\right)\right]_S + \omega_{X,0} \left(S_{S,0} - S_{X,0}\right) + \omega_{E,1} \left(S_{E,1} - S_{S,1}\right). \tag{5}$$

Here, subscript S denotes *survivors*, subscript X denotes *exiters* and subscript E denotes *entrants*. The variable $\omega_{X,0}$ is the value-added weighted mean labor share of exiters (by definition all measured in period t_0) and $\omega_{E,1}$ is the value-added weighted mean labor share of entrants (measured in period t_1). The term $S_{S,t}$ is the aggregate labor share of survivors in period t (i.e. firms that survived between periods t_0 and t_1), $S_{E,1}$ is the aggregate value-added share of entrants in period t_1, and $S_{X,0}$ is the value-added share of exiters in period t_0. 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, $\Delta \left[\sum (\omega_i - \bar{\omega}) \left(S_i - \bar{S}\right)\right]_S$, which reflects the change in the covariance between firm size and firm labor shares for surviving incumbents. Meanwhile, the last two terms account for contributions from exiting and entering firms.

[33]The Melitz and Polanec (2015) generalizes the Olley and Pakes (1996) productivity decomposition to allow for firm entry and exit.

[34]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.

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

Main Decomposition Results

In Figure 7, we show an illustrative plot for the Melitz-Polanec decomposition calculated for adjacent five-year periods for manufacturing payroll over value-added, cumulated over two 15-year periods: 1982-1997 and 1997-2012. The labor share declined substantially in both periods: -10.42 percentage points between 1982 and 1997 and -5.65 percentage points between 1997 and 2012. Consistent with the superstar firm framework, the reallocation among incumbents ("between") was the main component of the fall: -8.24 percentage points in the early period and -4.90 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 ten (1997-2012) times as large as the within-firm component. Notably, the within-incumbent contribution to the falling labor share is only 0.4 percentage points during 1997-2012, meaning that for the unweighted average incumbent firm, the labor share fell by under half 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, by -2.4 and -2.8 percentage points, respectively, in the early and later time interval. The fact that the high labor share firms within a sector are disproportionately likely to exit is logical since such firms are generally the less profitable. Conversely, the contribution from firm entry is positive in both periods: 2.7 and 2.4 percentage points in the early and later period respectively. 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 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 (1987-1992 and 2007-2012). The right panel of Table 4 repeats these 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. The last row shows, for example, that the compensation share fell by 18.5 percentage points between 1982 and 2012 and that essentially all of this change is accounted for by reallocation among incumbent firms. By contrast, the unweighted labor share for incumbents fell by only 0.24 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.[36] Figure 8 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 and utilities/transportation). Table 5 reports the decompositions over five-year periods underlying the sample totals plotted in Figure 8. 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 7 for payroll over value added within manufacturing, the total contribution of market share reallocation among incumbent firms (4.54 percentage points) is almost three times as large as the within-firm component (1.71 percentage points) for payroll over sales. Also 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. Indeed, this is exactly what is predicted by the model in Section II, as in that model, the unweighted average labor share is the flip side of the unweighted average markup. Proposition 2 shows that for sufficiently skewed firm productivity distributions (specifically, a log-convex distribution), an increase in the toughness of competition reduces margins for individual firms, but reallocates so much market share to firms with high markups and low labor shares that the aggregate labor share falls and the aggregate markup rises.

Robustness of the Decomposition Analysis

We have subjected the decomposition findings to a large number of robustness tests, some of which are reported below (and others considered in Appendix D.5). A key feature of the above decomposition analysis is that it is performed at the level of the entire firm (within a sector). While this is appealing because it closely aligns with the model, there is a potential complication as entry and exit can occur through firm merger and acquisition activity rather than de novo start-ups or closing down of establishments.[37] Additionally, since firms may span multiple industries, some of

[36] 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.

[37] For example, when a firm is taken over, its establishments are reallocated to those of the the acquiring firm, this leads to an "exit" of the acquired firm even though its establishments do not exit the economy. On the other hand,

the reallocation we measure in the baseline decomposition may reflect shifts of firm activity across four-digit industries.

In order to explore the importance of the specific firm definition in driving the decomposition results, we report in Table A.1 the results of a decomposition analysis at the both the establishment level (Panel A) and at the firm-by-four-digit SIC industry (Panel B).[38] In both cases, we find qualitatively similar patterns to our main estimates, reflecting the fact that the overwhelming number of firms have only a single establishment. In both cases, exit makes a larger contribution, but the sum of entry and exit is still small compared to the reallocation term.[39]

In Panel C of Appendix Table A.1, we perform the decomposition at 15-year intervals rather than five-year intervals. The pattern of findings persists, even though the definition of a "survivor" is now changed to comprise only firms that survive at least 15 years (rather than the baseline of five years).

In order to more concretely assess the magnitude of the between-industry reallocation in our baseline firm-level decomposition, we perform an extended decomposition that explicitly distinguishes between-industry versus within-industry but between-firm components. We first use a standard shift-share technique to decompose the overall change in the labor share into between-industry $\sum_j \left(\widetilde{S}_j \Delta\omega_j\right)$ and within-industry $\sum_j \left(\widetilde{\omega}_j \Delta S_j\right))$ components:

$$\Delta S = \sum_j \left(\widetilde{S}_j \Delta\omega_j\right) + \sum_j \left(\widetilde{\omega}_j \Delta S_j\right). \tag{6}$$

Here, $\widetilde{S}_j$ is the time average of the (size-weighted mean) labor share in industry j (S_j) over the two time periods, and $\widetilde{\omega}_j$ is the industry size share (e.g. value added share of industry j in total manufacturing value added), ω_j , averaged across the two time periods. We then use the industry specific version Equation (5) to split up within-industry $\sum_j \left(\widetilde{\omega}_j \Delta S_j\right)$ contribution into its four parts (technical details are in Appendix D).

We show the components of this five way decomposition in Tables A.3 and A.4.The first two panels report payroll over value-added and compensation over value-added (in manufacturing), while the next six panels are for payroll over sales (in all six sectors). Looking across Table A.4 as

if an incumbent firm creates a new greenfield establishment, this will not be counted as firm entry.

[38] This is the same definition used in Tables 2 and 3 linking changes in labor shares to changes in industry-level concentration.

[39] Additionally, motivated by concerns over the accuracy of firm identifiers in the Census panel (see Haltiwanger, Jarmin and Miranda, 2013), we applied a looser definition of what constitutes an ongoing firm by using the identity of ongoing establishments. Specifically, if an ongoing establishment experiences a change in firm identifier, we reclassify the firm to be the same if the "new" firm contains all the establishments of a previously exiting firm. Our results are again almost identical to those in Tables 7 and 8.

a whole, it is clear that the main qualitative finding that the fall in the labor share is dominated by a *within-industry* between-firm reallocation is robust to this alternative decomposition. In some segments, the *between-industry* contribution increases the labor share (e.g. services, utilities and transportation, and finance). In the others, it is relatively small compared to the reallocation term that operates between firms within an industry. For example, in the wholesale sector, the between-industry term is -0.3 as compared to -5.7 for reallocation between firms. In manufacturing, the between-industry term is -0.4 for payroll over sales; -2.2 for payroll over value-added and -2.9 for compensation over value-added, as compared to a total (between-firm reallocation contribution) change of -6.7 (-5.5); -16.1 (-7.9), and -18.5 (-10.3) respectively. These results are also in line with Kehrig and Vincent (2018), who extensively analyze changes in the labor share in manufacturing using full distributional accounting techniques. Like us, they find that the between-firm reallocation term dominates in accounting for the aggregate fall in the labor share.

IV.C Between-Firm Reallocation is Strongest in Concentrating Industries

We have established that across most of the U.S. private-sector 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 industries where concentration rose the most; and that the fall in labor share is primarily accounted forby between-firm reallocation of value-added sales rather than within-firm declines in labor share. Figure 9 examines the fourth prediction of the superstar firm model: the reallocation component of falling labor share should be most pronounced in the industries where concentration is differentially rising. This occurs in our model because superstar firms capture market share through their high relatively high productivity, meaning that they are aggressive competitors. If, contrary to our superstar firm hypothesis, rising concentration reflects weakening competition, we would instead expect to see a general rise in mark-ups, a rise in profit shares, and a fall in labor shares that is common across firms within an industry.

We explore the model's prediction in Figure 9 by plotting the relationship within each sector between changes in industry concentration and each of the four components of the Melitz-Polanec decomposition. In the figure, the upper bars report the coefficient estimates and standard errors from regressions of the reallocation component of the fall in the labor share (based on Table 5) on the change in the CR20. The bars directly underneath report the estimates that result from regressing the within-incumbent component of the change in the labor share on the change in concentration. The remaining two bars show the corresponding estimates for the firm entry and exit components. Appendix Table A.6 (column 2) reports the corresponding regressions underlying Figure 9 alongside analogous estimates using our two alternative measures of concentration. The pattern of results in Figure 9 is consistent across all sectors: the tight correlations between rising concentration and falling labor share reported earlier in Figure 6 are driven by the reallocation component. Specifically, the between-incumbent reallocation component shows up as negative and significant in all sectors, indicating that rising concentration predicts a fall in labor-share through between-incumbent reallocation. Conversely, 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, as in 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 8. 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 9, 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.[40]

[40]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 Markup Analysis

Our imperfect competition approach emphasizes that at the firm level, the labor share depends on the ratio of the output elasticity of labor to the markup (equation 1), while the economy-wide labor share depends on how market shares are distributed across these heterogeneous firms. A corollary of this approach is that for stable elasticities, markups should move in the opposite direction of labor shares. The formal model in Appendix A shows that the conditions under which the aggregate labor share falls are the same as those for obtaining a rise in the markup.

Measuring Markups

To empirically test this implication of the model, we must estimate markups, which is more challenging than measuring the labor share. Following the literature (e.g. de Loecker, Eeckhout and Unger, 2018) we can estimate markups by re-arranging and generalizing (equation 1):

$$m_{it} = \left(\frac{\alpha_{it}^{v}}{S_{it}^{v}}\right) \tag{7}$$

where $S_{it}^{v} = \left(\frac{W_{it}^{v} X_{it}^{v}}{P_{it} Y_{it}}\right)$ is the share of any variable factor of production X_{it}^{v} (with factor price W_{it}^{v}) in total sales: α_{it}^{v} is the output elasticity with respect to factor v. This is a very general result and assumes only that firms cost minimize; it therefore allows for non-constant returns, general technologies, etc. (see Hall, 1988, 2018). Although factor shares (S_{it}^{v}) are in principle observable, elasticities (α_{it}^{v}) are not. One simple way to recover the elasticity is to assume that the production function exhibits constant returns to scale, in which case we can measure α_{it}^{v} by the share of factor v in total costs ($\sum_f W_{it}^{f} X_{it}^{f}$). In this case the markup formula becomes:

$$m_{it} = \left(\frac{P_{it} Y_{it}}{\sum_f W_{it}^{f} X_{it}^{f}}\right) \tag{8}$$

where f indicates we are summing up over the costs of all factors f whether quasi-fixed (like capital) or quasi-variable (like labor). Equation (8) is simply the ratio of sales to total costs, which is used for measuring the markup by Antras, Fort and Tintelnot (2018) among others. We call this the "accounting approach" as it does not rely on econometric estimation. A second approach to recovering markups is to estimate α_{it}^{v} from a production function as recommended by de Loecker and Warzynski (2012). This relaxes the constant returns assumption implicit in the accounting approach but does require econometric estimation of a production function.

A practical data challenge for both the accounting or econometric approaches is that in the Economic Census, data on capital are unavailable outside of manufacturing, and data on intermediate input usage are sparse. Consequently, we focus on the Census of Manufactures where richer data are available. Appendix B details how we estimate plant-level production functions using methods due to *inter alia* Levinsohn and Petrin (2003) and Ackerberg, Caves and Frazer (2015). In all cases we allow all parameters to freely vary across the 18 two-digit SIC manufacturing industries and (in some specifications) we also allow the parameters to vary over time and across plants (e.g. using a translog production function). The plant markups are aggregated to the firm level using value added weights (for multi-plant firms).

Results

We summarize the results of this exercise here, with further details provided in Appendix B. Before exploring trends, Appendix Figure A.4 confirms that larger firms have higher markups, no matter how they are estimated, a finding that is consistent with standard IO models. In Figure 10, we present the trends in aggregate markups (where firm markups are weighted by value added) in red triangles across four alternative ways of calculating markups. Alongside the weighted markup, we also presents the median markup (green diamonds) and unweighted average markup (blue circles). Panel A uses the accounting in equation 8 and Panel B calculates markups using the Levinsohn and Petrin (2003) method of estimating a Cobb-Douglas production function. Panel C does the same as Panel B, but uses the Ackerberg, Caves and Frazer (2015) method of estimating a Cobb-Douglas. Panel D continues using the Ackerberg, Caves and Frazer (2015) method but generalizes Panel C to estimate a translog production function.

Although the exact level of the markup differs across the four panels of Figure 10, the broad patterns are quite similar. First, the weighted average mark-up always exceeds the unweighted markup (and the unweighted mean is above the median), reflecting the fact that larger firms have higher markups, as noted above. Second, aggregate markups have risen considerably over our sample period. For example, in Panel B the weighted markup has risen from about 1.2 in 1982 to 1.8 in 2012, similar to the finding in De Loecker, Eeckhout and Unger (2018) using publicly listed firms in Compustat across all sectors.[41] Third, across all methods, the aggregate markup

[41]Their Figure 11(a) suggests that the manufacturing markup rose from about 1.2 to 1.6. They also present production function based estimates of markups for Compustat, but they do not implement this method in the Census data, so our results are novel with respect to theirs. They do implement the accounting approach in the Census of Manufactures, although they use a slightly different method of calculating capital costs, employing estimates of cost shares from Foster, Haltiwanger and Syverson (2008). By contrast we use the approach of Antras et al (2017). Despite

has risen much more quickly than that of the typical firm. Indeed, median markups are flat or even falling in some specifications (e.g. Panel D). This implies that rising average markups are driven by the changing market shares and markups of the largest firms, a pattern consistent with the decomposition analysis of labor shares discussed above. This pattern again underscores the centrality of superstar firms for the evolution of the markup, which is consistent with the findings in de Loecker et al (2018) and Baqaee and Fahri (2018). We further explore the evolution of markups and subject our findings to many other robustness tests in Appendix B.

IV.E Concentrating Industries have Higher Innovation and Productivity Growth

The fifth prediction of the superstar model from Section II is that rising concentration is more prevalent in dynamic industries that exhibit faster technological progress, since our superstar firm framework emphasizes technological and competitive forces as driving the trend towards greater concentration and a reallocation of output towards high-productivity and low labor share firms. Before examining the industry-level relationship between the change in concentration and productivity, we first present underlying firm-level evidence that larger firms are more productive. For all firms in manufacturing, we measure firm-level productivity using the estimates of TFP that result from the estimated production function described above in Section IV.D. Appendix Figure A.2 shows that large firms in manufacturing are more productive, regardless of how we measure TFP. Indeed, Figure A.3 shows that large firms have higher labor productivity in all six sectors that we consider. The stylized fact that larger firms have higher TFP and lower labor shares is consistent with the model in Appendix A and underpins the industry-level prediction relating concentration and dynamism.

Moving to the industry level, we explore the relationship between dynamism and industry concentration by employ two commonly used measures of technical change, patent-intensity and productivity growth, along with other relevant industry characteristics. Table 6 displays regressions where the dependent variable is the (five-year) growth in concentration and the explanatory variables are proxies for industry dynamism.[42] Panel A focuses on the manufacturing sector where the data are richer, while Panel B reports results for all six sectors.

The first row shows that there is a significant and positive relationship between the growth of concentration and the growth of patent intensity across all three measures of concentration.

our methodological differences, it is reassuring that the markup estimates tell the same story.

[42]All regressions are weighted by the initial size of the industry, include year dummies and cluster the the standard errors by industry as in Tables 2 and 3.

The second row of Table 6 shows that industries that had faster growth in labor productivity (as measured by value-added per worker) had larger increases in concentration. This regression is similar to the reciprocal of the labor share (payroll over value added) regressions that we presented in subsection IV.A. There are at least two differences, however. First, the denominator of labor productivity is the number of workers whereas the denominator of the labor share measure is total payroll. Second, and more importantly, value-added is deflated by an industry-specific producer price index in the productivity measure in Table 6, but it is simply equal to the nominal labor share in Table 2. This is important as increased concentration may be associated with higher prices, meaning the correlation with the nominal, non-deflated labor productivity measures could be driven by higher markups rather than increased productivity. In fact, there seems to be little systematic correlation between increased concentration and higher prices (see Ganapati, 2018; Peltzman, 2018), but a rather strong relationship with real labor productivity. Of course, this relationship could still just be due to faster growth in input growth in these concentrating industries. Indeed, we do find the concentrating industries have faster growth in the capital-worker ratio, as is shown in the third row of Table 6. 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 in the fourth row, we find a significantly positive correlation between concentration growth and TFP growth.[43]

In Panel B of Table 6, we repeat these specifications for all six sectors. Due to the absence of value-added data outside of manufacturing, we measure productivity as output per worker. Despite this limitation, we find a positive relationship across all 18 regressions, with 12 coefficients significant at the five percent level, two at the ten percent level, and the remaining four insignificant. In net, we find that the industries exhibiting rising concentration are also those that are more dynamic as measured by innovative output and productivity growth.[44]

The above correlation between concentration and productivity supporting the superstar mechanism implies that the reallocation of sales and value-added towards the most productive firms

[43]This TFP measure is measured as a Solow-style residual based on deducting the cost-weighted inputs from deflated output. We also replicated these regressions using TFP measured from industry specific production functions identical to those we used when estimating price-cost markups as detailed in subsection (IV.D) and Appendix B. The qualitative results were unsurprisingly similar, since all TFP measures are strongly and positively correlated with each other.

[44]This evidence is consistent with the cross OECD evidence in Autor and Salomons (2018), who find that the labor share fall was greater in those industries where TFP growth had been most rapid. In our data if we regress the change in the labor share on five-factor TFP growth we obtain a coefficient (standard error) of -0.078 (0.018) in a specification the same as row 1 of Table 2 without concentration and of -0.092 (0.021) if we add four digit industry trends (i.e. in a specification the same as row 5 of Table 2 without concentration).

in each sector should contribute to overall productivity growth. Yet it is widely acknowledged that aggregate productivity growth in the U.S. and Europe slowed in the early 1970s, rebounded modestly in the mid-1990s, and then slowed again in the mid-2000s (Syverson, 2017). Thus, if the superstar mechanism is operative, this implies that there are countervailing forces that mute this effect. One possibility is that there has been a slowdown of productivity diffusion from industry leaders to laggards.[45]A second possibility is that underlying productivity differences between superstar firms and others are not economically large, but that changes in the economic environment have nevertheless yielded substantial reallocation of market shares towards competitors with modest productivity advantages. This would generate superstar effects without large gains in aggregate productivity. Reconciling the aggregate productivity puzzle remains an important topic for further study that we do not claim to resolve here.

IV.F Superstar Firm Patterns are International

The final empirical implication of the superstar framework that we test is that the patterns that we document in the U.S. should be observed internationally. Karabarbounis and Neiman (2013) and Piketty (2014) have documented that the fall in the labor share is an international phenomenon, although the speed and timing of the changes differ across countries. Using industry and firm-level data from various OECD countries, we document that the superstar firm patterns relating rising concentration to falling labor shares found in the U.S. are prevalent throughout the OECD. Our superstar firm framework emphasizes global technological forces for the trend towards greater concentration and a reallocation of output towards high-productivity and low labor share firms. As discussed in the Introduction, the precise mechanisms through which this occurs may include platform competition, adoption of more intangible capital by leading firms, or by toughening market competition, as formalized in the model in Appendix A. An alternative interpretation of these patterns is offered by Dottling et al (2018), who argue that *weakening* US antitrust enforcement has

[45] Andrews, Criscuolo, and Gal (2015) examine firm-level data in 24 OECD countries between 2001 and 2013 and find that while productivity growth has been robust at the global productivity frontier (referring to the most productive firms in each two-digit industry), productivity differences have widened between these frontier firms and the remainder of the distribution. These authors attribute this widening to a slowdown in technological diffusion from frontier firms to laggards, and infer that leading firms have become better able to protect their competitive advantages, which in turn contributes to a slowdown in aggregate productivity growth. Andrews, Criscuolo, and Gal (2015) do not look directly at labor shares, but a slowdown in technological diffusion could be a reason for the growth of superstar firms. We investigated this possibility by examining a measure of technology diffusion based on the speed of patent citations. Consistent with the hypothesis of Andrews, Criscuolo, and Gal, (2015), we find that in industries where the speed of diffusion (as indicated by a drop in the speed of citations) has slowed, concentration has risen by more and labor shares has 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.

led to an erosion of product market competition. The broad similarity of the trends in concentration, markups and labor shares across many countries that we document below casts some doubt on the centrality of these institutional explanations. Indeed, as Dottling et al (2018), emphasize antitrust enforcement has, if anything, strengthened in the European Union—and yet the labor share in OECD countries has seemingly fallen *despite* this countervailing force.

Concentration in the OECD

Obtaining comprehensive data on changes in sales concentration over time across countries is challenging. The most comprehensive source for such an analysis is “Multiprod”, a firm level database that the OECD produces in cooperation with the national statistical agencies in many countries. By design, these data are broadly similar to the US Economic Census. Bajgar et al (2018a) find that between 2001 and 2012, industry-level concentration levels rose within the ten European countries where comprehensive data are available. They estimate that the share of the top decline of companies (measured by sales) increased on average by two percentage points in manufacturing and three percentage points in non-financial market services. Because some of these European economies are small and heavily integrated in the broader EU economy, the authors also look at an alternative market definition based on considering Europe as a single market. Under this definition, they also find that concentration levels have risen, akin to findings for the United States. [46]

Correlation of Industry Labor Shares

Figure 1 documented the pervasive decline in the labor share across several OECD countries. Looking below these time series relationships, we perform a cross-national industry-level and firm-level analysis by exploring the correlation of the labor share (measured in levels) across the 32 industries that comprise the market sector. Appendix Figure A.17 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 its industry-level labor shares with the corresponding value from each of the other 11 countries. The correlation is high in all cases, with average correlation

[46] Dottling, Gutierrez and Philippon (2017) have argued the opposite—that concentration has been falling in the EU. Bajgar et al (2018b) trace the discrepancy to Dottling et al’s (2017) use of BVD Orbis data to calculate concentration rather than the near-population Multiprod data used by the OECD. While Orbis does a reasonable job of tracking sales in the largest firms, it has quite incomplete coverage of small and medium sized firms in many countries, especially in the late 1990s and early 2000s, which then improves thereafter. Consequently, Orbis overestimates overall industry sales growth after the early 2000s as it includes the increase in industry sales arising through expanding sample coverage. When using Orbis for both the numerator and denominator of concentration, Bajgar et al (2018b) reproduce Dottling et al’s finding of falling EU concentration. But when using the more consistent industry size measure from population data as the denominator for industry sales, they reverse this result and report rising concentration.

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, as expected, 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 Appendix Table A.7.

Industry Labor Shares and Concentration

We next examine the relationship between the change in industry-level labor shares and 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. COMPNET, developed by the European Central Bank, is originally a firm-level data set constructed from a variety of country-specific sources through the Central Banks of the contributor nations. The public use version of these data that we analyze are collapsed to the industry-year level. COMPNET reports measures of both the labor share and of industry-level concentration, defined as the fraction of industry sales produced by the top ten firms in a country. We estimate equation (2) in five-year (2006-2011) and ten-year (2001-2011, for countries where data are available) long differences separately across all of the 14 countries in the database. These estimates, reported in Appendix Table A.8, finds that in 12 of 14 countries, there is a negative relationship over the five-year first-difference between rising concentration and falling labor share, as predicted by the superstar firm model. In the longer ten-year difference model in column 2 (for which fewer countries are available), all countries but Belgium also show a negative relationship. These coefficients are imprecise, however, and the majority are 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

To explore the role of between-firm reallocation in falling labor share in cross-national data, we turn to data from BVD Orbis, which is currently the best available source for comparable, cross-national *firm-level* data. 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 six OECD countries for which reasonable quality data are available for the 2000s. For these countries, we decompose changes in labor share into between- and within-firm components, using the earliest five-year periods available for which Orbis has comprehensive data. These are the years 2003-2008 for the UK, Sweden and France, and 2005-2010 for Germany, Italy and Portugal. In all six countries, we see a decline in the aggregate labor share of value-added over this period. Appendix Figure A.18 reports the Olley-Pakes decomposition for the manufacturing sector for all six countries.[47] 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 and in all cases larger in absolute magnitude than the within-firm component. In three of six countries, this within-firm component is positive.

Markups

There has also been considerable recent work on markups using firm-level data across countries (Calligaris et al, 2018; de Loecker and Eeckhout, 2018). These findings appear consistent with the patterns that we document for the U.S., with markups being the flip-side of the pattern of the labor share. On average across countries, the weighted average markup has risen. This pattern appears largely driven by a reallocation of sales and value-added towards firms with high markups (low labor shares).

Summary on International Evidence

Although the international data are not as rich and comprehensive as those available for the United States, the pattern of cross-national findings mirrors the evidence from the more detailed U.S. data: (i) concentration has generally risen across the OECD, as with the US; (ii) the decline in the labor share has occurred in broadly similar industries across countries; (iii) the industries with the greatest increases in concentration exhibited the sharpest falls in the labor share; and (iv) the fall in the labor share is primarily accounted for by the reallocation of value-added or sales between firms rather than within-firm labor share declines; and of course, (v) the rise in markups can be read as the flip-side of the fall in labor shares. We read the international evidence as broadly consistent

[47] We focus on manufacturing as measurement of the labor share is more reliable for this sector. Appendix Table A.9 shows the details of the data and the decomposition.

with the hypothesis that a rise in superstar firms has contributed to the decline in labor's share throughout the OECD.

IV.G Magnitudes

The previous sections have shown evidence that is qualitatively in line with the seven empirical predictions of the superstar firm framework, most importantly by documenting the central role of between-firm reallocation in (proximately) driving the labor share decline. Ideally, we would like to answer the question of how *much* of the fall of the labor share is due to the underlying change in competitive conditions that gives rise to superstar firms. In the absence of an explicit quantitative macro model, it is difficult to precisely answer this question.[48]

To shed some light on the magnitudes, we performed two simple exercises. First, we take a model-based approach. We take logs of the size-aggregated version of equation (1) and write the aggregate labor share change as a function of the change in the weighted average markup and a residual term, ς, $\Delta \ln S = -\Delta \ln m + \varsigma$. The Cobb-Douglas production function underlying equation (1) implies that $\varsigma = \Delta \ln \alpha^L$, i.e. the part of the labor share unexplained by the markups is due to the changing output elasticity of labor.[49] We can implement this approach only for manufacturing, where we have the data necessary to properly measure mark-ups (see subsection IV.D above). Using Table 4, the proportionate fall in the labor share of value added ($\Delta \ln S$) is 40 percent (a 16.5 percentage point change divided by a 41 percent initial level). The percentage change in the markup ($\Delta \ln m$) depends on which measure we use. Using the accounting method in Panel A of Figure 10, there is a 17 percent rise in the markup (0.22/1.31) implying that we account for about two-fifths (17/41) of the labor share change.[50] By contrast, using the production function based measures of the markup, we account for essentially *all* of the labor share change (e.g. in Panel B, the growth of the markup is 50 percent (0.6/1.2), greater than the change in the labor share).

A second approach follows directly from our regression models. We can use the estimates of equation (2) to assess what would have been the change in the labor share had concentration not risen. The predicted aggregate change in the labor share over the whole 2012-1982 period

[48] Karabarbounis and Neiman (2018) rigorously quantitatively evaluate alternative macro-models of the labor share decline.

[49] See Nekarda and Ramey (2013) for what determines the labor share under more general models. For example, if the production function is CES then $\varsigma = \Delta \ln \alpha^L + \Delta \left(\frac{1}{\sigma} - 1\right) \ln \left(PY/B^L L\right)$ where σ is the elasticity of substitution between labor and capital and B^L is a labor augmenting efficiency parameter. If there are overhead labor costs, the residual will also include the ratio between the marginal wage and the average wage.

[50] Although part of the aggregate change in the markup may be due to markup growth at smaller firms, we showed in subsection IV.D that the vast majority of the aggregate markup growth is due to the superstar mechanism—that is, changes at the upper tail.

is $\Delta\widehat{S} = \sum_k \left(\omega_k \hat{\beta}_k \Delta\text{CONC}_k\right)$ where $k = 1, ..., 6$ indicates the broad sector, $\hat{\beta}_k$ is the estimated coefficient from equation (2), and ω_k is the relative size of the sector (value added weights from the NIPA). Excluding the financial sector, the predicted change in the labor share of sales (using the change in the CR20's from 4) is 0.97 percentage points, as compared to an overall fall in the labor share 1.86 percentage points. By this measure, rising concentration can account for about half of the fall in the labor share (52% = 0.97/1.86). If we additionally include the financial sector in these aggregate calculations, we account for even more of the overall change. Here, we predict an even larger labor share fall (-1.6 percentage points) since there has been a large increase in concentration in finance. As noted above, we are cautious about using this sector given the data concerns over the Census sales measures, and hence we prefer the more conservative non-financial estimates. Looking at this calculation sector-by-sector, we predict that the labor share of sales should have fallen in all sectors, especially in the post 2000 period. For example, although we account for only a tenth of the fall in the labor share of sales in manufacturing over the whole period, we account for over a third of the 1997-2012 change. [51]

All these estimates are highly speculative. The first, markup-based approach, probably overestimates the superstar contribution because the labor share implicitly enters some of the calculations of the markup. The second, regression-based approach, may underestimate the superstar effect as concentration is a coarse proxy. Nevertheless, both methods suggest that the key empirical relationships that we highlight in the paper appear economically large as well as statistically significant.

V Further Descriptive Evidence on Superstar Firms

The previous section documented empirical support for the main empirical predictions of the superstar firms framework derived in Section II. This section further explores the relationship between the rise of superstar firms and other economic phenomena of the last several decades.

V.A Import Exposure and Superstar Firms

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

[51] This is partly due to a faster rise in concentration after 1997 (see Figure 4) and partly due to the coefficient on concentration rising (see Figure A.2). From 1997 to 2012, the CR20 in manufacturing went up by around 6 percentage points and the labor share fell by around 6 percentage points. From Figure A.2, 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 $\frac{-0.34\times 6}{6} \times 100 = 34\%$ of the fall in the labor share in manufacturing over this period.

of total import intensity.[52] 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.10 reports regressions of changes in industry-level outcomes in U.S. manufacturing on changes in Chinese imports intensity using both OLS models and 2SLS models that apply 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. We further report results both including and excluding the post-2007 Great Recession. The first three columns of Appendix Table A.10 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.[53]

V.B Compustat Analysis: Publicly Listed Superstar Firms

Although it has the advantage of being comprehensive, Census data have the disadvantage that we are not permitted to illustrate the key fact patterns with specific examples (since the identity of individual companies is confidential). In addition, our Census data do not report on the international activity of these superstar firms. To provide these examples and explore the international scope of these superstar firms, we turn to Compustat data, which contains company accounts of

[52] 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.

[53] A key difference with Elsby, Hobijn and Sahin (2013) is that they pool data from both manufacturing and non-manufacturing industries whereas we analyze the impact of trade exposure on manufacturing oly. Using their approach, we are able to replicate the finding of a negative association between rising imports and falling labor share. But 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. Within manufacturing, cross-industry variation in import exposure appears to have little explanatory power for the fall in the labor share. Additionally, rising import exposure cannot readily explain why labor's share has fallen outside of manufacturing.

firms listed on stock markets. The details of these data and analysis are provided in Appendix C. We summarize findings here. Focussing on the largest 500 US based firms in Compustat, as defined (primarily) by their worldwide sales, we highlight four stylized facts.

First, the average size of such firms has increased substantially over time. For example, between 2015 and 1972 the average firm tripled in size as measured by real sales, and it rose by a factor of six in terms of market value.[54] The average employment in the top 500 also grew. But echoing the finding that large firms increasingly have scale without mass, employment growth at the mean was only 50 percent, which is far smaller than the growth in sales or market value. Second, concentration has risen among these top 500 superstar firms, especially since 2000. For example, the share in total sales of the 50 largest firms among the top 100 rose from 39 percent in 1999 to 48 percent in 2015 (and was 43 percent in 1973). The gap between firms at the 95th percentile of the sales distribution and others further down the distribution has risen particularly strongly. Third, the increase in concentration has been accompanied by an increase in the persistent dominance of top firms, with churn rates falling (consistent with Decker et al, 2018, on the Census LBD). For example, the probability that a firm in the top 500 (by sales) was also in that category five years earlier rose from 66 percent to 80 percent between 2000 and 2015. Similarly, the ten-year survival rate of firms in the top 500 rose from 55 percent in 2005 to 68 percent in 2015.

A fourth finding relates to the growing global engagement of U.S. firms. We estimate that the share of sales outside of the US for superstar manufacturing firms doubled between 1972 and 2012, from 30 percent to 60 percent, and tripled for superstar non-manufacturing firms, from 10 percent to 30 percent. This pattern raises the question of whether rising global engagement could itself be a driving force behind the fall of the labor share. This is particularly hard to explore in Compustat data because only a minority of firms reports payroll data in Compustat (it is not a mandatory reporting item). Looking among the firms that do report payroll, we find that globally engaged firms have somewhat higher labor shares and that the average labor share of globally engaged firms has fallen since 1982 (see also Hartman-Glaser, Lustig and Zhang, 2017). However, the labor share has fallen only slightly more among globally-engaged than non-globally engaged firms, as shown in Appendix Figure A.16. This pattern echoes our broader finding that the fall in the labor share, and the rise in concentration, are prevalent across non-traded sectors in Census data rather than being limited to the heavily traded manufacturing sector. This suggests that globalization, construed narrowly, is unlikely to be the key driver of falling labor shares—though we recognize that a fuller

[54] We report real 2015 prices deflated from their nominal values using the Consumer Price Index.

analysis of this question awaits a conceptual and empirical frame that encompasses the full set of general equilibrium forces in play.[55]

V.C Worker Power and the Rise in Concentration

There has been much recent discussion of whether the declining labor share reflects falling worker power (Krueger, 2018). Declining union power would be one potential mechanism contributing to the decline in the labor share, although the broad decline of labor shares in non-manufacturing (where unions have little presence), and in countries where union power has not fallen so steeply as in the US, would go against this story. Alternatively, some papers have suggested that the growth of superstar firms confers more monopsony power to employers, driving down both wages and employment. In row 5 of Panel A in Table 6 we find that the relationship between concentration and average wages (payroll per worker) in manufacturing is in fact positive, although insignificant. This suggests that concentrating sectors in manufacturing are those where the share of labor is falling, but the average wage is not.[56]

The sixth row of Panel A in Table 6 shows that concentrating industries in manufacturing have moved towards relying significantly more on materials inputs, which is consistent with greater intermediate goods outsourcing. We suspect that these concentrating industries are also relying more on intermediate service outsourcing, especially for low paid workers as seen for example in Germany (Goldschmidt and Schmieder, 2017). Unfortunately, the Census data do not report direct information on service inputs. We return to the issue of service outsourcing in our concluding remarks.

[55] Specifically, general equilibrium effects emanating from the overall expansion of global operations and offshoring may impact the financial structures of non-globally engaged firms, a force for which our descriptive analysis cannot account. At a practical level, although Compustat reflects the activities of foreign affiliates in its consolidated accounts, it does not include activities that are offshored and outsourced (e.g. Apple's manufacturing agreements with the independent Taiwanese company FoxConn).

[56] Payroll per worker is a crude measure of the price of labor as it does not account for composition effects (e.g. skills and demographics). Moreover, *local* labor market concentration is likely a better measure of monopsony power than national product market concentration. Several papers have found a negative link between local labor market concentration and local wages (e.g. Azar et al, 2018; Benmelech, Bergman and Kim, 2018; and Rinz, 2018). Although our conclusion that national sales concentration rates have risen is now widely reported (see Barkai, 2016; Gutierrez and Philippon, 2018), the trends in local concentration are less clear cut. For example, Benmelech et al (2018) find increases in local concentration whereas Rinz (2018) and Rossi-Hansberg, Sarte and Trachter (2018) find a decrease. A challenge for analyzing local measures of concentration is obtaining reliable data on local sales. The LBD used by Rinz (2018) and Benmelech et al (2018) contains employment but not sales data. The NETS database used by Rossi-Hansberg et al (2018) contains a large number of imputed establishment-level sales values.

VI Conclusions

In this paper we have considered a new "superstar firm" explanation for the widely remarked fall in the labor share of value-added. We hypothesize that markets have changed such that firms with superior quality, lower costs, or greater innovation reap disproportionate rewards relative to prior eras. We shows that, consistent with a simple model, these superstar firms have higher markups and a lower share of labor in sales and value-added. As superstar firms gain market share across a wide range of sectors, the aggregate labor share 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 in manufacturing and has actually risen in most of non-manufacturing. Fourth, this between-firm reallocation of the labor share is greatest in the sectors that are concentrating the most. Fifth, aggregate markups have been rising, but unweighted firm markups have not. Sixth, the industries that are becoming more concentrated are also growing relatively more productive and innovative. Seventh, these broad patterns are observed not only in U.S. data, but also internationally in other OECD countries. A final set of results shows that 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—though likely not the sole driver—of this trend.

The work in this paper is documents a set of robust and cohesive firm-level, industry-level, and cross-national facts that we believe any explanation of falling labor shares must accommodate. We have presented a formal model where the market-share consequences of productivity differences between firms is magnified when the competitive environment becomes more strenuous, turning leading firms into 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 most" aspect. Our evidence is consistent with this explanation but does not constitute a definitive causal test of it. 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 since the industries where concentration has grown are those that have been increasing their innovation most rapidly. 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 and policy (see Tirole, 2017; Wu, 2018). Future work therefore needs to understand more precisely the economic and regulatory forces that lead to the emergence of superstar firms.

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 to contract a wider range of activities previously done in-house to third party firms and independent workers. These activities may include janitorial work, food services, logistics, and clerical work (Weil, 2014; Katz and Krueger 2016; Goldschmidt and Schmieder, 2017). This apparent 'fissuring' of the workplace (Weil, 2014) can directly reduce the labor share by excluding a large set of workers from the wage premia paid by high-wage employers to rank-and-file workers. This fissuring may also reduce 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 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., 2019). 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.

References

Ackerberg, Daniel, Kevin Caves and Garth Frazer. 2015. "Identification Properties of Recent Production Function Estimators" *Econometrica* 83(6) 411-2451

Aghion, Philippe and Peter Howitt. 1992. "A Model of Growth. Through Creative Destruction." *Econometrica* 60(2) 323-351.

Akerman, Anders, Edwin Leuven, and Magne Mogstad. 2017. "Information Frictions, Broadband Internet and the Relationship between Distance and Trade." mimeo, University of Chicago.

Andrews, Dan, Chiara Criscuolo, and Peter Gal. 2015. "Frontier Firms, Technology Diffusion and Public Policy." OECD Future of Productivity Background Paper.

Antràs, Pol. 2004. "Is the U.S. Aggregate Production Function Cobb-Douglas? New Estimates of the Elasticity of Substitution." *The B.E. Journal of Macroeconomics*, 4(1): 1-36.

Antràs, Pol, Teresa Fort and Felix Tintelnot. 2017. "The Margins of Global Sourcing: Theory and Evidence from U.S. Firms." *American Economic Review* 107 (9): 2514-64.

Arkolakis, Costas, Costinot, Arnaud, David Donaldson and Andreas Rodriguez-Clare. 2018 "The Elusive Pro-competitive effects of trade" *Review of Economic Studies* 86(1) 46-80

Autor, David H., David Dorn, and Gordon H. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review*, 103(6): 2121–2168.

Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen. 2017a. "The Fall of the Labor Share and the Rise of Superstar Firms." NBER Working Paper 23396

Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen. 2017b. "Concentrating on the Fall of the Labor Share." *American Economic Review Papers and Proceedings*, 107(5): 180–185

Autor, David, Lawrence Katz, and Alan Krueger. 1998. "Computing Inequality: Have Computers Changed the Labor Market?" *Quarterly Journal of Economics*, 113 (4):1169-1214.

Autor, David and Anna Salomons. 2018. "Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share" *Brookings Papers on Economic Activity*, 1-63.

Azar, Jose, Ioana Marinescu, Marshall Steinbaum and Bledi Taska. 2018. "Concentration in US Labor Markets: Evidence from online vacancy data" NBER working Paper 24395

Azmat, Ghazala, Alan Manning, and John Van Reenen. 2012. "Privatization and the Decline of Labor Share: International Evidence from Network Industries." *Economica*, 79, 470-492.

Bailey, Martin, Charles Hulten and David Campbell. 1992. "Productivity Dynamics in Manufacturing Plants" *Brookings Papers on Economic Activity: Microeconomics*, 187-267.

Bain, Joseph. 1951. "Relation of Profit Rate to Industry Concentration: American Manufacturing 1936-1940*" Quarterly Journal of Economics* 65(3), 293-324.

Bajgar, Matej, Giuseppe Berlingieri, Sara Calligaris, Chiara Criscuolo and Jonathan Timmis. 2018a. "Industry Concentration in Europe and North America", Paris: OECD

Bajgar, Matej, Giuseppe Berlingieri, Sara Calligaris, Chiara Criscuolo and Jonathan Timmis. 2018b. "To Use or Not to Use (and How to Use): Coverage and Representativeness of ORBIS data", Paris: OECD

Baqaee, David and Emmanuel Fahri. 2017. "Productivity and Misallocation in General Equilibrium" NBER Working Paper 24007

Barkai, Simcha. 2016. "Declining Labor and Capital Shares." Working Paper, University of Chicago.

Bartelsman, Eric, John Haltiwanger and Stefano Scarpetta. 2013. "Cross-Country Differences in Productivity: The Role of Allocation and Selection." *American Economic Review*, 103(1): 305-34.

Bauer, Arthur and Lashkari, Daniel. 2018. "Information Technology and Returns to Scale" Yale mimeo

Bell, Brian. 2015. "Wage Stagnation and the Legacy Costs of Employment" *Centrepiece*, Fall, 20-23.

Berkowitz, Daniel, Hong Ma, and Shuichiro Nishioka. 2017. "Does Capital-Labor Substitution or Do Institutions Explain Declining Labor Shares?" University of Pittsburgh.

Benmelech, Efraim, Nittai Bergman and Hyunseob Kim. 2018. "Strong employers and Weak Employees: How does employer concentration affect wages?" NBER Working Paper 24307

Bernard, Andrew B., Stephen J. Redding, Peter K. Schott. 2010. "Multi-Product Firms and Product Switching" *American Economic Review*, 100, 70-97.

Bessen, James. 2017. "Information Technology and Industry Concentration" Boston University Law and Economics Paper No. 17-41

Blanchard, Olivier. 1997. "The Medium Run." *Brookings Papers on Economic Activity*, 2, 89-158.

Blanchard, Olivier and Francesco Giavazzi. 2003. "Macroeconomic Effects of Regulation And Deregulation In Goods and Labor Markets." *Quarterly Journal of Economics*, 118, 879-907.

Bockerman, Petri and Mika Maliranta. 2012. "Globalization, Creative Destruction, and Labor Share Change: Evidence on the Determinants and Mechanisms from Longitudinal Plant-Level Data," *Oxford Economic Papers*, 64, 259-80.

Boldrin, Michele and David K. Levine. 2008. *Against Intellectual Monopoly.* Cambridge University Press.

Bridgman, Benjamin. 2014. "Is labor's loss capital's gain? Gross versus net labor shares." *Bureau of Economic Analysis*, Washington DC.

Brynjolfsson, Erik, Andrew McAfee, Michael Sorell, and Feng Zhu. 2008. "Scale Without Mass: Business Process Replication and Industry Dynamics" Harvard Business School Technology and Operations Management Unit Research Paper No 07-016.

Calligaris, Sarah, Chiara Criscuolo and L. Marcolin. 2018. "Mark-ups in the digital era", OECD Science, Technology and Industry Working Papers, 2018/10

Cooper, Zack, Stuart Craig, Martin Gaynor and John Van Reenen. 2019. "The Price Ain't Right? Hospital prices and health spending on the privately insured" *Quarterly Journal of Economics* 134 (1), 51–107

Crouzet, Nicolas and Janice Eberly. 2018. "Understanding Weak Capital Investment: the Role of Market Concentration and Intangibles" , Northwestern mimeo

Dao, Mai, Mitali Das, Zsoka Koczan, and Weicheng Lian. 2017. "Why is Labor Receiving a Smaller Share of Global Income? Theory and Empirical Evidence," IMF Working Paper.

Decker, Ryan, John Haltiwanger, Ron Jarmin and Javier Miranda. 2018 "Changing Business Dynamism and Productivity: Shocks vs. Responsiveness" NBER Working Paper 24236

De Loecker, Jan and F. Warzynski. 2012. "Markups and Firm Export Status" *American Economic Review* 102(6) 2437-2471

De Loecker, Jan and Jan Eeckhout. 2018. "Global Market Power", CEPR Discussion Paper 13009

De Loecker, Jan, Jan Eeckhout and Gabriel Unger. 2018 "The Rise of Market Power", mimeo

De Loecker, Jan, Pinelopi Goldberg, Amit Khandelwal, Nina Pavcnik. 2016. "Prices, Markups, and Trade Reform" *Econometrica*, 84(2) 445-510

Demsetz, Harold. 1973. "Industry Structure, Market Rivalry and Public Policy." *Journal of Law and Economics*, 16: 1-10.

Dottling, Robin, German Gutierrez and Thomas Philippon. 2017. "Is There an Investment Gap in Advanced Economies? If So, Why?" NYU mimeo

Dube, Arindrajit and Ethan Kaplan. 2010. "Does Outsourcing Reduce Wages in the Low-Wage Service Occupations? Evidence from Janitors and Guards." *Industrial and Labor Relations Review*, 63(2), 287-306.

Edmond, Chris, Virgiliu Midrigan, and Daniel Yi Xu. 2015 "Competition, Markups, and the Gains from International Trade" *American Economic Review* 105(10): 3183–3221

Elsby, Mike, Bart Hobijn, and Aysegul Sahin. 2013. "The Decline of the U.S. Labor Share." *Brookings Papers on Economic Activity*, 1-42.

Fort, Theresa and Shawn Klimet. 2016. "The effects of Industry Classification changes on US employment composition" Dartmouth mimeo

Foster, Lucia, John Haltiwanger, and Chad Syverson. 2008. "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" *American Economic Review*, 98(1): 394-425.

Foster, Lucia, John Haltiwanger, and Chad Syverson. 2016. "The Slow Growth of New Plants: Learning about Demand?" *Economica*, 83(329): 91-129.

Furman, Jason and Peter Orszag. 2015. "A Firm-Level Perspective on the Role of Rents in the Rise in Inequality", Working Paper.

Ganapati, Sharat. 2018. "Oligopolies, Prices, Output, and Productivity", Georgetown mimeo

Gilbert, Richard and David Newbery. 1982. "Preemptive Patenting and the Persistence of Monopoly," *American Economic Review*, 72(3) 514-526.

Gollin , Douglas. 2002. "Getting Income Shares Right." *Journal of Political Economy*, 110(2), 458-74

Goldschmidt, Deborah and Johannes F. Schmieder. 2017. "The Rise of Domestic Outsourcing and the Evolution of the German Wage Structure." *Quarterly Journal of Economics*, 132(3), 1165-1217.

Gordon, Robert. 2016. *The Rise and Fall of American Growth: The U.S. Standard of Living Since the Civil War*. Princeton: Princeton University Press.

Gutierrez, German and Thomas Philippon. 2016. "Investment-less growth: An empirical investigation" NBER Working Paper 22897

Gutierrez, German and Thomas Philippon. 2018. "How EU markets became more competitive than US markets" NBER Working Paper 24700

Gopinath, Gita, Şebnem Kalemli-Özcan, Loukas Karabarbounis and Carolina Villegas-Sanchez (2017) "Capital Allocation and Productivity in South Europe", *Quarterly Journal of Economics*, 132(4), 1915–1967

Hamermesh, Daniel S. 1993. *Labor Demand*. Princeton University Press.

Hall, Robert. 1988. "The Relationship between Price and Marginal Cost in US Industry" *Journal of Political Economy*, 96(5), 921-947

Hall, Robert. 2018. "New Evidence on the Markup of Prices over Marginal Costs and the Role of Mega-Firms", NBER Working Paper 24574

Haltiwanger, John, Ron Jarmin and Javier Miranda (2013) "Who Creates Jobs? Small vs. Large vs. Young" *Review of Economics and Statistics*, 347-361

Hartman-Glaser, Barney, Hanno Lustig, and Mindy Zhang. 2017. "Capital Share Dynamics when Firms Insure Workers." forthcoming, *Journal of Finance*.

Hopenhayn, Hugo. 1992. "Entry and Exit in Long Run Equilibria." *Econometrica*, 60(5) 1127-1150

Hsieh, Chang-Tai and Peter J. Klenow. 2009. "Misallocation and Manufacturing TFP in China and India." *Quarterly Journal of Economics*, 124, 1403-1448.

Jones, Charles. 2003. "Growth, Capital Shares, and a New Perspective on Production Functions." Working Paper, UC Berkeley.

Kaldor, Nicholas. 1961. "Capital Accumulation and Economic Growth," in *The Theory of Capita*l, ed. F. A. Lutz and D. C. Hague, New York: St. Martin's Press: 177-222.

Kalecki, Michal. 1938."The Determinants of the Distribution of National Income." *Econometrica*, 6(2), 97-112.

Kalemli-Ozcan, Sebnem, Bent Sorensen, Carolina Villegas-Sanchez, Vadym Volosovych, and Sevcan Yesiltas. 2015. "How to Construct Nationally Representative Firm Level data from the

ORBIS Global Database" NBER Working Paper 21558.

Karabarbounis, Loukas and Brent Neiman. 2013. "The Global Decline of the Labor Share." *Quarterly Journal of Economics,* 129(1), 61-103.

Karabarbounis, Loukas and Brent Neiman. 2018. "Accounting for Factorless Income" NBER Working Paper 24404

Katz, Lawrence F. and Alan B. Krueger. 2016. "The Rise and Nature of Alternative Work Arrangements in the United States, 1995-2015." NBER Working Paper No. 22667.

Kehrig, Matthias and Nicolas Vincent. 2018. "The Micro-Level Anatomy of the Labor Share Decline", NBER Working Paper 25275

Kleiner, Morris and Alan Krueger. 2013. "Analyzing the Extent and Influence of Occupational Licensing on the Labor Market." *Journal of Labor Economics,* 31, S173–S202.

Klette, Toe and Samuel Kortum. 2004. "Innovating Firms and Aggregate Innovation" *Journal of Political Economy*, 112(5) 986-1018.

Koh, Dongya, Raul Santaeulalia-Lopis, and Yu Zheng. 2016. "Labor Share Decline and Intellectual Property Products Capital." SSRN Working Paper.

Krueger, Alan B. 2018. "Reflections on Dwindling Worker Bargaining Power and Monetary Policy", Presentation at Jackson Hole Conference

Lawrence, Robert. 2015. "Recent Declines in Labor's Share in Us Income: A Preliminary Neoclassical Account." NBER Working Paper No. 21296.

Lopez-Garcia, P., F. di Mauro, and the CompNet Task Force. 2015. "Assessing European competitiveness: the new CompNet micro-based database." European Central Bank, Working Paper Series No 1764.

Lucas, Robert E. 1978. "On the Size Distribution of Business Firms." *Bell Journal of Economics*, 9, 2, 508-523.

Melitz, Marc. 2003. "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity." *Econometrica*, 71, 1695–1725.

Melitz, Marc and Saso Polanec. 2015. "Dynamic Olley-Pakes Productivity Decomposition with Entry and Exit." *RAND Journal of Economics*, 46 (2): 362-375.

Melitz, Marc and Gianmarco Ottaviano. 2008. "Market Size, Trade, and Productivity" *Review of Economic Studies* (2008) 75, 295–316

Mrazova and Peter Neary. 2017. "Not So Demanding: Demand Structure and Firm Behavior" *American Economic Review*, 107(12): 3835–3874

Nekarda, Christopher and Valerie Ramey. 2013. "The Cyclical Behavior of the Price-Cost Markup" NBER Working Paper 19099

Oberfield, Ezra and Devesh Raval. 2014. "Micro Data and Macro Technology." Working Paper, Princeton University.

Olley, Steven and Pakes, Ariel. 1996. "The Dynamics of Productivity in the Telecommunications Industry." *Econometrica*, 64(6): 1263-1298.

O'Mahony, Mary and Marcel Timmer. 2009. "Output, Input and Productivity Measures at the Industry Level: the EU KLEMS Database," *Economic Journal*, 119(538) F374-503.

Paunov, Caroline and Dominique Guellec. 2017. "Digital Innovation and the Distribution of Income", OECD mimeo

Peltzman, Samuel. 2018. "Productivity and Prices in Manufacturing during an era of rising Concentration", University of Chicago mimeo

Pessoa, Joao P. and John Van Reenen. 2013. " Decoupling of Wage Growth and Productivity Growth? Myth and Reality", CEP Discussion Paper 1246.

Piketty, Thomas. 2014. *Capital in the Twenty-First Century.* Harvard University Press.

Rinz, Kevin. 2018. "Labor Market concentration, Earnings Inequality and Earnings Mobility" CARRA Working Paper 2018-10

Rognlie, Matthew. 2015. "Deciphering the Fall and Rise in the Net Capital Share: Accumulation or Scarcity?" *Brookings Papers on Economic Activity*, 1-69.

Rossi-Hansberg, Estaban, Pierre-Daniel Sarte and Nicholas Trachter. 2018. "Diverging Trends in National and Local Concentration" NBER Working Paper 25066

Schmalensee, Richard. 1987. "Collusion Versus Differential Efficiency: Testing Alternative Hypotheses." *Journal of Industrial Economics*, 35(4), June, 399-425.

Smith, Mathew, Daniel Yagan, Owen Zidar and Eric Zwick. 2017. "Capitalists in the Twenty-First Century" Chicago mimeo

Song, Jae, David J. Price, Fatih Guvenen, Nicholas Bloom, and Till von Wachter. 2019. "Firming up Inequality." *Quarterly Journal of Economics* 134(1), 1–50.

Syverson, Chad. 2017. "Challenges to Mismeasurement Explanations for the U.S. Productivity Slowdown." *Journal of Economic Perspectives*, Spring, 165-186

Tirole, Jean. 2017. *Economics for the Common Good,* Princeton: Princeton University Press

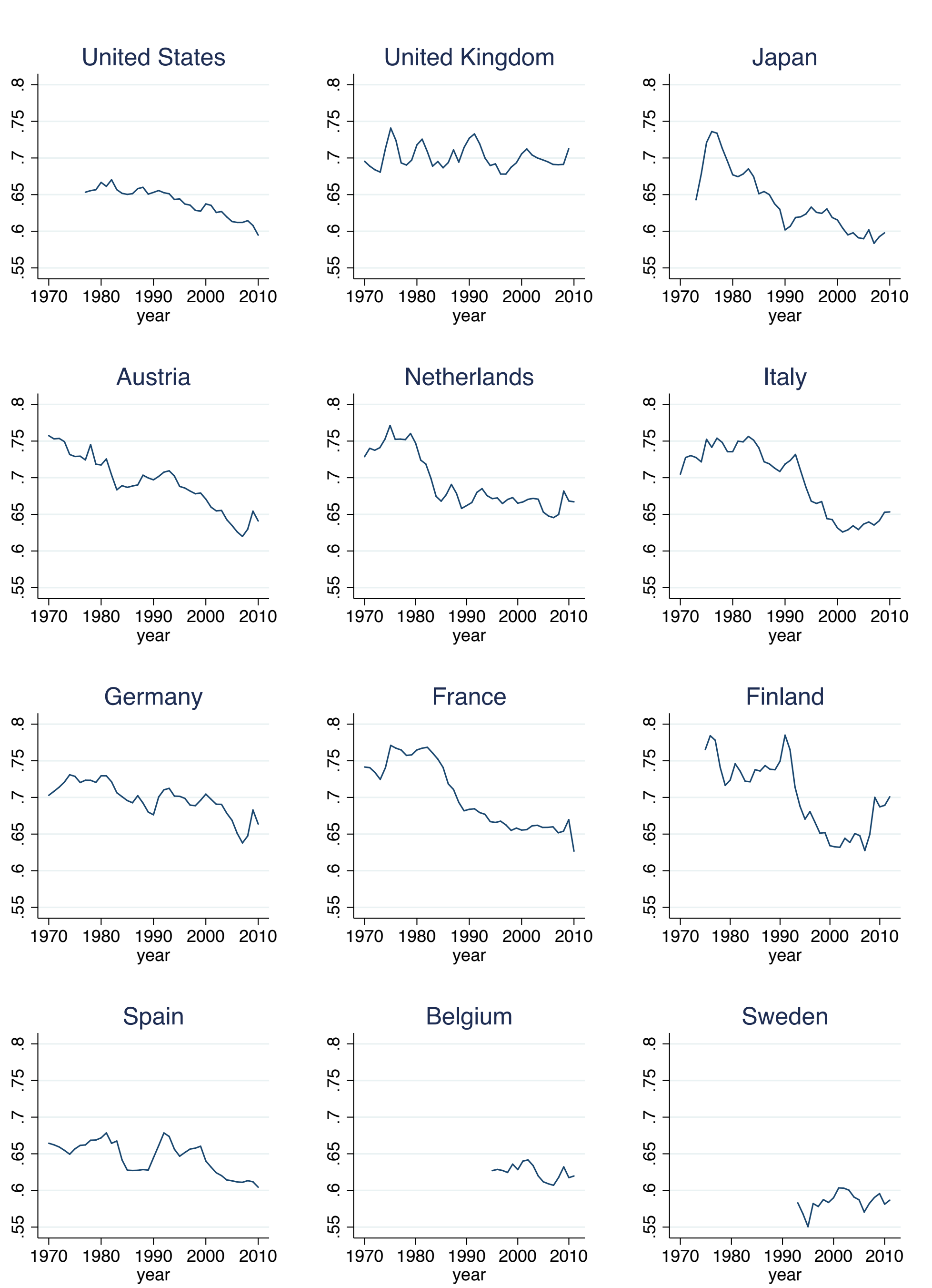
Unger, Gabriel. 2019. ***

Wu, Timothy. 2018. *The Curse of Bigness: Antitrust in the New Gilded Age,* New York: Columbia Press

Weil, David. 2014. *The Fissured Workplace.* Cambridge, MA: Harvard University Press.

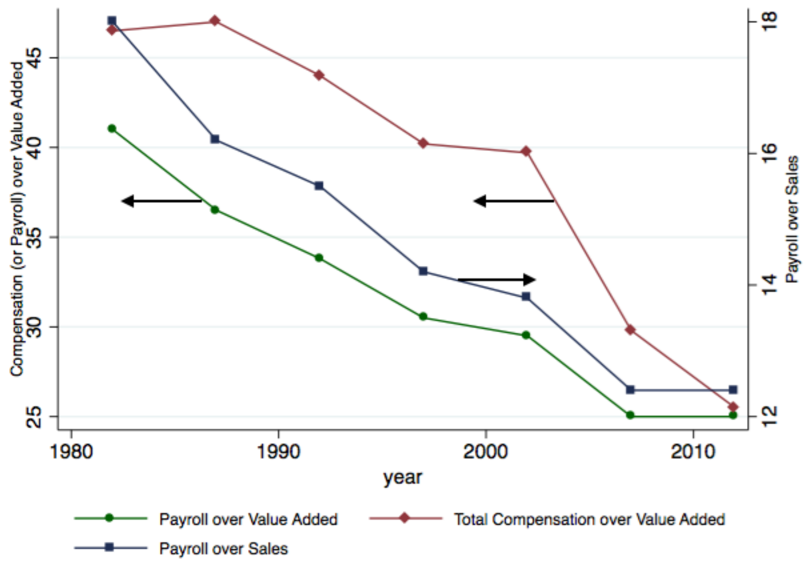
Figures and Tables

Figure 1: International Comparison: Labor Share by Country



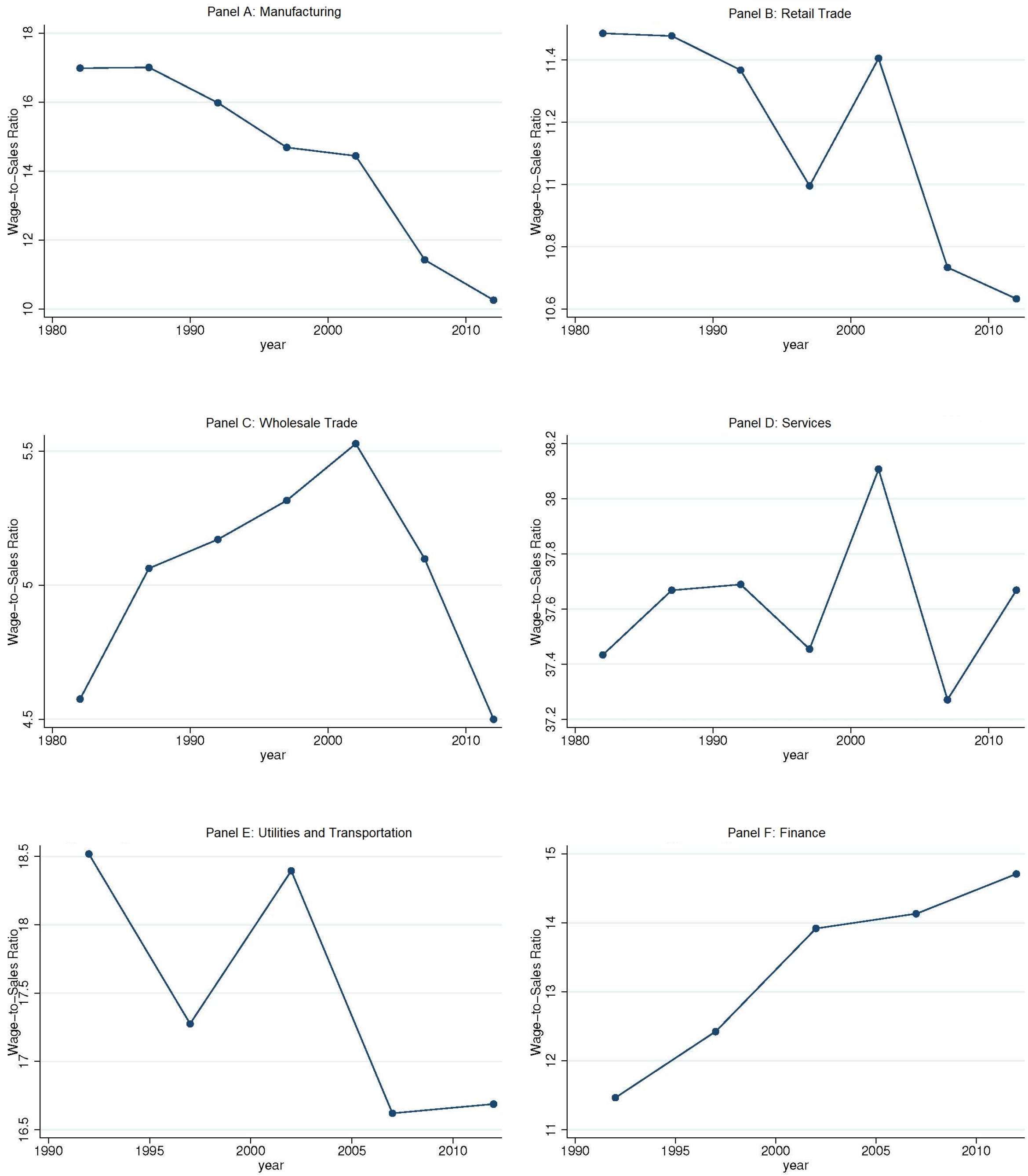
Notes. Each panel plots the ratio of labor compensation to gross value-added for all industries. Data is from EU KLEMS July 2012 release.

Figure 2: The Labor Share in Manufacturing



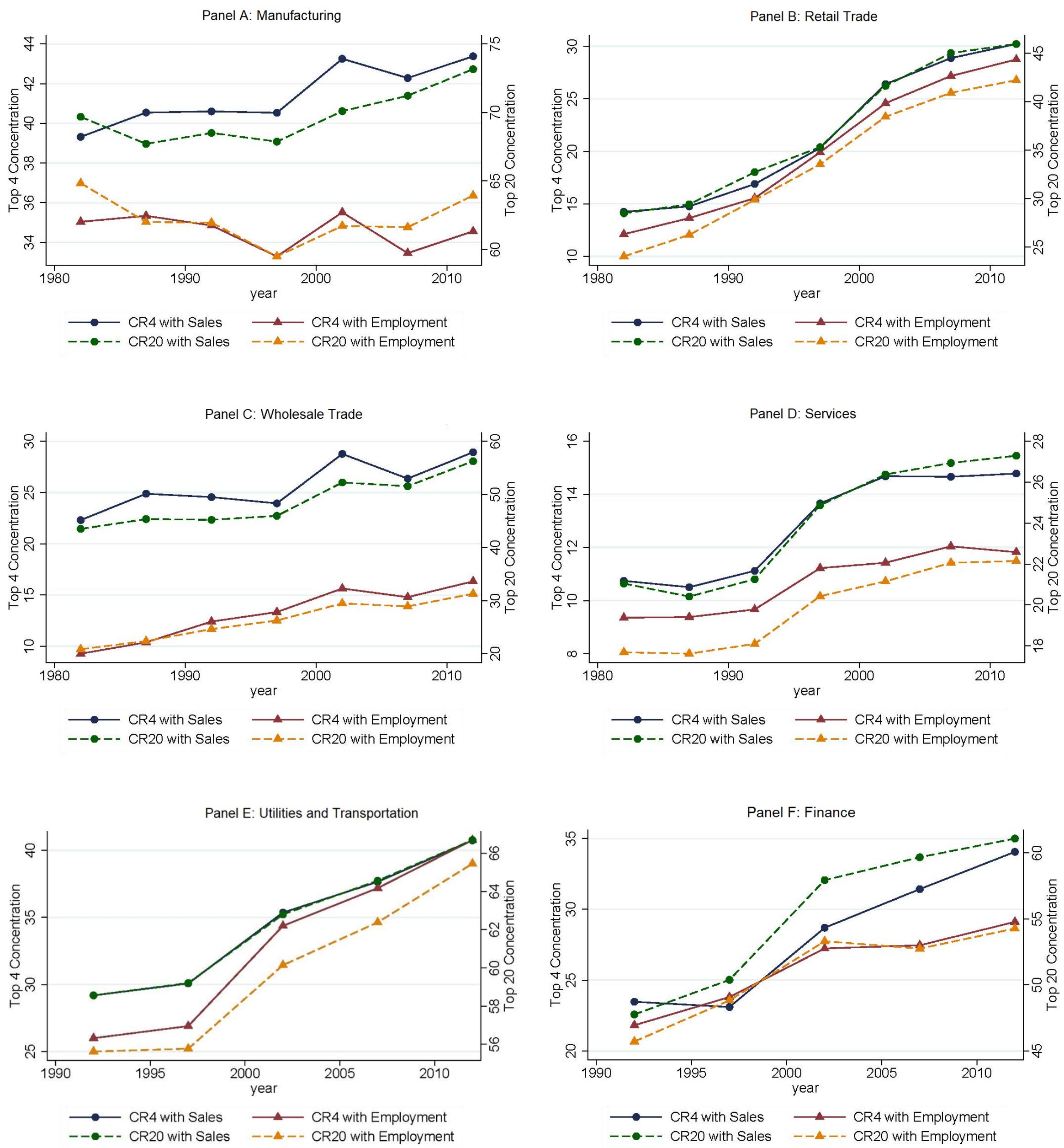
Notes. This figure plots the aggregate labor share in manufacturing from 1982-2012. The green circles (plotted on the left axis) represent the ratio of wages and salaries (payroll) to value-added. The red diamonds (also plotted on the left axis) include a broader definition of labor income and plots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

Figure 3: Average Payroll-to-Sales Ratio



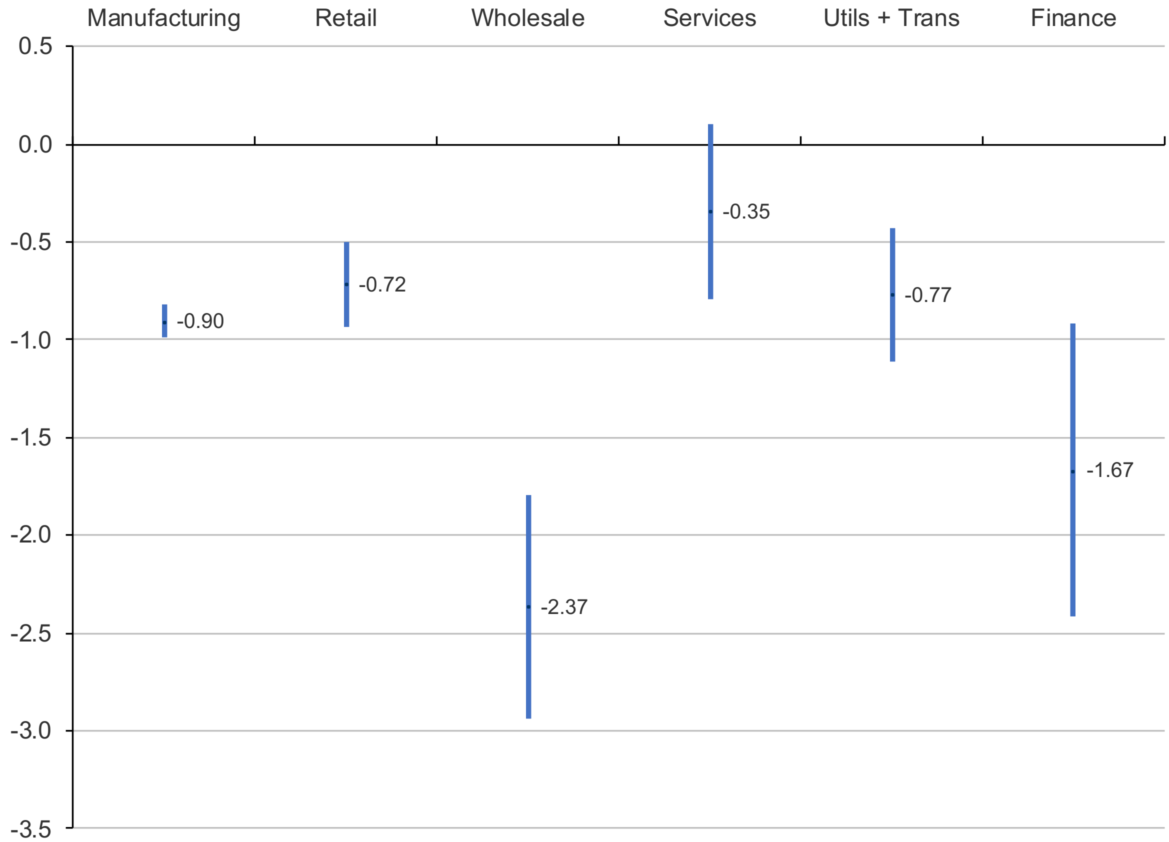
Notes. Each panel plots the overall payroll-to-sales ratio in one of the six major sectors covered by the U.S. Economic Census. Add to notes at the end "These figures update Autor et al (2017) to include more recently released Census data.

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



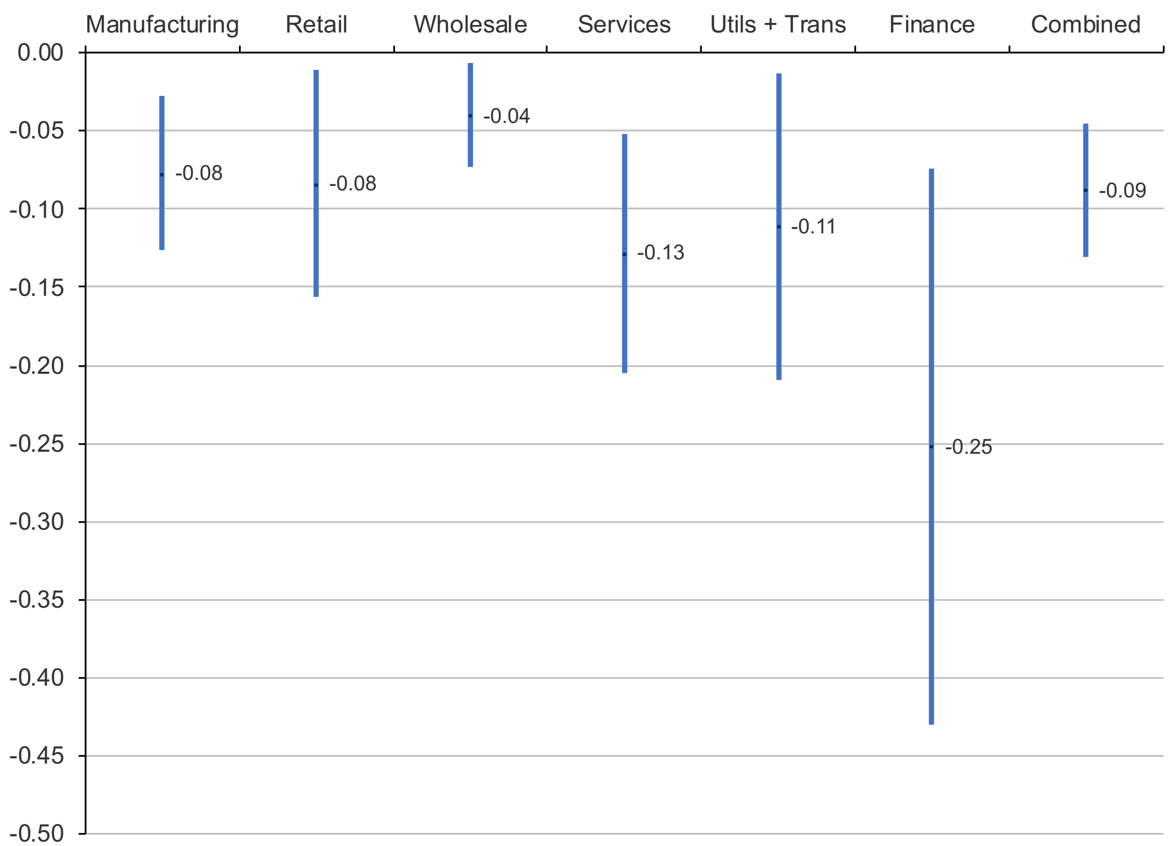
Notes. This figure plots the average concentration ratio in six major sectors of the U.S. economy. Industry concentration is calculated for each time-consistent four-digit industry code, and then averaged across all industries within each of the six sectors. The solid blue line (circles), plotted on 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



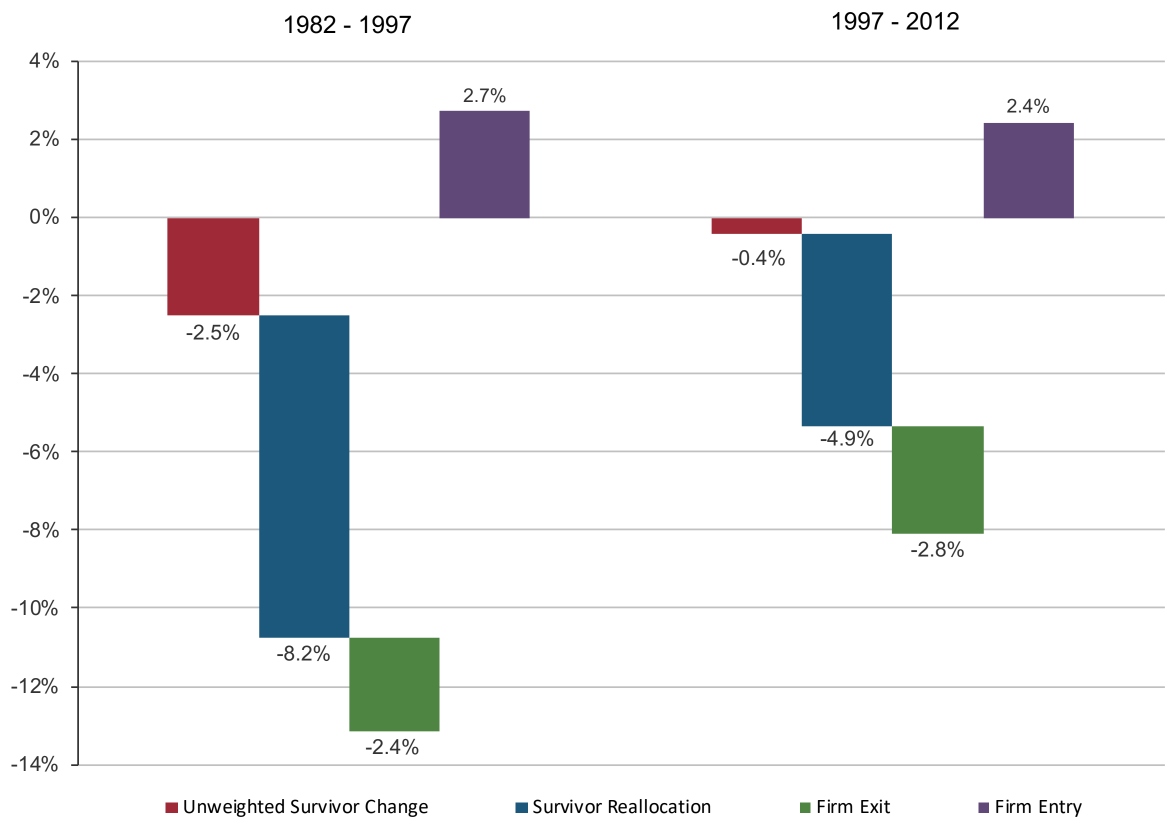
Notes. The dots indicate the coefficient estimates of a regression of a firm's labor share on its share of overall sales in its four-digit industry. The regressions include all years available for that sector, and year fixed effects. The labor share is defined as the payroll-to-sales ratio in each sector.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



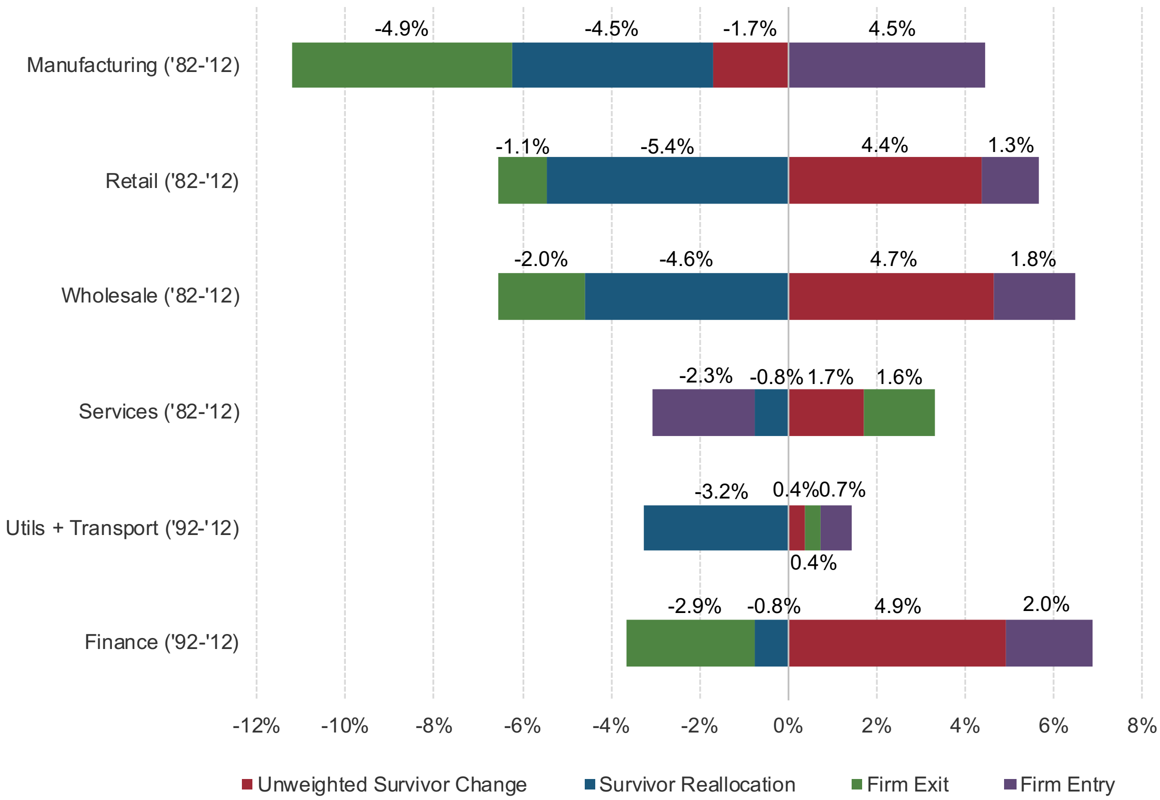
Notes. The figure indicates OLS regression estimates from ΔLabor Share (payroll over sales) on ΔCR20 (stacked five-year changes from 1982-2012 with dummies for each time period). Dots indicate coefficient estimates and lines indicate 95% confidence intervals. This is taken from panel A column (2) of Table 3 which also tabulates the full regression results using alternative measures of concentration and specifications.

Figure 7: Melitz-Polanec Decomposition of the Change in Labor Share in Manufacturing



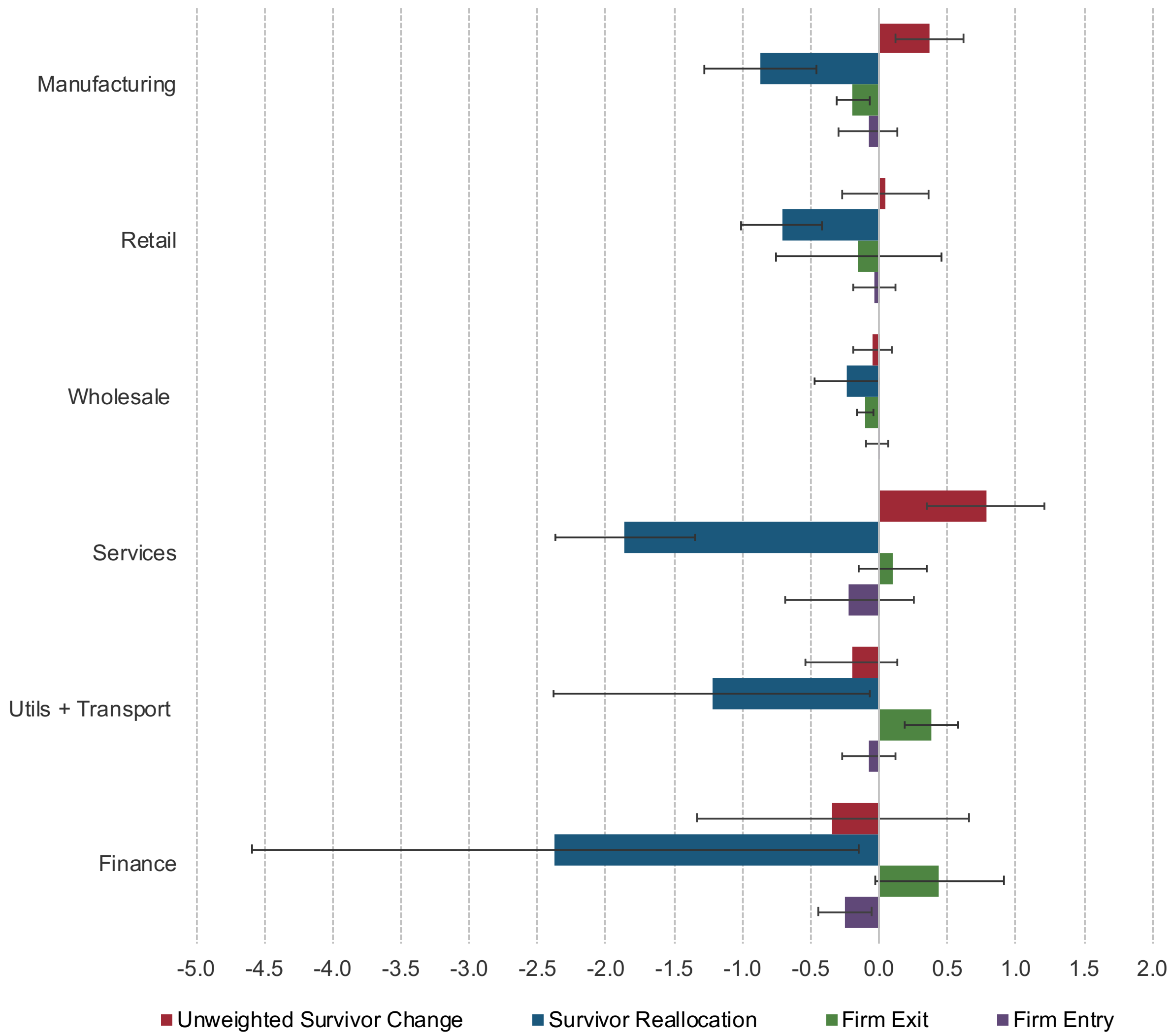
Notes. Each bar represents the cumulated sum of the Melitz-Polanec decomposition components calculated over adjacent five-year intervals. The left panel shows the sum of the decompositions from 1982-1987, 1987-1992 and 1992-1997 and the right panel shows the sum of the decompositions from 1997-2002,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

Figure 8: Melitz-Polanec Decomposition of the Change in Labor Share in all Six Sectors



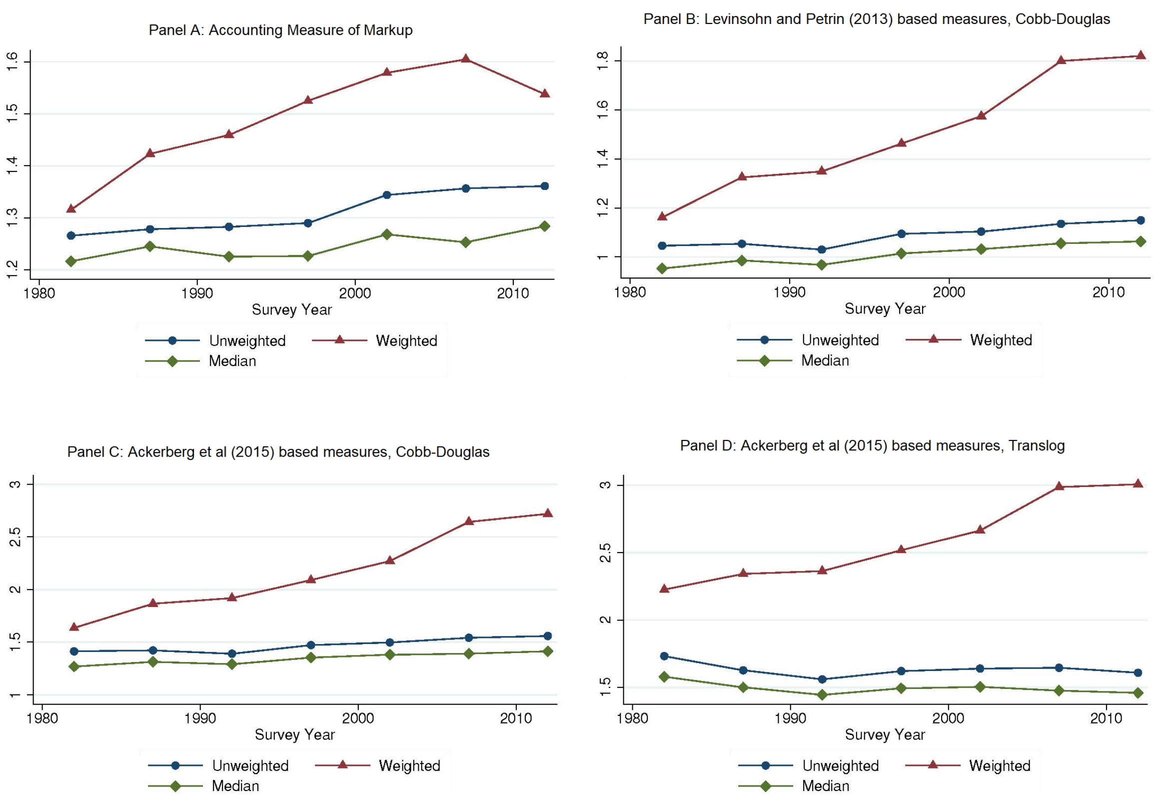
Notes. Each bar represents the cumulated sum of the Melitz-Polanec decomposition components calculated over adjacent five-year intervals. Table 5 reports the underlying year-by-year estimates.

Figure 9: Regressions of the Components of the Change in Labor Share on the Change in Concentration



Notes. Each bar plots ten times 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 10: Markup changes



Notes. These are all estimates of the markup of price over marginal cost in manufacturing using the first order condition described in the text (equation 7). Panel A uses Antras et al (2017) "accounting" method; Panels B-D use production function methods following de Loecker and Warzynski (2012). In these panels we estimate industry specific production functions (two-digit SIC). In Panels B and C the production function is assumed to be Cobb-Douglas and in Panel D it is assumed to be translog. Panels B uses the Levinsohn-Petrin (2003) approach and Panels C and D use the Ackerberg et al (2015) approach. Each panel presents three period specific estimates of the markup. The lower lines present the unweighted mean (blue circles) and median (green diamond) firm level markups. The upper line (red triangles) present the mean markups weighted by a firm's value added.

Tables

Table 1: Summary Statistics

	Mean (1)	SD (2)	Minimum (3)	Maximum (4)
	A. 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
	B. 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
	C. 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

	Mean (1)	SD (2)	Minimum (3)	Maximum (4)
		D. 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
		E. 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
		F. 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 manufacturing, 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 statistics 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 Changes						10-year Changes					
	CR4		CR20		HHI		CR4		CR20		HHI	
	(1)		(2)		(3)		(4)		(5)		(6)	
1 Baseline	-0.148	***	-0.228	***	-0.213	**	-0.132	***	-0.153	***	-0.165	*
	(0.036)		(0.043)		(0.085)		(0.040)		(0.055)		(0.093)	
2 Compensation Share	-0.177	***	-0.266	***	-0.256	**	-0.139	***	-0.151	**	-0.183	
of Value Added	(0.045)		(0.056)		(0.110)		(0.053)		(0.071)		(0.125)	
3 Deduct Service Intermediates	-0.339	***	-0.514	***	-0.502	***	-0.261	***	-0.353	***	-0.303	
from Value Added	(0.064)		(0.074)		(0.175)		(0.056)		(0.065)		(0.275)	
4 Value Added-based	-0.219	***	-0.337	***	-0.320	***	-0.210	***	-0.251	***	-0.289	***
Concentration	(0.028)		(0.045)		(0.060)		(0.037)		(0.054)		(0.075)	
5 Industry Trends	-0.172	***	-0.290	***	-0.243	**	-0.196	***	-0.240	***	-0.220	*
(Four-Digit Dummies)	(0.043)		(0.047)		(0.100)		(0.059)		(0.088)		(0.128)	
6 1992-2012 Sub-Period	-0.187	***	-0.309	***	-0.261	**						
	(0.043)		(0.061)		(0.102)							
7 Including Imports	-0.163	***	-0.285	***	-0.233	***						
(1992-2012)	(0.036)		(0.052)		(0.089)							
Coefficient on Fraction	18.809	***	20.467	***	20.957	***						
of Imports	(3.027)		(3.213)		(3.187)							
8 Control for initial capital	-0.146	***	-0.231	***	-0.214	***	-0.122	***	-0.148	***	-0.161	*
/Value Added	(0.035)		(0.042)		(0.084)		(0.040)		(0.053)		(0.092)	
Capital/Value Added	-1.242	***	-1.295	***	-1.278	***	-2.535	***	-2.648	***	-2.669	***
coefficient	(0.308)		(0.324)		(0.292)		(0.595)		(0.598)		(0.563)	
9 Employment-Based	0.036		0.024		0.160	**	0.018		0.029		0.082	
Concentration Measure	(0.036)		(0.033)		(0.075)		(0.035)		(0.040)		(0.083)	

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 manufacturing, 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 statistics have not yet been disclosed by the Census Bureau.

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

	Stacked 5-year Changes			Stacked 10-year Changes		
	CR4	CR20	HHI	CR4	CR20	HHI
	(1)	(2)	(3)	(4)	(5)	(6)
1 Manufacturing	-0.062 ***	-0.077 ***	-0.112 ***	-0.035	-0.034	-0.088 **
n=2,328; 1,164	(0.013)	(0.025)	(0.026)	(0.021)	(0.033)	(0.037)
2 Retail	-0.034 *	-0.084 **	-0.041	-0.043 **	-0.067 **	-0.068 ***
n=348; 174	(0.020)	(0.037)	(0.025)	(0.018)	(0.029)	(0.023)
3 Wholesale	-0.038 ***	-0.040 **	-0.084 **	-0.037 **	-0.036 *	-0.064
n=336; 168	(0.014)	(0.017)	(0.041)	(0.018)	(0.019)	(0.048)
4 Services	-0.091	-0.128 ***	-0.350 ***	-0.093	-0.137 ***	-0.377 **
n=570; 258	(0.057)	(0.039)	(0.084)	(0.070)	(0.042)	(0.156)
5 Utilities/Transport	-0.110 ***	-0.111 **	-0.320 ***	-0.064	-0.096 **	-0.226 **
n=144; 48	(0.031)	(0.050)	(0.082)	(0.044)	(0.038)	(0.098)
6 Finance	-0.221 **	-0.252 ***	-0.567 **	-0.236 **	-0.274 ***	-0.723 **
n=124; 62	(0.084)	(0.091)	(0.208)	(0.095)	(0.084)	(0.295)
7 Combined	-0.077 ***	-0.088 ***	-0.150 ***	-0.060 ***	-0.076 ***	-0.118 ***
n=3,850; 1,901	(0.017)	(0.022)	(0.028)	(0.018)	(0.023)	(0.032)

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 are 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 six 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 five-year period.

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

	Δ Un-weighted Mean (1)	Incumbent Re-allocation (2)	Exit (3)	Entry (4)	Total (5)
			A. Payroll Share of Value Added		
1982-1987	-3.03	-1.75	-0.59	0.86	-4.52
1987-1992	2.60	-5.26	-0.90	0.98	-2.58
1992-1997	-2.08	-1.24	-0.89	0.89	-3.32
1997-2002	0.00	-0.76	-1.00	0.69	-1.08
2002-2007	-3.06	-1.53	-1.12	1.23	-4.48
2007-2012	2.64	-2.61	-0.63	0.51	-0.09
1982-1997	-2.52	-8.25	-2.38	2.73	-10.42
1997-2012	-0.42	-4.90	-2.76	2.43	-5.65
1982-2012	-2.93	-13.15	-5.14	5.15	-16.07
			B. Compensation Share of Value Added		
1982-1987	-0.78	-5.66	-0.47	0.98	-5.93
1987-1992	3.73	-5.69	-1.00	1.05	-1.91
1992-1997	-2.78	-1.90	-0.93	0.97	-4.64
1997-2002	-2.07	1.11	-1.09	0.79	-1.25
2002-2007	1.26	-6.21	-1.20	1.55	-4.60
2007-2012	0.40	-0.32	-0.77	0.53	-0.15
1982-1997	0.17	-13.25	-2.40	3.01	-12.48
1997-2012	-0.41	-5.42	-3.06	2.88	-6.00
1982-2012	-0.24	-18.67	-5.46	5.89	-18.48

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: "Change in Unweighted Mean" is the change in the labor share due to a general fall in the share across all incumbent firms; "Incumbent Reallocation" 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. All calculations use micro-data from the quinquennial Census of Manufacturing. "15 year period" is the cumulated sum of each five year change over three five-year periods: e.g. -10.42% in column (1) for 1982-1997 is comprised of the sum of each 5 year period (-4.52%, -2.58%, -3.31%). "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

	Δ Un-weighted Mean	Incum-bent Re-allocation	Exit	Entry	Total	Δ Un-weighted Mean	Incum-bent Re-allocation	Exit	Entry	Total
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
		A. Manufacturing					*B. Retail*			
1982-1997	-0.44	-1.75	-2.58	2.46	-2.30	2.25	-2.72	-0.63	0.62	-0.49
1997-2012	-1.27	-2.80	-2.37	2.00	-4.43	2.14	-2.72	-0.47	0.67	-0.36
1982-2012	-1.71	-4.54	-4.94	4.46	-6.73	4.39	-5.44	-1.10	1.29	-0.85
		C. Wholesale					*D. Services*			
1982-1997	2.59	-1.96	-0.90	1.00	0.74	1.01	-1.31	2.04	-1.71	0.02
1997-2012	2.06	-2.64	-1.07	0.82	-0.82	0.72	0.55	-0.46	-0.59	0.21
1982-2012	4.66	-4.59	-1.97	1.82	-0.08	1.73	-0.76	1.57	-2.30	0.23
		E. Utilities and Transportation					*F. Finance*			
1992-2002	1.48	-2.18	0.14	0.43	-0.12	2.74	0.20	-1.36	0.87	2.46
2002-2012	-1.11	-1.07	0.22	0.26	-1.71	2.17	-0.95	-1.54	1.11	0.79
1992-2012	0.37	-3.25	0.36	0.69	-1.83	4.92	-0.75	-2.89	1.98	3.25

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. All analyses use micro-data from the quinquennial Censuses in the relevant industry.

Table 6: Characteristics of Concentrating Industries

	CR4 (1)		CR20 (2)		HHI (3)	
			A. Manufacturing Only			
Patents Per Worker	0.09	**	0.057	***	0.056	**
	(0.006)		(0.022)		(0.022)	
Value-Added Per Worker	0.126	***	0.074	***	0.067	***
	(0.028)		(0.020)		(0.025)	
Capital per Worker	0.067	**	0.057	***	0.024	
	(0.029)		(0.014)		(0.026)	
5-Factor TFP	0.055	***	0.024	*	0.028	*
	(0.019)		(0.013)		(0.017)	
Payroll Per Worker	0.013		0.005		0.016	
	(0.018)		(0.011)		(0.010)	
Material Costs Per Worker	0.120	***	0.074	***	0.068	***
	(0.028)		(0.018)		(0.023)	
			B. All Sectors			
Manufacturing Sales Per Worker	0.125	***	0.067	***	0.069	***
	(0.027)		(0.018)		(0.016)	
Retail Sales Per Worker	0.049		0.098		0.027	
	(0.048)		(0.067)		(0.023)	
Wholesale Sales Per Worker	0.16	***	0.207	***	0.031	**
	(0.058)		(0.042)		(0.013)	
Services Sales Per Worker	0.082		0.125	***	0.041	**
	(0.055)		(0.036)		(0.019)	
Utilities/Transportation Sales Per Worker	0.415	***	0.304	***	0.117	***
	(0.096)		(0.092)		(0.023)	
Finance Sales Per Worker	0.27	*	0.216	*	0.144	***
	(0.143)		(0.111)		(0.052)	
Combined	0.155	***	0.147	***	0.053	***
	(0.031)		(0.026)		(0.011)	

Notes. This table displays regressions where the dependent variable is the change concentration. Each cell represents a separate regression. Panel A regresses concentration in the manufacturing sector on six explanatory variables. Panel B regresses concentration on sales per work in all sectors. All regressions in Panel A are weighted by value-added, and all regressions in Panel B are weighted by sales. Independent and dependent variables are standardized so coefficients reflect correlations. Regressions in are estimated as five-year differences.

APPENDICES (NOT INTENDED FOR PUBLICATION UNLESS REQUESTED)

Appendix A MODEL OF SUPERSTAR FIRMS[57]

In this Appendix we derive conditions under which changes in the market environment will effect the equilibrium labor share. We derive three key results. First, larger firms will have lower labor shares. Second, an increase in the "toughness" of the market (e.g. because of increased market size due to globalization or greater competition) will reallocate output towards low labor share firms, which will in turn tend to lower the aggregate labor share (a "between firm effect"). Third, the increase in market toughness will *increase* individual firms' labor shares as mark-ups falls, a within-firm effect. The net effect of an increase in market toughness on aggregate industry-wide labor share will depend on the balance of these two forces. Which dominates depends on the underlying productivity distribution. When the pdf is log-linear (e.g. Pareto) the two forces will perfectly counterbalance and the labor share will be unchanged. When the pdf is log convex, the aggregate labor share will fall when markets gets tougher. The opposite is true for log-concavity.

Appendix A.1 Basic Environment

Consider an industry with monopolistic competition and firm-level heterogeneity in productivity (z). Ω denotes the set of differentiated varieties, Labor, V, is the only factor of production, cost functions are linear (so constant marginal cost, c), M denotes market size and w denotes the wage.

Demand Structure

Individual demand for any good $\omega \in \Omega$ takes the form

$$q(p_\omega) = p_\omega^{-\sigma} d\left(Ap_\omega\right) \tag{9}$$

where p_ω is the price of good ω; σ is an exogenous preference parameter; and A is an endogenous demand shifter. Each firm produces one good/variety. In addition we assume that $d(\cdot)$ is such that:

- There exists a "choke price" $\bar{p}$ such that $d(p) = 0$ for all $p \geq \bar{p}$
- $d(p) > 0$, $d'(p) < 0$, $d \ln d(p)/d \ln p < (\sigma - 1)$, and $d^2 \ln d(p)/d\left(\ln p\right)^2 < 0$ ("Marshall's Second Law") for all $p < \bar{p}$

Examples of utility and expenditure functions satisfying equation (9) include the Additively Separable Utility function, the Translog Expenditure Function, and the Quadratic Utility Function used by *inter alia* Melitz and Ottaviano (2008). A key feature of these demand systems is that they obey Marshall's Second Law of Demand that the absolute elasticity of demand is lower for higher levels of consumption (lower levels of price). For example, consider the Quadratic Utility Function:

$$U = q^0 + \alpha \int_{\omega\in\Omega} q_\omega d\omega - \frac{1}{2}\gamma \int_{\omega\in\Omega} \left(q_\omega\right)^2 d\omega - \frac{1}{2}\eta \left(\int_{\omega\in\Omega} q_\omega d\omega\right)^2$$

[57] We are extremely grateful to Arnaud Costinot for extensive help with this Appendix, which is largely based on earlier versions of Arkolakis et al (2018).

where $\alpha, \gamma, \eta > 0$ and q^0 and q_ω represent the individual consumption levels of the numeraire good and variety ω. γ indexes the degree of product differentiation between varieties (when $\gamma = 0$ the varieties are perfect substitutes). The inverse demand (when $q_\omega > 0$) for each variety is linear is:

$$q(p_\omega) = p_\omega \left[\frac{1}{p_\omega A} - \frac{1}{\gamma} \right],$$

where

$$A = \left[\frac{\alpha}{\eta N + \gamma} + \frac{\eta}{\gamma} \frac{\int_{\omega \in \Omega | q_\omega > 0} p_\omega d\omega}{\eta N + \gamma} \right]^{-1}.$$

and $N \equiv \int_{\omega \in \Omega} d\omega$ is the number of consumed varieties (where $q_\omega > 0$). This implies that $\sigma = -1$ and $d(p_\omega A) = \left(\frac{1}{p_\omega A} - \frac{1}{\gamma} \right)$.

Note that although most classical demand functions are consistent with Marshall's Second Law, there are exceptions.[58]

Entry, Pricing and mark-ups

Firms choosing to enter must bear an entry cost $\kappa > 0$. After fixed entry costs have been paid, firms receive a random productivity draw z from a commonly known distribution with pdf $\lambda(z)$. For a firm with productivity z, the cost of producing one unit of a good is given by $c = 1/z$. Consider the firm producing good ω. Let c_ω denote its constant marginal cost. The firm chooses its price p_ω in order to maximize profits

$$(p_\omega - c_\omega)\, q(p_\omega)$$

taking as given the demand shifter A. The associated first-order condition is

$$q(p_\omega) + (p_\omega - c_\omega)\, q'(p_\omega) = 0 \tag{10}$$

so that

$$\frac{p_\omega - c_\omega}{p_\omega} = -\frac{1}{p_\omega} \frac{q(p_\omega)}{q'(p_\omega)} = -\frac{1}{\varepsilon(p_\omega)}, \tag{11}$$

where $\varepsilon(p_\omega) \equiv d \ln q\,(p_\omega) / d \ln p_\omega$ is the demand elasticity. Using equation (9) we can express this elasticity as

$$q(p_\omega) = p_\omega^{-\sigma} d\,(A p_\omega)$$

$$\varepsilon(p_\omega) = A p_\omega d'\,(A p_\omega) / d\,(A p_\omega) - \sigma$$

Letting $m_\omega \equiv p_\omega / c_\omega$ denote the markup, we obtain

$$m_\omega = m(A p_\omega), \tag{12}$$

where

$$m(p) \equiv \frac{\sigma - p d'\,(p) / d\,(p)}{\sigma - 1 - p d'\,(p) / d\,(p)}. \tag{13}$$

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See Mrazova and Neary (2017) for a general discussion. For example, under Dixit-Stiglitz CES preferences the demand elasticity is constant so $d^2 \ln d(p) / d\,(\ln p)^2 = 0$.

Since labor is the only factor, unit cost is $c_\omega = wV/q$. So from the mark-up definition the share of labor in revenues is simply the inverse of the mark-up:

$$S_\omega \equiv \frac{wV}{p_\omega q_\omega} = \frac{c_\omega}{p_\omega} = \frac{1}{m_\omega}. \tag{14}$$

In order to see how the labor share changes we need to characterize the determination and distribution of mark-ups.

Appendix A.2 Firm level results

Claim 1: *Prices are strictly increasing with marginal costs.*

Proof: Note that from differentiating the markup definition and rearranging, we also have

$$\frac{\partial p(c_\omega, A)}{\partial c_\omega} = \frac{m\left(p_\omega\right)}{1 - m'(p_\omega)c_\omega} > 0$$

which is positive since $m\left(p_\omega\right) > 0$ and $m'(p_\omega) < 0$

Claim 2: *Markups are strictly decreasing with marginal costs.*

Proof: By equation (10), we know that

$$m(p) = 1 - \frac{1}{Apd'\left(Ap\right)/d\left(Ap\right) - \sigma + 1} \tag{15}$$

Since $d^2 \ln d(p)/d\left(\ln p\right)^2 < 0$, we therefore have $m'(p) < 0$. Since prices are increasing with marginal costs, by Claim 1, mark-ups are decreasing with marginal costs.

Claim 3: *There exists a cutoff $c^* = \bar{p}/A$ such that firms produce if and only $c_\omega \le c^*$. Furthermore, the markup for a firm with marginal cost c^* is equal to one.*

Proof: Since prices are strictly increasing with marginal costs and demand is zero if $p > \bar{p}/A$, there exists a cutoff c^* such that firms produce if and only if $c_\omega \le c^*$. At the cutoff c^*, the firm faces zero demand and charges $\bar{p}/A$. Thus, given equation (15), the firm has a markup equal to one, hence

$$c^* = \bar{p}/A. \tag{16}$$

Recalling that M = market size we can now derive a number of key objects of interest in terms of relative costs.

Claim 4: *Prices (p), markups (m), total output (Q), total sales (r), and total profits (π) can be expressed as*

$$\begin{aligned}
p(\ln c_\omega, \ln c^*) &= e^{\ln c_\omega} f(\ln c_\omega - \ln c^*) && (17)\\
m(\ln c_\omega, \ln c^*) &= f(\ln c_\omega - \ln c^*) && (18)\\
Q\left(\ln c_\omega, \ln c^*\right) &= Me^{-\sigma \ln c_\omega} h(\ln c_\omega - \ln c^*) && (19)\\
r(\ln c_\omega, \ln c^*) &= Me^{(1-\sigma)\ln c_\omega} f(\ln c_\omega - \ln c^*) h(\ln c_\omega - \ln c^*) && (20)\\
\pi(\ln c_\omega, \ln c^*) &= Me^{(1-\sigma)\ln c_\omega} \left[f(\ln c_\omega - \ln c^*) - 1\right] h(\ln c_\omega - \ln c^*) && (21)
\end{aligned}$$

where $f(x)$ is implicitly defined as the solution in y of the equation

$$y = m(\bar{p}ye^x)$$

and where $h(x)$ is defined by

$$h(x) \equiv (f(x))^{-\sigma} d(e^x f(x)\bar{p}).$$

Proof: By definition of the markup and equation (12) we know that

$$p_\omega = c_\omega m(Ap_\omega)$$

which can be rearranged as

$$\frac{p_\omega}{c_\omega} = m\left(\bar{p}\frac{p_\omega}{c_\omega}\frac{c_\omega}{c^*}\right) ,$$

given equation (16). Equation (17) directly derives from this expression. The other equations can be established by simple substitutions. Thus we can state:

Proposition 1 *Large firms will have lower labor shares.*
Proof. *Low marginal cost firms will be larger (they have lower prices and higher demand). By claim 2 they will also have higher mark-ups and labor share is the reciprocal of the mark-up (equation 14).*

Appendix A.3 Industry Level Results

One can think of c^*, which corresponds to the maximum feasible break-even price, as a measure of the toughness of the market. The lower is c^*, the tougher the market. How will changes in the toughness of the markets affect the distribution of firm mark-ups and the aggregate mark-up, and so the labor share?

Distribution of markups

Let $\Phi(m, c^*) = \Pr\{X \leq m | c \leq c^*\}$ denote the distribution of markups for a given level of toughness of the market. By Bayes' rule, this can be rearranged as

$$\begin{aligned}\Phi(m, c^*) &= \frac{\Pr\{f(\ln c - \ln c^*) \leq m, \ln c \leq \ln c^*\}}{\Pr\{\ln c \leq \ln c^*\}} \\ &= \frac{\Pr\left\{\ln c^* + f^{-1}(m) \leq \ln c \leq \ln c^*\right\}}{\Pr\{\ln c \leq \ln c^*\}},\end{aligned}$$

where the second inequality uses the fact that $f' < 0$.

Given our choice of numeraire, we know that $\ln c = -\ln z$. So letting $\ln c^* = -\ln z^*$, we can rearrange the previous expression as

$$\begin{aligned}\Phi(m, \ln z^*) &= \frac{\int_{\ln z^*}^{\ln z^* - f^{-1}(m)} \lambda(u) du}{1 - \Lambda(\ln z^*)} = \frac{\Lambda\left[\ln z^* - f^{-1}(m)\right] - \Lambda(\ln z^*)}{1 - \Lambda(\ln z^*)} \\ &= \frac{\Lambda\left[\ln z^* - f^{-1}(m)\right] - 1}{1 - \Lambda(\ln z^*)} + 1\end{aligned}$$

where λ and Λ are the pdf and cdf of log-productivity, respectively.

Thus the conditional density of markups (ϕ is the the PDF of Φ) is given by

$$\phi(m, \ln z^*) = \frac{-f^{-1\prime}(m)\, \lambda\left[\ln z^* - f^{-1}(m)\right]}{1 - \Lambda(\ln z^*)} \implies$$

$$\ln \phi(m, \ln z^*) = \ln\left[-f^{-1\prime}(m)\right] + \ln\left\{\lambda\left[\ln z^* - f^{-1}(m)\right]\right\} - \ln\left[1 - \Lambda(\ln z^*)\right] .$$

Notice that the above implies that

$$\frac{\partial^2 \ln \phi(m, \ln z^*)}{\partial m \partial \ln z^*} = \frac{\partial^2 \ln \left\{ \lambda \left[\ln z^* - f^{-1}(m) \right] \right\}}{\partial m \partial \ln z^*}$$

Since $\frac{\partial \ln \lambda[\ln z^* - f^{-1}(m)]}{\partial \ln z^*}$ is a function of $\ln z^* - f^{-1}(m)$ it is immediate that we have

$$\frac{\partial \ln \left\{ \lambda \left[\ln z^* - f^{-1}(m) \right] \right\}}{\partial m \partial \ln z^*} = \left[\frac{\partial \left(-f^{-1}(m) \right)}{\partial m} \right] \left(\frac{\partial^2 \ln \lambda \left[\ln z^* - f^{-1}(m) \right]}{\partial \ln (z^*)^2} \right) \tag{22}$$

Since $f' < 0$, $-f^{-1}(\cdot)$ is increasing in m so the first term on the right hand side of equation (22), $\left[\frac{\partial \left(-f^{-1}(m) \right)}{\partial m} \right]$ is positive.

Thus the sign of $\frac{\partial^2 \ln \phi(m, \ln z^*)}{\partial m \partial \ln z^*}$ is the same as the sign of $\frac{\partial^2 \ln \lambda \left[\ln z^* - f^{-1}(m) \right]}{\partial \ln (z^*)^2}$.

Accordingly, we have:

- ϕ log-supermodular in $(m, \ln z^*)$ if λ log-convex;
- ϕ log-submodular in $(m, \ln z^*)$ if λ log-concave;
- ϕ multiplicatively separable in $(m, \ln z^*)$ if λ log-linear.

Log-supermodularity implies the monotone likelihood ratio property (MLRP, cf. Costinot 2009). Thus, we can state the following proposition.

Proposition 2 *Consider $c^{*\prime} \leq c^*$. Then:*

- $\Phi(\cdot, c^*) \prec_{mlrp} \Phi(\cdot, c^{*\prime})$ *if λ log-convex;*
- $\Phi(\cdot, c^*) \succ_{mlrp} \Phi(\cdot, c^{*\prime})$ *if λ log-concave;*
- $\Phi(\cdot, c^*) = \Phi(\cdot, c^{*\prime})$ *if λ log-linear.*

Since dominance in terms of MLRP is stronger than dominance in terms of First Order Stochastic Dominance, we obtain the following corollary.

Corollary 3 *In tougher markets, the average labor share is lower (and markup is higher) if λ is log-convex, higher if λ is log-concave, and the same if λ is log-linear.*

Share of aggregate profits How do the previous results regarding the distribution of markups translate into predictions about the share of aggregate profits? Given equations (20) and (21), we can express aggregate revenues and aggregate profits as

$$\begin{aligned} R &= NM \int_{\ln z^*}^{\infty} e^{(\sigma-1)u} f(\ln z^* - u) h(\ln z^* - u) \lambda(u) du \\ \Pi &= NM \int_{\ln z^*}^{\infty} e^{(\sigma-1)u} \left[f(\ln z^* - u) - 1 \right] h(\ln z^* - u) \lambda(u) du \end{aligned}$$

where N is the number of firms and M is market size. Note that we have multiplied both integrals by M to go from individual to aggregate demand.

Changing variable, $v = \ln z^* - u$, we obtain

$$\begin{aligned} R &= NM \int_{-\infty}^{0} (z^*)^{\sigma-1} e^{(1-\sigma)v} f(v)h(v)\lambda(\ln z^* - v)dv \\ \Pi &= NM \int_{-\infty}^{0} (z^*)^{\sigma-1} e^{(1-\sigma)v} [f(v) - 1] h(v)\lambda(\ln z^* - v)dv \end{aligned}$$

Let us introduce $b(v, \delta) \equiv NMe^{(1-\sigma)v} [f(v) + \delta] h(v)$. By construction we have

$$\frac{b(v, 0)}{b(v, -1)} = \left[\frac{f(v)}{f(v) - 1}\right]$$

which is increasing with v, since $f'(\nu) < 0$. Thus $b(v, \delta)$ is log-supermodular in (v, δ).

Now let us write

$$B(\ln z^*, \delta) = e^{(\sigma-1)\ln z^*} \int_{-\infty}^{0} b(v, \delta)\lambda(\ln z^* - v)dv$$

If λ is log-concave then $\lambda(\ln z^* - v)$ is log-supermodular in $(\ln z^*, v)$. Since log-supermodularity is preserved by multiplication and integration, we have $B(\ln z^*, \delta)$ log-supermodular. This implies that if $\ln z^* \geq \ln z^{*\prime}$, then

$$\frac{B(\ln z^*, -1)}{B(\ln z^*, 0)} \leq \frac{B(\ln z^{*\prime}, -1)}{B(\ln z^{*\prime}, 0)}.$$

By construction we have

$$\begin{aligned} \Pi &= B(\ln z^*, -1) \\ R &= B(\ln z^*, 0) \end{aligned}$$

Thus the previous inequality implies that if λ is log-concave, then the share of aggregate profits is lower in tougher markets:

$$\left(\frac{\Pi}{R}\right)_{\ln z^*} \geq \left(\frac{\Pi}{R}\right)_{\ln z^{*\prime}}.$$

What if λ is log-convex? In this case, let us write

$$B(\ln z^*, \delta) = e^{(\sigma-1)\ln z^*} \int_{0}^{\infty} \widetilde{b}(u, \delta)\lambda(\ln z^* + u)du$$

where $\widetilde{b}(u, \delta) \equiv NMe^{-(1-\sigma)u} [f(-u) - \delta] h(u)$. Since λ is log-convex, $\lambda(\ln z^* + u)$ is log-supermodular in $(\ln z^*, u)$. Since $\widetilde{b}(u, \delta) \equiv b(-u, -\delta)$, $\widetilde{b}(u, \delta)$ is log-supermodular as well. Thus $B(\ln z^*, \delta)$ remains log-supermodular. But by construction, we now have:

$$\begin{aligned} \Pi &= B(\ln z^*, 1) \\ R &= B(\ln z^*, 0) \end{aligned}$$

Thus the log-supermodularity of $B(\ln z^*, \delta)$ now implies that if $\ln z^* \geq \ln z^{*\prime}$, then

$$\left(\frac{\Pi}{R}\right)_{\ln z^*} \leq \left(\frac{\Pi}{R}\right)_{\ln z^{*\prime}}.$$

If λ is log-linear, then the previous analysis immediately implies that the share of aggregate profits is the same in tougher markets. Since the labor share $S = 1 - \frac{\Pi}{R}$ we therefore have the following proposition.

Proposition 3 *In tougher markets, the aggregate share of labor in revenues is lower (and the share of aggregate profits higher) if λ is log-convex, the share is higher if λ is log-concave and the share is the same if λ is log-linear*

Appendix A.4 Discussion

Proposition 1 of the model delivers the intuitive result that mark-ups are higher for more productive firms. Thus, the labor share is lower for larger firms. An increase in market toughness will reallocate more output to these firms which will tend to reduce the aggregate labor share. However, a change in market toughness will also change the level of each individual firm's labor share. Greater toughness will tend to increase the elasticity of demand and (from equation 13) push down all individual firm mark-ups and so *increase* the firm-level labor share (a "within firm" effect). Propositions 2 and 3 show that when the underlying productivity distribution is log convex, the reallocation effect dominates the within firm effect so that the aggregate labor share unambiguously falls even though individual firms' labor share rises. Thus a rise in the aggregate mark-up does not necessarily indicate a fall in competition—it can mean the opposite.

Proposition 3 also shows that the net effect on the aggregate labor share is an empirical issue—it depends on the shape of the underlying productivity distribution. Interestingly, the standard assumption that the the underlying productivity distribution has a Pareto shape corresponds to a knife-edge case: Pareto is log-linear, and so it produces the result that the aggregate labor share is invariant to changes in market toughness. This is the result in the second part of Melitz and Ottaviano (2008) where they show that the profit share is invariant to changes in market size (L) and competition (γ). Although our proof uses a more general class of demand systems than theirs, we have shown that the reason for their invariance result is due to the assumption of a Pareto distribution for productivity.

Finally, note that the comparative statics on competition abstracts away from entry. When we endogenize entry there may be a change in the number of entrants and so the total expenditure on the sunk cost, κ. What effect this will have on the labor share will partly depend on how this sunk cost breaks down between labor and other factors of production that we have ignored in this Appendix. For example, consider the model of Section II where there are two productive factors, labor and capital. In this case, if the sunk cost is mainly capital and more firms choose to pay the sunk cost to take a productivity draw to enter the more "winner take all" market there will be a further fall in the labor share when market toughness rises. If the sunk cost splits in other ways this is less clear.[59]

Appendix B MARKUPS

Appendix B.1 Methodology

As noted in the main text, we implement an accounting approach and an econometric approach to estimate markups of price over marginal costs based on equation (7): $m_{it} = \left(\frac{\alpha^v_{it}}{S^v_{it}}\right)$. There are many well-known challenges in performing econometric estimation of production functions, and we apply

[59]A similar issue arises if we close the model and consider how the profits from market power are distributed. It seems reasonable that this is mainly distributed to equity holders, but in principle it could be appropriated by workers in the form of remuneration.

a variety of approaches to ensure that our conclusions are robust. For our benchmark specification, we follow Section II in estimating a Cobb-Douglas production function separately for each two digit manufacturing industry k:

$$lnY_{it} = \alpha_{kt}^{v} lnX_{it}^{v} + \beta_{kt} lnK_{it} + ln\theta_{it} + \varepsilon_{it} \tag{23}$$

where $ln\theta_{it}$ is an unobserved productivity shock and ε_{it} is the unanticipated shock to output (or measurement error). In order to estimate α_{it}^{v}, we follow the literature by using a control function approach while modeling $ln\theta_{it}$ as a first order Markov process. By inverting an input demand equation, we can write productivity as $ln\theta_{it} = h_{kt}(d_{it}, lnK_{it})$ where d_{it} could be a dynamic control such as investment (as in Olley and Pakes, 1996) or a static control such as intermediate inputs (as in Levinsohn and Petrin, 2003). Both approaches have two stages. In the first stage, we non-parametrically project output on inputs and the control variable:

$$lnY_{it} = \phi(lnX_{it}^{v}, lnK_{it}, d_{it}) + \varepsilon_{it} \tag{24}$$

where $\phi_{it} = \alpha_{kt}^{v} lnX_{it}^{v} + \beta_{kt} lnK_{it} + h_{kt}(d_{it}, lnK_{it})$. Assuming the productivity process can be written $ln\theta_{it} = g(ln\theta_{it-1}) + \xi_{it}$ gives rise to the moment condition $E[\xi_{it}(\alpha_{kt}^{v}) lnX_{it}^{v}] = 0$ which can be used to recover the output elasticity. In the second stage we estimate productivity from $ln\theta_{it} = \phi_{it} - \alpha_{kt}^{v} lnX_{it}^{v} - \beta_{kt} lnK_{it}$, where ϕ_{it} is recovered from the first stage equation. We can then obtain $\xi_{it}(\alpha_{kt}^{v})$ by projecting current productivity ($ln\theta_{it}$) on its lag ($ln\theta_{it-1}$). The key assumptions underlying this approach are that (1) the variable input responds to productivity shocks but it's lag does not; and (2) the lagged variable inputs are correlated with current use (via the persistence in productivity).

A very practical data challenge for both the accounting and econometric approaches to estimating markups is that outside manufacturing we do not observe capital or materials in the Census data. Consequently, in what follows, we perform estimates for manufacturing only. We estimate the production functions at the plant level and then use value-added to aggregate either to the firm level or aggregate level.

Appendix B.2 Results

Figure A.2 shows the relationship between firm-level estimated TFP and size. We aggregate the plant-level estimates of TFP using value added shares and use log(sales) as a size measure. The ordering of the panels follows those in Figure 10 in the main text. The underlying coefficients to calculate TFP in Panel A uses the accounting method of equation 8. Panel B uses the Levinsohn and Petrin (2003) method of estimating a Cobb-Douglas production function. Panel C does the same as Panel B, but uses the Ackerberg, Caves and Frazer (2015) method of estimating a Cobb-Douglas. Panel D continues using the Ackerberg, Caves and Frazer (2015) method but generalizes Panel C to estimate a translog production function. It is clear that there is a strong positive relationship between size and TFP regardless of the precise way in which the production function is estimated. This is unsurprising as a number of papers have found that productivity and size co-vary positively. Indeed, even using labor productivity we see a similar positive relationship. This is illustrated in Figure A.3 which present the relationship between labor productivity as measured by sales per worker and firm size for each of the six sectors. Recall, that the absence of data on intermediate inputs in the Census means we cannot calculate TFP for these sectors. In all six sectors there is a clear and strong positive relationship between productivity and size. Finally, Figure A.4 shows that large firms have higher markups, as noted in the main text.

Figure 10, which we discussed in the text, reports the results for the baseline accounting and three alternative econometric approaches. The key result is that the aggregate markup has risen substantially, which is of course the flip side of the fall in the labor share. Importantly, the typical firm (i.e., the median or unweighted average firm) has not had a large increase in the markup, whereas the markup at the weighted (by value-added) mean firm increased considerably. This is also consistent with our decomposition analysis.

We have implemented many robustness tests of these findings. First, note that apart from Hicks neutral technical change, we have assumed the production function parameters are stable over time. However, biased technological change may cause the output elasticities to change over time. To allow for this, we split the sample into two equal time periods (1982-1997 and 1997-2012) and estimated the production function separately in each. We find that the coefficients are broadly stable over time and the estimated markup trends change little. This calculation is also useful as the fall in the labor share might have in theory have been caused by a fall in the output elasticity of labor (see equation 1). Empirically, however there is no sign of such a decline; in fact, the mean estimated α^L_{kt} across industries rose slightly in the second period relative to the first. As a second robustness test, we estimated an output-based rather than value added-based production function .In two further robustness tests, we implemented a control function for sample selection following Olley and Pakes (1996), and we included time dummies instead of a time trend in our baseline specifications. Across all of these spermutations, we obtained little change to the results.

We also examined how quantiles of the markup have changed over time. Although there has been some increase in the variance of the markup, the changes are not very large. There is some evidence of falling markups in much of the distribution except for the upper tail. Note that although we show these trends for only our two baseline methods of estimating the markup (cost share and Levinsohn-Petrin), these patterns are similar using the other methods discussed.

Appendix B.3 Summary

If the output elasticity of labor is constant over time and across firms, then the change in the labor share is the inverse of changes in the markup from equation 1. In this Appendix, we have relaxed this assumption and estimated α^L_{kt} using an accounting method (following Antras et al, 2017) and a production function approach (following de Loecker et al, 2018). We find evidence that complements our main results for the falling labor share. Large firms have higher markups, and aggregate markups have risen in manufacturing. This is primarily due to changes at the right tail of the firm size distribution, with a growing share of sales and value-added accruing to large, high-markup firms.

Appendix C CHARACTERISTICS OF SUPERSTAR FIRMS

We provide additional descriptive evidence on what we term superstar firms based on Standard & Poor's Compustat database. Compustat derives its information from public filings of stock market-listed companies and is thus not subject to the non-disclosure rules that govern our main data from the Economic Census. We focus on the largest 500 firms in Compustat rather than all publicly listed firms, as the population of listed firms has changed substantially and non-randomly over time (see Comin and Philippon, 2006; Davis and Haltiwanger, 2007). The resulting sample will be close to the full set of largest non-government owned companies in the U.S., and thus seems suitable for the analysis of "superstar firms".[60] We focus on the largest firms (top 25, 50 and 500) as defined

[60] Compustat includes only firms that have a listing at a U.S. stock exchange, and is thus most complete for firms that are incorporated in the U.S.

by sales, but similar results arise if we select the largest firms by employment or market value.

Appendix C.1 The 25 Largest U.S. Firms

Table A.5 lists the 25 largest U.S. firms by global sales in 1985, 2000 and 2015. In 1985, the top 25 firms combined for $1.888 trillion in sales. By 2015, a new set of top 25 firms accounted for sales that were about twice as large in real terms ($3.744 trillion). There is considerable churning among the top firms, with only General Motors, Ford, Exxon Mobil, Chevron, and AT&T making the top 25 list in each of the three indicated years. Of the top three firms in 2015, only Exxon Mobil's predecessors Exxon and Mobil were already giants in 1985. Walmart, the largest firm in 2015, was just a regional power in 1985, and Apple, the third-largest firm in 2015, was only in its ninth year of operation and still more than two decades away from launching the iconic iPhone in 2007. Table A.5 are also indicates notable changes in industry composition among the largest firms. In 1985, 14 out of the top 25 firms were industrial conglomerates or companies engaged in heavy manufacturing or oil and gas. The representation of these sectors in the top 25 subsequently fell to nine firms in 2000, and to six firms in 2015. Simultaneously, Retail, the most rapidly concentrating sector according to our analysis of Census data (see Figure 4), increased its top 25 representation from four to six firms, with Wal-Mart rising to the very top of the ranking. Six of the companies that entered the ranking during the thirty-year window conduct activities associated with healthcare (i.e., pharmacies, drug wholesalers, and health insurance), while four new superstar firms operate in IT-related areas (computer hardware, software, and internet sales). We also see the rise and fall of finance: only one of the top 25 was in banking in 1985 (Citicorp). This number rose to five by 2000 then fell to two in by 2015 (JP Morgan and Bank of America).

Appendix C.2 Growing Firm Size

Figure A.10 provides additional evidence on the evolving size of the 500 largest U.S. firms, which increased strongly over the last four decades. In 1972, the combined global sales of the 500 largest U.S. firms was about $4 trillion. By 2015, this value was nearly $12 trillion. Market value expanded even faster, by a factor of six rather than three.[61] Employment in the top 500 firms grew at a considerably slower pace, however, increasing by only 50 percent.

This growth does not merely reflect the overall expansion of the U.S. economy. Figure A.11 plots the ratio of top 500 firms' domestic U.S. sales to U.S. GDP. This ratio tripled between 1978 and 2015, from less than 1.5 percent at the start of the period to roughly 4.5 percent in the final year. [62] This pattern is consistent with the overall increase in concentration documented in the Economic Census data throughout this paper.

Appendix C.3 Inequality Among the Largest firms

We next investigate whether concentration has risen *among* the top 500 superstar firms. Figure A.12 plots the share of the largest 50 firms in the combined sales of the largest 500 firms. Over the

[61] The market value reported in Figure A.10 corresponds to the numerator of Tobin's Q, as in Gabaix and Landier (2008). It is computed by summing up the stock market value (number of shares outstanding times closing stock price) and the value of debt (long-term debt and current liabilities). We obtain a similar time series for stock market value alone.

[62] Compustat distinguishes U.S. firms' domestic and foreign sales since 1978, while the global indicators reported in Figure A.10 are available since 1972. Roughly 20% of top 500 firms report total global sales but not U.S.-specific sales. We impute the missing data by multiplying a firm's global sales with the (U.S. sales / global sales) ratio among the top 500 firms for which both variables are available. Different from sales, employment is usually not reported separately for a firm's domestic and foreign operations.

full period, this share grew from 43 to 48 percent. By the end of the sample period, the largest 50 firms thus accounted for almost the same volume of sales as the next largest 450 firms combined. However, unlike the growth in size of the top 500 firms (Figure A.10), the growth of concentration among these largest firms was not rising monotonically over time. Instead, Figure A.12 shows that sales concentration was weakly falling until the late 1990s then increased until 2010 and leveled off thereafter.

Figure A.13 provides additional evidence for the rising concentration in sales among the largest 500 firms by examining changes in the cross sectional dispersion of sales among these firms. The first panel plots the time series for the mean, median, and 5th and 95th percentile of sales among the top 500 largest firms. The quantiles of the size distribution have fanned out over time, with the growth in the upper tail of the distribution (e.g. between firms at the 95th percentile and the median) being particularly stark. Sales growth has been stronger for the mean than the median and for the upper quantiles compared to the mean. The second panel normalizes each series to one at the start of the period and shows that the *relative* level of sales has become considerably more dispersed among the top 500 firms since about the year 2000.

The fact that the growth of sales concentration among large firms starts only after 2000 may come as a surprise given that we can see concentration rising since 1982 in the Census data. Several factors may contribute to this pattern. First, publicly listed firms account for only about a third of all US employees whereas the Census covers all firms in a given sector. Second, the sales and employment data in Compustat relate to global consolidated accounts covering U.S. and non-US employees, distinct from the Census' exclusive coverage of domestic U.S. employees. The most important reason, however, is that our Census analysis focuses on concentration within four-digit industries whereas the Compustat analysis combines firms from all sectors regardless of sector. When we perform an analogous exercise in the Census data, ignoring industry, we obtain patterns much more similar to those found in Compustat.

Appendix C.4 Dynamics

Growing concentration could be consistent with greater churn among the the largest 500 firms ("creative destruction") or decreasing churn ("persistent dominance"). Figure A.14 shows the fraction of the top 500 sales firms in each year that were among the 500 largest firms one, five, and ten years previously. It indicates that churning among the largest firms (at least for five and ten year churn rates) rose in the pre-2000 period, but has fallen since 2000—the period where we have shown that concentration rose. For example, of the firms that comprised the top 500 in the year 2000, two-thirds were already in the top 500 five years earlier. By the end of our sample period, the five-year survival rate in the top 500 had risen to more than eighty percent. Census data also show declining churn and dynamism since the 2000 period (see Decker, Haltiwanger, Jarmin and Miranda, 2018). So increasing inequality between firms seems to be accompanied by more persistent dominance rather than greater creative destruction.

Appendix C.5 Activity across Countries and Industries

One possible explanation for the rapidly growing size of superstar firms is the increasingly global scale of their operations. While the Compustat data reported above correspond to firms' worldwide activities, most U.S.-based Compustat firms also report a breakdown of their revenue between domestic and international sales. Panel A in Figure A.15 documents that the 500 largest U.S. *manufacturing* firms on average sold around about 30 percent of their output in foreign markets in the early 1980s. Foreign sales grew rapidly in importance during the 1990s and the 2000s, and accounted for 60 percent of the sales of top 500 manufacturing firms by 2010. The second panel in Figure A.15 shows that the fraction of foreign sales also expanded rapidly among the top 500 U.S. firms outside the manufacturing sector. The foreign sales share in this broad sector however is much lower than in manufacturing, rising from around 10 percent in the 1980s to a high of 30 percent in 2015. The growth in foreign sales during the 1990s and 2000s coincides not only with a rapid expansion of international trade but also with greater foreign direct investment. For instance, Walmart has exported its successful business model to several countries in Latin America, Europe and Asia, and now generates nearly 30 percent of its total sales abroad according to the Compustat data.

Another potential source of superstar firms' growth is an expansion of activity across industries. Berkshire Hathaway, one of the five largest U.S. companies by sales in 2015, operates across an eclectic range of industries from insurance to confectionery, railroads, home furnishing, newspapers, and energy. The retail giant Amazon also has extended its reach into a large number of different markets. We explored in the Census data whether firms that are among the top four sellers in a four-digit industry have increasingly become dominant players across in other four-digit industries as well. We do not find that there is a general trend towards greater diversification across industries among firms. The largest firm (by sales) in the four-digit industry in the Census operated on average in over 13 other four-digit industries in 1982, but this number fell to under nine by 2012. Similarly, conditional on a firm being among the top four firms (again by sales) in a four-digit industry in 1982, it was among the top four in 0.37 other industries in that same year (i.e. statistically speaking, being the top firm in one industry gave a firm almost a 40 percent chance of being among the top four in one other industry). This fraction fell to 0.24 by 2012. Thus, the "Amazon" pattern, where one firm appears to become dominant in multiple industries, does not seem to be representative of what is occurring among the largest firms.

Appendix C.6 Labor Share Trends in Compustat

In addition to the limitations imposed by partial coverage and the aggregation of firms' US and global activities, the Compustat data presenting several additional data issues for analyzing labor shares. 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.

Despite these multiple caveats, we obtain broadly similar patterns of results when examining Compustat data. For purposes of the Compustat analysis, we define the labor share as the ratio of wage bill to the sum of wage bill and EBITDA (earnings before interest, tax, depreciation and amortization). First, there is a clear decline in the aggregate labor share from nearly 60 percent the 1970s to 40 percent in 2015 in the subset of top 500 firms (for example from 59.5% in 1982 to 49.6% in 2012).[63]Second, the fall in labor share is smaller for the unweighted average than this weighted average, consistent with the importance of reallocation effects. Third, when we split the sample into firms that are globally engaged (i.e., reporting foreign sales) versus those that are not, we see in Figure A.16 that *both* groups of firms have seen falls in their labor shares, with a somewhat greater decline greater among globally-engaged firms. Between 2012 and 1982, globally engaged firms saw their aggregate labor share fall by 8.4 percentage points (from 64 percent to 55.6 percent) whereas the complementary set of non-globally engaged firms saw a labor share decline of 7.4 percentage

[63]Hartman-Glaser, Lustig and Zhang (2016) find a somewhat different overall trend from us, but they use non-manufacturing as well as manufacturing data and, further, impute missing values by using industry averages. Thus, our findings are not directly comparable.

points (from 51.6 percent to 44.2 percent). The commonality of labor share declines among globally engaged and non-engaged firms suggests that, while globalization may be one factor behind the trend of declining labor shares, it is unlikely to be the whole story given that this decline occurs among firms that have limited global exposure.

Appendix D DATA

Appendix D.1 Data Details

Our primary data are from the U.S. Economic Census conducted every five years by the Census Bureau.[64] We focus on six sectors for which we could access micro-data over a significant period of time: manufacturing, retail trade, wholesale trade, services, utilities and transportation and finance. 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 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 decomposition of changes in labor share into between-firm reallocation and within-firm components in Figure 7 and 8. 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 decomposition in Table 5 and 4. In this table, we define a firm using all establishments, regardless of industry. However, in Appendix Table A.1, we present decomposition in which we define a firm using the firm-by-industry pair.

The sales measure in Census is shipments so it includes exports. Since the labor used at the firm goes into the production of output destined for exports as well as domestic consumption, it seems

[64] 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

natural to use total sales. 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 in concentration measures (in a similar way that we consider adjusting for imports in some robustness tests in Table 2).

Appendix D.2 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 requires 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.

Finally, we were forced to exclude some industries that are not defined consistently over time in the Census. These are only in manufacturing, services and finance. From manufacturing, we drop industries the move outside manufacturing in the 1997 SIC-NAICS redefinition which 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). 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). 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).

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.

There are, of course, other ways of constructing consistent industry codes in the Census. A leading alternative is Fort and Klimek (2016), detailed in their Appendix A. They use NAICS codes are based in 2002 to code every LBD establishment. They do this by first using longitudinal data in LBD to fill in missing codes then they use concordances to assign all NAICS codes that map uniquely to a SIC code (i.e. NAICS codes that are full contained in a SIC code). They next use the longitudinal structure to assign NAICS codes to an establishment with an SIC code that maps to many NAICS. Finally, in instances where the longitudinal information is insufficient and the SIC code maps to multiple NAICS codes, they use random assignment to assign a NAICS code. In order to do a robustness check, we restricted our analysis to the set of six-digit NAICS industry codes that are consistently reported over time. These cover close to 98 percent of all employment and sales in our six Census sectors. We then calculate concentration and labor shares for this subset of industries and re-ran the analysis. We found results which were very similar to the main ones we report in the paper.

Appendix D.3 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.

Appendix D.4 Comparing Census and NIPA/BEA data

In this subsection, 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.

A second distinction between BEA/NIPA and Census is that the two agencies define the components of the labor share differently. Panel A of Figure A.6 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.6, 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.[65]

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.[66] 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.6).

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.7 shows the level of the payroll to value added ratio in NIPA in each of our six sectors. As is well known there is a clear downwards trend in these series since 1982, although the pattern is least

[65]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.

[66]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.

clear in utilities and transportation and finance.

Figure A.8 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 downward trend 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 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, measuring output in finance finance poses particular problems as we noted in the main text. In most sectors, BEA uses the Economic Censuses to construct gross output and then they work through data sources on intermediate inputs use to construct value added. For finance, however, BEA uses a very different approach using interest rate spreads between lending and deposit rates. 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). For these reasons, we reiterate that the results for the Finance sector must be treated with the most caution. Second, 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. Third, 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.

Appendix D.5 Decomposition Analysis: Details and Robustness

The decomposition analysis is described in the text. In this subsection we describe some of the robustness tests we implemented. The baseline analysis treats the firm as the unit of observation, so we aggregate all activity across the establishments belonging to a firm at a point of time in a Census segment. We also show robustness to implementing the decompositions at the establishment level and at the firm by four digit industry level.

We also considered a generalization of the decomposition breaking out the between industry component. As noted in the text we first use a standard shift-share technique as in Autor, Katz and Krueger (1998) to decompose the overall change in the labor share into between-industry $\sum_j \left(\widetilde{S}_j \Delta\omega_j\right)$ and within-industry $\sum_j \left(\widetilde{\omega}_j \Delta S_j\right)$ components:

$$\Delta S = \sum_j \left(\widetilde{S}_j \Delta\omega_j\right) + \sum_j \left(\widetilde{\omega}_j \Delta S_j\right). \tag{25}$$

Here, $\widetilde{S}_j$ is the time average of the (size-weighted mean) labor share, S_j, in industry j over the two time periods t_0 and t_1, and $\widetilde{\omega}_j$ is the time average of ω_j , the industry size share (e.g. value-added share of industry j in total manufacturing value added). Thus, the first term in this equation is the change in labor share due to shifts in industry size shares, holding average industry labor shares constant, while the second term is the change in labor share due to within-industry labor share shifts, holding average industry size shares constant. We next rewrite our primary Melitz-Polanec decomposition (Equation 5) at the industry level:

$$\Delta S_j = \Delta \bar{S}_{S,j} + \Delta \left[\sum_{i \in j} \left(\omega_{i,j} - \bar{\omega_j}\right)\left(S_{i,j} - \bar{S_j}\right) \right]_{S,j} \tag{26}$$

$$+ \sum_{i \in j} \omega_{X,0,i,j} \left(S_{S,0,i,j} - S_{X,0,i,j}\right) + \sum_{i \in j} \omega_{E,1,i,j} \left(S_{E,1,i,j} - S_{S,1,i,j}\right). \tag{27}$$

This notation makes explicit that the labor share of firm i (what we called S_i in Equation (5)) is also in industry j, so we now denote it explicitly $S_{i,j}$ and similarly for the firm size shares, $\omega_{i,j}$. Substituting Equation (26) into Equation (25) gives us a decomposition with five terms:

$$\Delta S = \sum_j \left(\widetilde{S}_j \Delta \omega_j\right) + \sum_j \widetilde{\omega}_j \Delta \bar{S}_{S,j} + \sum_j \widetilde{\omega}_j \Delta \left[\sum_{i \in j} \left(\omega_{i,j} - \bar{\omega_j}\right)\left(S_{i,j} - \bar{S_j}\right) \right]_{S,j}$$

$$+ \sum_j \widetilde{\omega}_j \sum_{i \in j} \omega_{X,0,i,j} \left(S_{S,0,i,j} - S_{X,0,i,j}\right) + \sum \widetilde{\omega}_j \sum_{i \in j} \omega_{E,1,i,j} \left(S_{E,1,i,j} - S_{S,1,i,j}\right) \tag{28}$$

A complication arises in equation 28 because we have to determine which four-digit SIC industry a firm (or plant) belongs in. We follow the Census attribution of an establishment to a four-digit industry (based on the amount of shipments in the product trailer). For multi-plant firms we set the main industry as the one which produces the most shipments within the firm. A further complication arises from the fact that plants and firms frequently switch their main industry, especially over the long 30 year period of time we consider (see Bernard, Redding and Schott, 2010). Using a time varying firm-industry definition attributes a large fraction of the changes to entry and exit, even though this type of churn may simply reflect a firm experiencing differential sales growth of one of its products.[67] Hence, in our main implementation of equation (28), we fix the firm's industry to be that in the first year we observe the firm. We also implemented a permutation where we fix the industry designation as the one observed in the last year that the firm is observed in the data (or the modal year). These adjustments make no material difference to the results.

Following the discussion of comparing the Census to NIPA labor shares above, we also implemented the baseline decomposition correcting for intermediate inputs using the NIPA. We take the fall in the NIPA labor share (ΔS^{NIPA}) as accurate and then calculate the contribution of each of the four components (within, reallocation, exit, entry) using the Census decomposition in Table 5. We assume that the fraction of the fall accounted for by each component is the ratio of the Census component to the sum of the (absolute values) of all Census components. Formally, define the contribution of component d as $C_d^{NIPA} = \Delta S^{NIPA} \times \left(\frac{C_d}{\Sigma_{d=1,2,3,4}|C_d|}\right)$ where C_d is the contribution as

[67]For example, consider a plant in period t_0 that ships six units of product A and four units of B and so will be allocated by the Census to industry A. If in period t_1, the units of A stay the same, but it expands shipments of product B to seven, the plant's will now be allocated to industry B. In the decomposition analysis it will be classified as an exit after period t_0 and an entrant in period t_1, whereas in fact it has just shifted its sales portfolio a bit.

calculated in Table 5 and $|C_d|$ is the absolute value of this. Figure ZZ shows the results graphically.

Appendix D.6 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. The panel data set Orbis is its most comprehensive product covering in principle the population of all public and private company accounts in the world (see Kalemli-Ozcan, Sorensen, Villegas-Sanchez, Volosovych and Yesiltas, 2015; Gopinath, Kalemli-Özcan, Karabarbounis and Villegas-Sanchez, 2017). BVD seeks to harmonize the data in a common format focusing on a subset 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 (see Bajgar et al, 2018b). 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.

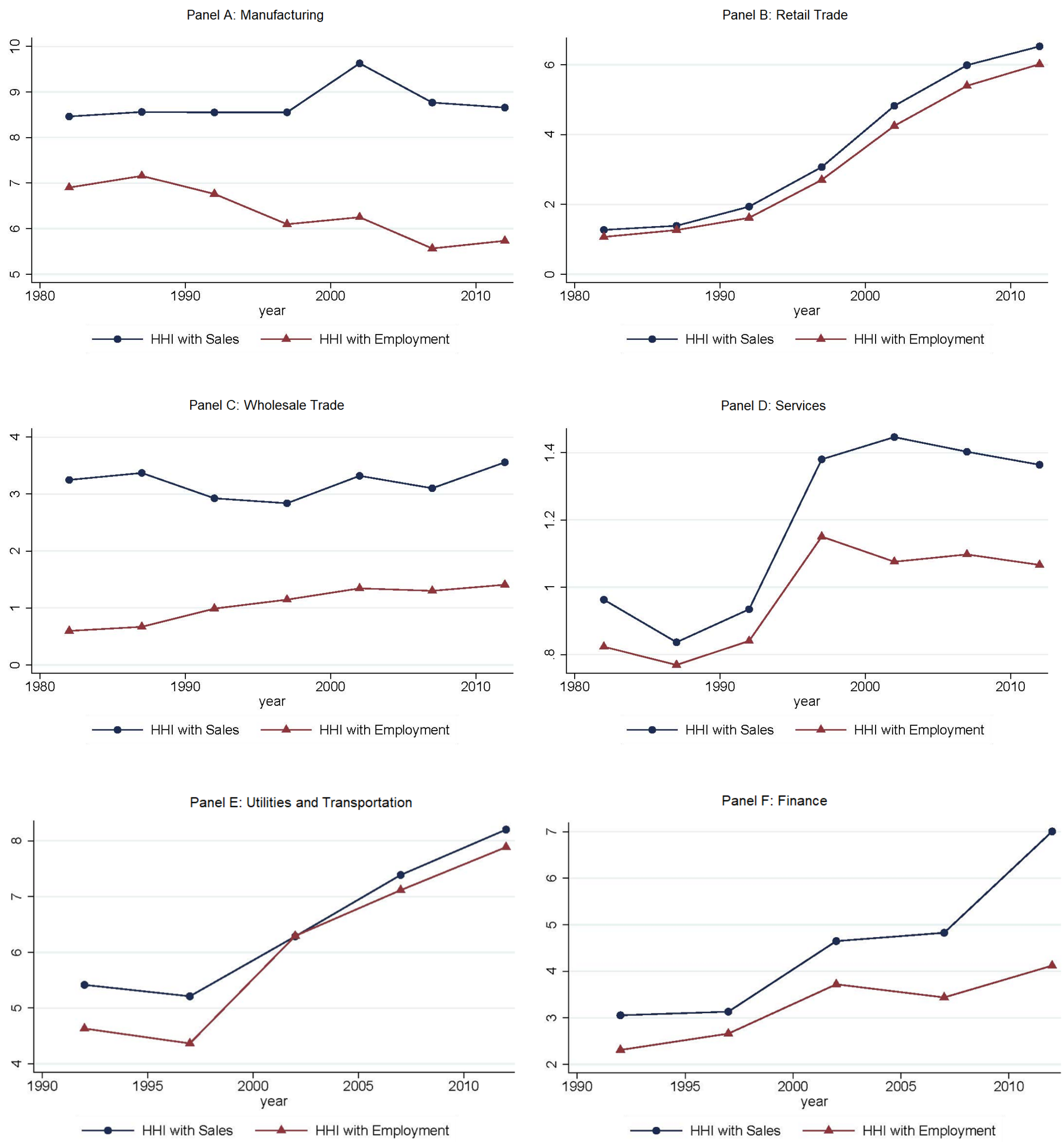
For our analysis we require firms have information on their primary industry and their payroll. To construct value-added, we sum payroll with gross profits (i.e. before tax, depreciation and interest have been deducted, sometimes known as EBITA, Earnings Before Interest Tax and Amortization). Intermediate 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.7. We used the five 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 invested 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. We weight the data to attempt to account for different firm sizes and sample response probabilities.

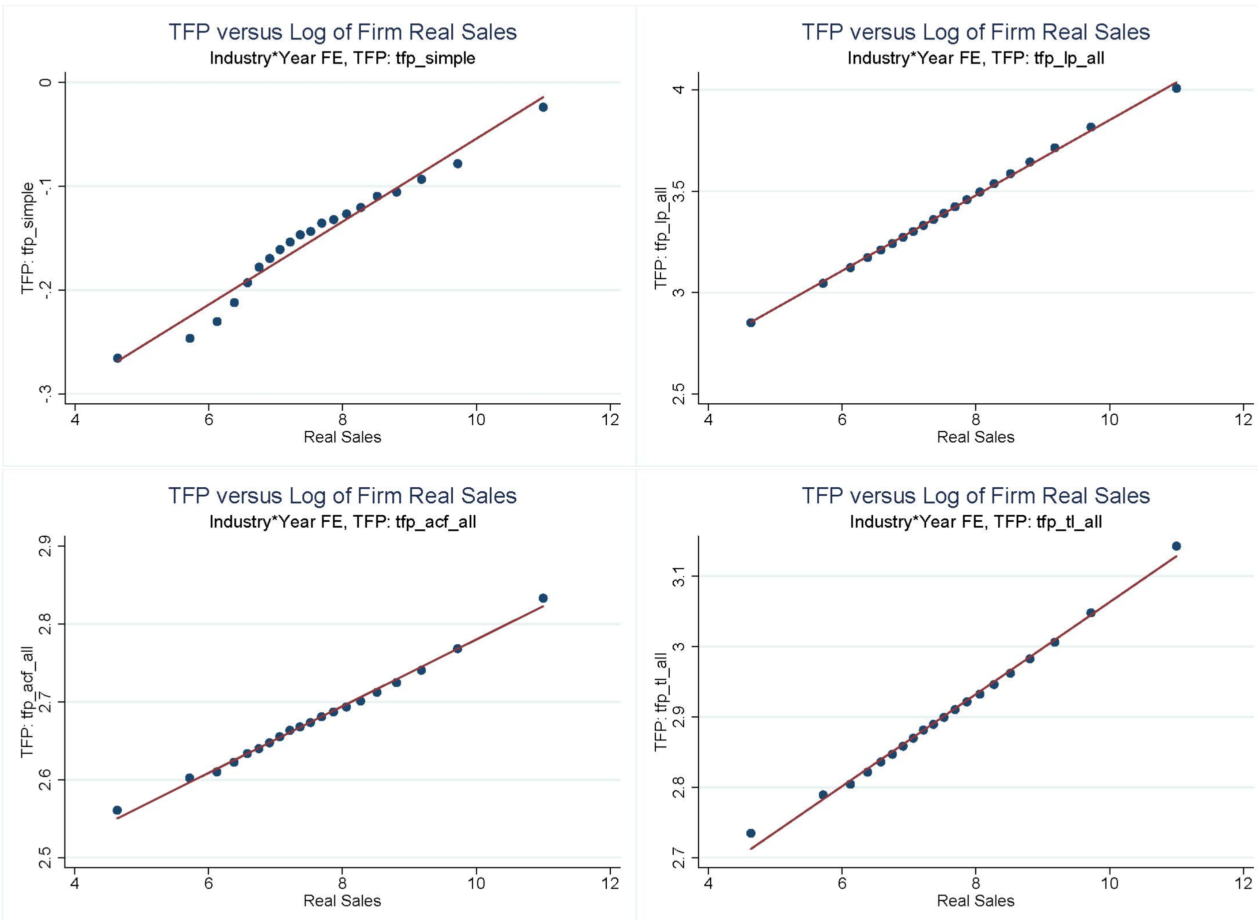
Appendix Figures

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



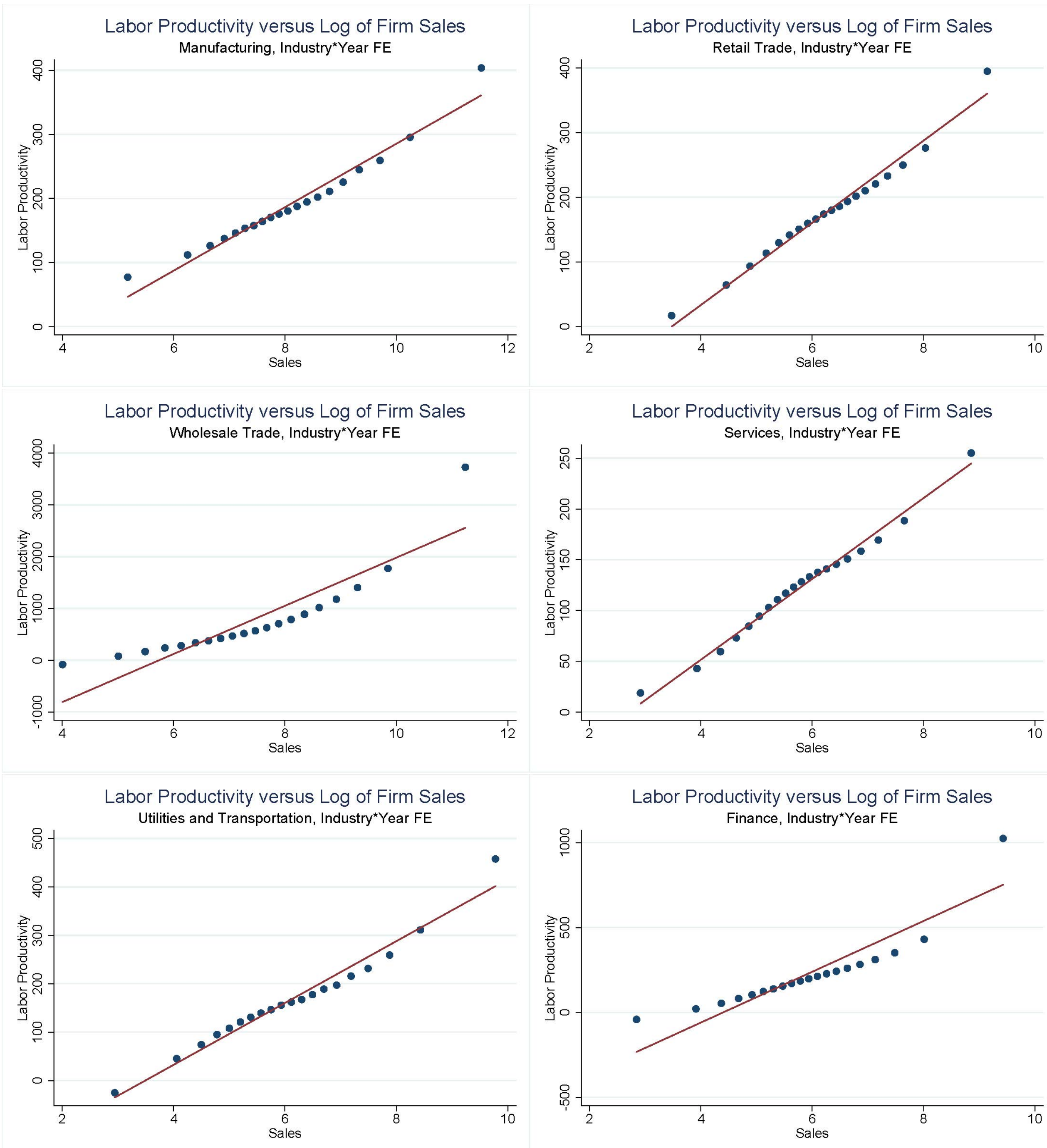
Notes. Each figure plots the average HHI calculated within four-digit industries. Industry concentration is calculated for each time-consistent four-digit industry code, and then averaged across all industries within each of the six sectors. The blue circles plot the HHI calculated using firm sales and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

Figure A.2: The Relationship between Estimated Total Factor Productivity and Firm Sales Using Four Methods of Estimating TFP



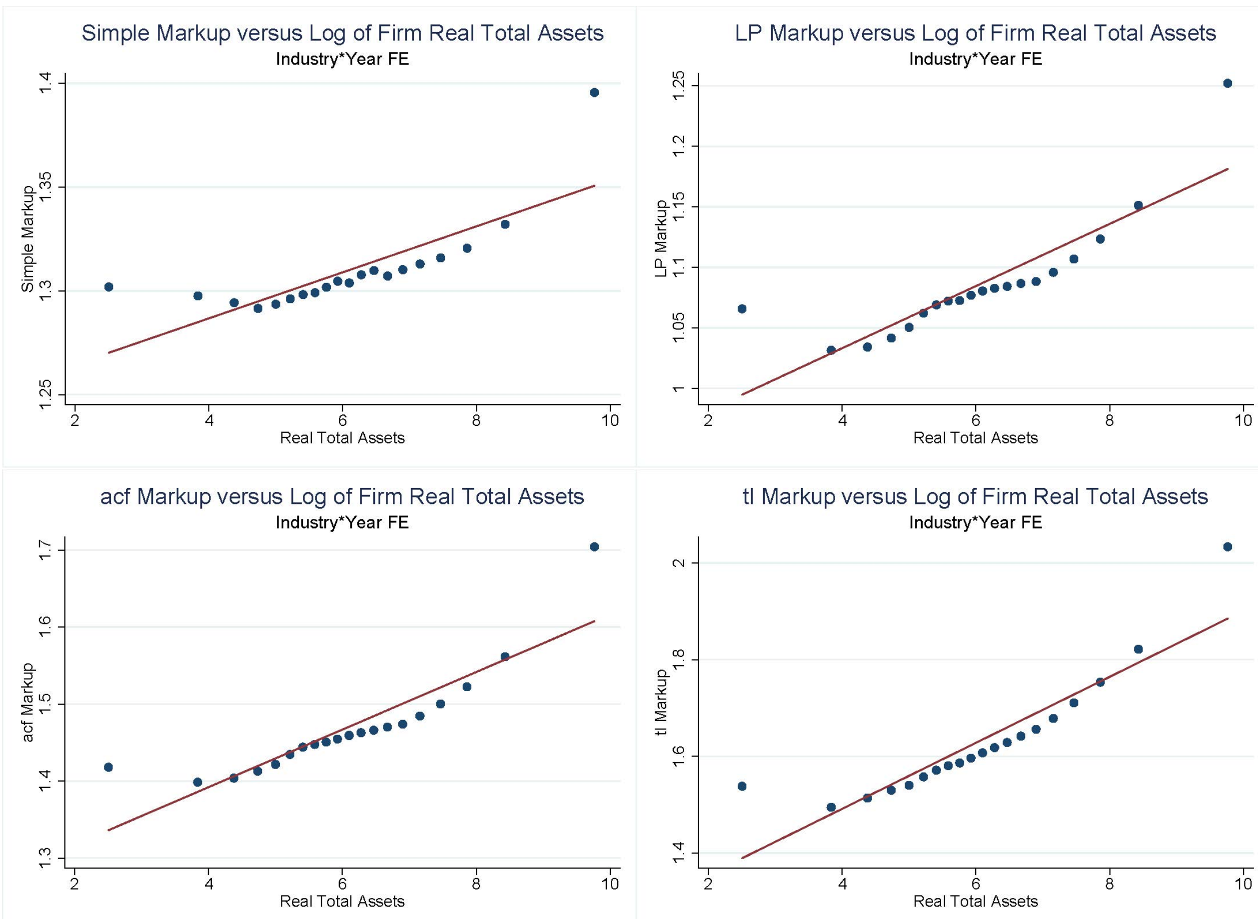
Notes. XXX.

Figure A.3: The Relationship between Labor Productivity and Firm Sales by Sector



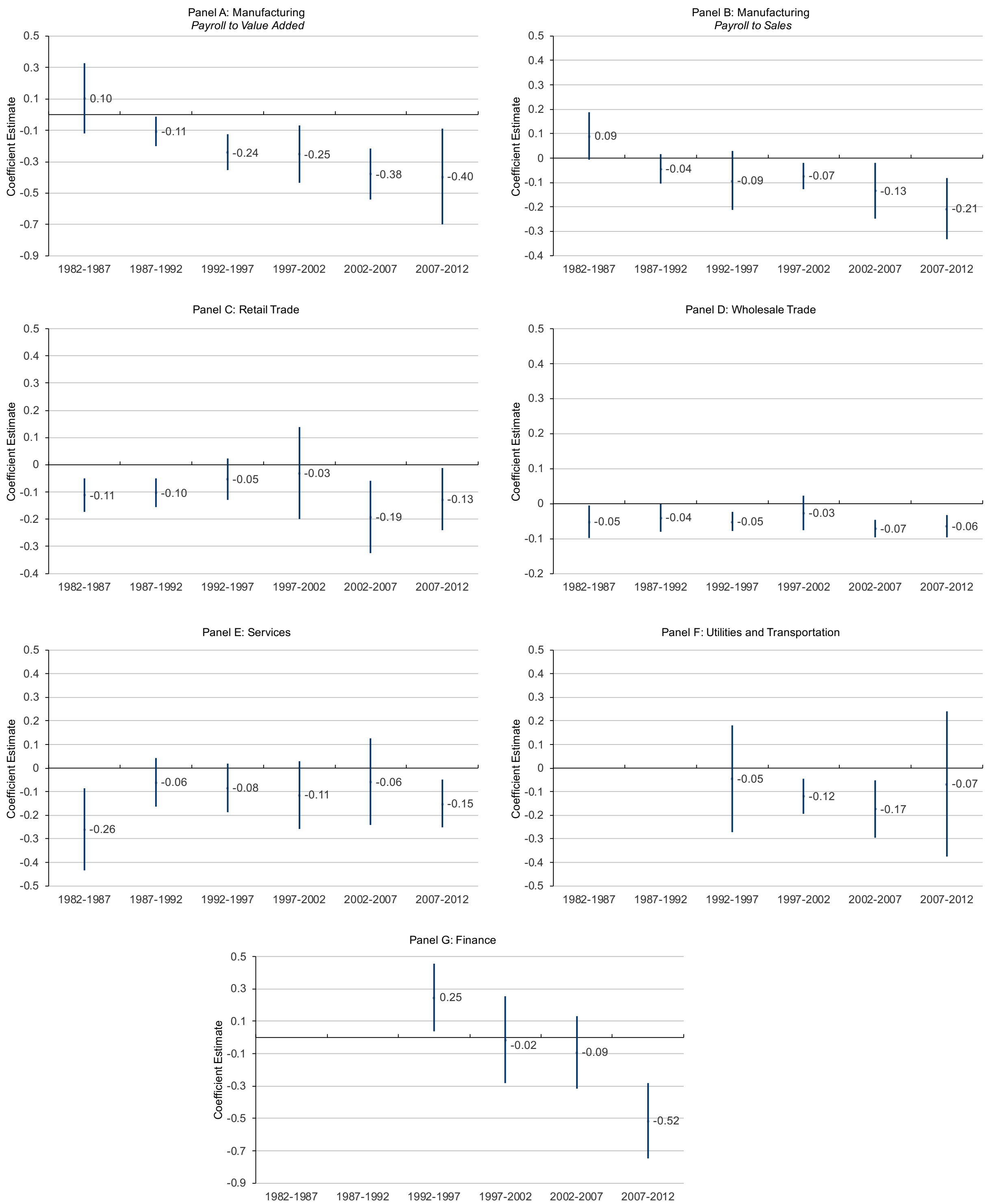
Notes. XXX.

Figure A.4: The Relationship between Estimated Markups and Firm Real Assets Using Four Methods of Estimating Markups



Notes. XXX.

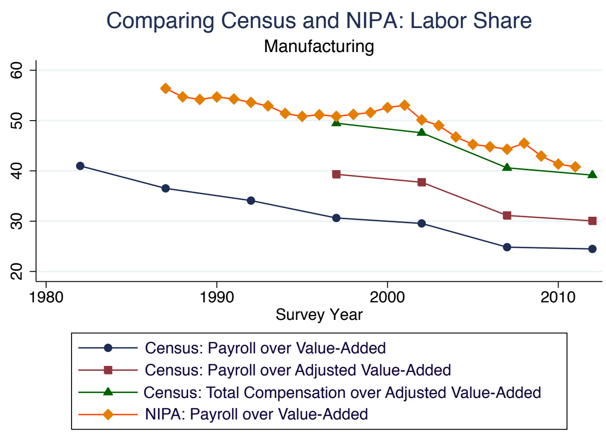
Figure A.5: Correlation Between the Change in Labor Share and the Change in Concentration: Period Specific Estimates



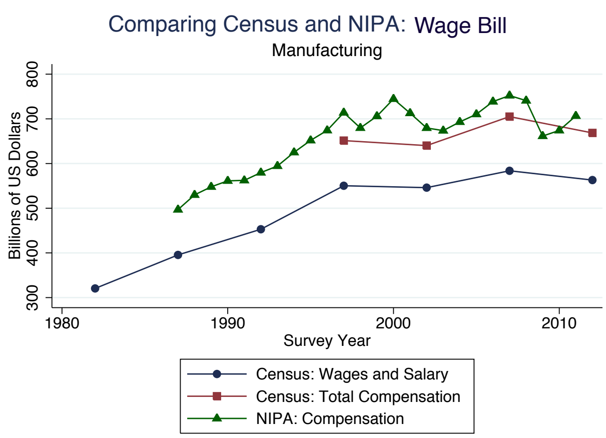
Notes. For manufacturing, the labor share is defined using the payroll to value-added ratio in panel A, and each industry is weighted by the industry's 1982 share of value-added. For all other panels, the labor share is defined as the ratio of payroll to sales, and each industry is weighted by its initial 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.

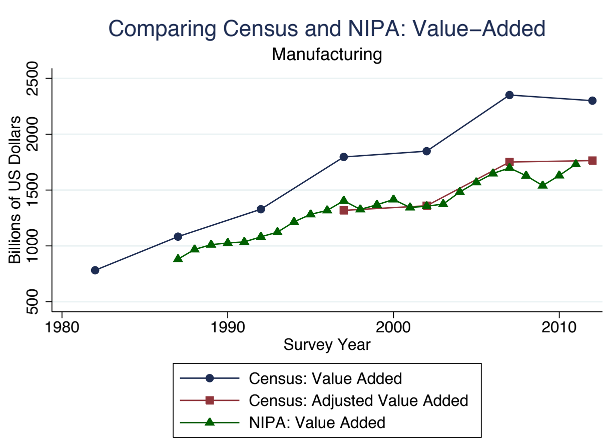
Figure A.6: Comparing Labor Share in NIPA and Census: Manufacturing Only

Panel A: The Labor Share



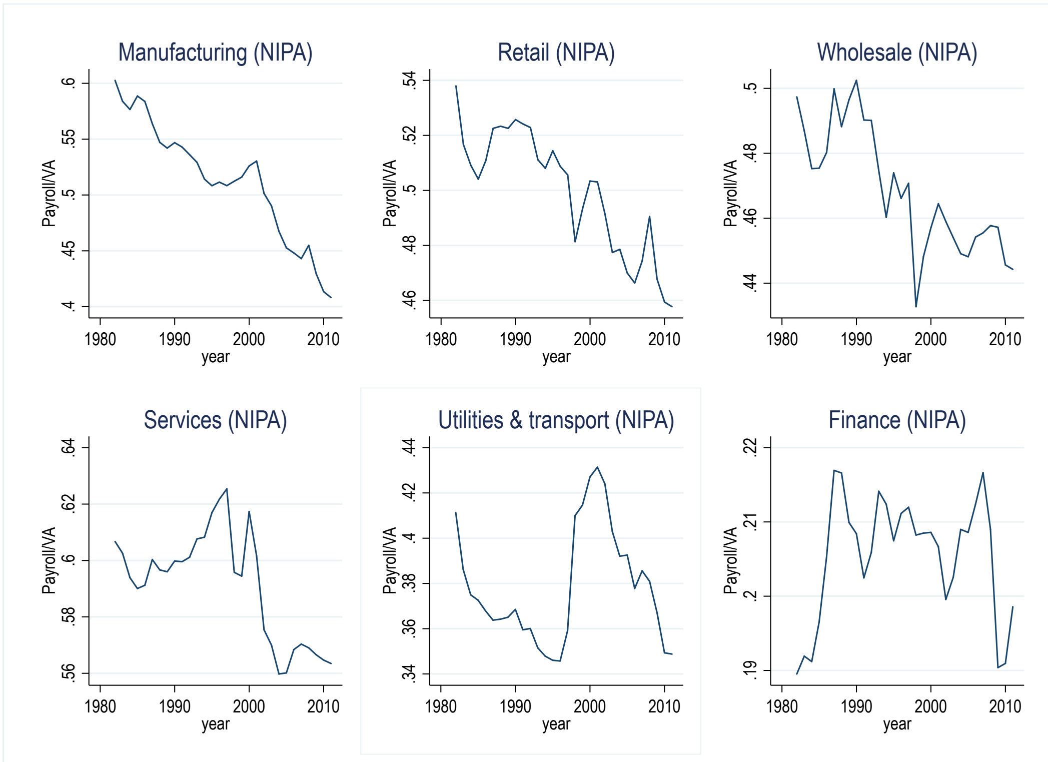
Panel B: Components of the Labor Share





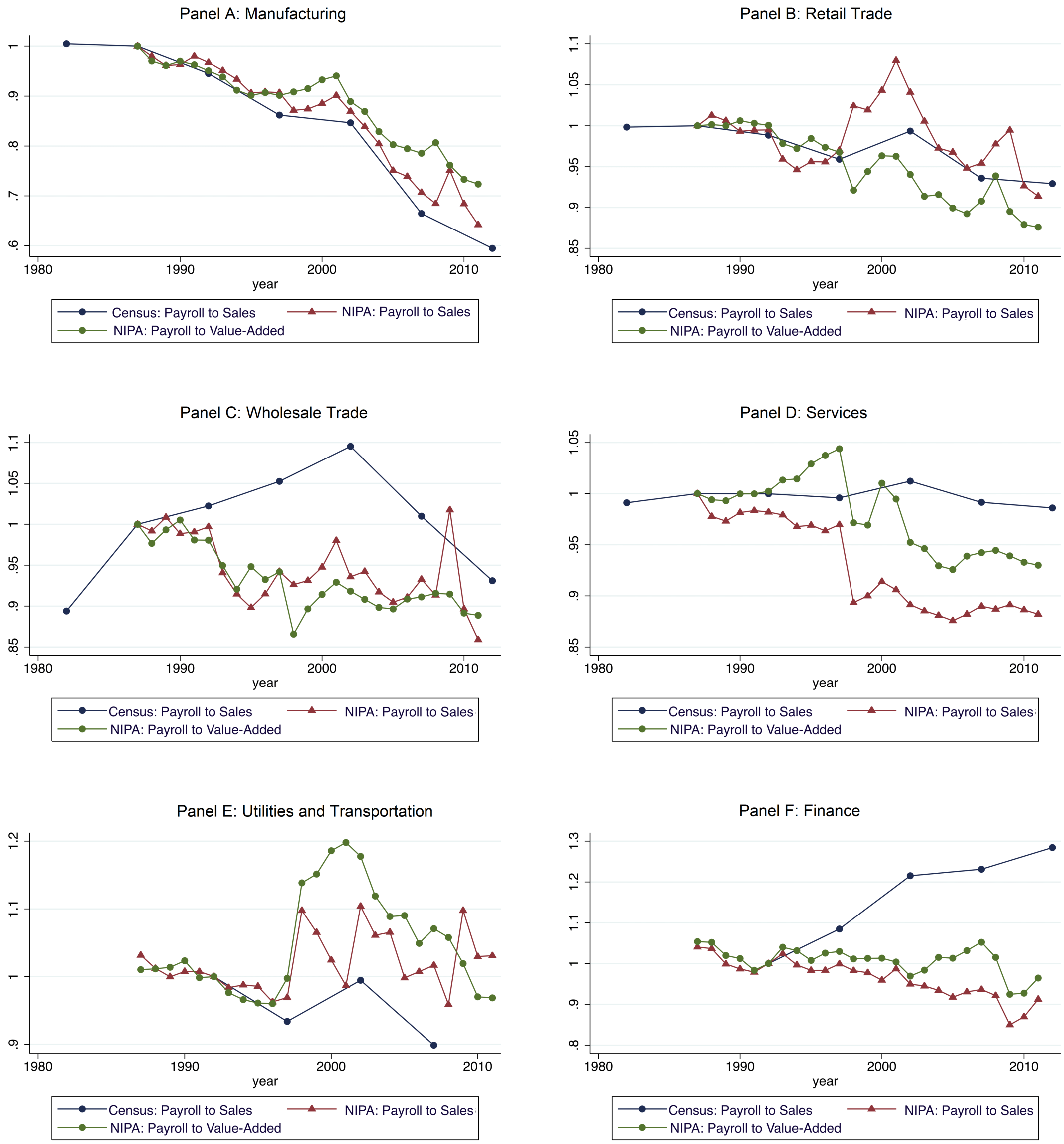
Notes. Panel A plots the aggregate labor share in Manufacturing calculated from the Census and NIPA/BEA data. Blue circles show the labor share calculated in the Census as the ratio of payroll to value-added. Red squares show the same ratio, but here value-added is adjusted by subtracting intermediate 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.7: Labor Share in NIPA



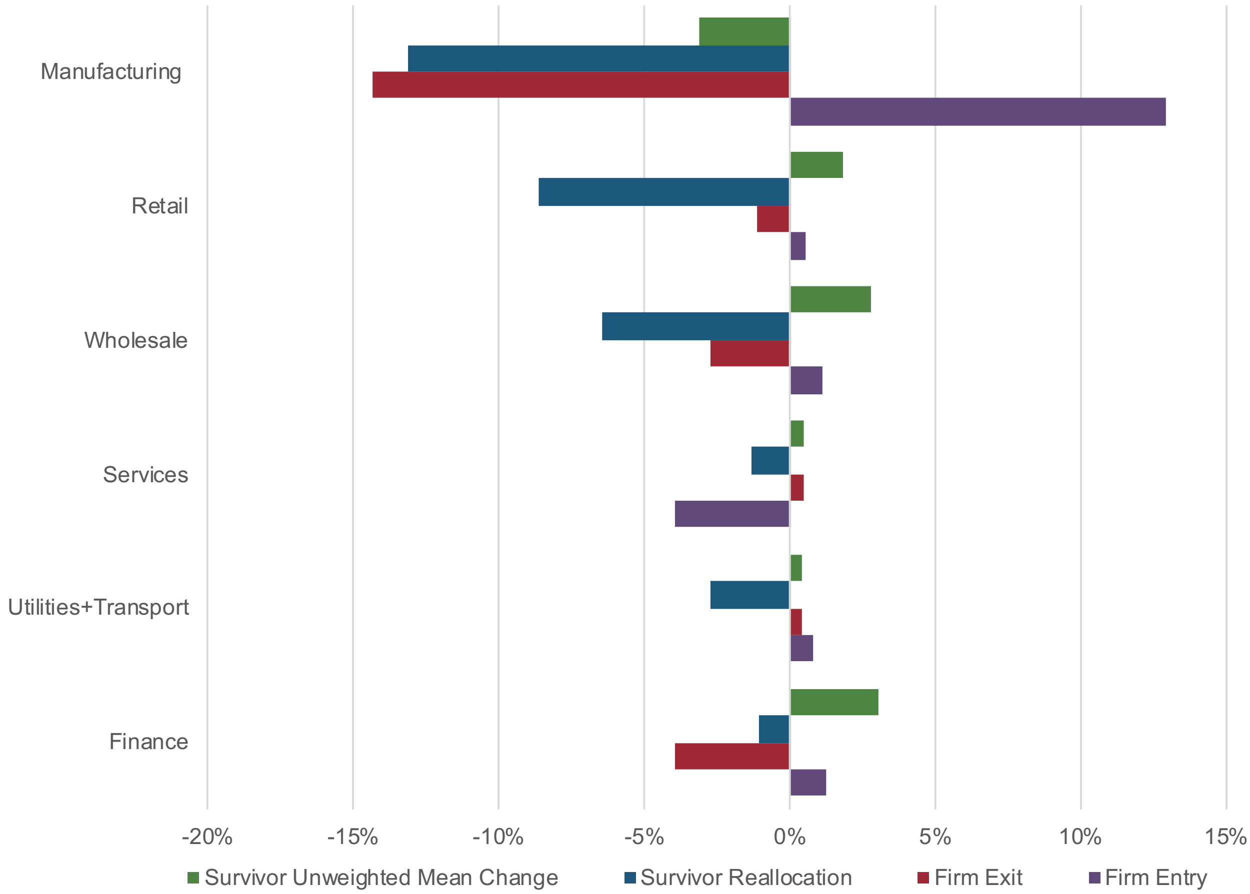
Notes. These are graphs of the ratio of payroll to value added taken from the NIPA/BEA data presented separately for each Census Sector. See text for details.

Figure A.8: Comparing the Payroll-to-Sales Ratio in the Census with the Labor Share in NIPA



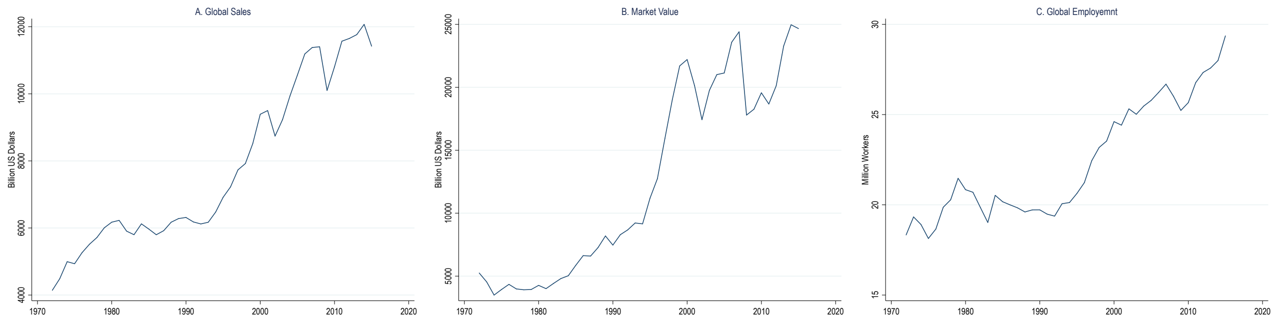
Notes. Each panel shows the payroll to sales ratio in the Census, the payroll to gross-output ratio in the NIPA/BEA data, and the payroll to value-added ratio in the NIPA/BEA data. All series are normalized to one in 1987.

Figure A.9: Decomposition of the Labor Share Decline by Sector in the National Income and Product Accounts (NIPA)



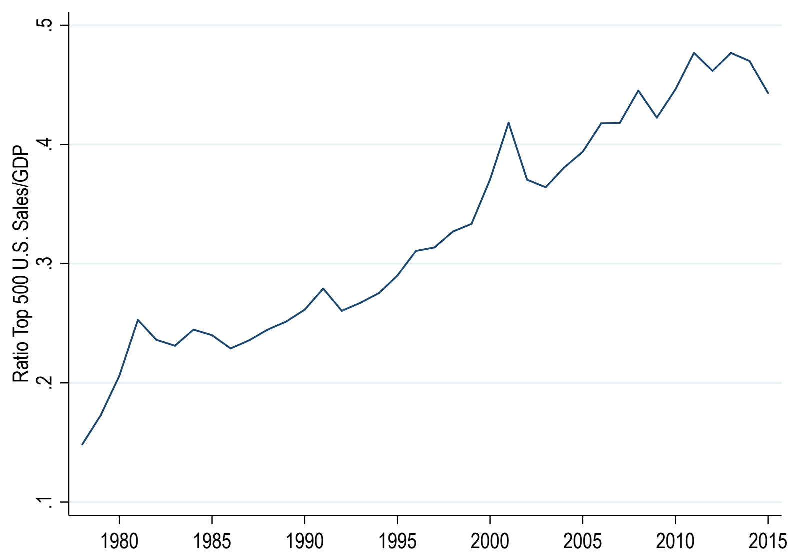
Notes. Melitz-Polanec decomposition of fall of labor share (payroll to value added) using NIPA and Census data. See text for details.

Figure A.10: Size of the Top 500 U.S. Firms



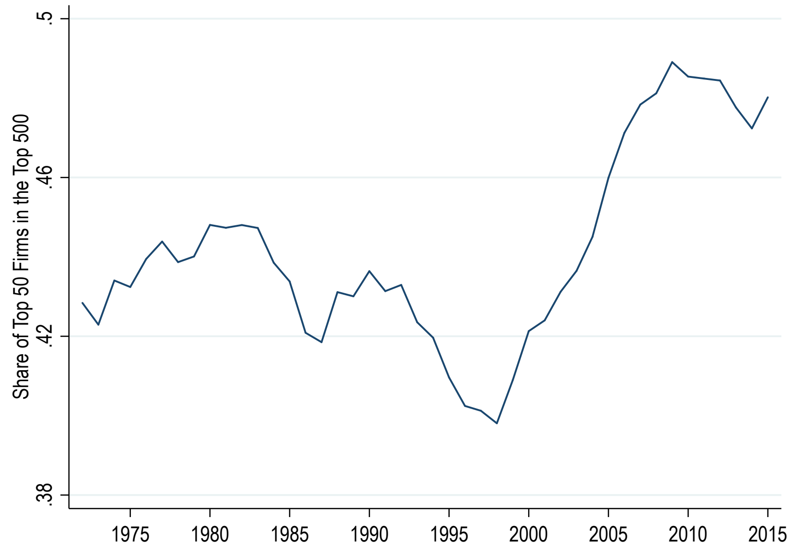
Notes. Panel A shows the total global sales for the 500 firms with the largest global sales from 1972 to 2015. Panel B shows the total market value for the 500 firms with the largest global sales from 1972 to 2015. Panel C shows the total global employment for the 500 firms with the largest global sales from 1972 to 2015. Sales and market value variables are deflated using the CPI.

Figure A.11: Ratio of Top 500 Firms' U.S. Sales to U.S. GDP



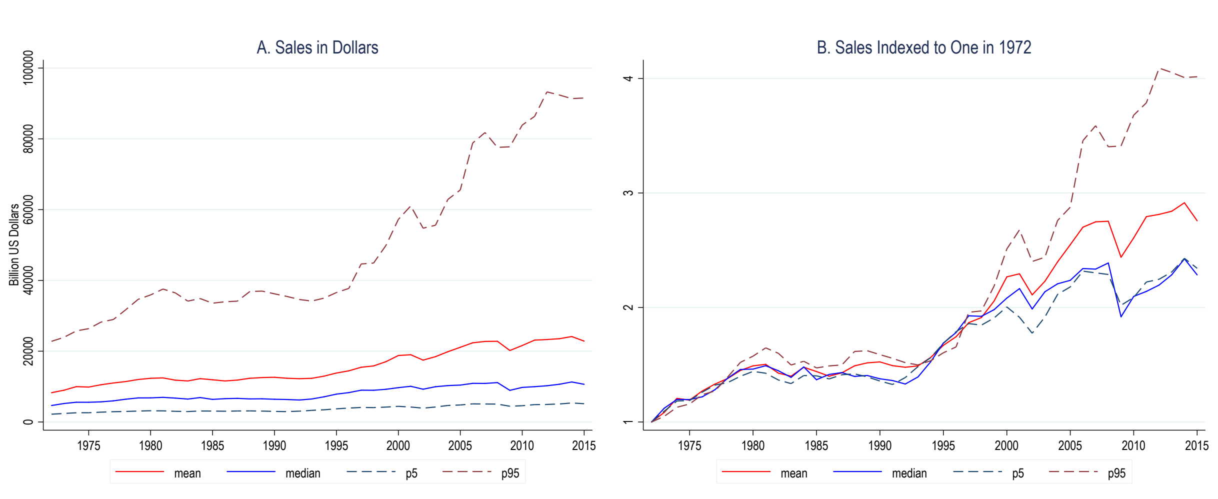
Notes. This numerator of this figure is the sum of the domestic sales of the top 500 firms defined by global sales. The denominator is gross domestic product. Both are deflated using the CPI.

Figure A.12: Share of Top 50 Firms in Combined Sales of Top 500 Firms



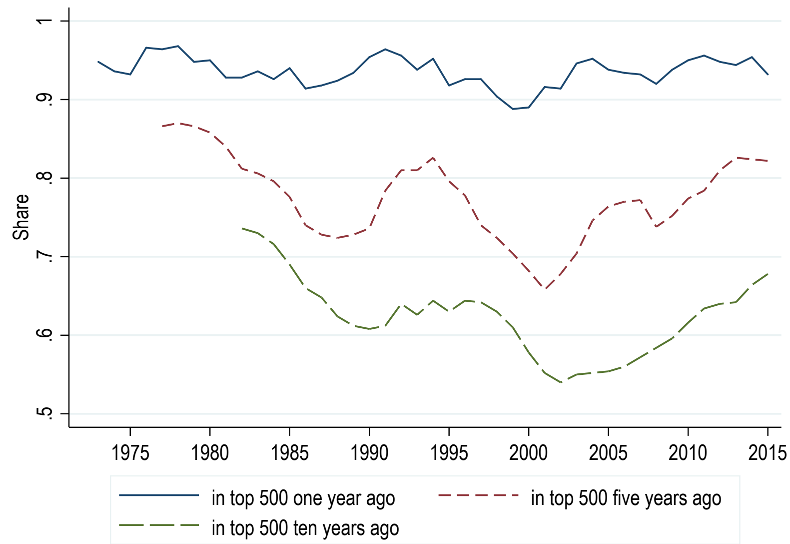
Notes. This numerator of this figure is the sum of global sales of the top 50 firms defined by global sales. The denominator is the sum of global sales of the top 500 firms defined by global sales. Both are deflated using the CPI.

Figure A.13: Quantiles of the Sales Distribution among the Top 500 Firms



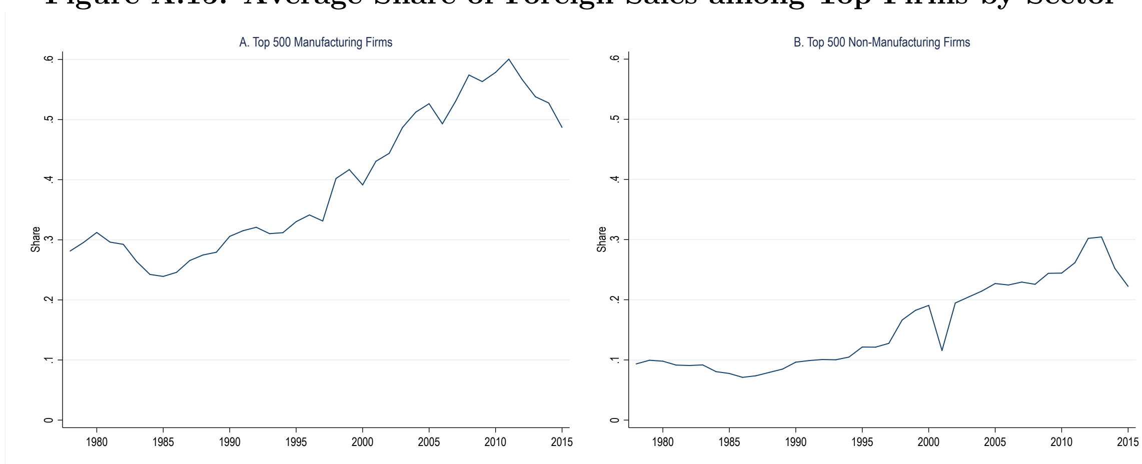
Notes. Panel A shows the time series from 1972 to 2015 for the mean, median, and 5th and 95th percentile of global sales among the top 500 largest firms defined by global sales. Panel B shows the same time series in Panel A, with all indexed to one in 1972. All are deflated using the CPI.

Figure A.14: Persistence of Firms in the Top 500



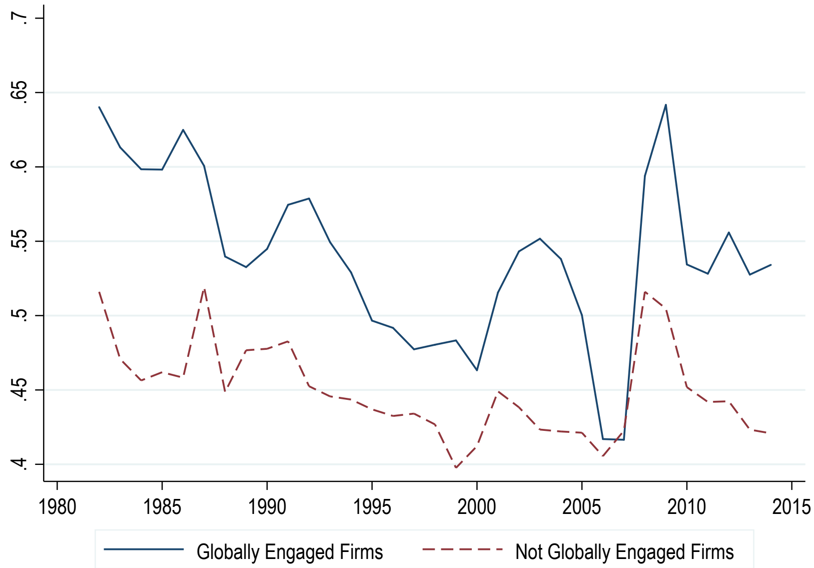
Notes. This figure plots the number of firms in the top 500 (defined by global sales) that were in the top 500 1/5/10 years ago, divided by 500, from 1972 to 2015.

Figure A.15: Average Share of Foreign Sales among Top Firms by Sector



Notes. Panel A shows the average of ratio of total foreign sales to total sales by top 500 manufacturing firms defined by global sales. Panel B shows the same ratio for non-manufacturing firms. All series displayed from 1978-2015 and deflated using the CPI.

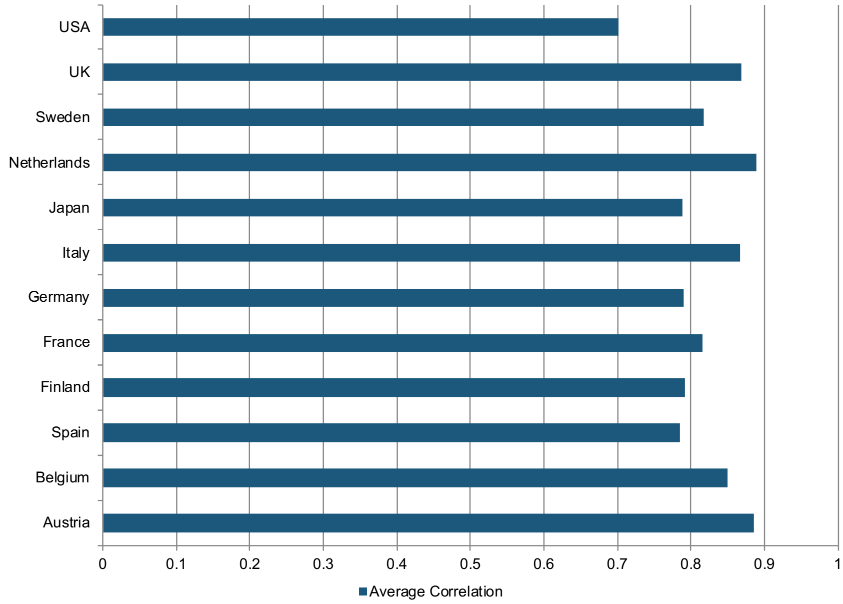
Figure A.16: Average Labor Share of Globally Engaged vs. Non Globally Engaged Top Firms



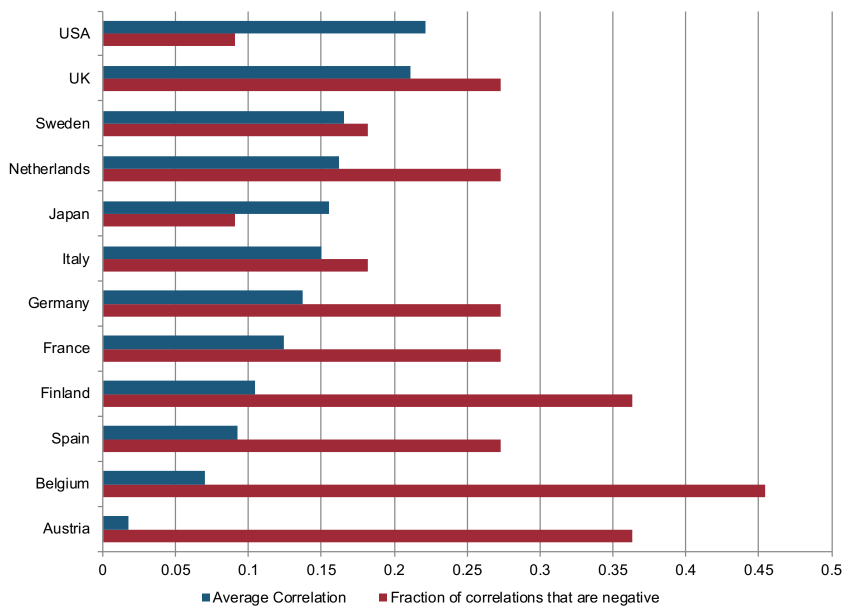
Notes. The line with circular markers shows the time series for the average labor share of the top 500 firms (defined by global sales) that had some foreign sales. The line with triangular markers shows the time series for the average labor share of the top 500 firms (defined by global sales) that had no foreign sales.

Figure A.17: Industry-Level Cross-Country Comparisons of Labor Shares

Panel A: Levels

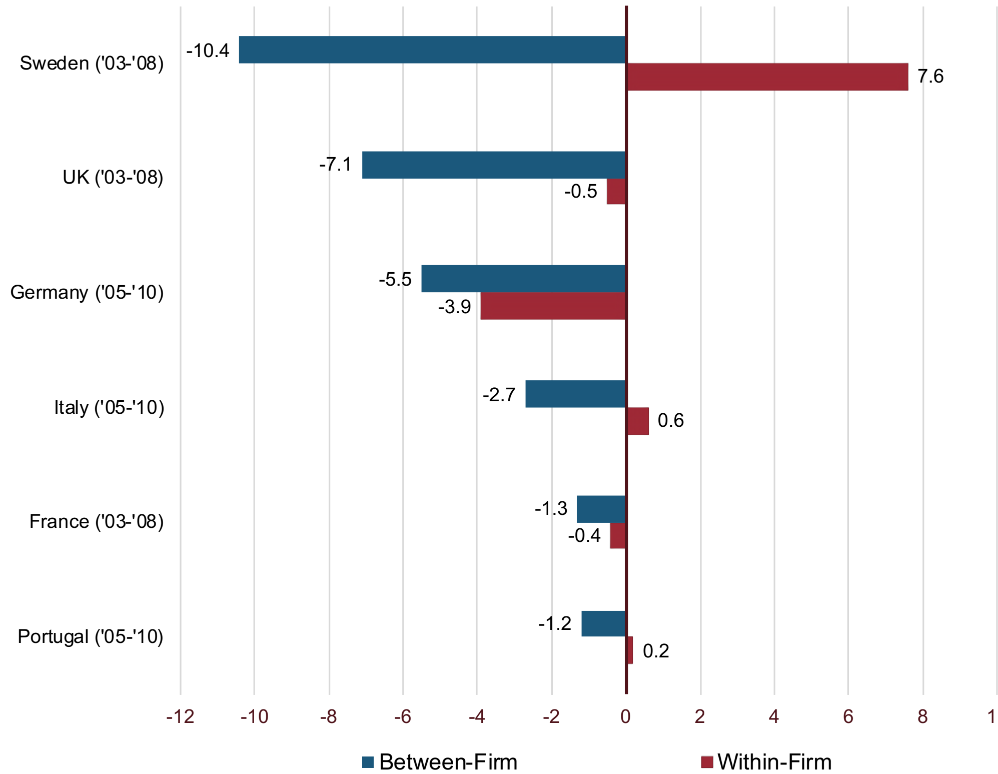


Panel B: Changes



Notes. Panel A plots, for each country, the correlation of the *level* of its labor share 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 contributes twice to the calculation, as the correlation between the USA and the UK would enter the average correlation for the U.S. and the average correlation for the U.K. 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. The sample period in both panels is 1997-2007, and 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 A.18: 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.

Appendix Tables

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

	Wage Bill Share of Value Added				Compensation Share of Value Added			
	Δ Un-weighted Mean (1)	Incumbent Re-allocation (2)	Exit (3)	Entry (4)	Δ Un-weighted Mean (5)	Incumbent Re-allocation (6)	Exit (7)	Entry (8)
	A. Plant Level							
1982-1987	-3.20	-0.85	-1.07	0.59	-3.20	-0.85	-1.07	0.59
1987-1992	2.32	-4.10	-1.12	0.31	2.32	-4.10	-1.12	0.31
1992-1997	-1.95	-1.42	-0.60	0.65	-1.95	-1.42	-0.60	0.65
1997-2002	0.51	-0.88	-0.75	0.03	0.51	-0.88	-0.75	0.03
2002-2007	-2.68	-1.58	-0.54	0.31	-2.68	-1.58	-0.54	0.31
2007-2012	2.34	-2.24	-0.36	0.17	2.34	-2.24	-0.36	0.17
Mean '82-'12	-0.44	-1.84	-0.74	0.34	-0.44	-1.84	-0.74	0.34
1982-1997	-2.83	-6.37	-2.78	1.56	-2.83	-6.37	-2.78	1.56
1997-2012	0.18	-4.69	-1.65	0.51	0.18	-4.69	-1.65	0.51
1982-2012	-2.65	-11.06	-4.43	2.07	-2.65	-11.06	-4.43	2.07
	B. Firm by Industry Level							
1982-1987	-3.20	-0.85	-1.07	0.59	-1.84	-4.02	-1.18	1.30
1987-1992	2.32	-4.10	-1.12	0.31	3.46	-5.18	-1.63	1.60
1992-1997	-1.95	-1.42	-0.60	0.65	-3.01	-1.70	-1.63	1.54
1997-2002	0.51	-0.88	-0.75	0.03	-2.05	0.95	-1.54	1.37
2002-2007	-2.68	-1.58	-0.54	0.31	1.22	-6.44	-1.98	2.32
2007-2012	2.34	-2.24	-0.36	0.17	0.00	0.11	-1.78	1.20
Mean '82-'12	-0.44	-1.84	-0.74	0.34	-0.37	-2.71	-1.62	1.55
1982-1997	-2.83	-6.37	-2.78	1.56	-1.39	-10.90	-4.44	4.44
1997-2012	0.18	-4.69	-1.65	0.51	-0.82	-5.38	-5.31	4.88
1982-2012	-2.65	-11.06	-4.43	2.07	-2.21	-16.28	-9.75	9.32
	C. 15-Year Decompositions, Firm Level							
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. "Change in Unweighted Mean" is the change in the labor share due to a general fall in the share across all incumbent plants; "Incumbent Reallocation" 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. All calculations use micro-data from the quinquennial Censuses of Manufacturing. Panel A reports the decomposition at the plant level, Panel B at the firm-by-industry level, and Panel C at the firm level over adjacent 15-year periods.

Table A.2: **Output Elasticities for Production Function Estimates**

		LP				ACF			
		K		L		K		L	
Industry	Obs	(1)		(2)		(3)		(4)	
Food and kindred products	85500	0.260	***	0.472	***	0.345	***	0.693	***
Textile mill products	21000	0.164	***	0.611	***	0.183	***	0.796	***
Apparel and other textile products	81500	0.213	***	0.523	***	0.293	***	0.627	***
Lumber and wood products	86000	0.191	***	0.600	***	0.210	***	0.803	***
Furniture and fixtures	44000	0.168	***	0.558	***	0.293	***	0.833	***
Paper and allied products	31500	0.213	***	0.557	***	0.229	***	0.796	***
Printing and publishing	134000	0.171	***	0.631	***	0.209	***	0.823	***
Chemicals and allied products	55000	0.253	***	0.428	***	0.330	***	0.663	***
Petroleum and coal products	12500	0.223	***	0.383	***	0.341	***	0.664	***
Rubber and misc. plastics products	66000	0.196	***	0.543	***	0.230	***	0.750	***
Leather and leather products	6600	0.173	***	0.525	***	0.201	***	0.785	***
Stone, clay, and glass products	75500	0.228	***	0.468	***	0.247	***	0.709	***
Primary metal industries	31500	0.180	***	0.620	***	0.219	***	0.804	***
Fabricated metal products	163000	0.160	***	0.648	***	0.193	***	0.817	***
Industrial machinery and equipment	194000	0.144	***	0.670	***	0.219	***	0.863	***
Electronic & other electric equipment	54000	0.165	***	0.575	***	0.193	***	0.818	***
Transportation equipment	34500	0.175	***	0.607	***	0.204	***	0.836	***
Instruments and related products	44500	0.197	***	0.566	***	0.214	***	0.813	***
Miscellaneous manufacturing industries	58500	0.167	***	0.564	***	0.217	***	0.793	***

Notes. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$. Table reports output elasticities from industry specific estimates of the production function. Analysis uses plant-level panel data from the Census of Manufactures 1982-2012. Columns (1) and (2) apply the Levinsohn and Petrin (2003) method, while columns (3) and (4) use the Ackerberg, Caves and Frazer (2015) method. Both are based on Cobb-Douglas approaches with time trends. See text for further details.

Table A.3: Decomposition of the Change in Payroll to Value-Added Ratio, Breaking Out Between- and Within-Industry Effects: Manufacturing Sector

		Industry Shift-Share		Within-Industry Melitz-Polanec Decomposition				
	Total	Between Industry Shifts	Within-Industry Changes	Δ Unweighted Mean	Incumbent Reallocation	Exit	Entry	Total Reallocation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Payroll-to-Value added Ratio								
1982-87	-4.52	0.08	-4.60	-2.82	-1.56	-0.39	0.15	-1.79
1987-92	-2.58	-0.80	-1.78	1.16	-2.64	-0.60	0.30	-2.94
1992-97	-3.32	0.09	-3.41	-2.24	-1.08	-0.41	0.32	-1.17
1997-02	-1.08	-0.43	-0.65	1.07	-1.43	-0.49	0.21	-1.71
2002-07	-4.48	-0.70	-3.78	-3.29	-0.54	-0.53	0.57	-0.49
2007-12	-0.09	-0.48	0.39	1.06	-0.63	-0.33	0.30	-0.67
1982-12	-16.07	-2.23	-13.84	-5.07	-7.88	-2.76	1.87	-8.77
B. Compensation-to-Value added Ratio								
1982-87	-5.93	0.03	-5.96	-2.41	-3.29	-0.44	0.18	-3.55
1987-92	-1.91	-0.96	-0.94	2.16	-2.62	-0.75	0.27	-3.10
1992-97	-4.64	0.16	-4.81	-2.80	-1.90	-0.44	0.33	-2.01
1997-02	-1.25	-0.55	-0.70	-0.24	-0.12	-0.60	0.26	-0.46
2002-07	-4.60	-1.01	-3.59	-0.69	-3.05	-0.58	0.73	-2.91
2007-12	-0.15	-0.54	0.39	-0.14	0.64	-0.40	0.29	0.53
1982-12	-18.48	-2.86	-15.62	-4.12	-10.35	-3.21	2.06	-11.50

Notes. Table reports an extended version of the decomposition as used in Table 4 where we break out the between four-digit SIC industry component from the within-industry component following Equation (28) in the text.

Table A.4: Decomposition of the Change in Payroll to Sales Ratio, Breaking Out Between- and Within-Industry Effects: All Sectors

	Ind Shift-Share		Within-Industry MP Decomp				Ind Shift-Share		Within-Industry MP Decomp			
	Between Industry Shifts	Within-Industry Changes	Δ Unweighted Mean	Incumbent Reallocation	Exit	Entry	Between Industry Shifts	Within-Industry Changes	Δ Unweighted Mean	Incumbent Reallocation	Exit	Entry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
			A. Manufacturing						*B. Retail*			
1982-87	1.20	-1.21	-0.13	-1.02	-0.10	0.04	0.10	-0.10	-0.06	0.04	-0.02	-0.06
1987-92	-0.07	-0.98	0.96	-1.83	-0.18	0.07	0.06	-0.21	1.10	-1.12	-0.08	-0.11
1992-97	0.28	-1.61	-0.46	-1.15	-0.18	0.18	-0.17	-0.17	0.99	-1.11	-0.04	-0.01
1997-02	-0.19	-0.09	1.01	-0.99	-0.17	0.07	-0.01	0.37	1.36	-0.92	-0.05	-0.03
2002-07	-0.88	-2.11	-1.86	-0.22	-0.19	0.17	-0.06	-0.57	0.32	-0.79	-0.11	0.00
2007-12	-0.75	-0.33	-0.04	-0.26	-0.12	0.09	0.01	-0.25	0.76	-0.99	-0.06	0.03
1982-12	-0.41	-6.32	-0.52	-5.47	-0.95	0.61	-0.06	-0.94	4.47	-4.88	-0.35	-0.18
			C. Wholesale						*D. Services*			
1982-87	0.32	0.19	0.82	-0.61	-0.14	0.12	0.37	-0.34	-0.07	-0.08	0.66	-0.85
1987-92	0.22	-0.02	1.11	-0.94	-0.18	0.00	0.55	-1.06	0.23	-0.99	0.42	-0.72
1992-97	0.20	-0.01	1.32	-1.26	-0.12	0.05	0.27	-0.88	1.16	-2.07	0.41	-0.37
1997-02	-0.33	0.67	1.81	-1.28	-0.14	0.27	0.37	0.38	0.66	-0.32	0.28	-0.24
2002-07	-0.19	-0.33	0.05	-0.37	-0.16	0.15	0.20	-1.35	-0.58	-0.46	-0.21	-0.10
2007-12	-0.42	-0.29	0.91	-1.06	-0.25	0.11	0.25	-0.17	0.37	-0.28	-0.36	0.10
1982-12	-0.21	0.21	6.01	-5.52	-0.99	0.70	2.02	-3.40	1.77	-4.19	1.20	-2.18
			E. Utilities and Trnasportation						*F. Finance*			
1992-97	-0.24	-1.02	1.01	-1.96	0.08	-0.15	1.18	-0.17	2.00	-1.65	-0.28	-0.24
1997-02	0.88	0.26	0.57	-0.50	0.39	-0.21	0.17	1.21	0.92	0.36	-0.13	0.06
2002-07	-0.26	-1.62	-0.29	-1.47	0.65	-0.51	1.22	-1.15	1.02	-2.15	-0.03	0.01
2007-12	0.16	-0.32	0.30	-0.59	0.26	-0.29	-1.18	1.98	1.80	0.31	-0.13	0.00
1992-12	0.54	-2.71	1.58	-4.51	1.39	-1.17	1.40	1.88	5.74	-3.12	-0.57	-0.17

Notes. Table reports an extended version of the decomposition as used in Table 4 where we break out the between four-digit SIC industry component from the within-industry component following Equation (28) in the text.

Table A.5: Top 25 Largest Publicly Listed U.S. Firms by Global Sales in 1985, 2000 and 2015

	1985			2000			2015		
Rank (1)	Company (2)	Industry (3)	Sales $bn (4)	Company (5)	Industry (6)	Sales $bn (7)	Company (8)	Industry (9)	Sales $bn (10)
1	General Motors Co	Automobiles	209.3	Exxon Mobil Corp	Petroleum	280.7	Wal-Mart Stores Inc	Merch. Stores	479.4
2	Exxon Corp	Petroleum	188.3	Wal-Mart Stores Inc	Merch. Stores	260.1	Exxon Mobil Corp	Petroleum	236.8
3	AT&T Corp	Telecom	122.6	General Motors Co	Automobiles	246.0	Apple Inc	Computers	234.1
4	Mobil Corp	Petroleum	121.6	Ford Motor Co	Automobiles	231.7	Berkshire Hathaway	Conglomerate	210.8
5	Ford Motor Co	Automobiles	114.6	General Electric Co	Conglomerate	174.4	McKesson Corp	Drugs Wholes.	190.7
6	IBM Corp	Computers	108.7	Citigroup Inc	Banking	152.3	Unitedhealth Group	Insurance	157.1
7	Texaco Inc	Petroleum	100.6	Enron Corp	Energy	137.3	CVS Health Corp	Pharmacies	153.3
8	Chevron Corp	Petroleum	90.7	IBM Corp	Computers	120.4	General Motors Co	Automotive	152.4
9	Sears Roebuck &Co	Dept Stores	88.4	AT&T Corp	Telecom	89.9	Ford Motor Co	Automotive	149.6
10	Du Pont Co	Chemicals	63.7	Verizon Comm. Inc	Telecom	88.3	AT&T Inc	Telecom	146.8
11	General Electric Co	Conglomerate	61.4	Altria Group Inc	Tobacco	86.2	AmerisourceBergen	Drugs Wholes.	136.2
12	Travelers Group	Insurance	60.6	JPMorgan Chase	Banking	80.3	Verizon Comm. Inc	Telecom	131.6
13	Amoco Corp	Petroleum	58.5	Bank of America	Banking	78.9	Chevron Corp	Petroleum	122.6
14	Kmart Corp	Merchandise St	48.9	SBC Comm. Inc	Telecom	70.1	Costco Wholesale	Merch. Stores	116.2
15	Citicorp	Banking	48.9	Boeing Co	Airplanes	69.9	General Electric Co	Conglomerate	115.2
16	Atlantic Richfield	Petroleum	47.2	Texaco Inc	Petroleum	68.2	The Kroger Co	Food Stores	109.7
17	Chrysler Corp	Automobiles	46.2	HP Inc	Computers	66.7	Amazon.com Inc	Internet Sales	107.0
18	Shell Oil Co	Oil and Gas	44.1	Duke Energy Corp	Oil and Gas	66.6	Walgreens Boots	Pharmacies	103.5
19	Safeway Inc	Food Stores	42.7	The Kroger Co	Food Stores	66.4	HP Inc	Computers	103.4
20	Aetna Inc.	Insurance	40.4	Chevron Corp	Petroleum	63.4	Cardinal Health Inc	Drugs Wholes.	102.7
21	USX Corp	Steel	40.0	AIG Inc	Insurance	62.6	Express Scripts Co	Pharma Svc	101.8
22	The Kroger Co	Food Stores	37.2	Morgan Stanley	Banking	62.0	JPMorgan Chase	Banking	100.5
23	Cigna Corp	Insurance	35.2	Home Depot Inc	Hardware St.	62.0	Boeing Co	Aircraft	96.1
24	GTE Corp	Telecom	34.2	Merrill Lynch & Co	Banking	61.1	Microsoft Corp	Software	93.7
25	Phillips Petroleum	Petroleum	34.0	Compaq Computer	Computers	57.7	Bank of America Co	Banking	93.1
	Total Sales Top 25 Firms		1,888	Total Sales Top 25 Firms		2,803	Total Sales Top 25 Firms		3,744

Notes. Dollar values are inflated to 2015 using the Consumer Price Index.

Table A.6: Regressions of the Components of the Change in the Payroll-to-Sales Ratio on the Change in Concentration

	CR4		CR20		HHI	
	(1)		(2)		(3)	
			A. Incumbent Reallocation			
Retail	-0.038	**	-0.071	***	-0.038	
Wholesale	-0.013		-0.023	*	-0.038	
Services	-0.167	***	-0.186	***	-0.434	***
Manufacturing	-0.063	***	-0.087	***	-0.08	**
Utilities/Transportation	-0.102	*	-0.122	**	-0.325	***
Finance	-0.247		-0.237	**	-0.543	**
Combined	-0.077		-0.086	***	-0.119	***
			B. Change in Unweighted Mean			
Retail	0.003		0.005		0.005	
Wholesale	-0.016	*	-0.005		-0.016	
Services	0.066	***	0.078	***	0.104	**
Manufacturing	0.015	*	0.037	***	-0.003	
Utilities/Transportation	-0.014		-0.020		-0.014	
Finance	0.001		-0.034		-0.038	
Combined	0.005		0.006		-0.010	
			C. Entry			
Retail	0.007		-0.015		0.021	
Wholesale	-0.008	**	-0.010	***	-0.017	
Services	0.001		0.010		-0.007	
Manufacturing	-0.004		-0.019	***	-0.004	
Utilities/Transportation	0.034	***	0.038	***	0.077	**
Finance	0.034	**	0.044	*	0.045	
Combined	0.004		-0.002		0.006	
			D. Exit			
Retail	-0.007		-0.003		-0.029	**
Wholesale	-0.001		-0.001		-0.012	
Services	0.017		-0.022		-0.001	
Finance	-0.010		-0.008		-0.025	
Manufacturing	-0.028	*	-0.007		-0.056	*
Utilities/Transportation	-0.008		-0.025	**	-0.031	*
Combined	-0.008	*	-0.006	*	-0.027	**

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 (6). Regressions are weighted by the share of sales of the four-digit industry in total sector sales in the initial year.

Table A.7: Industry-Level Cross-Country Comparisons of Labor Shares

	Outcome Mean	Austria	Belgium	Spain	Finland	France	Germany	Italy	Japan	Nether-lands	Sweden	UK	USA
							A. Correlations of Average Value-Added Share Levels, 1997 - 2007						
Austria	65.47	1.00											
Belgium	64.95	0.73	1.00										
Spain	67.17	0.54	0.93	1.00									
Finland	65.79	0.73	0.81	0.75	1.00								
France	64.90	0.82	0.93	0.85	0.91	1.00							
Germany	64.52	0.75	0.87	0.71	0.80	0.89	1.00						
Italy	63.82	0.75	0.94	0.87	0.84	0.95	0.89	1.00					
Japan	62.89	0.63	0.81	0.80	0.81	0.82	0.75	0.82	1.00				
Netherlands	65.33	0.76	0.82	0.75	0.81	0.92	0.67	0.88	0.78	1.00			
Sweden	62.93	0.45	0.87	0.82	0.82	0.82	0.77	0.81	0.83	0.79	1.00		
UK	65.91	0.74	0.92	0.83	0.83	0.93	0.76	0.89	0.80	0.90	0.80	1.00	
USA	62.48	0.82	0.93	0.87	0.88	0.95	0.80	0.90	0.86	0.92	0.86	0.95	1.00
							B. Correlations of 10-Year Value-Added Share Levels, 1997 - 2007						
Austria	-0.60	1.00											
Belgium	-0.61	-0.06	1.00										
Spain	-0.48	0.22	0.45	1.00									
Finland	-0.53	0.53	0.22	0.48	1.00								
France	-0.36	-0.23	0.43	0.40	0.11	1.00							
Germany	-0.88	0.52	-0.15	-0.20	0.23	-0.13	1.00						
Italy	-0.53	0.09	0.28	0.26	-0.16	0.13	-0.02	1.00					
Japan	-1.02	0.23	0.29	-0.09	0.15	0.04	0.27	0.08	1.00				
Netherlands	-1.00	0.11	0.24	0.01	0.23	0.29	0.24	0.09	0.23	1.00			
Sweden	-0.93	0.16	-0.02	-0.39	0.28	0.06	0.28	-0.34	0.29	0.11	1.00		
UK	-1.06	-0.14	0.44	0.53	0.06	0.51	-0.39	0.08	-0.08	-0.10	0.06	1.00	
USA	-1.02	0.07	0.21	0.11	0.32	0.22	0.11	-0.31	-0.05	0.27	0.53	0.18	1.00

Notes. Correlations include 32 industries both within and outside of manufacturing. In each correlation, industries are weighted by their value-added share over the two countries in the comparison. Panel A correlates labor share levels, averaged between 1997 and 2007. Panel B correlates 10-year changes in labor share between 1997-2007. To reduce measurement error, we estimate correlations using centered 5-year moving averages.

Table A.8: **International COMPNET Regressions of the Change in Labor Share on the Change in Concentration (Industry level, all sectors)**

	5 Year Δ		10 Year Δ		Obs
	(1)		(2)		(3)
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 ten largest firms. Regression includes five-year changes for 2006-2011 and ten-year changes (when available) for 2001-2011. Observations are weighted by the sector's share of the country's total value-added. Models are estimated by OLS with standard errors clustered at the sector level.

Table A.9: Decomposing the Wage Bill Share Using Firm-Level Data from Different Countries

	Period	Obs	Initial Labor Share	Δ Labor Share	Δ Unweighted Mean	Incumbent Reallocation	Exit	Entry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UK	2003-08	112,007	68	-7.5	-0.1	-7.0	-2.5	2.2
Sweden	2003-08	154,741	74	-2.7	0.1	-10.4	7.1	0.2
France	2003-08	704,276	76	-1.7	1.3	-1.3	-1.5	0.0
Germany	2005-10	117,817	81	-4.5	0.0	-4.3	-0.2	0.1
Italy	2005-10	697,939	74	2.5	5.7	-2.2	-0.9	0.0
Portugal	2005-10	202,590	72	-4.8	2.9	-6.8	-1.9	1.0

Notes. Table uses firm-level data from BVD Orbis. Value-added is constructed by adding wage bill to pre-tax profits (EBIT) for 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.10: The Labor Share and the Rise in Chinese Imports

Δ Years	Sales (1)		Wages (2)		Value-Added (3)		CR4 (4)		CR20 (5)		HHI (6)		Labor Share (7)		Wage-to-Sales (8)	
							A. OLS Estimates									
5 Year Δ's	-1.98	**	-0.46	*	-0.79	**	1.16		0.341		1.18		6.64	**	2.28	
1992-2012	(0.77)		(0.28)		(0.35)		(4.39)		(4.12)		(2.00)		(2.98)		(1.82)	
10 Year Δ's	-2.55	***	-0.83	**	-1.36	***	-4.89		-1.80		-0.85		12.38	***	6.85	***
1992-2012	(0.76)		(0.34)		(0.43)		(7.91)		(7.30)		(3.64)		(2.98)		(1.14)	
5 Year Δ's	-2.66	***	-0.66	**	-0.67	**	16.58	*	7.36	**	11.17	**	-1.44		-1.10	
1992-2007	(1.00)		(0.30)		(0.26)		(9.23)		(3.25)		(5.39)		(2.98)		(1.12)	
							B. 2SLS Estimates									
5 Year Δ's	-3.72	***	-0.78	**	-1.17	***	4.69		3.50		4.80		8.17	**	3.60	**
1992-2012	(1.41)		(0.34)		(0.42)		(5.24)		(4.01)		(3.17)		(3.30)		(1.79)	
10 Year Δ's	-4.10	***	-1.21	***	-1.93	***	-3.15		3.47		2.03		15.77	***	8.42	***
1992-2012	(1.26)		(0.43)		(0.56)		(9.34)		(7.13)		(5.38)		(3.30)		(1.61)	
5 Year Δ's	-2.66	***	-1.05	***	-1.17	***	17.60	*	9.84	**	13.12	**	0.52		-0.95	
1992-2007	(1.00)		(0.38)		(0.40)		(9.57)		(4.49)		(6.20)		(3.30)		(1.42)	

Notes. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$. Panel A reports OLS regressions of various industry-level outcomes on the change in the labor share for manufacturing industries. Panel B reports 2SLS estimates using the growth in imports from China to eight other developed countries as an instrument for the contemporaneous growth in Chinese imports to the U.S. (as in Autor et al. 2013). For example, column 1 of Panel B reports the estimated effect of Chinese imports on industry log 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 regression for five- and ten-year changes over 1992-2012 is 76.25 and 50.30, respectively. The partial F-statistic for the first stage regression for five- and ten-year changes over 1992 and 2007 is 89.79 and 97.25, respectively.