

THE FALL OF THE LABOR SHARE AND THE RISE OF SUPERSTAR FIRMS*

DAVID AUTOR
DAVID DORN
LAWRENCE F. KATZ
CHRISTINA PATTERSON
JOHN VAN REENEN

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 article, 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 toward 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

*This is an extensively revised version of NBER Working Paper no. 23396 (Autor et al. 2017a). The project began in 2013 when Autor and Van Reenen were both visiting professors in Harvard Economics, and we are grateful to LEAP for funding the visits. We thank Andrei Shleifer, Pol Antràs, five anonymous referees, our formal discussants—Joe Altonji, Fatih Guvenen, John Haltiwanger, Loukas Karabarbounis, Matthias Kehrig, and Jonathan Vogel—as well as Daron Acemoglu, Eric Bartelsman, Erik Brynjolfsson, Luis Diez-Catalan, Jason Furman, John Haltiwanger, Gianmarco Ottaviano, Anna Salomons, Richard Schmalensee, Lawrence Summers, and participants in numerous seminars for helpful discussions. Arnaud Costinot has been particularly generous with help on the theoretical model. We acknowledge the excellent research assistance provided by Brandon Enriquez, Juliette Fournier, and Jacopo Orlandi. This research was funded by Accenture LLC, the Economic and Social Research Council, the European Research Council, IBM Global Universities Programs, the MIT Initiative on the Digital Economy, the National Science Foundation, Schmidt Futures, the Sloan Foundation, the Smith Richardson Foundation, and the Swiss National Science Foundation (BSSG10-155804). Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed.

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The Quarterly Journal of Economics (2020), 645–709. doi:10.1093/qje/qjaa004.
Advance Access publication on February 3, 2020.

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. *JEL* Codes: E25, J3, L11.

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 I](#) illustrates this general decline in labor's share in 12 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 ([Jones 2005](#); [Elsby, Hobijn, and Sahin 2013](#)). 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 ([Gollin 2002](#); [Elsby, Hobijn, and Sahin 2013](#)), intangible capital ([Koh, Santaaulalia-Lopis, and Zheng 2018](#)), and business owners taking capital instead of labor income ([Smith et al. 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

1. The main issue in terms of housing is the calculation of the contribution of owner-occupied housing to GDP, which is affected by property price fluctuations. We sidestep this by focusing on the Economic Census, which includes firms (the "corporate sector" of the NIPA), not households. Similarly, the census enumerates only employer firms and does not have the self-employed. There remains an issue of how business owners allocate income, but [Smith et al. \(2019\)](#) show that this can account for only a minority of the decline in the labor share.

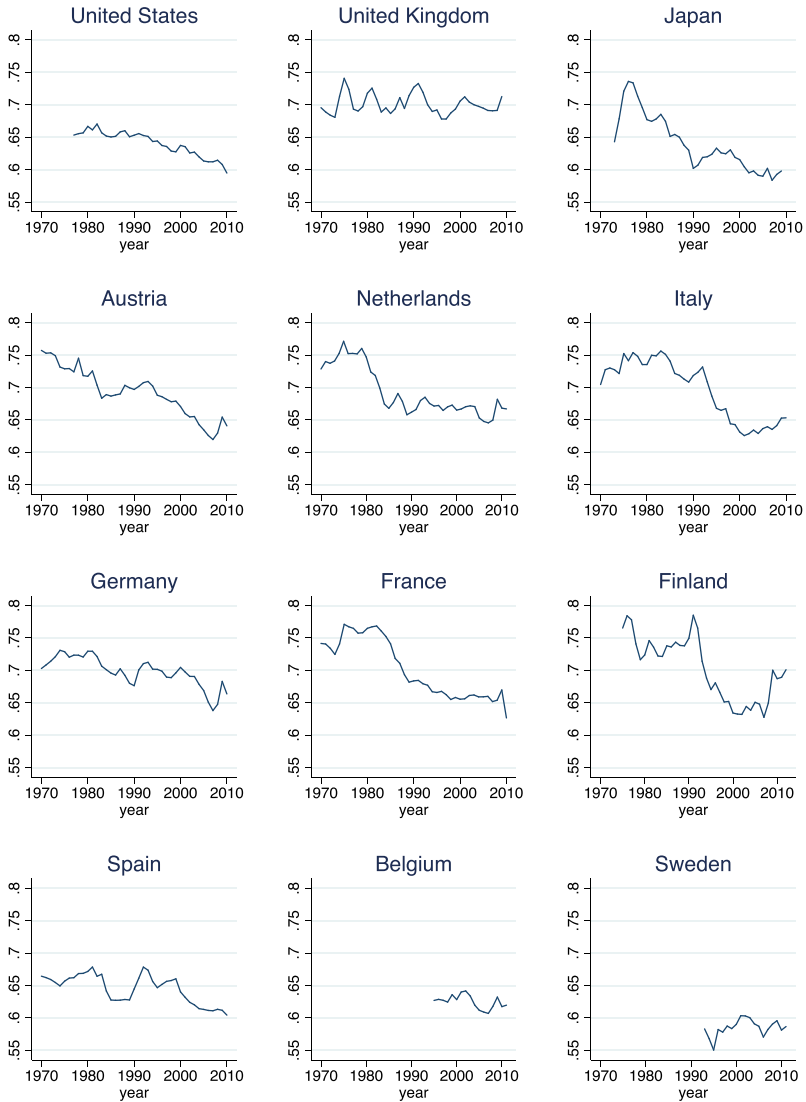


FIGURE I

International Comparison: Labor Share by Country

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

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 1.² [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). In addition, we observe a decline in labor's share in largely nontraded 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 evolutions of unionization and other labor market institutions somewhat vitiates this argument.³

In this article, 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

2. [Karabarbounis and Neiman \(2013\)](#) provide evidence for an elasticity above 1, but the bulk of the empirical literature suggests an elasticity of below 1 (e.g., [Hamermesh 1990](#); [Antràs 2004](#); [Oberfield and Raval 2014](#); [Lawrence 2015](#)). 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 nonautomated tasks ([Acemoglu and Restrepo 2019](#)).

3. [Blanchard \(1997\)](#) 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.

improved search technologies (e.g., greater availability of price comparisons on the internet leading to greater buyer sensitivity, as in [Akerman, Leuven, and Mogstad 2017](#)). Our “winner takes most” mechanism could also arise because of the growth of platform competition in many industries or scale advantages related to the growth of intangible capital and advances in information technology. 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 article’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, although 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 with homogeneous changes in the labor share across firms within an industry.⁴ 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 takes most” feature where a small number of firms gain a large share of the market.⁵ Third, we present a substantial body of evidence from the past 30 years using a variety of U.S. and international data sets that broadly aligns with the superstar firm hypothesis.

4. Exceptions are [Bockerman and Maliranta \(2012\)](#) who use longitudinal plant-level data to decompose changes in the labor share in Finnish manufacturing into between- and within-plant components, and [Kehrig and Vincent \(2018\)](#), who find results consistent with ours in a decomposition of U.S. Census of Manufactures micro data.

5. See [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.

We establish 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 the increased specialization of leading firms on core competencies and large firms getting bigger. The share of U.S. employment in firms with more than 5,000 employees rose from 28% in 1987 to 34% 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 for the average firm;
- (iv) the reallocation-driven fall in the labor share is most pronounced in the industries exhibiting 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;
- (vii) these patterns are not unique to the United States 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,

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

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 information 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 weaker U.S. antitrust enforcement (Döttling, Gutiérrez, and Philippon 2017). Our findings on the similarity of trends in the United States and Europe, where antitrust authorities have acted more aggressively on large firms (Gutiérrez 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 industries (see Cooper et al. 2019 on healthcare for example).

Our article 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 seem 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 on rising aggregate markups. Where Barkai's analysis uses exclusively industry-level and macro data, a major contribution of our

7. See Crouzet and Eberly (2018), Karabarbounis and Neiman (2018), Koh, Santaaulalia-Lopis, and Zheng (2018), Aghion et al. (2019), Lashkari, Bauer, and Boussard (2019), and Unger (2019) for variants of this argument. Koh, Santaaulalia-Lopis, and Zheng (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 Boussard (2019).

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 view our contribution and that of [Barkai \(2017\)](#) as complementary. Our work also corroborates and helps interpret the observation of [De Loecker, Eeckhout, and Unger \(2020\)](#) that the weighted average markup of price over variable cost for publicly listed firms has been rising in the United States (where, *ceteris paribus*, a rise in the markup means a fall in the labor share). As with these papers, our model implies rises in aggregate markups due to a reallocation of market share toward superstar firms with both low labor shares and high markups. We confirm these patterns in our micro census data.

In this article, we build on earlier work ([Autor et al. 2017b](#)) by formalizing the superstar firm theory, presenting firm-level decompositions of the change in the labor share, exploring cross-industry correlations of the change in the 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 article 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 [Online 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

8. A 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.

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 (Hopenhayn 1992; Melitz 2003). 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:

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

where $m_i = \frac{P_i}{c_i}$ 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 because they produce more efficiently, charge lower prices, and capture a higher share of industry output. If they 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, $\omega_i = \frac{P_i Y_i}{\sum_i (P_i Y_i)}$. The reason is because markups (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, $m_i = \frac{\eta_i}{\eta_i - 1}$. 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,

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

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

11. Mrazova and Neary (2017) discuss the implications of a wide class of utility functions (generating “demand manifolds”) including those which are not consistent with Marshall’s second law.

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 ($m = \frac{\eta}{\eta-1}$). 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 toward 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 if there is no fall in the labor share at any given firm. In Online 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 important, 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. Because the demand functions obey Marshall's second law, we obtain the first result that larger firms will have lower labor shares.

As is standard (e.g., Arkolakis 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 toward more

12. See the discussion in Arkolakis et al. (2018). In the time series, the empirical trade literature finds incomplete pass-through of marginal cost shocks to price with elasticities of less than unity, which implies higher 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.

13. Denote fixed overhead labor as F and variable labor as V , with total labor $L = V + F$. In this case, $S_i = \frac{\alpha^L}{m} + \frac{wF}{P_i Y_i}$. Because high z_i firms are larger, they will have a lower share of fixed costs in value added ($\frac{wF}{P_i Y_i}$) and lower observed labor shares (see Bartelsman, Haltiwanger, and Scarpetta 2013).

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.

Because 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. Although the prediction that rising market toughness could generate an increase in concentration and the profit share may seem counterintuitive, the ambiguous relationship between concentration, profit shares, and the stringency of competition often arises in industrial organization.¹⁴

The model in [Online 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;

14. The interpretation of the relationship between profit margins and the concentration level is a classic issue in industrial organization. In the [Bain \(1951\)](#) “structure-conduct-performance” tradition, higher concentration reflected greater entry barriers, which led to an increased risk of explicit or implicit collusion. [Demsetz \(1973\)](#), by contrast, posited a “differential efficiency” model closer to the one in [Online 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.

- (ii) in those industries where concentration rises the most, labor shares will fall the most (assuming that the underlying distribution of productivity draws is log-convex);
- (iii) the fall in the labor share will have a substantial reallocation component between firms, rather than being a purely within-firm phenomenon;
- (iv) in those industries where concentration rises the most, the reallocation from firms with high to low labor shares will be the greatest;
- (v) the industries that are becoming more concentrated will be those with the largest productivity growth;
- (vi) due to high-markup firms expanding, the aggregate markup will rise; and
- (vii) similar patterns of changes in concentration and labor 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 data sets for the United States and other OECD countries.

Our stylized model is meant to illustrate our intuition for the connection between the rise of superstar firms and the decline in labor share. Similar results could occur from any force that makes the industry more concentrated—more “winner takes 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 are (Gilbert and Newbery 1982). A more worrying explanation of growing concentration would be if incumbent advantage were enhanced by 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 Gutiérrez and Philippon 2016, 2018). Explanations for growing concentration from weakening antitrust enforcement have starkly different welfare implications than those based on innovation or toughening competition. We partially—but 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 describe the main features of our data. Further details on the data sets are contained in [Online 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 sectors make up approximately 80% 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 sector, 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 employer contributions to pension plans, all reported in pretax 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,

15. Data 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 does not cover government-owned establishments in the covered industries, and we have to omit the construction sector because of data limitations. We also drop some industries in finance, services, and manufacturing that are not consistently covered across these six sectors. See [Online Appendix D](#) for details.

and we 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 National Income and Product Accounts (NIPA), the Bureau of Economic Analysis (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 results for 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 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 [Online Appendix D](#)). We build 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 data sets. First, we draw on the 2012 release

16. Additional compensation costs are only collected for the subset of census establishments in the Annual Survey of Manufactures and are imputed by the Census Bureau for the remainder.

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

18. A 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 [Online 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 industry definitions.

of the EU KLEMS database (see [O'Mahony and Timmer 2009](#), <http://www.euklems.net/>), an industry-level panel data set covering OECD countries since 1980. We use the KLEMS to measure international trends in the labor share and 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 to 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 a time series for each industry 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 and seeks to cover all nonfinancial 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.

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

20. The six country groups are Canada; eight other developed countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland); Mexico and members of the Central American Free Trade Agreement; China; all low-income countries other than China; and the rest of the world.

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

22. Most important, for our purposes, countries use different reporting thresholds in the definition of their sampling frames. For example, the Belgian data cover all firms, whereas French data include only firms with high sales. Consequently, countries differ in the fraction of employment or value added included in the sample.

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-Özcan 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 explore the characteristics of firms in that group. Further details on data construction are reported in [Online Appendix D](#), and the Compustat analysis is found in [Online Appendix C](#).

III.B. Initial Data Description

[Figure I](#) plots labor share of value added since the 1970s in 12 developed economies. 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 II](#) 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 construct the labor share using payroll, which is the standard labor cost measure 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 nonwage labor costs (such as employer health insurance contributions), which are only provided in the Census of Manufactures and not the other parts of the Economic Census. Last, we also plot payroll normalized by sales, rather than value-added, because this is the measure that can be constructed outside of manufactures in the

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

24. Of the 12 countries, Sweden and the United Kingdom seem the exceptions with no clear trend. [Bell \(2015\)](#) suggests that the United Kingdom does have a downward trend in the labor share when the data are corrected for the accounting treatment of payments into (underfunded) 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 nonwage compensation of current employees.

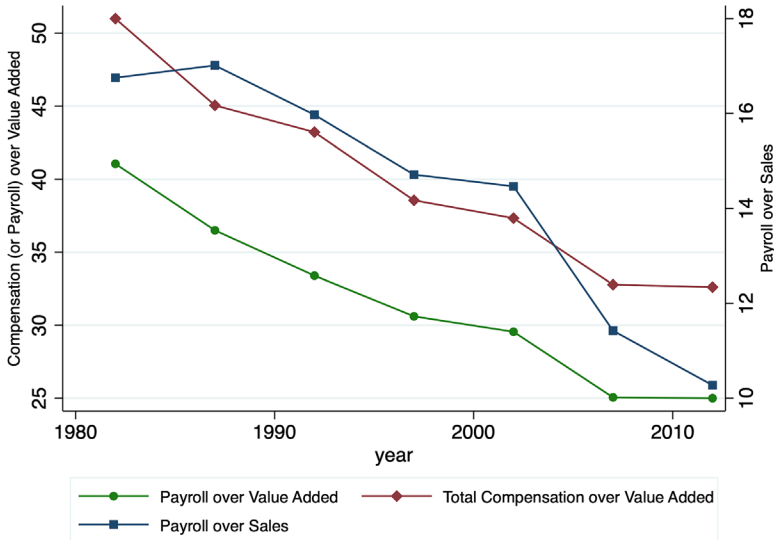


FIGURE II

The Labor Share in Manufacturing

This figure plots the aggregate labor share in manufacturing from 1982 to 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 renormalized by sales rather than value added (plotted on the right axis using a separate scale). Color version available online.

Economic Census. [Figure II](#) shows that all three series show a clear downward trend, although 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 III](#). Finance stands out as the only sector with a clear upward trend in the labor share. As discussed already, 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 and then partly

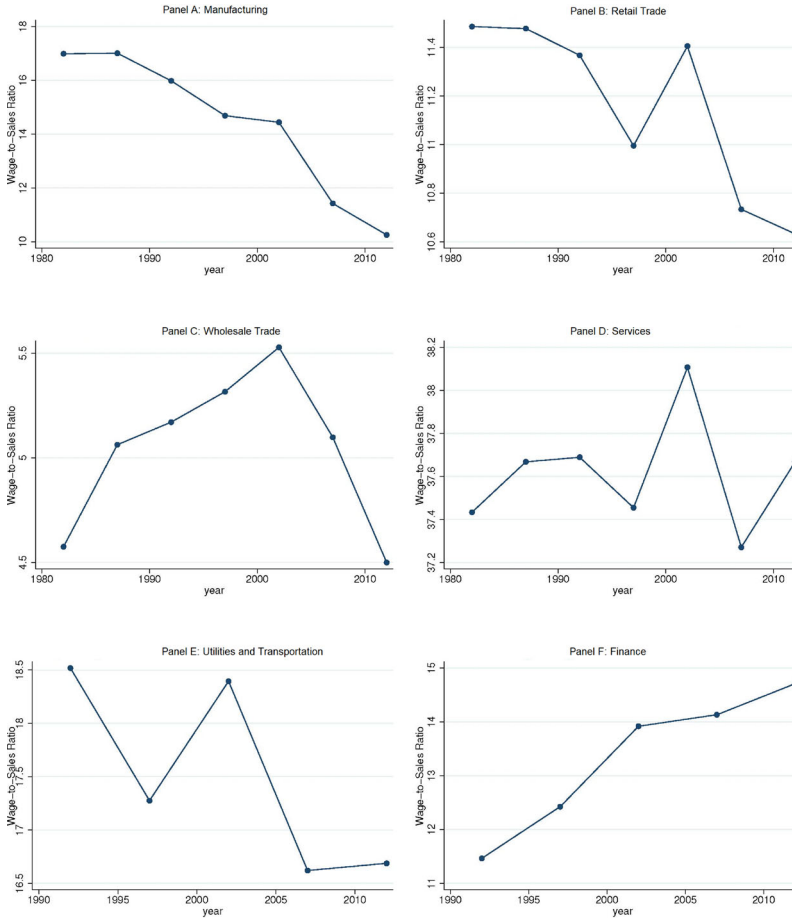


FIGURE III
Average Payroll-to-Sales Ratio

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.

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. [Online 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. [Online Appendix Figure A.7](#) shows that all nonfinance 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 the mid-1980s to the Great Recession (before 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 IV](#) plots the sales-weighted average sales- and employment-based CR4 and CR20 measures of concentration across four-digit industries for the six major sectors using updated data from the census. [Online Appendix Figure A.1](#) shows a corresponding plot for the 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 et al. \(2008\)](#) call “scale without mass.” Third, a comparison of [Figure IV](#) and [Online Appendix 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 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

25. Because 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.

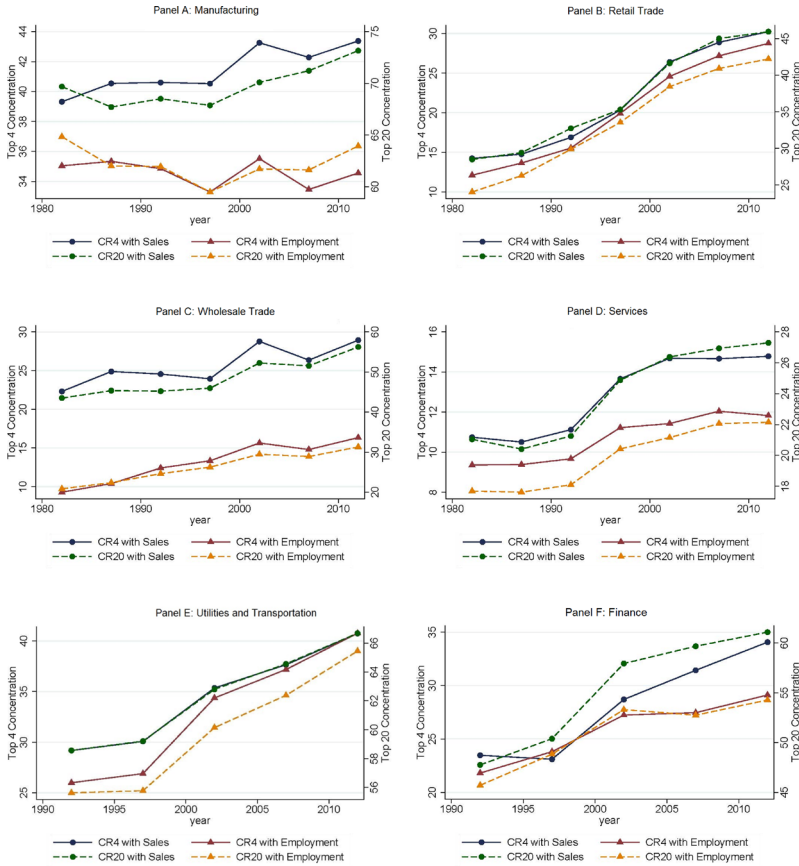


FIGURE IV

Average Concentration across Four-Digit Industries by Major Sector

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 the six sectors. 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 used 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. Color version available online.

this count fell to below 9 by 2012. Similarly, conditional on a firm being among the top four firms in a four-digit industry in 1982, it was on average among the top four in 0.37 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 I](#) provides further descriptive statistics for sample size, labor share, and sales concentration in the six sectors.

Next we present evidence of the cross-sectional relationship between firm size and labor share. As discussed in [Section II](#), our conceptual framework is predicated on the idea that because superstar firms produce more efficiently, they are both larger and have lower labor shares. To check this implication, [Figure V](#) 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 THE SUPERSTAR FIRM MODEL

IV.A. *Rising Concentration Correlates with Falling Labor Shares*

1. *Manufacturing.* [Table II](#) 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 the six sectors, we separately estimate OLS regressions in long differences (indicated by Δ) of the form

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

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 II](#) report estimates of β from [equation \(2\)](#). The first three columns present stacked 5-year differences, and the

TABLE I
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)
A. Manufacturing (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)
B. Retail trade (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)
C. Wholesale trade (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)
D. Services (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)
E. Finance (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)
F. Utilities and transportation (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, and reflect totals for the entire sector, with the standard deviation across years in parentheses. Columns (3)-(10) indicate the levels and five-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.

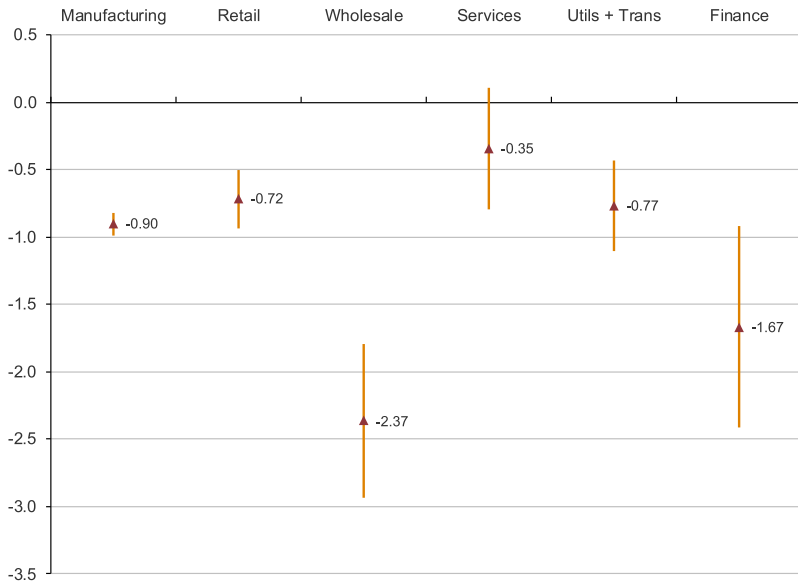


FIGURE V

The Relationship between Firm Size and Labor Share

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.

last three columns present 10-year differences. Since the left- and right-side variables cover the same time interval in each estimate, the coefficients have a comparable interpretation in the 5-year and 10-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% 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 II](#) 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

TABLE II
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)	-0.155*** (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 subperiod	-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 \times 6 five-year periods) in columns (1)–(3) (except $N = 1,552$ in rows 6 and 7) and $N = 1,164$ (388 industries \times 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 rows 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, and 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 five-year changes during the 1992–2012 period, while row 6 indicates estimates from the baseline regression for this shorter period. * $p \leq .10$, ** $p \leq .05$, *** $p \leq .01$.

fringe benefits, such as private health insurance, which accounts 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 try to account for intermediate service inputs that are not included in the census data (see Online 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, our results may be misleading. We address this issue in several ways. Because 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, Table II, row 6 reestimates our baseline model for the shortened period and finds a slightly stronger relationship between labor share and concentration. Row 7 adds in the growth in imports over value added in each five-year period on the right 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 effect 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 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

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

superstar mechanism linking falling industry-level average labor shares to rising concentration is not 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 II](#). Interestingly, the coefficients switch signs and are positive (but insignificant, with one exception). 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 with 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-based concentration among Intellectual Property and human capital-intensive firms.

2. All Sectors. We 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 II](#) in [Table III](#) 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

27. [Table I](#) 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

TABLE III
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 (1)	CR20 (2)	HHI (3)	CR4 (4)	CR20 (5)	HHI (6)
1 Manufacturing <i>n</i> = 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 <i>n</i> = 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 <i>n</i> = 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 <i>n</i> = 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 <i>n</i> = 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 <i>n</i> = 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 <i>n</i> = 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 three columns (*x*) and the last three 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* ≤ .10, ** *p* ≤ .05, *** *p* ≤ .01.

Figure VI 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 Table III, column (2)). It is clear from both Figure VI and Table III that rising concentration is uniformly associated with a fall in the labor share outside of manufacturing and within it. The coefficient on the concentration measure is negative and significant at the 5% 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 III, labeled “combined”), we again find a strong negative association between rising concentration and falling labor share.

Table III also reports several variants of this regression using alternate measures of concentration as well as stacked 10-year

labor share as payroll over value added instead of payroll over sales (e.g., −0.148 for the CR4 in Table II, column (1), compared to −0.062 in Table III).



FIGURE VI

The Relationship between the Change in Labor Share and the Change in Concentration across Six Sectors

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 Table III, Panel A, column (2), which also tabulates the full regression results using alternative specifications.

changes rather than 5-year changes. The relationship is negative in all 36 specifications in Table III, rows 1–6, and significantly so at the 10% or higher 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 given the other results, we find that

28. To assess whether the results are driven by the number of firms in the industry rather than their concentration, we additionally included the count of firms as a separate control variable in changes and initial levels. Although the coefficient on concentration tends to fall slightly in such specifications, it remains generally significant, suggesting that it is the distribution of market shares that matters and not simply the number of firms.

the change in the CR1 is negatively associated with changes in the labor share in all specifications in all six sectors.²⁹ Because 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 whole U.S. economy.

3. Robustness Tests. We implemented many robustness tests on these regressions and discuss several of them here. First, we repeated the robustness tests applied to manufacturing in [Table II](#) for the full set of six sectors to the extent that the data permit. For example, following the model of [Table II](#), row 5, we added a full set of four-digit industry trends to the five-year first-difference-by-sector estimates in [Table III](#). All coefficients were negative across the three measures of concentration and 14 of the 18 were significant at the 5% 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 lower-tech industries. 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

29. For the five-year difference specifications, the coefficient (standard error) on the CR1 in manufacturing was -0.124 (0.041) for payroll over value added, -0.146 (0.054) for compensation over value added, and -0.060 (0.014) for payroll over sales. The correlation between changes in CR1 and payroll over sales is also negative in the other five sectors and significant in all sectors but retail.

30. We followed [Decker et al. \(2018\)](#) 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. Rerunning our primary model with this classification, we found that the coefficient on concentration is negative and significant in both subsamples but is almost twice as large in absolute magnitude in the high-tech subsample. 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 .

heterogeneity between years into account only through the inclusion of time dummies. [Online Appendix](#) Figure A.5 shows the regression coefficients that result from separate period-by-period estimates of [equation \(2\)](#) using CR20 as the measure of industry concentration as an illustration. Under either definition of the labor share denominator (value added or sales) in manufacturing, the relationship between the change in the labor share and the change in concentration is significantly negative in all periods except for 1982–1987 and generally strengthens over the sample period. 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*

1. 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, because 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

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

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

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

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

we write the Olley-Pakes decomposition as:

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

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

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

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

2. Main Decomposition Results. In Figure VII, we show an illustrative plot for the Melitz-Polanec decomposition calculated for adjacent 5-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 survivors was the main component of the fall: –8.24 percentage points in the early period and –4.90 percentage points in the later period. Although the unweighted firm average component is negative over both periods, the reallocation component among survivors is 3 (1982–1997) to 12 (1997–2012) times as large as the within-firm component. Notably, the within-survivor contribution to the falling labor share is only 0.4 percentage points during 1997–2012, meaning

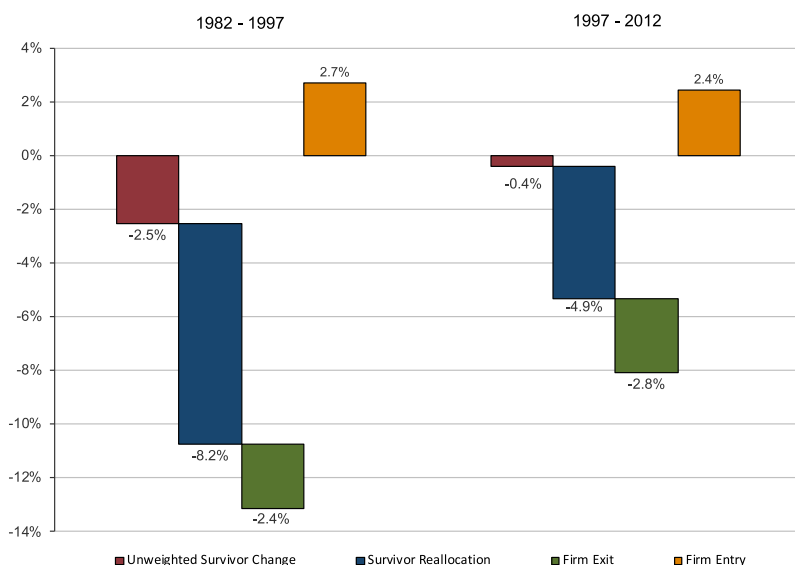


FIGURE VII

Melitz-Polanec Decomposition of the Change in Labor Share in Manufacturing

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 side shows the sum of the decompositions from 1982–1987, 1987–1992, and 1992–1997 and the right side shows the sum of the decompositions from 1997–2002, 2002–2007, and 2007–2012. [Table IV](#) reports the underlying estimates for each five-year period.

that for the unweighted average survivor firm, the labor share fell by under half a percentage point over the entire 15-year period.

In addition to the reallocation effect among 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 because 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

TABLE IV
DECOMPOSITIONS OF THE CHANGE IN THE LABOR SHARE, MANUFACTURING

	Δ Un- weighted mean of survivors (1)	Survivor re- allocation (2)	Exit (3)	Entry (4)	Total (5)
Panel A: Payroll share of value added					
1982–1987	–3.03	–1.75	–0.59	0.86	–4.52
1987–1992	2.60	–5.26	–0.90	0.98	–2.58
1992–1997	–2.08	–1.24	–0.89	0.89	–3.32
1997–2002	0.00	–0.76	–1.00	0.69	–1.08
2002–2007	–3.06	–1.53	–1.12	1.23	–4.48
2007–2012	2.64	–2.61	–0.63	0.51	–0.09
1982–2012	–2.93	–13.15	–5.14	5.15	–16.07
Panel B: Compensation share of value added					
1982–1987	–0.78	–5.66	–0.47	0.98	–5.93
1987–1992	3.73	–5.69	–1.00	1.05	–1.91
1992–1997	–2.78	–1.90	–0.93	0.97	–4.64
1997–2002	–2.07	1.11	–1.09	0.79	–1.25
2002–2007	1.26	–6.21	–1.20	1.55	–4.60
2007–2012	0.40	–0.32	–0.77	0.53	–0.15
1982–2012	–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 and 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.

Manufactures). Since the contribution of entry and exit is broadly similar, these two terms approximately cancel in our decomposition exercise.

Table IV 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 surviving firms contributes negatively to the labor share in every five-year period whereas unweighted average firm movements contribute positively in two of the six time periods (1987–1992 and 2007–2012). Panel B 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-survivor reallocation of value added. The

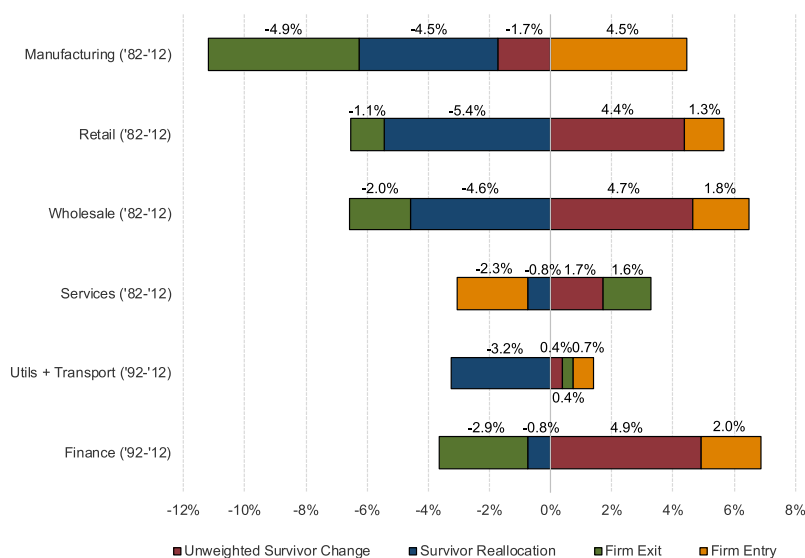


FIGURE VIII

Melitz-Polanec Decomposition of the Change in Labor Share in All Six Sectors

Each bar represents the cumulated sum of the Melitz-Polanec decomposition components calculated over adjacent five-year intervals for payroll over sales. [Table V](#) reports the underlying estimates for each five-year period.

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 surviving firms. By contrast, the unweighted labor share for survivors 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 six sectors we consider.³³ [Figure VIII](#) 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 V](#) reports the decompositions over five-year periods underlying the sample totals plotted in [Figure VIII](#). Recall that we do not have firm-level

33. The level of the payroll-to-sales ratio differs substantially across sectors due partly to differences in intermediate input costs (see [Figure III](#)), and we thus implement decompositions separately by sector.

TABLE V
DECOMPOSITIONS OF THE CHANGE IN THE PAYROLL-TO-SALES RATIO, ALL SECTORS

	Δ Un-weighted mean of survivors (1)	Survivor re-allocation (2)	Exit (3)	Entry (4)	Total (5)	Δ Un-weighted mean of survivors (1)	Survivor re-allocation (2)	Exit (3)	Entry (4)	Total (5)
	Panel A: Manufacturing					Panel B: Retail				
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
	Panel C: Wholesale					Panel D: Services				
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

TABLE V
CONTINUED

	Δ Un-weighted mean of survivors (1)	Survivor re-allocation (2)	Exit (3)	Entry (4)	Total (5)	Δ Un-weighted mean of survivors (1)	Survivor re-allocation (2)	Exit (3)	Entry (4)	Total (5)
	Panel E: Utilities and Transportation					Panel F: Finance				
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 IV.

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 VII](#) for payroll over value added within manufacturing, the total contribution of market share reallocation among surviving 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-survivor reallocation effect contributes to the decline in the payroll share in each of the other five sectors. By contrast, the unweighted firm mean 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.

3. Robustness of the Decomposition Analysis. We examine the robustness of our decomposition findings (with further probes considered in [Online 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 because entry and exit can occur through firm merger and acquisition activity rather than de novo start-ups or closing down of establishments.³⁴ In addition, 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 [Online Appendix Table A.1](#) the results of a decomposition analysis at the establishment level (Panel A) and the firm-by-four-digit SIC industry level

34. For 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.

(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 [Online Appendix Table A.1](#), Panel C, we perform the decomposition at 15-year intervals rather than 5-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 5 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:

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

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 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 [Online Appendix D](#)).

We show the components of this five-way decomposition in [Online Appendix Tables A.2 and A.3](#). The two panels of [Online Appendix Table A.2](#) report payroll over value added and compensation over value added (in manufacturing), and the six

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

36. In addition, 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 IV and V](#).

panels of [Online Appendix 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 with 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 with -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 with a total (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 IX](#) 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 with their 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 common across firms within an industry.

We explore the model's prediction in [Figure IX](#) by plotting the relationship in each sector between changes in four-digit industry concentration and the four components of the Melitz-Polanec decomposition. In the figure, the upper bars report the

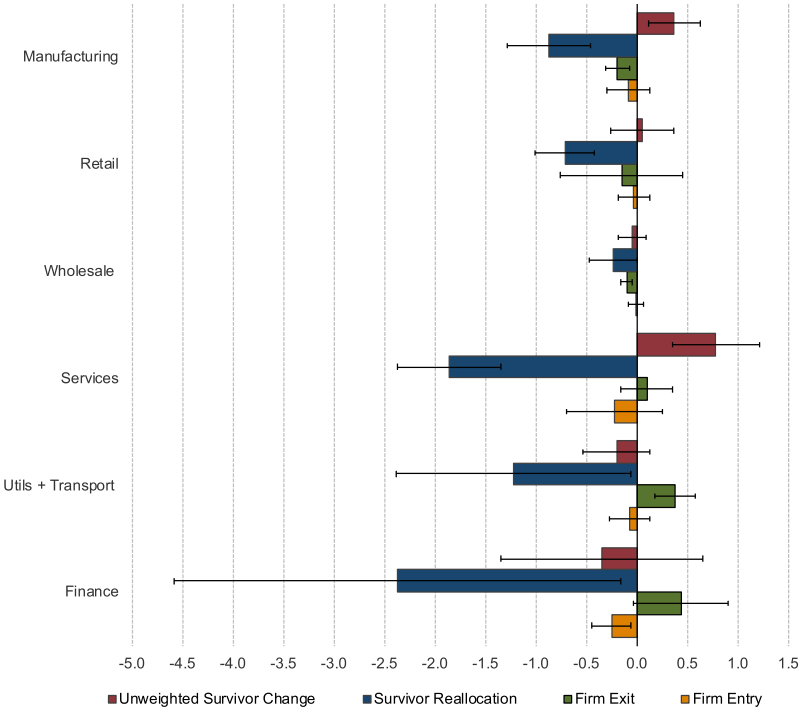


FIGURE IX

Regressions of the Components of the Change in Labor Share on the Change in Concentration

Each bar plots 10 times the regression coefficient resulting from regressions of the Melitz-Polanec decomposition components on the change in CR20 concentration. Regressions include year dummies, and standard errors are clustered at the four-digit industry level. Each industry is weighted by its initial share of total sales. Whisker lines represent 95% confidence intervals.

coefficient estimates and standard errors from regressions of the within-survivor component of the fall in the labor share (based on Table V) on the change in the CR20. The bars directly underneath report the estimates that result from regressing the survivor 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. Online Appendix Table A.6 (column (2)) reports the corresponding regressions underlying Figure IX alongside analogous estimates using our two alternative measures of concentration. The

pattern of results in Figure IX is consistent across all sectors: the tight correlations between rising concentration and falling labor share reported in Figure VI are driven by the reallocation component. Specifically, the survivor reallocation component shows up as negative and significant in all sectors, indicating that rising concentration predicts a fall in labor share through survivor 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-survivor reallocation component. The results provide further evidence, consistent with the superstar firm hypothesis, that concentrating industries experienced a differential reallocation of economic activity toward firms with 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 like those underlying Figure VIII. 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 IX, 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

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

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)). 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 Online 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.

1. Measuring Markups. To empirically test this implication of the model, we must estimate markups. Following the literature (e.g., De Loecker, Eeckhout, and Unger 2020), we can estimate markups by rearranging and generalizing equation (1):

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

where $S_{it}^v = (\frac{W_{it}^v X_{it}^v}{P_{it} Y_{it}})$ 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 nonconstant returns and more general technologies (see Hall 1988, 2018). Although factor shares (S_{it}^v) are directly observable in principle, 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 's costs ($W_{it}^v X_{it}^v$) in total costs ($\sum_f W_{it}^f X_{it}^f$). In this case, the markup formula becomes:

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

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 Antràs, Fort, and Tintelnot (2017), among others. We call this the “accounting approach” because 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 De Loecker and Warzynski (2012).

This approach relaxes the constant returns assumption implicit in the accounting approach but requires 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. [Online Appendix B](#) details how we estimate plant-level production functions using various methods such as [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 multiplant firms.

2. Results. We summarize the results of these exercises here and provide further details in [Online Appendix B](#). Before exploring trends, [Online Appendix](#) Figure A.4 confirms that larger firms have higher markups, no matter how they are estimated. In [Figure X](#), 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; color version of figure available online). Panel A uses 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 function. 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 panels of [Figure X](#), 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

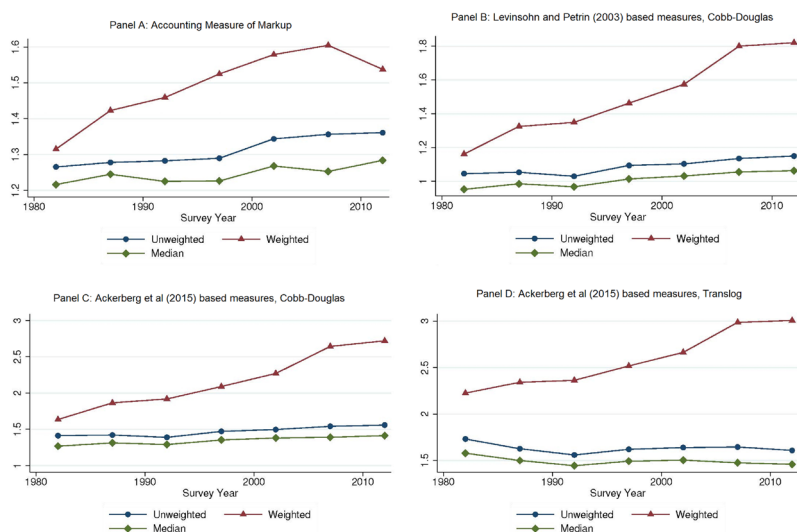


FIGURE X
Markup Changes

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 [Antràs et al. \(2017\)](#) “accounting” method, and 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 and 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) presents the mean markups weighted by a firm’s value added. Color version available online.

[De Loecker, Eeckhout, and Unger \(2020\)](#) using publicly listed firms in Compustat across all sectors.³⁸ Third, across all methods, the aggregate markup has risen much more quickly than

38. [De Loecker, Eeckhout, and Unger \(2020\)](#) report an increase in the aggregate markup from 1.2 in 1980 to 1.6 in 2016 among publicly listed firms. They present production function–based estimates of markups for Compustat but not for the census data, so our census production function–based results are distinctive. [De Loecker, Eeckhout, and Unger \(2020\)](#) 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 [Antràs, Fort, and Tintelnot \(2017\)](#). Despite these methodological differences, it is reassuring that both sets of markup estimates tell broadly the same story.

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 already. The pattern underscores the centrality of superstar firms for the evolution of the markup consistent with the findings in [De Loecker, Eeckhout, and Unger \(2020\)](#) and [Baqae and Farhi \(2020\)](#). We further explore the evolution of markups and subject our findings to many other robustness tests in [Online Appendix B](#).³⁹

IV.E. Concentrating Industries Have Higher Growth of Innovation and Productivity

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 toward greater concentration and a reallocation of output toward 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 in [Section IV.D](#). [Online Appendix Figure A.2](#) shows that large firms in manufacturing are more productive, regardless of how we measure TFP. [Online Appendix Figure A.3](#) shows that large firms have higher labor productivity in the six sectors that we consider. The finding that larger firms have higher TFP and lower labor shares is consistent with the model in [Online Appendix A](#) and underpins the industry-level prediction relating concentration and dynamism.

39. [Edmond, Midrigan, and Xu \(2015, 2018\)](#) 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 2020](#)). 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 2020](#) using Compustat data). Fortunately, using input weights gives the same qualitative patterns as [Figure X](#), 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).

TABLE VI
CHARACTERISTICS OF CONCENTRATING INDUSTRIES

	CR4 (1)	CR20 (2)	HHI (3)
Panel A: Manufacturing only			
1 Patents per worker	0.090** (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 Five-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)
Panel B: All sectors			
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	0.270* (0.143)	0.216* (0.111)	0.144*** (0.052)
13 Combined sales per worker	0.155*** (0.031)	0.147*** (0.026)	0.053*** (0.011)

Notes. $N = 2,328$ (388 industries \times 6 five-year periods) in Panel A, and various sector-specific numbers of observations as reported in Table IV 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. * $p \leq .10$, ** $p \leq .05$, *** $p \leq 0.01$

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 VI displays regressions where the dependent variable is the five-year growth in concentration and the

explanatory variables are proxies for industry dynamism.⁴⁰ Panel A focuses on the manufacturing sector where the data are richer, and 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 VI](#) 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 [Section 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 important, value added is deflated by an industry-specific producer price index in the productivity measure in [Table VI](#), but it is simply equal to the nominal labor share in [Table II](#). This is important as increased concentration may be associated with higher prices, meaning the correlation with the nominal, nondeflated 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 be attributable to faster input growth in these concentrating industries. Indeed, we find that the concentrating industries experience faster growth in the capital–worker ratio, as is shown in the third row of [Table VI](#). Nevertheless, even when we control for output increases arising from five possible factor inputs (labor, structures capital, equipment capital, energy inputs, and nonenergy material inputs) in our TFP measure in the fourth row, we find a significantly positive correlation between concentration growth and TFP growth.⁴¹

40. All regressions are weighted by the initial size of the industry, include year dummies, and cluster standard errors by industry as in [Tables II](#) and [III](#).

41. This 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 [Section IV.D](#) and [Online Appendix B](#). The qualitative results were similar, since all TFP measures are strongly and positively correlated with each other.

In [Table VI](#), Panel B we repeat these specifications for all six sectors. Due to the absence of value-added data outside of manufacturing, we measure productivity as sales per worker. Despite this limitation, we find a positive relationship across all 18 regressions, with 12 coefficients significant at the 5% level, two significant at the 10% 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

The positive correlation between changes in concentration and productivity supporting the superstar firm mechanism implies that the reallocation of sales and value added toward the most productive firms in each sector should contribute to overall productivity growth. Yet it is widely acknowledged that aggregate productivity growth in the United States and Europe slowed from the early 1970s, rebounded modestly in the mid-1990s, and then slowed again from 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

42. This evidence is consistent with the evidence across OECD countries in [Autor and Salomons \(2018\)](#), who find 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 II](#) 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 II](#) without concentration).

43. [Andrews, Criscuolo, and Gal \(2015\)](#) examine firm-level data in 24 OECD countries between 2001 and 2013 and find that although 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 has slowed (as indicated by a drop in the speed of citations), concentration has risen by more and labor shares have fallen by more. For example, in

not economically large, but changes in the economic environment have nevertheless yielded substantial reallocation of market shares toward 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 United States should be observed internationally. Karabarbounis 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 United States are prevalent throughout the OECD. Our superstar firm framework emphasizes global technological forces for the trend toward greater concentration and a reallocation of output toward high-productivity and low labor share firms. The precise mechanisms leading to the rise in superstar firms and decline in labor share may include platform competition, 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 Online Appendix A. An alternative interpretation of these patterns is offered by Döttling, Gutiérrez, 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 Döttling, Gutiérrez, and Philippon (2017) emphasize, antitrust enforcement has, if anything, strengthened in the European Union—yet the labor share appears to have fallen and industry concentration appears to have risen despite this countervailing force.

1. Concentration in the OECD. The construction of comprehensive data on changes in sales concentration over time across

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.

countries is challenging. The most comprehensive source for such an analysis is Multiprod, an OECD initiative that analyses firm-level administrative data from multiple 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 in the 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 2 percentage points in manufacturing and 3 percentage points in nonfinancial 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

2. Correlation of Industry Labor Shares. [Figure I](#) 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 make up the market sector using international KLEMS data. [Online Appendix 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 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

44. [Döttling, Gutiérrez, and Philippon \(2017\)](#) have argued the opposite—that concentration has been falling in the EU. [Bajgar et al. \(2018b\)](#) trace the discrepancy to [Döttling, Gutiérrez, and Philippon's \(2017\)](#) use of BVD Orbis data to calculate concentration rather than the near-population Multiprod data used by the OECD.

three-quarters of all cases (51 of 66). The correlation matrices underlying these summary tables are reported in [Online Appendix Table A.7](#).

3. Industry Labor Shares and Concentration. We 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 the labor share and industry-level concentration, defined as the fraction of industry sales produced by the top 10 firms in a country. We estimate [equation \(2\)](#) in 5-year (2006–2011) and 10-year (2001–2011) long differences separately for the 14 countries in the database. The estimates, reported in [Online 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 10-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, 5 of the 10 coefficients are negative and significant at the 10% level or greater, and four additional countries have negative but insignificant coefficients.

4. 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 United Kingdom, 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. [Online 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 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 the countries, this within-firm component is positive.

5. Markups in Different Countries. There has also been considerable recent work on markups using firm-level data across countries ([Calligaris, Criscuolo, and Marcolin 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 toward firms with high markups (and low labor shares).

6. 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 broadly mirror the evidence from the more detailed U.S. data: (i) concentration 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 reallocating 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.

45. We focus on manufacturing because measurement of the labor share is more reliable for this sector. [Online Appendix Table A.9](#) shows the details of the data and the decomposition.

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, ς , $\Delta \ln S = -\Delta \ln m + \varsigma$. 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 from 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 [Section IV.D](#)). Using [Table IV](#), the proportionate fall in the labor share of value added ($\Delta \ln S$) is 40% (a 16.1 percentage point change divided by a 41% initial level). The percentage change in the markup ($\Delta \ln m$) depends on which measure we use. Using the accounting method in [Figure X](#), Panel A, there is a 17% rise in the markup ($\frac{0.22}{1.31}$), implying that we account for about two-fifths ($\frac{17}{40}$) of the labor share change.⁴⁸ By contrast, using the production function-based measures of the markup, we account for essentially all of the labor share change (e.g., in [Figure X](#), Panel B, the growth of the markup is 50% ($\frac{0.6}{1.2}$)).

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

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

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

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 X](#). For the accounting-based method, this reduces the proportion of the labor share fall explained by about half (to 18.5%).

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 $\Delta\hat{S} = \sum_k (\omega_k \hat{\beta}_k \Delta\text{CONC}_k)$ 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 IV](#)) is –0.97 percentage points, as compared with 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 ($52\% = \frac{0.97}{1.86}$).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,

49. If we also 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, we are cautious about using this sector given the data concerns over the census sales measures, and hence we prefer the more conservative nonfinancial estimates.

50. This is partly because of a faster rise in concentration after 1997 (see [Figure IV](#)) and partly because the coefficient on concentration was rising (see [Online Appendix 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 [Online Appendix 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 $(\frac{-0.34 \times 6}{6}) \times 100 = 34\%$ of the fall in the labor share in manufacturing over this period.

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 here are economically important.

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 few decades.

V.A. *Import Exposure and Superstar Firms*

Using data from manufacturing and nonmanufacturing 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. [Online Appendix Table A.10](#) reports regressions of changes in industry-level outcomes in U.S. manufacturing on changes in Chinese imports intensity using 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 report results both including and excluding the post-2007 Great Recession period, when import growth slowed considerably. The first three columns of [Online Appendix 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

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

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). Because the negative effect of rising Chinese import exposure on industry payroll is smaller in absolute magnitude than its negative effect on industry value added and sales, the labor share of sales or value added tends to rise with growth of industry import exposure.⁵²

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 [Online 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 more than 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 about

52. A key difference with [Elsby, Hobijn, and Sahin \(2013\)](#) is that they pool data from manufacturing and nonmanufacturing 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 probably 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 nonmanufacturing. Within manufacturing, 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 the labor share has fallen outside of manufacturing.

53. Sales and market values are deflated by the GDP deflator and reported in constant 2015 dollars.

60%, 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 41% in 1999 to 48% in 2015 (and was 43% in 1972). 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% to 82% between 2000 and 2015. Similarly, the 10-year survival rate of firms in the top 500 rose from 55% in 2005 to 68% in 2015.

A fourth finding relates to the growing global engagement of U.S. firms. We estimate that the share of sales outside of the United States for superstar firms grew from 21% to 38% from 1978 to 2011, before declining slightly from 2011 to 2015.

The evolution of the labor share is harder to explore in Compustat data because only a minority of firms report 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 2019](#)). This pattern echoes our broader finding that the fall in the labor share and the rise in concentration are prevalent across nontraded sectors in census data rather than being limited to the heavily traded manufacturing sector. Thus, construed narrowly, globalization appears unlikely to be the main driver of falling labor shares.

54. We 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. [Gutiérrez 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.

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 a potential mechanism contributing to the decrease in the labor share, although the broad decline of labor shares in nonmanufacturing (where unions have had little presence) and in countries where union power has not fallen so steeply as in the United States somewhat mitigates against this hypothesis. Alternatively, the growth of superstar firms could confer more monopsony power to employers, negatively impacting both wages and employment. In Table VI, Panel A, row 5, we find that the relationship between changes in concentration and changes in average wages (payroll per worker) in manufacturing is in fact slightly positive, but insignificant. This suggests that concentrating sectors in manufacturing are those where the share of labor is falling, but the average wage is not.⁵⁵

Table VI, Panel A, row 6 shows that concentrating industries in manufacturing have moved toward an increased reliance on materials inputs, consistent with greater intermediate 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 article proposes and evaluates evidence for a new superstar firm explanation for the fall in the labor share of value added.

55. Payroll 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 (Azar et al. 2018; Benmelech, Bergman, and Kim 2018; Rinz 2018). Although our conclusion that national sales concentration rates have risen is now widely reported (see Barkai 2017; Gutiérrez 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) has a large number of imputed establishment-level sales values.

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 giving advantages to 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 nonmanufacturing. 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, 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 anticompetitive forces, is an important driver—though likely not the only one—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 increasingly have 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 large 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 positions. 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 analyze 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 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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SUPPLEMENTARY MATERIAL

An [Online Appendix](#) for this article can be found at *The Quarterly Journal of Economics* online. Data and code replicating tables and figures in this article can be found in [Autor et al. \(2020\)](#), in the Harvard Dataverse, doi: [10.7910/DVN/6LVZM7](#).

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