

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 push sales towards the most productive firms in each industry, product market concentration will rise as industries become increasingly dominated by superstar firms, which have high markups and a low labor share of value-added. 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; (vi) the aggregate markup will rise more than the typical firm’s 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 documents a decline in the share of GDP going to labor in many nations over recent decades (e.g., Blanchard, 1997; Elsby, Hobijn 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 in twelve OECD countries 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, 2005). 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, Hobijn, and Sahin, 2013; Gollin, 2002), intangible capital (Koh, Santaaulalia-Lopis, and Zheng, 2018) and business owners taking capital instead of labor income (Smith, Yagan, Zidar, and Zwick, 2019), 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, Hobijn and Sahin (2013) argue for the importance of trade and international outsourcing especially with China. We also 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 such industries do experience employment declines). Additionally, we observe a decline in labor’s share in largely

¹The 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, Yagan, Zidar and Zwick (2019) show that this can account for only an eighth of the decline in the labor share.

²Karabarbounis and Neiman (2013) provide evidence for an elasticity above one, but the bulk of the empirical literature suggests an elasticity of below one (e.g., Lawrence, 2015; Oberfield and Raval, 2014; Antras, 2004; Hamermesh, 1990). This is a hard parameter to identify empirically, however. ICT improvements that facilitate the automation of tasks previously done by labor can directly reduce the labor share if worker displacement effects from the automated tasks outweigh increased demand for newly created non-automated tasks (Acemoglu and Restrepo, 2019).

non-traded sectors such as wholesale trade, retail trade, and utilities, where international 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 share of value-added generated by the most productive firms (‘superstars’) in each sector, those with above-average markups and below-average labor shares, grows. Such a rise in superstar firms would occur if consumers have become more sensitive to quality-adjusted prices due to, for example, greater product market competition (e.g., through globalization) or improved search technologies (e.g., greater availability of price comparisons on the Internet leads to greater buyer sensitivity, 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 and advances in information technology (e.g. Walmart’s massive investment in proprietary software to manage their logistics and inventory control—see Bessen, 2017; and Unger, 2019). The superstar firm framework implies that the reallocation of economic activity among firms with differing heterogeneous productivity and labor shares is key to understanding the fall in the aggregate labor share—implications that we test extensively below.

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. More 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 within an industry.⁴

³Blanchard (1997) and Blanchard and Giavazzi (2003) also stress labor market institutions. Azmat, Manning and Van Reenen (2012) put more weight on privatization, at least in network industries. Krueger (2018) emphasizes declines in worker power, such as through increased employer monopsony power.

⁴Exceptions 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, and Kehrig and Vincent (2018) who find results consistent with ours in a decomposition of U.S. Census of Manufactures micro data.

Second, we formalize a new “superstar firm” model of the labor share change. The model is based on the idea that industries are increasingly characterized by a “winner take most” feature where a small number of firms gain a very large share of the market.⁵ Third, we present a substantial body of evidence from the last 30 years using a variety of U.S. and international datasets that broadly aligns with the superstar firm hypothesis.

We establish the following seven facts that are consistent with our model’s predictions for how the rise of superstar firms can lead to a fall of labor’s share: (i) There has been a rise in sales concentration within four-digit industries across the vast bulk of the U.S. private sector, reflecting both the increased specialization of leading firms on core competencies and from large firms just getting bigger. The share of U.S. employment in firms with over 5,000 employees rose from 28 percent in 1987 to 34 percent in 2016.⁶ (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 and value-added 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 the industries that 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 U.S. but are also present in other OECD countries. The evidence presented here highlights the insights gained from taking a firm-level perspective on the changes in the labor share.

Our formal model, detailed below, generates superstar effects from increases in the toughness of product market competition that raise the market share of the most productive firms in each sector at the expense of less productive competitors. 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 information technology and intangible capital, such as software, could give large firms an advantage if there is a large overhead (or fixed) cost element to adoption or if the relative marginal product of infor-

⁵See Furman and Orszag (2015) for an early discussion. Berkowitz, Ma and Nishioka (2017) also stress the potential link of changes in market power and the labor share in an analysis of Chinese micro-data.

⁶Based on 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.

mation technology rises with firm scale.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 U.S. antitrust enforcement (Dotting, 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 be important in some specific industries (see Cooper et al, 2019, on healthcare for example).

Our paper is also closely related to Barkai (2017), 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 industry 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 with the evidence we present below on rising aggregate markups. Where Barkai's analysis uses exclusively industry-level and macro data, a major contribution of our micro-level approach is to explore the firm-level contributions to these patterns and link them to our conceptual framework, particularly the implications and evidence on between-firm (output reallocation) versus within-firm contributions to falling industry- and aggregate-level labor shares. We thus view our contribution and that of Barkai (2017) as complementary. Our work also corroborates and helps to interpret the observation of de Loecker, Eeckhout and Unger (2018) that the weighted average markup of price over variable cost has been rising in the U.S. (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 with both low labor shares and high markups. We confirm these patterns in our micro Census data.

In this paper, we build on earlier work (Autor et al, 2017b) by formalizing the superstar firm

⁷See Crouzet and Eberly (2018), Karabarbounis and Neiman (2018), Koh et al (2018), Aghion et al (2019), Lashkari, Bauer and Boussard (2019), and Unger (2019) for variants of this argument. Koh et al (2018) argue that the labor share would have declined little if investments into intangible capital were treated as expenditures rather than investments. However, the accounting treatment of intangibles cannot mechanically explain a decline in the payroll-to-sales ratio, or the rising concentration of sales which we find to be correlated with declining labor shares at the industry level. The fact pattern we document is more consistent with scale-biased technological changes in which larger firms benefit disproportionately from information technology advances such as falling computer software or hardware prices, and are thus able to increase their market shares, as emphasized by Unger (2019) and Lashkari, Bauer and Broussard (2019).

theory; presenting firm-level decompositions of the change in labor share; exploring cross-industry correlations of the change in labor share with changes in concentration and other factors influencing concentration; directly analyzing price-cost markups; examining international superstar firm patterns; and providing a quantitative characterization of U.S. superstar firms and their changing importance 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

We provide a formal model in Appendix A deriving conditions under which changes in the product market environment can increase the importance of superstar firms and reduce the labor share. 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.¹⁰ From the static first order condition for labor we can write the share of labor costs (wL_i) in nominal value-added ($P_i Y_i$) as:

$$S_i \equiv \left(\frac{wL_i}{P_i Y_i} \right) = \frac{\alpha^L}{m_i} \quad (1)$$

where $m_i = (P_i/c_i)$ is the markup, 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 markup is higher. Superstar firms (those with high z_i) will be larger as they produce more efficiently, charge lower prices and so capture a higher share of industry output. If they have

⁸A point of overlap with Autor et al (2017b) is that we again present U.S. industry concentration trends by broad sector. However, we have updated and expanded the earlier data by incorporating the full 2012 Economic Census.

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

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

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 markups for firms with a higher market share, $\omega_i = P_i Y_i / \sum_i (P_i Y_i)$. The reason 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 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 markups 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 markups are the same across all firms of whatever size and productivity ($m = \eta / (\eta - 1)$). In Autor et al (2017a), 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, the average labor share declines 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. Since the demand functions obey Marshall’s Second Law, we obtain the first result that larger firms will have lower labor shares.

¹¹Mrazova 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.

¹²See 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 markups for low cost firms. A smaller literature estimating cross sectional markups finds larger markups for bigger firms (e.g., de Loecker and Warzynski, 2012). Below, we empirically confirm this pattern in our U.S. Census data.

¹³Denote fixed overhead costs of labor F and variable labor costs V , with total labor cost $L = V + F$. 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 ($wF/P_i Y_i$) and lower observed labor shares (see Bartelsman, Haltiwanger and Scarpetta, 2013).

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 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 markup for any individual firm, labor shares at the firm level will *rise*. 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 that the aggregate labor share will indeed fall following this change in the economic environment if the underlying productivity density $\lambda(z)$ is log-convex, 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 productivity follows a Pareto distribution. 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 $\lambda(z)$ is 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 may seem counter-intuitive, the ambiguous relationship between concentration, profit shares, and the stringency of competition often arises 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

¹⁴The 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.

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 firms is global). We take these predictions to a series of newly constructed micro-datasets for the U.S. and other OECD countries.

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 or scale-biased technological change from information technology advances, as long as high market share firms have lower labor shares. 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 if incumbents are more likely to innovate than entrants (Gilbert and Newbery, 1982). 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 antitrust 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.¹⁵ The covered establishments in these six sectors comprise approximately 80 percent of both total employment and GDP. To implement our industry-level analysis, we assign each establishment in each year to a 1987 SIC-based, time-consistent, four-digit industry code. We need to slightly aggregate some four-digit SIC industries to attain greater time consistency in industry coding and end up with 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.¹⁶ 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.¹⁷ 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 includes information on value-added at the establishment level. Value-added

¹⁵Data coverage for the utilities and transportation sector and the finance sector begins in 1992. Within the six sectors, several industries are excluded from the Economic Census: rail transportation is excluded from transportation; postal service is excluded from wholesale trade; funds, trusts and other financial vehicles are excluded from finance; and schools (elementary, secondary, and colleges), religious organizations, political organizations, labor unions and private households are excluded from services. The Census also does not cover government-owned establishments within the covered industries, and we have to omit the construction sector due to data limitations. We also drop some industries in Finance, Services, and Manufacturing that are not consistently covered across these six sectors. See [Appendix D](#) for details.

¹⁶Additional 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.

¹⁷For the banking sector, for example, BEA calculates value-added from interest rate spreads between lending and deposit rates.

is calculated by subtracting the total cost of materials, supplies, fuel, purchased electricity, and contract work from the total value of shipments, and then adjusting for changes in inventories over that year. Thus, we can present a more in-depth analysis of key variables in manufacturing than in the other sectors.

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 calculated measures and those based on published data is almost perfect, however, when using the native but time-varying industry definitions.¹⁸

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.¹⁹

Second, we use data on industry imports from the UN Comtrade Database from 1992-2012 to construct adjusted measures of imports broken down by industry and country. To compare these data to the industry data in the Census, we convert six-digit HS product codes in Comtrade 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.²⁰

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,

¹⁸One 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.

¹⁹We choose the 2012 KLEMS release because subsequent versions of EU KLEMS are not fully backward compatible and provide shorter time series for many countries.

²⁰The 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.

and seeks to cover all non-financial corporations.²¹ 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.²² Consequently, we estimate specifications separately for each country and focus on a within-country analysis.

Fourth, to implement firm-level decompositions of the labor share 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 et al., 2015).²³

Finally, 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 also explore the characteristics of the largest firms within that group. Further details on data construction are reported in [Appendix D](#), and the Compustat analysis is found in [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.²⁴ Focusing in on the United States, Figure 2 presents three measures of labor’s share in U.S. manufacturing that can be aggregated from the micro establishment-level data in the U.S. Economic Census. We first construct the labor share using payroll, which is the standard labor cost measure that is available at the micro level for all sectors in the Economic Census, 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

²¹See Lopez-Garcia, di Mauro and CompNet Task Force (2015) for details.

²²Most 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. Consequently, countries differ in the fraction of employment or value-added included in the sample.

²³Unfortunately, due to partial reporting of revenues, BVD Orbis cannot be used to comprehensively construct sales concentration measures.

²⁴Of 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.

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 in the Economic Census. 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. Finance stands out as the only sector where there is a clear upward trend in the labor share. As discussed 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 2007 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 in the NIPA, 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 linked 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).²⁵ 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 sales-weighted average sales- and employment-based CR4 and CR20 measures of concentration across four-digit

²⁵Since we calculate concentration at the four-digit 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.

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). The two figures show a consistent pattern. First, there is a clear upward trend over time: according to all measures of sales concentration, 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 more weight to firms outside the top 20 where concentration has risen by less.

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 a four digit industry in the Census operated on average in 13 other four-digit industries in 1982, but this count fell to below nine 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 additional industries. By 2012, this fraction had fallen by a third to 0.24. Thus, the data suggest that companies like Amazon, which are becoming increasingly dominant across multiple industries, are the exception. Overall, firms are becoming more concentrated in their primary lines 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.

We next 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’ shares 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 across four-digit manufacturing industries for our sample window of 1982 through 2012. We begin with the manufacturing sector as these data are richest, but then present 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

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

where S_{jt} is the labor share of four-digit SIC industry j at time t , CONC_{jt} is a measure of concentration, τ_t is a full set of period 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 stacked five-year differences, and the last three columns present ten-year 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 (CR4, CR20, 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 for CR4 and CR20 and marginally significant (at the 10% level) for HHI where the estimates are less precise. The subsequent rows of Table 2 present 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, to account for a growing fraction of labor costs (Pessoa and Van Reenen, 2013). Row 3 uses an adjusted value-added measure (for the denominator of labor share) based on 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 market concentration using value-added rather than sales. Row 5 provides 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.²⁶ 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. 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 potential role of trade in explaining the fall in the labor share.

Karabarbounis and Neiman (2013) stress the the impact of falling investment goods prices on the declining labor share. To broadly 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 (2013) 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 falling industry-level average labor shares to rising concentration is not a simply a manifestation of differential trends according to industry capital intensity.

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, are the appropriate metric for concentration, not employment. Indeed, many of the canonical superstar firms such as Google and Facebook employ relatively few workers compared to their market capitalization, underscoring that 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-

²⁶This is a minor concern in non-manufacturing sectors, where there are comparatively few imports.

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 models for five year changes in the first three columns, all coefficients remain negative, statistically significant, and quantitatively similar.²⁷

Figure 6 plots the coefficients (and 95% confidence intervals) 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 (corresponding to 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 relationship is 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.²⁸ 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

²⁷Table 1 indicates that the average start-of-period level and the average five-year change of payroll over value-added (31.7% and -2.2%, respectively) are slightly more than twice as large as the level and change of payroll normalized by sales (13.6% and -0.9%, respectively) in manufacturing. Similarly, the coefficients on concentration are just over twice as large in the regression that measures the labor share as payroll over value added instead of payroll over sales (e.g. -0.148 for the CR4 in column (1) of Table 2 compared to -0.062 in Table 3).

²⁸To 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.

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 sectors.²⁹ 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.

Robustness tests

We have implemented many robustness tests on these regressions and discuss several of them here. First, we repeated the robustness tests applied to manufacturing in Table 2 for the full set of six sectors to the extent that the data permit. For example, following the model of row 5 of 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 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 than in the complementary set of non high-tech sectors.³⁰

Third, 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

²⁹For 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. The correlation between changes in CR1 and payroll over sales is also negative in each of the other five sectors, and significant in all sectors but retail.

³⁰We 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 at -0.067, with a standard error of 0.031.

sample period. Outside of manufacturing the same broad patterns emerge: a negative relationship is evident across most years and tends to become stronger over time.

IV.B Between-Firm Reallocation Drives the Fall in the 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 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 can be applied readily to the labor share.³¹ We write the level of the aggregate labor share in an industry (or broad sector) as

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

where the size-weight, ω_i , is firm i 's share of value-added in the industry (or broad sector), $\omega_i = P_i Y_i / \sum_i P_i Y_i$, \bar{S} is the unweighted mean labor share of the firms in the industry (or broad sector), and $\bar{\omega}$ is the unweighted mean value-added share.³²

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:

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

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

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

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

³¹Melitz and Polanec (2015) generalize the Olley and Pakes (1996) productivity decomposition to allow for firm entry and exit.

³²The 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.

$t = 1$). 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, $\Delta [\sum (\omega_i - \bar{\omega}) (S_i - \bar{S})]_S$, 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.

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.

In addition to the reallocation effect among incumbent survivors 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 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 Panel A, 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). Panel B 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.³³ Figure 8 plots the Melitz-Polanec decomposition for each sector cumulated now over the entire sample period for which data are available (i.e., 1982-2012 for the first four sectors in the figure and 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 in this sector (4.54 percentage points) is almost three times as large as the within-firm component (1.71 percentage points) for payroll over sales for the full 1982-2012 period. Echoing the findings in manufacturing, we find that the between-incumbent reallocation effect contributes to the decline in the payroll share in each of the other five sectors. 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 and raises the labor share 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.

³³The 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.

Robustness of the Decomposition Analysis

We next examine the robustness of our decomposition findings (with further probes considered in [Appendix D.5](#)). Our baseline decomposition analysis is performed at the level of the entire firm (within a sector). Although 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.³⁴ Additionally, since firms may span multiple industries, some of the reallocation we measure in the baseline decomposition may reflect shifts of firm activity across four-digit industries.

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 both the establishment level (Panel A) and the firm-by-four-digit SIC industry level (Panel B).³⁵ 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 survivor reallocation term.³⁶

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).

To assess the magnitude of the between-industry reallocation in our baseline firm-level decomposition, we perform an extended decomposition that explicitly distinguishes shifts that occur between four-digit industries from those that take place between firms within an industry. We first use a standard shift-share technique to decompose the overall change in the labor share into between-industry $\sum_j (\tilde{S}_j \Delta \omega_j)$ and within-industry $\sum_j (\tilde{\omega}_j \Delta S_j)$ components:

$$\Delta S = \sum_j (\tilde{S}_j \Delta \omega_j) + \sum_j (\tilde{\omega}_j \Delta S_j). \quad (6)$$

³⁴For example, when a firm is taken over, its establishments are reallocated to those of the acquiring firm, leading to an “exit” of the acquired firm even though its establishments do not exit the economy. On the other hand, an incumbent firm creating a new greenfield establishment is not counted as firm entry.

³⁵The latter is the same definition used in [Tables 2](#) and [3](#) linking changes in labor shares to changes in industry-level concentration.

³⁶Additionally, 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 4](#) and [5](#).

Here, \tilde{S}_j is the time average of the (size-weighted mean) labor share in industry j , S_j , over the two time periods, and $\tilde{\omega}_j$ 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 of equation (5) to split up the within-industry $\sum_j (\tilde{\omega}_j \Delta S_j)$ contribution into its four parts (details are in [Appendix D](#)).

We show the components of this five way decomposition in [Tables A.2 and A.3](#). The two panels of [Table A.2](#) report payroll over value-added and compensation over value-added (in manufacturing), while the six panels of [Table A.3](#) are for payroll over sales (in all six sectors). The main qualitative finding is that the fall in the labor share is dominated by a *within-industry* between-firm reallocation. In some sectors, 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 -0.2 as compared to -5.5 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 in line with those of Kehrig and Vincent (2018), who extensively analyze changes in the labor share in manufacturing using full distributional accounting techniques. Like us, Kehrig and Vincent (2018) find that the 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 for by between-firm reallocation of value-added and 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 as superstar firms capture market share through their high relatively high productivity and toughening competition. If rising concentration reflects weakening competition, we would instead expect to see a general rise in markups, 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 four-digit 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 within-incumbent 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 between-incumbent reallocation 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.³⁷

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). And 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 output 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. Following the literature (e.g., de Loecker, Eeckhout and Unger, 2018), we can estimate markups by re-arranging and generalizing equation 1:

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

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, and α_{it}^v is the output elasticity with respect to factor v . This result requires only that firms minimize cost; it therefore allows for non-constant returns and more general technologies (see Hall, 1988, 2018). Although factor shares (S_{it}^v) are, in principle, directly 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:

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

where f indicates that 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 (2017), among others. We call this the “accounting approach” as it does not rely on an econometric estimation. A second approach to recovering markups is to estimate α_{it}^v from a production function as recommended by

³⁷The covariance term in the shift-share analysis ($\sum [\Delta\omega_i \Delta S]_S$) is a non-trivial component although it does not seem related to increases in concentration. The magnitude of the covariance term appears to be sensitive to outliers due to the fact is it the product of two differences..

de Loecker and Warzynski (2012). This approach 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 the methods of Levinsohn and Petrin (2003) and Akerberg, Caves and Frazer (2015). 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 in case of multi-plant firms.

Results

We summarize the results of these exercises here, and provide further details in [Appendix B](#). Before exploring trends, [Appendix Figure A.4](#) confirms that larger firms have higher markups, no matter how they are estimated. 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 average markup, the figure also indicates the median markup (green diamonds) and unweighted average markup (blue circles). Panel A uses the accounting the accounting approach of equation (8). 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 Akerberg, Caves, and Frazer (2015) method of estimating a Cobb-Douglas. Panel D continues using the Akerberg, Caves, and Frazer (2015) method but generalizes Panel C by estimating 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 markup always exceeds the unweighted markup (and the unweighted mean is above the median), reflecting the fact that larger firms have higher markups. 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.³⁸ Third, across all methods, the aggregate markup has risen much

³⁸Figure 11(a) of de Loecker, Eeckhout, and Unger (2018) 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 not for the Census

more quickly than that of the typical firm. Indeed, median markups are flat or even falling in some specifications. Rising aggregate (weighted-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. The pattern underscores the centrality of superstar firms for the evolution of the markup consistent with the findings in de Loecker, Eeckhout, and Unger (2018) and Baqaee and Farhi (2020). We further explore the evolution of markups and subject our findings to many other robustness tests in [Appendix B](#).³⁹

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. 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 functions 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. [Figure A.3](#) shows that large firms have higher labor productivity in all six sectors that we consider. The finding 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 employing 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

data, so our Census production function based results are distinctive. De Loecker, Eeckhout, and Unger (2018) 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), whereas we use the approach of Antras, Fort, and Tintelnot (2017). Despite these methodological differences, it is reassuring that both sets of markup estimates tell the same story.

³⁹Edmond, Midrigan, and Xu (2015) argue that input-weighted markups are a better welfare related measure than the output-weighted markups shown here (as in de Loecker, Eeckhout, and Unger, 2018). A practical problem in Census data is that we cannot observe some potentially quantitatively important fixed inputs (e.g. relating to intangible capital). Thus the input bundle will be underestimated and this may be systematically worse for larger, high markup firms (as shown in de Loecker, Eeckhout, and Unger, 2018, using Compustat data). Fortunately, using input weights gives the same qualitative patterns as [Figure 10](#), though there are quantitative differences. For the production function based methods, the changes are practically identical to those shown in Panels B-D. For the accounting based method, the increase in the aggregate markup is smaller over our time period (about half the size of that in Panel A).

are proxies for industry dynamism.⁴⁰ 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. 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 input growth in these concentrating industries. Indeed, we do find that the concentrating industries experience 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.⁴¹

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. The results suggest that the industries exhibiting rising concentration are more dynamic as measured by innovative output and productivity growth.⁴²

⁴⁰All regressions are weighted by the initial size of the industry, include year dummies and cluster standard errors by industry as in Tables 2 and 3.

⁴¹This TFP measure is measured as a Solow-style residual based on deducting the cost-weighted inputs from deflated output. We 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 similar, since all TFP measures are strongly and positively correlated with each other.

⁴²This evidence is consistent with the evidence across OECD countries in Autor and Salomons (2018), who find

The positive correlation between changes in concentration and productivity supporting the superstar firm mechanism implies that the reallocation of sales and value-added towards the most productive firms 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.⁴³ 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, leading to superstar effects without large gains in aggregate productivity.

IV.F Superstar Firm Patterns are International

The final empirical implication of the superstar framework that we test here is that the patterns we document in the U.S. should be observed internationally. Karabarounis and Neiman (2013) and Piketty (2014) showed 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. The precise mechanisms leading to rise in superstar firms and decline in labor share may include platform competition,

that the labor share fall was greater in those industries where TFP growth had been most rapid. If we regress the change in the labor share on five-factor TFP growth in our data, 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).

⁴³ 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.

adoption of more intangible capital by leading firms, scale-biased technical change from information technology advances, or toughening market competition, as formalized in the model in [Appendix A](#). An alternative interpretation of these patterns is offered by Dottling, Gutierrez, and Philippon (2017), who argue that *weakening* U.S. antitrust enforcement has 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 such U.S. specific institutional explanations. Indeed, as Dottling, Gutierrez, and Philippon (2017) emphasize, antitrust enforcement has, if anything, strengthened in the European Union—and yet the labor share appears to have fallen and industry concentration appears to have risen in the European Union despite this countervailing force.

Concentration in the OECD

The construction of comprehensive data on changes in sales concentration over time across countries is challenging. The most comprehensive source for such an analysis is “Multiprod”, an internal 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 U.S. 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 decile 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, Bajgar et al (2018a) also look at an alternative market definition that considers Europe as a single market. Under this definition, they also find that concentration levels have risen, akin to our findings for the United States.⁴⁴

⁴⁴Dottling, Gutierrez and Philippon (2017) have argued the opposite—that concentration has been falling in the EU. Bajgar et al (2018b) trace the discrepancy to Doting 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 Doting 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.

Correlation of Industry Labor Shares

Figure 1 documented the pervasive decline in the labor share across several OECD countries. Looking beyond these time series relationships, we perform a cross-national industry-level and firm-level analysis. We first explore the cross-country correlations of the labor share (measured in levels) for the 32 industries that comprise the market sector using international KLEMS data. Figure A.10 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 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. As expected, the correlations in changes are weaker than those in levels, but the bulk of the evidence still indicates that declines in the labor share tend to occur in the same industries across countries: the average correlation is positive for each country, and there is a positive correlation across industries between country pairs in over three-quarters of all cases (51 of 66). The correlation matrices underlying these summary tables are reported in 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 an 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 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) long differences separately for the 14 countries in the database. The estimates, reported in Appendix Table A.8, find 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. However, the

coefficients are imprecisely estimated, and the majority are insignificant for the five-year changes. 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, the best available source for comparable, cross-national *firm-level* data. Orbis is a compilation of firm accounts in electronic form from many countries. Accounting regulations and Orbis coverage differ across countries and time periods, however, so we confine the analysis to a set of six OECD countries for which reasonable quality data are available for the 2000s. We decompose changes in labor share into between- and within-firm components, using the earliest five-year periods with comprehensive data (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.11 reports the Olley-Pakes decomposition for the manufacturing sector for all six countries.⁴⁵ 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. The 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 in Different Countries

There has also been considerable recent work on markups using firm-level data across countries (Calligaris et al, 2018; de Loecker and Eeckhout, 2018). The findings appear consistent with the patterns that we document for the United States, 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 (and 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 cross-national findings mirror the evidence from the more detailed U.S. data: (i) con-

⁴⁵We focus on manufacturing as measurement of the labor share is more reliable for this sector. Table A.9 shows the details of the data and the decomposition.

centration has generally risen across the OECD; (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; (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 (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 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 presented evidence that is qualitatively consistent with the seven empirical predictions of the superstar firm framework, importantly by documenting the central role of between-firm reallocation in (proximately) driving the labor share decline. A remaining question is how *much* of the fall of the labor share is due to the underlying change in competitive, technological, or regulatory conditions that give rise to superstar firms. In the absence of an explicit and cleanly-identified quantitative macro model, it is difficult to precisely answer this question.⁴⁶

To shed some light on the magnitudes, we perform 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, $\Delta \ln S = -\Delta \ln m + \varsigma$. The Cobb-Douglas production function underlying equation (1) implies that $\varsigma = \Delta \ln \alpha^L$, implying the change of the labor share unexplained by the markups is due to the changing output elasticity of labor.⁴⁷ We can implement this approach only for manufacturing, where we have the data necessary to properly measure markups (see subsection IV.D). Using Table 4, the proportionate fall in the labor share of value added ($\Delta \ln S$) is 40 percent (a 16.1 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 (17/40) of the labor share change.⁴⁸ By contrast, using the production function based measures of the

⁴⁶Karabarbounis and Neiman (2018) quantitatively evaluate alternative macro-models of the labor share decline.

⁴⁷See Nekarda and Ramey (2013) for what determines the labor share under more general models. For example, if the production function is CES then $\varsigma = \Delta \ln \alpha^L + \Delta \left(\frac{1}{\sigma} - 1\right) \ln(PY/B^L L)$ 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.

⁴⁸Although 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.

markup, we account for essentially *all* of the labor share change (e.g., in Panel B of Figure 10, the growth of the markup is 50 percent (0.6/1.2) and greater than the change in the labor share). Alternatively, we can use the input-weighted aggregate markups to do these calculations. For the production function based methods, the results are basically identical for the output weighted methods of Figure 10. For the accounting based method, this reduces the proportion of the labor share by about half (to 18.5 percent).

A second approach to benchmarking magnitudes 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 1982-2012 period is $\Delta\hat{S} = \sum_k \left(\omega_k \hat{\beta}_k \Delta\text{CONC}_k \right)$ where k indicates the six broad sectors, $\hat{\beta}_k$ 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 Figure 4) is -0.97 percentage points, as compared to an overall fall in the labor share of -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).⁴⁹ 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.⁵⁰

We stress that all of 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 are economically important.

⁴⁹If 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.

⁵⁰This 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.5). 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.5, the average coefficient relating the change in concentration to the change in labor share in manufacturing over this period was -0.34 , implying that concentration explained $\left(\frac{-0.34 \times 6}{6} \right) \times 100 = 34\%$ of the fall in the labor share in manufacturing over this period.

V Further Descriptive Evidence on Superstar Firms

The previous section documented evidence supporting 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 of total import intensity.⁵¹ They conclude that the offshoring of 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. 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 period when import growth slowed considerably. The first three columns of Table A.10 corroborate the well-documented finding that industries that were more exposed to Chinese imports had significantly greater falls in sales, payroll and value-added. The next three columns find a largely positive correlation between the growth of Chinese import penetration and the rise of industry concentration, although this relationship is imprecisely estimated and significant only for the period through 2007. The last two columns find that an increase in Chinese imports predicts a *rise* in industry labor share (though this relationship is weak prior to the Great Recession). While this result is unexpected in light of Elsby, Hobijn and Sahin (2013), it is implied by the estimates in columns (1) through (3). Since 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 sales, the labor share of sales or value-added tends to rise with growth of industry import exposure.⁵²

⁵¹They 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 United States to produce all goods domestically.

⁵²A 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 only. 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 than non-manufacturing. Within manufacturing,

V.B Compustat Analysis: Publicly Listed Superstar Firms

Although the micro data from the Economic Census has the advantage of being comprehensive, the confidential nature of Census data means we are not permitted to illustrate the key fact patterns with specific examples of superstar firms. Our Census data also do not report on the international activity of the superstar firms. To provide such examples and explore the international scope of these superstar firms, we turn to Compustat data, which contain company accounts of firms listed on U.S. stock markets. The details of these data and analysis are provided in [Appendix C](#). Focusing on the largest 500 U.S. based firms in Compustat, as defined by their worldwide sales, we highlight four facts.

First, the average size of the largest 500 U.S. firms has increased substantially over time. For example, between 1972 and 2015, the average firm tripled in size as measured by real sales, and it grew by a factor of six in terms of real market value.⁵³ Average employment in the top 500 also expanded. 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.⁵⁴

Second, concentration has risen *among* the top 500 superstar firms, especially since 2000. For example, the share of the 50 largest firms in total sales of the top 500 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 also has risen.

Third, the increase in concentration has been accompanied by an increasing persistence of the same firms among the top 500 largest by sales, with churn rates falling since 2000 (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

cross-industry variation in import exposure appears to have little explanatory power for the fall in the labor share. Of course, rising import exposure cannot readily explain why labor’s share has fallen outside of manufacturing.

⁵³Sales and market values are deflated by the Consumer Price Index and reported in constant 2015 dollars.

⁵⁴We find that the ratio of the largest 500 firms’ sales to U.S. gross output declined sharply during the 1980s, and then grew rapidly during the 1990s and 2000s. Gutierrez and Philippon (2019) find a similar pattern for the ratio of the top 20 firms’ sales relative to U.S. GDP. Some of this pattern is the consequence of fluctuations in the oil price, which led to a rapid growth in oil firms’ sales in the 1970s, and a decline in the 1980s. If the oil sector is omitted from the analysis, then the ratio of top firms’ sales to U.S. output in the 2000s is well above its values in the 1980s and 1990s.

share of sales outside of the U.S. for superstar firms grew from 21 percent to 37 percent from 1978 to 2012, before declining slightly from 2012 to 2015.

The evolution of the labor share is harder to explore in Compustat data because only a minority of firms reports payroll data (which is not a mandatory reporting item). Looking among the firms that do report payroll, we find a sizable decline of the labor share from nearly 60% in the early 1980s to 47% in 2015. The decline is of similar magnitude for firms with stronger and those with weaker global engagement, defined as having a share of foreign sales above or below the industry median (see also Hartman-Glaser, Lustig and Zhang, 2017). 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. Thus, globalization, construed narrowly, appears unlikely to be the main driver of falling labor shares.

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 had little presence), and in countries where union power has not fallen so steeply as in the United States, somewhat mitigate against this hypothesis. Alternatively, the growth of superstar firms could confer more monopsony power to employers, negatively impacting both wages and employment. In row 5 of Panel A in Table 6, we find that the relationship between changes in concentration and changes in average wages (payroll per worker) in manufacturing is, in fact, slightly 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.⁵⁵

The sixth row of Panel A in Table 6 shows that concentrating industries in manufacturing have moved towards an increased reliance on materials inputs, consistent with greater intermediate

⁵⁵Payroll per worker is a crude measure of the price of labor that does not account for compositional changes (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, 2017; Gutierrez and Philippon, 2018), the trends in local concentration are less clear cut. For example, Benmelech, Bergman, and Kim (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, Bergman, and Kim (2018) contains employment but not sales data. The NETS database used by Rossi-Hansberg, Sarte, and Trachter (2018) contains a large number of imputed establishment-level sales values.

goods outsourcing. We suspect these concentrating industries are also relying more on intermediate service outsourcing, especially for low paid workers as in Germany (Goldschmidt and Schmieder, 2017). Unfortunately, the Census data do not report direct information on service inputs.

VI Conclusions

This paper proposes and evaluates evidence for a new “superstar firm” explanation for the 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 show that, consistent with a simple model, 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 (sector-wide) 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 is rising across a large set of industries. Second, those industries where concentration has risen the most exhibit 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 becoming 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.

In combination, the set of robust and cohesive firm-level, industry-level, and cross-national facts documented here are ones 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 are 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 increasingly

a “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 needs to 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 contract a wider range of activities previously done in-house to third party firms and independent workers. Such activities may include janitorial work, food services, logistics, and clerical work (Weil, 2014; Goldschmidt and Schmieder, 2017; Katz and Krueger, 2019). The 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. It 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.

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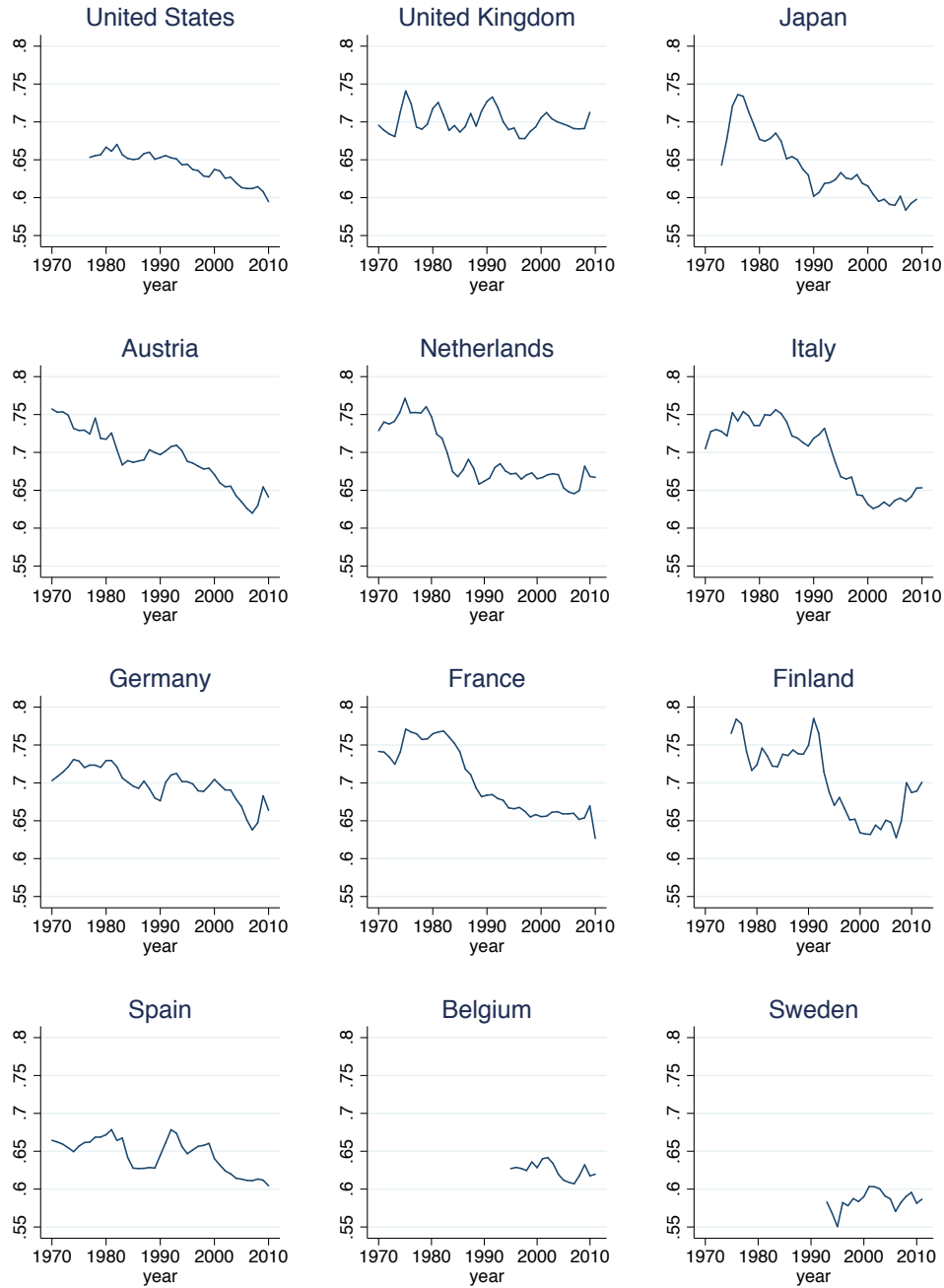
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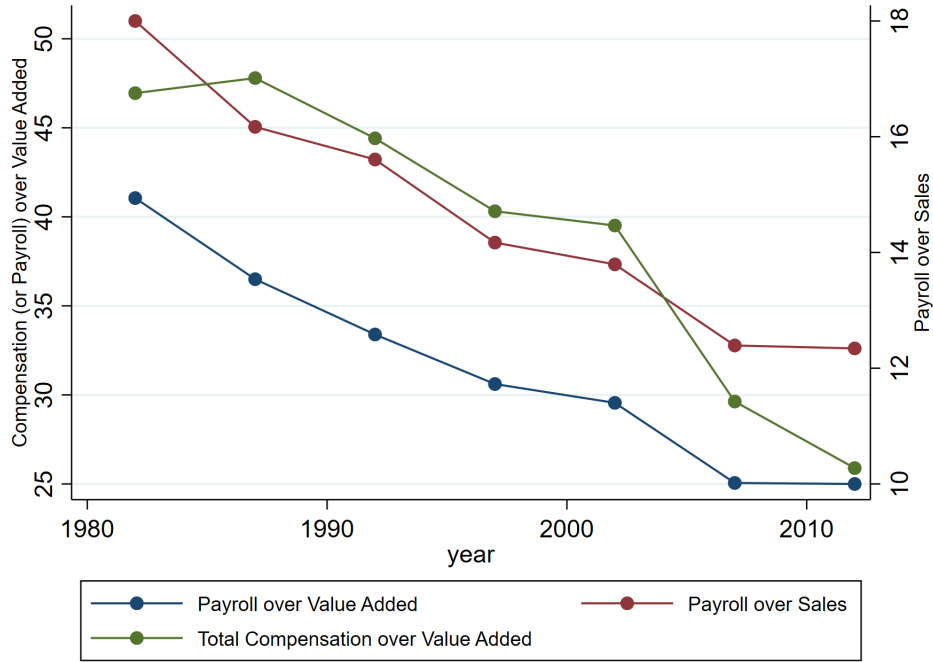
Figures and Tables

Figure 1: International Comparison: Labor Share by Country



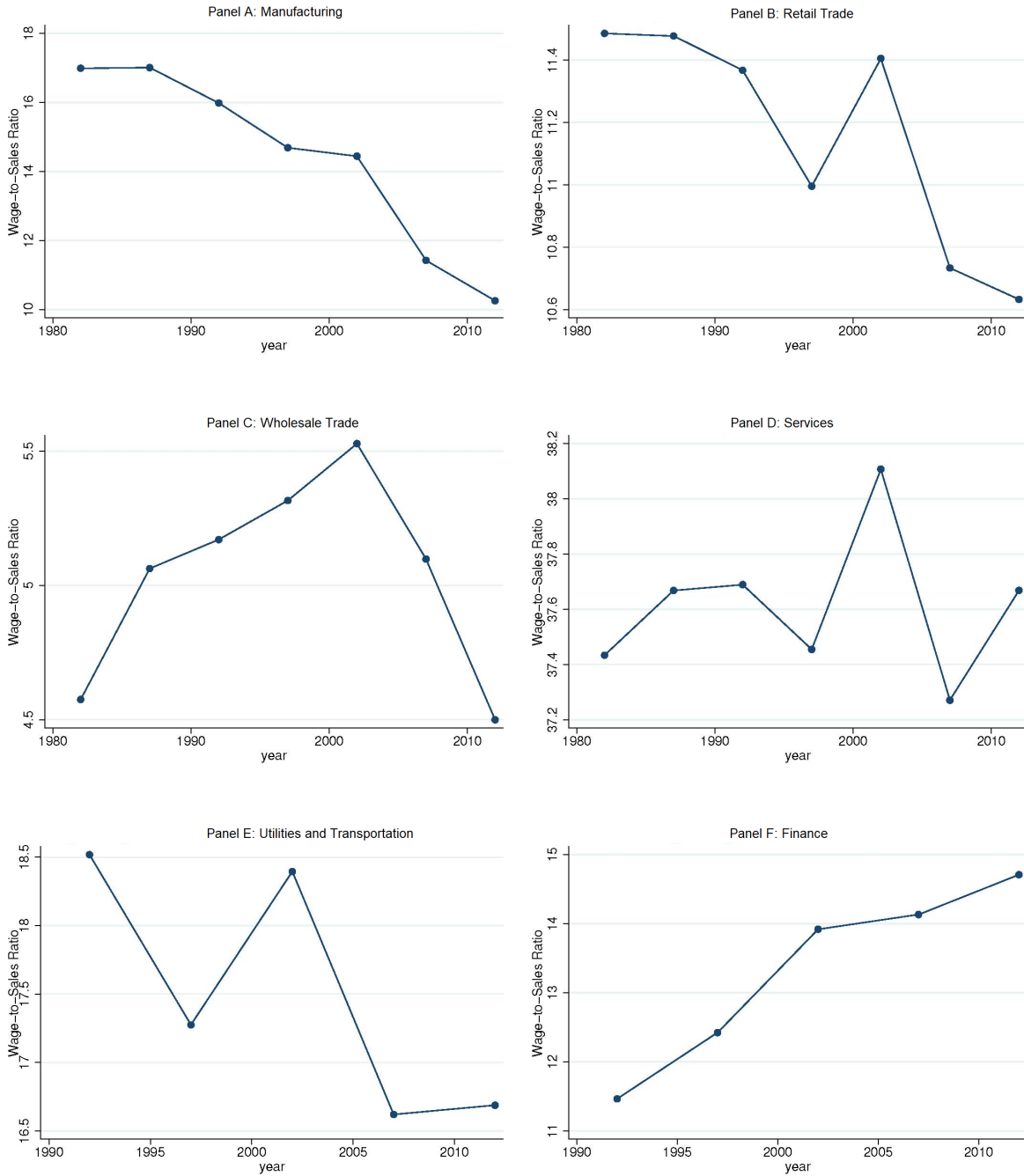
Notes. Each panel plots the ratio of labor compensation to gross value-added for all industries. Data is from EU KLEMS July 2012 release.

Figure 2: The Labor Share in Manufacturing



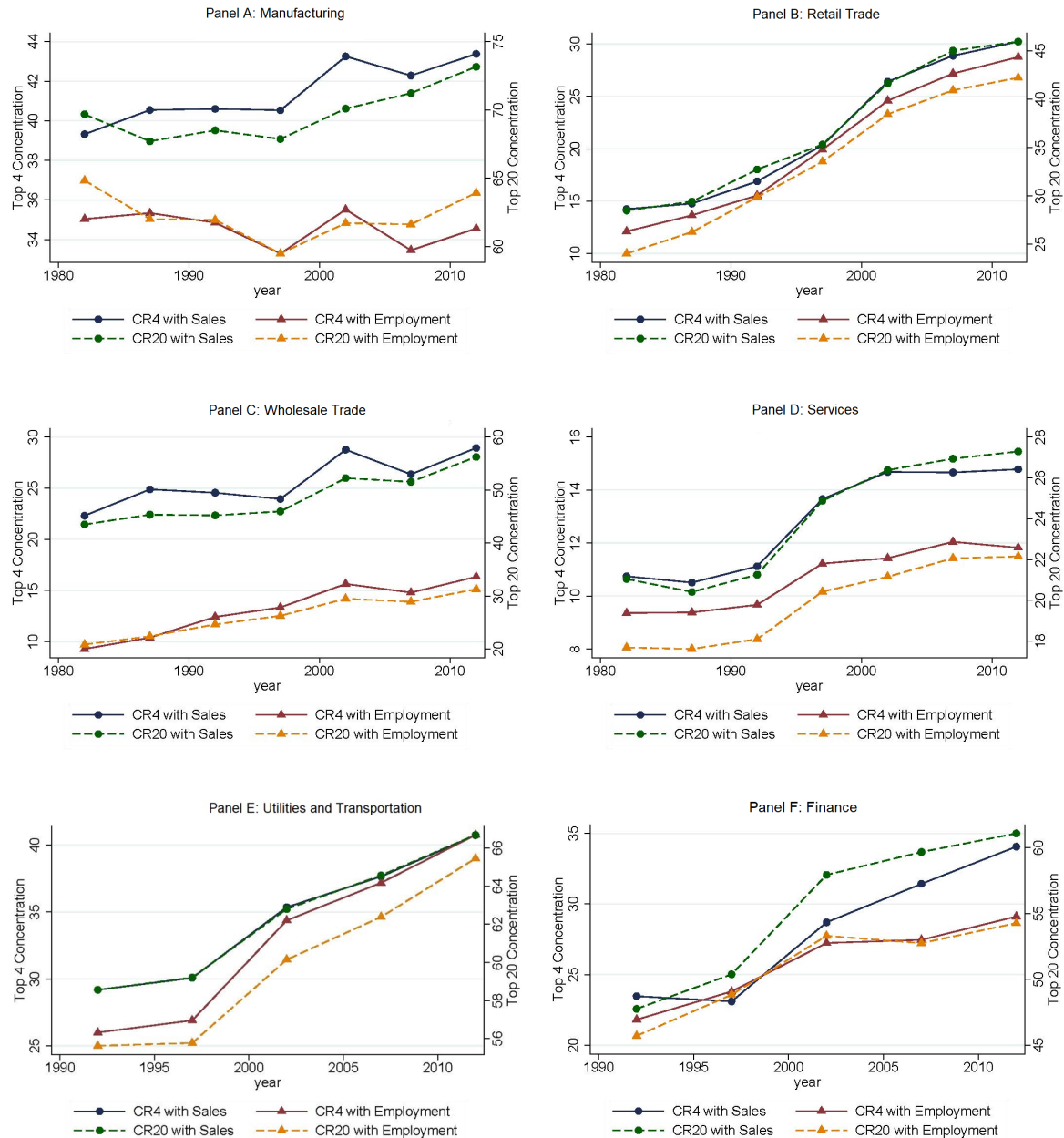
Notes. This figure plots the aggregate labor share in manufacturing from 1982-2012. The green circles represent the ratio of wages and salaries (payroll) to value-added (plotted on the left axis). The red diamonds include a broader definition of labor income and plots the ratio of wages, salaries and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

Figure 3: Average Payroll-to-Sales Ratio



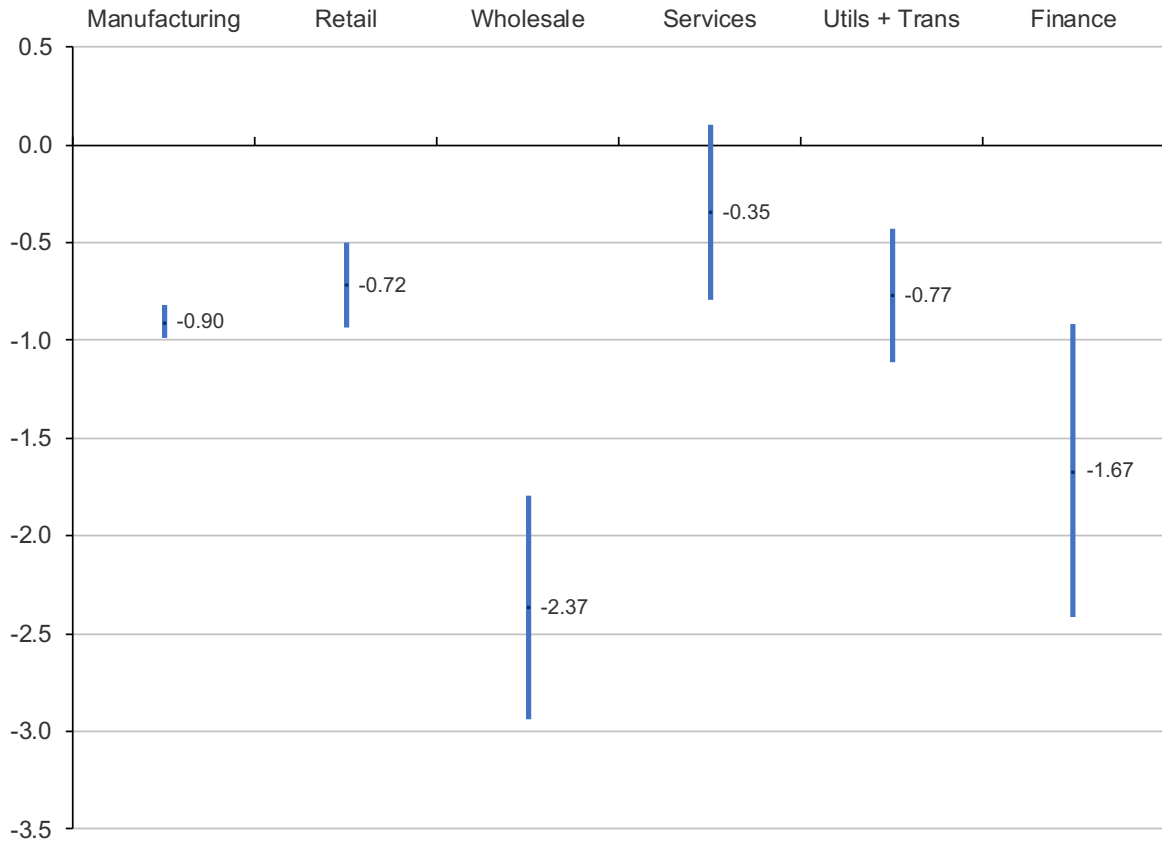
Notes. Each panel plots the overall payroll-to-sales ratio in one of the six major sectors covered by the U.S. Economic Census. These figures update Autor et al (2017a) to include more recently released Census data.

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



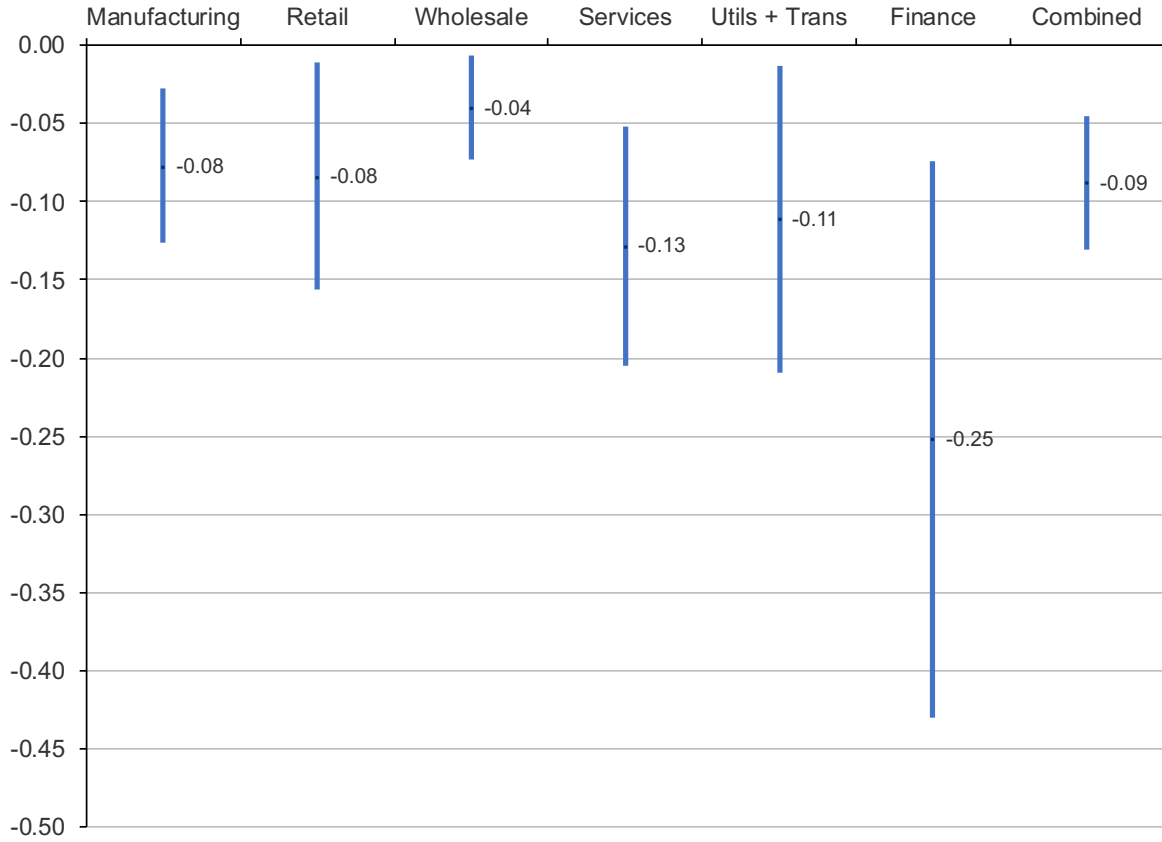
Notes. This figure plots the average concentration ratio in six major sectors of the U.S. economy. Industry concentration is calculated for each time-consistent four-digit industry code, and then averaged across all industries within each of the six sectors. For both sales and employment concentration, each industry is weighted by its share of total sales within the sector. 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



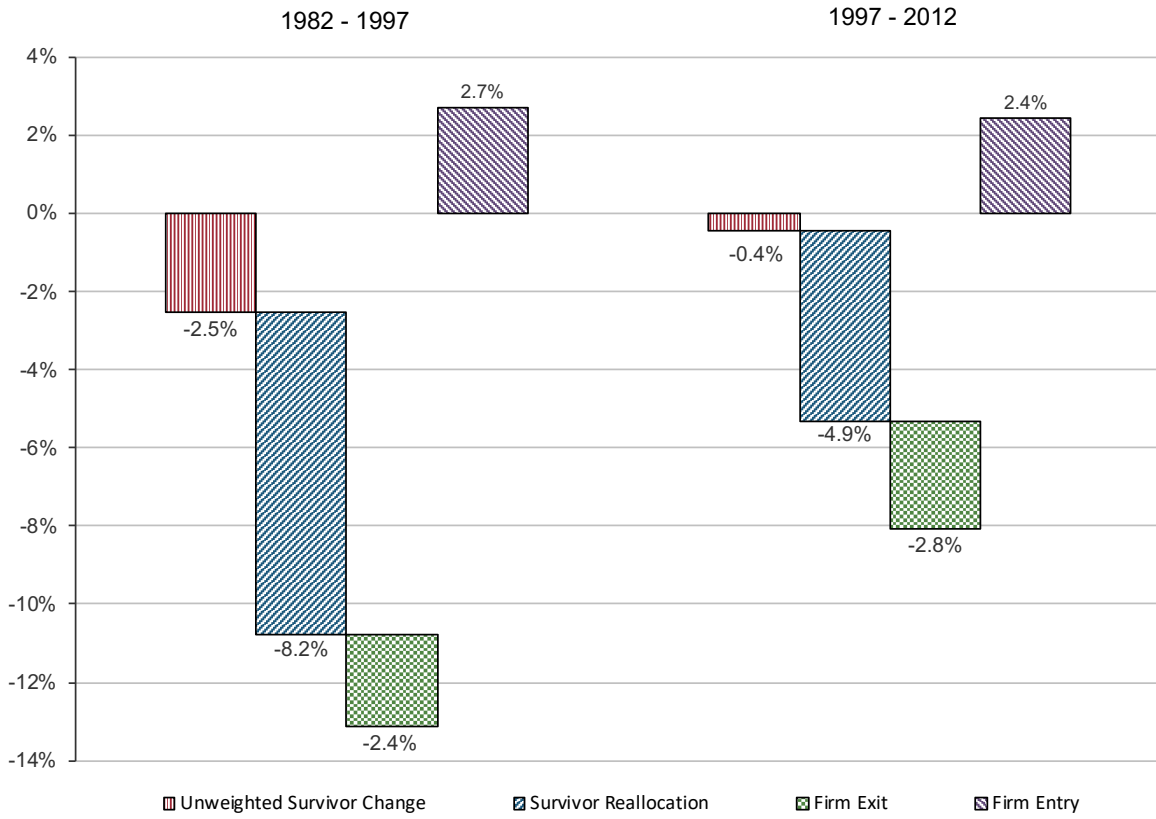
Notes. The figure indicates OLS regression estimates that relate the level of a firm's labor share (payroll-to-sales ratio) to its share of overall sales in its four-digit industry. The six sector-specific regressions include all years available for that sector, and control for year fixed effects. Industries are weighted by their sales in the initial year. Dots indicate coefficient estimates and lines indicate 95% confidence intervals based on standard errors clustered at the four-digit industry level.

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



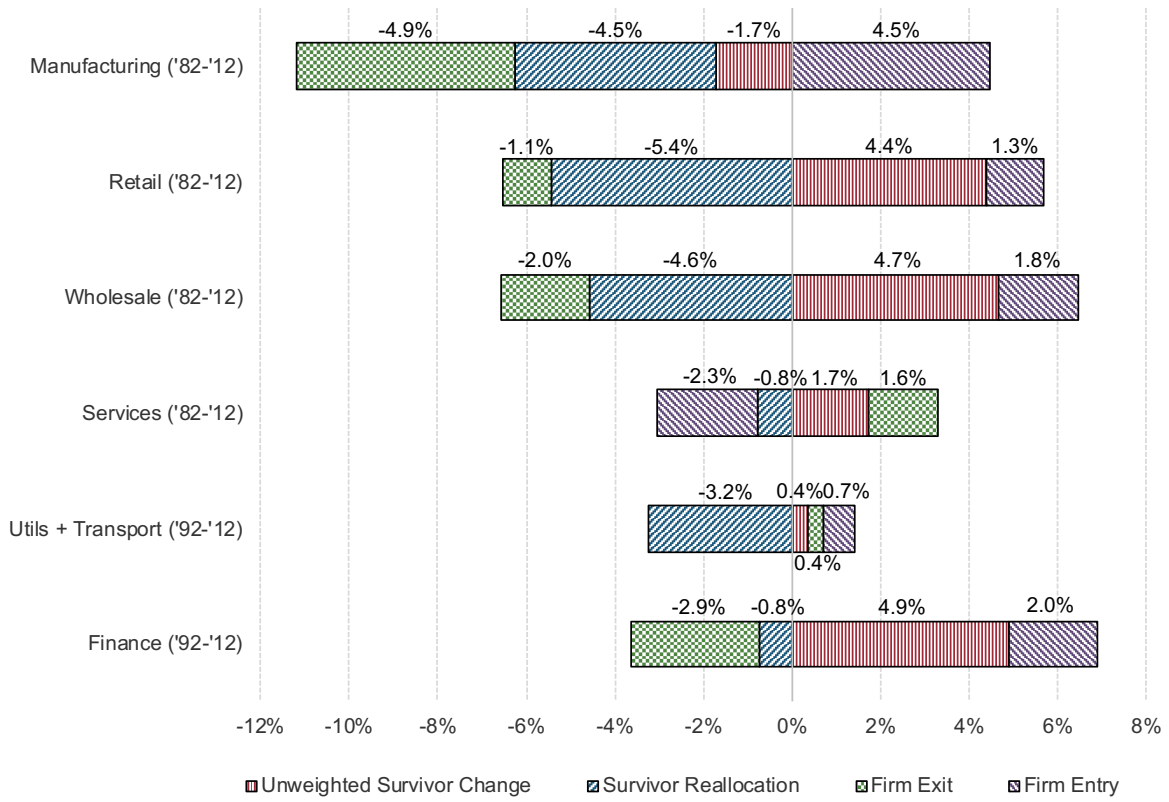
Notes. The figure indicates OLS regression estimates that relate Δ Labor Share (payroll over sales) to Δ CR20. The six sector-specific regressions include stacked five-year changes from 1982 to 2012 (1992 to 2012 in Utilities/Transportation and Finance) and control for period fixed effects. Industries are weighted by their sales in the initial year. Dots indicate coefficient estimates and lines indicate 95% confidence intervals based on standard errors clustered at the four-digit industry level. . The estimates in this figure correspond to panel A column (2) of Table 3, which also tabulates the full regression results using alternative specifications.

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



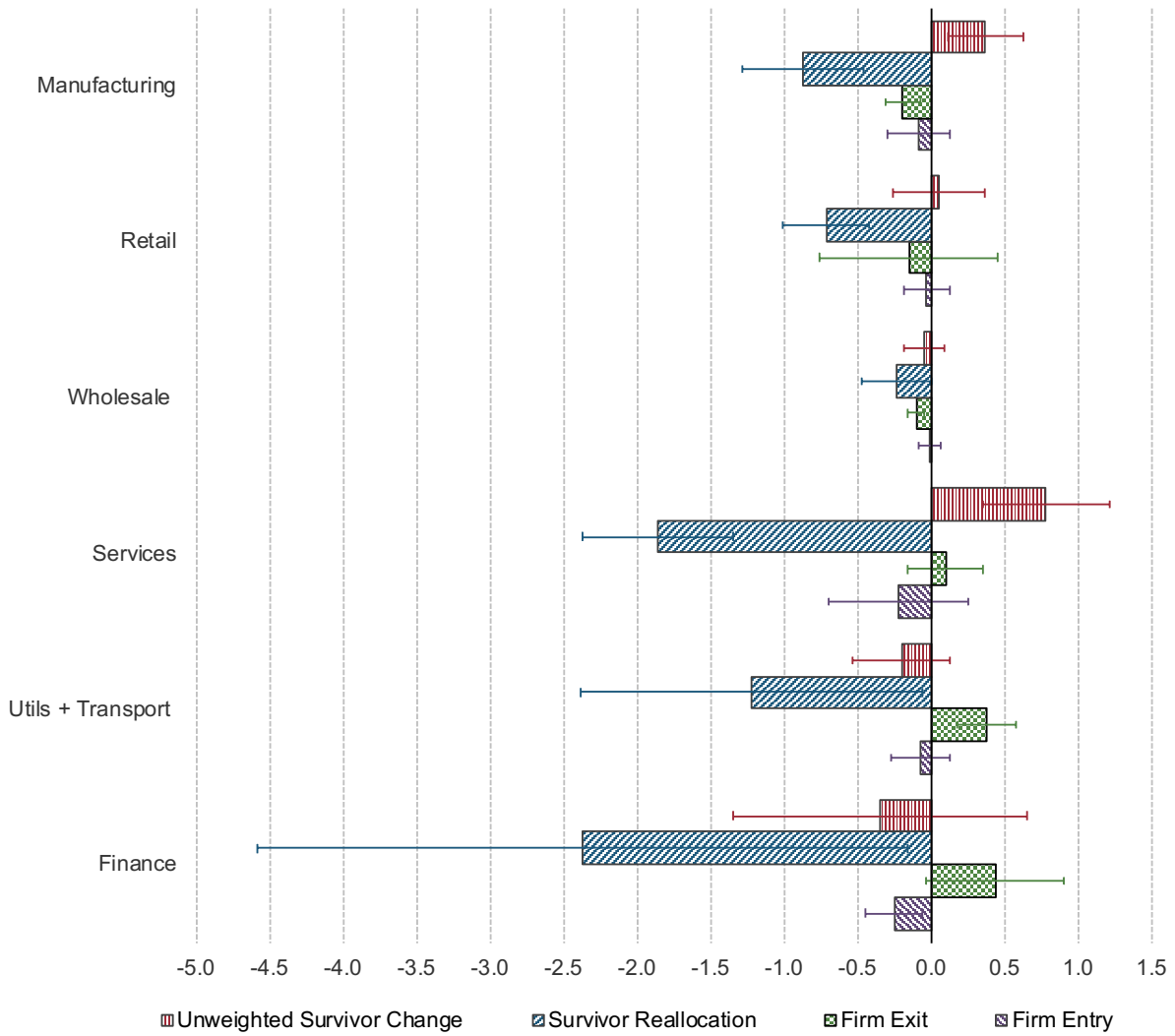
Notes. Each bar represents the cumulated sum of the Melitz-Polanec decomposition components calculated over adjacent five-year intervals for payroll over value-added. The left panel shows the sum of the decompositions from 1982-1987, 1987-1992 and 1992-1997 and the right panel shows the sum of the decompositions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

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



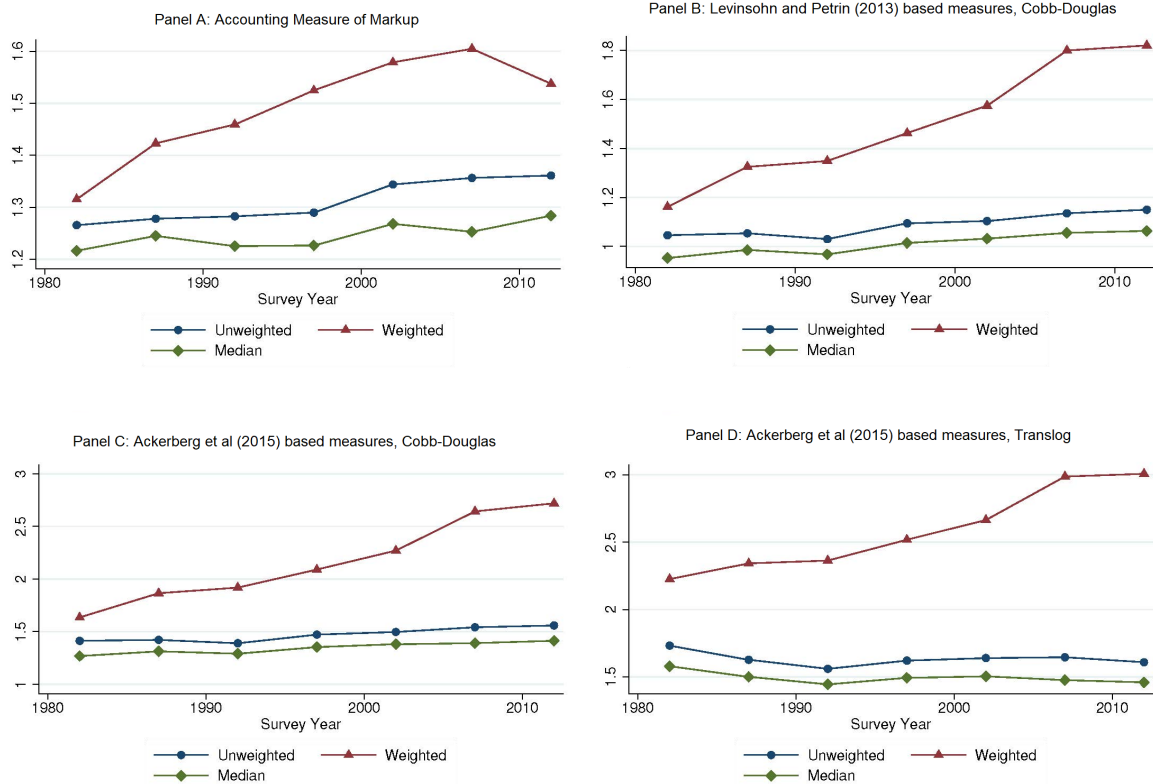
Notes. Each bar represents the cumulated sum of the Melitz-Polanec decomposition components calculated over adjacent five-year intervals for payroll over sales. Table 5 reports the underlying estimates for each five year period.

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-Polane 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 intervals.

Figure 10: Markup Changes



Notes. Each panel indicates 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 the Antras et al (2017) “accounting” method, while Panels B-D use production function methods following de Loecker and Warzynski (2012) where we estimate industry specific production functions for two-digit SIC industries. In Panels B and C, the production function is assumed to be Cobb-Douglas and in Panel D it is assumed to be translog. Panel B uses the Levinsohn-Petrin (2003) approach and Panels C and D use the Akerberg 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

	Establish- ments (1)	Firms (2)	Payroll to Sales (3)	Δ Payroll to Sales (4)	Payroll to Value- Added (5)	Δ Payroll to Value- Added (6)	CR4 (7)	Δ CR4 (8)	CR20 (9)	Δ CR20 (10)
<i>A. Manufacturing</i> (388 industries, 2,328 obs)	183,400 (12,560)	141,300 (11,490)	13.58 (8.15)	-0.92 (2.10)	31.65 (12.27)	-2.18 (5.35)	42.97 (21.66)	1.00 (7.08)	72.33 (22.04)	0.87 (4.50)
<i>B. Retail Trade</i> (58 industries, 348 obs)	1,499,000 (57,400)	1,001,000 (20,040)	11.25 (5.77)	-0.10 (0.89)			22.10 (19.71)	2.34 (4.58)	38.01 (25.95)	2.71 (3.94)
<i>C. Wholesale Trade</i> (56 industries, 336 obs)	391,000 (12,850)	303,500 (14,310)	5.007 (3.27)	0.05 (0.84)			24.62 (11.91)	0.79 (6.82)	47.92 (16.97)	1.68 (6.75)
<i>D. Services</i> (95 industries, 570 obs)	2,058,000 (300,800)	1,744,000 (212,600)	36.12 (10.93)	-0.40 (2.23)			13.59 (13.39)	0.75 (4.50)	24.56 (18.76)	1.01 (4.78)
<i>E. Finance</i> (31 industries, 124 obs)	675,600 (71,480)	434,500 (43,430)	12.88 (8.55)	0.85 (3.58)			28.21 (13.53)	1.79 (6.57)	57.84 (17.55)	3.32 (6.10)
<i>F. Utilities and Transportation</i> (48 industries, 144 obs)	291,100 (18,560)	192,500 (6,545)	17.27 (8.23)	-0.39 (2.39)			32.66 (20.90)	1.14 (7.39)	61.44 (22.38)	1.17 (5.80)

Notes. Summary statistics are based on the Economic Census of 1982-2012 for manufacturing, services, wholesale trade and retail trade, and 1992-2012 for finance and utilities and transportation. In manufacturing, we observe 388 consistently defined industries during six periods, and thus have $6 \times 388 = 2,328$ observations. Columns 1 and 2 indicate the number of establishments and number of firms reflect totals for the entire sector, with the standard deviation across years in parentheses. Columns 3 to 10 indicate the levels and 5-year changes in payroll-to-sales, payroll-to-value added in manufacturing, and CR4 or CR20 sales concentration. These sector-level variables are based on weighted averages of the underlying four-digit industries within a sector, where the weight is the industry's share of sales in the initial year when a sector is first covered by our data.

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

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

Notes. N=2,328 (388 industries x 6 five-year periods) in columns 1-3 (except N=1,552 in rows 6 and 7) and N=1,164 (388 industries x 3 10-year periods) in columns 4-6. Each cell displays the coefficient from a separate OLS industry-level regression of the change in labor share on period fixed effects and the change in the concentration measure indicated at the top of each column. Industries are weighted by their total value added in the initial year, and standard errors in parentheses are clustered by four-digit industries. The models in row (2) and (3) replace the baseline outcome variable (the change in payroll divided by value added) with the ratio of total compensation to value added, and payroll to value added net of intermediate services, respectively. Row (4) replaces the baseline regressor (the change in sales concentration) with the change in concentration of value added, while row (9) uses concentration measures based on employment. Row (5) augments the baseline model with a full set of four-digit industry dummies, and thus controls for linear time trends in each industry. Rows (7) and (8) respectively extend the baseline specification with controls for the change in the ratio of imports to value added, and the initial level of capital to value added. Since the import measure is only available since 1992, the row (7) model is estimated only for 5 year changes during the 1992-2012 period, while row (6) indicates estimates from the baseline regression for this shorter period. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

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

Notes. Numbers 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 from a separate OLS industry-level regression of the change in labor share (payroll-to-sales ratio) on period fixed effects and the change in the concentration measure indicated at the top of each column. Industries are weighted by their sales in the initial year, and standard errors in parentheses are clustered by four-digit industries. In manufacturing, retail, services and wholesale, we pool data from 1982-2012 and in finance and utilities and transportation, we pool data from 1992-2012. The combined regression in row (7) includes six sector fixed effects. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table 4: Decompositions of the Change in the Labor Share, Manufacturing

	Δ Un- weighted Mean of Survivors (1)	Incumbent Re- allocation (2)	Exit (3)	Entry (4)	Total (5)
<i>A. Payroll Share of Value Added</i>					
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
1982-2012	-2.93	-13.15	-5.14	5.15	-16.07
<i>B. Compensation Share of Value Added</i>					
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
1982-2012	-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 for the payroll share of value-added in Panel A and for the compensation share of value-added in Panel B using the dynamic Melitz-Polanec (2015) methodology as described in the text. We divide the change in the overall labor share (column 5) into four components: Column (1) indicates the change in the labor share due to a general decline across all surviving firms; column (2) captures reallocation among incumbent (surviving) firms 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); columns (3) and (4) respectively indicate the contribution of firm exit and firm entry to the decline in the industry-level labor share.

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

	Δ Un- weighted Mean of Survivors	Incum- Allocation Re-	Exit	Entry	Total	Δ Un- weighted Mean of Survivors	Incum- Allocation Re-	Exit	Entry	Total
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	<i>A. Manufacturing</i>					<i>B. Retail</i>				
1982-1987	-0.73	0.68	-0.77	0.83	0.02	0.03	-0.04	-0.19	0.19	-0.01
1987-1992	0.99	-1.92	-0.78	0.68	-1.02	0.92	-0.98	-0.20	0.15	-0.11
1992-1997	-0.71	-0.51	-1.03	0.95	-1.30	1.29	-1.70	-0.24	0.27	-0.37
1997-2002	0.50	-0.82	-0.68	0.75	-0.24	1.41	-1.11	-0.08	0.18	0.41
2002-2007	-2.24	-0.73	-0.94	0.90	-3.02	0.27	-0.94	-0.23	0.23	-0.67
2007-2012	0.47	-1.24	-0.74	0.35	-1.17	0.46	-0.67	-0.15	0.26	-0.10
1982-2012	-1.71	-4.54	-4.94	4.46	-6.73	4.39	-5.44	-1.10	1.29	-0.85
	<i>C. Wholesale</i>					<i>D. Services</i>				
1982-1987	0.71	-0.40	-0.21	0.38	0.49	-0.20	0.56	0.83	-0.95	0.23
1987-1992	0.68	-0.52	-0.35	0.30	0.11	-0.15	0.08	0.73	-0.64	0.02
1992-1997	1.20	-1.03	-0.35	0.32	0.15	1.36	-1.95	0.48	-0.12	-0.23
1997-2002	1.61	-1.39	-0.42	0.42	0.21	0.37	0.02	0.22	0.05	0.65
2002-2007	-0.29	-0.08	-0.30	0.25	-0.43	-0.24	0.20	-0.31	-0.49	-0.84
2007-2012	0.75	-1.16	-0.34	0.15	-0.60	0.58	0.33	-0.37	-0.15	0.40
1982-2012	4.66	-4.59	-1.97	1.82	-0.08	1.73	-0.76	1.57	-2.30	0.23
	<i>E. Utilities and Transportation</i>					<i>F. Finance</i>				
1992-1997	1.14	-2.38	-0.34	0.34	-1.24	1.10	0.22	-0.66	0.30	0.96
1997-2002	0.35	0.20	0.48	0.09	1.12	1.65	-0.02	-0.70	0.57	1.50
2002-2007	-0.98	-1.19	0.21	0.18	-1.78	1.51	-1.49	-0.45	0.64	0.21
2007-2012	-0.13	0.12	0.00	0.08	0.07	0.66	0.54	-1.09	0.47	0.58
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 Table 5.

Table 6: Characteristics of Concentrating Industries

	CR4		CR20		HHI	
	(1)		(2)		(3)	
<i>A. Manufacturing Only</i>						
1 Patents Per Worker	0.09 (0.006)	**	0.057 (0.022)	***	0.056 (0.022)	**
2 Value-Added Per Worker	0.126 (0.028)	***	0.074 (0.020)	***	0.067 (0.025)	***
3 Capital per Worker	0.092 (0.041)	**	0.026 (0.022)		0.081 (0.029)	***
4 5-Factor TFP	0.055 (0.019)	***	0.024 (0.013)	*	0.028 (0.017)	*
5 Payroll Per Worker	0.013 (0.018)		0.005 (0.011)		0.016 (0.010)	
6 Material Costs Per Worker	0.120 (0.028)	***	0.074 (0.018)	***	0.068 (0.023)	***
<i>B. All Sectors</i>						
7 Manufacturing Sales Per Worker	0.125 (0.027)	***	0.067 (0.018)	***	0.069 (0.016)	***
8 Retail Sales Per Worker	0.049 (0.048)		0.098 (0.067)		0.027 (0.023)	
9 Wholesale Sales Per Worker	0.16 (0.058)	***	0.207 (0.042)	***	0.031 (0.013)	**
10 Services Sales Per Worker	0.082 (0.055)		0.125 (0.036)	***	0.041 (0.019)	**
11 Utilities/Transportation Sales Per Worker	0.415 (0.096)	***	0.304 (0.092)	***	0.117 (0.023)	***
12 Finance Sales Per Worker	0.27 (0.143)	*	0.216 (0.111)	*	0.144 (0.052)	***
13 Combined	0.155 (0.031)	***	0.147 (0.026)	***	0.053 (0.011)	***

Notes. N=2,328 (388 industries x 6 five-year periods) in Panel A, and various sector-specific numbers of observations as reported in Table 4 in panel B. Each cell displays the coefficient from a separate OLS industry-level regression of the change in sales concentration on period fixed effects and the change in the indicated variable. Industries are weighted by their value added in the initial year in Panel A and by their initial-year sales in Panel B. Standard errors in parentheses are clustered by four-digit industries. Independent and dependent variables are standardized so coefficients reflect correlations.

APPENDICES (NOT INTENDED FOR PUBLICATION UNLESS
REQUESTED)

Appendix A MODEL OF SUPERSTAR FIRMS⁵⁶

In this Appendix we derive conditions under which changes in the market environment will affect 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 markups fall, 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, and that is in turn determined by the underlying productivity distribution. When the underlying probability density function of firm productivity draws is log-linear (e.g. Pareto) the two forces will perfectly counterbalance and the labor share will be unchanged. When this 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 (implying a 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

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

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 $d^2 \ln d(p) / d (\ln p)^2 < 0$ (“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 according to which the absolute elasticity of demand is

⁵⁶We are extremely grateful to Arnaud Costinot for extensive help with this Appendix, which is largely based on earlier versions of Arkolakis et al (2018).

lower for higher levels of consumption (lower levels of price). For example, consider the Quadratic Utility Function:

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

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:

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

where

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

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.⁵⁷

Entry, Pricing and markups

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

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

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

$$\begin{aligned} q(p_{\omega}) &= p_{\omega}^{-\sigma} d(A p_{\omega}) \\ \varepsilon(p_{\omega}) &= A p_{\omega} d'(A p_{\omega}) / d(A p_{\omega}) - \sigma \end{aligned}$$

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

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

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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 $d^2 \ln d(p) / d(\ln p)^2 = 0$.

where

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

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

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

In order to see how the labor share changes, we need to characterize the determination and distribution of markups.

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

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

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

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

Proof: By equation (10), we know that

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

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

Claim 3: *There exists a cutoff $c^* = \bar{p}/A$ such that firms produce if and only $c_\omega \leq c^*$. 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 $c_\omega \leq c^*$. 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

$$c^* = \bar{p}/A. \quad (16)$$

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*

$$p(\ln c_\omega, \ln c^*) = e^{\ln c_\omega} f(\ln c_\omega - \ln c^*) \quad (17)$$

$$m(\ln c_\omega, \ln c^*) = f(\ln c_\omega - \ln c^*) \quad (18)$$

$$Q(\ln c_\omega, \ln c^*) = Me^{-\sigma \ln c_\omega} h(\ln c_\omega - \ln c^*) \quad (19)$$

$$r(\ln c_\omega, \ln c^*) = Me^{(1-\sigma) \ln c_\omega} f(\ln c_\omega - \ln c^*) h(\ln c_\omega - \ln c^*) \quad (20)$$

$$\pi(\ln c_\omega, \ln c^*) = Me^{(1-\sigma) \ln c_\omega} [f(\ln c_\omega - \ln c^*) - 1] h(\ln c_\omega - \ln c^*) \quad (21)$$

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 markups and labor share is the reciprocal of the markup (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 market affect the distribution of firm markups 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

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

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

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

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

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

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

Notice that the above implies that

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

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

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

Since $f' < 0$, $-f^{-1}(\cdot)$ is increasing in m , the first term on the right hand side of equation (22), $\left[\frac{\partial(-f^{-1}(m))}{\partial m} \right]$, 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 $\frac{\partial^2 \ln \lambda [\ln z^* - f^{-1}(m)]}{\partial \ln(z^*)^2}$.

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 $c^{*'} \leq c^*$. Then:

- $\Phi(\cdot, c^*) \prec_{mlrp} \Phi(\cdot, c^{*'})$ if λ log-convex;
- $\Phi(\cdot, c^*) \succ_{mlrp} \Phi(\cdot, c^{*'})$ if λ log-concave;
- $\Phi(\cdot, c^*) = \Phi(\cdot, c^{*'})$ 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 1. 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

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

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, $v \equiv \ln z^* - u$, 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 $f'(v) < 0$. 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 $\ln z^* \geq \ln z^{*'}$, then

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

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:

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

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

$$B(\ln z^*, \delta) = e^{(\sigma-1)\ln z^*} \int_0^{\infty} \tilde{b}(u, \delta) \lambda(\ln z^* + u) du$$

where $\tilde{b}(u, \delta) \equiv NMe^{-(1-\sigma)u} [f(-u) - \delta] h(u)$. Since λ is log-convex, $\lambda(\ln z^* + u)$ is log-supermodular in $(\ln z^*, u)$. Since $\tilde{b}(u, \delta) \equiv b(-u, -\delta)$, $\tilde{b}(u, \delta)$ 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 $\ln z^* \geq \ln z^{*'}$, then

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

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 is $S = 1 - \frac{\Pi}{R}$, 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 markups are higher for more productive firms. Thus, the labor share is lower for larger firms. An increase in market toughness that reallocates 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 shares rise. Thus a rise in the aggregate markup 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. If we endogenized entry, there may be a change in the number of entrants and thus in 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 takes 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.⁵⁸

⁵⁸A similar issue arises if we close the model and consider how the profits from market power are distributed.

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): $m_{it} = \left(\frac{\alpha_{it}^v}{S_{it}^v}\right)$. There are many well-known challenges in performing econometric estimation of production functions, and we apply 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 :

$$\ln Y_{it} = \alpha_{kt}^v \ln X_{it}^v + \beta_{kt} \ln K_{it} + \ln \theta_{it} + \varepsilon_{it} \quad (23)$$

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 $\ln \theta_{it} = h_{kt}(d_{it}, \ln K_{it})$ 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:

$$\ln Y = \phi(\ln X_{it}^v, \ln K_{it}, d_{it}) + \varepsilon_{it} \quad (24)$$

where $\phi_{it} = \alpha_{kt}^v \ln X_{it}^v + \beta_{kt} \ln K_{it} + h_{kt}(d_{it}, \ln K_{it})$. Assuming the productivity process can be written $\ln \theta = g(\ln \theta_{it-1}) + \xi_{it}$ gives rise to the moment condition $E[\xi_{it}(\alpha_{kt}^v) \ln X_{it}^v] = 0$, which can be used to recover the output elasticity. In the second stage we estimate productivity from $\ln \theta_{it} = \phi_{it} - \alpha_{kt}^v \ln X_{it}^v - \beta_{kt} \ln K_{it}$, 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 its lag does not; and (2) the lagged variable inputs are correlated with current use (via the persistence in productivity).

A key 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 industry 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 $\ln(\text{sales})$ 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 Akerberg, Caves and Frazer (2015) method of estimating a Cobb-Douglas. Panel D continues using the Akerberg, Caves and Frazer (2015) method but generalizes

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.

Panel C to estimate a translog production function.⁵⁹ 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 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_{kt}^L 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 permutations, 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 across all of our estimation methods.

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_{kt}^L 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.

⁵⁹Table A.4 indicates our underlying estimates for the output elasticities of the production functions.

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 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 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 Walmart 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.12 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. Panel A in Figure A.13 plots the ratio of top 500 firms’ sales to gross output of the U.S. private sector. This

⁶⁰Compustat 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.

⁶¹The market value reported in Figure A.12 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.

ratio increased from about 0.36 in 1972 to 0.40 in 2015. The increase was not monotone through this time period, however, but rather featured substantial fluctuations. Some of these fluctuations, especially during the 1970s and 1980s, were due to large changes in oil prices that translated to a high volatility in oil firms' sales over time. The real oil price more than doubled from 1973 to 1981, and the oil industry accounted for seven of the eleven largest U.S. firms by sales in 1981. After 1981, the oil price declined rapidly, and with it the sales of oil firms. To purge variation that stems from the cyclical behavior of oil prices, Panel B in Figure A.13 indicates the ratio of top 500 non-oil firms' sales to the gross output of the U.S. private non-oil sector. This time series shows a stronger and less volatile growth of the largest firms' sales relative to U.S. output. The pattern of relatively rapid sales growth in the largest U.S. firms 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.14 plots the share of the largest 50 firms in the combined sales of the largest 500 firms. Over the 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.12), the growth of concentration among these largest firms was not rising monotonically over time. Instead, Figure A.14 shows that sales concentration was weakly falling until the late 1990s then increased until 2010 and leveled off thereafter.

Figure A.15 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 increases 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 a fraction of all economic activity in the U.S. whereas the Census covers all firms in a given sector. Second, most sales and employment data in Compustat relates to globally consolidated accounts covering both firms' operations in the U.S. and abroad, which is distinct from the Census' exclusive coverage of domestic U.S. employees and sales by domestic establishments. 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 because it comprises a much lower number of firms. When we perform an analogous exercise in the Census data, ignoring industry, we obtain a time series of concentration much more similar to the one 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.16 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 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 since 1978.⁶² Figure A.17 documents that the 500 largest U.S. firms on average sold around about 20 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 more than 35 percent of the sales of top 500 firms by 2010. 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’ U.S. and global activities, the Compustat data presents several additional data issues for analyzing labor

⁶²A breakdown of the top 500 firms’ domestic versus foreign sales based on geographic segment data is missing for 13% of all firm-years. We sequentially impute missing foreign sales shares by (i) using data on the geographic composition of sales from operating segment data, (ii) using the the foreign sales share of the nearest year in which the firm did report this information, or linearly interpolating if the geographic breakdown is available for both an earlier and a later year, and (iii) imputing the foreign sales share using the average value for the same year of other top 500 firms of the same 2-digit industry, or of the same broad sector (manufacturing or non-manufacturing) if there are no other firms from the same industry. Compustat does usually not report a geographic breakdown of employment.

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 for labor share when examining Compustat data. For purposes of the Compustat analysis, we define the labor share as the ratio of wage bill to the best proxy for value added—the sum of wage bill and EBITDA (earnings before interest, tax, depreciation and amortization). There is a clear decline in the aggregate labor share from nearly 60 percent in the early 1980s to 47 percent in 2015 in the subset of top 500 firms for which data are available. Figure A.18 reports the change in labor share separately for firms whose share of foreign sales in total sales is above or below the median of a firm’s 2-digit industry. Firms with more global engagement have higher labor shares on average in most years. While the data usually do not provide a breakdown of employment by location, it is possible that firms with greater foreign sales also have a larger proportion of their production employment abroad, and major economies like Germany or the United Kingdom have higher labor shares than the U.S. as shown in Figure 1. Despite this difference in the levels of labor shares, firms with greater or smaller foreign sales shares both experience very similar declines in the labor share over the full 1978 to 2015 period. The commonality of labor share declines among more and less globally 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.

Appendix D DATA

Appendix D.1 Economic Census

Our primary data are from the U.S. Economic Census conducted every five years by the Census Bureau.⁶³ 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, value-added, assets, material costs, and salaries and wages, 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 99th 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 reallo-

⁶³More 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

cation and within-firm components in Figure 7 and 8. We confirmed the robustness of our results to alternative 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 that belong to the same broad sector and are thus covered in the same segment of the Economic Census. 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 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.

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 to 1997, the establishments are given a 1987 SIC code, and from 1997 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 code 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 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 find results that are very similar to the main ones we report in the paper. For example, in the first three columns of Table 3 (the labor share vs. concentration regressions), all 18 coefficients across the six segments are negative and 16 of these coefficients are significant at the 5 percent level or greater.

Appendix D.3 Correcting Census Value-Added for Service Intermediate Inputs using KLEMS

The measure of value-added in the Census of Manufactures adjusts for intermediate purchased goods. It is defined as sales (item TVS) less inventory investment for final goods (difference between FIE and FIB) and work in progress goods (difference between WIE and WIB), resales (item CR), material inputs (sum of items CP, CW and MIB less MIE) and energy expenditures (sum of items CF and EE). This definition does not adjust for intermediate purchased services, however,⁶⁴ meaning that an increase over time in intermediate purchased services will appear in the Census data as an increase in value-added (and possibly exaggerates the fall in the labor share). The KLEMS data provide information on use of intermediate services by U.S. industries based on the

⁶⁴There is a deduction for contract work, CW, but this is narrowly defined.

input-output framework of the BEA. They thus 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) with either correction for purchases of intermediate services, but the trends are similar across the original and adjusted data series.

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 an 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 first 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 second 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. 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 C shows, subtracting off the intermediate purchased services within manufacturing almost exactly closes the gap in value-added across the two data sources. Indeed, using this modified value-added series results in aggregate labor shares from the Census that are near identical to those from NIPA 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 trend 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 the 1980s in most sectors.

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, which distorts the NIPA series.

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 in sales and output. First, measuring output in 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 an entirely 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

⁶⁵The 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.

⁶⁶Note 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.

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 that 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 confirmed robustness to implementing the decompositions at the establishment level and at the firm by four-digit industry level.

We next 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 $\sum_j (\tilde{S}_j \Delta \omega_j)$ and within-industry $\sum_j (\tilde{\omega}_j \Delta S_j)$ components:

$$\Delta S = \sum_j (\tilde{S}_j \Delta \omega_j) + \sum_j (\tilde{\omega}_j \Delta S_j). \quad (25)$$

Here, \tilde{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 $\tilde{\omega}_j$ 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 re-write our primary Melitz-Polaneć decomposition (equation 5) at the industry level:

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

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

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:

$$\begin{aligned} \Delta S = & \sum_j \left(\tilde{S}_j \Delta \omega_j \right) + \sum_j \tilde{\omega}_j \Delta \bar{S}_{S,j} + \sum_j \tilde{\omega}_j \Delta \left[\sum_{i \in j} (\omega_{i,j} - \bar{\omega}_j) (S_{i,j} - \bar{S}_j) \right]_{S,j} \\ & + \sum_j \tilde{\omega}_j \sum_{i \in j} \omega_{X,0,i,j} (S_{S,0,i,j} - S_{X,0,i,j}) + \sum_j \tilde{\omega}_j \sum_{i \in j} \omega_{E,1,i,j} (S_{E,1,i,j} - S_{S,1,i,j}) \end{aligned} \quad (28)$$

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 that span several industries, 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 use the modal industry across all years). 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 $C_d^{NIPA} = \Delta S^{NIPA} \times \left(\frac{C_d}{\sum_{d=1,2,3,4} |C_d|} \right)$ where C_d is the contribution as calculated in Table 5 and $|C_d|$ is the absolute value of this. Figure A.9 shows the results graphically.

Appendix D.6 International Datasets

The KLEMS data derives from an international research collaboration that provides harmonized industry-level information on output, inputs and productivity taken from national statistical agencies. We use the U.S. KLEMS data to measure purchases of intermediate services, as detailed in Section Appendix D.3. We also draw on the 2012 release of the EU KLEMS database (see O’Mahony and Timmer, 2009, <http://www.euklems.net/>) in order to compare levels and changes in industry-level labor shares across countries.

In addition, we draw on two international firm-level 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 et al., 2015; Gopinath et al., 2017).

⁶⁷For 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.

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.

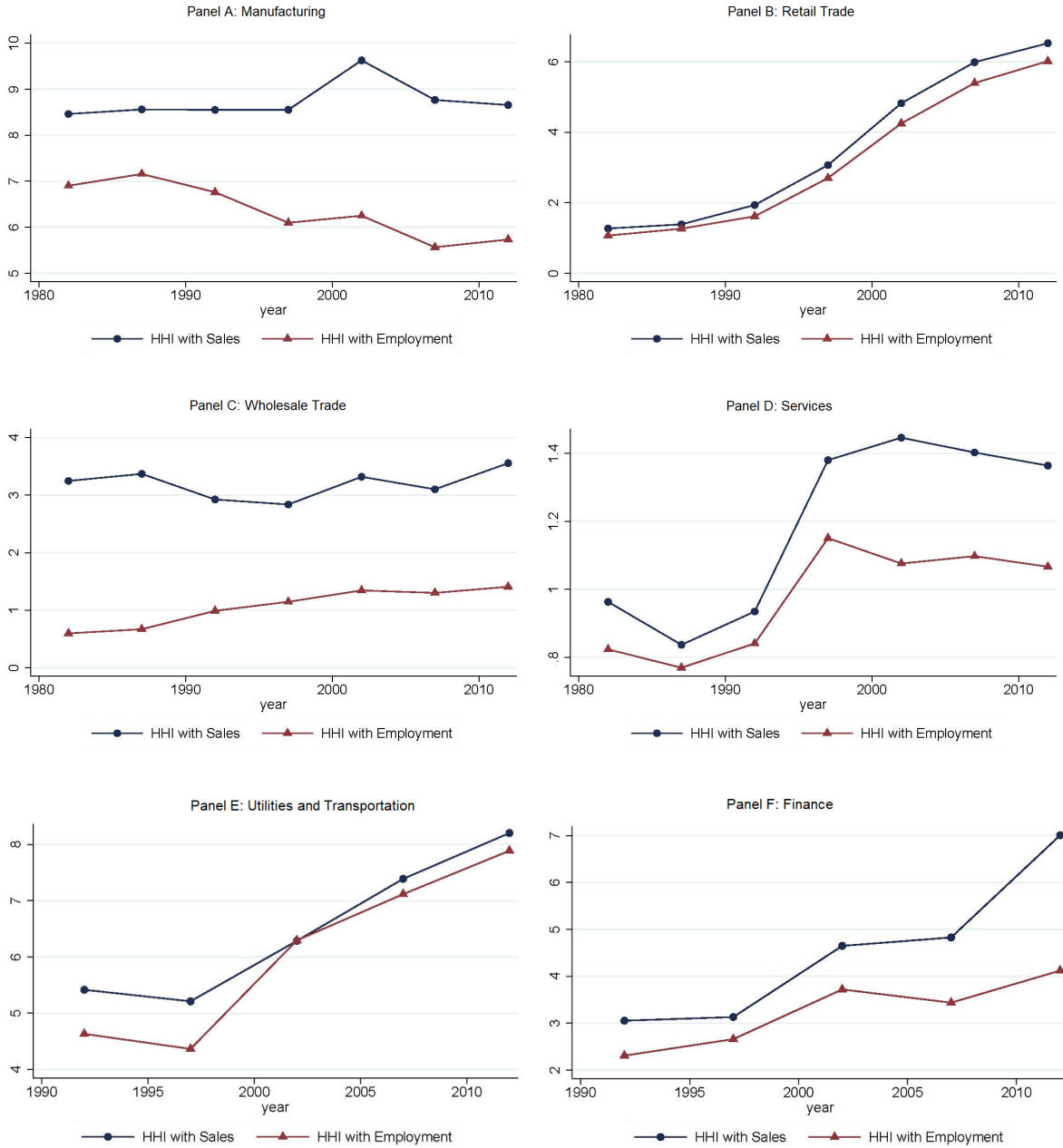
For our analysis we require that firms have information on their primary industry and their payroll. To construct value-added, we sum payroll with gross profits (i.e. before tax, depreciation and interest have been deducted (i.e., EBITA). Intermediate inputs are rarely reported in company accounts, so 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, and on the five year period with most comprehensive firm coverage for each country, which is 2003 to 2008 for the UK, Sweden and France, and 2005 to 2010 for Germany, Italy and Portugal.

The second international firm database is Compnet. Compnet 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.

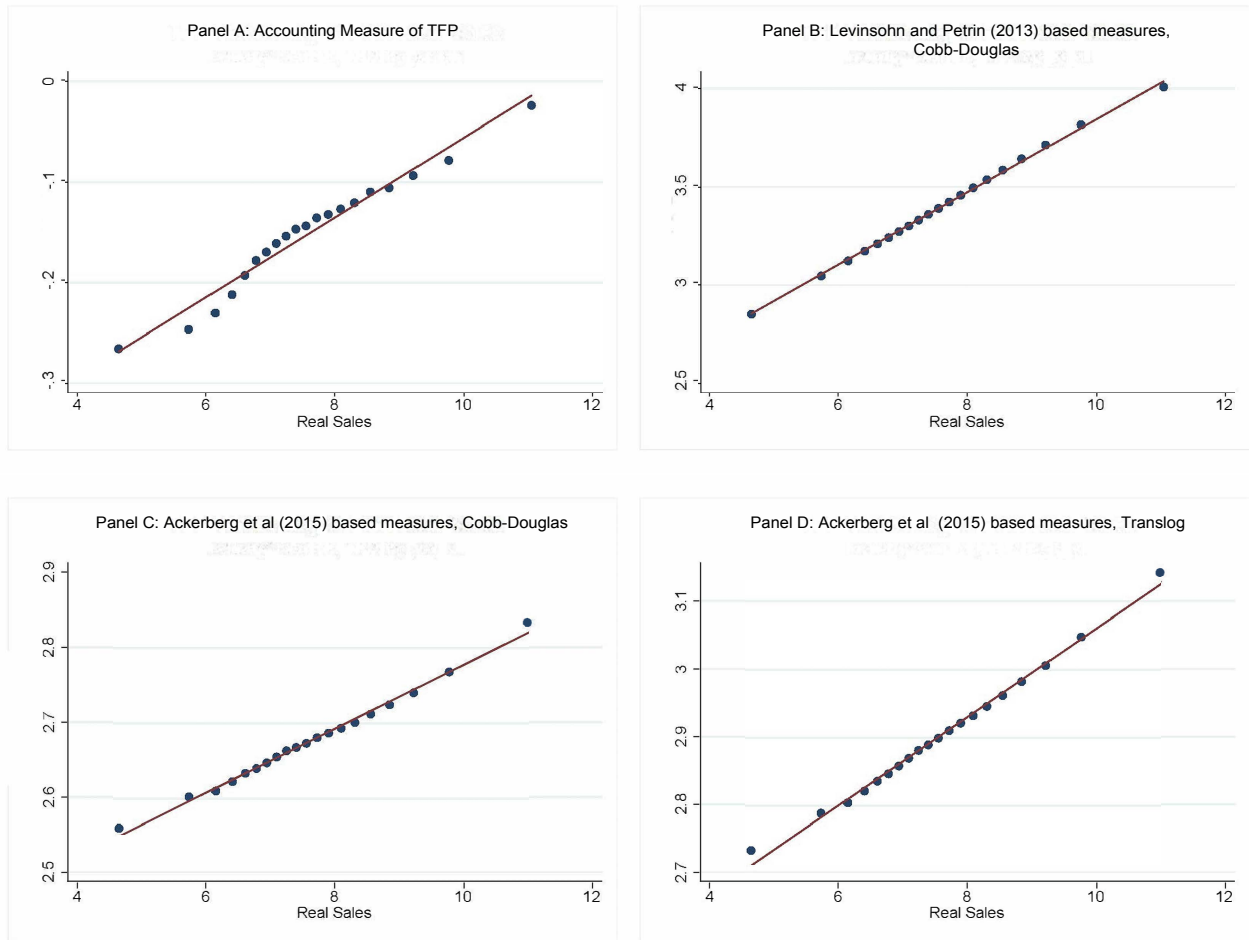
Appendix Figures

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



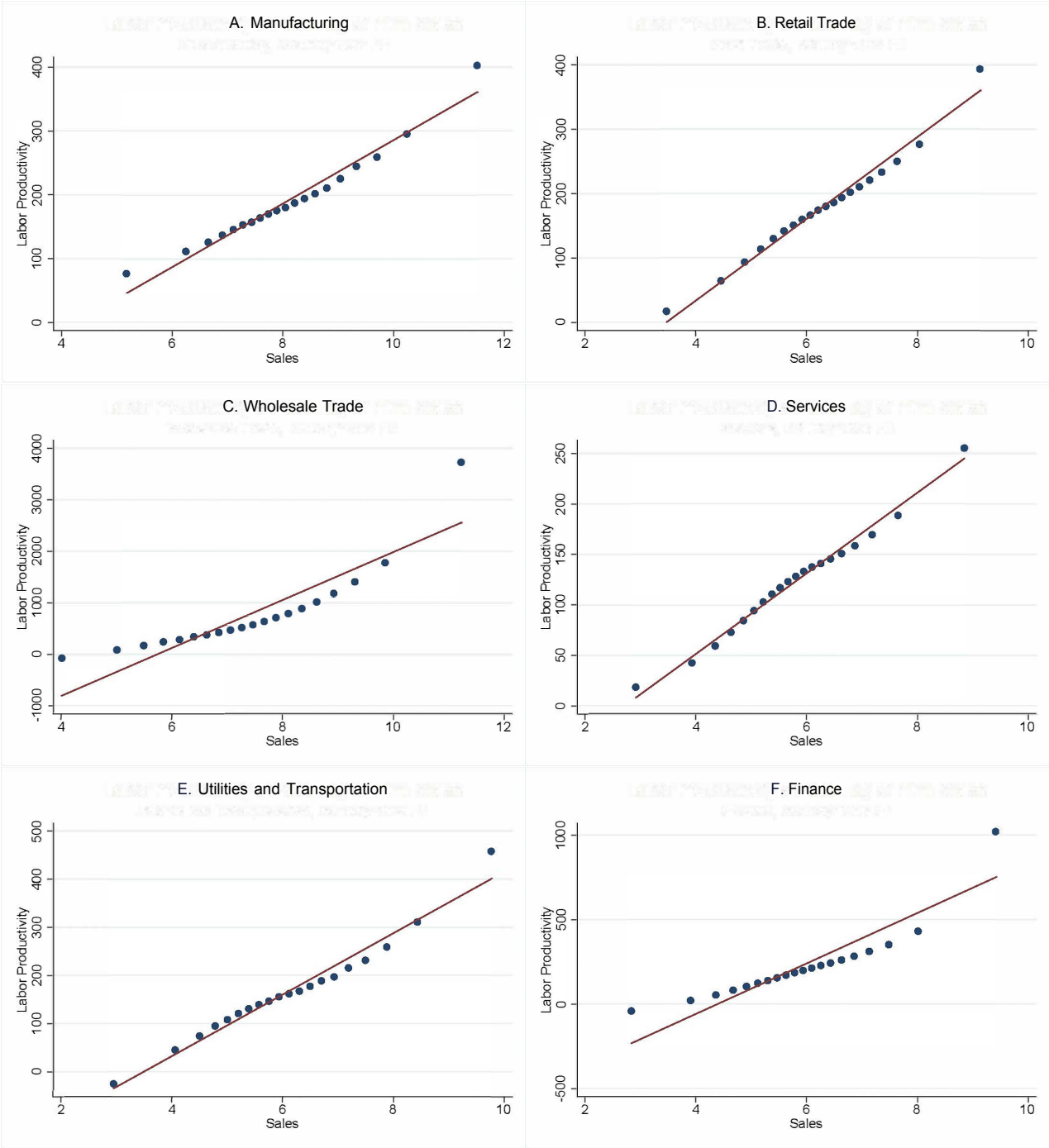
Notes. Each figure plots the average HHI calculated within four-digit industries. Industry concentration is calculated for each time-consistent four-digit industry code, and then averaged across all industries within each of the six sectors using the industry's share of total sales as the weight. The 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, Manufacturing



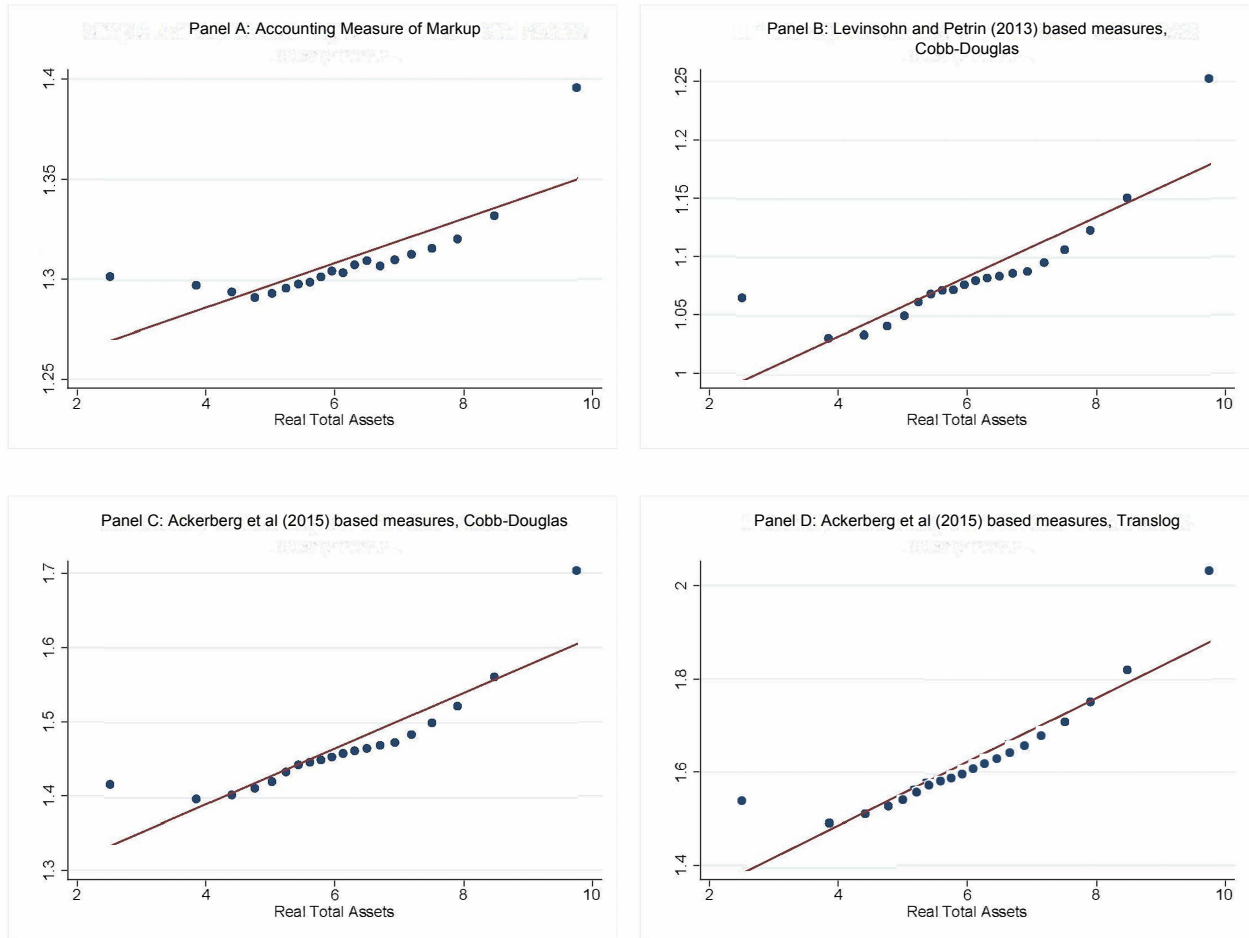
Notes. These are binscatters of firm TFP (y -axis) on the log of firm sales (x -axis), controlling for a full set of four-digit SIC industry by year dummies (so these are the relationships within an industry-year pair). Each panel has a different way of measuring TFP (the order of the panels follows that in Figure 10). The top left panel uses the accounting method which replaces output elasticities with the factor's share of total costs. The top right panel uses our plant-level, industry specific estimates of a Cobb-Douglas production function using the Levinsohn-Petrin method. The bottom left also uses estimates of a Cobb-Douglas production function, except using the Akerberg et al (2015) method. The bottom right also uses Akerberg et al (2015), but in the context of a translog production function. Labor services are measured by payroll, so each worker's input is weighted by their wage (as in Hsieh and Klenow, 2009).

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



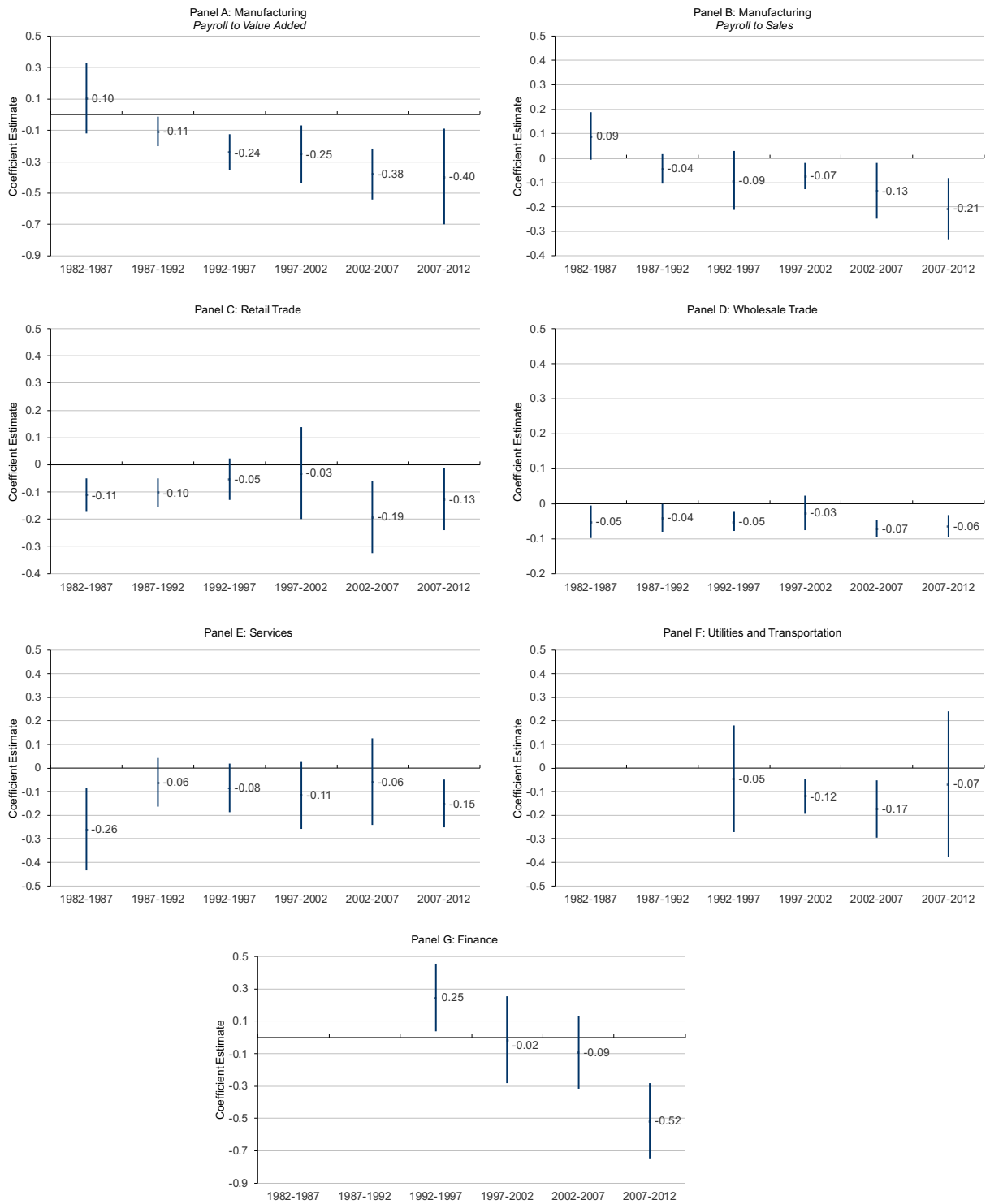
Notes. These are binscatters of firm $\ln(\text{output per worker})$ on the y -axis and firm $\ln(\text{sales})$ on the x -axis. We control for a full set of four-digit SIC industry by year dummies (so these are the relationships within an industry-year pair).

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



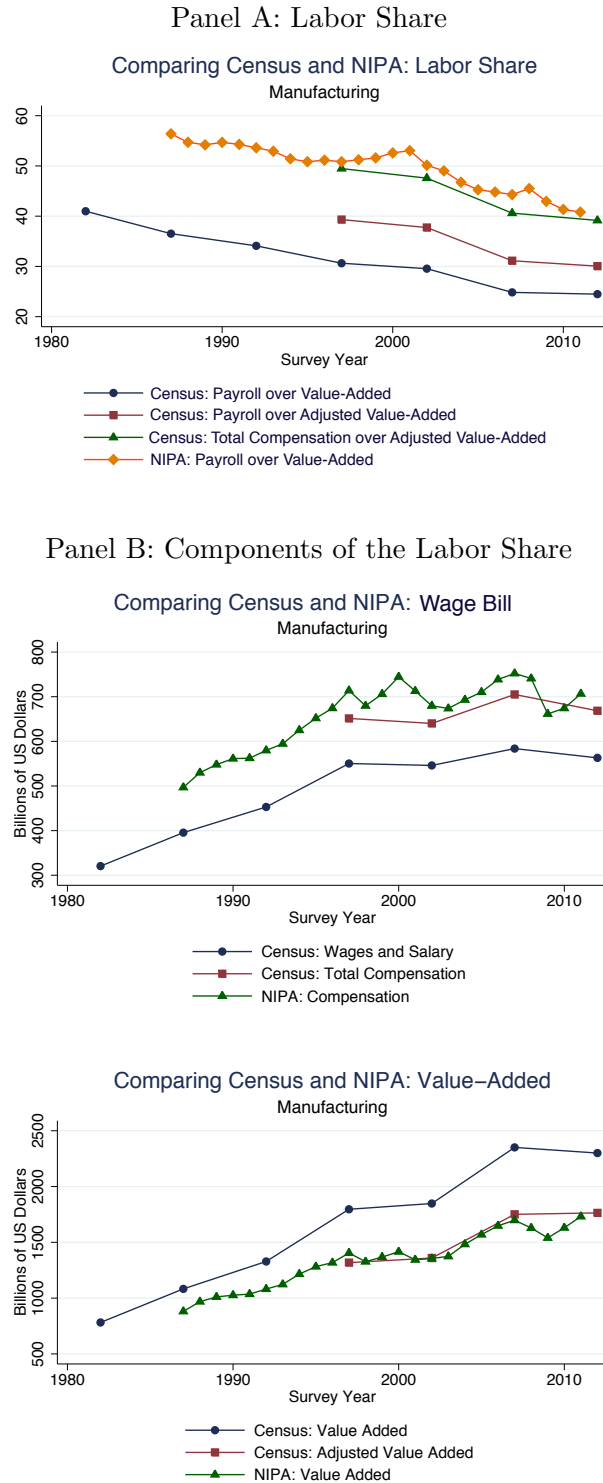
Notes. These are binscatters of firm markups on the y -axis and firm $\ln(\text{capital})$ on the x -axis. We control for a full set of four-digit SIC industry by year dummies (so these are the relationships within an industry-year pair). The ordering of the panels follows Figure 10 in the main text.

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



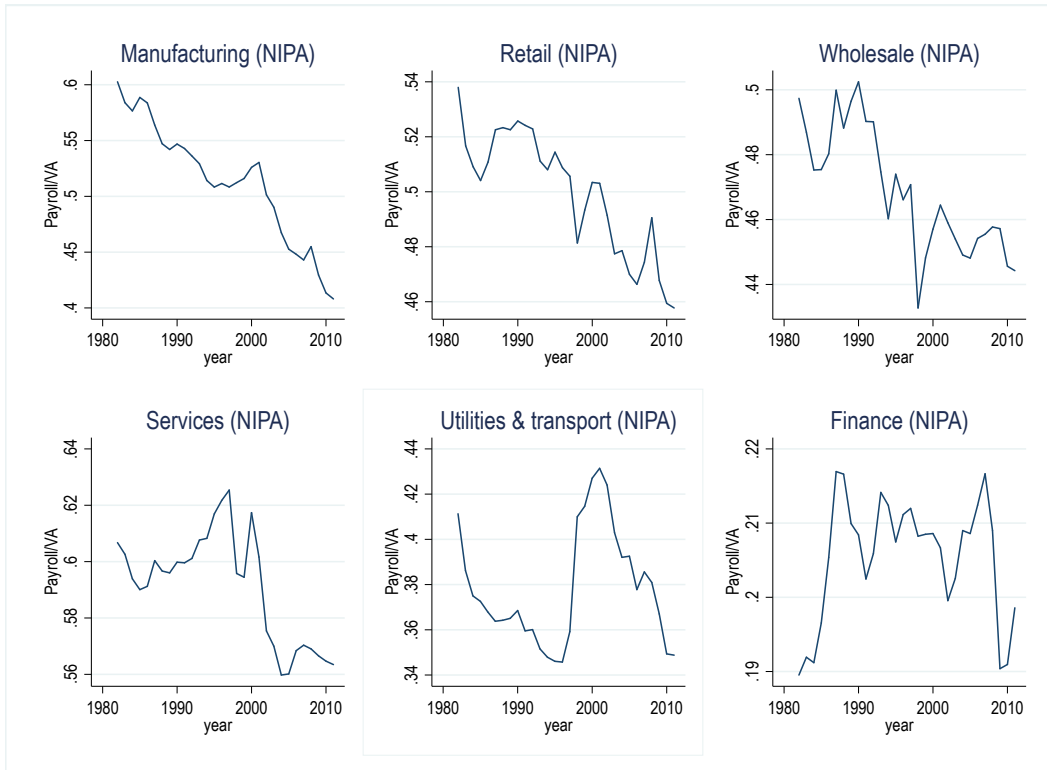
Notes. The labor share is defined using the payroll to value-added ratio in panel A, and each industry is weighted by the industry's 1982 share of value-added. For all other panels, the labor share is defined as the ratio of payroll to sales, and each industry is weighted by its initial share of sales 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. Vertical lines represent the 95% confidence intervals.

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



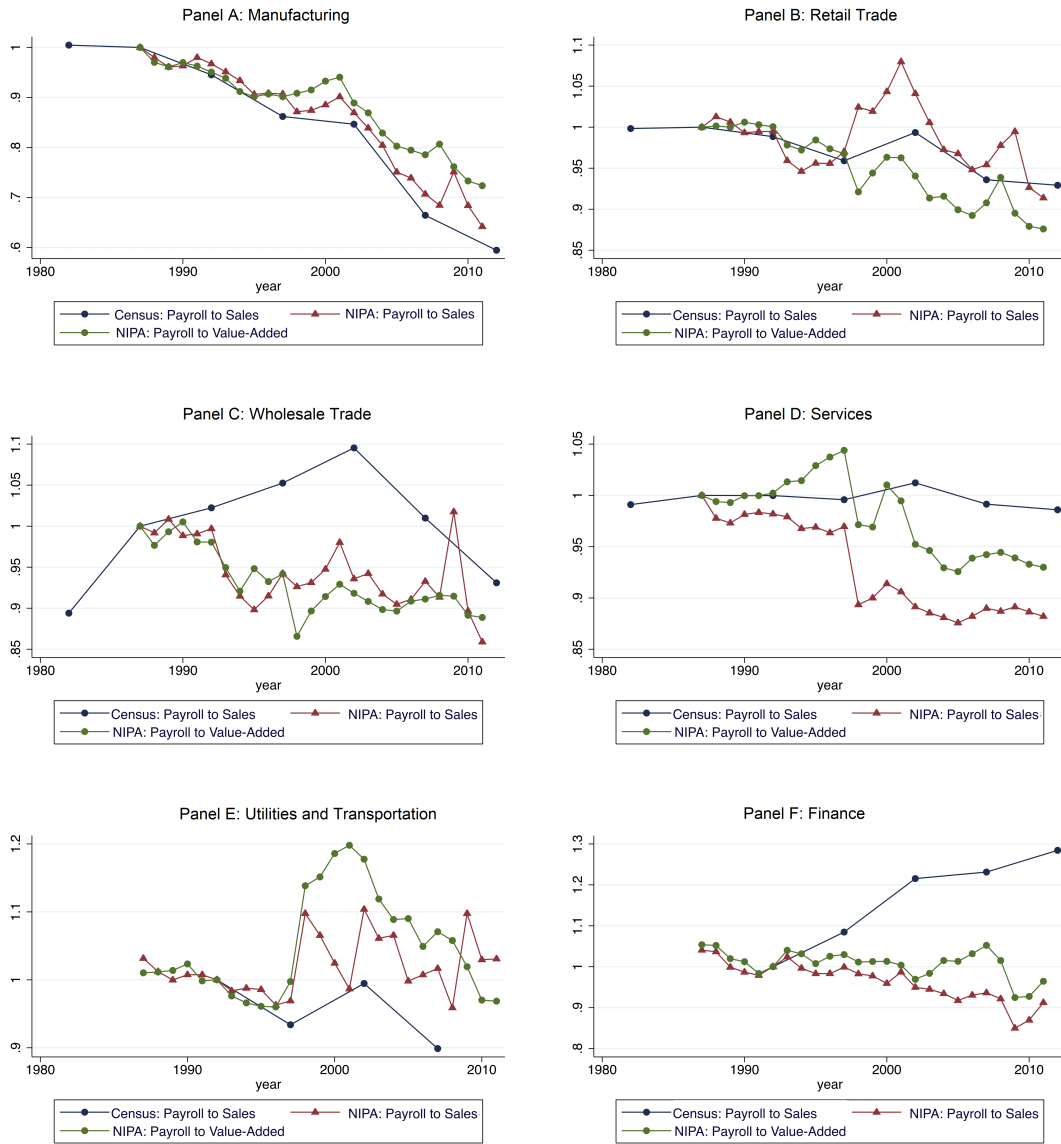
Notes. Panel A plots the aggregate labor share in Manufacturing calculated from the Census and NIPA/BEA data. Blue circles show the labor share calculated in the Census as the ratio of payroll to value-added. Red squares show the same ratio, but here value-added is adjusted by subtracting intermediate 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 separately plots the numerator (payroll) and denominator (value added) used in the construction of the labor shares in Panel A. These figures were from an initial disclosure and thus do not include the revised 2012 update of the Census.

Figure A.7: Labor Share in NIPA



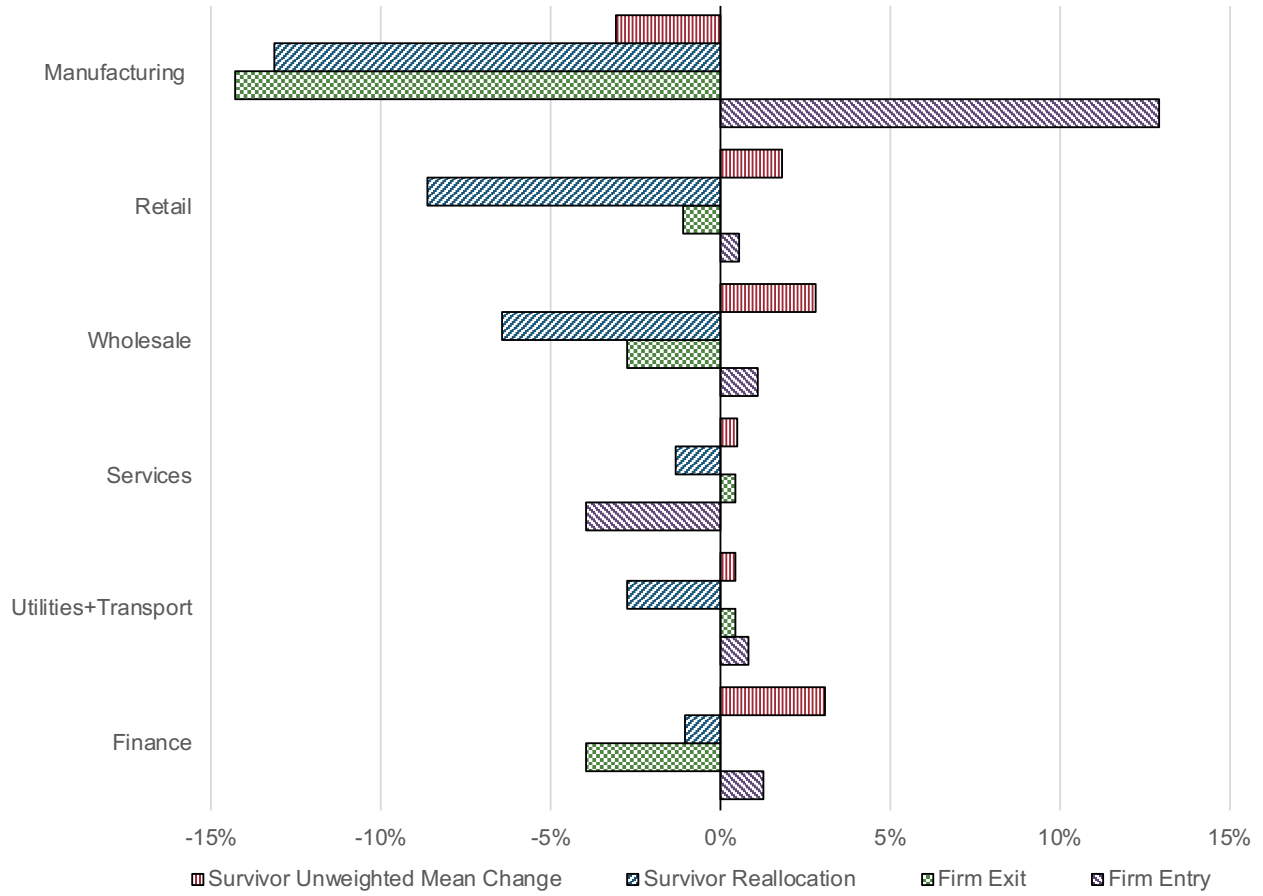
Notes. These are graphs of the ratio of payroll to value added taken from the NIPA/BEA data presented separately for each Census Sector. See text for details.

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



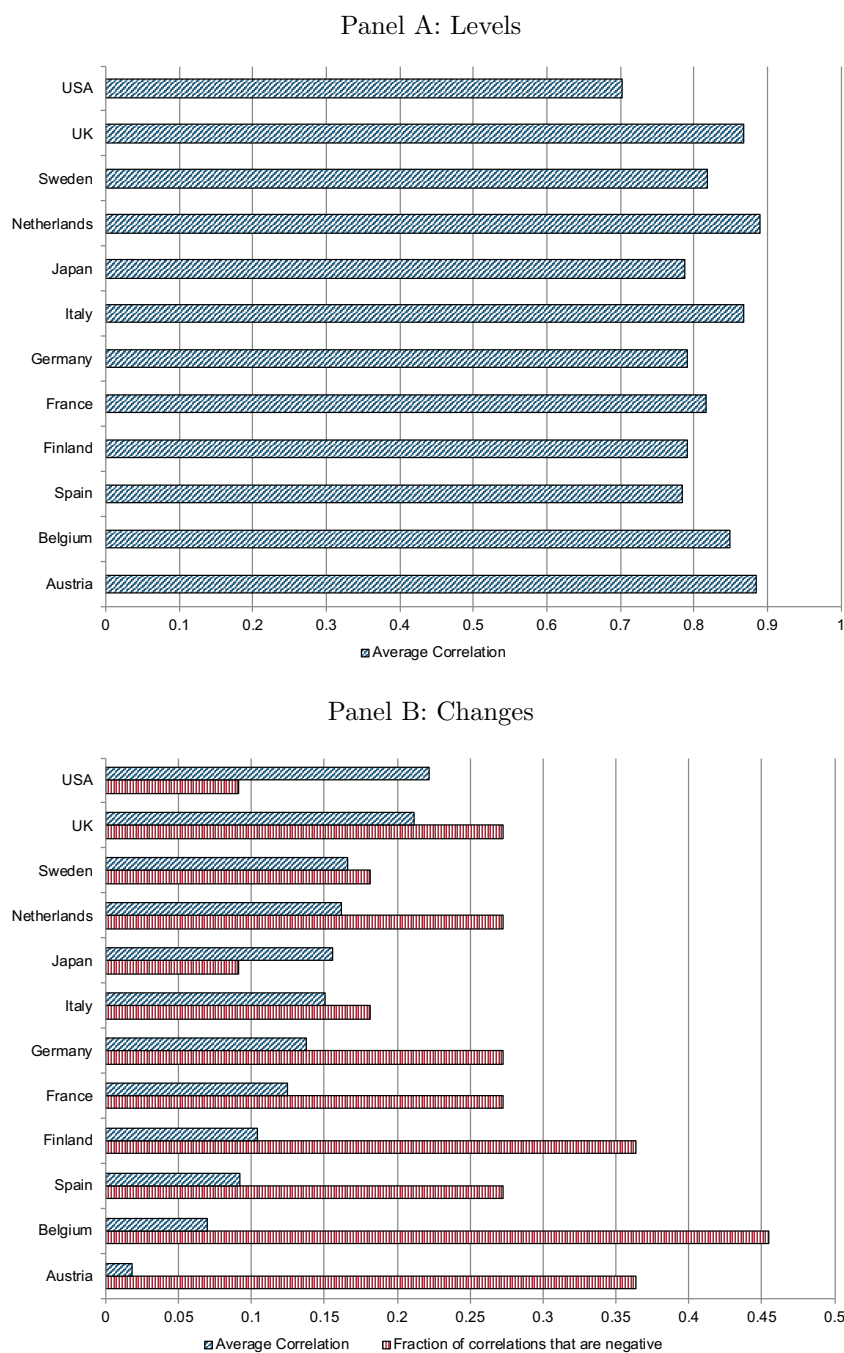
Notes. Each panel shows the payroll to sales ratio in the Census, the payroll to gross-output ratio in the NIPA/BEA data, and the payroll to value-added ratio in the NIPA/BEA data. All series are normalized to one in 1987. These figures were from an initial disclosure and thus do not include the revised 2012 update of the Census.

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



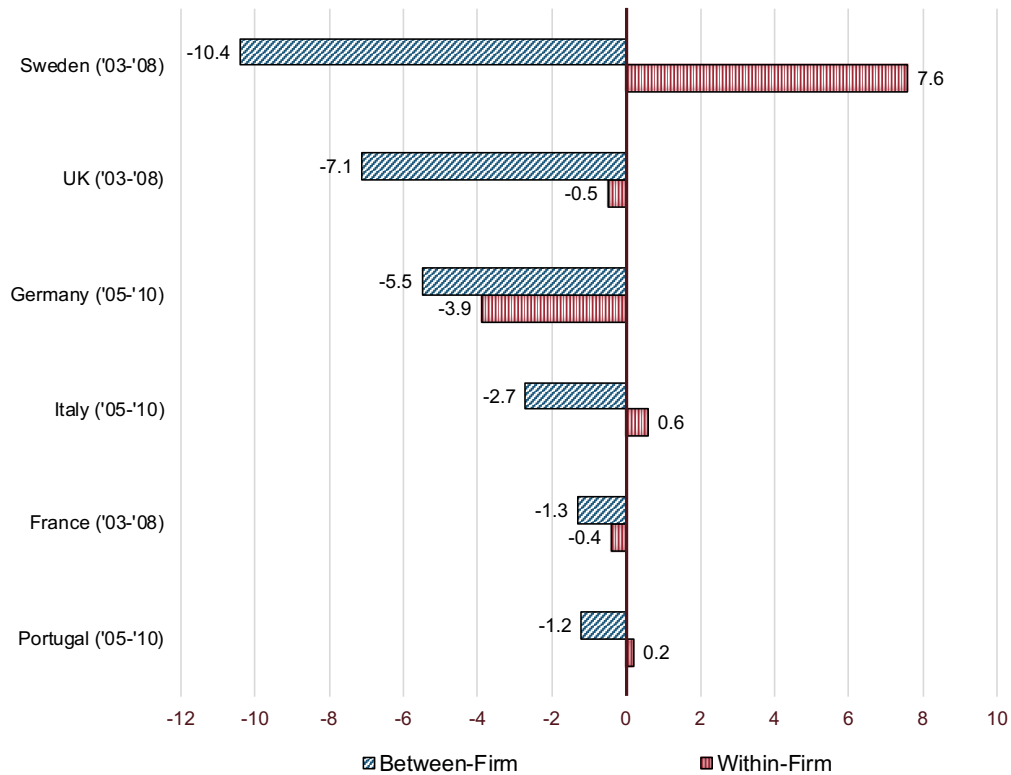
Notes. Melitz-Polanec decomposition of fall of labor share (payroll to value added) using NIPA and Census data. See text for details.

Figure A.10: Industry-Level Cross-Country Comparisons of Labor Shares



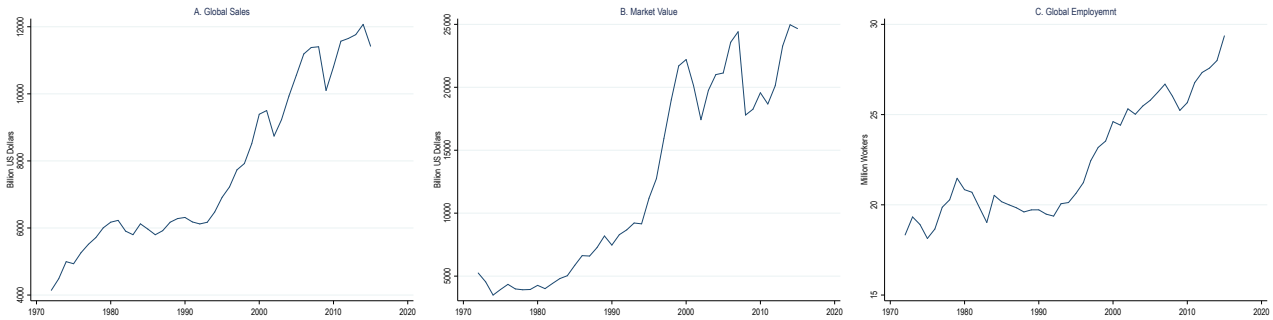
Notes. Using international KLEMS data, Panel A plots for each country the correlation of the *level* of its labor share in 32 industries with the corresponding industry-level labor shares in 11 other countries, averaged over the 11 pairwise correlations with each other country. Note that each cross-country 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.11: Decomposing the Payroll Share Using Firm Level Data from Different Countries



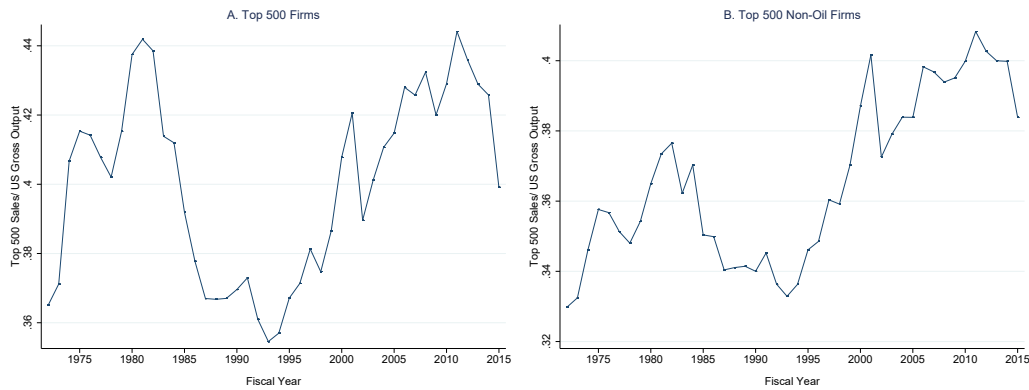
Notes. This figure plots Olley-Pakes decompositions of the change of the payroll share into between-firm and within-firm components (equation 4 in the text) using BVD Orbis Data. Between-firm refers to the reallocation component occurring between incumbent firms, while within-firm refers to the unweighted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

Figure A.12: Size of the Top 500 U.S. Firms



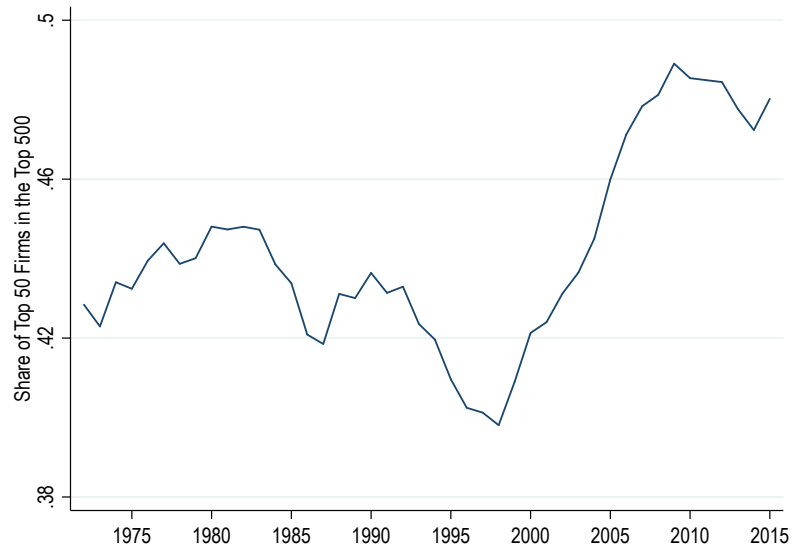
Notes. Panel A shows the total global sales for the 500 firms with the largest global sales from 1972 to 2015. Panel B shows the total market value for the 500 firms with the largest global sales from 1972 to 2015. Panel C shows the total global employment for the 500 firms with the largest global sales from 1972 to 2015. Sales and market value variables are deflated using the Consumer Price Index: All Items U.S. City Average Series (CPIAUCSL).

Figure A.13: Ratio of Top 500 Firms' Sales to U.S. Gross Output



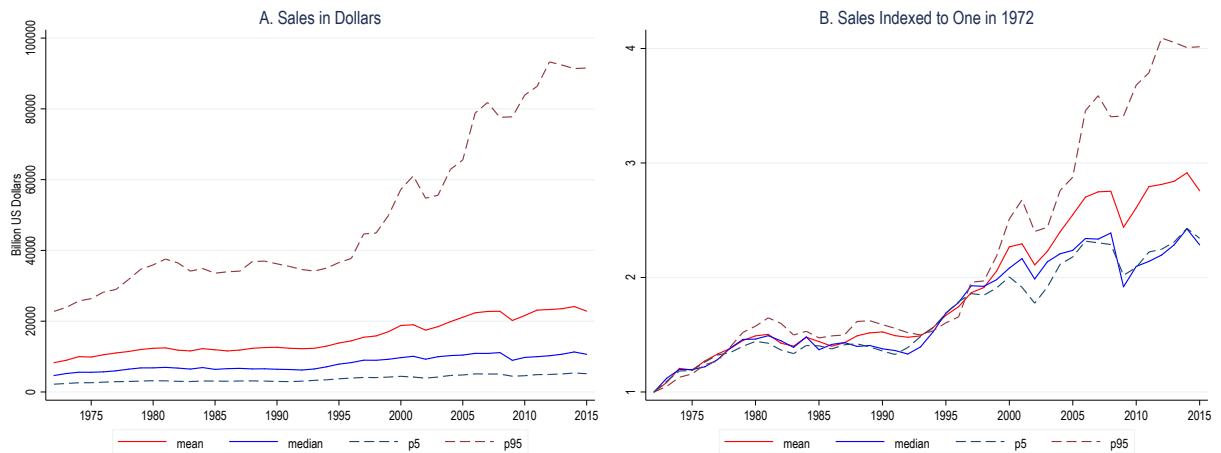
Notes. Panel A reports the ratio of aggregate global sales of the top 500 U.S. firms to total gross output of the U.S. private sector. Panel B reports the ratio of aggregate global sales of the 500 largest non-oil firms to total output of the non-oil private sector (omitting the oil and gas mining and petroleum refining industries).

Figure A.14: Share of Top 50 Firms in Combined Sales of Top 500 Firms



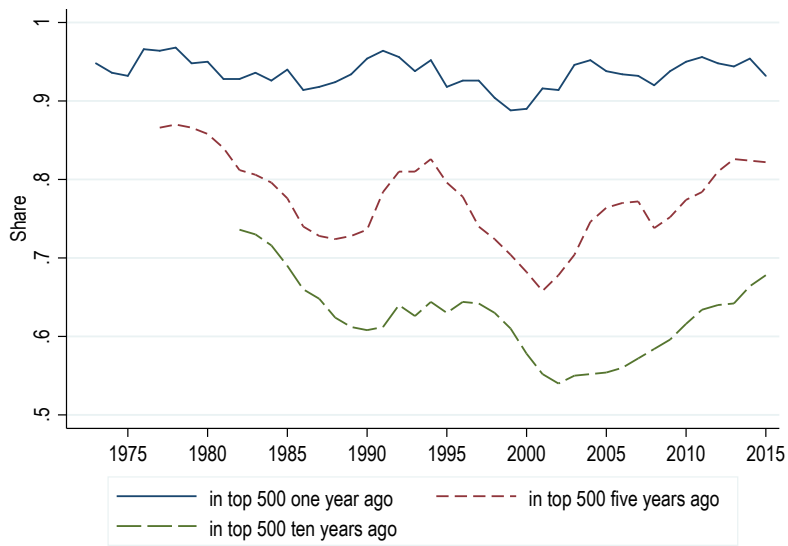
Notes. This numerator of this figure is the sum of global sales of the top 50 firms defined by global sales. The denominator is the sum of global sales of the top 500 firms defined by global sales.

Figure A.15: Quantiles of the Sales Distribution among the Top 500 Firms



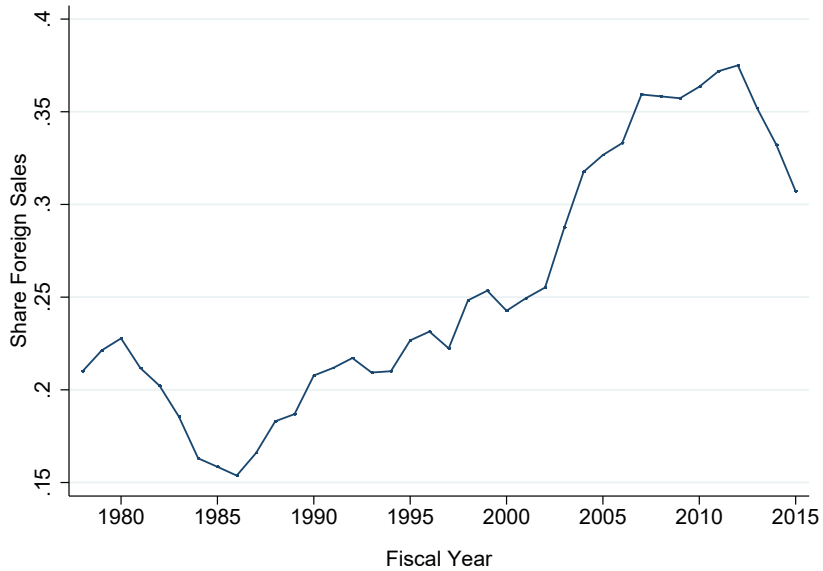
Notes. Panel A shows the time series from 1972 to 2015 for the mean, median, and 5th and 95th percentile of global sales among the top 500 largest firms defined by global sales. Panel B shows the same time series as in Panel A, with all series indexed to one in 1972. All dollar values are deflated using the CPI (All Items U.S. City Average Series).

Figure A.16: Persistence of Firms in the Top 500



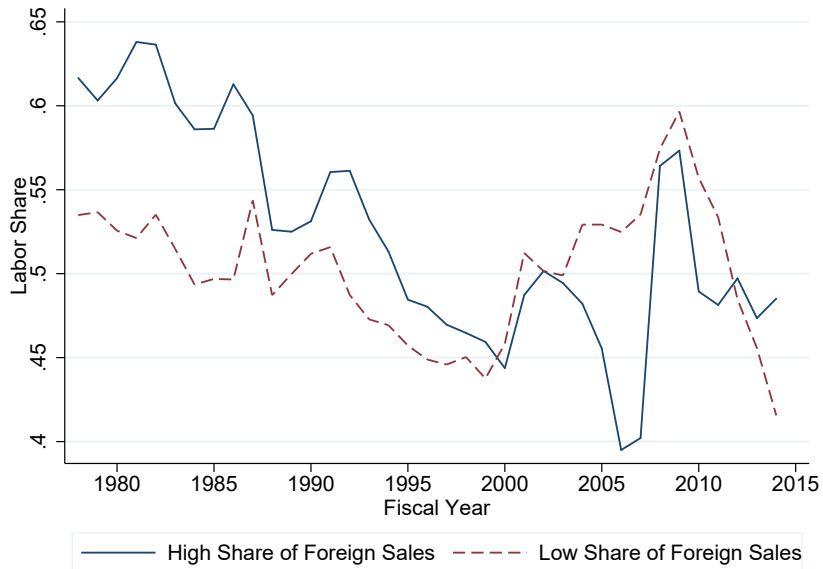
Notes. This figure plots the fraction of firms in the top 500 (defined by global sales) in the indicated year that were already in the top 500 1/5/10 years ago.

Figure A.17: Share of Foreign Sales among Top Firms



Notes. This figure shows the fraction of foreign sales in total sales among the top 500 firms defined by global sales.

Figure A.18: Labor Share among Top Firms by Extent of Global Engagement



Notes. This figure shows the average labor share separately for the top 500 firms by sales whose share of foreign sales in total sales is equal or larger than the median of their 2-digit industry (high share of foreign sales) and the firms with a foreign sales share below the industry median (low share of foreign sales). If there is only one top 500 firm in a given two-digit industry in a year, then the firm is classified as having a high share of foreign sales if its foreign sales share is equal or larger than the median for its broad sector (manufacturing or non-manufacturing). The average weights firms by sales, and omits firms for which the labor share cannot be measured in Compustat.

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-	Incumbent			Δ Un-	Incumbent		
	weighted Mean	Re- allocation	Exit	Entry	weighted Mean	Re- allocation	Exit	Entry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>A. Plant Level</i>								
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
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
<i>B. Firm by Industry Level</i>								
1982-1987	-3.46	-1.07	-1.35	1.36				
1987-1992	2.19	-4.72	-1.57	1.52				
1992-1997	-2.24	-1.10	-1.54	1.57				
1997-2002	-0.06	-0.79	-1.47	1.25				
2002-2007	-3.00	-1.58	-1.82	1.92				
2007-2012	2.40	-2.29	-1.31	1.11				
1982-1997	-3.51	-6.89	-4.46	4.45				
1997-2012	-0.66	-4.67	-4.60	4.28				
1982-2012	-4.18	-11.56	-9.06	8.73				
<i>C. 15-Year Decompositions, Firm Level</i>								
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. An analysis of compensation share of value-added at firm level was not disclosed by the Census Bureau.

Table A.2: 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-Polaneec Decomposition				
	Total	Between Industry Shifts	Within-Industry Changes	Δ Unweight- ed Mean	Incum- bent Re- allocation	Exit	Entry	Total Re- allocation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>A. Payroll-to-Value added Ratio</i>								
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
<i>B. Compensation-to-Value added Ratio</i>								
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. This 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 Appendix D.

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

Notes. This 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 Appendix D.

Table A.4: **Output Elasticities for Production Function Estimates**

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

Notes. The table reports output elasticities from industry specific estimates of the production function. The 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 Akerberg, Caves and Frazer (2015) method. Both are based on Cobb-Douglas approaches with time trends. See text for further details. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

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

Rank (1)	1985			2000			2015			
	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 CPI (All Items U.S. City Average Series).

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

	CR4 (1)		CR20 (2)		HHI (3)	
<i>A. Incumbent Reallocation</i>						
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	***
<i>B. Change in Unweighted Mean</i>						
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	
<i>C. Entry</i>						
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	
<i>D. Exit</i>						
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. Numbers of observations as indicated for models with five-year changes in Table 3. Each cell displays the coefficient from a separate OLS industry-level regression of the change in labor share (payroll-to-sales ratio) on period fixed effects and a component of the decomposition of changes in concentration as in Table (6). Industries are weighted by their sales in the initial year, and standard errors in parentheses are clustered by four-digit industries. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

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

Outcome		Nether-										
Mean	Austria	Belgium	Spain	Finland	France	Germany	Italy	Japan	lands	Sweden	UK	USA
<i>A. Correlations of Average Value-Added Share Levels, 1997 - 2007</i>												
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	1.00							
Germany	64.52	0.75	0.87	0.71	0.89	1.00						
Italy	63.82	0.75	0.94	0.87	0.95	0.89	1.00					
Japan	62.89	0.63	0.81	0.80	0.82	0.75	0.82	1.00				
Netherlands	65.33	0.76	0.82	0.75	0.92	0.67	0.88	0.78	1.00			
Sweden	62.93	0.45	0.87	0.82	0.82	0.77	0.81	0.83	0.79	1.00		
UK	65.91	0.74	0.92	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	0.95	0.80	0.90	0.86	0.92	0.86	0.95	1.00
<i>B. Correlations of 10-Year Value-Added Share Levels, 1997 - 2007</i>												
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	1.00

Notes. Correlations include 32 industries both within and outside of manufacturing, using international KLEMS data. 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 five-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 as the fraction of industry 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 industry's share of the country's total value-added. Models are estimated by OLS with standard errors clustered at the industry 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 Unweight- ed Mean	Incumbent Realloca- tion	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. The 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	ln(Sales) (1)	ln(Payroll) (2)	ln(Value- Added) (3)	CR4 (4)	CR20 (5)	HHI (6)	Labor Share (7)	Payroll- to-Sales (8)
<i>A. OLS Estimates</i>								
5 Year Δ 's 1992-2012	-1.98 ** (0.77)	-0.46 * (0.28)	-0.79 ** (0.35)	1.16 (4.39)	0.341 (4.12)	1.18 (2.00)	6.64 ** (2.98)	2.28 (1.82)
10 Year Δ 's 1992-2012	-2.55 *** (0.76)	-0.83 ** (0.34)	-1.36 *** (0.43)	-4.89 (7.91)	-1.80 (7.30)	-0.85 (3.64)	12.38 *** (2.98)	6.85 *** (1.14)
5 Year Δ 's 1992-2007	-2.66 *** (1.00)	-0.66 ** (0.30)	-0.67 ** (0.26)	16.58 * (9.23)	7.36 ** (3.25)	11.17 ** (5.39)	-1.44 (2.98)	-1.10 (1.12)
<i>B. 2SLS Estimates</i>								
5 Year Δ 's 1992-2012	-3.72 *** (1.41)	-0.78 ** (0.34)	-1.17 *** (0.42)	4.69 (5.24)	3.50 (4.01)	4.80 (3.17)	8.17 ** (3.30)	3.60 ** (1.79)
10 Year Δ 's 1992-2012	-4.10 *** (1.26)	-1.21 *** (0.43)	-1.93 *** (0.56)	-3.15 (9.34)	3.47 (7.13)	2.03 (5.38)	15.77 *** (3.30)	8.42 *** (1.61)
5 Year Δ 's 1992-2007	-2.66 *** (1.00)	-1.05 *** (0.38)	-1.17 *** (0.40)	17.60 * (9.57)	9.84 ** (4.49)	13.12 ** (6.20)	0.52 (3.30)	-0.95 (1.42)

Notes. N=1,552 in rows 1 and 4, N=776 in rows 2 and 5, and N=1,164 in rows 3 and 6 (388 manufacturing industries x 4/2/3 periods). Each cell displays the coefficient from a separate regression of the change in the variable indicated at the top of the column on the change in Chinese import penetration and period fixed effects. Industries are weighted by their total value added in 1982, and standard errors in parentheses are clustered by industries. Panel A reports OLS regressions while 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. 2019). * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.