

Growing Oligopolies, Prices, Output, and Productivity

by

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Abstract

American industries have grown more concentrated over the last forty years. In the absence of productivity innovation, this should lead to price hikes and output reductions, decreasing consumer welfare. Using public data from 1972-2012, I use price data to disentangle revenue from output. Difference-in-difference estimates show that industry concentration increases are positively correlated to productivity and real output growth, uncorrelated with price changes and overall payroll, and negatively correlated with labor's revenue share. I rationalize these results in a simple model of competition. Productive industries (with growing oligopolists) expand real output and hold down prices, raising consumer welfare, while maintaining or reducing their workforces, lowering labor's share of output.

Keyword:

JEL Classification:

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Does America have a monopoly problem? Market power within narrowly defined industries has risen over last forty years. Various papers have systematically and comprehensively laid out the implications of concentration on profits, productive factors, and markups.¹ However, research has not systematically measured consumer welfare and prices, a first order concern for antitrust authorities (Shapiro, 2010).² In the simplest economics examples (Tirole, 1988), monopolies charge higher prices and restrict output, maximizing profits and reducing consumer welfare. However, monopolies could be caused by innovation from “superstar” firms or scale economies, leading to falling prices or increased output (Autor et al., 2017; Van Reenen, 2018; Armstrong and Porter, 2007; Tirole, 1988). After showing that gains in national market concentration are highly correlated with productivity improvements, I test the relationship of prices, quantities, and market concentration across the vast majority of the US economy using 40 years of publicly available data. I then link these changes on the consumer side to productivity and labor shares.

I directly quantify how changes in industry concentration in the medium to long-run are related to changes in prices and real output by combining price data with revenue data.³ A 10% increase in the national market share of the four largest firms is correlated with a 1% increase in real output. Finding that higher output, but not price, is linked with higher concentration rates, I turn to the role of productivity. Industries with the most real productivity growth (as opposed to revenue-based productivity)⁴ are those with the largest increases in industry concentration. A 10% increase in the market share of the largest four firms is linked to a 1.6% increase in labor productivity. With both industry concentration and productivity, output growth is not accompanied by payroll growth. Growing monopolists and oligopolists are able to produce more output with fewer, but higher paid workers. A 10% increase in the market share of the largest four firms is correlated with a 1.3% decrease in the labor’s share of revenue.⁵

These correlations are interpreted through the lens of a simple model of competition. In this static model, fixed costs are used to reduce marginal costs. This combination can lead to decreases in competition and increases in output. If fixed costs come from capital expenditures, as opposed to labor expenses, I can further rationalize decreasing labor shares.⁶ Analogously I reject demand side interpretations, which would require decreases in output. Furthermore, this model

¹See Autor et al. (2017); Barkai (2016); Furman and Orszag (2015); Grullon et al. (2016); Gutiérrez and Philippon (2017); De Loecker and Eeckhout (2017); White and Yang (2017).

²Markups are relevant to consumer welfare, but if only paired with marginal and average cost data. See De Loecker and Eeckhout (2017) for detailed markup data.

³What does it mean for output expansion without falling prices? There are a few simple and consistent stories. Marginal cost reductions may be correlated with increases in demands. For example, an increase in demand enlarges the total market, allowing for new natural monopolies. Additionally, changes in marginal cost could be linked with unobservable quality, inducing demand.

⁴I primarily consider real labor productivity for data availability reasons; however, the Appendix shows results are robust to considering total factor productivity.

⁵Without considering general equilibrium effects, the net effect of oligopoly growth appears to be Pareto improving. This is distinct from Pareto optimal; there may be further Pareto gains from regulating a natural monopoly and redistributing the gains.

⁶This follows the classic notion that capital is a more dynamic input than labor as summarized in Akerberg et al. (2015).

allows for national market concentration increases, while holding local market concentration constant, as in Rossi-Hansberg et al. (2018); Rinz (2018).

Research investigating consumer surplus generally addresses three main questions. First, has increasing market concentration led to a decrease in consumer surplus? Second, could current consumer surplus be higher? Third, what does the future hold? This is the first paper to answer the first question on a systematic, economy-wide basis. The second question often requires detailed modeling of supply and demand and has been done for selected industries, but lacks economy-wide coverage. In particular, if new technologies create natural monopolies, is there a role for regulation and intervention? Monopolies may pass the benefits from technical innovation as profits, partially offsetting increases in markups. As market power is related with real productivity improvements, this paper lends credibility to this story, but there still may be room for further intervention. The third (and perhaps most important) question primarily lies in the realm of speculative analysis, paving the way for future work.

The results from this paper tie directly with a large and growing body of literature and public discussion.⁷ The rising trend toward monopolization has been linked to the growth of superstar firms, declining labor compensation (Furman and Orszag, 2015; Autor et al., 2017; Azar et al., 2017), and increased profits (Barkai, 2016). This missing link in this literature comes from the focus on upstream factor markets, not on downstream customers. This paper explicitly considers prices and uses this price data to disentangle revenue and real output, allowing consumer welfare comparisons. This approach considering prices and output is complementary with Barkai (2016) and Autor et al. (2017), which use similar datasets to fully describe trends in labor shares and productivity within the manufacturing sector.⁸ Peltzman (1977) runs a similar analysis on manufacturing sector from 1947 through 1967. This paper expands the scope of the analysis to the majority of the private sector, as the manufacturing sector only accounts for 12% economic output. De Loecker and Eeckhout (2017) use data on publicly traded companies to show that markups have increased, but cannot link this to prices. This paper is highly amenable with higher markups, as that could indicate large fixed costs that reduce marginal production costs. In contrast, Gutiérrez and Philippon (2017) find that declining competition may be responsible for reduced levels of investment.⁹

The finding that productivity and oligopoly are intertwined is related to the discussion of both the business dynamics of the US economy (Decker et al., 2016) and the proliferation of automatization (Acemoglu and Restrepo, 2016, 2017). Industries that become more productive require fewer workers. Industries that become monopolies hire fewer workers. This paper adds

⁷For example: Porter (2016) and The Economist (2016).

⁸Autor et al. (2017) performs similar analysis on productivity just within the manufacturing sector and finds broadly comparable results. Azar et al. (2017) finds that wages fall with industry concentration (monopsony). I do not find this due to likely compositional shifts. The authors control for worker types (especially geography), we consider the average wage paid across all workers. Individual worker pay may fall, but there may be a shift to different worker types/

⁹Gutiérrez and Philippon (2017) show that investment is negatively correlated with market share, but do not consider if higher investment led to higher market shares in the first place.

to the discussion by finding that these two set of industries are largely identical. Productivity (and the automatization, computerization, and the robotics that underpin it) enhancements do not appear 'free' and exogenous. Improvements are much more common in industries that move towards higher levels of monopolization. This paper cannot assign causality. Does productivity improvement lead to higher market shares, or does higher market shares lead to productivity investments? If productivity enhancements require large sunk costs, such as employing more expensive workers and building up intellectual property, this may prevent entry of new firms. Karabarbounis and Neiman (2013) point out that the decline in labor share can be accounted by the decline in the price of capital, but is there a minimum efficient scale to use this capital?¹⁰

Additionally, there have been many case studies that focus on the role of industry concentration, prices, outputs, consumer welfare, and innovation. In the 1950s, cross-industry analysis of profit rates and market concentration was formalized by Bain (1951); however, this literature suffered from measurement and endogeneity issues¹¹ and was supplanted by "New Industrial Organization (IO)." (Bresnahan, 1989; Sutton, 1991). Forming the bulk work in recent empirical industrial organization, "New IO" did away with cross-industry analysis and placed more structure on individual industries to understand the interaction of market power, profits, and consumer welfare.¹² A recent and complementary literature also addresses market concentration from both international trade and macroeconomic perspectives (Mongey, 2016; Head and Spencer, 2017; Hottman et al., 2016).¹³

A new series of papers have aimed at directly understanding the results of the aggregate trend of consolidation on various outcomes. Antón et al. (2016); Azar et al. (2016a,b) shows that prices and executive wages increase due to corporate ownership concentration. Within wholesale trade, Ganapati (2016) shows that while market concentration and prices may both increase, downstream customers may still benefit as higher operating profits cover substantial fixed costs to improve customer experiences and increase total overall sales. Results from these studies are mixed and likely also suffer from various forms of publication bias. Looking solely at price, Kwoka Jr (2012) performs a meta-analysis using results from a series of retrospective merger reviews and finds that there is a small average increase in price following mergers. However, that analysis is limited by the prior studies drawn on and the low number of mergers studied¹⁴. Blonigen and Pierce (2016) show that mergers do not seem to improve firm productivity. I consider aggregate market power expansion, which often occurs naturally, as opposed to through M&A behavior.¹⁵

¹⁰In the medium run explored in this paper, the change in the price of capital is largely constant between industries - and therefore is difficult to in a difference-in-difference framework with time fixed effects.

¹¹See Schmalensee (1989) and Peltzman (1977).

¹²See Armstrong and Porter (2007).

¹³Mongey (2016) uses a general equilibrium model to understand the role of market power on monetary policy. Head and Spencer (2017) argue for the return to oligopolistic competition in analysis of international trade. Hottman et al. (2016) show significant departures from monopolistic competition models for the largest firms in retail purchase datasets.

¹⁴48 data-points over 40 years.

¹⁵Two classic examples are Walmart and Amazon, who primarily grew through organic growth,

I describe the data in Section 1, before considering the relationship of changes in market concentration to economic outcomes in Section 2. I consider the role played by productivity in Section 3 before concluding with a simple explanatory model.

1 Data

Data comes from three main data sources. First, the U.S. Census Bureau’s Economic Censuses (EC), conducted every five years from 1997 to 2012, provide market concentration figures by North American Industry Classification System (NAICS) codes. The same surveys from 1972-1992 compiled data by Standard Industry Classification (SIC) codes. Second, the Manufacturing Industry Database compiled jointly by the National Bureau of Economic Research and the U.S. Census Bureau’s Center for Economic Studies (NBER-CES) provides detailed manufacturing industry statistics, including both input and output price levels. Third, for non manufacturing industries, the U.S. Bureau of Economic Analysis (BEA) provides price index and output volume data from 1977 to 2012. All data, including market shares and prices, refer to domestic producers. While manufactured goods prices may have fallen in aggregate (Feenstra and Weinstein, 2017), I focus on the price of domestically produced goods and follow the international trade literature in assuming there is imperfect substitutability between foreign and domestically produced goods.¹⁶

While firm sales are relatively straightforward to compute, market shares are more difficult to construct. One must identify competitors/industries, allow for companies to compete in multiple segments, and account for varying substitution margins between firms and markets. To simplify the analysis, industry definitions follow those computed by the US Census, across all establishments of all firms within a particular NAICS or SIC code. Industries are defined at the 6-digit NAICS level and at the 3 or 4-digit SIC level (depending on historical data availability).¹⁷ I measure market concentration using the aggregate market shares of the four largest firms by revenue (following Autor et al. 2017).

This combined dataset has market concentration, revenues, prices indices, employment, and payroll by industry every five years. I then derive real output, labor productivity, average wage and labor’s share of revenue from these initial data points. This covers the majority of the U.S. private sector, with over 75% of gross output in 2012. I measure revenues shares using gross output and productivity as gross output per worker (following Decker et al. 2016). See Appendix B for a fuller summary. The Appendix considers alternative measures for productivity (total factor productivity and hourly gross output) and for market shares (market shares using levels, the Herfindahl-Hirschman index and manufacturing import shares).

¹⁶Robustness checks from the Appendix adds four further data sources, covering international trade, hourly wages, and regulatory barriers. I directly control of import penetration and the growth of China following permanent normalization of trade relations. Imports have the expected effect, lowering prices, output, workers and wages. Additionally the baseline results hold when dropping all manufacturing sectors.

¹⁷An example 6-digit NAICS category is “327121-Brick and Structural Clay Tile Manufacturing” and a 4-digit SIC category is “3251-Brick and Structural Clay Tile (except slumped brick).”

1.1 Concentration Trends

The largest firms have grown disproportionately in size over the last forty years. Figure 1 shows the average market share growth of the largest four firms (4-Firm Share) across industries in five year intervals. For example, between 1997 and 2002, the largest four firms increased their market share by an average of 2.5 percent. Data for 1992-1997 is unavailable due to a change in the U.S. Census Bureau’s industry classification system. If changes in this time period are recovered through interpolation, the market share of the largest four firms in the average industry increased nearly 10 percentage points from 1977-2012, reaching nearly 40% by 2012. I refer the reader to Autor et al. (2017) for a fuller description of this trend.

1.1.1 Local versus national market power

One issue is that market concentration is only calculated at national levels, even though competition may be local. If markets are regional and national concentration increases are not correlated with local concentration changes, then downstream market power should remain constant. For example, if an east coast grocery chain merges with a west coast grocery store chain, downstream market power should stay constant.¹⁸

In the absence of consistent and comprehensive establishment-level revenue data across all sectors, I compute market shares using employment at different regional aggregations by 6-digit NAICS code from 1990-2015 using a unified crosswalk from Fort and Klimek (2016).¹⁹ In Figure 1, I show that market concentration exhibits similar patterns over different market definitions. In 1990, the largest four firms employed 15% of all workers in the average industry nationally, increasing to 19% in 2015. County-based markets show a similar trend, with equivalent market shares rising from 65% to 67%. Data at the 5-digit Zip code level finds that market shares have remained roughly constant, hovering around 90%.²⁰ The truth lies somewhere in the middle, national data shows increasing concentration, while zip code data shows markets that have always been concentrated, with little variation over time. To rationalize our data, we will consider both possibilities in the model section.

Notably, Rinz (2018) and Rossi-Hansberg et al. (2018) find that local market power is often decreasing, even though national market power is increasing. In the appendix, I show their results are largely due to compositional issues. First, extremely small market definitions can lead to locations with zero firms. Second, an unbalanced panel can lead to mis-measuring market power.

¹⁸This assumes away both upstream market effects and potential production synergies.

¹⁹Data on publicly traded firms is available through Compustat, but this data exists only at the national/global level. For example the entry for Amazon not only contains sales data for the United States, but also abroad. In addition to containing sales data for online retailing, this data further mingles data for IT computing services (cloud computing). While US Census establishment level data does not completely solve this aggregation issue, it significantly alleviates these concerns and includes on public and private firms. Data prior to 1990 are riddled with numerous errors and are highly variable.

²⁰In terms of HHI indices, average ZIP code levels are between 5700 and 6000. Nearly all markets qualify as “Highly Concentrated”, being over the 2500 cutoff.

2 Market Concentration and Outcomes

Baseline regressions are of the following form:

$$\Delta_5^{s,t} \log(X_{it}) = f_x \left[\Delta_5^{s,t} \log(\text{Concentration}_{it}) \right] + \epsilon_{it}$$

Observations are indexed by industry i and year t . $\text{Concentration}_{it}$ denotes the market concentration of industry i at time t .²² The residual ϵ_{it} reflects any residual unexplained variation and measurement error. Outcome variables X come from the following interlinked outcomes of economic interest:

$$\begin{aligned} & \Delta_5^{s,t} \log(\text{Price}) \\ & \Delta_5^{s,t} \log(\text{Real Output}) = \Delta_5^{s,t} \log(\text{Revenue}/\text{Price}) \\ & \Delta_5^{s,t} \log(\text{Labor Productivity}) = \Delta_5^{s,t} \log(\text{Real Output}/\text{Employees}) \\ & \Delta_5^{s,t} \log(\text{Average Wage}) = \Delta_5^{s,t} \log(\text{Wages}/\text{Employees}) \\ & \Delta_5^{s,t} \log(\text{Employees}) = \Delta_5^{s,t} \log(\text{Quantity}/\text{Labor Productivity}) \\ & \Delta \log(\text{Payroll}) = \Delta_5^{s,t} \log(\text{Average Wage} \times \text{Employees}) \\ & \Delta_5^{s,t} \log(\text{Wage Share}) = \Delta_5^{s,t} \log(\text{Wages}/\text{Revenue}) \end{aligned}$$

The operator $\Delta_5^{s,t}$ performs multiple functions, it takes a five year difference of the variables and demeans variables by top-level sector and year. The five-year time difference reflects medium-run changes and reflects data availability. Sectors s refer to top-level NAICS and SIC codes.²³ This controls for aggregate inflation and growth, as well as secular sectoral effects (such as the relative growth of healthcare and the relative decline in manufacturing). The non-parametric functions $f_x(\cdot)$ are identified off a difference-in-difference form. This form is convenient as it is (a) parsimonious, (b) requires only publicly available data, and (c) allows for simple decompositions

²¹The dataset used by Rossi-Hansberg et al. (2018) is not easily available, and the revenue portion of the data set has never been cross-validated with administrative datasets. I follow the approach of Rinz (2018), using US Census administrative data that uses tax data to verify employment and payroll records by establishment.

²²I use the logarithm of concentration, as opposed to the level or exponent. This is since the data may deflate the level of concentration at the bottom end of the data. Many markets are regional or local, as opposed to national. Such markets such as retail gasoline and childcare have extremely low market shares. In the data, the shares of the top four companies often shifts from 3% to 8%. On the other hand, in specialized manufacturing industries that are nationally dominated by one or two firms, a 5% change may simply indicate year-to-year noise. Using difference in the level using national market shares would effectively overweight these latter industries. However, as shown in Section ??, national market shares are good proxies for more local market shares. Using a logarithms gives these locally monopolistic, but nationally competitive industries more weight. Furthermore, as shown in the Appendix, regressions using levels, as opposed to logarithms, gives similar to the baseline results in the main text.

²³Such as manufacturing, retail, wholesaling, etc.

and extensions.

The primary issue to running regressions that directly test their relationships is that prices and quantities are equilibrium objects. Shifts in both supply and demand can alter both variables (Schmalensee, 1989). Lacking straightforward exogenous shifters of market concentration, these regressions are presented as correlational and are not used to calculate any counterfactual (which likely would need (a) macroeconomic effects and (b) detailed modeling of both the supply and demand sides).

These regressions are motivated by a simple model of free entry under Cournot competition (see Appendix for details). In such a model, a sufficient condition for an increase in market concentration to be welfare increasing is that prices stay constant/decrease and output stays constant/increases. Market power increases are driven by increases in the implied fixed cost of entry. If such fixed costs increase, but do reflect either product innovation or decreased marginal costs, then there will be a welfare loss. Examples include heightened barriers to entry from anti-competitive incumbent behavior or costly unproductive regulation. On the other hand if these increased fixed costs reflect sufficient innovation or production efficiency, then welfare will increase.

Returning to empirics, the various relationships summarized by the function $f(\cdot)$ are illustrated in Figure 3.²⁴ Outcomes can be simply summarized: increases in industry concentration are significantly correlated with higher output, higher revenue, higher labor productivity, average wages, and lower labor income shares. Monopolization is not correlated with significant changes in prices, employment, or aggregate payroll. Specifically a 10% increase in the market share of the largest four firms leads to 1% increase in output, flat prices, 2% increase in labor productivity, 0.5% increase in wages, 0.5% decrease in employment, flat total payroll, and 1% decrease in labor's share of output.

The choice of four firm concentration shares and real labor productivity are motivated by data availability. Alternative measures of productivity on a smaller sample of industries, such as using hours worked or total factor productivity yield similar results. Alternative measures of concentration, such as the Herfindahl–Hirschman Index, yield similar results. Additionally simplified regressions where $f(X) = \alpha X$ are conducted with industry-clustered standard errors, with similar results. See the Appendix for details.

Two endogeneity concerns warrant further discussion. First, a negative demand shock could lead to higher concentration and lower prices. In light of the expansion in output, this seems improbable. An ideal dataset would include a true demand instrument, however in the Appendix, I control for pre-trends in demand by including lagged output and a one-period change in lagged output. Results are largely unchanged. Second, a productivity shock may drive these results. As shown in the baseline results in Figure 3, productivity is highly correlated with market concentration. Omitting productivity in the baseline results would lead to potentially misleading

²⁴This figure is replicated as a bin-scatter plot in the Appendix Figure 6 and in levels in Appendix Figure 5. Results are similar.

results. Growth in output may not be due to oligopoly growth; the true underlying factor may be productivity growth.

3 Productivity

The third panel of Figure 3 highlights the strong relationship between productivity and market concentration. To investigate, I rerun a similar specification as before, but now use:

$$\Delta_5^{s,t} \log(X_{it}) = f_x \left[\Delta_5^{s,t} \log(\text{Labor Productivity}_{it}) \right] + \epsilon_{it}$$

The variables X represent real output, prices, payroll, mean wages, employees, and labor share. The results are presented in Figure 4.²⁵ All relationships are similar to those for market concentration, but magnified and precise. Higher labor productivity is correlated with higher output, lower prices, constant payroll, higher wages, fewer employees, lower labor shares.²⁶

To better compare these relationships between productivity and market concentration, I run regressions of the form:

$$\Delta_5 \log(X_{it}) = \alpha_1 [\Delta_5 \log(\text{Concentration}_{it})] + \alpha_2 [\Delta_5 \log(\text{Labor Productivity}_{it})] + \gamma Z + \epsilon_{it},$$

where Z is a vector of top-level sector-year fixed effects. For comparability, concentration and productivity are standardized by subtracting means and dividing by their standard errors. Results are presented in Table 1. Assuming away measurement error, it appears that almost the entirety of the correlation of market concentration and the other observed market outcomes is absorbed by productivity. There is a small positive correlation between prices and market concentration, but as shown in Figure 3, this is completely offset in aggregate as growth in productivity is highly correlated with concentration.²⁷ However both market concentration and productivity are measured with error, preventing a true disentangling of market power and productivity.²⁸ Over the last 40 years, productivity growth has been intrinsically tied with the rise of monopolies and oligopolies.

²⁵This figure is replicated as a bin-scatter plot in the Appendix Figure 7. Results are similar.

²⁶As with before, alternative measures of productivity on a smaller sample of industries, such as using hours worked or total factor productivity yield similar results. See the Appendix for results.

²⁷Assuming away measurement error, this means there is a small negative effect of monopoly, a one standard deviation increase in monopoly power offsets 1/5 of the price decrease from a one standard deviation increase in productivity. How should an observer interpret this? The most pessimistic reading is that after controlling for productivity, monopolies do increase prices. But this argument assumes that all other conditions including productivity remain constant. In the light of the close linkage of productivity and concentration, this seems untenable. In Table 5 in the Appendix, looking at only non-manufacturing firms that account for over 80% of the economy, this link between price and industry concentration vanishes.

²⁸As shown in the Appendix, measures of regulation seem to be uncorrelated with either productivity or market power.

3.1 Robustness

Even though these relationships are purely correlational, they are extremely robust. I consider nine alternative specifications (see the Appendix for full details). These alternative specifications are not to attribute causation, but rather test the strength of our baseline relationships.

3.1.1 Manufacturing vs Non-Manufacturing

Manufacturing makes up only around 10% of US GDP. However, Census data on manufacturing is widely available at fine levels of detail and make up nearly half of all observations. As a robustness check, I drop all manufacturing industries from the baseline data set. Results are largely the same. Increases in market concentration are positively correlated with output, revenue, and productivity. I do not find significant changes in wages, employment, or payroll, but confirm the negative correlation between output and labor's share of revenue. As in the baseline, when controlling for productivity, I find the relationship between market concentration and output/revenue insignificant.

3.1.2 Levels vs Logarithms

The logarithm of market shares compresses differences under large level changes. An alternative specification would consider level changes in the market shares. Thus a change from 10% to 20% would be roughly equivalent to the change from 30% to 40%. Under this specification, the results are quite similar to the baseline specification.

3.1.3 Herfindahl-Hirschman Index

This analysis considers four-firm market shares, as this data is widely available. However a four-firm market share is a crude instrument. Under certain forms of competition (Cournot), a classic Herfindahl-Hirschman Index (HHI) index is a more reliable indicator of market power. Substituting an HHI index for the four-firm market shares, where available within manufacturing, finds results broadly consistent with the baseline estimates.

3.1.4 Factor Price Inputs

Baseline estimates consider output, prices, and revenues without considering the role of input factor prices, such as for materials or capital goods. There may be co-movement in upstream markets, biasing results. For a subset of industries, I directly consider the prices of material and capital inputs. While these factors are quantitatively important, they do not significantly differ from the baseline estimates.

3.1.5 Total Factor Productivity

The baseline estimation considered labor productivity, as opposed to total factor productivity. As production becomes more capital intensive (Bureau of Labor Statistics, 2018), the baseline estimates could suffer from mis-measurement. Total factor productivity estimates would allow for better estimates. For a sample of manufacturing industries, substituting total factor productivity for labor productivity results in nearly identical results.

3.1.6 Hourly Labor Productivity

The baseline results measured labor productivity by considering the total number of workers. However there are long term trends in full-time versus part-time workers (Nardone, 1995). To account for this, in a subset of industries I consider labor productivity by considering the number of hours worked. Results are similar to the baseline results.

3.1.7 Import Penetration in Manufacturing

Manufactured goods imports have significantly increased over the sample period (Bernard et al., 2006). While the price indices consider only domestically manufactured goods, imports change the market power available to the largest domestic producers. If this trend is monotonic across time, yearly fixed effects will account for imports, but if there are differential trends across industries, market power will be mis-measured. In response I directly control for import penetration in manufacturing. Results are largely unchanged.

3.1.8 Regulation

Regulation is one possible source of scale economies (See (Nelson and Wohar, 1983) for a classic example). To control for regulation, I use data from “Regdata” database that considers US Federal industry-level regulation measures derived from textual analysis of federal laws (McLaughlin et al., 2017). While I find that regulation is quantitatively important, it does not change the baseline results.

3.1.9 Demand Controls

As mentioned earlier, the baseline results lack a true demand instrument. I control for pre-trends in demand by including lagged output and a one-period change in lagged output. Results are largely unchanged.

The core result, that increases in oligopoly are not directly correlated with price increases and output decreases is well supported in the data across all robustness exercises. Furthermore, the interaction between productivity and market power is extremely robust. More market power is extremely highly correlated with increased productivity - regardless of how market power or productivity are measured.

I find that while oligopoly is directly correlated with price increases in manufacturing, it indirectly decreases prices through increases in productivity - delivering a net zero effect.

4 Simple Model

To focus thoughts and explain the robust data correlations, consider a simple model with firms facing identical fixed costs F , constant marginal costs c , and linear demand ($p = a - bQ$). Assuming Cournot competition, total output Q and price p are functions of a , b , c , and the number of firms N :

$$Q = \frac{N(a - c)}{b(N + 1)}, \quad p = \frac{a + Nc}{N + 1}. \quad (1)$$

The number of operating firms N are further constrained by fixed costs F :

$$N = \frac{a - c}{\sqrt{Fb}} - 1.$$

A decrease in N reflects decreasing competition and can be caused by a few forces: (1) An increase in marginal costs c , (2) an increase in fixed costs F , (3) a negative demand shock decreasing a , or (4) an increase in the inverse demand slope b .

However, in the data, increasing oligopoly (an decrease in N) is correlated with a decrease in productivity (an analogue of marginal costs c). Furthermore, oligopoly is correlated with increases in Q and relatively unrelated to price. This is consistent with a relatively simple supply-side story. Due to new technology, decreases in c must be correlated with other changes in either the demand structure or a sufficient increase in fixed costs. The first story is implausible, as it would be correlated with a decrease in output.²⁹ This leaves the other possibility, decreases in marginal cost are linked with increases in fixed cost F .³⁰ Essentially monopolies are linked with the changing face of production.

Furthermore to be consistent with the labor share results, the bulk of these fixed costs should be paid to capital, rather than labor. This is consistent with conventional modeling of production functions, where capital is a dynamic investment and labor is more flexible. (See Akerberg et al. (2015) for a variety of approaches.)

While national market and country market shares are increasing, there is some debate if effective market shares are increasing. Data at the zip code level shows that 4-firm shares have remained high, averaging 90%. An increase in output, with no change in price, can be also rationalized in a world where the number of firms at the local level, N , is constant. A decrease

²⁹If this is driven by decrease in demand a , then output must fall. Similarly if this is increase by a increase in the slope b , output must fall. This is inconsistent with the data.

³⁰As shown in the Appendix, for every decrease in c , there exists a range of fixed costs (\underline{F}, \bar{F}) , that increase output.

in marginal cost c , paired with an increase in demand a , can lead to increasing Q and constant p . This is a plausible story, as national monopolies are correlated with an decrease in marginal costs (through increased productivity). However, to rationalize constant prices, national monopolies must be correlated with an increase in demand a . Finally to rationalize decreasing labor shares, national monopolies must lower their marginal costs by adopting technologies that are less labor intensive.³¹

While this model clearly abstracts away from rich real-world factors, it helps in the interpretation of the reduced form correlations.³²

5 Discussion

This paper aims to provide another piece of evidence in the ongoing debate over increases in market power. Industry concentration that is driven by the very largest firms should theoretically lead to higher prices and lowered output in the absence of true productivity innovation. However, concentration increases do not correlate to price hikes and correspond to increased output. This implies that oligopolies are related to an offsetting and positive force - these oligopolies are likely due to technical innovation or scale economies. My data suggests that national oligopolies are strongly correlated with innovations in productivity.

These price and quantity regressions are purely within-industry results and lack causality. They may suffer from omitted variable biases. Results are from 5-year difference-in-difference estimates and assume away general equilibrium effects. However, they show clear patterns between prices, quantities, productivity, and market concentration. Many - if not most - industries could be developing new and novel economies of scale. In retail, Walmart (Holmes, 2011) and Amazon (Houde et al., 2017) both exploit economies of scale to lower their marginal cost and increase market shares. While market power may increase, consumers benefit in the short to medium run through price reductions and real choice increases.³³ On the other hand, these effective firms do not expand their workforces, creating more while holding payroll constant.

This modeling framework also highlights directions for possible future work. We need better data on effective market shares. National and highly local market shares are both problematic. Markets are not mutually exclusive, as there is overlap between regions and industries (for example traditional and online retail). Adding complexity, market definitions may be changing over time, due to changes in both consumer preferences and producer technologies. Additionally, while regional consumption and price data exists for some markets, such as consumer packaged retail goods (Handbury and Weinstein, 2014), further work needs to be done to integrate such

³¹Alternatively, a decrease in the slope of demand, will decrease the quantity demanded and leave price constant. For this story, it must be then true that national monopolies are correlated with systematic shifts in reduced consumer price-sensitivity. However, we do find evidence that national monopolies are correlated with increases in productivity (and thus decreases in marginal costs), detracting from this story.

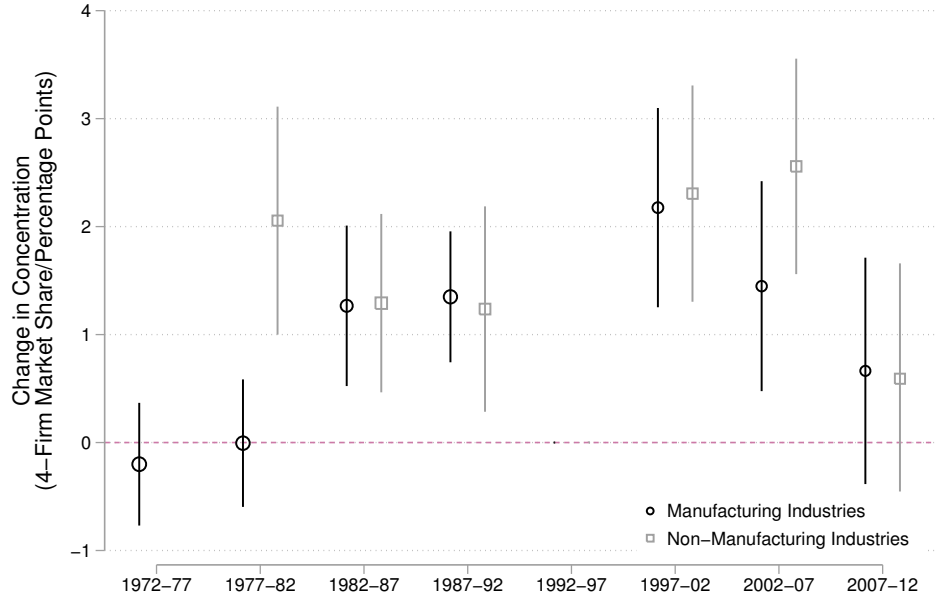
³²For both further details and a model with price competition, see the Appendix.

³³For an international trade context, see Atkin et al. (2015).

data across all markets with appropriate market share data. Welfare in almost all situations can be quickly summarized by both price and output levels, mis-measured market power alone is rarely a sufficient statistic.

Finally, taking the superstar firm hypothesis seriously does not imply that antitrust authorities should be powerless. Dominant firms may entrench themselves and use their newly dominant market positions to engage in anti-competitive behavior. Natural monopolies can give way to anti-competitive monopolies that act to raise prices and squelch innovation (Coll, 2017).

Figure 1: Average Change in Market Share of 4-Largest Firms over 5-year intervals



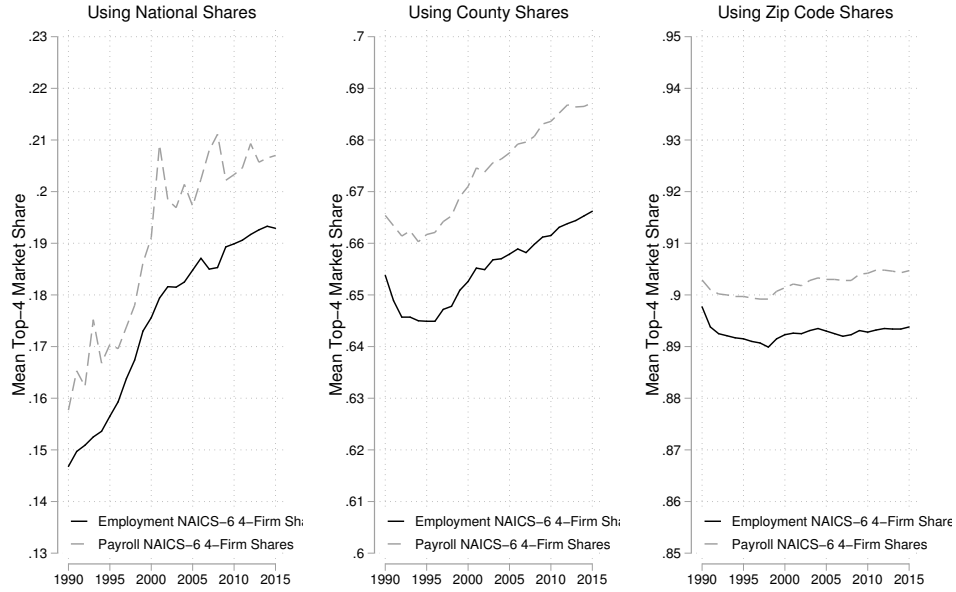
Notes: Results from a regression of change in 4-firm concentration shares by time period. From 1972-1992, average of 4-digit SIC codes for manufacturing industries and lowest levels of aggregation for non-manufacturing industries (A mixture of 3 and 4 digit SIC codes). From 1997 onwards, average of 6-digit NAICS codes for all industries. Data for non-manufacturing firms in 1972 is incomplete. Data from 1992 and 1997 are from non-comparable industrial classification systems.

Table 1: Market Concentration and Productivity Regressions

	$\Delta \ln \text{ Output}$	$\Delta \ln \text{ Price}$	$\Delta \ln \text{ Revenue}$	$\Delta \ln \text{ Labor Productivity}$
Std $\Delta \ln$ 4-Firm Share	-0.00230 (0.00474)	0.00992 (0.00253)	0.00763 (0.00564)	0.206 (0.0276)
Std $\Delta \ln$ Productivity	0.159 (0.0116)	-0.0520 (0.00746)	0.107 (0.0120)	
r2	0.331	0.588	0.311	0.151
	$\Delta \ln \text{ Mean Wage}$	$\Delta \ln \text{ Employees}$	$\Delta \ln \text{ Payroll}$	$\Delta \ln \text{ Labor Share}$
Std $\Delta \ln$ 4-Firm Share	-0.00452 (0.00745)	-0.00230 (0.00474)	-0.00682 (0.00868)	-0.0144 (0.00660)
Std $\Delta \ln$ Productivity	0.0543 (0.0111)	-0.0543 (0.0116)	-0.0000528 (0.00826)	-0.107 (0.0100)
r2	0.378	0.195	0.238	0.417
Observations	4349	4349	4349	4349

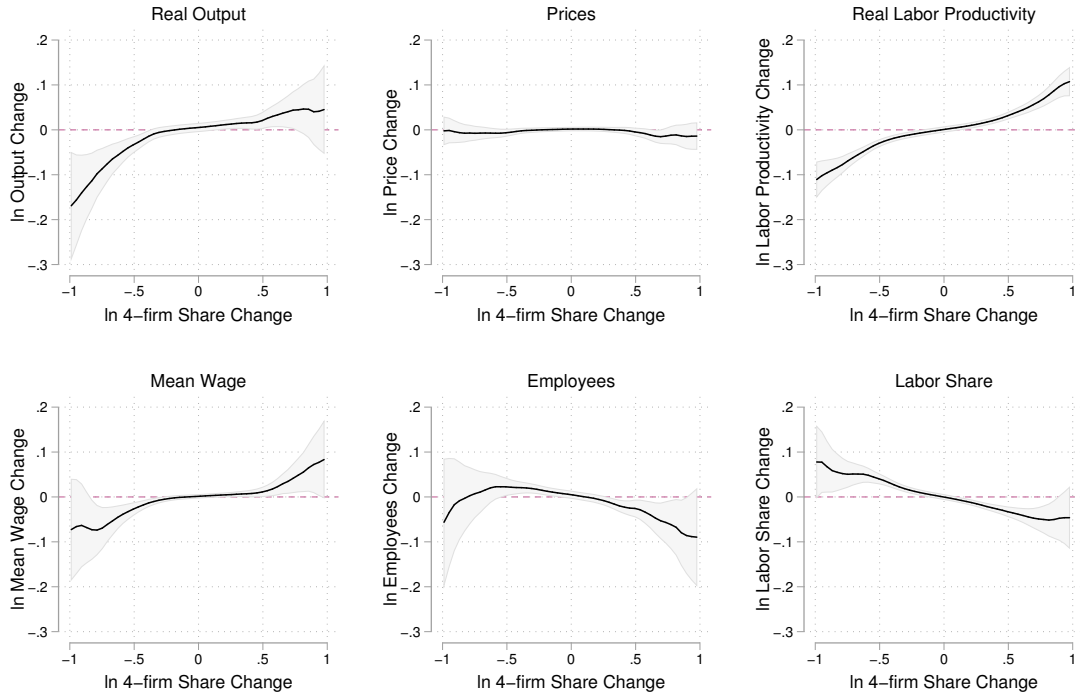
Notes: Robust standard errors clustered on BEA industry codes. Observations at the NAICS 6-digit level for 1997-2012 and at the SIC 3 and 4-digit level for 1972-1992. Data from 1992 and 1997 are from non-comparable industrial classification systems. Market shares and productivity changes are standardized by subtracting means and dividing by standard errors. Sources: Author's Calculations based on US BEA, BLS, Census, NBER-CES data

Figure 2: Market Share by Employment and Payroll, 1990-2015



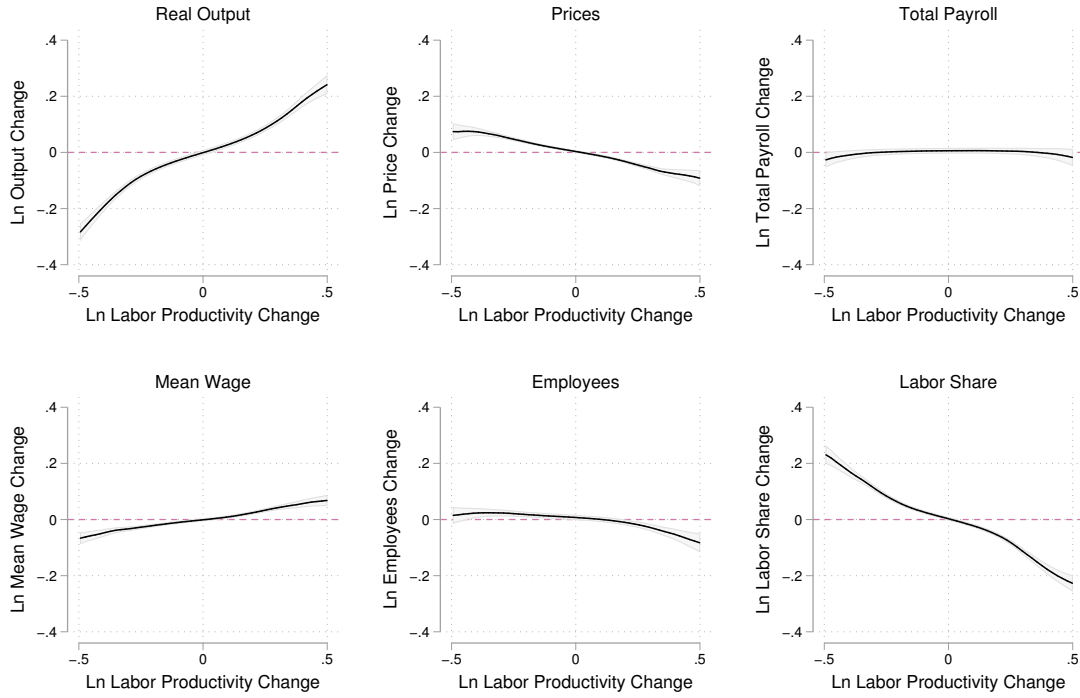
Notes: These three graphs plot changes in the average market share of the top four firms across 6-digit NAICS codes. Data drawn from a balanced panel from 1990 through 2015, with data weighted using employment levels in 1990. The left plots trends ranking firms using the top four firms by within-NAICS code employment and payrolls, using national market definitions. The center plots trends using county-level market definitions. The right plots trends using 5-digit zip code market definitions. The solid trend-line plots market shares computed using payroll. The dotted trend-line plots market share computed using employment. Data aligned from 1990-2005 to 2012 NAICS codings from the Longitudinal Business Database for all firms with either payroll or employment.

Figure 3: Correlation of Economic Outcomes to Market Concentration



Notes: Results from a non-parametric regression of 5-year changes change in the combined market share of the four largest firms by time period using residuals after demeaning for year-sector means. For example, the first panel roughly implies that a 1 standard deviation increase in market concentration is correlated with to 0.1 standard deviation increase in real output. From 1972-1992, data uses 4-digit SIC codes for manufacturing industries and lowest levels of aggregation for non-manufacturing industries (A mixture of 3 and 4 digit SIC codes). From 1997 onwards, 6-digit NAICS codes for all industries. Data from 1992 and 1997 are from non-comparable industrial classification systems.

Figure 4: Correlation of Economic Outcomes to Labor Productivity



Notes: Results from a non-parametric regression of 5-year changes in labor productivity using residuals after controlling for year-sector means. From 1972-1992, data uses 4-digit SIC codes for manufacturing industries and lowest levels of aggregation for non-manufacturing industries (A mixture of 3 and 4 digit SIC codes). From 1997 onwards, 6-digit NAICS codes for all industries. Data for non-manufacturing firms in 1972 is incomplete. Data from 1992 and 1997 are from non-comparable industrial classification systems.

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Appendix (For Online Publication)

A Simple Theoretical Models

I present two simple oligopoly models, first with Cournot competition and second with monopolistic competition under Bertrand pricing. Both models produce relationships that (a) provide a simple tractable framework and (b) allow for straightforward comparative statics.

A.1 Cournot Competition

Assume there are N identical firms indexed by i competing by setting quantity, with constant marginal costs:

$$c(q_i) = cq_i.$$

Assume market demand takes the form:

$$p(Q) = p\left(\sum_{i=1}^N q_i\right) = a - bQ$$

In a Cournot equilibrium, each firm produces output q_i at price p :

$$q_i = \frac{a - c}{b(N + 1)}, \quad p = \frac{a + Nc}{N + 1} \quad (2)$$

This produces total market output Q :

$$Q = \sum_i^n q_i = \frac{(a - c)N}{b(N + 1)}. \quad (3)$$

The last two equations are those that can be tested directly³⁴. As N decreases, p increases and total output Q falls, controlling for supply and demand shifters.

Now let us assume that there is a per-period fixed cost F that allow a firm to produce at marginal cost c . Then the number of firms in equilibrium is:³⁵

$$N^* = \frac{a - c}{\sqrt{Fb}} - 1.$$

Suppose, due to some exogenous innovation, a new technology $c' < c$ become available. This

³⁴Simple log-linear transforms can provide the following testable equations:

$$\begin{aligned} \log Q &= \log(a - c) + \log \frac{N}{N + 1} - \log b \\ \log p &= \log(a + Nc) - \log(N + 1). \end{aligned}$$

³⁵In reality, N^* is an integer, but I abstract away from that for analytic tractability.

simulates the rise of productivity. What is this technology? Is it some freely available new general purpose technology that may reduce/hold constant fixed cost F or is it a new technology that increases fixed costs? In terms of market power, market power will increase if the fixed cost of the new technology F' satisfies the following condition:

$$\frac{a - c}{a - c'} < \sqrt{\frac{F}{F'}}.$$

Furthermore, there exists a continuum of (F', c') , such that innovation is welfare improving.
36

Implicitly, the empirical specifications testing for the correlation between productivity (whose theoretical analog is $1/c$) and market concentration (whose theoretical analog is $1/N$) answer this question. In light of the empirical results, this model implies that higher fixed costs have simultaneously led to lower marginal costs and fewer market competitors.

There is a further question, is labor a larger component of the fixed costs or the operating costs (marginal cost)? The classic answer is rooted in the simultaneity issue in estimating production functions in Marschak and Andrews (1944); Griliches (1957). As operationalized by Olley and Pakes (1992), labor is more variable than capital. One interpretation of their framework is that fixed costs are equivalent to capital expenditures and that operating costs subsist of labor and materials.

Under this framework, total fixed costs (TF) paid by all firms are simply the product of the number of firms and each firm's fixed cost:

$$N \cdot F = F \left(\frac{a - c}{\sqrt{Fb}} - 1 \right).$$

Labor's share of revenues are:

$$\frac{c}{p} = \frac{c}{\frac{a + Nc}{N + 1}}.$$

Furthermore if both $N' < N$ and $Q' > Q$, then $c'/p' < c/p$, thus labor's share of income decreases.

A.2 Discrete Choice

Following Berry (1994), assume there are N identical firms indexed by i that face symmetric competition and compete by setting price, with constant marginal costs as before. Consumer j chooses the firm that maximizes utility U_{ij} :

$$U_{ij} = \beta - \alpha p_i + \epsilon_{ij},$$

³⁶I can run a similar exercise if fixed costs can be used to create a larger market $a' > a$. For example, if Apple pays a fixed cost $F' > F$ to acquire intellectual property to add a better camera to their phone, then $a' > a$. Similarly, there exists a continuum of (F', a') , such that innovation is welfare improving.

where ϵ_{ij} is an i.i.d shock drawn from a standard Gumbel distribution and $\alpha > 0$.

Market share for firm i is:

$$s_i(p) = \frac{\exp(\beta - \alpha p_i)}{\sum_{i=1}^N \exp(\beta - \alpha p_i)}.$$

Suppose that total market size is a function of the average utility level:

$$Q(p) = A \left(\sum_{i=1}^N \exp(\beta - \alpha p_i) \right)^\epsilon.$$

Where $3A > 0$ is a choke market size and $\epsilon > 0$ is the elasticity. Firms maximize profits Π_i :

$$\Pi_i = \max_{p_i} s_i(p) \cdot Q(p) \cdot (p - c).$$

Profit maximization by identical firms implies that:

$$p = \frac{1}{\alpha \left(1 + (\epsilon - 1) \frac{1}{N}\right)} + c, \quad Q = A (N \exp(\beta - \alpha p_i))^\epsilon. \quad (4)$$

As in the Cournot example, as the number of competitors increases, price falls and quantity sold increases, controlling for supply and demand shifters. Most common formulations of supply and demand will provide similar results. These examples also point to mechanisms where competition could fall, but prices fall and quantities increase. For example if a decrease in N is consistent with a high fixed cost technology that reduces marginal cost (mechanization, efficiency) or stimulates demand (advertising), it may break the linkage between market concentration, prices, and quantities.

B Data Appendix

For data from 1972-1992, the US Census does not publish statistics using a unified SIC system (the exception being in the Manufacturing sector, where in 1992 the Census published a retrospective tabulation unifying past SIC codes). There are two regimes, a 1972 system and a redefinition in 1987, with minor modification in between. Similarly, from 1997-2012 the US Census does not publish statistics using a unified NAICS system, with each of the 1997, 2002, 2007 and 2012 EC using a slightly different variation of NAICS codes. As this paper uses this publicly available data,³⁷ I do not merge or alter the Census defined markets and base the analysis on

³⁷See Ganapati and Greaney (2017) for analysis using a harmonized NAICS codes as published by Fort and Klimek (2016); results are stable to NAICS codes changes. In general, releasing additional, harmonized market share data from Census and administrative US sources is difficult, as disclosure would likely reveal confidential sales and revenue data for the largest firms.

consistently defined SIC/NAICS codes.³⁸ Market shares cannot be computed in real units of output, so they are computed using the revenue share of all the facilities a given firm operates within a SIC/NAICS category within the United States. the U.S. Bureau of Economic Analysis (BEA) provides price index and output volume data from 1977 to 2012.³⁹

Price indices and supply side controls for manufacturing data are drawn from the NBER-CES database in 4-digit SIC basis before 1997 and in 6-digit NAICS basis after 1997.⁴⁰ Price indices for non-manufacturing data come from BEA tables at the most disaggregate level of aggregation provided. As prices and quantities also reflect overall macroeconomic inflation and growth, the analysis in the next section will include year fixed effects and sectoral trends. All of these measured prices are derived from underlying data collected primary by the Bureau of Labor Statistics for the creation of producer and consumer price indices.

Table 3 shows the coverage of the data used from 1972 through 2012. There is continuous coverage for the manufacturing sector over the entire time period at an high level of detail. Coverage is at the 4-digit SIC and 6-digit NAICS levels. Coverage for non-manufacturing sectors is spottier. For wholesale and retail trade, coverage is from 1977 through 2012. However, this is at a higher level of aggregation than the manufacturing sector. From 1982 through 1992, this is at the 3-4 digit SIC level. From 1997 through 2012, this is at the 4-6 digit NAICS level. This level of aggregation is due to the limited availability of consistent price indices at finer levels of aggregation. Service data exists from 1977 through 2012. For 1977 and 1982, the data only covers personal (as opposed to business services) at the 3-4 digit SIC level. For 1982 and 1993, the data covers both personal and business services at the 3-digit level. From 1997 onwards, the data covers all services at the 4, 5 or 6-digit NAICS level. From 1977 through 1992, some transportation sectors (such as those related to automotive transport) and communication sector (such as mass media) data are included in the Service Economic Censuses at the 3-digit SIC level. From 1997 onwards, these sectors, joined by the Utilities and Finance are included at the 3- or 4-digit NAICS levels.

For the manufacturing sector under both SIC and NAICS codes, I add import and export data using concordances from Feenstra (1996, 1997); Pierce and Schott (2009) to better understand the role of import competition. To further consider this role, I directly use the timing of the normalization of trade with china (PNTR) from Pierce and Schott (2016) to look at a exogenous

³⁸For example, from 1997-2007, the Census published statistics for NAICS industries “311222 Soybean processing” and “311223 Other oilseed processing” separately. In 2012, the Census combined these two industries into a new industry “311224 Soybean and other oilseed processing”. I do not merge market share statistics for these two industries and treat them separately. This has the practical effect of decreasing the number of usable observations and increasing the number of industry fixed effects.

³⁹This data is not originally collected by the BEA; rather, the BEA aggregates Census and Bureau of Labor Statistics data to produce aggregated and consistent statistics. Prices are simply official government statistics, based on weighed prices, observed and collected by the Bureau of Labor Statistics. This is in contrast with the exact price indices in macroeconomic, international trade, and industrial organization models that can directly measure welfare under sets of modeling assumptions.

⁴⁰The NBER-CES data is currently only updated through 2011. I use values from 2011 NBER-CES database to correspond to the 2012 EC. Result are robust to the omission of 2012 data.

supply shock. To better decompose the difference between the number of hours worked and the number of employees, I add in number of worker hours by industry from the Bureau of Labor Statistics. Lastly for regulation, I use the RegData 3.0 database that quantifies the number of federal regulations pertaining to a NAICS sector by year. The database runs a machine learning algorithm on the entire corpus of federal regulation appearing the the Federal Register from 1970-2016. I consider the change in the number of “Industry Relevant Regulations” at the 6-digit NAICS level.

Table 2: Summary statistics

Variable	Mean	(Std. Dev.)	N
4-Firm Concentration	36.2	(21.9)	4349
log(4-firm Concentration)	3.3	(0.8)	4349
log(Output)	13.7	(2.2)	4349
log(Price)	1.7	(2.2)	4349
log(Revenue)	15.4	(1.6)	4349
log(Labor Productivity)	7.8	(5.6)	4349
log(Mean Wage)	3.4	(0.6)	4349
log(Employees)	5.9	(4.1)	4349
log(Payroll)	9.3	(4.2)	4349
log(Labor Share)	-6.1	(3.4)	4349
4-factor TFP index 1997=1.000	1	(0.3)	2743
8-Firm Concentration	47	(24.9)	4336
50-Firm HHI	756	(688.5)	1234
log(Mean Wage)	3.4	(0.6)	4349
log(Capital Price)	1.4	(2.1)	3937
Hourly Labor Productivity	11.2	(1.7)	3046
log(Hourly Pay)	3.6	(2.1)	3046
log(Labor Hours)	3.5	(1.3)	3046
Import Penetration	0.2	(0.2)	2426
Federal Industry Regulations	23458.1	(40917.6)	2229

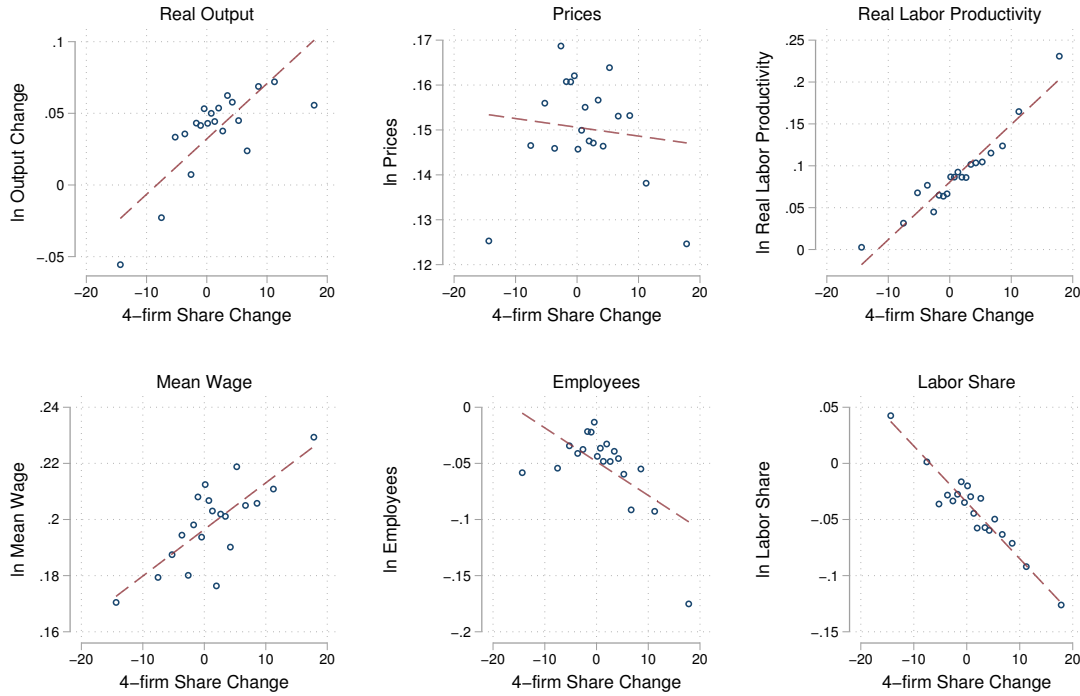
Table 3: Industry Coverage for both Price Indices and Concentration Statistics

Classification	1972	1977	1982	1987	1992	1997	2002	2007	2012
	SIC					NAICS			
Agriculture and related									
Mining									
Construction									
Manufacturing	X	X	X	X	X	X	X	X	X
Transportation		Partial	Partial	Partial	Partial	X	X	X	X
Communication		Partial	Partial	Partial	Partial	X	X	X	X
Utilities						X	X	X	X
Wholesale trade		X	X	X	X	X	X	X	X
Retail Trade		X	X	X	X	X	X	X	X
Finance, Insurance and						X	X	X	X
Real Estate									
Services		Partial	Partial	X	X	X	X	X	X

C Replication with Bin-Scatter Plots

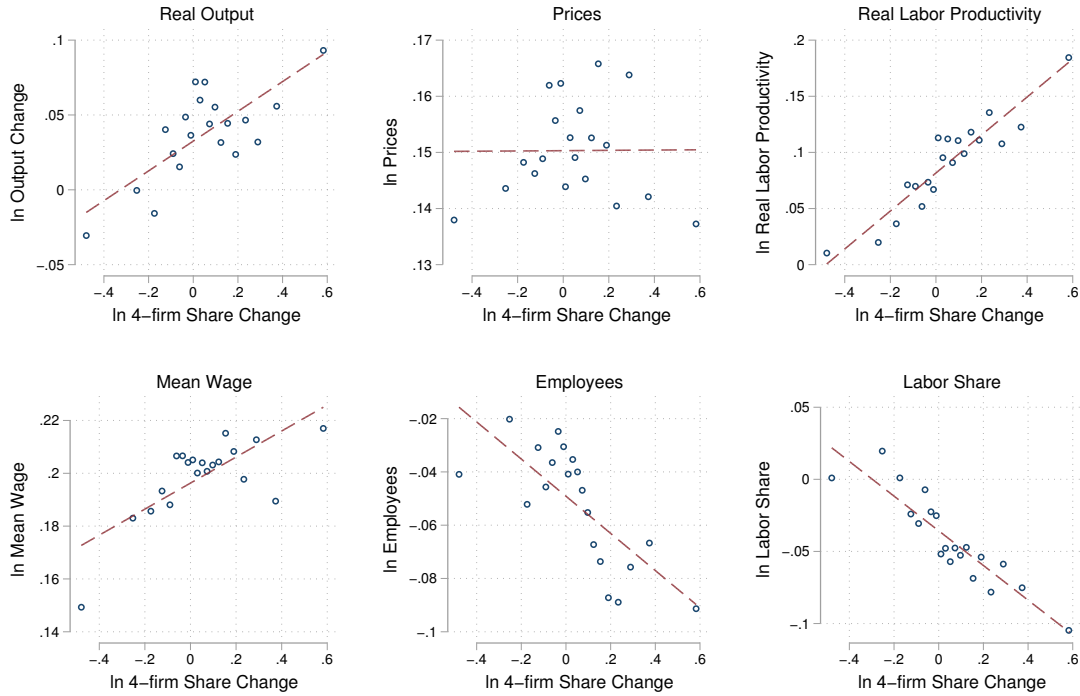
Figures 6 and 7 replicate figures 3 and 4 using bin-scatter plots instead of non-parametric regressions. Results are largely unchanged. Figure 5 replicates figures 6 using the levels of 4-firm changes instead of logarithms. Results are largely unchanged.

Figure 5: Correlation of Economic Outcomes to Market Concentration (Levels)



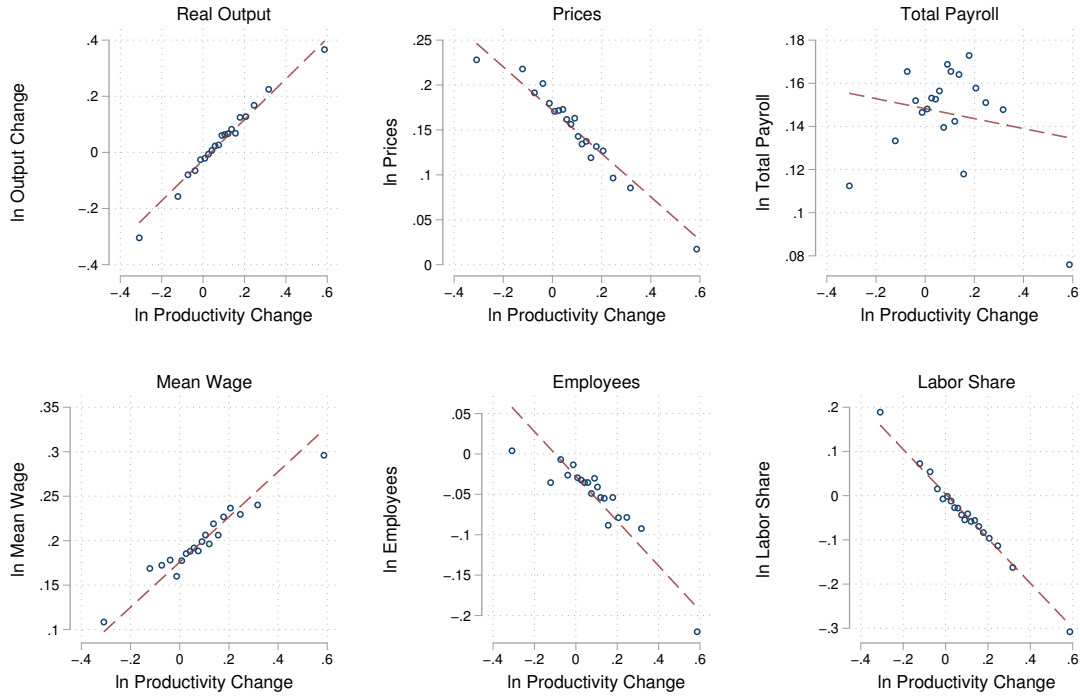
Notes: Results from a bin-scatter regression of 5-year changes change in the combined market share of the four largest firms by time period using residuals after demeaning for year-sector means. From 1972-1992, data uses 4-digit SIC codes for manufacturing industries and lowest levels of aggregation for non-manufacturing industries (A mixture of 3 and 4 digit SIC codes). From 1997 onwards, 6-digit NAICS codes for all industries. Data from 1992 and 1997 are from non-comparable industrial classification systems.

Figure 6: Correlation of Economic Outcomes to Market Concentration (Logarithms)



Notes: Results from a bin-scatter regression of 5-year changes change in the combined market share of the four largest firms by time period using residuals after demeaning for year-sector means. From 1972-1992, data uses 4-digit SIC codes for manufacturing industries and lowest levels of aggregation for non-manufacturing industries (A mixture of 3 and 4 digit SIC codes). From 1997 onwards, 6-digit NAICS codes for all industries. Data from 1992 and 1997 are from non-comparable industrial classification systems.

Figure 7: Correlation of Economic Outcomes to Labor Productivity



Notes: Results from a bin-scatter regression of 5-year changes in labor productivity using residuals after controlling for year-sector means. From 1972-1992, data uses 4-digit SIC codes for manufacturing industries and lowest levels of aggregation for non-manufacturing industries (A mixture of 3 and 4 digit SIC codes). From 1997 onwards, 6-digit NAICS codes for all industries. Data for non-manufacturing firms in 1972 is incomplete. Data from 1992 and 1997 are from non-comparable industrial classification systems.

D Results Robustness Appendix

Non-manufacturing Sector Only: See Table 4 for a replication of the baseline tables, subset to only non-manufacturing firms. Manufacturing data may be contaminated by import data (see table 9 for a comparison) and is therefore hard to directly compare.

Running analysis in Levels: See Table 6 for a replication of the baseline tables, using the level of 4-firm market concentration (as opposed to the logarithm of the 4-firm market concentration).

Using 50-firm Herfindahl-Hirschman index (HHI) Market Shares (Manufacturing sector only): See Table 6 for a replication of the baseline tables, using the Herfindahl-Hirschman index (HHI) computed using the 50 largest firms

Controlling for Material and Capital prices: See Table 7 for a replication of the baseline tables, controlling for input price indices in both materials and capital.

Using TFP (Manufacturing sector only): See Table 8 for a replication of the baseline tables using total factor productivity instead of labor productivity.

Using Hourly Productivity: See Table 9 for a replication of the baseline tables using hourly employee productivity instead of labor productivity.

Including Imports (Manufacturing sector only): See Table 10 for a replication of the baseline tables controlling for import shares and exogenous changes in PNTR status. Import share is computed as $\frac{imports}{domestic+imports}$. PNTR status comes from Pierce and Schott (2016). It is important to note here that the output prices and market concentrations are for domestic production only.

Including Regulation: See Table 11 for a replication of the baseline tables controlling observed federal regulations.

Controlling for Demand Pre-trends: See Table 12 for a replication of the baseline tables controlling for both lagged production and lagged production growth rates.

Table 4: Only Non-Manufacturing Firms

(a) 4-Firm Market Shares

	$\Delta \text{ Ln Output}$	$\Delta \text{ Ln Price}$	$\Delta \text{ Ln Revenue}$	$\Delta \text{ Ln Labor Productivity}$
Std $\Delta \text{ Ln 4-Firm Share}$	0.0477 (0.0123)	-0.00421 (0.00181)	0.0435 (0.0124)	0.233 (0.0454)
r2	0.138	0.461	0.185	0.150
	$\Delta \text{ Ln Mean Wage}$	$\Delta \text{ Ln Employees}$	$\Delta \text{ Ln Payroll}$	$\Delta \text{ Ln Labor Share}$
Std $\Delta \text{ Ln 4-Firm Share}$	0.00596 (0.0165)	-0.0126 (0.00762)	-0.00660 (0.0162)	-0.0501 (0.0108)
r2	0.0952	0.148	0.185	0.135
Observations	1606	1606	1606	1606

(b) 4-Firm Market Shares & Labor Productivity

	$\Delta \text{ Ln Output}$	$\Delta \text{ Ln Price}$	$\Delta \text{ Ln Revenue}$	$\Delta \text{ Ln Labor Productivity}$
Std $\Delta \text{ Ln 4-Firm Share}$	0.00941 (0.00789)	0.00111 (0.00238)	0.0105 (0.00854)	0.233 (0.0454)
Std $\Delta \text{ Ln Productivity}$	0.164 (0.0229)	-0.0228 (0.00506)	0.141 (0.0226)	
r2	0.339	0.498	0.335	0.150
	$\Delta \text{ Ln Mean Wage}$	$\Delta \text{ Ln Employees}$	$\Delta \text{ Ln Payroll}$	$\Delta \text{ Ln Labor Share}$
Std $\Delta \text{ Ln 4-Firm Share}$	-0.0180 (0.0141)	0.00941 (0.00789)	-0.00861 (0.0166)	-0.0191 (0.0136)
Std $\Delta \text{ Ln Productivity}$	0.103 (0.0214)	-0.0941 (0.0229)	0.00862 (0.0155)	-0.133 (0.0210)
r2	0.267	0.225	0.186	0.375
Observations	1606	1606	1606	1606

Notes: Robust standard errors clustered on BEA industry codes. Observations at the NAICS 6-digit level for 1997-2012 and at the SIC 3 and 4-digit level for 1972-1992. Data from 1992 and 1997 are from non-comparable industrial classification systems. Market shares and productivity changes are standardized by subtracting means and dividing by standard errors. Sources: Author's Calculations based on US BEA, BLS, Census, NBER-CES data

Table 5: 4-Firm Market Shares - In Levels

(a) 4-Firm Market Shares

	$\Delta \text{ Ln Output}$	$\Delta \text{ Ln Price}$	$\Delta \text{ Ln Revenue}$	$\Delta \text{ Ln Labor Productivity}$
Δ 4-Firm Share	0.00506 (0.00112)	-0.000202 (0.000299)	0.00486 (0.00113)	0.0352 (0.00295)
r2	0.125	0.512	0.234	0.177
	$\Delta \text{ Ln Mean Wage}$	$\Delta \text{ Ln Employees}$	$\Delta \text{ Ln Payroll}$	$\Delta \text{ Ln Labor Share}$
Δ 4-Firm Share	0.00181 (0.000302)	-0.00245 (0.000783)	-0.000633 (0.000839)	-0.00549 (0.000599)
r2	0.295	0.167	0.238	0.184
Observations	4349	4349	4349	4349

(b) 4-Firm Market Shares & Labor Productivity

	$\Delta \text{ Ln Output}$	$\Delta \text{ Ln Price}$	$\Delta \text{ Ln Revenue}$	$\Delta \text{ Ln Labor Productivity}$
Δ 4-Firm Share	-0.000556 (0.000896)	0.00168 (0.000353)	0.00112 (0.00102)	0.0352 (0.00295)
Std $\Delta \text{ Ln Productivity}$	0.159 (0.0120)	-0.0534 (0.00770)	0.106 (0.0122)	
r2	0.331	0.590	0.311	0.177
	$\Delta \text{ Ln Mean Wage}$	$\Delta \text{ Ln Employees}$	$\Delta \text{ Ln Payroll}$	$\Delta \text{ Ln Labor Share}$
Δ 4-Firm Share	-0.0000691 (0.000465)	-0.000556 (0.000896)	-0.000625 (0.000871)	-0.00175 (0.000513)
Std $\Delta \text{ Ln Productivity}$	0.0534 (0.0115)	-0.0537 (0.0120)	-0.000225 (0.00831)	-0.106 (0.0102)
r2	0.377	0.196	0.238	0.416
Observations	4349	4349	4349	4349

Notes: Robust standard errors clustered on BEA industry codes. Observations at the NAICS 6-digit level for 1997-2012 and at the SIC 3 and 4-digit level for 1972-1992. Data from 1992 and 1997 are from non-comparable industrial classification systems. Market shares and productivity changes are standardized by subtracting means and dividing by standard errors. Sources: Author's Calculations based on US BEA, BLS, Census, NBER-CES data

Table 6: Using 50-Firm Herfindahl-Hirschman index (HHI) Concentration Measures

(a) 50-Firm HHI				
	$\Delta \text{ Ln Output}$	$\Delta \text{ Ln Price}$	$\Delta \text{ Ln Revenue}$	$\Delta \text{ Ln Labor Productivity}$
Std $\Delta \text{ Ln 50-Firm HHI}$	0.00980 (0.0116)	0.00613 (0.00544)	0.0159 (0.0127)	0.142 (0.0323)
r2	0.0377	0.154	0.0852	0.0635
	$\Delta \text{ Ln Mean Wage}$	$\Delta \text{ Ln Employees}$	$\Delta \text{ Ln Payroll}$	$\Delta \text{ Ln Labor Share}$
Std $\Delta \text{ Ln 50-Firm HHI}$	0.00881 (0.00298)	-0.0205 (0.0107)	-0.0117 (0.0118)	-0.0276 (0.00534)
r2	0.0422	0.0168	0.0195	0.206
Observations	1150	1150	1150	1150

(b) 50-Firm HHI & Labor Productivity				
	$\Delta \text{ Ln Output}$	$\Delta \text{ Ln Price}$	$\Delta \text{ Ln Revenue}$	$\Delta \text{ Ln Labor Productivity}$
Std $\Delta \text{ Ln 50-Firm HHI}$	-0.0172 (0.0107)	0.0177 (0.00412)	0.000476 (0.0129)	0.142 (0.0323)
Std $\Delta \text{ Ln Productivity}$	0.190 (0.0134)	-0.0814 (0.0168)	0.109 (0.0227)	
r2	0.257	0.329	0.144	0.0635
	$\Delta \text{ Ln Mean Wage}$	$\Delta \text{ Ln Employees}$	$\Delta \text{ Ln Payroll}$	$\Delta \text{ Ln Labor Share}$
Std $\Delta \text{ Ln 50-Firm HHI}$	0.00581 (0.00307)	-0.0172 (0.0107)	-0.0114 (0.0120)	-0.0119 (0.00436)
Std $\Delta \text{ Ln Productivity}$	0.0211 (0.00406)	-0.0229 (0.0134)	-0.00187 (0.0151)	-0.110 (0.0147)
r2	0.0941	0.0210	0.0196	0.451
Observations	1150	1150	1150	1150

Notes: Robust standard errors clustered on BEA industry codes. Observations at the NAICS 6-digit level for 1997-2012 and at the SIC 3 and 4-digit level for 1972-1992. Data from 1992 and 1997 are from non-comparable industrial classification systems. Market shares and productivity changes are standardized by subtracting means and dividing by standard errors. Sources: Author's Calculations based on US BEA, BLS, Census, NBER-CES data

Table 7: Controlling for Factor Input Prices

(a) 4-Firm Market Shares

	$\Delta \text{ Ln Output}$	$\Delta \text{ Ln Price}$	$\Delta \text{ Ln Revenue}$	$\Delta \text{ Ln Labor Productivity}$
Std $\Delta \text{ Ln 4-Firm Share}$	0.0365 (0.00746)	0.000813 (0.00154)	0.0373 (0.00744)	0.226 (0.0218)
S.log(Material Price)	0.0116 (0.0914)	0.732 (0.0732)	0.744 (0.117)	-1.497 (0.319)
S.log(Capital Price)	-0.0177 (0.120)	0.0691 (0.0557)	0.0514 (0.106)	-0.821 (0.555)
r2	0.118	0.641	0.265	0.202
	$\Delta \text{ Ln Mean Wage}$	$\Delta \text{ Ln Employees}$	$\Delta \text{ Ln Payroll}$	$\Delta \text{ Ln Labor Share}$
Std $\Delta \text{ Ln 4-Firm Share}$	0.0133 (0.00192)	-0.0116 (0.00552)	0.00167 (0.00572)	-0.0356 (0.00404)
S.log(Material Price)	0.0415 (0.0153)	0.330 (0.0921)	0.372 (0.0945)	-0.372 (0.0437)
S.log(Capital Price)	0.0501 (0.0364)	0.157 (0.114)	0.207 (0.104)	0.156 (0.0706)
r2	0.556	0.172	0.258	0.248
Observations	3937	3937	3937	3937

(b) 4-Firm Market Shares & Labor Productivity

	$\Delta \text{ Ln Output}$	$\Delta \text{ Ln Price}$	$\Delta \text{ Ln Revenue}$	$\Delta \text{ Ln Labor Productivity}$
Std $\Delta \text{ Ln 4-Firm Share}$	-0.00254 (0.00573)	0.0131 (0.00194)	0.0105 (0.00621)	0.226 (0.0218)
Std $\Delta \text{ Ln Productivity}$	0.173 (0.00917)	-0.0543 (0.00612)	0.118 (0.00978)	
S.log(Material Price)	0.270 (0.0912)	0.651 (0.0584)	0.921 (0.132)	-1.497 (0.319)
S.log(Capital Price)	0.124 (0.107)	0.0244 (0.0405)	0.149 (0.110)	-0.821 (0.555)
r2	0.317	0.705	0.343	0.202
	$\Delta \text{ Ln Mean Wage}$	$\Delta \text{ Ln Employees}$	$\Delta \text{ Ln Payroll}$	$\Delta \text{ Ln Labor Share}$
Std $\Delta \text{ Ln 4-Firm Share}$	0.00625 (0.00173)	-0.00254 (0.00573)	0.00371 (0.00596)	-0.00684 (0.00226)
Std $\Delta \text{ Ln Productivity}$	0.0312 (0.00386)	-0.0402 (0.00917)	-0.00904 (0.00984)	-0.128 (0.00585)
S.log(Material Price)	0.0882 (0.0167)	0.270 (0.0912)	0.358 (0.0970)	-0.563 (0.0526)
S.log(Capital Price)	0.0756 (0.0276)	0.124 (0.107)	0.200 (0.104)	0.0512 (0.0470)
r2	0.599	0.185	0.259	0.614
Observations	3937	3937	3937	3937

Notes: Robust standard errors clustered on BEA industry codes. Observations at the NAICS 6-digit level for 1997-2012 and at the SIC 3 and 4-digit level for 1972-1992. Data from 1992 and 1997 are from non-comparable industrial classification systems. Market shares and productivity changes are standardized by subtracting means and dividing by standard errors. Sources: Author's Calculations based on US BEA, BLS, Census, NBER-CES data

Table 8: Controlling for Total Factor Productivity (Manufacturing Only)

(a) 4-Firm Market Shares

	$\Delta \text{ Ln Output}$	$\Delta \text{ Ln Price}$	$\Delta \text{ Ln Revenue}$	$\Delta \text{ Ln Labor Productivity}$
Std $\Delta \text{ Ln 4-Firm Share}$	0.0304 (0.00667)	-0.000775 (0.00157)	0.0296 (0.00695)	0.0850 (0.0406)
r2	0.120	0.512	0.231	0.0394
	$\Delta \text{ Ln Mean Wage}$	$\Delta \text{ Ln Employees}$	$\Delta \text{ Ln Payroll}$	$\Delta \text{ Ln Labor Share}$
Std $\Delta \text{ Ln 4-Firm Share}$	0.0107 (0.00220)	-0.0209 (0.00898)	-0.0103 (0.00963)	-0.0337 (0.00422)
r2	0.676	0.0785	0.252	0.189
Observations	2743	2743	2743	2743

(b) 4-Firm Market Shares & Total Factor Productivity

	$\Delta \text{ Ln Output}$	$\Delta \text{ Ln Price}$	$\Delta \text{ Ln Revenue}$	$\Delta \text{ Ln Labor Productivity}$
Std $\Delta \text{ Ln 4-Firm Share}$	0.00669 (0.00860)	0.00955 (0.00346)	0.0162 (0.0101)	0.0850 (0.0406)
Std $\Delta \text{ Ln TFP}$	0.153 (0.0433)	-0.0687 (0.00985)	0.0846 (0.0346)	
r2	0.327	0.622	0.309	0.0394
	$\Delta \text{ Ln Mean Wage}$	$\Delta \text{ Ln Employees}$	$\Delta \text{ Ln Payroll}$	$\Delta \text{ Ln Labor Share}$
Std $\Delta \text{ Ln 4-Firm Share}$	0.0105 (0.00220)	-0.0250 (0.00887)	-0.0145 (0.00952)	-0.0308 (0.00386)
Std $\Delta \text{ Ln TFP}$	0.00138 (0.00262)	0.0486 (0.0256)	0.0500 (0.0278)	-0.0346 (0.00771)
r2	0.676	0.112	0.278	0.234
Observations	2743	2743	2743	2743

Notes: Robust standard errors clustered on BEA industry codes. Observations at the NAICS 6-digit level for 1997-2012 and at the SIC 3 and 4-digit level for 1972-1992. Data from 1992 and 1997 are from non-comparable industrial classification systems. Market shares and productivity changes are standardized by subtracting means and dividing by standard errors. Sources: Author's Calculations based on US BEA, BLS, Census, NBER-CES data

Table 9: Use Hourly Measures of Productivity

(a) 4-Firm Market Shares

	$\Delta \text{ Ln Output}$	$\Delta \text{ Ln Price}$	$\Delta \text{ Ln Revenue}$	$\Delta \text{ Ln Labor Productivity}$
Std $\Delta \text{ Ln 4-Firm Share}$	0.0304*** (0.00667)	-0.000775 (0.00157)	0.0296*** (0.00695)	0.204*** (0.0294)
r2	0.120	0.512	0.231	0.0938
	$\Delta \text{ Ln Mean Wage}$	$\Delta \text{ Ln Employees}$	$\Delta \text{ Ln Payroll}$	$\Delta \text{ Ln Labor Share}$
Std $\Delta \text{ Ln 4-Firm Share}$	0.00862** (0.00310)	-0.0160 (0.00823)	-0.00739 (0.00809)	-0.0327*** (0.00380)
SectorYearFE	X	X	X	X
N	3045	3045	3045	3045
r2	0.496	0.116	0.260	0.216

(b) 4-Firm Market Shares & Hourly Labor Productivity

	$\Delta \text{ Ln Output}$	$\Delta \text{ Ln Price}$	$\Delta \text{ Ln Revenue}$	$\Delta \text{ Ln Labor Productivity}$
Std $\Delta \text{ Ln 4-Firm Share}$	-0.00457 (0.00795)	0.0172*** (0.00290)	0.0126 (0.00907)	0.204*** (0.0294)
Std $\Delta \text{ Ln Productivity}$	0.131*** (0.00705)	-0.0687*** (0.00781)	0.0621*** (0.0102)	
r2	0.274	0.629	0.288	0.0938
	$\Delta \text{ Ln Mean Wage}$	$\Delta \text{ Ln Employees}$	$\Delta \text{ Ln Payroll}$	$\Delta \text{ Ln Labor Share}$
Std $\Delta \text{ Ln 4-Firm Share}$	-0.00198 (0.00273)	-0.00457 (0.00795)	-0.00655 (0.00818)	-0.0192*** (0.00315)
Std $\Delta \text{ Ln Productivity}$	0.0521*** (0.00501)	-0.0562*** (0.00705)	-0.00416 (0.00804)	-0.0662*** (0.00540)
SectorYearFE	X	X	X	X
N	3045	3045	3045	3045
r2	0.594	0.154	0.260	0.369

Notes: Robust standard errors clustered on BEA industry codes. Observations at the NAICS 6-digit level for 1997-2012 and at the SIC 3 and 4-digit level for 1972-1992. Data from 1992 and 1997 are from non-comparable industrial classification systems. Market shares and productivity changes are standardized by subtracting means and dividing by standard errors. Sources: Author's Calculations based on US BEA, BLS, Census, NBER-CES data

Table 10: Controlling for Import Penetration (Manufacturing Only)

(a) 4-Firm Market Shares

	$\Delta \text{Ln Output}$	$\Delta \text{Ln Price}$	$\Delta \text{Ln Revenue}$	$\Delta \text{Ln Labor Productivity}$
Std $\Delta \text{Ln 4-Firm Share}$	-0.00412 (0.0177)	0.00861 (0.00741)	0.00449 (0.0186)	0.193 (0.0513)
S.log(Import Penetration)	-3.074 (0.473)	-0.326 (0.247)	-3.400 (0.495)	-2.122 (1.079)
PNTR Status x Post 1999	-0.238 (0.0827)	-0.0946 (0.0335)	-0.332 (0.0913)	0.503 (0.182)
r2	0.242	0.152	0.302	0.0726
	$\Delta \text{Ln Mean Wage}$	$\Delta \text{Ln Employees}$	$\Delta \text{Ln Payroll}$	$\Delta \text{Ln Labor Share}$
Std $\Delta \text{Ln 4-Firm Share}$	0.0120 (0.00448)	-0.0452 (0.0144)	-0.0333 (0.0156)	-0.0377 (0.00858)
S.log(Import Penetration)	-0.205 (0.0724)	-2.622 (0.409)	-2.827 (0.416)	0.573 (0.163)
PNTR Status x Post 1999	0.0569 (0.0156)	-0.345 (0.0755)	-0.288 (0.0760)	0.0443 (0.0361)
r2	0.0642	0.260	0.259	0.201
Observations	1002	1002	1002	1002

(b) 4-Firm Market Shares & Labor Productivity

	$\Delta \text{Ln Output}$	$\Delta \text{Ln Price}$	$\Delta \text{Ln Revenue}$	$\Delta \text{Ln Labor Productivity}$
Std $\Delta \text{Ln 4-Firm Share}$	-0.0403 (0.0147)	0.0244 (0.00661)	-0.0160 (0.0185)	0.193 (0.0513)
Std $\Delta \text{Ln Productivity}$	0.188 (0.0107)	-0.0816 (0.0202)	0.106 (0.0223)	
S.log(Import Penetration)	-2.675 (0.406)	-0.500 (0.212)	-3.175 (0.497)	-2.122 (1.079)
PNTR Status x Post 1999	-0.332 (0.0749)	-0.0535 (0.0329)	-0.385 (0.0889)	0.503 (0.182)
r2	0.478	0.330	0.363	0.0726
	$\Delta \text{Ln Mean Wage}$	$\Delta \text{Ln Employees}$	$\Delta \text{Ln Payroll}$	$\Delta \text{Ln Labor Share}$
Std $\Delta \text{Ln 4-Firm Share}$	0.00891 (0.00452)	-0.0403 (0.0147)	-0.0314 (0.0160)	-0.0155 (0.00673)
Std $\Delta \text{Ln Productivity}$	0.0159 (0.00460)	-0.0254 (0.0107)	-0.00945 (0.0115)	-0.115 (0.0175)
S.log(Import Penetration)	-0.171 (0.0670)	-2.675 (0.406)	-2.847 (0.412)	0.328 (0.217)
PNTR Status x Post 1999	0.0489 (0.0146)	-0.332 (0.0749)	-0.283 (0.0756)	0.102 (0.0329)
r2	0.0960	0.266	0.260	0.465
Observations	1002	1002	1002	1002

Notes: Robust standard errors clustered on BEA industry codes. Observations at the NAICS 6-digit level for 1997-2012 and at the SIC 3 and 4-digit level for 1972-1992. Data from 1992 and 1997 are from non-comparable industrial classification systems. Market shares and productivity changes are standardized by subtracting means and dividing by standard errors. Sources: Author's Calculations based on US BEA, BLS, Census, NBER-CES data, Pierce and Schott (2016, 2009); Feenstra (1996)

Table 11: Controlling for Measures of Federal Industry Regulation

(a) 4-Firm Market Shares				
	$\Delta \text{Ln Output}$	$\Delta \text{Ln Price}$	$\Delta \text{Ln Revenue}$	$\Delta \text{Ln Labor Productivity}$
Std $\Delta \text{Ln 4-Firm Share}$	0.0431 (0.00957)	0.00241 (0.00206)	0.0455 (0.00964)	0.259 (0.0301)
S.log(Regulations)	0.0981 (0.0398)	0.0268 (0.0181)	0.125 (0.0408)	0.126 (0.126)
r2	0.140	0.202	0.197	0.200
	$\Delta \text{Ln Mean Wage}$	$\Delta \text{Ln Employees}$	$\Delta \text{Ln Payroll}$	$\Delta \text{Ln Labor Share}$
Std $\Delta \text{Ln 4-Firm Share}$	0.0138 (0.00276)	-0.0120 (0.00698)	0.00181 (0.00741)	-0.0437 (0.00581)
S.log(Regulations)	0.0135 (0.00908)	0.0712 (0.0304)	0.0846 (0.0309)	-0.0402 (0.0247)
r2	0.157	0.226	0.252	0.258
Observations	2229	2229	2229	2229

(b) 4-Firm Market Shares & Labor Productivity				
	$\Delta \text{Ln Output}$	$\Delta \text{Ln Price}$	$\Delta \text{Ln Revenue}$	$\Delta \text{Ln Labor Productivity}$
Std $\Delta \text{Ln 4-Firm Share}$	-0.000606 (0.00718)	0.0153 (0.00335)	0.0147 (0.00844)	0.259 (0.0301)
Std $\Delta \text{Ln Productivity}$	0.169 (0.0111)	-0.0499 (0.0111)	0.119 (0.0151)	
S.log(Regulations)	0.0767 (0.0304)	0.0331 (0.0176)	0.110 (0.0356)	0.126 (0.126)
r2	0.339	0.313	0.284	0.200
	$\Delta \text{Ln Mean Wage}$	$\Delta \text{Ln Employees}$	$\Delta \text{Ln Payroll}$	$\Delta \text{Ln Labor Share}$
Std $\Delta \text{Ln 4-Firm Share}$	0.00537 (0.00255)	-0.000606 (0.00718)	0.00477 (0.00784)	-0.00995 (0.00362)
Std $\Delta \text{Ln Productivity}$	0.0326 (0.00539)	-0.0440 (0.0111)	-0.0114 (0.0121)	-0.130 (0.00979)
S.log(Regulations)	0.00933 (0.00867)	0.0767 (0.0304)	0.0861 (0.0307)	-0.0237 (0.0171)
r2	0.241	0.241	0.253	0.598
Observations	2229	2229	2229	2229

Notes: Robust standard errors clustered on BEA industry codes. Observations at the NAICS 6-digit level for 1997-2012 and at the SIC 3 and 4-digit level for 1972-1992. Data from 1992 and 1997 are from non-comparable industrial classification systems. Market shares and productivity changes are standardized by subtracting means and dividing by standard errors. Sources: Author's Calculations based on US BEA, BLS, Census, NBER-CES data, Mercatus Center

Table 12: Controlling for Lagged Demand and Pre-trends

(a) 4-Firm Market Shares

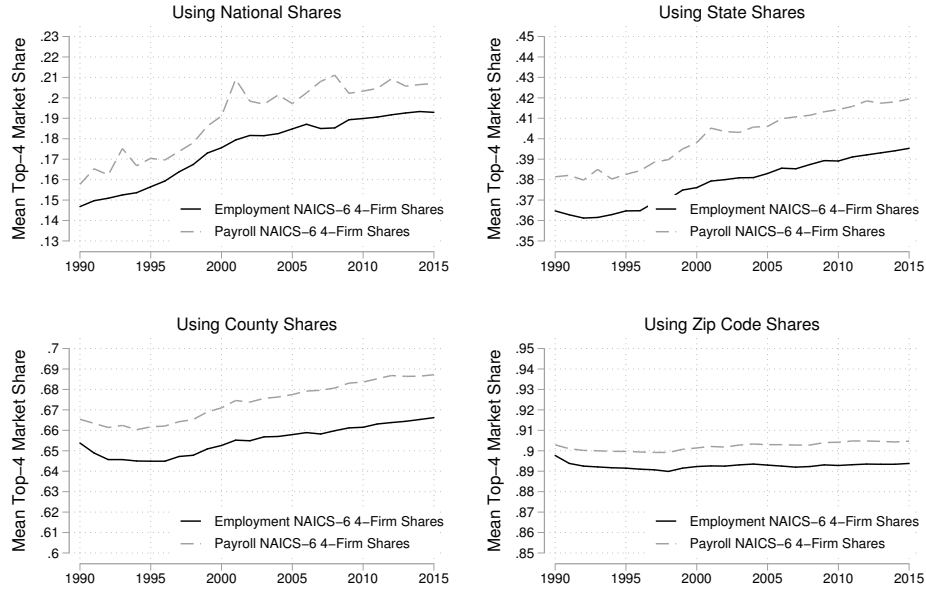
	$\Delta \text{Ln Output}$	$\Delta \text{Ln Price}$	$\Delta \text{Ln Revenue}$	$\Delta \text{Ln Labor Productivity}$
Std $\Delta \text{Ln 4-Firm Share}$	0.0331 (0.00915)	0.00144 (0.00187)	0.0346 (0.00946)	0.200 (0.0305)
L.log(Output)	0.00730 (0.00499)	0.00144 (0.00256)	0.00875 (0.00556)	-0.00559 (0.0188)
LS.log(Output)	0.0999 (0.0394)	-0.0191 (0.0123)	0.0808 (0.0392)	-0.0261 (0.0840)
r2	0.138	0.408	0.155	0.159
	$\Delta \text{Ln Mean Wage}$	$\Delta \text{Ln Employees}$	$\Delta \text{Ln Payroll}$	$\Delta \text{Ln Labor Share}$
Std $\Delta \text{Ln 4-Firm Share}$	0.0139 (0.00409)	-0.00957 (0.00621)	0.00432 (0.00657)	-0.0303 (0.00600)
L.log(Output)	-0.000971 (0.00196)	0.00849 (0.00418)	0.00752 (0.00432)	-0.00122 (0.00327)
LS.log(Output)	0.0103 (0.0100)	0.105 (0.0384)	0.116 (0.0391)	0.0350 (0.0147)
r2	0.371	0.152	0.215	0.117
Observations	2770	2770	2770	2770

(b) 4-Firm Market Shares & Labor Productivity

	$\Delta \text{Ln Output}$	$\Delta \text{Ln Price}$	$\Delta \text{Ln Revenue}$	$\Delta \text{Ln Labor Productivity}$
Std $\Delta \text{Ln 4-Firm Share}$	-0.00256 (0.00635)	0.0107 (0.00279)	0.00815 (0.00751)	0.200 (0.0305)
Std $\Delta \text{Ln Productivity}$	0.178 (0.00868)	-0.0462 (0.00732)	0.132 (0.0122)	
L.log(Output)	0.00830 (0.00406)	0.00118 (0.00240)	0.00948 (0.00521)	-0.00559 (0.0188)
LS.log(Output)	0.105 (0.0380)	-0.0203 (0.0109)	0.0842 (0.0394)	-0.0261 (0.0840)
r2	0.371	0.480	0.270	0.159
	$\Delta \text{Ln Mean Wage}$	$\Delta \text{Ln Employees}$	$\Delta \text{Ln Payroll}$	$\Delta \text{Ln Labor Share}$
Std $\Delta \text{Ln 4-Firm Share}$	0.00551 (0.00312)	-0.00256 (0.00635)	0.00295 (0.00664)	-0.00520 (0.00373)
Std $\Delta \text{Ln Productivity}$	0.0418 (0.00728)	-0.0350 (0.00868)	0.00679 (0.00987)	-0.125 (0.00925)
L.log(Output)	-0.000738 (0.00171)	0.00830 (0.00406)	0.00756 (0.00432)	-0.00192 (0.00250)
LS.log(Output)	0.0114 (0.00962)	0.105 (0.0380)	0.116 (0.0392)	0.0317 (0.0124)
r2	0.433	0.164	0.215	0.459
Observations	2770	2770	2770	2770

Notes: Robust standard errors clustered on BEA industry codes. Observations at the NAICS 6-digit level for 1997-2012 and at the SIC 3 and 4-digit level for 1972-1992. Data from 1992 and 1997 are from non-comparable industrial classification systems. Market shares and productivity changes are standardized by subtracting means and dividing by standard errors. Sources: Author's Calculations based on US BEA, BLS, Census, NBER-CES data,

Figure 8: Market Share by Employment and Payroll, 1990-2015 - Balanced Panel

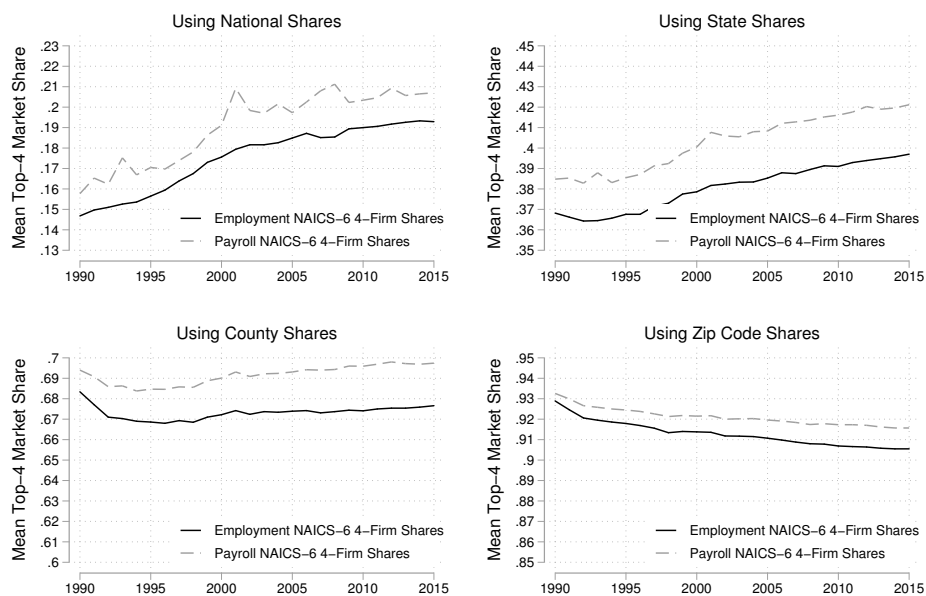


Notes: These four graphs plot changes in the average market share of the top four firms across 6-digit NAICS codes. Data drawn from a balanced panel from 1990 through 2015, with data weighted using employment levels in 1990. Counterclockwise from the top left, I use national market definitions, state market definitions, county market definitions, and finally 5-digit Zip code market definitions. The solid trend-line plots market shares computed using payroll. The dotted trend-line plots market share computed using employment. Data aligned from 1990-2005 to 2012 NAICS codings from the Longitudinal Business Database for all firms with either payroll or employment.

E Market Concentration Robustness

Rinz (2018) and Rossi-Hansberg et al. (2018) find that local market concentration has decreased, while I find that market concentration at the Zip code level is relative constant. I broadly replicate their findings and show that this is simply due to disappearing markets and extremely small markets. Suppose a world has two locations, a city and small town. For simplicity, assume that the underlying population stays constant. The city has many highly competitive firms. The small town has a set of firms that operates as an oligopoly. Suppose that some time passes and the firms in the city become more concentrated and all the firms in the small town become bankrupt. Has the average level of market concentration gone up or down? This depends on how you aggregate markets without any firms. See this table:

Figure 9: Market Share by Employment and Payroll, 1990-2015 - Unbalanced Panel



Notes: These four graphs plot changes in the average market share of the top four firms across 6-digit NAICS codes. Data drawn from a *unbalanced* panel from 1990 through 2015, with data weighted using employment levels in 1990. I use national market definitions, state market definitions, county market definitions, and finally 5-digit Zip code market definitions. The solid trend-line plots market shares computed using payroll. The dotted trend-line plots market share computed using employment. Data aligned from 1990-2005 to 2012 NAICS codings from the Longitudinal Business Database for all firms with either payroll or employment.

Market	Market Weight	HHI by Year	
		1990	2010
City	0.9	1000	1200
Town	0.1	5000	

HHI Statistic	HHI by Year	
	1990	2010
Unbalanced Panel	1400	1200
Balanced Panel	1000	1200

If we use a balanced sample, we only consider the market share in the city - where we have a continuous sample. And market shares then increase - entirely due to the effect in the city. On the other hand if we use an unbalanced sample, then market share decreases, as the highly concentrated town drops out of the sample, completely masking the increased market share in the city. With an unbalanced panel, if an area loses a monopolist, aggregate concentration decreases. This does not occur with a balanced panel.

For example a grocery store may go out of business. This is extremely common in our data at the Zip Code - 6-digit NAICS level. There are approximately 42,000 5-digit zip codes and 1,000 6-digit NAICS industries. Combined, there are 42 million possible markets. In 1999, there were only 5,408,174 active establishments. In 2015, there were 6,786,097 active establishments.⁴¹ Zero market shares are extremely common.⁴²

Figures 8 and 9 compare these two approaches, first using a balanced panel and the second using an unbalanced panel.⁴³ Data at the National and State level look largely identical. Results start diverging at the County or Zip code level. The balanced panel finds small increases in market concentration at the county level and nearly no change in market concentration at the zip code level. The unbalanced panel finds slight decreases at both the county and zip code level. For example, the 4-firm payroll concentration at the zip-code level decreases from 93% to 92%. While there is a slight decrease, this also obscures a related point. If bins are drawn extremely narrowly (such as at the zip code level), concentration will mechanically be extremely high.

Extremely local market concentrations can be misleading. Furthermore, this approach assumes that markets are *mutually exclusive*, without spillovers. Consumers may switch to a store in a neighboring zip code, or buy products from a superstore that combines both groceries and consumer durables. To illustrate this point, consider Hudson County, which includes Hoboken and West New York. It is part of New Jersey, and part of the New York MSA and commuting zone 19600. New York County is across the Hudson river and consists of Manhattan. It is part of New York State, part of the New York City MSA, but part of commuting zone 19400.

⁴¹See US Census Business Dynamics Statistics at https://www.census.gov/ces/dataproducts/bds/data_firm2015.html.

⁴²For example there were 8,721 pawnshops operating in the United States in 2012, but over 42,000 zip codes. Even split between 3,000 counties, many counties will not have a pawn shop.

⁴³Results that vary weights by time period show broadly similar results.

If we use national markets or MSAs, these counties are part of the same market. If we use counties, states, or commuting zone, these counties are part of different markets. The Industrial Organization literature seriously accounts for this, by looking at the cost of distance, in a market-by-market fashion (For an example see Davis, 2006). However this has not been systematically exploited at a macro-economic scale, looking across industries - likely for data availability reasons.

The analysis by Rinz (2018) aims to look at local labor markets finds that as more workers move to dense agglomerations, monopsony power decreases. As a retail worker may switch sectors, but still work within retail, Ritz aggregates data to commuting zones and high-level industry aggregates. The analysis by Rossi-Hansberg et al. (2018) is a bit different. The authors look at market concentrations at the 8-digit level, using a proprietary dataset that claims to include establishment level revenue counts. As such data is quite imprecise, even when using administrative tax data, more work needs to be done to understand the nature of the underlying data set. For example, what happens to internal firm transfers? How are data validated? How is value-added attributed up and down the supply chain?