Industrial Concentration and the Declining Labor Share*

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Abstract

The labor share of national income in the United States has declined since the 1980s and especially after 2000. My paper focuses on the role played by technological change in this process. In particular, firms that adopt new technologies achieve a low labor share, and grow and take a larger market share over time. An example is online retailers such as Amazon, empowered by information technology, that have a lower labor share than traditional retailers, and have continually expanded over the last 20 years. This reallocation process drives down the aggregate labor share. I first document three facts: (i) across sectors, there is a negative correlation between change in concentration and change in the labor share; (ii) large firms usually exhibit a smaller labor share; (iii) in sectors where the labor share declines, the decline is especially strong among large firms. Specifically, gains in labor productivity are not associated with comparable increases in wages. Then I provide a rationale for these facts by assuming that capital and labor are complementary inputs and technological progress is labor saving and embodied in the capital stock. Under these assumptions, my model predicts a negative correlation between firm size and labor share. Further, the adoption of new technologies diminishes the labor shares in large firms and increases their market share. As a consequence, the aggregate labor share declines. This technological channel is consistent with the evolution of labor productivity across sectors during the last 30 years.

JEL classification: E23, E25, L11, O33
Keywords: Labor share, firm size, concentration, capital-labor complementarity, technological change

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1 Introduction

The long-run constancy of labor share (LS) is typically viewed as a stylized fact of economic growth. Among other things, it justifies the widespread use of an aggregate Cobb-Douglas production function in macroeconomics. However, the recent literature documents the break of this constancy: in the United States the share of national income that goes to labor has oscillated cyclically during the whole post-WWII period and, more relevant in this context, it has clearly been declining for more than three decades. Albeit to different extents, this long-term decline is visible also in other advanced countries (Elsby et al. (2013); Karabarbounis and Neiman (2014b); Piketty and Zucman (2014)). My paper studies the role played by technological change in this process. In particular, new technologies create, or are adopted by, firms that achieve a low labor share, and grow and take a larger market share over time. An example is online retailers such as Amazon, empowered by information technology, that have a lower labor share than traditional retailers, and have continually expanded over the last 20 years.[1] This reallocation process drives down the aggregate labor share.

My research is motivated by three empirical facts documented in the paper. First, there is a negative correlation between change in market concentration—measured as the share of total revenue in a sector attributable to its largest firms—and change in labor share, in that sector. Even though the aggregate labor share has declined, the decline is not universal across sectors. The decline concentrates in several sectors, namely, manufacturing, retail and wholesale trade[2], and transportation & warehousing. These are also sectors where concentration has increased the most. From 1997[3] to 2012, the revenues share of the 50 largest firms increased from 20.3% to 27.6% in wholesale trade, from 25.7% to 36.9% in retail trade, and from 30.7% to 42.1% in transportation. This negative correlation between change in concentration and change in labor share also holds across more disaggregated manufacturing sectors (i.e. at various digits North American Industry Classification System (NAICS) sectors), and is robust for different periods, for a range of cutoffs for what constitutes a "large" firm, and to adding other control variables and sector fixed effect. Concentration ratio for the whole manufacturing sector is relatively stable from 1960s to around 1980, and increases thereafter. The manufacturing labor share shows a similar but opposite pattern: relatively stable until around 1980, and declines in the last 3-4 decades. In almost all the other service and finance sectors, the labor share did not fall and concentration increased at a much slower pace.

[1] The payroll-sales ratio in "Electronic shopping and mail-order houses" subsector is 30% lower than that in the retail trade sector in 2012. From 1992 to 2014, the share of nonstore sales (the majority of which are electronic shopping) in retail sales increases from about 6% to 13%. Of course, electronic commerce increases labor demand in the transportation sector. However, the increases in labor productivity in retail trade and in the distribution sector which contains trade and transportation are almost the same, suggesting this spillover effect is secondary.

[2] To avoid confusion I should point out that the term "trade" is used to denote wholesale trade and retail trade in the text.

[3] The NAICS system replaced the old Standard Industrial Classification (SIC) system in 1997, so the data used for non-manufacturing sectors are from 1997 onward.

Second, the *relative* labor share of large firms, defined as the ratio between the labor share in these firms to the average in the sector, tend to be smaller than that of other firms. In 2002, labor share for the 50 largest manufacturing firms[4] was 67% of that for the manufacturing sector as a whole. In the same year, the relative labor share for 50th to 100th, 101st to 150th, 151st to 200th largest firms, and 201st largest and smaller firms in the manufacturing sector were 73%, 82%, 97%, and 121%, respectively. Large firms typically offer a higher wage than do small firms. However, wage differentials compensate only partially for the even wider gap in labor productivity between large and small firms, which results in a lower labor share in the former.

Third, the relative labor share for large manufacturing firms has been declining since around 1980 and this coincides with the time when the labor share in the manufacturing sector began to decline. The relative labor share for 50 largest firms in manufacturing was 98% in 1967, 97% in 1977, 92% in 1987; it then declined steadily to 72% and 59% in 1997 and 2012, respectively. The implication is that, in comparison with other firms, the decline of labor share in large manufacturing firms has been especially pronounced. From 1967 to 1977, the relative labor productivity of top-50 firms increased from 128% to 143% and their relative wage increased at about the same rate: from 127% to 139%[5]. However, there has been an increasing divergence between the two series since the late 1970s. From 1977 to 2012, the relative labor productivity of top-50 firms increased from 143% to 242%; yet at the same time, their relative wage was essentially stable: 139% in 1977 and 144% in 2012. Increasing concentration, i.e. the rising market share of large firms that have a lower labor share and the decline of labor shares within large firms are the driving forces behind the overall decline of aggregate labor share in manufacturing.

Large firms in non-manufacturing sectors also have a lower labor share. However, their relative labor share exhibits a different time pattern across sectors. In particular, it declines in the trade and transportation sectors, but does not exhibit a clear trend in most service and finance sectors. For trade and transportation, just as for manufacturing, the relative labor share of large firms decreases over time owing to a combination of these firms' increasing relative labor productivity and a fairly stagnant relative wage. From 1997 to 2012, the relative labor productivity of the top-50 firms in wholesale trade increased by 95.9% yet their relative wage increased only by 16.2%. In transportation, the increase in relative labor productivity of top-50 firms was 32.8%—significantly greatly than the 1.6% increase in relative wage. In retail trade, the increase in relative labor productivity of large firms is 4.2% greater than the relative wage.

I provide a rationale for these empirical facts that is based on two assumptions. First, for a given technology—embodied in machines—capital and labor are complementary inputs. In a constant elasticity of substitution (CES) production function, this is equivalent to an

[4] These Census data give concentration ratios for the 50, 20, 8, and 4 largest firms. In the baseline case, I use the 4 largest firms for 6 digit NAICS sectors, and the 50 largest firms for 2 digit sectors. As shown in the text, the empirical pattern is robust to different choices in this regard.

[5] Relative labor productivity (resp. wage) of large firms is defined as the ratio of labor productivity in these firms to labor productivity (resp. wage) in their sector.

elasticity of substitution that is less than 1. Second, technological progress is labor saving in this sense: new technology embodied in new machines allows for less labor input per unit of output. I start from a static model featuring N vintages of capital. Under these two assumptions, my model predicts a negative correlation between firm size[6] and labor share. In particular, more advanced technologies increase output and decrease the labor share. The intuition is as follows. Technology complements capital and increases its productivity, which further increases demand for effective labor.Therefore firms using more advanced technologies produce more output with less labor, reducing the labor share of income.

I then extend the static model to a dynamic general equilibrium one by incorporating heterogeneous firms and capital accumulation. Each firm is endowed with a level of own-productivity, and each firm optimally choose to adopt one technology from all feasible ones. The fixed cost of installing a machine is assumed to be an increasing function of the technological vintage it embodies. Firms with low own-productivity find it optimal to avoid the large fixed cost of advanced technologies by adopting less advanced and cheaper ones. On the other hand, firms with high own-productivity find it convenient to pay the fixed cost of adopting advanced technologies and therefore use them. Due to the negative effect of technology on labor share, more productive firms exhibit a lower labor share.

Given a fixed number of technological vintages, capital-labor complementarity and fixed labor supply, the economy arrives at a steady state. When a new and more advanced technological vintage becomes exogenously available, the most productive firms find it profitable to switch to that new technology. This response increases their market share because, as established for the static case, technology has a positive effect on firm size; in other words, concentration increases with technological change. Furthermore, the more advanced technology reduces the labor share as firms increase in size. As a consequence, the aggregate labor share declines. Next, to illustrate the dynamics of the model in the simplest possible case, I calibrate a steady-state economy in which, initially, there are two technological vintages and a third more advanced one becomes available.

For a CES production function in which capital and labor are complementary inputs, any labor saving technological change that reduces the labor share will simultaneously increase labor productivity. Hence we should observe a faster increase in labor productivity in sectors, or in periods, characterized by declining labor share. From 1987 to 1997, the labor share in manufacturing declined 10.3% while labor productivity increased 34.7%. Since the late 1990s, both decreases in labor share and increases in labor productivity have accelerated. From 1997 to 2007, the labor share fell 20.2% while labor productivity rose 59.0%. From 1987 to 2016, the economy-wide labor productivity has increased by 72.7%; during the same period, labor productivity increases in manufacturing, wholesale trade and retail trade amounted to (respectively) 146.4%, 123.5%, and 128.8%. This evi-

[6] In the static case, each technology is interpreted as a firm. This presupposition will be relaxed when I discuss the general equilibrium.

dence strongly supports the technological channel - as opposed to monopoly power - as the main driver of the negative correlation between concentration and labor share. Labor productivity is measured as the ratio of real value added (net of price changes) to hours worked. An increase in monopoly power, alone, would have driven up prices but would have not increased labor productivity.

Two recent papers, Barkai (2016) and Autor et al. (2017), also independently document a negative correlation between change in concentration and change in labor share. Barkai (2016) focuses on the fact that an increase in monopoly power decreases both labor and capital shares while increasing the share of profits. Autor et al. (2017) conjectures that the concentration-LS correlation is driven by the rise of superstar firms, which have a lower labor share since the fixed overhead labor cost is distributed over a larger output base. My paper differs from both in that I argue it is technological advancement that drives down labor share in large firms and drives up concentration, with the result that the aggregate labor share declines.

Koh et al. (2016) claim that the decline in the U.S. labor share is accounted for by the growing share of Intellectual Property Products (IPP) in total capital stock: two thirds of the decline is driven, in the data, by the higher depreciation rate of IPP capital. Karabarbounis and Neiman (2014a) finds that capital depreciation explains about 45% of the 4.7% decrease in gross labor share in the U.S. corporate sector, and that both net and gross labor shares have declined 'meaningfully', worldwide, since 1975. In light of these facts I have adjusted the labor shares I use by netting out the depreciation of capital (but not the net return to IPP capital as in Koh et al. (2016)), both traditional and IPP, and found that the patterns studied in my paper are robust to these adjustments.

This paper relates most closely to the macroeconomic literature on the determinants of the aggregate labor share, which dates back to at least the early-to-middle 20th century (e.g. Kaldor (1957); Solow (1958)), and the recent studies of its decline in the United States and in other developed countries. Karabarbounis and Neiman (2014b) attributes the decline of labor share to decreases in the relative price of investment goods while Piketty and Zucman (2014) attributes it entirely to the process of capital accumulation. In a CES production function, these channels lead to a lower LS if capital and labor are substitutes, i.e. if the elasticity of substitution between capital and labor is greater than 1. My paper departs from these approaches by featuring a production function for which the elasticity of substitution between capital and labor ranges between 0 and 1, which is consistent with the majority of empirical estimations[7]. In addition, at the aggregate level the return

[7] For example, Brown and DeCani (1963) estimates that the elasticity of substitution ranged from 0.08 to 0.44 over the period from 1890 to 1958. David and van de Klundert (1965) estimates an elasticity of 0.32, and the estimate in Wilkinson (1968) is 0.5. Most recent estimates also obtain values between 0 and 1. The estimated elasticity of substitution between capital and (skilled) labor is 0.67 in Krusell et al. (2000). In Antras (2004), the estimated elasticity of substitution between capital and labor ranges between 0.6 and 0.9. Klump et al. (2007) estimates the elasticity to be 0.51. Herrendorf et al. (2015) estimates the elasticity of substitution to be 0.80 in manufacturing, and 0.84 for the whole economy. Oberfield and Raval (2014) use plant level data, and they estimate the elasticity of 0.51 at that level and 0.71 for the Manufacturing sector.

to capital, measured using National Income and Product Accounts (NIPA) tables while accounting for changes in relative prices of investment goods, has not declined over the last three to four decades. See Gomme et al. (2011) and the discussion in Section 4.2 of this paper.

Elsby et al. (2013) decompose declines of aggregate labor share into sectors, and they identify the offshoring of labor-intensive tasks as a potential driver. My paper complements that research because offshoring, no differently than other forms of technological change, such as automation, enables reduced (domestic) labor input per unit of output and thus is viewed as a labor-saving technology. The increase of offshoring is heavily concentrated in Manufacturing[8]. The LS declines in both trade and transportation are also substantial, but the extent of offshoring in these sectors has not changed significantly during the last 15-20 years. The technological channel proposed in my paper has the potential to explain the decline of labor share in a wider context.

Several papers use firm level data in seeking to understand the decline of aggregate labor share. Loecker and Jan (2017) document a rise in the average markups across public firms since 1980, which they argue could account for the reduction in labor share. Kehrig and Vincent (2017) also report a reallocation of market share towards hyper-productive manufacturing plants, which arrive at a low labor share by gradually increasing value added while keeping employment and compensation unchanged. These authors show how this pattern can be explained: the concave response of hiring to total factor productivity shocks is becoming more concave over time. My proposed explanation is consistent with the firm-level evidence, yet it also comports with observed sector heterogeneity in terms of concentration, labor share and labor productivity.

The rest of paper is organized as follows. The empirical facts are documented in section 2, and Section 3 develops a model that rationalizes those facts and presents a quantitative exercise to illustrate the mechanism. I discuss several related issues in Section 4, including the return to capital, the evolution of labor productivity across sectors, and firm level capital/labor ratios. Section 5 concludes.

2 Empirical Facts

Several empirical facts are presented in this section. First, I document a negative correlation—across manufacturing sectors—between change in concentration (measured as the value-added share of large firms)[9] and change in labor share. The baseline definition of "large" firms is the 4 largest firms in an NAICS 6-digit sector or the 50 largest firms at the 2-digit

[8] See Figure 6.2 in the Appendix.

[9] Value added is used whenever the necessary data are available; otherwise, I use the share of revenue as the measure of concentration. Appendix Figure 6.6 compares these two measures vis-à-vis manufacturing and shows that the difference is negligible.

level.[10] If large firms have a lower labor share, then increases in concentration (i.e., an increased market share for large firms) lead to a lower labor share for the sector. I introduce the concept of *relative labor share*, defined as the ratio of the labor share in a subset of firms to sector labor share, and find that the relative labor share for large manufacturing firms is less than that for other firms. Note also that the relative labor share of large firms is stable from the 1960s to the late 1970s but declines thereafter. The relative LS for the 50 largest manufacturing firms was 98% in 1967 and 97% in 1977 but then declined steadily to 59% in 2012.

This empirical pattern observed in manufacturing holds also in other sectors. Declining labor share is characteristic not only of manufacturing but also of retail trade, wholesale trade, and transportation & warehousing. In these sectors, concentration has risen significantly over the same period while the relative labor share of large firms has declined. In contrast, the labor share does not decline in most finance and services sectors, where the relative labor share of large firms does not exhibit a clear time trend.

2.1 Manufacturing

Figure 2.1 plots the labor share in manufacturing from 1947 to 2015.[11] The manufacturing LS is relatively stable from the 1940s to the early 1980s and declines steadily thereafter. The magnitude of decline from 1980 to 2015 is nearly 20%. From 1997 to 2007, the baseline period for which I have disaggregated data, the labor share in manufacturing decreases by about 6%.

The disaggregated data are from the Annual Survey of Manufactures (ASM), a survey of manufacturing establishments with one or more paid employees. A summarized and simplified version of the ASM data is provided in the NBER-CES data set. Included in the data are payroll and value added for manufacturing sectors at various NAICS digit levels. The labor share is the fraction of payroll in value added, and concentration is measured as the share of value added due to a sector's 4 largest firms (*Share04*). The concentration data are available every five years from the Economic Census, for which 2012 is the most recent publication.

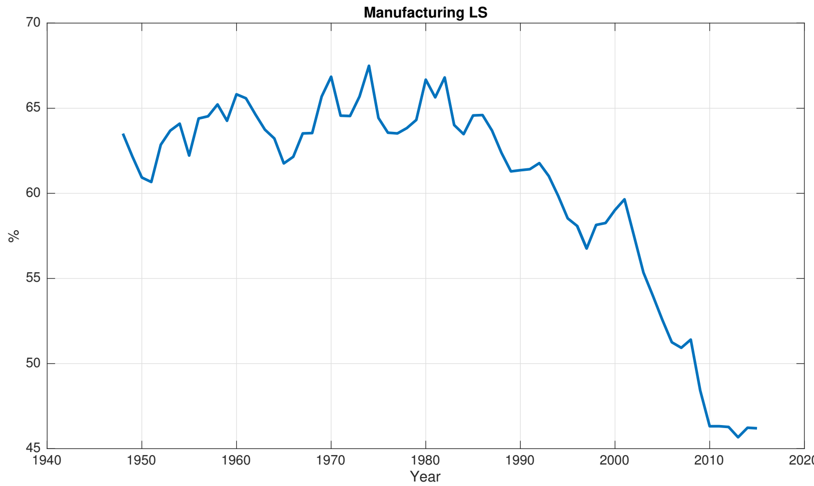
Figure 2.2 plots change in labor share against change in concentration (*share04*), across 6 digit manufacturing sectors, from 1997 to 2007[12]. This graph reveals the negative and

[10] The choice of 4 and 50 reflect, inter alia, the availability of data. However, the described pattern is robust to other definitions of a large firm.

[11] Labor share in Figure 2.1 is calculated as compensation of employees *divided by* manufacturing value added. The general trend—stable then declining—is robust to adjustments for proprietor income and depreciation. The nonadjusted series is chosen as the benchmark measure for consistency with respect to the measure used in manufacturing *sub*sectors, for which data on proprietor income and depreciation are not available.

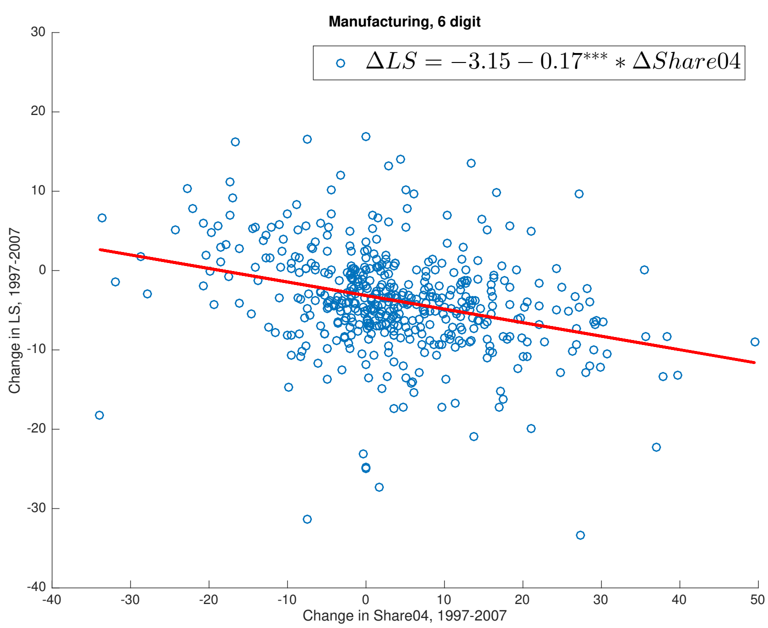
[12] NAICS has been in use since 1997. I chose 2007 as the ending year because the 6-digit code underwent a major revision in 2012. A similar result is obtained if concentration is measured in terms of revenue rather than value added.

Figure 2.1: Labor Share in Manufacturing, 1947-2015



Note: Labor share (LS) is measured as the fraction of compensation in value added.

Figure 2.2: Change in Labor share versus Change in Concentration, MFG 1997-2007



Note: Labor share (on the vertical axis) is the fraction of payroll in value added; concentration (on the horizontal axis) is the value added share of the 4 largest firms. Each circle represents an NAICS 6-digit manufacturing sector.

significant correlation between change in concentration and change in labor share. When a sector becomes more concentrated, its labor share tends to decline. From 1997 to 2007, ASM data shows that the manufacturing LS decreased by 5.61%, due mostly (73%[13] to within-sector declines. Over this period, concentration has increased in nearly two thirds of the 465 6-digit manufacturing sectors.

The result of a single variable regression, where the dependent variable is change in the labor share and the independent variable is change in *Share04*, is[14]

$$\Delta \text{LS} = -3.15 - \underbrace{0.17^{***}}_{(0.02)} \times \Delta Share04 + \epsilon, \qquad R^2 = 0.1025,\ N = 464;$$

As shown in the Appendix (see Table 6.1 and 6.3 and Figure 6.3, the negative correlation between concentration and labor share also holds across manufacturing sectors at the 3-, 4-, and 5-digit levels and across different periods. Moreover, the results are robust to measuring concentration by the value added share of the 8, 20, and 50 largest firms (instead of 4 largest firms) within a sector. The result is not affected by the omission of fringe benefits when measuring labor share. Since 2005, the publicly available ASM tables have provide information on payroll as well as benefits. "Compensation" is the sum of payroll and total fringe benefits, which include the employer's cost for health insurance, defined benefit pension plans, other defined contribution plans, and other fringe benefits. Appendix Table 6.4 reports a similar negative and significant correlation between change in concentration and change in the revised labor share.[15] Last, as shown in Appendix Table 6.2, this correlation is robust in panel regressions with sector fixed effect and other control variables.

Concentration in Manufacturing has been increasing. For industrial classifications, the Census of Manufactures (published every five years) used SIC codes before 1992 and switched to NAICS codes in 1997. Although each system underwent revision, the total numbers of SIC 4-digit manufacturing sectors (444 in 1977) is comparable to the number of NAICS 6-digit sectors (467 in 2007).[16] Manufacturing concentration—measured as the average *Share04* (and the average *Share08*) across SIC 4-digit sectors until 1992 and across NIACS 6-digit sectors starting in 1997—weighted by revenue[17]. Results from the 1963–2012 period[18] are presented in Figure 2.3.

[13]This number is based on a standard within-between decomposition.

[14]Blank magnetic and optical recording media manufacturing (NAICS code 334613), has a labor share exceeding 100% in 2007, so that subsector is excluded in my calculation

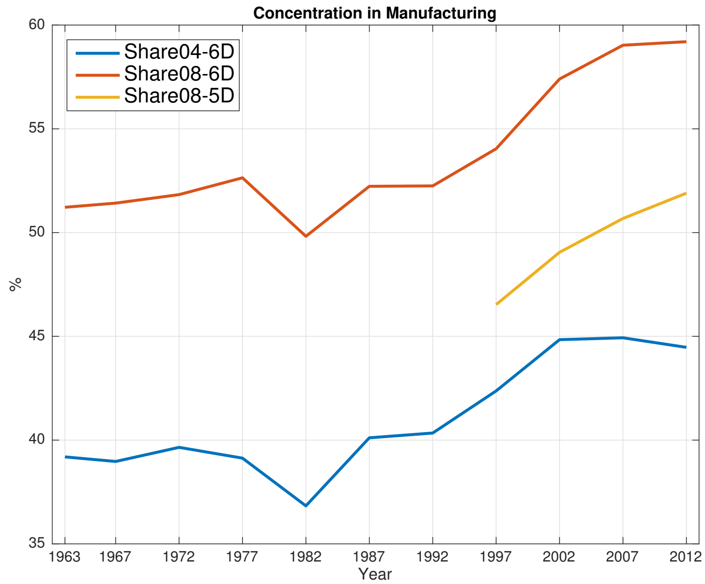
[15]In 2012, the total numbers of NAICS 6-digit manufacturing sectors was reduced from 467 to 362. I therefore use data at the 5-digit level, which are fairly stable: there were 184 5-digit manufacturing sectors in 2007 and 180 in 2012, of which 175 were unchanged.

[16]For details, see Appendix Table 6.8.

[17]The concentration measure is given in terms of revenue (rather than value added) because that is the measure until 1992 for disaggregated manufacturing sectors. Yet the pattern is robust to various measures. See Appendix Table 6.8.

[18]The original full reports of the Census of Manufactures could not be found for 1947, 1954 and 1958, so those years are excluded from the date set. However, the 1958 summary report indicates that concentration is stable in most sectors for the 1947–1958 period.

Figure 2.3: Concentration in Manufacturing, 1963-2012



Note: The blue (resp. red) line plots the average revenue share of the 4 (resp. 8) largest firms across 6-digit manufacturing sectors; the yellow line is the average revenue share of the 8 largest firms across 5-digit manufacturing sectors. All values are weighted by revenue.

Concentration in Manufacturing was relatively stable from the 1960s to the early 1980s, but it has increased steadily over the past three decades. Before 2000, the increasing concentration was due mainly to the 4 largest firms in each sector (the increase in average share of the 8 largest firms was similar to that of the 4 largest). After 2000, the average *share04* was relatively stable but the average *share08* continued to increase, which suggests that the expansion of large firms—though not the very largest—has driven up concentration in the past decade. From 2007 to 2012, the total number of NAICS 6-digit manufacturing sectors was reduced from 467 to 364. The figure also plots *Share08* at the 5-digit level, which is consistently defined across the period shown.

The increase in concentration means that market share has been transferred from small to large firms. If the labor share is lower in large firms, then an increase in concentration reduces sector LS in a mechanical way. The labor shares of different firms can be compared using concentration data from the Economic Census. Toward that end, I define the relative labor share (RLS) for a subset of firms (e.g. 50 largest firms)—where firm size is measured by value added or revenue—as the ratio of LS for these firms to the sector's LS. So if the top-50 firms have an RLS that is less than 100%, then the labor share of these firms is lower than the sector average.

Table 2.1: Share of Industry Statistics (%) for the Manufacturing Sector, 2002

Firm groups	Emp.	Payroll	Vadd.	Rel. LP	Rel. Wage	Rel. LS
50 largest	12.1	16.9	25.3	209	140	67
50th to 100th largest	5.3	6.1	8.4	158	115	73
101st to 150th largest	3.9	4.1	5.0	128	105	82
151st to 200th largest	3.1	3.6	3.7	119	116	97
201st and smaller	75.5	69.3	57.5	76	92	121

Note: Firms/companies are ranked by value added, and a firm/company is defined as a business organization consisting of one establishment or more under common ownership or control.
Data Source: "Concentration Ratios: 2002 Economic Census, Manufacturing, Subject Series", in *Census of Manufactures*, 2002.

The relative labor share for the top-50 firms is calculated as follows:

$$\text{RLS-top50} \equiv \frac{\text{LS-top50}}{\text{LS-Sector}} \times 100\% = \frac{\text{Payroll-top50 / Payroll-Sector}}{\text{Vadd-top50 / Vadd-Sector}} \times 100\%$$

That is, the relative labor share for top-50 firms equals their payroll share in the sector *divided by* their value added share; the relative labor productivity and relative wage are defined similarly. Labor productivity (LP) is measured as value added per worker[19]. The relative labor productivity (resp. wage) for top-50 firms is measured as the ratio of labor productivity (resp. wage) for those firms to that of sector. It follows that the relative LS of top-50 firms equals the ratio of their relative wage to their relative labor productivity.

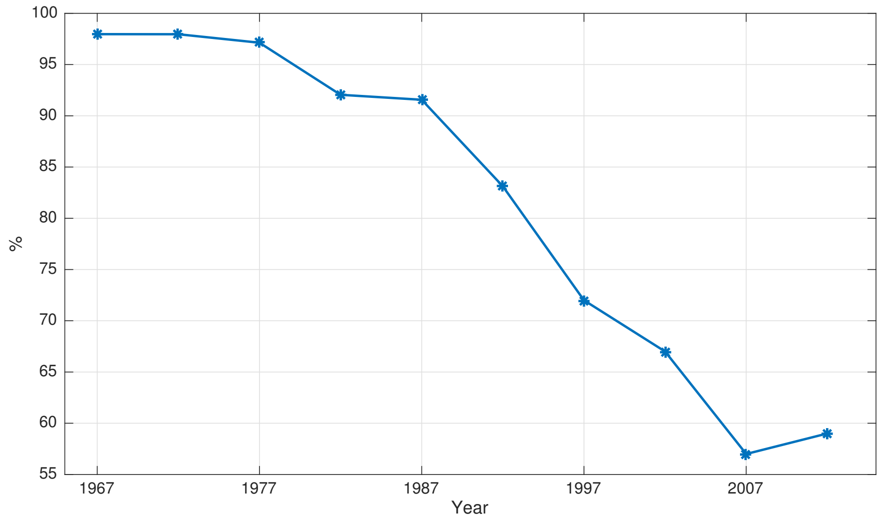
Table 2.1 presents relevant statistics for manufacturing in 2002. The repirted values for share of employees, payroll, and value added are from original (sourced) tables; the valued for relative LP, relative wage, and RLS are calculated as just described.

Both labor productivity and wage are higher in large firms, but the labor share in large firms is lower. The RLS for the 50 largest manufacturing firms (as ranked by valued added) is 67% of the entire sector. Although the wage in small firms is lower, it accounts for a larger portion of the per-capita value added in these firms—as reflected in their 121% of relative labor share. The pattern that large firms have smaller labor shares also holds for other years. Appendix Table 6.9 reports results for 1997, 2007 and 2012.

The trend of relative labor share for 50 the largest manufacturing firms(again ranked by value added) from 1967 to 2012 is plotted in Figure 2.4. That RLS remains fairly constant from the 1960s to the 1980s, but the figure shows a clear downward trend thereafter. The relative labor share for the 50 largest manufacturing firms was 98% in 1967 and 97% in

[19]The actual labor productivity is output—not value added which is equal to output times price—per hours worked. As defined in the text, relative LP reflects the differences in actual LP across firms *provided that* those firms do not exhibit significant differences in prices and average working hours per worker

Figure 2.4: Relative Labor Share of the 50 largest MFG firms



Note: The relative labor share in this graph is calculated as LS in the 50 largest manufacturing firms *divided by* LS in the entire manufacturing sector.

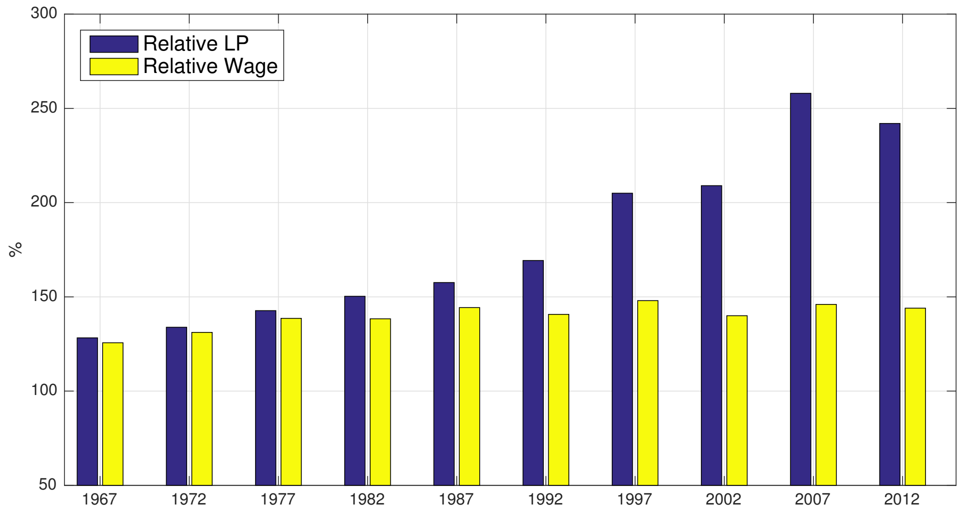
1977, but it declined steadily to 59% in 2012.

Recall that the relative LS equals the ratio of relative wage to relative labor productivity. Figure 2.5 displays the trends of relative LP and relative wage for the 50 largest manufacturing firms. From 1967 to 1977, the relative LP of these top-50 firms increased from 128% to 143% while their relative wage increased at about the same rate: from 127% to 139%. From 1977 to 2012, however, the relative labor productivity of those firms increased from 143% to 242%. Yet their relative wage was practically stable, increasing only to 144% in 2012. The clear divergence between relative LP and relative wage since the 1980s suggests that marginal workers in large and small firms are easily substitutable with each other. The Census of Manufactures public data also allows me to calculate relative labor shares for the 100 and 200 largest firms; Appendix Table 6.10 establishes that the overall patterns are similar.[20]

In the 1990s and 2000s, the relative labor share of large firms was significantly smaller than for other firms; an increase in concentration thus leads to a decline in sector labor share. In the 1960s and early 1970s there was not much difference between the la-

[20]The manufacturing sector comprises many heterogeneous subsectors, and the top-50 constitute but a small subset of total firms. From 1997 to 2012, the value added share of the top-50 firms increased from 24.5% to 26.1%. This small increase reflects the concomitant modest increases for large (but not top-50) firms in the sector. For instance, the value added share of the 200 largest manufacturing firms increased by 2.9% for the same period; and the average share of the 50 largest firms across 3-digit manufacturing sectors increases 5.7%. Even so, the RLS of the top-50 firms is still informative—as evidenced by the strongly similar RLS pattern of the 100 and 200 largest firms. Data for top-50 firms are available also for non-manufacturing sectors and are therefore used as the baseline (to ensure consistency across sectors).

Figure 2.5: Relative Labor Productivity and Relative Wage of the 50 Largest MFG Firms



Note: Relative labor productivity (, resp. relative wage) is calculated as the LP (resp. wage) in the 50 largest manufacturing firms *divided by* the LP (resp. wage) in the manufacturing sector.

bor shares of large versus small firms, so one would expect that increased concentration would lead to a relatively smaller decline in labor share. These statements are confirmed in Appendix Table 6.3, which reports results from single-variable regressions (with changes in the labor share and in concentration as the dependent and independent variable, respectively) from 1963 to 1966 and also from 1972 to 1977. The coefficients for concentration are significantly smaller than these two periods than those for the 1980s, 1990s, and 2000s.

The pattern that large firms have lower labor shares continues to hold in more disaggregated manufacturing sub-sectors. I find public data that enables calculation of subsector-level relative labor shares in the Census of Manufactures report for 1977 but not for more recent years. The original data include payroll and value added for the 4, 8, 20, and 50 largest firms in each SIC 4-digit sector. Firms are classified into four groups: ”1-4”, the 4 largest firms in terms of value added; ”5-20”, the 5th to 20th largest firms; ”21-50”, the 21st to 50th, and ”≥51”, the 51th and smaller firms. Table 2.2 summarizes the calculated RLS values, and it shows the same pattern as before: the relative labor share of large firms is less than that for other firms.

Compustat data can be used to investigate the evolution of relative labor shares of large firms within more disaggregated manufacturing sectors. Among Compustat firms, about 85% report sale numbers but only 22% report total staff expenses. The latter include wages, salaries, pension costs, profit sharing and incentive compensation, payroll taxes and other employee benefits; this expense category corresponds closely to NIPA’s ”compensation of employees”. Because value-added data for firms are not directly available, I

Table 2.2: Relative Labor Share in the Manufacturing Sector, 1977

SIC	Index	1-4	5-20	21-50	$\geq$51
4 digit	average	91.0%	99.4	108.8	119.5
4 digit	weighted average	91.6	97.2	108.6	119.8

Note: "1-4" denotes the 4 largest firms, (weight=value added).

Table 2.3: Correlation between Size and Labor Share in the Manufacturing Sector

	70-74	75-79	80-84	85-89	90-94	95-99	00-04	05-09	10-14
Size	0.41^{***}	0.48^{***}	0.22^{**}	-0.22^{**}	0.01	-0.88^{***}	-1.61^{***}	-1.31^{***}	-1.93^{***}
	(0.12)	(0.10)	(0.12)	(0.12)	(0.12)	(0.15)	(0.15)	(0.15)	(0.13)
Sector D.	Yes	–	–	–	–	–	–	–	–
Year D.	Yes	–	–	–	–	–	–	–	–
R^2	0.46	0.40	0.37	0.24	0.23	0.22	0.27	0.26	0.32
Obs.	1674	1847	1428	1222	1166	1145	1035	957	1528

Note: $***: p < 1\%$, $**: p < 5\%$; $*: p < 10\%$. Size is measured as assets (in log). LS is the share of compensation in revenue. Results are qualitatively similar if using employments.
Data Source: Compustat, Manufacturing firms ($SIC \in [2000, 3999]$).

use the the fraction of compensation in sales as a proxy for firm-level labor share. Sector dummies are assigned for each SIC 2-digit sector (e.g. textile mill products; electronic & other electronic equipment). From 2010 to 2014, there were, on average 18 firms per sector.

The following regression is performed for manufacturing firms (i.e., SIC $\in [2000, 3999]$) for each five-year period:

$$\text{LS}_i = \beta_0 + \beta_1(\text{Size}_i) + \text{Sector dummies} + \text{Year dummies} + \varepsilon_i.$$

Size is measured by (log) assets. Table 2.3 presents the coefficients β_1 for different periods. The correlation coefficient here also shows a downward trend[21] consistent with the aggregate outcomes. The implication is that the trend seen in Figure 2.4 reflects actual changes between large and small firms within sectors—that is, rather than simply a shift of large firms towards less labor intensive sectors.[22]

[21] The coefficient is positive in the 1970s and early 1980s, which accords with the top-50s' RLS being higher than the RLS of the top 100 and top 200 firms before 1980. This result may reflect relatively stronger union power in the largest manufacturing firms in the 1970s and early 1980s.

[22] Of the 50 largest manufacturing firms in 1980, 18 are related to petroleum & coal products, 2 to computer & other electronic products, and 0 to pharmaceuticals. In 2012, the corresponding numbers are 9, 8, and 5.

2.2 Non-Manufacturing sectors

I now turn from manufacturing to non-manufacturing sectors, where the negative correlation between changes in concentration and changes in labor share holds as well. Furthermore, in non-manufacturing sectors where the labor share declines, the concentration increases and the relative labor share of large firms falls—just as in Manufacturing.

Following Elsby et al. (2013), the change in aggregate labor share can be decomposed into a within-sector component and a between-sector component. Formally, we can write

$$\mathrm{LS} = \Sigma_i \omega_i \mathrm{LS}_i \implies \Delta\mathrm{LS} \approx \underbrace{\Sigma_i \mathrm{LS}_i \Delta\omega_i}_{\text{between}} + \underbrace{\Sigma_i \omega_i \Delta\mathrm{LS}_i}_{\text{within}},$$

where i denotes a sector and ω_i represents the share of sector i's value added in the economy. Average values of LS and ω are used to calculate the "between" and "within" components. The baseline measure of sector labor share is the fraction of compensation in value added. As shown in Appendix Table 6.15, the within-sector component accounts for most of the decline in labor share; structural change (i.e. the between-sector component) plays a secondary role.[23]. Table 2.4 summarizes the within-sector component. Sectors in which labor share declined significantly are manufacturing, whole trade, retail trade, and transportation. At the same time, the labor share in most finance and services sectors sectors did not decrease.

These results are robust to adjusting labor share for depreciation and proprietor's income. Appendix Table 6.16 gives the decomposition results when value added is adjusted for capital depreciation, which includes depreciation not only of traditional capital (equipment and structures) but also of the newly capitalized Intellectual Property and Products (IPP). Proprietor's income does not significantly alter the baseline pattern; the reason is that, in most sectors, the share of proprietors' income in value added (reported in Appendix Table 6.17) is relatively stable.[24]

[23]The reported statistics exclude agriculture and government; they also excludes mining, construction, and management of companies & enterprises because these three sectors lack concentration data. The included sectors together accounted, in 2012, for 77% of gross domestic product (GDP) and 89% of private sector GDP. From 1987 to 2013, the labor share in mining decclined by about 20%; that decrease was most pronounced during the years of 2000 and 2003. The labor share in construction declined moderately over this period and primarily during two recessions. Given the relatively small value added of these excluded sectors, their changes in labor share have limited effects on overall labor share. The results in Appendix Table 6.15 are in substantial agreement with those of Elsby et al. (2013). The slight difference might be explained by two factors. First, I depart from their approach by focusing on the *nonfarm private* sector (rathern than the corporate sector) and by excluding three subsectors for which there are no concentration data. Second, the data used here reflect IPP revisions whereas Elsby et al. (2013) use pre-revision data.

[24]Scholars often adjust labor share for proprietors' income by assuming a constant labor share for proprietors and the corporate sector. In this approach, labor share under is defined as compensation/ (value added − proprietor income). The decreasing shares of proprietors' income in value added for the health care sector and the professional, scientific, & technical services sector are partly responsible for the increase of their labor share (reported in Appendix Table 6.15).

Table 2.4: Within-sector Component of Declines in LS, 1987-2013

Sector	Aggr.	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔLS	-3.62%	2.25	-18.02	-7.36	-6.07	-10.0	-3.79	0.22
$\omega\Delta LS$		0.06	-3.43	-0.56	-0.51	-0.38	-0.23	0.02
	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ΔLS	-0.99	8.88	2.36	1.72	5.25	3.97	-0.45	10.21
$\omega\Delta LS$	-0.16	0.70	0.08	0.02	0.42	0.05	-0.02	0.33

Note: LS is the share of compensation in value added. (1)-Utilities; (2)-Manufacturing; (3)-Wholesale Trade; (4)-Retail Trade; (5)-Transportation and Warehousing; (6)-Information; (7)-Finance and Insurance; (8)-Real Estate, rental and leasing; (9)-Professional, Scientific and Technical Services; (10)-Administrative and Waste Management Services; (11)-Educational Services; (12)-Health Care and Social Assistance; (13)-Arts, Entertainment, and Recreation; (14)-Accommodation and Food Services; (15)-Other Services. Data Source: NIPA Value-added-by-Industry.

Figure 2.6 presents the relation between change in labor share and change in concentration across 2-digit non-manufacturing sectors.[25]. Labor share is measured as the share of compensation of employees in Value added, and concentration is measured as the 50 largest firms' share of a sector's revenue[26].

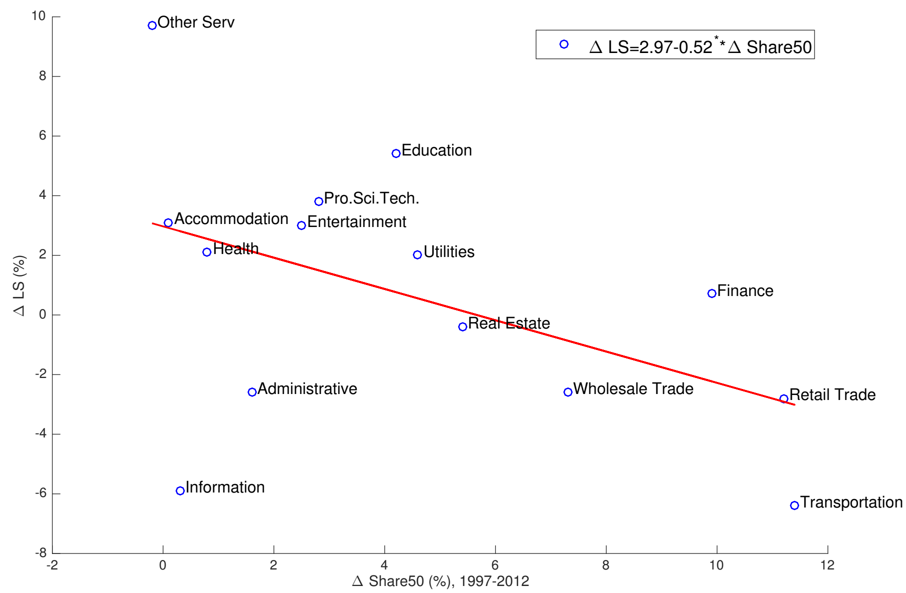
From 1997 to 2012, there is a similar negative association between changes in labor share and changes in concentration. The correlation is significant at the 10% level. Out of Manufacturing, the decline of LS was most evident in transportation, retail trade, and wholesale trade; these are also the subsectors in which concentration increased the largest. The decline of LS in the information sector and in the administrative & waste management sector is probably more reflective of the temporary increase of labor share around 2000 (due, in part, to stock options being realized during the dot-com bubble) than of a long run trend.[27] In most finance and service sectors, labor share actually increased slightly

[25]Labor share can not be measured systematically for disaggregated non-manufacturing sectors because value added data are not available. For services sectors and in 1997, concentration measures are available only for establishments subject to federal income tax. The same measure for these sectors is used in 2012. See Appendix Figure 6.4 for the relation between changes in labor share and changes in concentration (measured as revenue share) of the 4 largest firms. In some sectors, the LS fluctuates instead of exhibiting a monotonic trend. Appendix Table 6.11 reports the labor shares for all 15 sectors. Based on observing the trend, I tried to make minimum adjustments to the sample dates selected. In particular, I use the 1996 (rather than 1997) labor share for the information sector,; I also use the average LS between 1996 and 1998 for education services instead of the 1997 valued. The pattern that results from these two revisions are presented in Appendix Figure 6.5.

[26]For non-manufacturing sectors, the Economic Census reports concentration in terms of revenue instead of value added. Concentration ratios for the 4, 8, 20 and 50 largest firms in each sector are available. Overall, average concentration ratios for the 4 largest firms at the 6-digit level are comparable to those for 50 largest firms at the 2-digit level.

[27]For the labor share in 2-digit sectors from 1987 to 2015, see Table 6.11 and Figure 6.7 in the Appendix. Note that the information services sector is a combination of traditional subsectors (e.g. newspaper publishing) and othres that are more prone to technological change. In the Broadcasting and Telecommunication subsector (the sector where AT&T belongs to), there is also a declining trend of labor share and rising

Figure 2.6: Changes in Labor Share versus Change in Concentration, NON-MFG 1997-2012



Note: Labor share (on the vertical axis) is the ratio of employee compensation to value added; concentration (on the horizontal axis) is the revenue share of the 50 largest firms.

from 1997 to 2012 while increases in concentration were likewise moderate.

For non-manufacturing sectors, relative labor share is approximated by the ratio of large firms' payroll share to their revenue share (instead of value added shares, as in the case of manufacturing sectors). Once again, firms are ranked by revenue.[28] Appendix Table 6.13 presents the relative labor share in non-manufacturing sectors at various NAICS digit levels.[29] Just as in manufacturing, the relative labor share for large non-manufacturing firms is less than that for their smaller peers. At the 6-digit level, the average labor share in a sector's 4 largest firms is 18% lower than that for the entire sector whiere a typical firm of the smallest size has a LS that is 20% higher than the sector average.

In wholesale trade, retail trade, and transportation—sectors that saw steep declines in labor share—the relative labor share of large firms also decreased. From 1997 to 2012, the

concentration.

[28]This approximation implicitly assumes that, within a sector, the rank of firms based on value added is the same as that based on sales—especially for the largest firms. It also assumes that the share of value added by large firms is similar to their share of revenue. The first assumption seems reasonable enough; the second can be directly verified from available manufacturing data, which include (for large firm) both share of value added and revenue. Appendix Figure 6.6 confirms that there are only small differences between these two measures.

[29]There are several sectors, especially at the 6-digit level, in which the relative labor share exceeds 200% for the "51st largest and smaller" firms. The value added share and payroll share of small firms in these sectors are typically both very small. These sectors are excluded from the analysis.

Table 2.5: Relative Labor Share, Relative Labor Productivity and Relative Wage of Top-50 Firms

	Wholesale Trade			Retail Trade			Transportation		
	R. LS	R. LP	R. Wage	R. LS	R. LP	R. Wage	R. LS	R. LP	R. Wage
1997	39.9%	323.7	129.1	96.4	85.3	82.3	103.7	108.7	112.7
2002	36.4	332.1	120.9	95.2	92.9	88.5	86.6	126.1	109.2
2007	30.8	383.3	117.8	95.4	97.4	93.0	81.9	141.3	115.7
2012	26.9	419.6	112.9	92.9	101.0	93.8	80.1	142.5	114.1
Δ 97-12	-13.0%	95.9	-16.2	-3.5	15.7	11.5	-23.6	32.8	1.6

Note: Relative labor share (resp. labor productivity, wage) in this table is calculated as the ratio of labor share (resp. labor productivity, wage) for the 50 largest firms to the sector average.

RLS of the 50 largest firms decreased from 39.9% to 26.9% in wholesale trade, from 96.4% to 92.9% in retail trade, and from 103.7% to 80.1% in transportation.

As mentioned previously, the relative labor share can be decomposed into relative labor productivity and relative wage. Table 2.5 presents the relative labor productivity and wage for trade and transportation sectors. From 1997 to 2012, the relative labor productivity of large firms in wholesale trade increased by 95.9% while their relative wage *decreased* by 16.2%. In transportation, the 32.8% increase in relative labor productivity is likewise significantly greater than the 1.6% increase in relative wage. This gap is as wide in retail trade as in wholesale trade or transportation, but the increase in relative labor productivity is nonetheless 4.2% higher than relative wage.[30]

In contrast, the relative labor share of large firms in most finance and services sectors does not show a clear trend over the past 15-20 years.[31] These results all continue to hold when, instead of the 50 largest firms in each sector, I use the 20 largest (see Appendix Table 6.19) and, for the most part, at more disaggregated levels.[32]

[30]The reason that the relative labor productivity and relative wage of large firms are smaller than 100% in the retail trade sector could be that the top-50 retail firms category is a mix of traditional and new online retailers. In 2012, for example, Walmart was the largest US retailer in terms of revenue and Amazon was ranked 15th. The relative LP for the 4 largest firms in this sector was 96.1% in that year; this percentage was higher (106.6%) for the 5th to 8th largest firms and higher still (108.4%) for the 9th to 20th largest.

[31]See Appendix Table 6.18 for details.

[32]See Appendix Table 6.20. It is worth emphasizing that results at the 2-digit level are less sensitive to the problem of classifying of multi-establishment firms, changes in industrial code, and reclassification of firms over time. For example, the retail trade sector's increase in concentration is partly caused by the rise of online retailers (e.g. Amazon) that sell goods in various categories. The NAICS 3-digit code for Amazon is 454 (nonstore retailers) while the code for a typical book store is 451 (sporting goods, hobby, book, and music stores). At the NAICS 2-digit level, both types of stores are grouped in 44-45 (retail trade).

Table 2.6: Economy-wide Labor Share, Concentration, and Relative Labor Share of Top-50 Firms

Year	1987	1992	1997	2002	2007	2012
LS	51.83%	51.48	50.49	51.21	50.30	49.00
Share50	26.00%	26.57	26.69	29.52	30.51	31.31
RLS-Top50	82.20%	81.23	79.37	78.20	74.86	76.37

Note: Labor share is calculated as the fraction of compensation in value added. Agriculture, government, mining, construction, and management of companies & enterprises are excluded in the statistics.

2.3 The aggregate pattern

The facts presented so far mar be summarized as follows. In manufacturing, trade, and transportation sectors, both the sector labor share and the relative labor share of large firms have been declining. In most services sectors, the labor share has not declined; in these sectors, the relative labor share of large firms does not exhibit an identifiable trend. Finally,concentration has increased across all sectors—but more in manufacturing, trade, and transportation and less in services. Although sector heterogeneity helps to identify the driving forces, this paper seeks to explain the decline of the *aggregate* labor share.[33]

Table 2.6 shows, for the period 1987 to 2012, the economy's labor share as well as the concentration and the relative Labor share for the 50 largest firms.[34] The reported values are averaged across 2-digit sectors, with weight equal to the average value added share of a sector from 1987 to 2012,[35]

[33] Concentration can increase for reasons that are unrelated to technology. For instance, relaxing the laws that constraint mergers and acquisitions might contribute to the rising concentration in some sectors. This paper does not address the services sector's moderate increase of concentration.

[34] As before, the labor share is not adjusted for proprietor's income—for the sake of consistency with the measure in more dis-aggregated sectors. The choice of 50 is based mainly on data availability. In general, 50 would be too small a number for sectors such as manufacturing (where the 50 largest firms accounted for 26% of 2012 value added) and would be too large a number for sectors such as utilities (where the value added share of the 50 largest firms was 69% in that year). Any choice of a simple cutoff would be forced to make the same trade-off. The relative labor share of top-50 firms in administrative & support and waste management & remediation sector inexplicably rose from 109% in 2007 to 125% in 2012. The value for "RLS-Top50" in 2012 would be 75.86 (rather than 73.37) if the 2007 value were used for this sector.

[35] Recall that the industrial classification standard changed in 1997 from SIC to NAICS. In 1987 and 1992, both concentration and RLS are available for manufacturing, retail trade, and wholesale trade. For 2-digit sectors in transportation, finance, and services, I first check for whether concentration and and relative labor share exhibited any linear trend from 1997 to 2012. When there was a linear trend (significant at the 10% level), I use that trend to obtain values for 1987 and 1992; When there was no significant trend, I use average values from 1997 to 2012 as an approximation for 1987 and 1992.

Table 2.7: Decomposition of Declines in Labor Share, 1987-2012

Δ LS	*Increase in concentration*	*Fall in large*	*Fall in small*
-2.83%	-0.80%	-1.48%	-0.57%
% contributed	28%	52%	20%

Note: See text for details.

Note that change in LS can be decomposed as

$$\text{LS} = \Sigma_{i=l,s}\text{LS}_i\omega_i \implies \Delta\text{LS} \approx \underbrace{\Delta Concentration * (\text{LS}_l - \text{LS}_s)}_{\text{increase in concentration}} + \underbrace{\omega_l * \Delta\text{LS}_l}_{\text{fall in large}} + \underbrace{\omega_s * \Delta\text{LS}_s}_{\text{fall in small}}$$

where l and s denote (respectively) large and small firms. The decline in aggregate LS stems from three sources: decline of labor share in large firms, decline of labor share in small firms, and increasing concentration. From 1987 to 2012, the economy wide labor share declines 2.83%. During the same period, economy-wide concentration increased by 5.31% while the average difference between the LS of large firms and small firms was 15.12%. The first term, "increase in concentration", is responsible for 0.80% of the decline in labor share; the respective contributions of the second and the third components can be calculated similarly. Table 2.7 presents the decomposition results.

The labor share's decline is due mainly to the fall of labor share in large firms (which accounts for 52% of the aggregate decline) and the increasing concentration (which accounts for another 28%); the contribution of "fall in small" firms is only 20%. It is important to bear two facts in mind. First, the labor share in small firms is 55.07% in 1987 and 54.28% in 2012. Its contribution would be smaller if the cutoff for "large" firms were relaxed to include more than 50 firms. Second, the labor share in small firms was 55.85% in 2007. If this value is used (rather than the 2012 value), then the "fall in small" term actually increases the aggregate labor share. As a result, in this paper I focus on the first two components.

Large firms in the the 2010s may little resemble large firms in the 1980s. According to *Compustat* firm-level data, a large portion of LS declines occurs within the same firms in the manufacturing and transportation sectors.[36] In both wholesale and retail trade, the decline seems to come mainly from the creation of new firms (e.g. online retailers) that have lower labor shares and grow large over time. In both cases, large firms in the 2010s had both lower labor shares and larger market shares as compared with their counterparts in the 1980s. Each of these trends is associated with declining aggregate labor share.

[36]See Appendix Figures 6.8 and 6.9 for the labor share (measured as the fraction of compensation in revenue) in large manufacturing and transportation firms.

3 Model

In this section I develop a model that rationalizes the empirical facts. As noted earlier, my model builds on two assumptions: (i) for a given technology (embodied in machines), capital and labor are complementary inputs; and (ii) technological progress is labor saving. Here I begin, in Section 3.1, by using a static model to illustrate the effect of technologies on size (i.e. output) and labor share—namely, more advanced technologies result in larger sizes and smaller labor shares. Then, in Section 3.2, I add capital accumulation and heterogeneous firms and extend the static model into general equilibrium. It is established there that the introduction of new technologies increases concentration and also reduces the labor shares of large firms. As a result, the aggregate labor share declines.

3.1 Static model

There are N vintages of capital, each of which embodies a distinct generation of technology. Denote by $j = 1, 2, ..., N$ the vintage of capital. In the static model, a technology is interpreted as a firm. Technology j combines capital j and labor to produce a single final goods:

$$[(1-\alpha)k_j^{\rho} + \alpha(\gamma_j \ell)^{\rho}]^{\frac{1}{\rho}}$$

here γ_j denotes the level of technology embodied in capital j. The assumptions I make are expressed formally as follows.

Assumption 1. [Capital-labor complementarity] $\rho < 0$.

Assumption 2. [Labor-saving technological progress] γ_j *increases with j.*

The elasticity of substitution between capital and labor is given by $\frac{1}{1-\rho}$. The first assumption states that, given a technology (embodied in machines), the elasticity of substitution between capital and labor ranges between 0 and 1; that is, *capital and labor are complementary inputs*. This assumption is consistent with most empirical estimates (e.g. Antras (2004); Klump et al. (2007); Herrendorf et al. (2015)). Recently, Oberfield and Raval (2014)) use plant-level data from the Census of Manufactures to estimate an average (plant-level) elasticity of substitution of about 0.5 for 1987. The estimated aggregate elasticity in manufacturing is 0.71 in 1987 and 0.75 in 2007.

Assumption 2 states that *technological progress is labor saving* in the sense that new technology embodied in new machines requires less labor input per unit of output. Labor-augmenting technological progress is typically assumed in growth models to be consistent with a balanced growth path (Barro and Sala-iMartin (2004). see Acemoglu (2003) and Jones (2005) for theoretical justifications).

Let k_j denote the supply of capital j and let L denote the supply of labor. In order to isolate the effect of technology in the static model, all the k_j are fixed at 1 and the inelastic labor supply is also normalized to 1. Labor moves freely among firms. I study the labor allocation problem and investigate the effects of technologies on firm size and labor share. The marginal productivity of labor in firm j is

$$\mathrm{MPL}_j = \left[(1-\alpha)\left(\frac{k_j}{\ell}\right)^{\rho} + \alpha\gamma_j^{\rho}\right]^{1/\rho-1} \alpha\gamma_j^{\rho}.$$

When the employment in firm j approaches zero, the firm's marginal productivity of labor is

$$\mathrm{MPL}_j(0) = \alpha^{1/\rho}\gamma_j.$$

Since capital is fixed at a positive number, it follows that the marginal productivity of labor at zero employment is not equal to infinity (i.e. the Inada condition does not hold). Hence some firms might not hire any labor in equilibrium. In addition, firms that use more advanced technologies have a higher marginal productivity of labor at zero employment. The employment flow always begins with firm $j = N$ and moves downwards, step by step. Thus the first unit of labor goes to the most productive firm, N. As firm N accumulates labor, its marginal productivity of labor declines. As soon as that level falls to the *second* advanced firm's marginal productivity of labor (at zero employment), that second firm begins to hire labor. This process continues until full employment is reached.

The labor market equilibrium condition is[37]

$$w = \mathrm{MPL}_j = \left[(1-\alpha)\left(\frac{k_j}{\gamma_j\ell_j}\right)^{\rho} + \alpha\right]^{1/\rho-1} \alpha\gamma_j.$$

As a result, technologies that are more advanced (i.e., with a higher γ_j) will cause a decline in the adjusted capital/labor ratio, $k_j/\gamma_j\ell_j$.[38] The labor share in firm j is

$$\mathrm{LS}_j = \frac{w\ell_j}{y_j} = \left(\frac{1-\alpha}{\alpha}\left(\frac{k_j}{\gamma_j\ell_j}\right)^{\rho} + 1\right)^{-1}.$$

Because the labor share is an increasing function of $k_j/\gamma_j\ell_j$, firms that use more advanced technologies have a lower labor share.

Technology also affects firm size, which is (as in the concentration data) equal to value added *divided by* revenue. Combining the formula for firm size and the labor market–clearing condition now yields the following expression:

$$y_j = k_j\left[\frac{1-\alpha(w/\alpha\gamma_j)^{-\rho/(1-\rho)}}{1-\alpha}\right]^{-1/\rho}.$$

[37] This condition holds only for firms that have positive employment in equilibrium.

[38] I remark that the true capital labor ratio, k_j/ℓ_j, can be either increasing or decreasing in γ_j. The direct effect of technologies with a higher γ is to substitute raw labor. Yet that technology also increases the productivity of capital, which in turn increases labor demand. The equilibrium k_j/ℓ_j depends on which effect dominates (see the appendix for a detailed discussion). In Section 3.2, I show that, if capital is adjustable, then the capital/labor ratio is a positive function of the technology parameter, γ.

According to this formula, output is greater if the value of γ_j is higher. In other words, a more advanced technology increases firm size. Therefore, the single parameter of technology (γ_j) is enough to generate a negative correlation—as observed in the data—between firm size and labor share. Formally, the following proposition holds.

Proposition 1. [Effects of technology on firm size and labor share]

- *If $j > j'$, then $\mathrm{LS}(j) < \mathrm{LS}(j')$; that is, firms that use more advanced technologies have a lower labor share.*
- *If $j > j'$, then $y(j) > y(j')$; that is, firms that use more advanced technologies produce more output.*

To see the intuition behind this result, recall that technology (γ) both complements capital and increases the productivity of capital, which further increases demand for effective labor ($\gamma\ell$). Hence firms produce more when they use more advanced technologies; however, technology is a substitute for raw labor and so reduces labor's share of income.

3.2 Dynamic general equilibrium

It is now possible to incorporate capital accumulation and heterogeneous firms into the model just developed. The goal here is to develop a model that can be used to study how concentration and labor share are affected by the creation of new technologies.

Firms are introduced in the tradition of "span of control" models (cf. Lucas (1978)) but without their career choice component. Production requires three inputs: capital and labor (as before) and also entrepreneurial skill. Hereafter I shall use the terms productivity and entrepreneurial skill interchangeably and without prejudice. There is a continuum of firms $i \in [0,1]$, each endowed with some productivity. Firm i draws its productivity z_i from the following Pareto distribution[39] (at the beginning of time):

$$z_i \sim f(z) = \begin{cases} \lambda/z^{\lambda+1} & \text{if } z \geq 1, \\ 0 & \text{otherwise.} \end{cases}$$

Firms optimally choose to adopt one among N technologies, which are embodied in different machines. A firm i that adopts technology j thereby accesses the production function

$$y_i(j) = z_i^{1-\eta}[(1-\alpha)k(j)^\rho + \alpha(\gamma(j)\ell)^\rho]^{\eta/\rho},$$

where η ($0 < \eta < 1$) is the span-of-control parameter. Note that the time subscript t has been omitted. To simplify analysis, I assume the following structure of capital. The household supplies and accumulates what I call the *general* capital, which firms purchase at a common interest rate and convert into capital of vintage j at some cost. One unit of

[39] Axtell (2011) documents that the distribution of firm size is well approximated by a Pareto distribution, as employed by Buera et al. (2011) and Dinlersoz and Greenwood (2016).

the general capital can be converted into $1/q(j)$ units of vintage-j capital. In addition, firms are able to adopt technology j—or, equivalently, to use capital of vintage j—only by first paying a lump-sum fixed cost $\phi(j)$. My last assumption is formalized next.

Assumption 3. *Both $\phi(j)$ and $q(j)$ are increasing in j; that is, more advanced technologies require a larger fixed cost. Also, machines that embody more advanced technologies are more costly to produce.*

Firms optimally choose technology j, and employ capital $k_i(j)$ and labor ℓ_i, while taking wage and the interest rate as given. If none of the N technologies generates a net positive profit, then firms will be inactive. Firm i's optimal choice problem is written as[40]

$$\Pi_i \equiv \max\left\{ \max_{j,k_i(j),\ell_i} y_i(j) - r(q(j)k_i(j)) - w\ell_i - \phi(j),\, 0 \right\}.$$

For future reference, I define an indicator $\sigma_i(j)$ as

$$\sigma_i(j) = \begin{cases} 1 & \text{if firm } i \text{ adopts technology } j, \\ 0 & \text{otherwise.} \end{cases}$$

Note that if firm i chooses to remain inactive and so does not adopt any of the N technologies, then $\sigma_i(j) = 0$ for all j.

There exists a representative household that accumulates the general capital and also inelastically supplies L units of labor to maximize present-value utilities:

$$\sum_{t=0}^{\infty} \beta^t \log C(t);$$

here β is the discount factor and C denotes consumption. The household obtains income from wages, rental income, and profits, and it distributes total income into consumption C and investment I. Its budget constraint is

$$C(t) + I(t) \leq w(t)L + r(t)K(t) + \int \Pi_i(t)\, dF(z_i),$$

where $F(z_i)$ is the cumulative distribution function of z_i. In addition, the household respects the following law of motion for the general capital:

$$K(t+1) = (1-\delta)K(t) + I(t);$$

here δ denotes the depreciation rate.

The model economy's competitive equilibrium is defined as a sequence of prices $\{r(t)\}_{t=0}^{\infty}$ and $\{w(t)\}_{t=0}^{\infty}$ and a sequence of aggregate quantities $\{C(t)\}_{t=0}^{\infty}$ and $\{K(t)\}_{t=0}^{\infty}$—as well as, for all i, technological adoption decisions $\{\sigma_i(j,t)\}_{t=0}^{\infty}$ and demand for capital $\{k_i(j,t)\}_{t=0}^{\infty}$ and labor $\{\ell_i(t)\}_{t=0}^{\infty}$—such that the following statements hold.

[40] Firms can freely switch technologies from period to period. The model does not incorporate firms' growth because I am focusing instead on how labor share and firm size distribution are affected by technology.

1. Given prices, $\{C(t)\}_{t=0}^{\infty}$ and $\{K(t)\}_{t=0}^{\infty}$ maximize the representative household's utility.

2. Given prices, the technology choices $\sigma_i(j,t)$ and factor demands $k_i(j,t)$ and $\ell_i(t)$ maximize firms' profits for all t.

3. Markets clear:

   - capital market,
$$\int \Sigma_j k_i(j,t)\sigma_i(j,t)q(j)\,dF(z_i) = K(t) \quad \forall t;$$
   - labor market,
$$\int \ell_i(t)\,dF(z_i) = L \quad \forall t;$$
   - goods market,
$$C(t) + K(t+1) - (1-\delta)K(t) + \int \Sigma_j \sigma_i(j,t)\phi(j)\,dF(z_i) = \int y_i(t)\,dF(z_i) \quad \forall t.$$

Technology, labor share, and firm fize The static model showed that more advanced technologies lead to lower labor shares and higher output. Those findings apply also in this extended model. To reduce notation, write the conversion cost $q(j)$ as a function of $\gamma(j)$—thus, q_γ. The production function of a firm i that uses capital of vintage j is

$$y_i = z_i^{1-\eta}\left[(1-\alpha)\left(\frac{k_i}{q_\gamma}\right)^{\rho} + \alpha(\gamma\ell_i)^{\rho}\right]^{\eta/\rho};$$

here k_i is the general capital which commands a common interest rate r. From the first-order conditions of firm $i's$ optimization it follows that the capital intensity (K/L)[41] in firm i can be written as

$$\frac{k_i}{\ell_i} = \left(\frac{1-\alpha}{\alpha}\frac{w}{r}\right)^{1/(1-\rho)}(\gamma q_\gamma)^{-\rho/(1-\rho)}.$$

In other words, firms that use more advanced technologies have a higher capital/labor ratio. The labor share in firm i is

$$\mathrm{LS}_i \equiv \frac{w\ell_i}{y_i} = \frac{\eta\alpha}{\alpha + (1-\alpha)\left(\frac{r}{w}\frac{\alpha}{1-\alpha}\right)^{-\rho/(1-\rho)}(\gamma q_\gamma)^{-\rho/(1-\rho)}}.$$

Thus a more advanced technology (i.e., a higher value of γ) results in a lower labor share. All firms face the same wage and so labor productivity, defined as

$$\mathrm{LP}_i \equiv \frac{y_i}{\ell_i} = \frac{w}{\mathrm{LS}_i},$$

[41] The capital used in measuring capital intensity is the general capital. In the data, capital stock's value already contains price information about different machines that reflects quality differences.

is an increasing function of γ. Observe that all these three properties are independent of firm productivity z_i.

Firm $i's$ output y_i is[42]

$$y_i = z_i \underbrace{\left(\frac{\eta(1-\alpha)}{r}\right)^{\eta/1-\eta} q_\gamma^{-\eta/1-\eta} \left[(1-\alpha) + \alpha\left(\frac{r}{w}\frac{\alpha\gamma q_\gamma}{1-\alpha}\right)^{\rho/1-\rho}\right]^{\eta(1-\rho)/\rho(1-\eta)}}_{\equiv g(\gamma,r,w)} \tag{1}$$

The effect of technology on firm size, measured as output, has two aspects. On the one hand, more advanced technology increases demand for capital and effective labor and also increases firm size, as in the static case; on the other hand, the conversion cost makes it optimally for firms to cut back on their use of not only labor but also capital.

Firms' technology adoption decision Firm $i's$ profit is

$$\begin{aligned} \Pi_i &= y_i - w\ell_i - rk_i - \phi \\ &= (1-\eta)y_i - \phi \\ &= (1-\eta)z_i g(\gamma, r, w) - \phi \end{aligned}$$

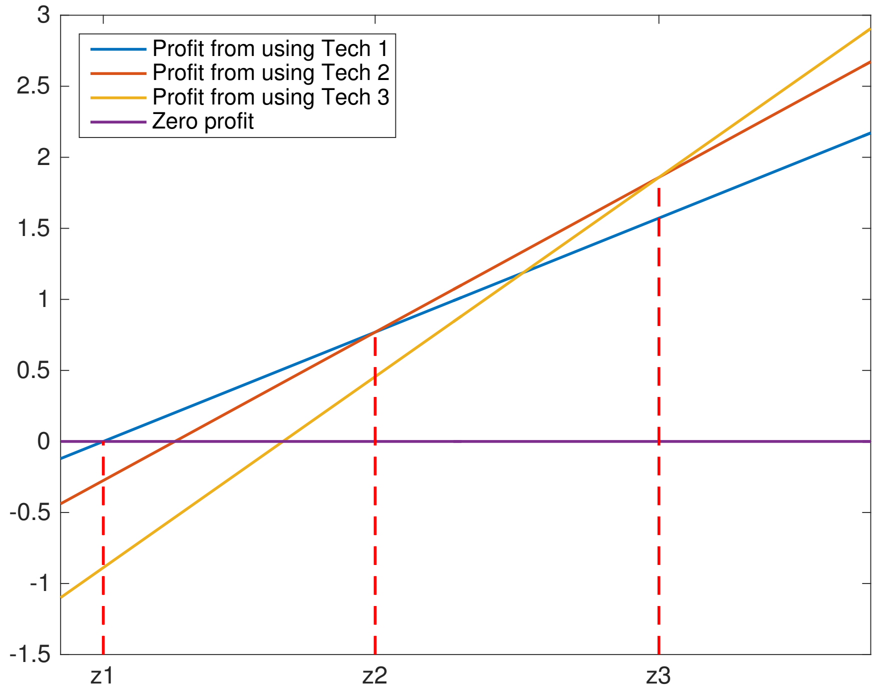
where $g(\gamma, r, w)$ is defined in the firm size formula (1). A nice property is that profit Π_i is a linear and increasing function of productivity z_i. If $g(\gamma, r, w)$ is an increasing function of γ then the profit function, as a function of productivity z_i, has a smaller intercept ($-\phi$) and a larger slope ($g(\gamma)$) for technologies that are more advanced. In this case, the more productive firms optimally choose more advanced technologies. Formally, we have the following proposition.

Proposition 2. [Firms' optimal technology adoption] *Let $g'(\gamma) > 0$ for $g(\gamma)$ as defined in equation (1). If it is optimal for firm i with productivity z_i to adopt technology j, then firm i' with productivity $z_{i'} > z_i$ adopts technology $j' \geq j$.*

Figure 3.1 illustrates the intuition by showing an example case of three technologies, where technology 1 is the least advanced and technology 3 the most advanced. This figure's plot of the profit function associated with technology 1 starts high and increases slowly, whereas the technology 3 function starts low and increases rapidly. Let $\Pi(z_i, \gamma_j)$, $j = 1, 2, 3$, denote the profit function when the firm adopts technology j. There are three intersection points: $\bar{z}_1$, where $\Pi(z_i, \gamma_1)$ intersects the zero-profit line; $\bar{z}_2$, the intersection of $\Pi(z_i, \gamma_2)$ and $\Pi(z_i, \gamma_1)$; and $\bar{z}_3$, the productivity level at which $\Pi(z_i, \gamma_3)$ surpasses

[42] See the Appendix for an expression for capital and labor demand in firm i. Substituting capital and labor demand into the firm's production function gives this result.

Figure 3.1: Profit Functions and Technology Adoption



Note: This graph shows profit functions in an example case involving three technologies. Technology 1 (resp. 3) is the least (resp. most) advanced. The horizontal axis marks firm productivity.

$\Pi(z_i, \gamma_2)$. Firms' technology adoption therefore follows a threshold rule:[43]

$$T_i = \begin{cases} \text{stay inactive} & \text{if } z_i < \bar{z}_1, \\ \text{adopt technology 1} & \text{if } z_i \in [\bar{z}_1, \bar{z}_2), \\ \text{adopt technology 2} & \text{if } z_i \in [\bar{z}_2, \bar{z}_3), \\ \text{adopt technology 3} & \text{if } z_i \geq \bar{z}_3. \end{cases}$$

A sufficient condition for $g'(\gamma) > 0$ is that the conversion cost q_γ being a constant. In this case, more advanced technology increases firms' output. The intuition derives from the static case: advanced technology (γ) complements capital and increases employment of effective labor ($\gamma\ell$)[44]. By continuity, , $g'(\gamma) > 0$ holds as long as $q'(\gamma)$ is small enough. In the quantitative analysis, I always choose the conversion cost function such that $g'(\gamma) > 0$. This procedure rules out the uninformative case in which new machines cost so much that *no* firms will adopt them.

[43] It is possible for (say) ϕ_3 to be slightly smaller than ϕ_2 and hence for the inequality $\bar{z}_3 < \bar{z}_2$ to hold. This situation is equivalent to the case of only two available technologies. I do not consider that possibility because the discussion of N technologies is sufficiently general.

[44] This statement follows also from equation (1) by putting $q_\gamma = c$.

Firms that are more productive choose to adopt more advanced technologies. Because firm size (as measured by output or value added) is an increasing function of both productivity and technology, firms with higher productivity are also larger. Recall from the static case that more advanced technologies induce higher labor productivity and lower labor share. Hence the extended model predicts a negative relation between firm size and labor share.

Technological change In an economy with N technologies and in which capital and labor are complementary while labor is fixed, the economy will arrive at a steady state. In that steady state, productive firms choose more advanced technologies, are larger, and have a lower labor share. Technological change is modelled as an (exogenous) arrival of the $(N+1)$th technology. This new technology drives the economy to a new steady state. In this subsequent steady state, the most productive firms find it profitable to switch to the cutting-edge technology, and become even larger (which increases concentration) and have lower labor shares than before. As a result, the aggregate labor share declines.[45] To demonstrate this effect more clearly, I next calibrate a version of the model initially with two technologies and study how concentration and labor shares are affected by the introduction of new, third technology.

3.3 Quantitative evaluation

This section offers a quantitative evaluation of the mechanism proposed in the paper. The economy initially has two vintages of technology; technological progress is modeled as a third and more advanced technology being exogenously available. I begin with just two vintages of technology since it corresponds to the binary division of firms into large and small ones, for which data is available for calibration; two is also the minimum number needed to demonstrate the mechanism.

The model has five parameters in preference and production functions: the discount rate β, depreciation rate δ, span-of-control parameter η, elasticity of substitution ρ between capital and labor, labor weight α in the production function, and one-tail parameter λ in the Paretro distribution of productivity. The model also has five technology and cost parameters, of which the first four are the levels γ_1 and γ_2 of labor-saving technology and the two fixed costs ϕ_1 and ϕ_2. The conversion cost of capital j, denoted $q(j)$, is assumed to be a power function of $\gamma(j)$: $q(\gamma) = \gamma^{\varepsilon}$. The fifth parameter is ε, the conversion cost parameter. The fixed labor supply is normalized to 1.

The discount rate β and depreciation rate δ are widely used in the macroeconomics literature. I choose $\beta = 0.96$ to match an annual interest rate of 4%, and the discount rate is set at $\delta = 6\%$ per year. In the model, the span-of-control parameter η determines the share of profit (which is usually considered to be part of capital income) in firms' value added.

[45] There will be some equilibrium effect on wage owing to the availability of new technology and associated capital accumulation. I show in Section 3.3 that this equilibrium effect is small.

I pick $\eta = 0.75$, which corresponds to 25% of profit share.[46]

As for the elasticity of substitution between capital and labor—$\rho/(1-\rho)$ in my model—most empirical estimates obtain values that are less than 1. Using micro-level Census of Manufactures data and a CES production function, Oberfield and Raval (2014) estimate the average plant-level elasticity of substitution to be 0.5 and the aggregate elasticity of substitution for the manufacturing sector to be 0.71 in 1987 and 0.75 in 2007. I target an elasticity of substitution of 0.5 at the firm/plant level and set $\rho = -1$.

In a 2-digit sector, 50 firms typically account for only a small fraction of the total number of firms in that sector. Large firms typically have multiple establishments, but the model presented here does not distinguish between firms and establishments. I implement the following adjustment procedure. Business Dynamics Statistics (BDS) data classify firms into "bins" of different sizes; size is measured by number of employees, so those bins range from "1 to 4 employees" to "more than 10,000 employees". I use the average number of establishments for firms in the largest-size bin to approximate the number of establishments in the 50 largest firms and then calculate their fraction in the total establishments for each sector. This sector-level fraction is summed up to obtain the economy-wide values. Calculated this way, the 50 largest firms accounted for 1.93% of all establishments in 1987.

According to Table 2.6, top-50 firms account for 26% of revenue share in 1987. Concentration in the mode is a combination of two forces: higher productivity which is governed by the tail parameter λ; and more advanced technology, which is determined by technology γ and conversion costs ε. We do the following to to back out the tail parameter λ: Table 2.6 shows a negative correlation between labor share and concentration over time. In particular, results from a single variable regression is

$$Share50 = 115.6 - 1.72 * LS$$

The labor share is of course affected by technological heterogeneity. In 1987, the relative labor share of top-50 firms is 82.2%. Based on information in Table 2.6, a hypothetical labor share in the case where there is no technological heterogeneity (i.e. RLS of top-50 firms is 100%) can be calculated. We then combine this hypothetical labor share and the relation above to obtain a measure of concentration where there is no technological heterogeneity among firms. The resulted ratio is 20.9%, i.e. the 50 largest firms (or 1.93% of all firms) account for 20.9% of value added. These yield the tail parameter of the Pareto distribution, $\lambda = 1.66$.

There are still six parameters to be determined. labor weight in the production function, α, technology parameter γ_1 and $_2$, fixed costs ϕ_1 and ϕ_2, and conversion cost parameter, ε. For technology 1, the level of labor saving technology is normalized to $\gamma_1 = 1$. Since

[46]This value for η is slightly smaller than the 0.85 typically used in literature (e.g., Atkeson and Kehoe (2007); Midrigan and Xu (2014)). A slightly larger profit share is targeted because, in my model, firms must pay fixed costs out of their profit.

Table 3.1: Summary of Calibration Results

Para.	Meaning	Values	Target/sources
β	discount rate	0.96	4% interest rate
δ	depreciation rate	0.06	6% capital depreciation
η	span-of-control	0.75	25% profit share
ρ	elasticity of substitution, K and L	-1	Oberfield and Raval (2014)
λ	shape of Pareto distribution	1.66	20.9% in tail
γ_1	technology para. in Tech. 1	1	normalization
jointly calibrated parameters			
α	labor weight in prod. fun.	0.44	labor share in 1987
γ_2	technology para. in Tech.	1.5	relative LS-*top-50* in 1987
ϕ_1	fixed cost of Tech. 1	0.16	5% exit rate
ϕ_2	fixed cost of Tech. 2	0.45	revenue share-*top-50* in 1987
ε	power in conversion cost fun.	0.9	emp. share -*top-50* in 1987

technology affects both labor share and size, the relative labor share and concentration data in 1987 are chosen as two moments to target in the calibration. The labor weight α affects labor share across all firms and thus the aggregate labor share, which is used as a third moment. A 5% exit rate for firms or establishments is used as the fourth moment since exit is a function of fixed costs[47]. A higher conversion cost reduces demand for the general capital; hence the rate of net labor-saving technological progress, which reduces equilibrium employment, is amplified by the conversion cost parameter ε.[48] The last moment used is concentration of employment in top-50 firms in 1987[49]. The five parameters are jointly calibrated to match these five moments.[50] Table 3.1 summarizes the calibration results.

[47] The establishment exit rate, calculated using BDS data, was 11.9% in 1987. Because the model does not have firm entry and exit, I choose a more conservative target of 5% inactive firms.

[48] To see this, note that the production function in terms of the general capital is

$$y_i = z_i^{1-\eta}\left[(1-\alpha)\left(\frac{k}{q_\gamma}\right)^\rho + \alpha(\gamma\ell)^\rho\right]^{\eta/\rho}.$$

given that $q_\gamma = \gamma^\varepsilon$, the rate of labor-saving technological progress is $(1+\varepsilon)\dot{\gamma}/\gamma$.

[49] The employment share of top-50 firms is an weighted average of this share across 2-digit sectors. At the two digit level, the share is interpolated for values in 1987 and 1992 in some sectors. The same interpolation method as in constructing the revenue share is employed. This share for the aggregate economy is 20.00% in 1987, 19.85% in 1992, 19.63% in 1997, 21.55% in 2002, 20.66% in 2007, and 20.90% in 2012.

[50] An equal weights on all five moments would give a relatively large value for the conversion cost parameter ε; Due to the convexity of the cost function, a large ε would greatly dampen technology adoption of firms when a new technology becomes available. Generally, the value ε needs to be high in order to match the employment share and the relative labor share of large firms. To avoid the unwanted case where new technology are so expensive that no firms would like to adopt them, I choose to assign a lower weight for these two moments in the calibration.

Under these parameter values, the aggregate labor share in the model economy is 51.72% and top-50 firms accounts for 26.07% of total revenue and 25.09% of total employment. In equilibrium, 5.2% of firms/establishments stays inactive. The equilibrium wage is 1.11, and the two productivity cutoffs are 1.03 and 2.57. Equivalently: 4.8% of firms exit, 74.3% of (small) firms adopt technology 1 and have a labor share of 55.77%; and the remaining 20.9% of (large) firms adopt technology 2 and have a labor share of 49.77%.

As mentioned earlier, technological progress is modeled as the exogenous availability of a more advanced technology that is more labor saving. That is, this new and more advanced technology has a higher value of γ_3. Furthermore, The fixed cost ϕ_3 associated with this new technology is also larger. We choose the technology parameter γ_3 and the fixed cost ϕ_3 such that in equilibrium, exactly top-50 firms choose to adopt this new technology, and the increase in their concentration ratio matches what is observed in data.

When this more advanced technology becomes available, the most productive firms (*top-50* firms in this case) optimally switch to the new technology, which reduces the labor share in these firms to 45.67%. The concentration ratio, measured as the value-added share of top-50 firms, increases from 26.07% to 31.36%; at the same time, the aggregate labor share declines from 51.72% to 50.35%, or 48.4% of the decline as observed in the data.[51] Note that there is an equilibrium effect when a more advanced technology arrives: capital accumulates and so the wage's absolute level might rise.[52] Under the calibrated parameter values, the wage increases, and this slight increase accounts for the reduced output and also for the increase in small firms' labor shares. The increase in equilibrium wage also induces more firms to exit. In the new steady state, 9.1% of firms choose to exit—as compared with 4.8% before introduction of the new technology.

Large firms in the model grow by adopting labor saving technologies. One implication of the model is that the increase in employment concentration will be slower than the increase in revenue concentration. In the data, the employment share of top-50 firms has increased 0.90% from 1987 to 2012, while their revenue share increases 5.31% for the same period.[53] While the revenue increase is a target in the model, the implied increase in the employment share in the model increases 3.43%, much smaller than the increase in revenue share.

[51] The facts presented in the empirical section show that technological progress, particularly labor saving technological progress, is of first order importance in driving up concentration. It is possible that concentration might increase for non-technological reasons. I tried a more conservative calibration where 50% of increase in concentration observed in data from 1987 to 2012 is caused by technological change. In that case, the technological channel accounts for 21.2% of the decline of labor share for the same period.

[52] The new technology is also a substitute for labor and therefore reduces wages. How the equilibrium wage changes depends on which of these effects dominates.

[53] Even though not focusing on concentration, Kehrig and Vincent (2017) use census data and reports that hyper productive manufacturing firms increases their revenue while maintain their employment relatively unchanged.

4 Discussions and Further Evidence

This section addresses three related issues. First, I calculate the return to capital using NIPA data and while explicitly accounting for changes in the relative prices of investment goods. Second, I present the evolution of sector labor productivity and show that the (labor-saving) technological progress that lowers the labor share also raises labor productivity. Third, because my arguments rely on the assumption of technological heterogeneity across firms, I document (using Compustat data) the heterogeneity of capital intensity at the firm level.

4.1 The return to capital

With a production function where capital and labor are complementary, a declining rate of return to capital would encourage capital accumulation and increase the labor share. It has been well documented that the relative price of investment goods (i.e., the price of investment goods *divided by* the price of consumption goods) has declined since 1980 (Karabarbounis and Neiman (2014b)). Yet changes in the price of investment goods reflect only the capital gain component of investment, so the return to capital is equal to the capital gain *plus* the real return. Gomme et al. (2011) measures the return to capital as

$$R_t = \frac{\text{After-tax capital income at } t}{\text{Capital stock at } t} + \frac{\text{Relative price of investment goods at } t}{\text{Relative price of investment goods at } t-1} - 1;$$

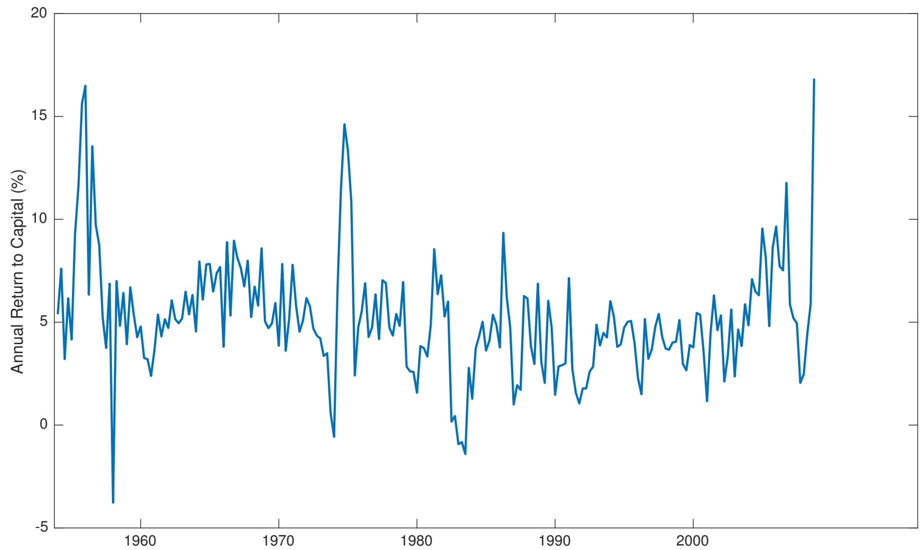
here capital stock excludes housing, and capital income (calculated using NIPA data) equals after-tax nonlabor income. The second term captures the capital gain of investment—that is, changes in the relative prices of investment goods over time. Figure 4.1 presents the (annualized) results from Gomme et al.. The return to capital fluctuates around a value of 5.16% and shows no declining trend since the 1980s.

4.2 Labor productivity

According to the model, new (labor-saving) technologies that decrease the labor share simultaneously increase labor productivity. Labor share declines occurred mostly in the sectors of manufacturing, trade, and transportation. A greater increase in labor productivity should also be observed in these sectors. Note that there need not be any ex ante relation between labor share (WL/PY) and labor productivity (Y/L). For example, in a Cobb-Douglas production function, irrespective of changes in labor productivity, the labor share is a constant. On the empirical side, labor productivity has been increasing for hundreds of years, while the decline of labor share is a fairly recent phenomenon.

The Labor Productivity and Costs program of Bureau of Labor Statistics provides data on labor productivity for different sectors. Labor productivity is the ratio of real output (net

Figure 4.1: Return to Capital, 1954-2008



Note: The return to capital is equal to the real return plus capital gains.
Data Source: Table 2 in Gomme et al. (2011).

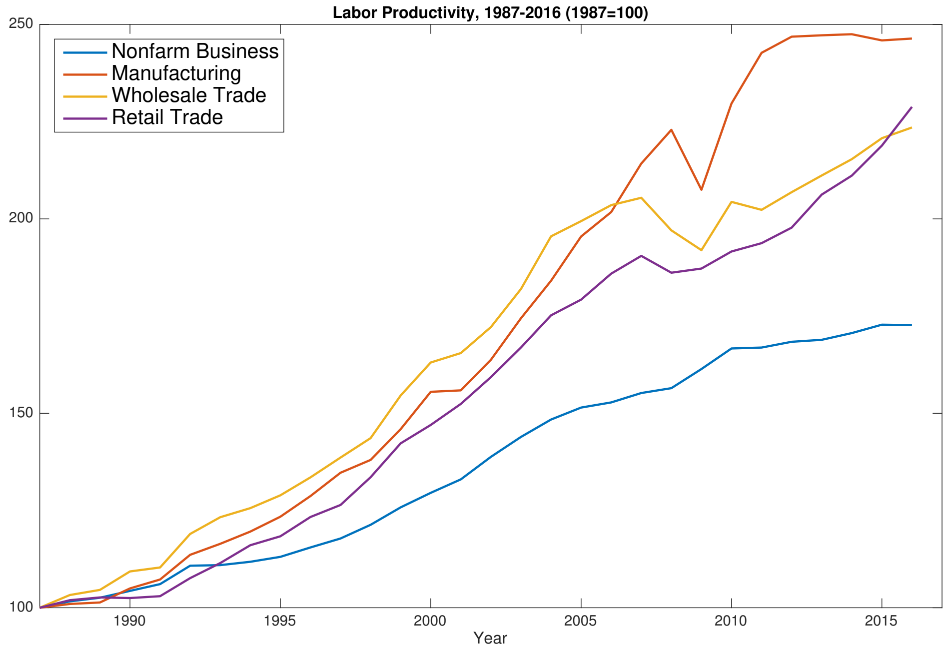
of price change) to hours of labor input.[54] Figure 4.2 plots labor productivity for the overall economy (nonfarm business sector) and also for the manufacturing, wholesale trade, and retail trade sectors from 1987 to 2016 (the 1987 values are normalized to 100).[55]

Economy-wide labor productivity increased from 100 in 1987 to 172.7 2016—a 72.7% rise. Increases for the same period in the manufacturing, wholesale trade, and retail trade sectors were (respectively) 146.4%, 123.5%, and 128.8%. It is clear that, over the last three decades, labor productivity in manufacturing and trade increased much faster than

[54]BLS uses different output concepts to measure labor productivity. For the non-farm business sector, real output is measured net of inter-industry transactions and is equivalent to value added. For manufacturing, retail trade and wholesale trade, what is employed is sector output which is total output minus intra-industry transactions. intermediates goods are not included value added, but included in sector output. We can calculate the share of out-of-sector intermediate goods in a sector's output from input-output tables in order to evaluate the potential bias. For manufacturing, this share was 26.30% in 1997 and 29.50% in 2016; for retail trade, this ratio was 30.95% in 1997 and 36.16% in 2016; the same share increases slightly from 27.56% to 27.82 in the wholesale trade sector from 1997 to 2016. These relatively small changes suggest that the difference in output measures is not likely to be the driver for the much larger divergence in labor productivity.

[55]Prior to 1987, labor productivity data were not available for different industries. The BLS Labor Productivity and Cost by Industry tables do not include labor productivity data for the transportation & warehousing (NAICS 48–49) sector. The message from subsectors is mixed: labor productivity in air transportation (NAICS 481) increased 134% from 1987 to 2016; the increase in line-haul railroads (NAICS 482111) was 196% for the same period. From 1987 to 2016, labor productivity increased 16% in postal service (NAICS 491) but decreased by 43% in couriers and messengers (NAICS 492).

Figure 4.2: Labor Productivity, 1987–2016 (1987=100)



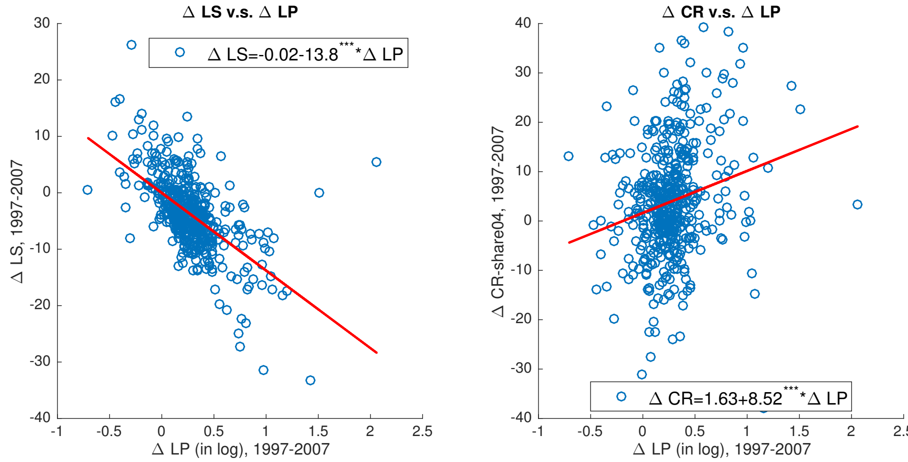
Note: Labor productivity is the ratio of real value added to total working hours.
Data Source: Bureau of Labor Statistics, Labor Productivity and Costs program.

the rest of the economy.[56] This piece of evidence also supports the technological channel, rather than monopoly power, as the likely explanation for the negative correlation between changes in concentration and changes in labor share. Since labor productivity is measured as real output (net of price changes) per hour, it follows that increasing monopoly power drives up the price but does *not* increase labor productivity.[57]

[56] One example of technological progress in retail trade is adoption of information technology by online retailers, such as Amazon. From 1987 to 2016, labor productivity in retail trade increased 128.8%; the corresponding increase in nonstore retailers was 860% and in electronic shopping & mail-order houses was 1486%. In 2012, the share of payroll in total revenue for the retail trade sector (NAICS 44–45) was 8.74%, for nonstore retailers (NAICS 454) was 7.03%, and for the electronic shopping & mail-order houses (NAICS 4541) was 6.12%.

[57] Additional evidence against the monopoly power account can be found in the finance sector. In finance and insurance (NAICS 52), the concentration ratio—measured by revenue share of the 50 largest firms—increased from 38.6% in 1997 to 46% in 2007 and to 48.5% in 2012. (A similar pattern is observed for other concentration measures; for example, revenue share of the 20 largest firms increased from 22.6% in 1997 to 28.5% in 2007 and to 31.6% in 2012, and the average revenue share of 4 largest firms across NAICS 6-digit finance sectors increased from 26.0% in 1997 to 36.1% in 2007 and to 35.4% in 2012.) In finance, the sector labor share (measured as the fraction of compensation in value added) actually increased slightly from 23.2% in 1997 to 25.4% in 2007 but declined during the financial crisis. The gist of these observations is that concentration alone cannot fully explain the behavior of labor share. The Compustat data provide information on labor shares (measured as the fraction of compensation in revenue) in large financial firms; see Appendix Figure 6.10. Over the period in question, the labor share actually increased in most large financial firms and by a nontrivial amount in many of them. These features of the data reveal the value of

Figure 4.3: Labor Productivity, Labor Share, and Concentration, MFG 1997–2007



Note: Labor share is the fraction of payroll in value added; labor productivity LP is the ratio of real value added to total working hours; concentration CR is the value-added share of the 4 largest firms. Each circle represents an NAICS 6-digit sector.

Appendix Figure 6.11 plots the manufacturing sector's labor productivity and labor share from 1987 to 2014. From 1987 to 1997, labor productivity increased 34.7% while the labor share declined 10.3%. Since the late 1990s, both of these trends have accelerated. From 1997 to 2007, labor productivity rose 59.0% and the labor share fell 20.2%.

Labor productivity in more disaggregated manufacturing sectors can be measured using Census of Manufactures data. The census data provide—for each 6-digit manufacturing sector—value added, employment, number of production workers, hours of production workers, and a deflator for the value of shipments (1997 $=$ 1). Total hours are constructed by assuming that the average working hours of nonproduction workers are the same as those of production workers. Labor productivity is calculated as the ratio of value added to total working hours. The deflator for value of shipments is used for each sector to obtain the real value added. Figure 4.3 plots the change in labor share and concentration against labor productivity for 6-digit manufacturing sectors. From 1997 to 2007, the following dynamic prevailed: larger increases in sector labor productivity lead to greater declines in the labor share and also to an increase in concentration.

Congress (1995) offers a detailed description of how progress in information technology since the 1980s has transformed the transportation and trade sectors. The use of sophisticated information systems and automation (e.g., bar-coding) has contributed to the rise of carriers such as UPS (United Parcel Service) and Federal Express. Information tech-

combining concentration and changes of labor shares within firms, especially large ones, for understanding the behavior of aggregate labor share. That large financial firms continue to have a larger market share and larger labor share seems not to be a technologically driven phenomenon and so is beyond the scope of this paper.

nology has changed the wholesale trade sector from a system of stocked warehouses to one of fewer but larger-scale distribution centers. Prominent technologies include electronic data interchange (a.k.a. computer-to-computer information interchange), which facilitates the communication of inventory and demand information; bar-coding, which has improved logistics and inventory control while raising the percentage of accurate deliveries; and automation of distribution facilities (e.g., a conveyor system). These new technologies replace certain tasks previously performed by labor, so they increase both productivity and concentration—since facilities must be large enough to support dedicated automated equipment and achieve economies of scale.

At the firm level, one implication of my model is that large firms expand by adopting more advanced technologies that improve their labor productivity. Data from the Economic Census can be used to identify differences between large and small firms. I therefore calculated, for different firm groups, the percentage increase in employment if revenue were to increase by 1%. The benchmark period is from 2007 to 2012. "Large" firms are defined as the top 4 firms (in terms of revenue) in a 6-digit non-manufacturing sector; all other firms in that subsector are then "small " firms. Table 4.1 reports the results. A 1% increase in revenue is associated with an 0.84% increase in employment by small firms as compared with an 0.62% increase by large ones. This difference is both statistically significant and economically large. In addition, the pattern is robust to redefining "large" firms via different cutoffs and to using various digit levels and different years. These findings indicate that growth in small firms relies heavily on more hiring whereas most of the growth in large firms is due to improved labor productivity. Further confirmation is provided by this table's reported R^2 values: the value for small firms (0.69, in column (2)) is much higher than for large firms (0.29, in column (1)).

4.3 Firm size, concentration and capital intensity

My model implies that large firms adopt advanced technologies which are more capital intensive (higher K/L).[58] Firm-level capital intensity can be measured using data from *Compustat*. The data that I use cover the period from 1980 to 2016; in total, there are 421,501 firm $\times$ year observations. Firm size is measured by assets (and also, for robustness checks, by employment and sales). Capital is defined as the sum of two items: *PPEGT* (property, plant and equipment-total (gross)) and *INTAN* (intangible assets-total). Capital intensity is defined as capital *divided by* number of employees (and is log-transformed).

Table 4.2 gives the results of ordinary least-squares (OLS) regressions in which the dependent variable is (log) capital intensity and the only independent variable is firm size. Dummies for each year and each SIC 4-digit sector are included as controls. I find that capital intensity is positively and significantly correlated with firm size.

[58] Abow et al. (1999) shows that firms paying higher wages in French are more productive and also more capital intensive.

Table 4.1: Employment Changes associated with 1% Increase in Revenue, 2007–2012

	(1) Large	(2) Small	(3) All	(4)-WLS All
RC_REV	0.62***	0.84***	0.84***	0.79***
	(0.04)	(0.03)	(0.05)	(0.05)
Large			0.02	0.04**
			(0.02)	(0.02)
RC_REV*Large			-0.22***	-0.26***
			(0.06)	(0.06)
R^2	0.29	0.69	0.38	0.35
NO.	489	488	977	977

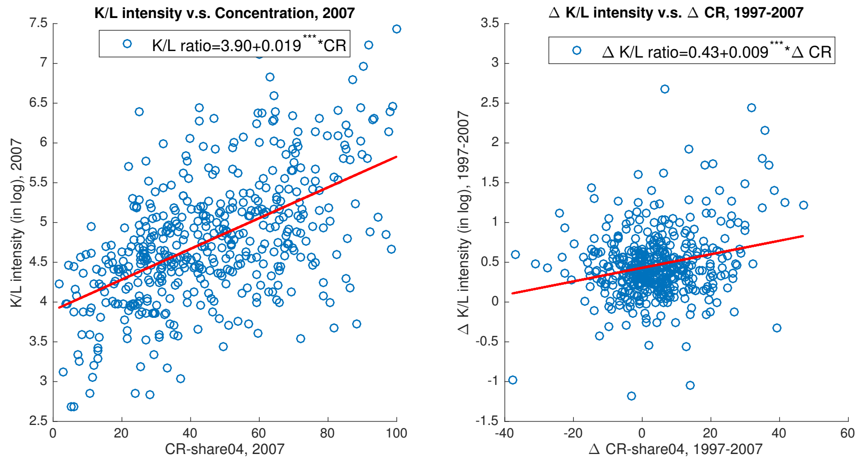
Note: The dependent variable is the percentage change of employment from 2007 to 2012; the independent variable, "*RC_REV*" the percentage change of revenue for the same period. 'Large' is a dummy and denotes 4 largest firms in a NAICS 6-digit sector. Column (4) uses sector employment in 2007 as weights.

Table 4.2: Results from Regressing Capital Intensity on Firm Size

	(1)	(2)	(3)	(4)	(5)	(6)
log-assets	0.18***			0.21***		
	(0.001)			(0.001)		
log-sales		0.10***			0.14***	
		(0.001)			(0.001)	
log-emp.			0.03***			0.07***
			(0.001)			(0.002)
Year D.	Yes	Yes	Yes	Yes	Yes	Yes
Sector D.	Yes	Yes	Yes	Yes	Yes	Yes
Sample	1980-	1980-	1980-	2000-	2000-	2000-
R^2	0.62	0.62	0.57	0.58	0.58	0.50
Obs.	225,798	212,927	225,811	107,875	98,103	107,885

Note: Capital intensity is measured as capital *divided by* number of employees (and is log-transformed). Sector dummies are assigned for each SIC 4-digit sector.
Data Source: Compustat, 1980-2016.

Figure 4.4: Concentration and Capital Intensity in the Manufacturing Sector



Note: Capital intensity, on the vertical axis, is the ratio of capital (equipment + structure) to number of employees; concentration, on the horizontal axis, is the value-added share of the sector's 4 largest firms. Each circle represents an NAICS 6-digit sector.

The Census of Manufactures also provides values of capital stock for manufacturing subsectors. The capital stock contains equipment and structures both of which are measured in real terms.[59] Capital intensity is defined as the ratio of real capital to number of employees. Figure 4.4 plots capital intensity against the concentration ratio (measured as the value-added share of the 4 largest firms) in 6-digit manufacturing sectors. Sectors that are more capital intensive tend to be more concentrated. Over time, sectors in which concentration increases also become more capital intensive.

5 Conclusion

This paper documents firm heterogeneity with regard to labor share; in particular, large firms tend to have a lower labor share. . It also shows that a declining aggregate labor share is due to falling labor share in large firms combined with the rising market share of those firms (higher concentration). The sectors of manufacturing, trade, and transportation exhibit the most decline in labor share; these are also the sectors in which concentration has increased the most and the relative labor share of large firms has declined the most. The increases in labor productivity of large firms in these sectors far exceed the increases in wage.

I provide a rationale for these empirical facts by assuming that capital and labor are complementary inputs and that technological progress is labor saving. Under these assumptions, my model predicts a negative correlation between firm size and labor share. Given

[59]The recently capitalized Intellectual Properties and Products (IPP) are not included in the Census of Manufactures data.

the complementarity of capital and labor, (labor-saving) technology increases the productivity of capital and the demand for effective labor, thereby increasing output; however, technology substitutes raw labor and so reduces the latter's share of income. Furthermore, the adoption of new technologies diminishes the labor shares in large firms and increases their market share. Hence the aggregate labor share declines.

This technological channel is consistent with the evolution of labor productivity across sectors during the last 30 years. From 1987 to 2016, economy wide labor productivity increased by 72.7%. For the same period, the labor productivity increases in manufacturing, wholesale trade, and retail trade were (respectively) 146.4%, 123.5%, and 128.8%.[60]

The model does not address sector heterogeneity. A promising extension would be to embed that heterogeneity into the model for quantitative analysis. Also, in some sectors, new technologies are adopted by small firms that grow large over time (e.g. Amazon in retail trade). Another extension would be to capture a richer firm dynamics by incorporating the creation and death of incumbents firms into the model.

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[60] My paper focuses on post-1980 period. Possibly at a slower pace, there is of course labor saving technological change before 1980s. Two facts suggest the mechanism proposed in the paper also work before 1980. First, as reported in Table 6.3, the negative correlation between change in concentration and change in labor share holds in 1960s and 1970s; Second, the labor share calculated using post-2013 revision NIPA data shows a slower and declining trend before 1980 (See Koh et al. (2016)). The stationary concentration ratio in manufacturing in late 1960 and 1970s might be due to counteracting forces (e.g. union power) and I leave that for future investigation.

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6 Appendix

K/L ***intensity under different technologies in Static Case.*** The equilibrium condition in the labor market is

$$w = \mathrm{MPL}_j = \left[(1-\alpha)\left(\frac{k_j}{\ell_j}\right)^{\rho} + \alpha\gamma_j^{\rho}\right]^{1/\rho-1} \alpha\gamma_j^{\rho}.$$

Note that this expression contains two γ_j. The last γ_j^{ρ} captures a direct effect: technology with a higher γ_j increases labor productivity and requires less labor to produce. The first γ_j^{ρ} captures the opposite effect—namely, that this technology allows firms to operate at a larger scale, which increases labor demand.

Rewrite the labor market marginal condition as

$$(1-\alpha)\left(\frac{k}{\ell}\right)^{\rho} = \left(\frac{w}{\alpha\gamma^{\rho}}\right)^{\rho/(1-\rho)} - \alpha\gamma^{\rho} \equiv f(\gamma).$$

A sufficient condition for a positive correlation between γ and k/ℓ is $f'(\gamma) < 0$. Note that

$$f'(\gamma) = \left(\frac{w}{\alpha}\right)^{\rho/(1-\rho)} \left(-\frac{\rho^2}{1-\rho}\right)\gamma^{-\rho^2/(1-\rho)-1} - \alpha\rho\gamma^{\rho-1}$$

and that $f'(\gamma) < 0$ is equivalent to

$$\gamma > \left(\frac{w}{\alpha}\right)^{1/(1-\rho)} \left(\frac{-\rho}{1-\rho}\frac{1}{\alpha}\right)^{1/\rho}.$$

Therefore, this condition is satisfied if γ is large enough[61].

Firm size and employment in general equilibrium Let MPK stand for the marginal productivity of capital. Then the optimal conditions in a competitive equilibrium are as follows:

$$\mathrm{MPK}_i = \eta z_i^{1-\eta}\left[(1-\alpha)\left(\frac{k_i}{q_\gamma}\right)^{\rho} + \alpha(\gamma\ell_i)^{\rho}\right]^{\eta/\rho-1}(1-\alpha)q_\gamma^{-\rho}k_i^{\rho-1} = r;$$

$$\mathrm{MPL}_i = \eta z_i^{1-\eta}\left[(1-\alpha)\left(\frac{k_i}{q_\gamma}\right)^{\rho} + \alpha(\gamma\ell_i)^{\rho}\right]^{\eta/\rho-1}\alpha\gamma^{\rho}\ell_i^{\rho-1} = w.$$

Firm i's demand for capital and labor may be written as

$$k_i = z_i\left(\frac{\eta(1-\alpha)}{r}\right)^{1/(1-\eta)} q_\gamma^{-\eta/(1-\eta)}\left[(1-\alpha) + \alpha\left(\frac{r}{w}\frac{\alpha\gamma q_\gamma}{1-\alpha}\right)^{\rho/(1-\rho)}\right]^{(\eta-\rho)/\rho(1-\eta)} \quad \text{and}$$

$$\ell_i = z_i\left(\frac{\eta\alpha}{w}\right)^{1/(1-\eta)} \gamma^{\eta/(1-\eta)}\left[(1-\alpha)\left(\frac{1-\alpha}{\alpha\gamma q_\gamma}\frac{w}{r}\right)^{\rho/(1-\rho)} + \alpha\right]^{(\eta-\rho)/\rho(1-\eta)},$$

[61] Note that it follow from the marginal condition of labor market, $(1-\alpha)(\frac{k}{\ell})^{\rho} = (\frac{w}{\alpha\gamma^{\rho}})^{\frac{\rho}{1-\rho}} - \alpha\gamma^{\rho}$, that $(\frac{w}{\alpha\gamma^{\rho}})^{\frac{\rho}{1-\rho}} - \alpha\gamma^{\rho} > 0$, or equivalently, $\gamma > \frac{w}{\alpha}(\frac{1}{\alpha})^{\frac{1-\rho}{\rho}}$.

respectively. Therefore, the net effect of technology on employment size is unclear. The reason is that technology has two effects on employment, as illustrated in the static case above.

Data Source

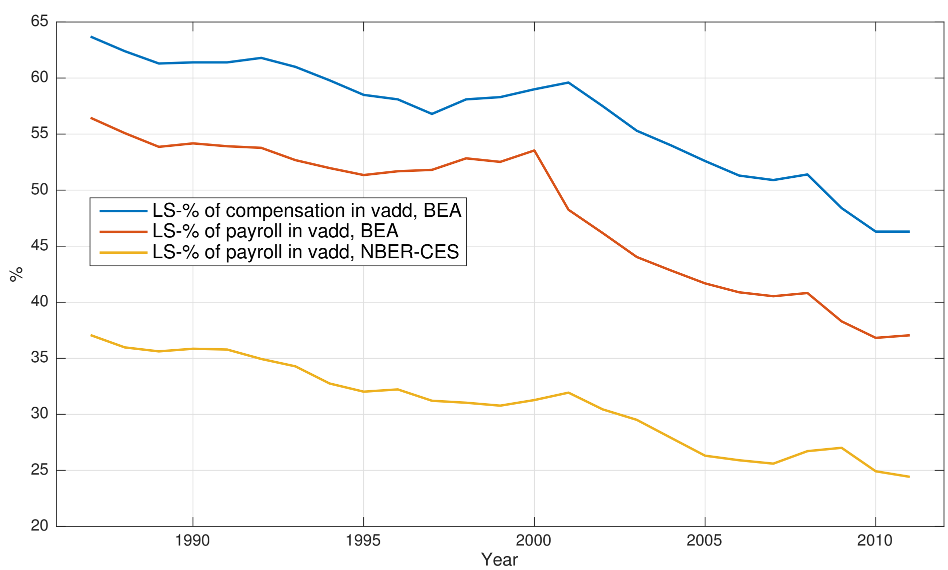
- Data used to calculate labor share for 2-digit sectors are from the industry accounts of the Bureau of Economic Analysis (BEA). Labor share for detailed manufacturing sectors is calculated using data from the Annual Survey of Manufactures. A simplified version of the ASM by 6-digit sectors is summarized in the NBER-CES data set. These data are available for 6-digit manufacturing sectors from 1958 to 2011.

- Concentration ratios for 2002, 2007, and 2012 are from the US Census Bureau's American FactFinder website and from various pre-1997 publications of the Census Bureau. This measure gives shares of the 4, 8, 20, and 50 largest firms in total sales (receipts, or value of shipments). For manufacturing, concentration ratios in terms of value added are also available.

Classification of multi-establishment enterprises The NAICS is designed to facilitate the collection, tabulation, presentation, and analysis of data relating to establishments (see Parker (2012)). For industry classification of multi-unit firms[62] with diverse production activities, the NAICS uses a multiple stage "hierarchical" approach. In the first stage, the firm is assigned to a major sector based on highest share of payroll. Within that major sector, the firm is then assigned to a subsector, based on the highest share across the subsectors within the major sector (cf. Awuku-Budu and Robbins (2014)). This process continues through to the most disaggregated level of industry classifications.

Labor Share in Census of Manufacturing versus NIPA

Figure 6.1: MFG LS in ASM/NBER-CES and BEA-NIPA



[62]"unit and "establishment" are used interchangeably. In this context,"firms", "enterprises", and "companies" amounts to the same things.

Offshoring index

Following Feenstra and Hansen (1996) and Feenstra and Hansen (1998), I measure sector i's offshoring intensity as

$$\text{OS}_i = \Sigma_j \frac{\text{Input from sector } j}{\text{Total intermediate input in } i} \times \text{Import intensity of } j.$$

The import intensity of j is measured as the fraction of imports in expenditures, which equals the value of shipments (plus imports and minus exports) in sector j. Offshoring intensity is calculated using the input–output tables of 1997 and 2015 for 66 private industries. Figure 6.2 presents the results. The measured offshoring intensity increases in most industries, but the increases are more prominent in manufacturing than in non-manufacturing sectors.

Figure 6.2: Offshoring intensity, 1997-2015

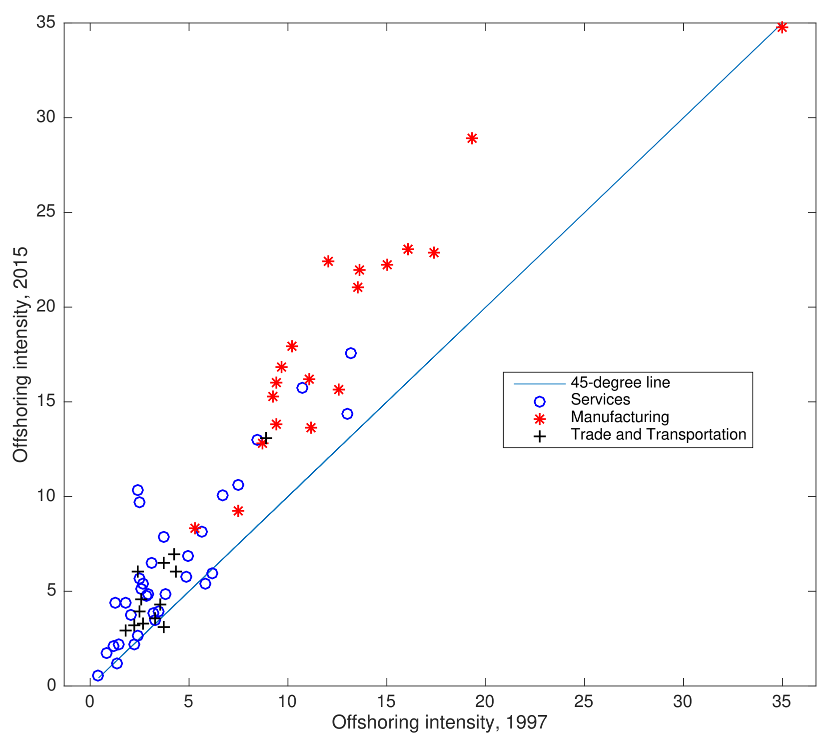


Table 6.1: Concentration and Labor Share. Depend. var.: ΔLS, 1997-2007

	OLS				WLS			
	3 digit	4 digit	5 digit	6 digit	3 digit	4 digit	5 digit	6 digit
Δ*CR04*	-0.239**	-0.206***	-0.237***	-0.171***	-0.117	-0.175***	-0.191***	-0.156***
	(0.099)	(0.054)	(0.033)	(0.024)	(0.084)	(0.043)	(0.032)	(0.024)
R^2	0.23	0.16	0.22	0.10	0.09	0.16	0.16	0.08
Δ*CR08*	-0.213***	-0.126**	-0.175***	-0.146***	-0.125**	-0.132***	-0.147***	-0.125***
	(0.073)	(0.062)	(0.041)	(0.029)	(0.057)	(0.046)	(0.037)	(0.029)
R^2	0.31	0.05	0.09	0.05	0.20	0.09	0.08	0.04
Δ*CR20*	-0.318***	-0.149*	-0.210***	-0.157***	-0.132	-0.203***	-0.247***	-0.169***
	(0.115)	(0.077)	(0.049)	(0.036)	(0.084)	(0.063)	(0.053)	(0.040)
R^2	0.29	0.04	0.09	0.04	0.11	0.11	0.11	0.04
Δ*CR50*	-0.347*	-0.137	-0.211***	-0.124***	-0.168	-0.226***	-0.260***	-0.176***
	(0.167)	(0.100)	(0.062)	(0.048)	(0.113)	(0.084)	(0.067)	(0.054)
R^2	0.19	0.02	0.06	0.01	0.11	0.08	0.08	0.02
Obs.	21	86	183	464	21	86	183	464

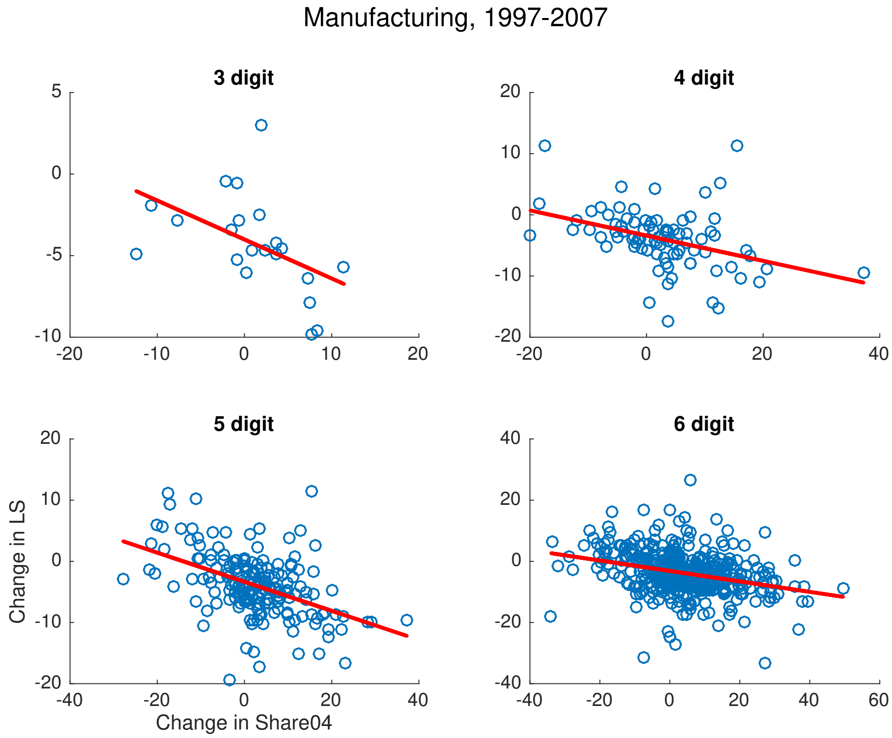
Note: The single variable regression results are for manufacturing sectors, at various digit levels. The dependent variable is change in labor share and the independent variable is change in concentration from 1997 to 2007. Δ*CR04* refers to the change in *Share04*, which itself measure the share of value added accounted for by the largest 4 firms in a sector. In WLS regressions, the weight used is given by the average value added between 1997 and 2007.

Table 6.2: Regression with panel data; Dependent Variable.: ΔLS

	(1)	(2)	(3)
Δ*CR04*	-0.183***	-0.283***	-0.084***
	(0.029)	(0.048)	(0.024)
Δ *k-l ratio (ln)*			-0.322
			(0.760)
Δ *per-capita vadd (ln)*			-30.249***
			(0.812)
Δ *% production worker*			0.656***
			(0.081)
Fixed effect	No	Yes	Yes
Obs.	927	927	927

Note: The panel regression results are for manufacturing sectors at the 6 digit level. There are two period, change from 1997 to 2002, and change from 2002 to 2007. LS is the ratio of payroll to value added.

Figure 6.3: ΔLS v.s. $\Delta Share04$, MFG



Note: Labor share on the vertical axis is calculated as the fraction of payroll in value added. Concentration on the horizontal axis is the value added share of 4 largest firms.

Table 6.3: Dependent Variable:ΔLS

	1963-1967		1972-1977		1977-1982		1987-1992	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
$\Delta CR04$	-0.101**	-0.059**	-0.118***	-0.023	-0.190***	-0.240***	-0.174***	-0.128***
	(0.039)	(0.030)	(0.040)	(0.044)	(0.057)	(0.062)	(0.036)	(0.032)
R^2	0.02	0.01	0.02	0.001	0.03	0.03	0.05	0.03
$\Delta CR08$	-0.117***	-0.079***	-0.108***	-0.011	-0.164**	-0.147**	-0.195***	-0.121***
	(0.035)	(0.030)	(0.040)	(0.036)	(0.058)	(0.064)	(0.040)	(0.036)
R^2	0.02	0.02	0.02	0.03	0.02	0.001	0.05	0.03
$\Delta CR20$	-0.187***	-0.103***	-0.113**	-0.067	-0.105	-0.180**	-0.207***	-0.171***
	(0.046)	(0.036)	(0.045)	(0.053)	(0.067)	(0.073)	(0.049)	(0.044)
R^2	0.04	0.02	0.01	0.004	0.006	0.01	0.04	0.03
$\Delta CR50$	-0.167***	-0.076	-0.101*	-0.075	-0.134*	-0.274***	-0.229***	-0.141**
	(0.059)	(0.048)	(0.053)	(0.057)	(0.080)	(0.068)	(0.069)	(0.059)
R^2	0.02	0.007	0.001	0.004	0.007	0.03	0.02	0.01
Obs.	400	400	442	442	437	437	448	448

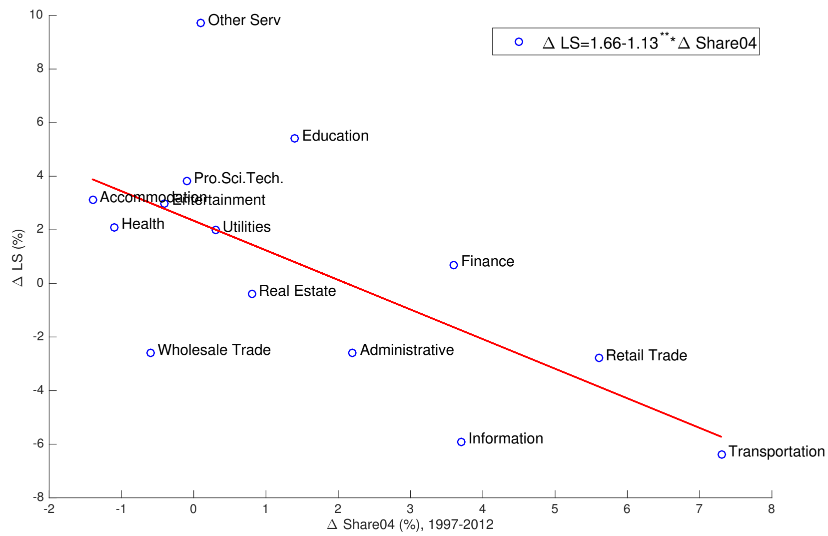
Note: The single variable regression results are based on 4 digit SIC manufacturing sectors. The dependent and independent variables are the change in labor share and concentration, from 1963 to 1967 in the first two columns, and from 1972 to 1977 in the last two columns. $\Delta CR04$ refers to the change in *Share04*, which itself measure the share of value of shipment by the 4 largest firms in a sector. The weights used in WLS regressions are the average value added of beginning and end years for each period.

Table 6.4: Dependent Variable.: ΔLS, 2007-2012

	LS1-OLS	LS2-OLS	LS1-WLS	LS2-WLS
$\Delta CR04$	-0.292**	-0.386***	-0.267***	-0.348***
	(0.041)	(0.051)	(0.032)	(0.043)
R^2	0.23	0.25	0.29	0.28
$\Delta CR08$	-0.352***	-0.475***	-0.363***	-0.476***
	(0.049)	(0.061)	(0.038)	(0.051)
R^2	0.23	0.26	0.34	0.33
$\Delta CR20$	-0.400***	-0.558***	-0.442***	-0.581***
	(0.065)	(0.081)	(0.050)	(0.067)
R^2	0.18	0.22	0.31	0.30
$\Delta CR50$	-0.357***	-0.558***	-0.442***	-0.714***
	(0.092)	(0.115)	(0.050)	(0.096)
R^2	0.08	0.12	0.31	0.24
Obs.	175	175	175	175

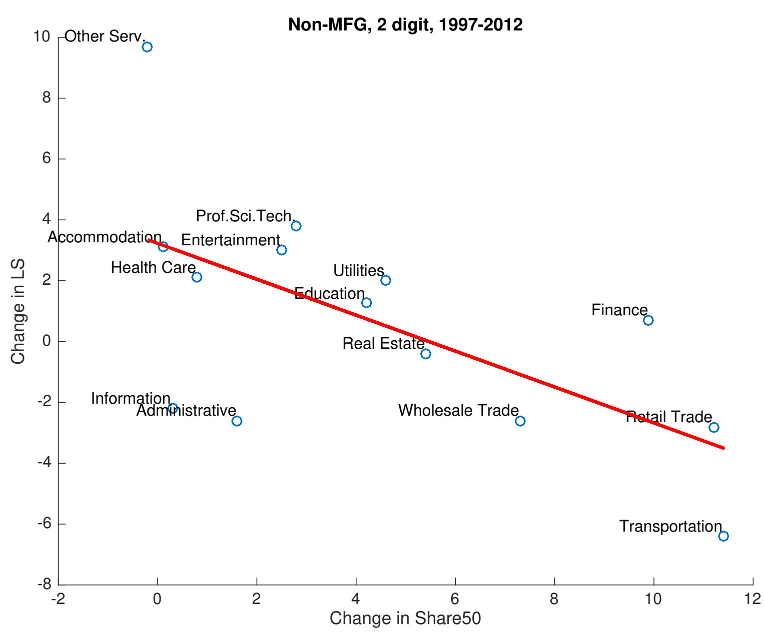
Note: The single variable regression results are for manufacturing sectors at the 5 digit level. LS1 is the ratio of payroll to value added, and LS2 the ratio of compensation (=payroll+benefit) to value added. The average value added between 2007 and 2012 is used as the weight in WLS.

Figure 6.4: ΔLS v.s. $\Delta Share04$, NON-MFG, 1997-2012



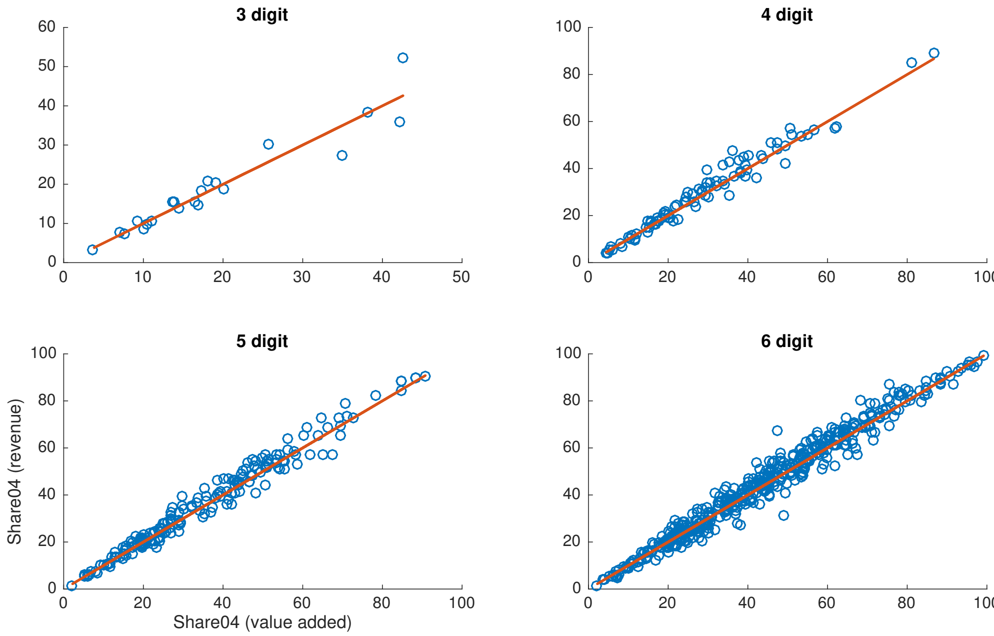
Note: LS in the vertical axis is the fraction of compensation of employees to value added. Concentration in the horizontal axis is the revenue share of 4 largest firms.

Figure 6.5: ΔLS v.s. $\Delta Share50$, NON-MFG, 1997-2012



Note: Labor share on the vertical axis is measured the fraction of compensation of employees to value added. Concentration on the horizontal axis is the revenue share of 50 largest firms. In this graph, I made minimum adjustments to LS in 1997 based on data in Table 6.11. In particular LS for *Information* in 1996, instead of 1997, and the average LS for *Education* between 1996 and 1998, instead of 1997, are employed.

Figure 6.6: Share of Top-4 Firms: Value Added versus Revenue, MFG 2002



Note: The vertical axis is the revenue share of 4 largest firms (in terms of revenue); and the horizontal axis is the value added share of 4 largest firms (in terms of value added).

Table 6.5: Dependent Variable: Share04 in terms of Revenue, MFG 2002

	3 digit	4 digit	5 digit	6 digit
Share04_vadd	0.917***	0.948***	0.959***	0.956***
	(0.043)	(0.014)	(0.008)	(0.007)
R^2	0.92	0.97	0.97	0.97
Obs.	21	86	183	467

Note: The dependent variable is the revenue share of the 4 largest firms (ranked by revenue); and the independent variable is the value added share for the 4 largest firms (ranked value added).

Table 6.6: Concentration in the Manufacturing Sector-I

	Share04				Share08			
Year	3-D	4-D	5-D	6-D	3-D	4-D	5-D	6-D
1997	19.82	29.99	35.12	42.37	27.43	40.29	46.53	54.04
2002	20.81	32.19	37.52	44.84	29.38	43.01	49.05	57.40
2007	20.88	32.18	37.48	44.93	30.92	44.38	50.68	59.03
2012	21.64	32.63	38.26	44.47	32.56	45.20	51.90	59.20
	Share20				Share50			
Year	3-D	4-D	5-D	6-D	3-D	4-D	5-D	6-D
1997	39.82	54.59	60.98	69.59	52.61	67.00	73.23	79.15
2002	42.21	56.63	63.07	71.20	54.81	68.44	74.56	80.07
2007	44.27	58.65	65.29	73.22	56.53	70.60	76.77	83.61
2012	46.16	60.27	67.06	74.28	58.28	72.30	78.61	84.97

Note: Share04 refers to the weighted average of revenue share for the 4 largest firms, with revenue used as weights. 3-D means NAICS 3-digit sectors. The total number of 6-digit sectors decreased from 467 in 2007 to 362 in 2012. Industrial classification codes are consistent over time at other digit levels.

Table 6.7: Concentration in the Manufacturing Sector-II

Year	Share04	Share08	Share20	Share50	Obs.
1963	39.19%	51.22	65.28	76.63	410
1967	38.97	51.42	65.51	77.47	408
1972	39.65	51.83	67.23	79.15	449
1977	39.13	52.64	67.96	79.86	444
1982	36.83	49.82	65.39	78.96	441
1987	40.11	52.23	67.23	79.23	451
1992	40.34	52.25	67.82	79.81	455
1997	42.37	54.04	69.59	79.15	470
2002	44.84	57.40	71.20	80.07	471
2007	44.93	59.03	73.22	83.61	467
2012	44.47	59.20	74.28	84.97	362

Note: Share04 measures the revenue share of the 4 largest firms. The indices are weighted average across SIC 4-digit sectors before 1992 and NAICS 6-digit sectors after 1997, weighted by revenue. The last column shows the total number of sectors.

Table 6.8: Total NO of Firms (unit: thousand)

Year	1977	1982	1987	1992	1997	2002	2007	2012
Economy	3147.9	3604.0	4179.8	4377.1	4752.3	4908.7	5240.0	4979.5
MFG	261.2	272.9	290.8	296.0	303.2	283.4	267.8	234.4
WHO	277.9	307.6	337.0	354.8	372.9	349.6	341.4	310.8
RET	942.8	912.7	953.0	939.8	955.6	949.5	980.0	953.0
TCP	121.3	130.5	153.9	162.2	187.9	190.1	195.6	185.4
FIRE	298.0	299.5	347.2	358.1	393.7	429.8	489.7	435.9
SRV	1122.5	1288.5	1600.8	1741.6	1924.9	2055.0	2344.1	2355.5

Note: MFG-Manufacturing; WHO-Wholesale trade; RET-Retail trade; TCP-Transportation, communication and public utilities; SRV-Services.
Source: Business Dynamics Statistics

Relative Labor Share in the Manufacturing Sector

Table 6.9: Share of Industry Statistics (%), Manufacturing

Firm groups	Emp.	Payroll	Val. add.	Rel. LP	Rel. Wage	Rel. LS
1997						
50 largest	11.7%	17.3	24.5	205	148	72
50th to 100th largest	4.4	5.3	7.7	175	120	69
101st to 150th largest	3.6	4.2	5.2	144	117	81
151st to 200th largest	2.8	3.0	3.8	136	107	79
201st and smaller	77.5	70.2	59.3	73	91	118
2007						
50 largest	9.9%	14.5	25.5	258	146	57
50th to 100th largest	5.3	6.3	9.1	141	120	85
101st to 150th largest	4.3	4.7	5.3	130	108	83
151st to 200th largest	2.3	2.8	3.6	185	107	65
201st and smaller	78.3	71.8	56.5	73	91	125
2012						
50 largest	10.8%	15.5	26.1	242	144	59
50th to 100th largest	6.1	7.3	8.6	172	119	69
101st to 150th largest	4.0	4.3	5.2	123	109	89
151st to 200th largest	2.0	2.4	3.7	157	122	78
201st and smaller	77.2	70.5	56.4	72	92	127

Note: Relative labor productivity is defined as share of value added *divided by* share of employment. Relative wage is the ratio of share of payroll to that of employment. Relative labor share is the ratio of payroll share to value added share.

Table 6.10: Relative LS, Relative LP and Relative Wage for Top-100 (200) MFG Firms

	1967	1972	1977	1982	1987	1992	1997	2002	2007	2012
50 largest										
Rel. LS	98%	98	97	92	92	83	72	67	57	59
Rel. LP	128	134	143	150	158	169	205	209	258	242
Rel. Wage	126	131	139	138	144	141	148	140	146	144
100 largest										
Rel. LS	94	93	94	90	87	79	71	68	60	66
Rel. LP	132	136	140	147	158	171	200	194	228	205
Rel. Wage	123	127	132	133	138	136	140	132	137	135
200 largest										
Rel. LS	93	92	92	90	87	81	73	72	65	68
Rel. LP	131	132	137	141	150	160	181	174	200	191
Rel. Wage	120	122	125	126	130	129	132	125	130	129

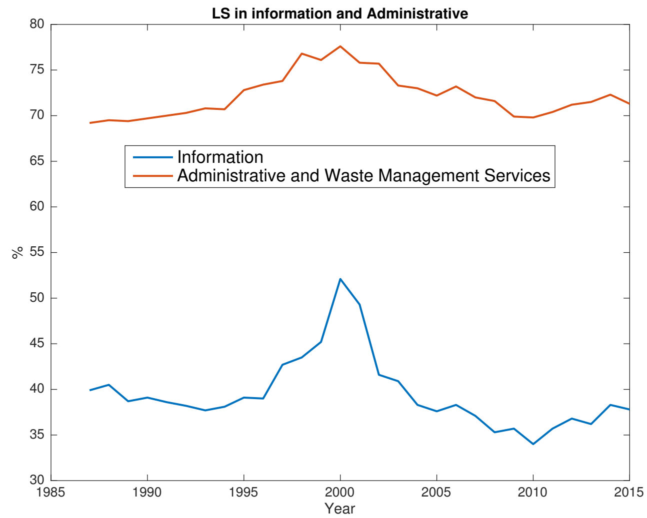
Data source: Census of Manufacturers.

Table 6.11: Labor Share (%), 2-digit Sectors

Year	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
1987	24.6	63.7	54.1	60.5	68.8	39.9	23	6.5	60.9	69.2	86.9	78.8	50.7	64.4	60.9
1988	24.9	62.4	53.9	60.5	67.5	40.5	23.1	6.7	61.4	69.5	86.5	79.8	51.6	65.2	61.4
1989	23.7	61.3	54.3	59.9	68.7	38.7	22.4	6.5	60.9	69.4	86.4	78.9	49.5	64.8	61.2
1990	23.9	61.4	54.9	60.6	69.9	39.1	22.2	6.4	60.8	69.7	87.5	79.2	48.9	65.7	62.2
1991	24.1	61.4	53.7	60.7	68.7	38.6	21.8	6.2	61.1	70	86	79.4	50	65.5	62.3
1992	24.6	61.8	54.4	60.9	69.2	38.2	22.5	6	61.5	70.3	87	79.9	49	65.7	62
1993	24.3	61	52.2	58.6	66.6	37.7	22.6	5.9	61.3	70.8	86.9	79.7	51.9	63.7	61.3
1994	23.3	59.8	50.2	58.2	65.1	38.1	22.1	5.9	61	70.7	86.1	79.6	52.1	63	60.2
1995	22.5	58.5	51.3	58.4	65.3	39.1	21.9	5.8	62.2	72.8	86.4	80.3	52.9	62.9	61.1
1996	22.9	58.1	50.7	57.7	65.9	39	22.4	5.9	62.8	73.4	86.9	81	53.6	62	61.7
1997	24.5	56.8	50.2	57.6	65.2	42.7	23.2	5.9	65	73.8	82.5	81.5	51.9	61.2	61.2
1998	26.3	58.1	51.1	57.1	64.9	43.5	24.3	6.3	67.1	76.8	86.4	82.1	55.3	62.8	61.5
1999	26.2	58.3	51.6	57.5	66.5	45.2	24.2	6.2	67.4	76.1	86.4	82.1	55.1	62.5	61.1
2000	27.9	59	52.5	58.3	66.8	52.1	24.6	6.4	70.5	77.6	86.5	82.1	55.8	61.1	61.4
2001	29.3	59.6	53.4	58.4	67.6	49.3	24.4	6.1	69	75.8	86.9	81.8	60	62.6	66.5
2002	30.3	57.5	53.3	58	67.6	41.6	23.6	6.1	65.2	75.7	89.9	81.7	59.27	60.9	66.1
2003	28.3	55.3	52.1	57.3	65.3	40.9	23.5	6	64.5	73.3	88.4	82.2	57.7	61.9	68.9
2004	27.4	54	50.8	57.2	63.2	38.3	24.5	6.2	64.2	73	87.2	82.4	56.9	62	69
2005	27.9	52.6	49.9	56.3	61.7	37.6	24.1	6.1	65.6	72.2	87.2	82.9	56	62.1	67.2
2006	26.5	51.3	49.6	56.1	59.1	38.3	24.8	6.3	67.1	73.2	86.8	83.1	56.1	61.5	67.2
2007	26.8	50.9	49.9	57.7	62.5	37.1	25.4	6.1	67.6	72	87	83.7	55.9	62.8	69.9
2008	27.9	51.4	49.6	58.5	60.5	35.3	25.8	5.8	65.7	71.6	86.5	82.8	57.5	63.9	72.5
2009	26.7	48.4	49.3	56.3	60.5	35.7	22.7	5.4	66.9	69.9	85.6	82.1	56.6	63.3	71.6
2010	25.3	46.3	47.5	55.2	57.8	34	23	5.3	66.8	69.8	85.8	82.4	55.1	62.7	70
2011	26.2	46.3	48.1	55.7	58.2	35.7	23.4	5.3	67.7	70.4	86.8	83	55.4	63.5	71
2012	26.5	46.3	47.6	54.8	58.8	36.8	23.1	5.5	68.8	71.2	87.9	83.6	54.9	64.3	70.9
2013	26.8	45.7	46.7	54.4	58	36.2	23.1	5.5	69.8	71.5	88.6	84	54.7	63.9	71.1
2014	26.3	46.2	46.9	54.5	57.7	38.3	23.1	5.7	70.4	72.3	89.1	84.1	54.8	64.6	71.7
2015	27	46.2	46.8	54.2	58.1	37.8	23.3	5.8	70.4	71.3	89	83.6	54	64.4	71.2

Note: Labor share is the share of compensation in value added. (1)-Utilities; (2)-Manufacturing; (3)-Wholesale Trade; (4)-Retail Trade; (5)-Transportation and Warehousing; (6)-Information; (7)-Finance and Insurance; (8)-Real Estate, rental and leasing; (9)-Professional, Scientific and Technical Services; (10)-Administrative and Waste Management Services; (11)-Educational Services; (12)-Health Care and Social Assistance; (13)-Arts, Entertainment, and Recreation; (14)-Accommodation and Food Services; (15)-Other Services.
Data Source: NIPA Value-added-by-Industry.

Figure 6.7: Labor Share in Information and Administrative Sectors



There are surges in LS both in Information and Administrative (i.e. Administrative and Support and Waste Management and Remediation Services) sectors . This is partly caused by the realization of stock options, which is counted as labor compensation, during the internet bubble (Moylan (2008)). In 1998, labor compensation in the Administrative sector increased 11.7%, while the increase in value added is 7.4%, which results in an increase in labor share by 3% in that single year.

Information sector (NAICS 51) contains 6 sub-sectors: Publishing industries (except internet) (NAICS 511); Motion Picture and Sound Recording Industries (NAICS 512); Broadcasting (except internet) (NAICS 515); Telecommunications (NAICS 517); Data Processing, Hosting, and Related Services (NAICS 518); Other Information Services (NAICS 519). In 2012, the first and second sub-sectors account for 26%, and 15% of value added in the aggregate *Information* sector. Broadcasting and Telecommunication accounts for 52%, and the remaining 7% goes to the last two sub-sectors combined. Table 6.12 lists labor share, measured as share of compensation in valued added in each sub-sectors around 2000.

Table 6.12: Labor Share in Information Subsectors

	1998	1999	2000	2001	2002
Publishing industries, except internet	56.4%	50.6	65.6	65.7	51.0
Motion Pictures and sound recording industries	39.2	32.1	37.6	35.2	31.1
Broadcasting and telecommunications	35.2	38.5	39.1	38.3	36.7
Data processing, internet publishing, and other info. serv.	66.7	105.1	170.6	103.3	54.8

Table 6.13: Relative Labor Share in Non-Manufacturing sectors, 2002

	(1)-Average				(2)-Weight=revenue				(3)-Weight=employment			
NAICS	1-4	5-20	21-50	$\geq$ 51	1-4	5-20	21-50	$\geq$51	1-4	5-20	21-50	$\geq$51
1997												
2 digit	79.4%	88.0	84.3	104.9	56.3	86.9	67.9	109.0	79.8	93.2	85.7	104.0
3 digit	86.2	90.6	92.4	115.1	71.1	80.6	76.8	115.9	90.5	91.8	90.7	108.1
4 digit	83.4	91.8	99.4	113.5	80.8	83.4	90.1	118.3	90.0	92.7	97.4	109.1
5 digit	82.7	92.9	102.8	114.3	83.6	86.5	94.4	119.0	90.3	93.9	99.9	109.5
6 digit	84.4	95.3	103.9	113.8	83.7	86.3	94.8	120.3	90.8	94.0	100.0	110.0
2002												
2 digit	79.1%	83.4	84.4	107.2	65.6	72.5	78.4	113.0	79.2	89.8	86.9	106.1
3 digit	76.7	86.3	96.4	118.5	64.8	80.5	87.1	118.9	84.2	90.5	92.7	109.3
4 digit	81.7	90.4	99.7	113.7	81.3	85.8	91.9	116.8	87.4	92.3	96.4	108.9
5 digit	81.5	92.6	102.2	115.7	82.1	89.4	95.8	116.6	87.5	94.3	98.1	108.6
6 digit	83.3	94.5	102.7	115.3	83.2	88.4	96.6	118.6	88.5	94.1	98.3	109.7
2007												
2 digit	81.6%	84.4	79.2	108.0	66.1	72.3	70.7	112.8	87.0	89.8	82.4	105.9
3 digit	81.6	86.2	88.7	116.7	64.5	78.3	83.2	119.0	89.5	89.6	89.6	109.1
4 digit	83.4	89.6	97.8	112.7	82.0	84.6	87.4	116.0	89.0	92.4	93.6	108.7
5 digit	81.6	91.7	102.2	117.6	82.3	87.6	94.0	118.9	88.7	93.6	96.7	109.5
6 digit	83.0	93.6	103.4	117.1	82.6	87.8	94.5	120.6	89.8	93.5	96.9	110.4
2012												
2 digit	83.8%	80.8	87.2	107.7	59.6	63.1	78.2	115.7	87.0	87.5	89.5	106.1
3 digit	83.3	88.5	89.9	117.2	62.6	77.1	84.2	122.1	90.1	93.8	91.4	109.1
4 digit	82.8	91.6	95.6	114.3	83.5	85.5	88.8	117.3	89.9	94.2	94.2	108.5
5 digit	80.6	93.6	101.7	118.0	82.6	87.7	95.3	118.6	89.5	95.8	96.1	108.2
6 digit	82.3	95.1	103.1	116.7	82.0	87.5	96.4	119.7	89.6	95.2	96.8	108.9

Note: 1-4 denotes the 4 largest firms. For services sectors in 1997, the indices are for establishments subject to federal taxes due to data availability.

Table 6.14: Relative Labor Share, 2-digit Non-Manufacturing Sectors, 2002

NAICS	Sector	Rel. LS				Rel. LP				Rel. Wage			
		1-4	5-20	21-50	≥51	1-4	5-20	21-50	≥51	1-4	5-20	21-50	≥51
22	Utilities	116.5%	98.0	105.3	90.7	105.4	108.2	97.8	92.5	122.4	106.1	103.0	84.0
42	Wholesale trade	10.4	35.0	61.2	123.8	834.1	343.2	210.8	79.3	87.1	120.2	128.9	98.1
44-45	Retail trade	95.7	97.9	90.1	102.2	96.2	92.7	89.0	103.7	92.0	90.7	80.2	106.0
48-49	Transportation	94.6	81.5	78.2	106.6	107.8	141.3	155.1	90.7	101.7	115.2	121.2	96.7
51	Information	84.6	74.0	88.9	130.7	125.9	165.2	107.5	70.7	106.5	122.3	95.6	92.4
52	Finance	91.0	76.1	70.9	118.4	124.2	128.0	159.1	82.0	113.1	97.4	112.8	97.0
53	Real Estate	93.9	64.1	86.4	106.9	87.4	163.2	165.3	92.6	82.0	104.6	142.8	99.0
54	Prof. Sci. Tech.	74.6	90.2	88.4	102.8	167.0	117.0	99.3	97.0	126.0	104.7	86.4	100.0
56	Administrative	68.9	124.8	100.8	99.5	281.7	80.2	121.1	96.4	195.0	100.1	122.1	95.9
61	Education	91.1	85.5	96.7	102.8	172.8	178.3	210.0	88.9	141.0	142.1	181.5	93.3
62	Health Care	73.1	91.2	91.0	103.3	139.9	138.0	111.8	96.5	108.6	126.0	102.6	98.5
71	Entertainment	53.1	69.6	69.7	99.8	218.9	102.0	142.6	93.9	95.8	70.0	97.4	102.7
72	Accommodation	94.0	104.1	99.9	99.8	121.0	126.5	127.4	94.3	113.7	131.7	127.3	94.1
81	Other Services			93.5	101.9			163.4	96.8			109.1	100.0

Note: Relative labor share for a subset of firms in a sector is calculated as the payroll share of these firms *divided by* their share of value added. 1-4 denotes the 4 largest firms.

Table 6.15: Between-Within Decomposition of Labor Share, 1987-2013

	(1)-vadd share, %			(2)-labor share, %			(3)-decompstion	
Sector	1987	2013	change	1987	2013	change	between	within
Nonfarm Private	–	–	–	51.82	48.90	-2.92	0.84	-3.62
Utilities	3.38	2.09	-1.29	24.59	26.84	2.25	-0.33	0.06
Manufacturing	23.58	15.83	-7.75	63.69	45.67	-18.02	-4.32	-3.43
Wholesale Trd.	7.67	7.79	0.12	54.06	46.70	-7.36	0.06	-0.56
Retail Trade	9.28	7.54	-1.74	60.48	54.41	-6.07	-1.01	-0.51
Transportation	4.11	3.79	-0.32	68.80	58.02	-10.00	-0.21	-0.38
Information	5.98	6.16	0.18	39.94	36.15	-3.79	0.07	-0.23
Finance	7.58	8.84	1.26	56.12	56.35	0.22	0.70	0.02
Real Estate	15.21	16.79	1.58	6.51	5.52	-0.99	0.09	-0.16
Prof. Sci. Tech.	6.01	8.93	2.92	60.93	69.8	8.88	1.90	0.70
Administrative	2.35	3.85	1.50	69.18	71.54	2.36	1.08	0.08
Education	0.90	1.44	0.54	86.91	88.63	1.72	0.47	0.02
Health Care	6.58	9.24	2.66	78.75	84.00	5.25	2.17	0.42
Entertainment	0.90	1.28	0.33	50.69	54.66	3.97	0.21	0.05
Accommodation	3.21	3.60	0.39	64.38	63.93	-0.45	0.25	-0.02
Other Serv.	3.25	2.83	-0.42	60.87	71.08	10.21	-0.27	0.33

Note: Labor share is measured as the fraction of Compensation of employees in Value added.
Data source: BEA's Value-added-by-Industry Data.

Table 6.16: Between-Within Decomposition of Labor Share (adjusted for Capital Depreciation), 1987-2013

Sector	(1)-vadd share, %			(2)-labor share, %			(3)-decompstion	
	1987	2013	change	1987	2013	change	between	within
Nonfarm Private	–	–	–	59.81	57.20	-2.61	0.45	-2.95
Utilities	2.98	1.73	-1.25	32.19	37.98	5.79	-0.43	0.13
Manufacturing	23.25	14.97	-8.28	74.54	56.51	-18.03	-5.56	-3.32
Wholesale Trade	8.15	8.49	0.34	58.74	50.13	-8.61	0.19	-0.71
Retail Trade	10.19	8.11	-2.08	63.58	59.15	-4.43	-1.29	-0.40
Transportation	3.85	3.75	-0.10	84.71	68.53	-16.18	-0.08	-0.59
Information	5.43	5.39	-0.04	50.71	48.28	-2.43	-0.02	-0.13
Finance	7.82	9.07	1.25	62.85	64.28	1.43	0.79	0.13
Real Estate	13.54	15.14	1.60	8.44	7.16	-1.28	0.13	-0.18
Prof. Sci. Tech.	6.53	9.52	2.99	64.68	76.62	11.94	2.11	1.00
Administrative	2.56	4.16	1.60	73.36	77.50	4.14	1.23	0.15
Edu. & Health Care	7.96	11.41	3.45	86.54	92.63	6.09	3.08	0.60
Entertainment	0.87	1.29	0.42	60.37	63.20	2.83	0.27	0.03
Accommodation	3.38	3.93	0.55	70.56	68.54	-2.02	0.38	-0.07
Other Services	3.50	3.04	-0.46	65.21	77.40	12.19	-0.32	0.42

Note: Value added is adjusted for consumption of fixed capital (depreciation). Education and health care are merged since the adjusted labor share in educational services exceeds 100% in some years.
Data source: BEA Value-added-by-Industry Data; NIPA Table 3.4: ESI Current-Cost Depreciation of Private Fixed Assets.

Table 6.17: Share (%) of Proprietors' Income in Value-added

Sector	1998	2013	change	Sector	1998	2013	change
Nonfarm Private	6.53	6.14	-0.39	Real Estate	3.84	2.43	-1.39
Utilities	0.50	-4.49	-5.99	Prof. Sci. Tech.	19.63	16.52	-3.09
Manufacturing	1.20	1.35	0.15	Admin. & Manage.	4.10	5.12	1.02
Wholesale Trade	3.87	3.82	-0.05	Education	3.16	3.25	0.09
Retail Trade	7.34	7.91	0.57	Health Care	11.67	9.55	-2.12
Transportation	9.43	7.43	-2.00	Entertainment	15.16	14.85	-0.31
Information	1.67	2.62	0.95	Accommodation	6.21	4.49	-1.72
Finance	4.35	4.18	-0.17	Other Services	30.14	31.13	0.99

Note: Average share from 2010 to 2013, instead of 2013, for the information sector is used. Data for proprietors's income in administrative & waste management services and management of companies and enterprises are merged.
Data source: BEA Value-added-by-Industry Data, NIPA Table 6.12D: Nonfarm Proprietors' Income by Industry.

Table 6.18: Concentration and Relative Labor Share, Top-50 firms

	CR (Share50)				RLS-Top50			
	1997	2002	2007	2012	1997	2002	2007	2012
Wholesale Trade	20.3	27.2	24.9	27.6	39.9	36.4	30.8	26.9
Retail Trade	25.7	31.7	33.3	36.9	96.4	95.2	95.4	92.9
Transportation	30.7	33.0	42.7	42.1	103.7	86.6	81.9	80.1
Utilities	64.5	69	70.1	69.1	94.9	104.2	102.4	107.3
Information		62	62	62.3		81.2	81.2	80.7
Finance	38.6	44.9	46	48.5	77.9	77.5	78.7	72.1
Real Estate	19.5	24.4	26.1	24.9	73.4	78.7	69.1	74.2
Prof. Sci. Tech.	16.2	16.5	18.6	19.0	84.6	85.8	84.7	93.8
Administrative	22.1	21.9	23.0	23.7	96.4	101.8	109.2	125.2
Education	19.6	23.2	23.5	23.8	79.7	90.8	87.7	90.6
Health Care	18.8	17.2	17.4	19.6	86.5	84.0	86.8	86.9
Entertainment	21.8	23.5	24.1	24.3	75.3	65.2	65.8	70.2
Accommodation	21.1	23.1	23.7	21.2	100.3	100.7	100.9	102.2
Other Services	12.8	14	13.8	12.6	94.9	88.3	91.4	100.4

Note: For most services sectors in 1997, statistics are only available for establishments subject to federal income taxes (instead of all establishments) in Service sectors. To be consistent, the same criteria is applied to 2002, 2007, and 2012.

Table 6.19: Revenue Share and Relative Labor Share of Top-20 Firms

	CR (Share20)				RLS-Top20			
	1997	2002	2007	2012	1997	2002	2007	2012
Manufacturing	–	–	–	–	–	–	–	–
Wholesale Trade	12.9	18.7	16.6	18.1.6	42.1	25.2	22.4	11.1
Retail Trade	18.5	23.9	25.4	27.8	99.9	96.9	102.4	97.2
Transportation	21.8	25.2	34.9	33.7	111.3	89.2	85.3	81.1
Utilities	40.6	44.9	44.5	48	85.7	103.5	110.8	116.0
Information		48.5	49.9	50.7		79.1	77.5	69.21
Finance	22.6	28.2	28.5	31.6	80.9	81.4	81.3	68.6
Real Estate	14.1	17.1	16.3	15.8	80.9	75.4	76.7	78.8
Prof. Sci. Tech.	11.6	11.3	12.7	12.6	84.1	84.7	80.3	91.5
Administrative	14.2	14.9	15.2	16.7	88.6	102.3	117.5	133.9
Education	13.3	16	16.1	16.7	76.6	88.2	85.2	95.1
Health Care	14.2	13.3	13.1	14.9	85.9	81.9	82.3	82.3
Entertainment	15.1	14.7	15.6	15.9	70.6	62.4	62.5	63.6
Accommodation	14.8	16.5	17.4	15.1	99.3	101.1	102.5	103.4
Other Services	8.5	10	10	8.3	97.3	86.2	92.9	104.5

Note: For most services sectors in 1997, statistics are only available for establishments subject to federal income taxes, rather than all establishments. For consistency, the same criteria is applied to 2002, 2007, and 2012.

Table 6.20: Revenue Share and Relative Labor Share for Top-4 Firms, 6-digit Average

	Share04				Relative LS			
	1997	2002	2007	2012	1997	2002	2007	2012
Wholesale Trade	24.3%	31.4	29.1	30.8	55.4%	51.3	51.2	47.0
Retail Trade	18.5	26.8	31.0	34.6	89.8	89.4	90.4	84.6
Transportation	23.6	24.5	30.8	35.2	94.7	89.6	92.5	89.7
Utilities	25.8	23.2	23.0	24.2	86.1	90.8	86.5	111.7
Information		49.83	52.4	52.0		87.1	92.7	92.5
Finance	26.0	32.0	36.1	35.4	94.1	96.2	92.5	97.8
Real Estate	18.8	24.0	25.1	23.3	92.9	76.4	72.8	83.2
Prof. Sci. Tech.	15.0	15.1	17.9	18.3	82.1	78.6	80.6	81.8
Administrative	21.8	23.1	24.4	24.4	94.3	94.5	95.5	99.3
Education	16.6	19.4	19.4	19.4	80.1	90.2	92.5	91.1
Health Care	16.2	15.1	15.1	17.0	92.0	90.1	97.6	97.4
Entertainment	19.2	20.5	21.5	21.6	86.1	79.6	87.8	80.0
Accommodation	13.8	17.4	18.5	16.0	103.4	103.5	107.9	105.7
Other Services	13.8	14.7	15.0	14.1	100.3	94.0	94.8	97.2

Note: Both concentration and Relative Labor Share are weighted average across NAICS 6-digit sectors, with revenue as weights.

Labor share (measured as the share of compensation in revenue). *Data Source:* Compustat.

Figure 6.8: LS in Selected MFG firms, 1970-2016

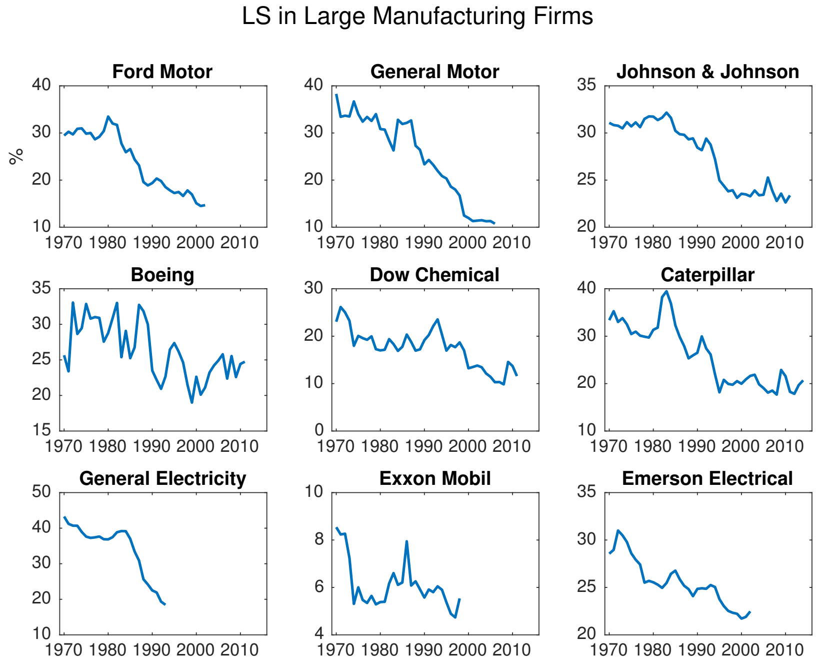


Figure 6.9: LS in Selected Transportation firms, 1970-2016

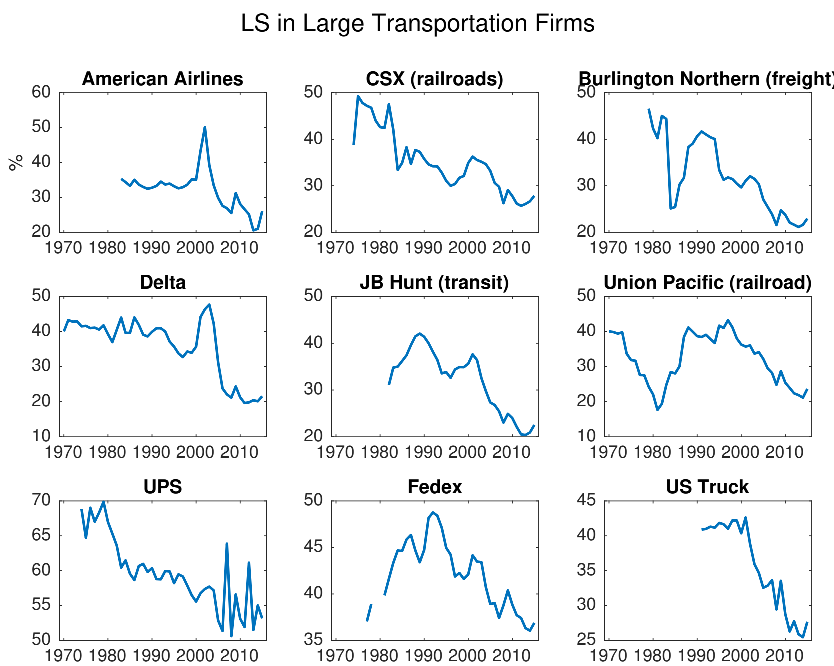


Figure 6.10: LS in Selected Finance firms, 1970-2016

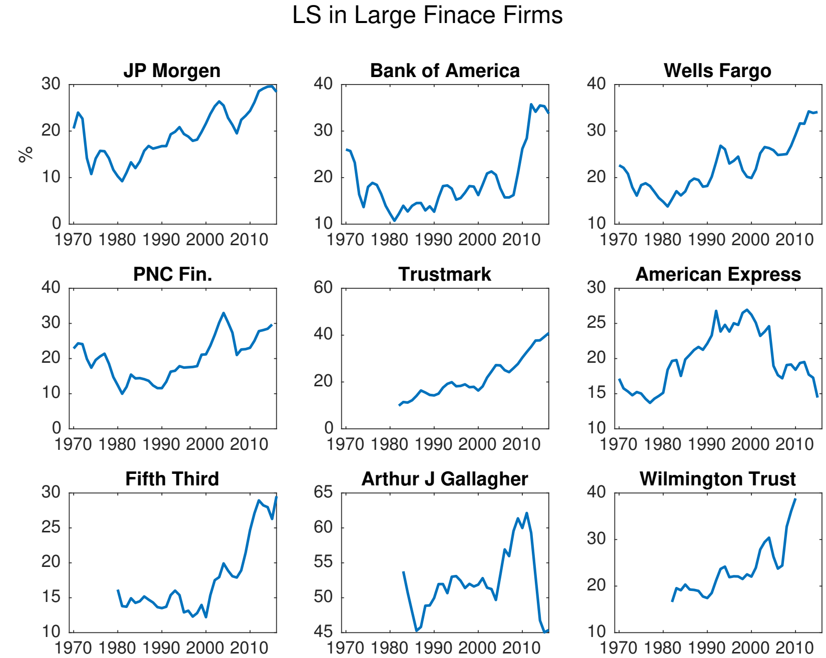
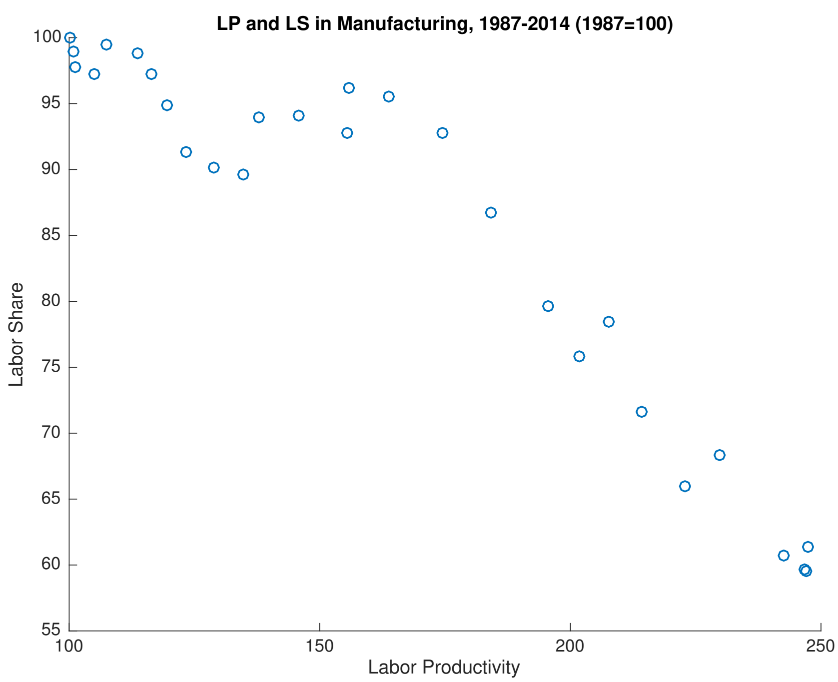


Figure 6.11: Labor Productivity and Labor Share, Manufacturing 1987-2014 (1987=100)



Note: A circle represents a year.
Data Source: The 'Labor Productivity and Costs' program of Bureau of Labor Statistics.