The Industrial Revolution in Services *

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Abstract

The U.S. has experienced an industrial revolution in services. Firms in service industries, those where output has to be supplied locally, increasingly operate in more markets. Employment, sales, and spending on fixed costs such as R&D and managerial employment have increased rapidly in these industries. These changes have favored top firms the most and have led to increasing national concentration in service industries. Top firms in service industries have grown entirely by expanding into new local markets that are predominantly small and mid-sized U.S. cities. Market concentration at the local level has decreased in all U.S. cities but by significantly more in cities that were initially small. These facts are consistent with the availability of a new menu of fixed-cost-intensive technologies in service sectors that enable adopters to produce at lower marginal costs in any markets. The entry of top service firms into new local markets has led to substantial unmeasured productivity growth, particularly in small markets.

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1. Introduction

Modern production relies on scale: The ability to use a technology to produce the same product or service innumerable times. In manufacturing industries, inventions such as the steam-engine, electricity, and Ford's assembly line allowed firms to scale up production in a single large plant. For many goods, the cost advantages of a larger scale overwhelmed the cost of transporting the goods to final consumers, leading to great reductions in total average costs. This ability to scale up production in a single plant was, however, of little use outside of manufacturing. Producing many cups of coffee, retail services, or health services in the same location is of no value, since it is impractical to bring them to final consumers. Modern large-scale production in these industries had to wait for a different technology, one that allowed firms to replicate cheaply the same production process in multiple locations close to consumers.

We argue that new ICT-based technologies together with the adoption of new management practices have finally made it possible for firms outside of manufacturing to scale up production over a large number of locations. This expansion in the number of markets per firm has been particularly pronounced for the top firms in non-tradable industries and has led to an increase in their national market share; a central fact about the US economy in the last three or four decades documented by Autor et al. (2017). This evolution is the result of a new industrial revolution. One that has taken place in many non-traded service sectors.

Consider Gawande (2012)'s account of how the Cheesecake Factory brought "chain production to complicated sit-down meals." The Cheesecake Factory has invested in technologies that determine optimal staffing and food purchases for each restaurant and each day. The company also has a well-oiled process via which they introduce new items on their menu. This process starts in a centralized "kitchen" in Calabasas, CA – their R&D facility so to speak – where Cheesecake's top cooks cull ideas for new dishes and "figure out how to make each recipe reproducible, appealing, and affordable." The cooks in the R&D facility then teach the new recipes to the kitchen managers of each restaurant at a bi-annual meeting in California. The kitchen managers then follow a finely honed procedure to teach the new recipes to the cooks in each restaurant. The roll out time, from the time the kitchen managers arrive at Cheesecake's central kitchen in California to when the new dishes are put on the menu in each restaurant, is 7 weeks.

The standardization of production over a large number of establishments that has taken place in sit-down restaurant meals due to companies such as the Cheesecake Factory has taken place in many non-traded sectors. Take hospitals as another example. Four decades ago, about 85% of hospitals were single establishment non-profits. Today, more than 60% of hospitals are owned by for-profit chains or are part of a large network of hospitals owned by an academic institution (such as the University of Chicago Hospitals).[1] As an example of the former, consider the Steward Health Care Group. This company was created by the Cerberus private equity fund in 2010 when it purchased 6 Catholic hospitals in Boston. In Gawande (2012)'s account, Cerberus' goal was to create the "Southwest Airlines of healthcare" by figuring out and codifying best practices and implementing these practices over a large scale. Gawande (2012) describes the scene in Steward's remote intensive care unit (ICU) in a Boston suburb that monitors the ICUs in all of Steward's hospitals:

> "Banks of computer screens carried a live feed of cardiac-monitor readings, radiology-imaging scans, and laboratory results from ICU patients throughout Steward's hospitals. Software monitored the stream and produced yellow and red alerts when it detected patterns that raised concerns. Doctors and nurses manned consoles where they could toggle on high-definition video cameras that allowed them to zoom into any ICU room and talk directly to the staff on the scene or to the patients themselves."

Technologies such as the remote ICU has enabled Steward to provide consistent care in all the ICUs in its hospitals. Steward also adopted a common medical data platform in all its hospitals and out-patient clinics.[2] By 2019, Steward had expanded from its 6 original hospitals in Boston to 38 hospitals and 271 outpatient clinics located in 10 states and Malta.[3]

The rise in industry concentration is due to companies similar to the Cheesecake Factory and Steward Healthcare that have adopted technologies that enable them to standardize and scale up the delivery of non-traded *services*. In this sense, what has

[1] The employment-weighted share of multi-establishment hospitals in the Longitudinal Business Database increased from 15% in 1977 to 62% in 2013.

[2] Steward uses software by Meditech. The dominant medical software company is EPIC in Madison, Wisconsin.

[3] Steward's hospitals and out-patient clinics are in Massachusetts, New York, Ohio, Florida, Arkansas, Louisiana, Texas, Arizona, Pennsylvania, New Hampshire, Utah and Malta.

happened in non-traded services is akin to the industrial revolution unleashed by Henry Ford more than a hundred years ago when Ford introduced mass production to a car industry dominated by independent artisans.

We use micro-data from the Longitudinal Business Database from 1977 to 2013, supplemented with sales data at the establishment level from the micro-data of the Economic Censuses from 1977 to 2012, to document six main facts. First, we show that growth in the number of markets per firm has been large and heterogeneous across industries. We measure a market as an establishment, county, zipcode, or a metropolitan statistical area (MSA). The growth in the number of local markets served by a typical firm has been much more pronounced outside the broad construction and manufacturing sectors, but broad sectoral classifications are imperfect. Non-traded service industries that exhibit large expansions in markets per firm can be found in all sectors of the economy, including in sectors that are classified as "manufacturing."

Second, service industries where markets per firm have increased have grown faster than other industries in the U.S. economy. The larger growth is evident for all our definitions of a market and when we use either employment or sales. This evidence is consistent with our view that the rise of markets per firm is driven by forces such as the adoption of new technologies or management practices that ultimately raise aggregate industry total factor productivity (TFP).

Third, industries in which the number of markets per firm has increased also experienced large increases in observable fixed-cost expenditures such as total employment in R&D and headquarter establishments. The measured elasticity of these fixed-costs to establishments per firm across industries is as large as 1.5, and even larger with respect to MSAs per firm.

Forth, the number of markets per firm is driven by the top firms in the industry. For example, in the industries that experienced the fastest growth in markets per firm of the top 1% of firms in an industry expanded the number of markets per firms more than twice as fast as the average firm.

Fifth, the increase in national industry concentration documented by Autor et al. (2017) and others, is driven by the expansion in markets per firms by top firms. National employment and sales concentration, measured by the share of the top 1% or top 10% of firms or by the Herfindahl-Hirschman index (HHI), has risen much more significantly in sectors with higher establishments per firm or MSAs per firm. In fact, more than 100% (155%) of the employment expansion of the top 10% firms in an industry is driven by an increase in the number of establishments, since the average establishment has shrunk over time. When we define a market by as an MSA, this finding is less pronounced but still large: 94% of the expansion of top 10% firms is across MSAs rather than within.[4]

Sixth, the new local markets where top firms enter tend to be smaller. The share of top firms in local employment has grown significantly in small and mid-sized U.S. cities. In contrast, in the very largest U.S. cities, there is no change in the employment share of top firms. The increasing presence of top firms has decreased *local* concentration as the new establishments of top firms gain market share from local incumbents. The share of the top firms in the local market and the Herfindahl-Hirschman index (HHI) has declined throughout the city distribution, but the decline has been much more pronounced for smaller cities.[5]

We use a simple theory of firm size and local market entry to show that a key ingredient of the industrial revolution in services, documentedby our six main facts, are new fixed-cost-intensive technologies that lower the marginal cost of production in all markets served by the firm.[6] The adoption decision of firms involves a trade-off between a proportional reduction in all establishment's variable costs and an increase in the firm's fixed cost. Firms that adopt the new fixed-cost-intensive technology in an industry expand by serving new markets that are now viable due to their lower marginal cost. Top firms, which are more productive, find the trade-off between fixed and variable costs more beneficial and so they adopt the new technology more intensively, which leads to a rise in industry concentration. It also leads to industry expansion relative to industries where these new technologies are less useful or more costly. For example, we show that in industries where goods are easily tradeable and so geographic replication is unnecessary (as in many manufacturing industries), firms adopt these new fixed-cost-intensive technologies less.

The industrial revolution in services has aggregate and local implications that we also corroborate in the data. Since top firms expand by entering new markets and

[4]Similar results hold when we measure expansion based on sales rather than employment.

[5]Using a different dataset (the National Establishment Time Series), Rossi-Hansberg et al. (2018) also find that local concentration has fallen significantly.

[6]Our theory is reminiscent of Gaubert (2018), but it allows firms to serve multiple local markets, as Ramondo (2014) does in an international context. See also Cao et al. (2019) and Oberfield et al. (2020).

these markets tend to be smaller, we see the share of top firms grow particularly in small markets. The increasing presence of top firms has decreased local concentration in local markets as the new establishments of top firms gain market share from local incumbents. We see the share of the top firm and the local Herfindahl-Hirschman index decline everywhere, but the decline is much more pronounced in small cities. Contrary to popular narratives, the entry of these top firms has been accompanied by significantly faster employment growth in small cities. As a result, we see that job destruction due to exit or incumbents' employment decline does not vary much by city size. The larger increase in the share of top firms in most cities, but most markedly in small ones, implies that consumers opted to buy from them and so probably gained from their presence. The gain from entry by top national firms into local markets is not measured in official price statistics because current statistical procedures only measures prices from *incumbent* establishments. Following the methodology in Aghion et al. (2019a), we calculate "missing growth" to be 1.2% per year in the smallest cities, as low as 0.2% in the largest ones, and 0.5% in the aggregate.

Previous work has identified elements of the technological changes we underscore here. Sutton (1991) argues for the presence of new sunk cost technologies and describes their effect on market concentration, although he does not emphasize the increasing geographic scope of firms, nor their resulting specialization. Hortaçsu and Syverson (2015) provide a description of the evolution of concentration and scale in the retail industry consistent with the geographic expansion we emphasize. Holmes (2011) focuses on a single firm (Walmart) and studies its geographic expansion to form a distribution network and inventory system. Similarly, Ganapati (2018) studies the wholesale industry and the expansion of the warehouses and international input use of the top firms. We view these industry studies as examples of the general evolution we document.

It is perhaps hard to set apart a number of concurrent technological changes, all of which are naturally intertwined. Information and communication technology (ICT) started in the 60's with the systematic use of corporate databases, then continued with the invention and rapid adoption of personal computers, electronic communication technologies and the internet, and the invention and subsequent explosion in the use of smartphones.[7] There is a vast literature on the effect of these changes on the or-

[7] See Hobijn and Jovanovic (2001) for the diffusion of ICT technologies.

ganization of production.[8] The form of technological change we emphasize here was certainly enabled by ICT, at least partly, which explains its timing. The examples of fixed-cost based technologies described above all have a component that was facilitated either by better data collection and analysis or by better communication and diffusion of information. It is undoubtedly the case that new business processes that reduce the cost of managing many different establishments require easy communication, as well as cheap data gathering and processing. Managing many hospitals and exploiting the synergies between them would be impractical without the heavy use of ICT-based systems. Thus, ICT is an essential part of the industrialization of services. It is the general purpose technology, as defined by Rosenberg and Trajtenberg (2004), that has enabled the geographic expansion of firms (particularly in retail, services, and wholesale) by allowing them to replicate and control establishments dispersed across space. Perhaps this is where the gains from ICT have been hiding.[9]

Another phenomenon closely related to the new industrial revolution in services is the rise in intangible capital. As Haskel and Westlake (2017) and Crouzet and Eberly (2018) document, intangible investments became increasingly important during the period of our analysis. Intangible investments in marketing, technology, information, or training, all facilitate scale and replication and as such amount to the use of new technologies with higher fixed (or sunk) costs. Hence, the rapid expansion of intangibles is a consequence of the type of technological change we suggest has occurred.

Finally, there is a large recent literature that has interpreted the increase in industry concentration as an indication of the augmented market power of top firms, perhaps facilitated by entry barriers or regulatory capture. This view has been supported by evidence that points to increasing profits and markups (Gutierrez and Philippon, 2017; De Loecker et al., 2018) and a decrease in market dynamism (Decker et al., 2017). Together with a number of other papers in the literature (Autor et al., 2017; Hopenhayn et al., 2018; Syverson, 2019; Edmond et al., 2019), we argue that the industrialization of

[8] A number of papers have studied the way in which ICT has changed the organization of production (Caroli and Van Reenen, 2001), the decentralization of decision making (Bresnahan et al., 2002), the span of control of managers (Rajan and Wulf, 2006; Garicano and Rossi-Hansberg, 2006), and the distribution of firm sizes (Garicano and Rossi-Hansberg, 2004). More recently, Aghion et al. (2019b) study the growth implications of the ability of firms to manage more establishment due to improvements in ICT.

[9] Syverson (2017) argues that if we were mismeasuring the gains from ICT, the high-tech sector would need to be much larger than it is. If ICT is used for fixed costs investments, as we argue, this is not necessarily the case.

services that we document is technological, not institutional. Nevertheless, although we chose to model this process in a world with CES preferences and, therefore, fixed markups, in a model with variable markups these same technological changes could generate increases in markups. We do not focus on this dimension of the industrial revolution of services partly because we do not have the data to estimate markups and partly because we find that the geographic expansion of top firms leads to declines in local concentration, as in Rossi-Hansberg et al. (2018).[10]

The rest of the paper is organized as follows. Section 2 describes the data sets we use and their construction. Section 3 presents our empirical findings organized in six facts. Section 4 presents the theory and derives the implications of the availability of a menu of new technologies offering combinations of fixed and variable costs. Section 5 discusses the implications of the industrial revolution in services for local outcomes and presents computations of its contribution to aggregate and local TFP growth. Section 6 concludes. The Appendix includes more details on our data, a number of additional empirical exercises that establish the robustness of our results, as well as the proofs of propositions in Section 4.

2. Data

Our main dataset is the micro-data from the U.S. Census Longitudinal Business Database (LBD). The LBD is based on administrative employment records of every nonfarm private establishment in the U.S. economy. The establishment-level variables we use are employment, geographic location (county and zipcode), industry (4-digit SIC from 1977 to 2000, 6-digit NAICS from 2001 to 2013, and 6-digit 2002 NAICS code provided by Fort and Klimek (2018) from 1977 to 2013), the establishment's ID, and the ID of the firm that owns the establishment. We restrict the sample to observations from 1977 to 2013 and drop establishments in the public, educational, agricultural, and mining sectors.[11]

We aggregate the 2002 NAICS industry classifications provided by Fort and Klimek (2018) into 445 consistently defined industries from 1977 to 2013. Hereafter, when we

[10]The magnitude of the trend in markups is still controversial. See the discussion in Traina (2018) and Karabarbounis and Neiman (2018).

[11]We also drop commercial banking (2002 NAICS code 522110) because the 1994 Riegle-Neal interstate banking law removed restrictions on interstate banking.

refer to an industry we mean one of these 445 industries. Appendix G provides additional details on Fort and Klimek (2018)'s industry classification and how we aggregate them into our industry codes.

We group counties into metropolitan areas (MSAs) defined based on the 1980 Population Census.[12] For the counties that were not part of an MSA in 1980, we group them into "pseudo-MSAs" corresponding to their respective states. We end up with a total of 329 MSAs. We therefore have four measures of local markets: establishments, zipcodes, counties, and MSAs (based on the 1980 census).

We supplement the LBD with sales data at the establishment level from the micro-data of the Economic Censuses every five years from 1977 to 2012. Specifically, we use the micro-data from the Censuses of Auxiliary Establishments, Construction Industries, Manufacturing, Retail Trade, Services, and Wholesale Trade every five years from 1977 to 2012. We also use the micro-data of Census of Finance, Insurance, and Real Estate every five years from 1992 to 2012 and the Census of Transportation, Communications, and Utilities every five years from 1987 to 2012. We use the establishment ID to match the establishments in the Economic Censuses to the establishments in the LBD. Our final sample from the Economic Censuses are establishments with sales data that are matched to the LBD. Appendix A shows the summary statistics of our samples from the LBD and Economic Censuses.

We use the establishment's firm ID to do two things. First, we use the firm ID to aggregate employment and sales of establishments to a firm in an industry.[13] Second, we use the firm ID to measure employment in establishments that provide R&D and headquarter services for the firm's establishments in a given industry. Specifically, we identify a firm's research and development (R&D) centers and "headquarters" (HQ) as establishments with Fort and Klimek (2018)'s NAICS codes beginning with 54 (R&D) and 55 (HQ) that have the same firm ID. For firms with establishments in multiple industries (outside of R&D and HQ), we split employment in R&D and HQ into the industries served by the firm using the firm's employment share in each industry (omitting employment in R&D and HQ).

[12]https://www2.census.gov/programs-surveys/metro-micro/geographies/reference-files/1983/historical-delineation-files/83mfips.txt

[13]For establishments that are franchises, the firm ID in the LBD refers to the owner and not the franchisee. For such establishments, using the firm ID will understate the share of firms for which franchising is an important margin.

From this data, we calculate the change from 1977 to 2013 in three variables at the industry level:

1. Number of markets (establishment, county, zipcode, and MSA) per firm in an industry. We focus on the number of markets served by an average firm in an industry, by the top 1% of firms, and by the top 10% of firms in the industry, where top firms are defined by the number of markets they serve.

2. Total sales and employment of all firms in an industry and total employment in R&D centers and HQ of these firms.

3. Economic concentration in an industry, measured as the sales and employment share of the top 1% and top 10% of firms in an industry, where the top firms are defined by sales and employment, and the Herfindahl-Hirschman index (HHI) measured by sales and employment.

We weight the variables at the industry level by the Sato-Vartia weights of each industry between 1977 and 2013.[14]

We also calculate changes from 1977 to 2013 of two variables at the MSA-industry level:

1. Employment share in a MSA-industry of top firms, where top is measured by the number of establishments or employment in the industry in *all* MSAs.

2. Employment and sales concentration in a MSA-industry, measured as the employment and sales share of the top firm in the MSA-industry and the employment and sales HHI in a MSA-industry.

We aggregate the variables at the MSA-industry level to the MSA level using the Sato-Vartia weights of the MSA-industry in 1977 and 2013. Appendix A shows the summary statistics of these industry and MSA-level statistics.

[14]The Sato-Vartia weight of industry j is defined as $\frac{\frac{\Delta L_j}{\Delta \log L_j}}{\sum_{k=1}^{J} \frac{\Delta L_k}{\Delta \log L_k}}$ where J denotes the set of industries, L_j denotes employment in industry j, and Δ is the change between 1977 and 2013.

3. Facts

We highlights six facts from the LBD and Economic Censuses data.

Fact 1: Growth in markets per firm has been large and heterogeneous across industries

Our first fact is the increase in the number of markets per firm. The left panel of Figure 1 shows that the number of establishments per firm grew by .093 log points from 1977 to 2013 in the median four digit industry. This increase in establishments per firm was not uniform across industries. The top quintile of industries with the fastest increase in establishment per firms, saw an increase of more than .4 log points in the same period, while the bottom quintile saw a reduction of about .12 log points. The same pattern is evident in the right panel of Figure 1 where we plot the change in the number of MSAs in which a firm is present. Again, we see an increase in the number of MSAs per firm in the median industry between 1977 and 2013, albeit smaller than for establishments, and a large increase of more than .15 log points for the top quintile.[15][16]

Table 1 presents the change in log average markets per firm in each one-digit sector. The expansion in the number of markets per firm was fastest in finance, retail, and "other" services (which includes industries such as business services, restaurants, gyms, and healthcare), and slowest on average in construction and manufacturing. The table presents four different geographic units, going from individual establishments to zip codes, counties, and MSAs. All of these measures show similar patterns. Thus, in what follows, we present results for establishments and MSAs in the main text and relegate results for zipcodes and counties to Appendix B.

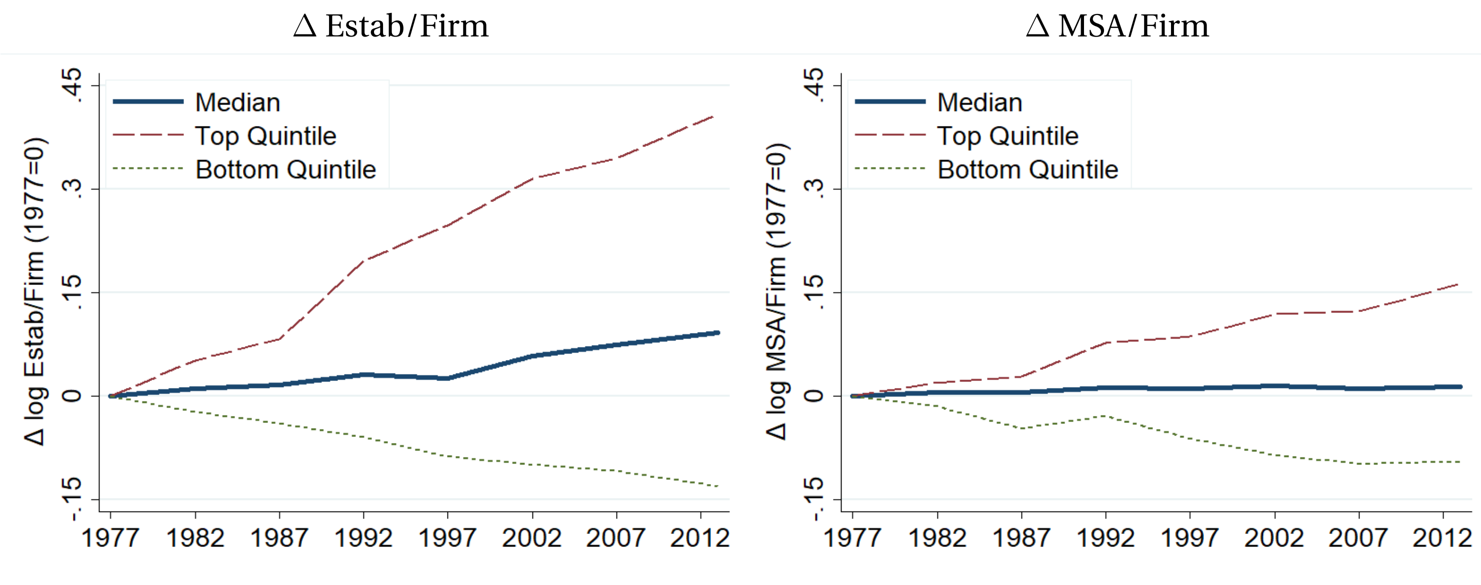
The expansion in the number of markets per firm varies tremendously across broad sectors, but also across industries within them. This can be seen in large standard deviation in the change in markets per firm within one-digit sectors in Table 2.[17] Figure 2 adds

[15]Appendix Figure B1 shows that a similar pattern holds for the number of counties and zipcodes per firm.

[16]Consistent with our findings, Cao et al. (2019) use data from the Quarterly Census of Employment and Wages between 1990 and 2015 to document an increase in the average number of establishments per firm. They also show that the increase is more pronounced for larger firms and in the service sector.

[17]A regression of the change in log establishments per firm of the average firm in a four digit industry on indicator variables for one-digit sector has an R-squared of 0.124. A similar regression of the change in log MSAs per firm on indicator variables for one-digit sector has an R-squared of 0.039.

Figure 1: Δ in log Establishments and MSAs per Firm, 1977-2013



Note: Unit of observation is a 4-digit industry (N=445). Figure shows cumulative change from 1977 to 2013 of log establishment/firm and MSA/firm of the average firm in the median industry, top quintile industry, and bottom quintile industry, weighted by Sato-Vartia employment share of each four-digit industry in 1977 and 2013.

to this evidence by showing the CDF of log changes in markets per firm. It shows that all sectors include some "service" industries where the expansion in the number of markets per firm has been substantial. Naturally, sectors like other services, wholesale, retail, utilities and transportation, and finance include many more of these service industries. For example, in retail about 43% of industries expanded the number of establishments per firm by more than .425 log points between 1977 and 2013. The large heterogeneity within one-digit sectors in the change in markets per firm indicates that it is inaccurate to simply define an industry as a non-tradable service based on the sector to which it belongs. Hence, our approach is to measure whether firms in an industry provide local services using the observed change in the number of local markets per firm between 1977 and 2013. That is, the change in markets per firm will be our metric for the extent to which firms in an industry want to be close to their customers and, therefore, the extent to which they are affected by the industrial revolution in services.

Fact 2: Industries where markets per firm increased grew faster

Fact 1 showed that the average firm in service industries has increased significantly

Table 1: Average and standard deviation of Δ log Markets per Firm by Sector, 1977-2013

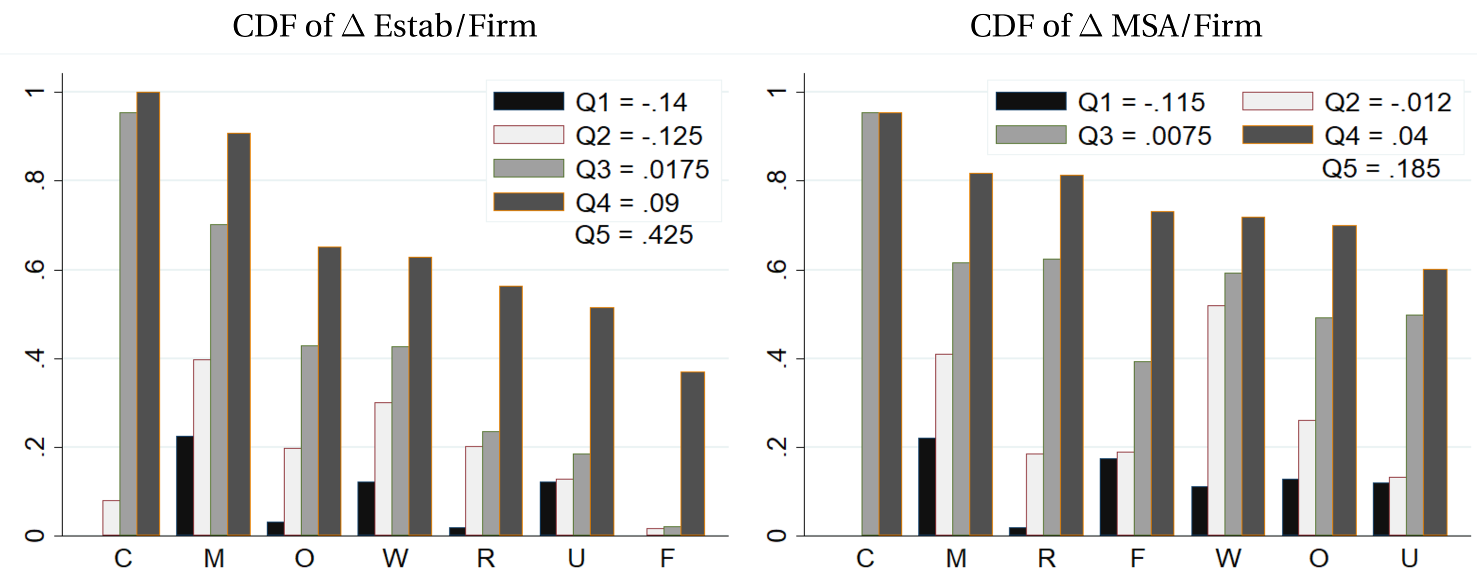
	Estab/Firm	Zipcode/Firm	County/Firm	MSA/Firm
Construction	.016	.017	.015	.012
	(.034)	(.031)	(.028)	(.020)
Manufacturing	.019	.017	.012	.006
	(.141)	(.132)	(.115)	(.089)
Other	.180	.179	.081	.050
	(.229)	(.200)	(.150)	(.094)
Wholesale	.156	.139	.076	.030
	(.248)	(.239)	(.156)	(.084)
Retail	.216	.186	.096	.040
	(.237)	(.185)	(.126)	(.078)
Util and Trans	.172	.275	.101	.070
	(.234)	(.202)	(.180)	(.148)
Finance	.299	.211	.099	.044
	(.215)	(.170)	(.137)	(.109)

Note: Table shows weighted average and standard deviation of Δ log establishment/firm, zipcode/firm, county/firm, and MSA/firm of the average firm in each 4-digit industry *within* each 1-digit sector, weighted by Sato-Vartia average of the employment share of each 4-digit industry in 1977 and 2013.

the number of markets they serve. Our next fact shows that these industries have also expanded in terms of total employment and sales. Figure 3 presents a kernel regression of the relationship between the change in the log of markets per firm and the change in log employment and sales between 1977 and 2013.[18] The left panel uses establishments as the definition of a market, while the right one uses MSAs. The figure shows clearly that these elasticities are significantly positive and roughly similar throughout the range of industries. Furthermore, the results are almost identical for employment and sales. We do note that the number of industries declines substantially, and therefore the standard errors grow, when we look at industries with expansions in the number of establishments per firm larger than .4 log points (.2 for MSAs per firm). Fact 2 implies that the changes experienced by these industries, that motivated firms to expand their number of markets, have also made the industries larger. This expansion is consistent with positive technological innovations in service industries.

[18]The change in log sales is from 1977 to 2012, except for finance (1992 to 2012) and utilities and transportation (1987 to 2012).

Figure 2: Cumulative Distribution of Δ in log Markets per Firm by Sector, 1977 to 2013



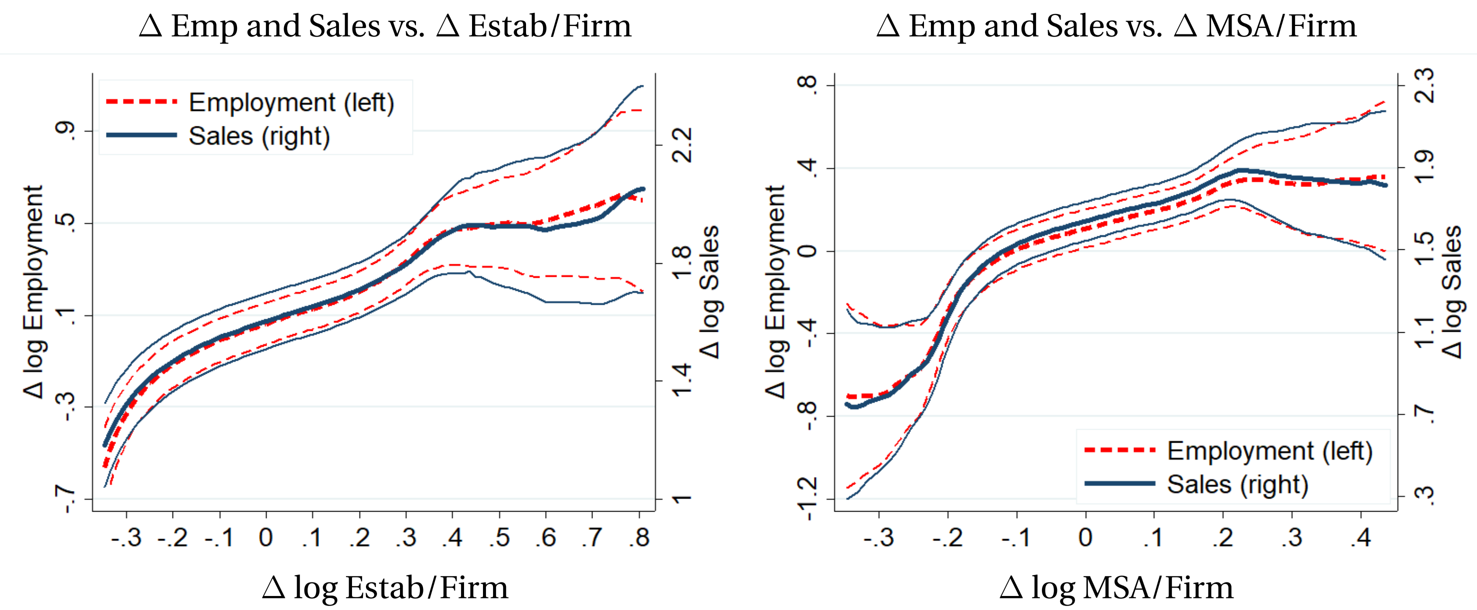
Note: Sectors are manufacturing (M), construction (C), other (O), wholesale trade (W), retail trade (R), utilities and transportation (U), and Finance, Insurance, and Real Estate (F). Figure shows cumulative distribution of the change in log establishments/firm and MSA/firm from 1977 to 2013 across 4-digit industries in each broad sector in quintiles of the change of establishments/firm and MSA/firm (also from 1977 to 2013) across all 445 four-digit industries. Average change in log establishments/firm in each quintile is -.14, -.125, .0175, .09, and .425 in quintiles 1 through 5, respectively. The corresponding change in log MSA/firm in each quintile is -.115, -.012, .0075, .04, and .185. Top quintile is omitted in figure.

Table 4 summarizes the results in Figure 3 when we impose a constant elasticity between the change in log industry employment or sales and the change in log markets per firm. As we noted before, all these elasticities are positive and significant. Both for employment and sales, the elasticity is larger when we define the number of markets using MSAs instead of establishments. This is natural, if the underlying industry change is a technological innovation; expanding across MSAs requires a larger innovation than the one needed to add another local store, and so the innovation also implies a larger expansion of the industry.

Fact 3: Total employment in R&D and headquarter establishments grew in industries where markets per firm increased

Incorporating the technological and management innovations that allow firms to expand the number of markets comes at the cost of increasing fixed production costs. Measuring these costs precisely is hard since the distinction between fixed and marginal

Figure 3: Δ log Industry Employment and Sales vs. Δ log Markets per Firm



Note: Unit of observation is a 4-digit industry (N=445). Figure shows point estimate and 95% confidence interval of non-parametric regression of Δ log total employment or total sales of the industry on Δ log establishments/firm (left panel) and Δ log MSA/firm (right panel) of average firm in the industry. Regressions with employment growth use change from 1977 to 2013 for all variables. Regressions with sales growth are from 1977 to 2012 for sales growth and from 1977 to 2013 for the change in markets/firm, except for utilities and transportation and finance where sales are from 1987 to 2012 and 1992 to 2012 and change in markets per firm are from 1987 to 2013 and 1992 to 2013, respectively.

costs is conceptual and not directly observable. Firm-level fixed costs should include firm expenditures that benefit all establishments, and so are not rival. Two natural examples are a firm's management and its R&D expenditures. Management decisions, as well as new designs or product innovations, can be used repeatedly across establishments without depleting them. Of course, the more useful are these fixed-cost-intensive technologies in lowering the cost of operating local establishments, the more firms will choose to adopt them and increase their observed fixed costs.

Consider again the case of the Cheesecake Factory. Between 2003 and 2018, employment in the company grew rapidly from 14200 to 38100 employees. This tremendous growth was accompanied by a large expansion in the number of establishments, from 61 to 214, which resulted in a reduction in the average number of employees per establishment, from 233 to 178. The evolution of the company headquarters is quite different, though. The number of employees in headquarter establishments, a measure

Table 2: Regression of Industry Growth on Δ log Markets per Firm, 1977-2013

	Δ log Employment	Δ log Sales
Δ log Est/Firm	0.845	1.192
	(0.169)	(0.206)
Δ log MSA/Firm	1.444	2.926
	(0.415)	(0.468)

Note: Unit of observation is a 4-digit industry (N=445). Table shows coefficient estimates and standard errors from weighted regressions of Δ log aggregate employment (column 1) and sales (column 2) in the industry on Δ log establishments/firm (row 1) and MSA/firm (row 2) of average firm in the industry. Columns 1 and 2 are from 1977 to 2013. Sales growth are from 1977 to 2012 and growth in the number of markets per firm are from 1977 to 2013, except for utilities and transportation and finance where sales are from 1987 to 2012 and 1992 to 2012 and change in markets per firm are from 1987 to 2013 and 1992 to 2013, respectively. Weights are Sato-Vartia average of industry employment in 1977 and 2013.

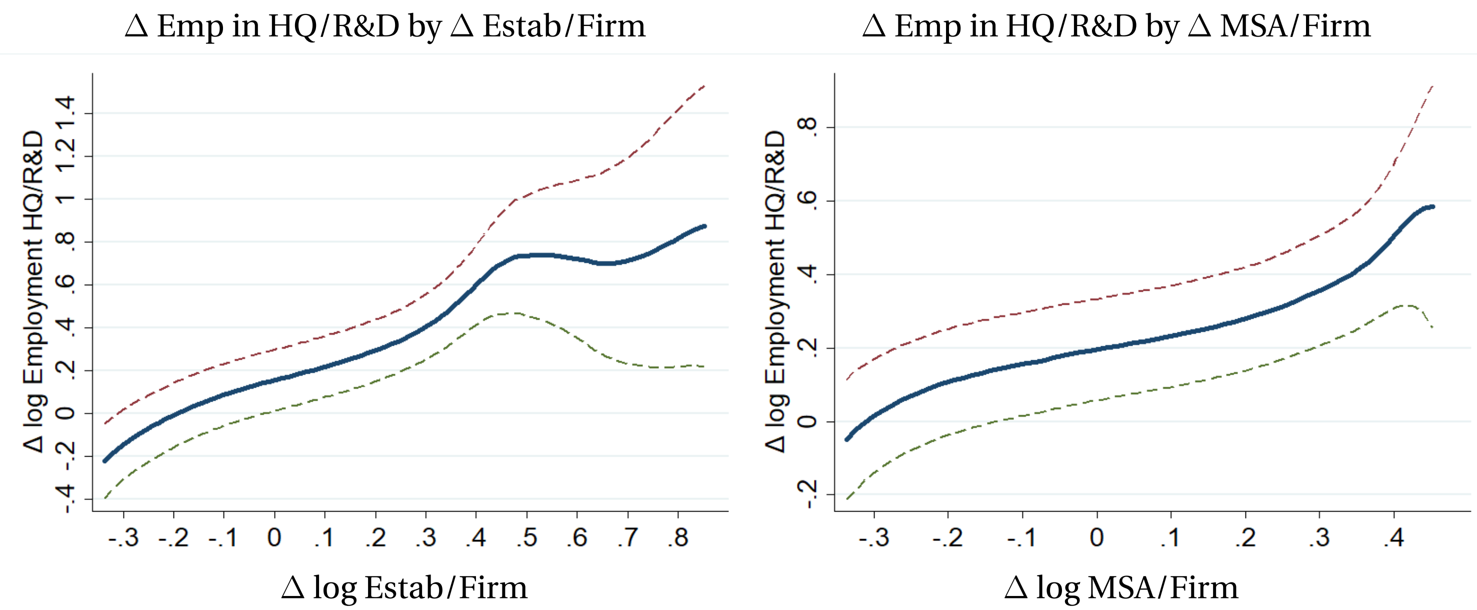
of the firm's fixed costs, grew from 140 to 450.[19] We interpret this large expansion in headquarter employees as the firm's investment in fixed-costs-intensive technologies.

We can measure a firm's employment in establishments classified as doing either R&D or serving as the firm's headquarters (HQ). Figure 4 presents a kernel regression of the relationship between changes in log employment in R&D and HQ establishments serving all firms in an industry against changes in log markets per firm in the industry. It shows that this elasticity is, indeed, positive throughout. Namely, industries where firms were motivated to expand the number of markets rapidly, our service industries, also spent more on these two measures of fixed costs.

Table 3 presents our estimates of the elasticity of fixed costs with respect to markets per firm when we impose the restriction that the elasticity is constant across industries (a reasonable restriction given the results in Figure 4). The table also presents estimates of elasticities for employment in R&D and HQ establishments separately. The elasticity is about the same for these two types of fixed costs, independently of the definition of a market. In contrast, the market definition is important. The elasticity doubles in magnitude when we use MSAs rather than establishments. Again, this is consistent with larger technological or management innovations in service industries motivating

[19]This information comes from the 2003 and 2018 Form 10-K of The Cheesecake Factory Inc.

Figure 4: Δ in log R/D and HQ Employment vs. Δ in log Markets per Firm, 1977-2013



Note: Unit of observation is a 4-digit industry (N=445). Figure shows coefficients and 95% confidence interval of non-parametric regression of Δ log aggregate employment in headquarters and R&D of establishments in an industry from 1977 to 2013 on Δ log establishments (left panel) or MSAs (right panel) per firm of the average firm in the industry from 1977 to 2013. See text for details on how we identify R&D and headquarter establishments of firms in each industry.

firms to expand their presence across cities and not only within them. These larger innovations, in turn, motivate firms to invest more in fixed-cost-intensive technologies in order to reduce the cost of operating in the larger number of markets.

Fact 4: Growth in markets per firm is driven by top firms in the industry

The increase in the number of markets per firm that we have documented so far has been much more pronounced for the top firms in an industry.[20] Here, we measure top firms by the number of markets in which they operate, but defining top firms by total sales or employment yields similar results. Figure 5 presents the non-parametric relationship between the average change in log markets per firm for the top 1% or 10% firms in the industry and the average change in log markets per firm for all firms in an industry. As the figure clearly illustrates, the slope of the positive relationship is larger than one in all cases (the dashed green line is the 45 degree line). Namely, in industries where we see a large expansion in the number of markets per firm on average, we see

[20] Figure C1 in Appendix C shows the change in markets per firm of top firms in the average industry.

Table 3: Regression of Δ in log Employment in HQ/R&D on Δ in log Markets per Firm, 1977-2013

	Δ Emp R&D and HQ	Δ Emp R&D Only	Δ Emp HQ Only
Δ log Estab/Firm	1.491	1.595	1.772
	(0.266)	(0.290)	(0.257)
Δ log MSA/Firm	3.520	3.697	4.052
	(0.667)	(0.728)	(0.648)

Note: Unit of observation is a 4-digit industry (N=445). Table shows coefficient estimates and standard errors from weighted regression of Δ log aggregate employment in R&D and headquarters (column 1), R&D only (column 2), and headquarters only (column 3) of all firms in the industry on Δ log establishments/firm (row 1) and MSA/firm (row 2) of the average firm in the industry, all from 1977 to 2013. See text for details on how we identify R&D and headquarter establishments of firms in each industry. Weights are Sato-Vartia average of the employment share of the industry in 1977 and 2013.

a larger expansion for the top 10% firms, and an even larger expansion for the top 1% of firms. This implies that the increase in the average is driven by the top firms. In fact, in Appendix D we show that the elasticity of markets per firm is large and significantly positive only for firms in the 9th and 10th deciles of the distribution of markets per firm (both for establishments and MSAs).

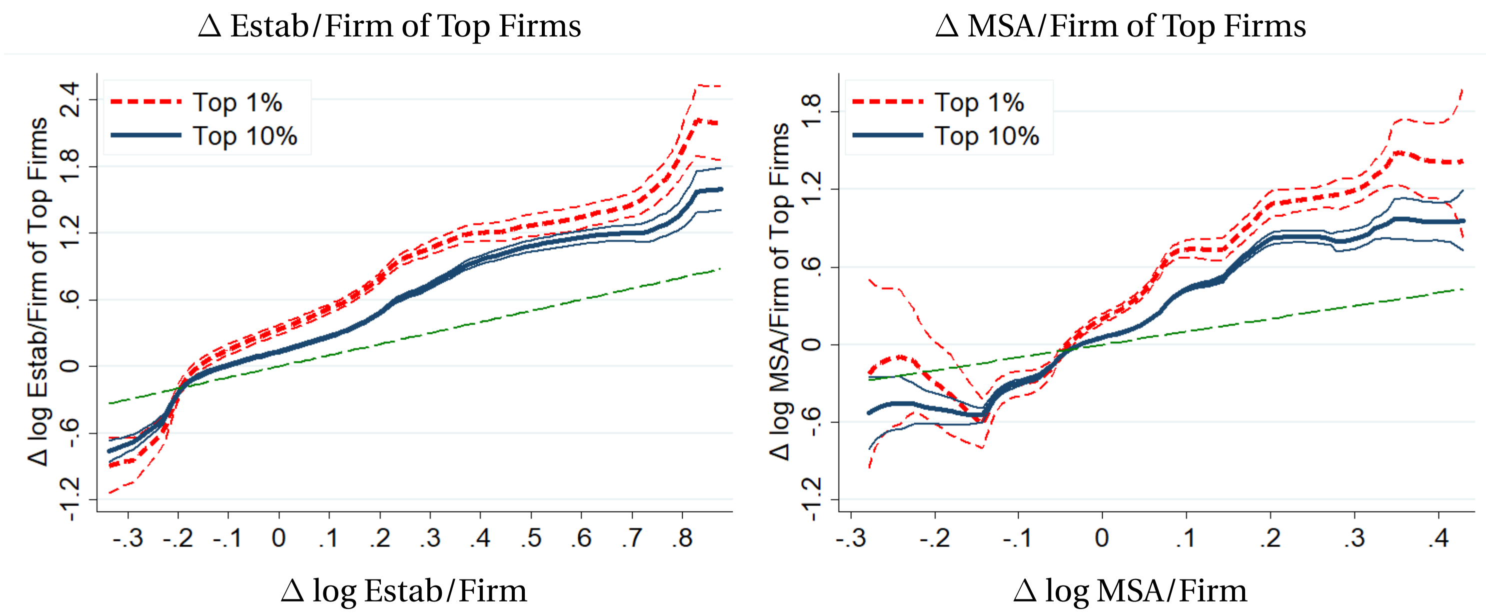
Table 4 present results when we estimate a constant elasticity across industries. The elasticity of establishments per firm for the top 10% firms to establishments per firm for all firms is 2, and grows to 2.4 for top 1% firms. For MSAs per firm, the elasticities are much larger, so growth in MSAs per firms is even more skewed towards the largest firms. The elasticity of MSAs per firm for top 1% firms to MSAs per firm for all firms is as large as 4.5.

Fact 5: The increase in national industry concentration is driven by the expansion of markets per firm by top firms

It is well known that many industries in the U.S. have experienced concentration of employment and sales since the late 70's (as documented by Autor et al. (2017), Rossi-Hansberg et al. (2018) among many others).[21] This increase in concentration is particu-

[21] Figure C2 in Appendix C shows that the employment share of top 10% firms in each industry (measured by employment) increased by almost 0.1 log points between 1977 and 2013. The employment share of top 1% firms increased by about .2 log points over the same period.

Figure 5: Δ in log Markets per Firm: Top Firms vs. All Firms, 1977-2013



Note: Unit of observation is a 4-digit industry (N=445). Top firms defined by number of establishments (left panel) or MSAs (right panel) of the firm. Figure shows point estimate and 95% confidence interval of non-parametric regression of the change from 1977 to 2013 of log establishment/firm or MSA/firm of the top 1% and top 10% firms in the industry on the change in log establishment/firm or MSA/firm of average firm in the industry, also from 1977 to 2013. Green dashed line is the 45 degree line.

Table 4: Regression of Δ in log Markets per Firm of Top Firms on Δ in log Markets per Firm of All Firms

	Δ log Markets per Firm of Top Firms	
	Top 1%	Top 10%
Δ log Estab/Firm	2.309	2.060
	(0.098)	(0.046)
Δ log MSA/Firm	4.343	3.331
	(0.182)	(0.060)

Note: Unit of observation is a 4-digit industry (N=445). Top firms defined by establishments per firm in row 1 and MSA per firm in row 2. Entries are coefficient estimates and standard errors from weighted regression of Δ log establishments per firm (row 1) or MSA per firm (row 2) of top firms in the industry on Δ log establishments/firm (row 1) or MSA/firm (row 2) of average firm in the industry. Weights are Sato-Vartia averages of the industry's employment share in 1977 and 2013.

larly large in service industries where, as we showed in Fact 4, top firms have increased fast the number of markets in which they operate. We show next that the growth in industry concentration is, in fact, mostly due to the growth in markets per firm of top firms. Table 5 presents our estimates for the relationship between employment concentration and the change in log markets per firm. We presents results for three alternative concentration measures (the share of top 1% firms, the share of top 10% firms, and the Herfindahl-Hirschman index, HHI) as well as measures of concentration using either employment or sales. When we use measures of concentration based on employment, the relationship is positive and highly significant. As with other facts, it is larger for MSAs per firm, indicating that cross-city expansion reveals a larger underlying industry level change. The results for sales are also positive and mostly significant, although a bit smaller and more noisy.

Table 5: Regression of Δ Employment and Sales Concentration on Δ in log of Markets per Firm

	Employment Concentration			Sales Concentration		
	Top 1%[1]	Top 10%[1]	HHI	Top 1%[2]	Top 10%[2]	HHI
Δ log Estab/Firm	0.665	0.326	0.086	0.358	0.244	0.053
	(0.062)	(0.023)	(0.014)	(0.072)	(0.026)	(0.022)
Δ log MSA/Firm	1.317	0.592	0.104	0.679	0.477	0.089
	(0.161)	(0.062)	(0.036)	(0.168)	(0.062)	(0.051)

[1] Top 1% and 10% of Firms by Employment.
[2] Top 1% and 10% of Firms by Sales.
Note: Unit of observation is an industry (N=445). Entries are point estimates and standard errors of weighted regression of the change in employment concentration (log share of top 1%, log share of top 10%, and HHI in columns 1-3) or sales concentration (log share of top 1%, log share top 10%, and HHI in columns 4-6) on the change in log markets/firm (establishments in row 1 and MSA in row 2) of the average firm in each industry. Employment based concentration regressions use 1977 to 2013 for all variables. Sales based concentration regressions use the change from 1977 to 2012 for concentration and 1977 to 2013 for growth in markets per firm, except for utilities and transportation and finance where concentration changes are from 1987 to 2012 and 1992 to 2012 and change in markets per firm are from 1987 to 2013 and 1992 to 2013, respectively. Weights are Sato-Vartia average of employment share of the industry in 1977 and 2013.

The change in the employment share of the top firms in an industry can be decomposed into the contribution of the relative growth in the number of markets per firm of the top firms and the change in the relative average employment size of these markets for top firms. For example, if we define a market as an MSA, the decomposition is given by

$$\Delta \log \frac{L_{top}}{L} = \Delta \log \frac{\#MSA_{top}}{\#MSA} + \Delta \log \frac{\frac{L_{top}}{\#MSA_{top}}}{\frac{L}{\#MSA}}. \tag{1}$$

The first term in equation 1 is the contribution from growth in the number of MSAs of the top firms and the second term is the contribution from changes in employment per MSA of the top firms (both relative to all firms in the industry). The first two columns of Table 6 show the results of this decomposition for the relative number of establishments vs employment per establishment (row 1) and relative number of MSAs vs. employment per MSA (row 2).[22] The last two columns show the same decomposition using sales rather than employment. The first rows shows that average employment per establishment of top firms *falls* by more than .5 log points, and that average sales per establishments of top firms falls by almost .3 log points. Thus, necessarily, more than 100% of concentration growth has to come from the increase in the number of establishments served by the top firms. The second row shows that, for MSAs, most of the growth in concentration also comes from growth in the number of cities served by top firms. Only about 6% of the growth in concentration comes from increased employment per city, and about 21% comes from increased sales per city.

Figure 6 plots the non-parametric relationship between changes in concentration, as measured by the change in the log employment share of top 10% firms, and changes in the log number of markets of top 10% firms relative to all firms (left panel) or changes in the log average size per market of top 10% firms relative to all firms (right panel). The slopes of both curves in the left panel of Figure 6 are positive, indicating that in industries where top firms have expanded the most, they have done so by expanding geographically through more establishments, or by reaching more MSAs. Note that the slope increases as we adopt narrower definitions of a market. It is the smallest for MSAs and the largest for establishments. The right panel shows that the opposite is true for changes in employment per market. Namely, the relationship with the change

[22]Specifically, the first two columns of Table 6 show the decomposition of the Variance of $\Delta \log \frac{L_{top}}{L}$ into the Variance of $\Delta \log \frac{\#Estab_{top}}{\#Estab}$ and the Variance of $\Delta \log \frac{\frac{L_{top}}{Estab_{top}}}{\frac{L}{\#Estab}}$ where the contribution of the covariance between the last two terms is equally split between the two terms.

Table 6: Δ Share of Top 10% Firms by Employment or Sales: Number of Markets vs. Average Size

	Employment Share		Sales Share	
	Markets	Size	Markets	Size
Establishments	1.522	-0.522	1.289	-0.289
	(0.092)	(0.092)	(0.094)	(0.094)
MSA	0.941	0.059	0.789	0.211
	(0.072)	(0.072)	(0.073)	(0.073)

Note: Unit of observation is a 4-digit industry (N=445). Column 1 ("Markets") shows point estimates and standard errors from a regression of Δ log MSA or Establishments of top 10% firms (measured by employment) relative to all firms from 1977-2013 on Δ log employment share of top 10% firms from 1977-2013. Column 2 ("Size") shows the results from regression of Δ log employment per MSA or establishment of top 10% firms relative to all firms from 1977 to 2013 on the same independent variable. Columns 3 and 4 show similar regressions using the Δ log sales share or Δ log sales per MSA or establishment of the top 10% firms measured by sales. The change in sales are from 1977 to 2012, except for utilities and transportation and finance where the change are calculated from 1987 to 2012 and 1992 to 2012, respectively.

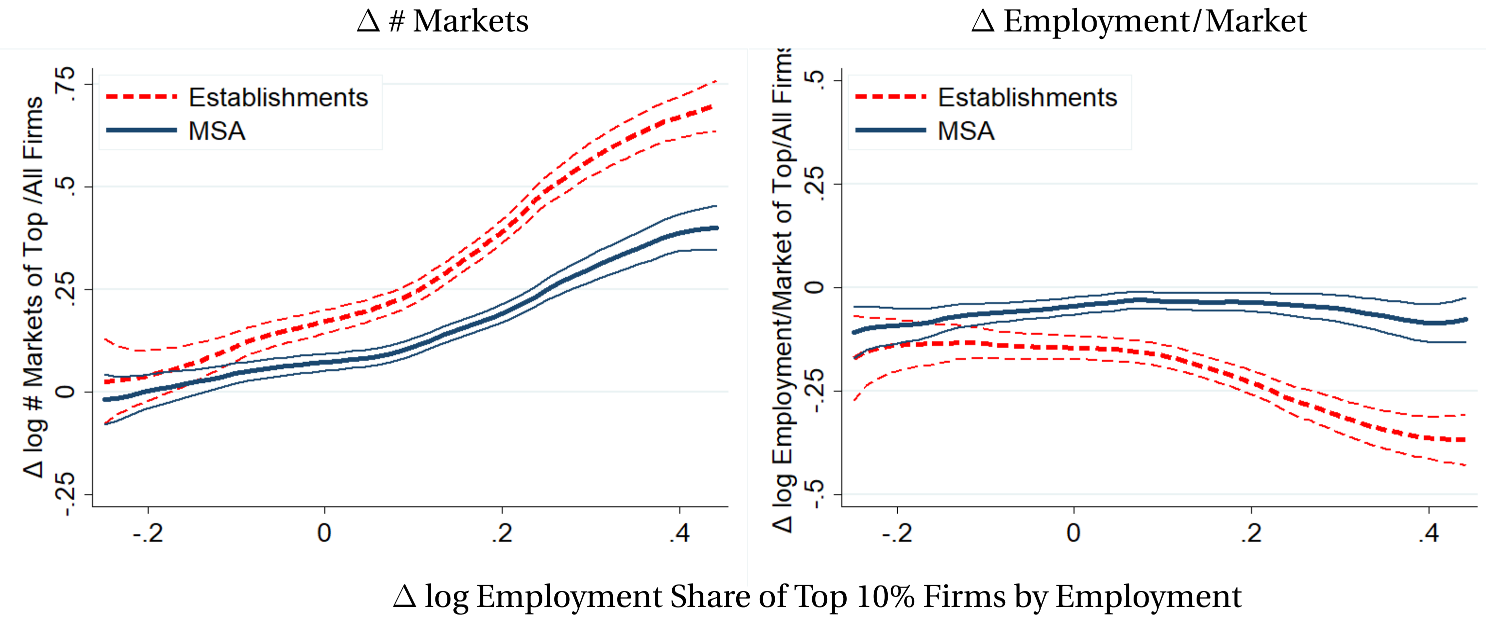
in employment of top firms is negative. In sum, these results show that the variation in the change in concentration across industries is entirely driven by variation across industries in the expansion of top firms into new markets.

Fact 6: Top firms have expanded their presence in small MSAs.

We have shown that the number of markets per firm has increased on average and, particularly, in non-traded service industries. We have also shown that this increase is accompanied by an expansion in industry employment and sales as well as by an expansion in HQ and RD employment. Furthermore, the expansion is driven by the top firms in the industry, and has generated increases in employment and sales concentration. We now ask *where* have these top firms added new markets.

Table 7 probes for evidence that top firms have expanded into smaller and more marginal local markets. Specifically, we measure the size of the local market as total employment (in all industries) in the MSA. The size of a *firm's* local market is then the average size of *all* the local markets in which a given firm has an establishment. Table 7 shows the regression of Δ log size of the local market of a top firm in the industry relative to the size of the local market of an average firm in the industry on Δ log employment

Figure 6: Growth of Top Firms: Number of Markets vs. Average Size



Note: Unit of observation is a 4-digit industry (N=445). Top firm defined as top 10% in an industry measured by employment. Figure shows point estimate and 95% confidence interval of non-parametric regression of Δ log # Markets of top firms relative to all firms (left panel) and Δ log employment/market of top firms relative to all firms (right panel) against Δ log employment share of top 10% firms in the industry, all from 1977-2013. A market is an establishment or a MSA.

share of the top 10% firms (measured by employment) in the industry (both are calculated from 1977 to 2013). The first column defines a top firm as the top 10% of firms in an industry as measured by their employment; the second column defines a top firm as the top 10% of firms as measured by the number of establishments. Table 7 shows that the elasticity of the change in the relative size of the market of top firms with respect to the change in the market share of top firms is negative and precisely estimated. So top firms on average expand by entering into *smaller* MSAs.[23] Of course, the expansion patterns of specific industries might look different. For example, Holmes (2011) shows that Walmart grew by expanding into new local markets that are typically close to its headquarters and *larger* than its existing markets.

We next directly show the employment share of top national firms in each MSA in 1977 and 2013. Figure 7 plots the average share of employment of the top 10% national

[23] Table B6 in the appendix shows that the same pattern holds when a local market is defined as a county or a zipcode.

Table 7: Δ Market Size of Top 10% Firms

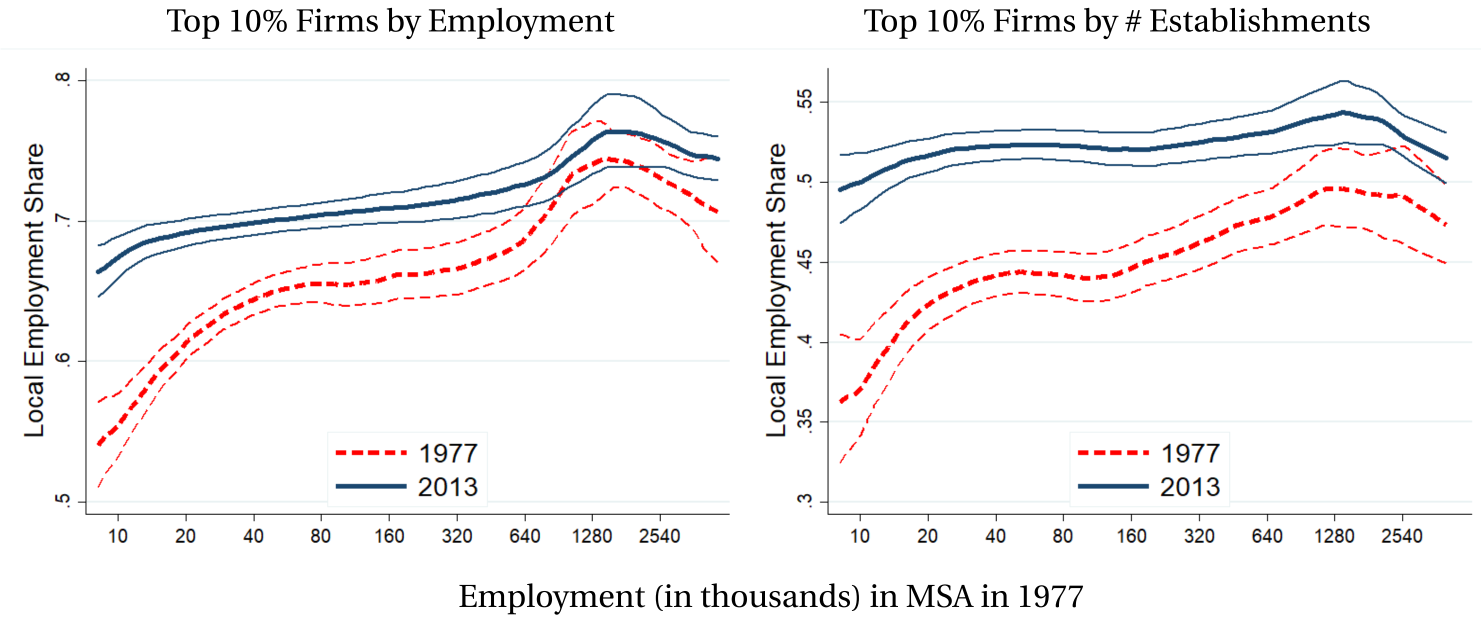
	Top 10% Firms *by* Employment	Top 10% Firms *by* Estab/Firm
Δ MSA Size of Top Firms/All Firms	-0.262	-0.059
	(0.065)	(0.014)

Note: Unit of observation is a 4-digit industry (N=445). Market size of a firm is total employment (in all industries) in the MSA, averaged across all the MSAs in which the firm operates. Top firms in an industry defined by employment (column 1) or # of establishments (column 2). Column 1 shows weighted regression of Δ log of the ratio of market size of top 10% firms to the market size of average firm in the industry on Δ log employment share of the top 10% firms. Column 2 shows weighted regression of Δ log of the ratio of the market size of top 10% firms to the market size of the average firm in the industry on Δ log establishments per firm of the top 10% firms in the industry. All variables are from 1977 to 2013. Weights are Sato-Vartia average of industry employment in 1977 and 2013.

firms in an industry in each MSA by total employment of the MSA in 1977. The left panel defines top firms by their industry employment, while the right panel defines top firms by the number of establishments, as we have done above. In 1977, this share was markedly lower in small cities than in large ones. In contrast, by 2013, the presence of top firms varies significantly less across markets. Small cities in 1977, like Missoula, MT (employment 19 thousand in 1977) have seen enormous entry of establishments of top firms, while large cities such as Washington DC (employment 1.2 million in 1977) have seen no significant increase in the share of top firms operating in the city. Clearly, top firms have increased the number of markets per firm by entering much more aggressively into small cities. The observed changes in the share of top firms between 1977 and 2013 are extremely large, the share of top 10% firms has increased by about 15 percentage points for the smallest cities, but not at all for the largest ones (independently of the measure of top firm we use).

Put together, these fact paint, we believe, a consistent picture. The industrial revolution in services has affected service industries by providing fixed-cost-intensive technologies that lower the cost of operating in individual geographic markets, particularly for high productivity firms in the industry. These firms, the top firms, have expanded the number of markets in which they operate. This expansion is accompanied by an overall increase in the size of the industry, an increase in industry national concentration, as

Figure 7: Local Employment Share of Top 10% Firms



Note: Unit of observation is a MSA (N=329). Top 10% firms defined by total employment (left panel) or number of establishments (right panel) in the industry (and in all MSAs in the country). Figure shows coefficients and 95% confidence intervals of non-parametric regression of the weighted average of the employment share of the top 10% firms in each MSA-industry in 1977 or 2013 on the log of employment in the MSA in 1977. Weights are Sato-Vartia average of the industry in each MSA in 1977 or 2013.

well as more investments in fixed costs as measured by employment in R&D and HQ establishments. The expansion of top firms has made them enter more marginal markets in smaller cities. We now propose a formal model that makes more precise this narrative about the nature and implications of the industrial revolution in services.

4. A simple model of firm size and market entry

Our aim in this section is to propose a simple theory of firm production decisions that is rich enough to speak to the facts in the previous section. The main purpose of the theory is to define precisely a form of technological change and trace its implications. This new technology is, we believe, a useful abstract description of the innovations that have driven the large secular changes we have documented in the U.S. economy between 1977 and 2013.

4.1. The model

Consider a firm i that produces a non-traded service j. The firm uses plants to produce in different locations n, out of a continuum of locations with mass N. The price of service j in location n is given by p_{jn}. Assume that the only way to serve market n is to put an establishment there. A firm pays a fixed cost F_j (in units of the numeraire) to produce service j and another fixed cost f (in units of the numeraire, but index by the local wage w_n) to set up an establishment in market n. The firm's productivity $a_{ijn}A_{ij}$ has two components, one that applies to its establishments in all locations, and one that is idiosyncratic to the market, a_{ijn}, and helps account for firm idiosyncratic entry patterns.[24] Labor is the only factor of production, so a firm that hires L_{ijn} units of labor produces $Y_{ijn} = a_{ijn}A_{ij}L_{ijn}$ units of output with local revenues given by $R_{ijn} = p_{jn}a_{ijn}A_{ij}L_{ijn}$.

Now suppose that demand is CES and firms compete monopolistically. The profit maximizing price is $p_{jn} = E_n Y_{ijn}^{-\frac{1}{\sigma}}$, where $\sigma > 1$ is the constant elasticity of substitution across varieties within an industry and E_n is a function of local real industry expenditure and the local industry price index determined in the spatial equilibrium. Conditional on serving market n, profit maximizing employment in the local market is given by

$$L_{ijn} = \left(a_{ijn}A_{ij}\right)^{\sigma-1}\left[\left(1-\frac{1}{\sigma}\right)\frac{E_{jn}}{w_n}\right]^{\sigma}. \tag{2}$$

The firm will serve market n if local profits are positive, which is the case when the firm's productivity A_{ij} is above a threshold α_n defined by

$$A_{ij} \geq \alpha\left(f_{in}, w_n, E_{jn}\right) \equiv \left(\frac{f}{\tilde{\sigma} a_{ijn}^{\sigma-1} w_n^{1-\sigma} E_{jn}^{\sigma}}\right)^{\frac{1}{\sigma-1}}, \tag{3}$$

where $\tilde{\sigma} \equiv (\sigma-1)^{\sigma-1}/\sigma^{\sigma}$. Hence, the firm is more likely to enter a market where its local productivity a_{ijn} is higher, wages w_n are smaller, and total real expenditures E_{jn} are larger. Also, firms enter more markets the smaller the local fixed cost f.

Suppose the distribution of a firm's α_{in} is given by a cumulative distribution function

[24] Alternatively we could make the firm's local fixed cost idiosyncratic to explain idiosyncratic entry across markets.

$\Gamma(\cdot)$ with density $\gamma(\cdot)$. This distribution $\Gamma(\cdot)$ is determined by parameters, the set of available markets, the distribution of idiosyncratic local productivity a_{ijn} which we assume is i.i.d. across firms, and the joint distribution of E_n and w_n, which is determined in equilibrium. The latter distribution is determined by the distribution of amenities, productivity, housing and other geographic factors, as well as a variety of other mobility and trade frictions. Here, we stop short of specifying a fundamental model of the distribution $\Gamma(\cdot)$ to gain generality and simplify the exposition. For concreteness, Appendix K7 provides a parametric example.

Now consider the decision of the firm to enter industry j. The firm will enter if total profits from industry j are greater then zero, namely,

$$\int_{n \text{ s.t. } A_{ij}>\alpha_{in}} \left[\tilde{\sigma}\left(a_{ijn}A_{ij}\right)^{\sigma-1} w_n^{1-\sigma} E_{jn}^{\sigma} - f\right] dn - F_j > 0,$$

where $\alpha_{in} \equiv \alpha(f_{in}, w_n, E_{jn})$ is defined in (3). The profits of a firm that enters industry j are given by

$$\Pi\left(A_{ij}, F_j, f, \Gamma\right) = \int_0^{A_{ij}} \left(\left(\frac{A_{ij}}{\alpha}\right)^{\sigma-1} - 1\right) f\Gamma\left(d\alpha; f\right) - F_j. \tag{4}$$

which is increasing in firm productivity, A_{ij}, and decreasing in industry fixed costs, F_j (and in local fixed costs, f, through their effect on $\Gamma(\cdot)$). Thus, denote by $\underline{A}\left(F_j, f, \Gamma\right)$ the unique productivity level such that $\Pi\left(\underline{A}\left(F_j, f, \Gamma\right), F_j, f, \Gamma\right) = 0$. Active firms in industry j are such that $A_{ij} \geq \underline{A}\left(F_j, f, \Gamma\right)$.

4.2. A menu of new technologies

Sutton (1991) argues new sunk-cost-intensive technologies leads to market concentration. We now borrow this idea and examine the effect of a menu of new technologies that increases the fixed costs of producing a given service in exchange for a reduction in the variable cost (and, for now, leaves the fixed cost of creating plants, f, constant). We consider a menu of new technologies indexed by h, where adopting the new technology h results in an increase in fixed costs to $h^{\eta}F_j$ and an increase in productivity to hA_{ij}, for $h \geq 1$ and $\eta > 0$. The old technology is given by $h = 1$. We start by showing that, for a given h, the most productive firms are the ones that adopt the new technology and expand by entering new markets. All proofs are relegated to the Appendix K.

Proposition 1 *Given the distribution* Γ*, there exists a threshold* $H(F_j, f, \Gamma, h, \eta) > 0$ *such that if* $A_{ij} \geq H(F_j, f, \Gamma, h, \eta)$ *then firm* i *adopts the new technology. Thus, in equilibrium the highest productivity firms use the new technology and the lowest productivity ones (if active) use the old technology. Firms that adopt the new technology are larger in employment and sales and enter more markets.*

Now consider the case when firms can choose the level of $h \geq 1$. Assume that $\eta > \sigma - 1$, so the profit function is concave in h. It is easy to show that more productive firms will choose technologies with higher h. They also adopt more the more useful is the technology, parameterized by a lower η.

Proposition 2 *Given the distribution* Γ*, if a firm with productivity* A *chooses a technology* $h(A)$*, then firms in the same sector with technology* $A' \leq A$ *chooses technology* $h(A') \leq h(A)$*. That is,* $h(\cdot)$ *is a weakly increasing function. Furthermore, there exists a threshold* η_0 *such that if* $\eta < \eta_0$*,* $h(A) > 1$ *and strictly increasing in* η *for all* A*.*

We can also show that the new menu of technologies results in more industry concentration, with a relative expansion of top firms into new markets relative to the average firm in the industry. Furthermore, these effects will be heterogenous across industries with different η.

Proposition 3 *Given the distribution* Γ*, the menu of new technologies increases industry concentration and the number of markets of the most productive firms relative to average firms. It also increases average employment per market. The effects are more pronounced for small values of* η*, with no effect if* η *is sufficiently large.*

4.3. A technology that reduces local fixed costs too

The model above implies that the advent of the new technology results in increases in an adopter firm's average employment in a market. This prediction is consistent with the evidence if we interpret a market as a city (MSA). However, it is counterfactual if we interpret a market as a single establishment, where employment and sales of the average establishment of an adopter firm falls. To generate declines in the average size of adopters we need to allow the new menu of technologies to reduce local fixed costs as well.

Suppose that the new menu of technologies is as before but, in addition, local fixed costs are now given by $fh^{-\varphi}$. The exponent $\varphi > 0$ determines the extent to which fixed costs decline with the new chosen technology h. The exponent should depend on the definition of a market. For a large geographic area we might think that the cost did not change much beyond the overall firm fixed costs, and so $\varphi = 0$. For a smaller area, like the one covered by a single establishment, $\varphi > 0$, due to the ease in replicating standardized establishments (as exemplified by companies like Starbucks). The next proposition shows that if local fixed costs fall sufficiently the minimum and average establishment size declines.

Proposition 4 *Given the distribution of markets Γ, if the new technology also reduces local fixed cost to $fh^{-\varphi}$, the minimum employment size of the firm's establishments falls, and average establishment size falls if, conditional on η, φ is large enough.*

4.4. Non-traded services vs. traded goods

The fundamental difference between firms producing non-traded services vs. firms producing traded goods (as in many manufacturing industries) is that the former have to deliver their services locally, while the latter can ship goods at a relatively low cost from a distance. This allows traded good producers to concentrate in one (or a few) large plants that supply many locations. In the extreme case when transporting manufacturing goods is free, the firm will produce in only one location. The model above then applies to traded good industries but with firms that produce in a single location and so pay local fixed costs only there. Namely, the profits of a firm i in a traded good industry j are given by

$$\max_m \int_n \left[(A_{ij} a_{ijm})^{\sigma-1} \tilde{\sigma} w_m^{1-\sigma} E_{jn}^{\sigma} \right] dn - f - F_j > 0,$$

which can be written in terms of the distribution $\Gamma(\cdot)$ as

$$\max_m \int \left(\frac{A_{ij}}{\alpha} \right)^{\sigma-1} \left(\frac{a_{ijm}}{w_m} \frac{w_n}{a_{ijn}} \right)^{\sigma-1} f\Gamma(d\alpha; f) - f - F_j.$$

Firms choose their location optimally, so $\frac{a_{ijm}}{w_m} \geq \frac{w_n}{a_{ijn}}$, with equality when n is the preferred location. Hence $\left(\frac{a_{ijm}}{w_m}\frac{w_n}{a_{ijn}}\right)^{\sigma-1} > 1$. Perhaps not surprisingly, since firms in traded industries do not expand by adding new plants, the menu of new fixed-cost-intensive technologies is less relevant for them. The new technologies encourages productive firms in non-traded service industries to reach more costumers by adding additional establishments, a margin that is not present for firms producing traded goods since they can already reach all consumers. Thus, conditional on their initial sales and fixed costs, service firms invest in the new technologies more intensively compared to traded goods firms.

Proposition 5 *Conditional on sales and fixed costs, firms in traded goods industries adopt the new technologies less intensively than non-traded service firms.*

4.5. New technologies and industry expansion

Consider now industries that vary in the level of fixed costs needed to implement the new technologies, namely η_j. We assume that agents have nested CES preferences with elasticity of substitution across industry consumption bundles given by $\rho > 1$. Because of CES preferences across industries with elasticity of substitution greater than one, given the distribution of wages, the industry price index will fall with the adoption of the new technology, and aggregate industry quantities and sales will increase more than proportionally. This implies, for η_j small and given the distribution of wages and local price indexes, that industry expenditures in all markets increase, and so does total industry employment. In contrast, when η_j is large, firms do not invest and the industry does not change. The implication is that the advent of the menu of new technologies increases employment and sales in industries with low η_j.

Proposition 6 *Given the distribution of local wages, w_n, and price indexes, P_n, if η_j is sufficiently low such that $h_j(A_{ij}) > 1$ for some i, and $\rho > 1$, then industry sales and employment are decreasing in η_j.*

Put together, these results show that a menu of new fixed-cost-intensive technologies naturally generates firm behaviour consistent with the facts associated with the new industrial revolution in services that we documented in the previous section. We now turn to study some of the implications on local markets.

5. Implications and evidence for local markets

In the previous section, we show that top firms that take advantage of new technologies for delivering non-traded services grow by expanding into new local markets. Furthermore, these new local markets are typically smaller. In this section, we examine the effect on local markets of the entry of top national firms.

5.1. Top firm entry and local market concentration

The increasing presence of top firms, particularly in the smallest cities, allows local residents to access new varieties of good and services. In the model we presented in Section 3, the local employment and sales share of firm i producing product j in market n is given by

$$s_{ijn} = \frac{a_{ijn} A_{ij}^{\sigma-1}}{\int_{i \in \mathcal{I}_{jn}} \left(a_{ijn} A_{ij}\right)^{\sigma-1} di}$$

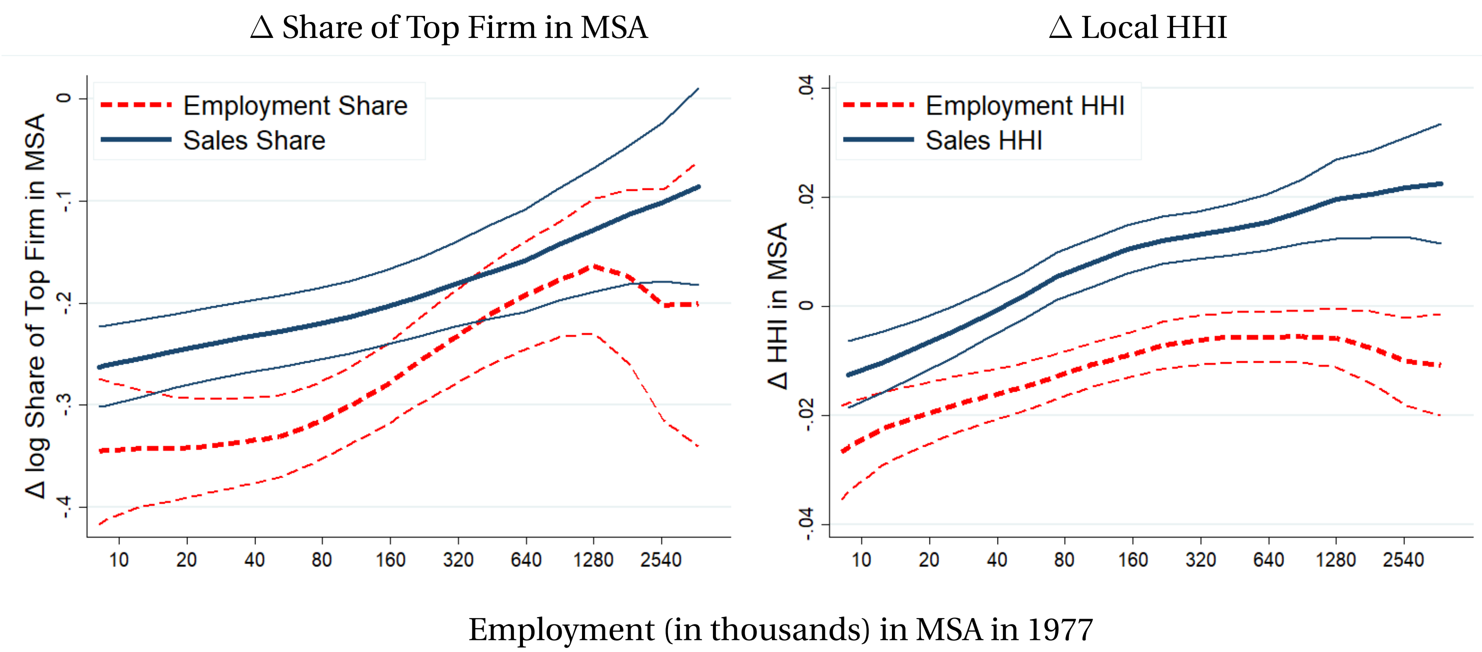
where $\mathcal{I}_{jn}$ is the set of producers of good j in market n. Employment or sales shares depend directly on the relative productivity of firms in a market. Top firms gain large market shares when they enter since they tend to be more productive than local incumbents. Consistently, Figure 7 shows that the share of top firms increased significantly in small and mid-sized local markets.

Within each market, however, we also see the share of the largest firm in each industry-city falling everywhere and particularly in cities that were small in 1977. Specifically, we calculate the change in the log employment and sales share of the top firm in each industry and city from 1977 to 2013, and then take the weighted average across all the industries in a city.[25] Figure 8 (left panel) plots the change in the average employment or sales share of the top firm in the MSA-industry against the size (total employment) of the city in 1977. The log employment share of the top firm in each industry-city declined by about 20% between 1977 and 2013 in the largest cities and by about 35% in the smallest ones. For sales the decline is 25% in the smallest cities and about 10% in the largest ones. The figure suggests that top firms entering new markets gained market share by competing with local providers that had very large market shares themselves. Rather

[25] We use Sato-Vartia employment weights for each industry-city in 1977 and 2013 to aggregate across all the industries in a given MSA that exist in the two years.

than seeing new top firms monopolizing the new markets where they enter, we see top firms taking away some of the market share of local monopolists (or oligopolists).

Figure 8: Δ Local Concentration from 1977 to 2013 by MSA Size in 1977



Note: Unit of observation is a MSA (N=329). Figure shows point estimate and 95% confidence intervals of non-parametric regression of weighted average of the change in the log share (of employment or sales) of the top firm (left panel) or HHI (also employment or sales) (right panel) in each industry-MSA from 1976 to 2013 on the log of total employment in the MSA in 1977. Weights are the Sato-Vartia average of the employment share of each industry-MSA in 1976 and 2013.

The right panel in Figure 8 shows the average change in the Herfindahl–Hirschman Index (HHI) in each MSA between 1977 and 2013. Here we calculate the HHI for each industry in the MSA as the sum of the squares of the employment or sales share of each firm in the industry in the MSA, and take the weighted average using Sato-Varia-weights of the change in this index between 1977 and 2013 across all industries in the MSA present in the two years. Local employment concentration has fallen across MSAs of all sizes. This is consistent with the evidence in Rossi-Hansberg et al. (2018) that shows the diverging trends between increasing national and decreasing local product market concentration. Furthermore, as is the case with the share of the top local firm, the fall in the local HHI is particularly pronounced in smaller cities where top firms have entered more. For sales, we also see a decline in MSA HHI for the smallest cities, but an increase for the largest ones. The pattern across cities is similar, but the level of the change is significantly larger.

5.2. Introducing new products to local markets

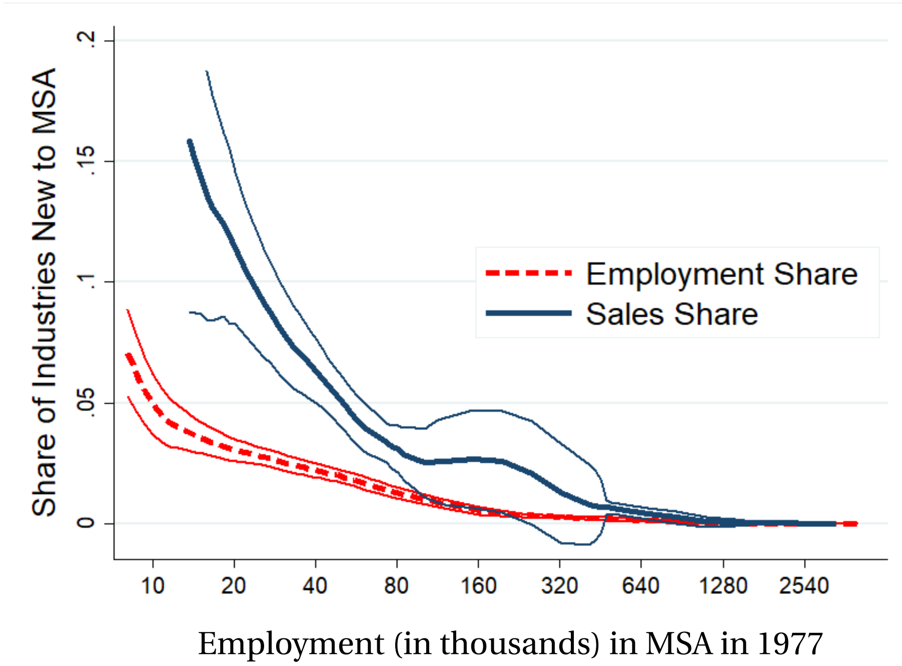
Top firms can come to new markets to compete with local producers, as we showed above, but they also introduce new products into these markets. Figure 9 shows the local share of employment and sales in 2013 of top firms in industries that were not present in 1977.[26] That is, it measures the extent to which top firms are responsible for bringing new industries to particular cities. The employment share of new industries in 2013 is as large as 7% for the cities that were among the smallest in 1977, but negligible for the cities among the largest in 1977. The sales share of new industries in 2012 in the smallest cities in 1977 is even larger at almost 15%, while again is zero for the largest cities in 2012. Hence, not only are top firms changing the distribution of market shares, s_{ijn}, by changing the local distribution of productivities and potentially adding new varieties, but they are also changing the set of industries available in a market. Of course, in our model, both margins increase consumer welfare since agents exhibit "taste for variety" modulated by the parameter σ for varieties within an industries and ρ for products across industries.

5.3. Local markets employment implications

The entry of top firms, particularly in small cities, can generate new employment in those locations, or mostly replace current employment by simply redistributing existing workers to the top firms. In our framework, an additional top firm can never reduce total employment in an industry-city since we are assuming an elasticity of substitution between varieties greater than one, $\sigma > 1$. The extent to which employment in the aggregate increases as a result of the entry of top firms depends on the elasticity of local population to local real wages. In turn, this depends on mobility costs, preference heterogeneity, and other characteristics of the moving behavior of agents that we have not fully specified. In any case, our hypothesis and model suggest that small cities that have seen the bulk of the increase in top-firm-establishment entry should have

[26]The sales data excludes finance and utilities and transportation as the micro-data for these industries are not available in the 1977 Economic Censuses.

Figure 9: Employment and Sales Share of New Industries



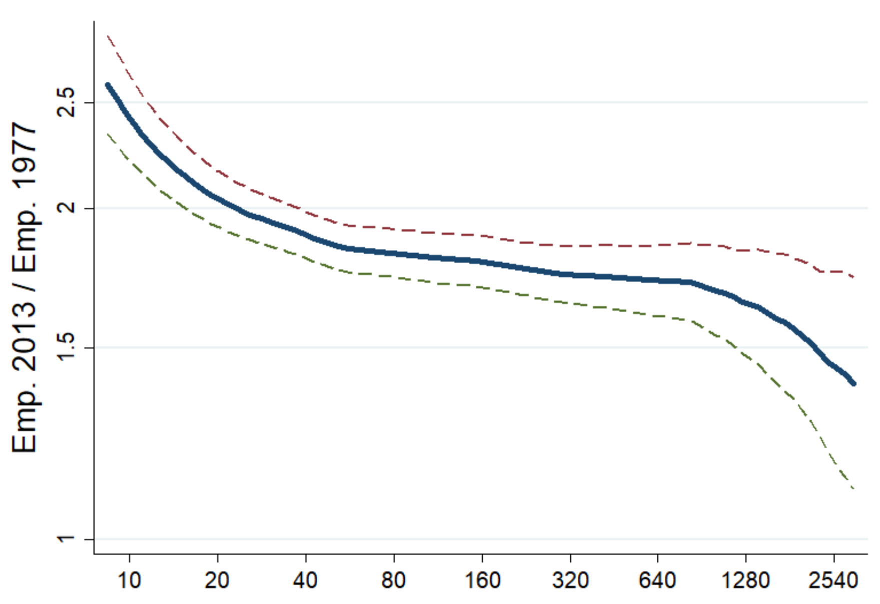
Note: Unit of observation is a MSA (N=329). Figure shows coefficients and 95% confidence intervals from non-parametric regression of employment or sales of top firms in industries new to the MSA in 2013 (employment) or 2012 (sales) as a share of total MSA employment or sales on total MSA employment in 1977. New industries in MSA are industries not in the MSA in 1977. Top firms are top 10% firms in each industry in 2013 (employment) or 2012 (sales). Sales share excludes finance and utilities and transportation.

grown faster than larger ones since the late 70's. Figure 10 shows that this is indeed the case. On average, the smallest cities in 1977 such as Missoula, MT (employment of 19 thousand in 1977) doubled their size between 1977 and 2013, while the largest cities such as New York increased by only 35%. The documented scale dependence in employment at the MSA level over this long period is a violation of Gibrat's Law, that states that city growth is independent of city size.[27] The secular changes that resulted from the industrial revolution in services are a likely culprit.

The entry of top firms can potentially have negative implications for some local residents if it leads to job destruction and exit by incumbents. In turn, these forces can potentially be compensated or overwhelmed by overall local employment growth, particularly in small cities were employment growth was faster, as documented in Figure

[27]In the literature Gibrat's law has been established using population data, not employment as in Figure 10. See for example Gabaix and Ioannides (2004).

Figure 10: Local Employment Growth by City Size

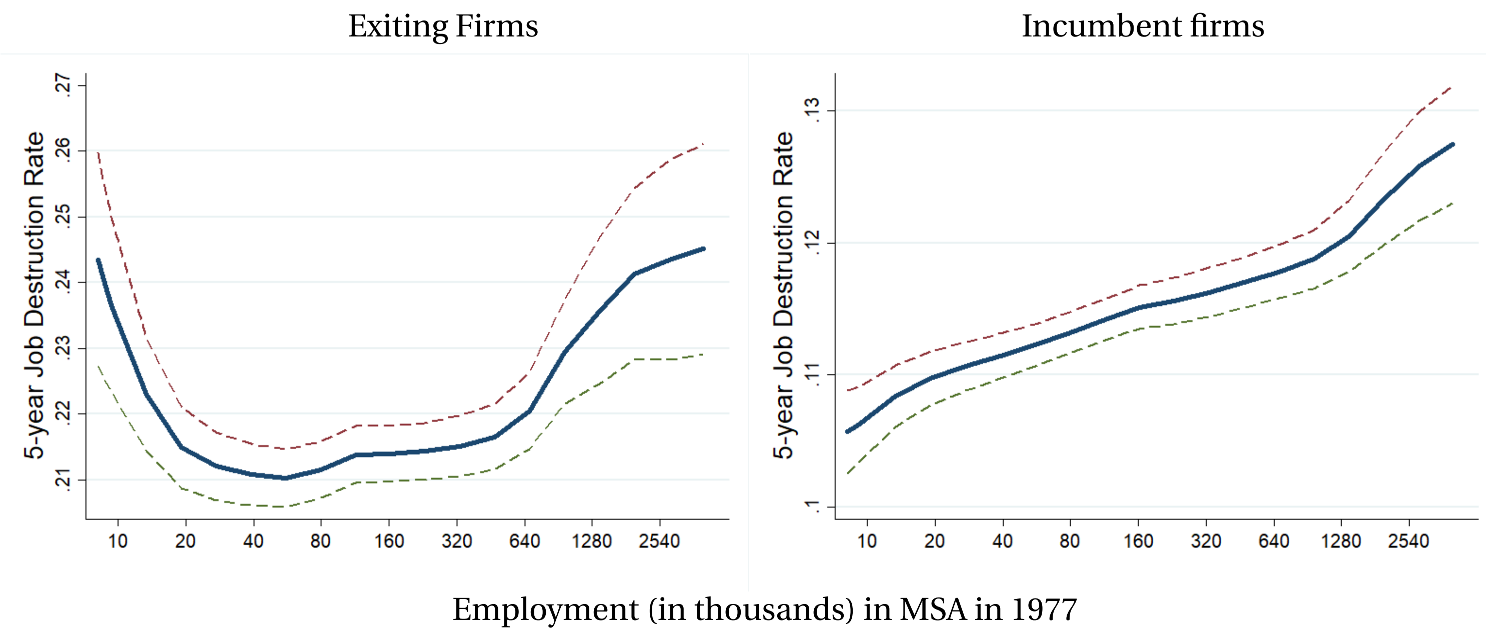


Note: Unit of observation is a MSA (N=329). Figure shows coefficients and 95% confidence intervals from non-parametric regression of ratio of total employment in the MSA in 2013 to employment in the MSA in 1977 (on y-axis) against total employment in the MSA in 1977 (on x-axis).

10. The implications of the industrial revolution in services for job destruction and its variation across cities of different sizes is, therefore, ambiguous. Figure 11 plots the average 5-year job destruction rate between 1977 and 2013 as a function of city sizes at the beginning of the sample.[28] The left panel plots job destruction due to firms that exit the MSA, while the right panel plots job destruction due to shrinking employment in incumbent firms in the MSA. Perhaps surprisingly, job destruction does not seem to vary much by initial city size and, if anything, the relationship is positive when we look at MSAs with more than 20 thousand jobs in 1977. That is, there is more job destruction due to exit and incumbent downsizing in large rather than in small cities.

[28] Following Davis and Haltiwanger (1992), we measure the job destruction rate by exiting firms between t and $t+1$ as the ratio of employment at time t of firms that exit the MSA by $t+1$ to the average of total employment in the MSA in t and $t+1$. The job destruction rate of incumbent firms between t and $t+1$ as the ratio of employment losses of firms in the MSA that shrink between t and $t+1$ to the average of total employment in the MSA in the two years.

Figure 11: Job Destruction Rate by MSA Size



Note: Unit of observation is a MSA (N=329). Figure shows point estimates and 95% confidence intervals of non-parametric regression of job destruction rate in each MSA calculated over five-year periods from 1977 to 2013 from exiting firms (left panel) and incumbent firms that shrink (right panel) in each five-year period on total employment in the MSA in 1977. Job destruction rate calculated as total jobs lost from exiting firms or shrinking incumbent firms as a share of the average of total employment in the MSA in the beginning and end of each five year period.

5.4. Missing growth and the industrial revolution in services

We now estimate the implications of the technological revolution in the service sector for TFP growth. Aggregate TFP in locality n is defined as $TFP_n = Y_n/L_n = R_n/(P_nL_n)$. In the data, employment L_n and nominal expenditures R_n can be easily measured, but measuring prices P_n is complicated since it requires the prices per unit of quality of goods and services sold in each market. These complications are particularly salient for the service industries, where quality adjusted prices are notoriously hard to measure. In the service sector, the BLS measures the price of real output as the price of a well-defined service in the same establishment. However, we have shown that the growth of top firms in the service sectors is entirely driven by entry of top firms into new markets. As argued by Aghion et al. (2019a), quality growth due to firm entry into new markets is not measured by the BLS.

We use Aghion et al. (2019a)'s procedure to measure the growth not captured by the BLS due to entry of new establishments. We differ in that we measure missing growth in each location, and then aggregate missing growth across all locations. As we mentioned in Section 4, utility of the representative consumer in n is given by

$$U_n \equiv \left(\int_{j \in \mathcal{J}_n} Q_{jn}^{\frac{\rho-1}{\rho}} \, dj \right)^{\frac{\rho}{\rho-1}}$$

where $\mathcal{J}_n$ is the set of industries present in location n, which can change over time. Q_{jn} is consumption of varieties of industry j, which are aggregated according to

$$Q_{jn} \equiv \left(\int_{i \in \mathcal{I}_{jn}} Y_{ijn}^{\frac{\sigma-1}{\sigma}} \, di \right)^{\frac{\sigma}{\sigma-1}}$$

where $\mathcal{I}_{jn}$ is the set of firms in industry j in location n, which again can change over time.

Following Feenstra (1994), the growth rate (denoted by $\widehat{\ }$) of the ideal price of Q_{jn} between t and $t+1$ is

$$\widehat{P}_{jn,t} = \widehat{P}_{jn,t \,|\, i \in \mathcal{I}_{jn,t}} - \frac{1}{\sigma - 1} \widehat{s}_{jn,t \,|\, i \in \mathcal{I}_{jn,t}} \tag{5}$$

where $\mathcal{I}_{jn,t}$ denotes the set of *incumbent* firms in industry j in locality n between t and $t+1$ and $s_{jn,t \,|\, i \in \mathcal{I}_{jn,t}} \equiv \int_{i \in \mathcal{I}_{jn,t}} s_{ijn} \, di$ is the sales share of the incumbent firms in industry j in locality n. The first term in equation 5 is the growth in the ideal price of the varieties produced by incumbent firms in the locality. Since the BLS collects prices from incumbent firms in a location, this term in theory is captured by official price statistics. The second term in equation 5 is the change in the price index due to the entry of new establishments into the local market, which is *not* measured by the BLS. The resulting bias is given by the change in the nominal sales share of the *incumbent* firms in sector j in location i multiplied by $1/(\sigma - 1)$. Since they did not have sales data, Aghion et al. (2019a) proxy the sales share by the employment share. In our case, we will use the sales data from the Economic Censuses to measure the change in the sales share of incumbent firms, $\widehat{s}_{jn,t \,|\, i \in \mathcal{I}_{jn,t}}$. Specifically, for each industry in a location over each 5 year period, we measure "missing growth" from firm entry in a location-industry as the product of $1/(\sigma - 1)$ and the change in the log sales share of incumbent firms in each industry in the city over the 5 year period.

Aggregating across all the products in a city and using equation 5, the growth rate of the aggregate local price in n between t and $t+1$ is then given by

$$\widehat{P}_{n,t} = \underbrace{\int_{j \in J_{n,t}} \beta_{jn,t} \widehat{P}_{jn,t \,|\, i \in \mathcal{I}_{jn,t}} dj}_{\text{measured by BLS}} - \underbrace{\frac{1}{\sigma - 1} \int_{j \in J_{n,t}} \beta_{jn,t} \widehat{s}_{jn,t \,|\, i \in \mathcal{I}_{jn,t}} dj}_{\substack{\text{missing growth} \\ \text{new varieties}}} - \underbrace{\frac{1}{\rho - 1} \widehat{s}_{n \,|\, j \in J_{n,t}}}_{\substack{\text{missing growth} \\ \text{new industries}}} \tag{6}$$

where $\beta_{jn,t}$ is the Sato-Vartia weight of industry j and $J_{n,t}$ the set of incumbent *industries* in location n in t and $t+1$. The first term in equation 6 is the Sato-Vartia weighted average of the growth in prices by incumbent establishments in the incumbent products (the first term in equation 5). The last two terms are not measured by the BLS and capture the effect of entry into the local market on the price index. The second term is the Sato-Vartia weighted average of missing growth due to the entry of new varieties for the incumbent industries (the second term in equation 5). The third term is missing growth term from entry of new *industries* into the local market. As shown in Figure 9, top firms also create brand new service industries in the cities they enter, and this effect is larger in smaller cities. This effect is the last term in equation 6, which is the change in the sales share of the incumbent industries multiplied by $1/(\rho - 1)$. Total missing growth in a local market is the sum of missing growth due to entry by top firms into incumbent industries and into industries that are new to the city.

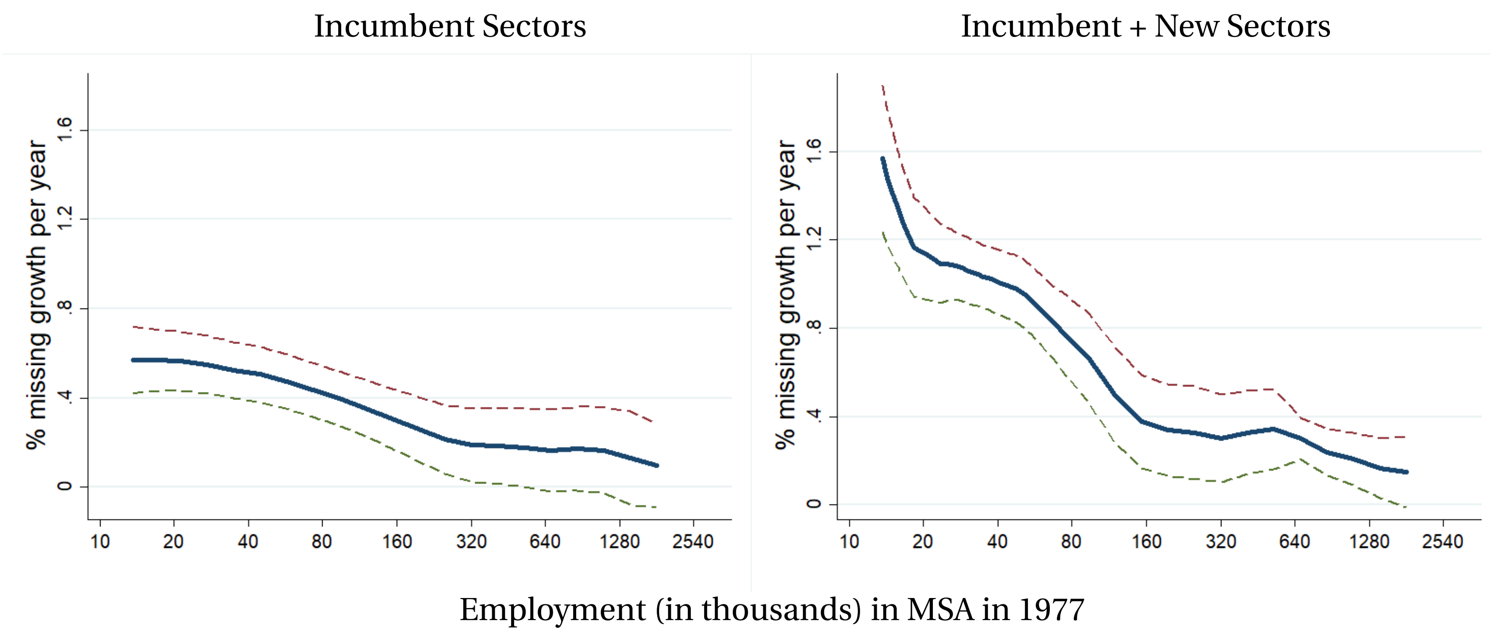
Figure 12 presents the resulting estimates of missing growth for each MSA based on sales data from the Economic Censuses every five years between 1977 and 2012.[29] We limit the industries to those with micro-data on sales over this entire period.[30] The unit on the y-axis is the average annual growth rate per year in each MSA between 1977 and 2012 missed by BLS. The left panel displays missing growth only from industries that were present in the MSA throughout each five year period (the second term in equation 6). Missing growth due to entry of top firms into local markets in incumbent industries is 0.6% per year in small cities but only 0.1% in the largest ones. The right panel in Figure 12 adds to the missing growth in the incumbent industries the contribution of missing

[29]We assume $\sigma = 3$ and $\rho = 2$.

[30]We omit finance and utilities and transportation. The micro-data for the former is only available starting in 1992 and for the latter starting in 1987. Figure J1 in the Appendix shows missing growth for *all* industries (including finance and utilities and transportation) based on employment data in the LBD.

growth due to the local entry of establishments in new industries (third term in equation 6). According to this calculation, the BLS' procedures understate TFP growth by 1.6% per year in the smallest U.S. cities and by a more modest 0.2% per year in the largest cities. Top firms have not brought new industries to the largest cities; they have always been there, so missing growth in large U.S. cities is all due to entry into incumbent industries.

Figure 12: Local Missing Growth by MSA Size



Note: Unit of observation is a MSA (N=329). Figure shows the coefficients and 95% confidence intervals from non-parametric regression of the average annual missing growth from 1977 to 2012 in the MSA due to entry of top firms into incumbent sectors in the MSA (left panel) and all sectors in the MSA (right panel) on total MSA employment in 1977. Missing growth is calculated for each five year period from sales data using equation 6. Incumbent sectors are present in MSA at the beginning and end of each five year period. New sectors are in the MSA at the end but not at the beginning of each five year period. Establishments in finance and utilities and transportation are excluded.

Finally, after we aggregate missing growth across all MSAs, aggregate missing growth due to the entry of top firms into local markets averaged 0.5% per year from 1977-2012. To be clear, our estimates of "missing growth" only capture the effect of entry of top firms in a locality in a 5 year period. New establishments of top firms could have grown post-entry, and this growth in theory is measured by the BLS. But, of course, it is an open question whether the BLS' procedures capture quality growth in incumbent service sector establishments.

5.5. A discussion on markups

Our data does not allow us to measure markups or profits of top firms that enter into new local markets. In the model in Section 4, the markup of all firms is constant at $\sigma/(\sigma-1)$. Of course, the number of entrants and the scale of production vary so that total firm profits cover establishment and firm level fixed costs in each industry where the firm is active. Hence, if firm-industry fixed costs have risen and firms are paying more local fixed costs to open establishments in more locations, total fixed cost paid by top firms must have risen as well. These fixed costs could take the form of investments in intangibles such as marketing, information technology, and worker training. This is consistent with the evidence in Haskel and Westlake (2017) that investment in intangibles has risen in the U.S. in the period we study. Furthermore, in Fact 3 in Section 3 we showed that employment in headquarters and R&D has grown in industries where firms have expanded the number of establishments per firm. Our mechanism also implies that profits by top firms must also have increased to pay for these fixed costs, which is consistent with the evidence in Barkai (forthcoming). In short, an integral part of our hypothesis is the industrial revolution in services leads to rising investments in fixed costs, some of which could be intangibles, and rising profits by top firms.

Of course, our monopolistic competition model with fixed markups could be extended to incorporate firms with variable markups. In such models, dominant firms in a market could take advantage of local consumers by rising prices, particularly if other competitors have exited or cannot produce similar products. However, in most models with variable markups, profits would fall in markets where the top firm has a smaller employment share and market concentration in terms of the HHI index has fallen. Vogel (2008) presents a model of a local market where firms can position their product (by, for example, choosing their location) and choose their price. It shows that, if the dispersion in firm productivities is not too large, the unique sub-game perfect Nash equilibrium exhibits firm profits that are proportional to local population size and quadratic in market share. The result is that total local profits are proportional to the HHI index, which we have shown has fallen, especially in small cities. Most models of variable markups produce similar results.

6. Conclusion

Over the last four decades the U.S. economy has experienced a new industrial revolution that has enabled firms to scale up production over a large number of establishments dispersed across space. The adoption of these technologies has particularly favored productive firms in non-traded service industries.

The industrial revolution in services has had its largest effect in smaller and mid-sized local markets. Top non-traded service firms have expanded into small local markets, but have always been present in the largest US cities. Over the last four decades, small and mid-sized US cities saw the largest declines in local concentration and the highest growth rate of employment. The gain to local consumers from access to more, better, and novel varieties of local services from the entry of top firms into local markets is not captured by the BLS. We estimate that such "missing growth" is as large as 1.6% in the smallest markets, and averages 0.5% per year from 1977 to 2013 across all U.S. cities. Although quite large, this number is *not* an estimate of the full effect of the industrial revolution in services on aggregate TFP. To provide one we would also need to estimate productivity growth of top firms after they enter into each local market, as well as estimate the effect of entry of top firms on competition and markups in each local market.

We leave two important questions for future work. First, it is important to establish more precisely what this new technology is. We know it has been implemented by hiring more workers in headquarters and RD establishments. The timing of these trends also suggests that general purpose innovations in information and communication technologies have probably facilitated these fixed-cost based sectoral innovations. We gave some examples in our narrative in the introduction about the Cheesecake Factory and the Steward Health Care Group, but that only scratches the surface. We believe that a blend of quantitative and narrative accounts of this new industrial revolution, in the style of Chandler (1993)'s seminal work on the history of the industrial revolution in U.S. manufacturing, would be very useful.

Second, the industrial revolution in services has implications on the employment of workers of different skills across locations. If labor markets are industry specific and local, the decline in local concentration of employment caused by the entry of top firms should reduce the monopsony power of employers in small markets. However, as we have argued, the revolution in services implies a relative shift from employment of workers in local establishments to workers needed for the firm-wide fixed cost investments. The fixed costs are likely to be skilled-worker intensive and can be located anywhere. Hence, top firms may choose to hire workers performing them in large and skill abundant cities. Drawing out some of these implications more fully seems potentially fruitful.

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Appendix to "The Industrial Revolution in Services"

(Not for publication)

May 12, 2021

A Summary Statistics

Table A1 presents the total number of establishments, firms, employment, and sales in the LBD and the Economic Census.

Table A1: Aggregate Summary Statistics, 1977 and 2013

	1977	2013
Longitudinal Business Database		
Establishments	4.1	6.6
Firms	3.4	5.1
Employment	65	110
Economic Censuses		
Establishments	3.1	5.8
Firms	2.6	4.3
Sales	3.6	30.2

Note: Establishments, firms, and employment in millions. Sales in trillion current dollars. The Economic Censuses are for 1977 and 2012 (not 2013) and only include establishments with sales data matched to the LBD. The economic census for utilities and transportation starts in 1987 and for finance in 1992; summary statistics for the economic censuses in 1977 do not include these two censuses.

Table A2 presents the summary statistics at the industry level, which are establishments per firm, MSAs per firm, and employment and sales based concentration measures for the average four digit industry.

Table A3 shows the summary statistics at the MSA level, which are the employment share of top national firms (defined as the top 10% measured by number of establishments or by employment) in the MSA, the share of the top firm in an industry in the MSA, and the local Herfindahl index in an industry in the MSA.

Table A2: Industry Level Summary Statistics, 1977 and 2013

	1977	2013
Establishments/Firm		
Average Firm	1.3	5.3
Top 1% Firm (by # Establishments)	15.3	32.4
Top 10% Firm (by # Establishments)	3.5	5.3
MSA/Firm		
Average Firm	1.2	1.2
Top 1% Firm (by # MSAs)	8.6	11.9
Top 10% Firm (by # MSAs)	2.5	2.9
Employment Concentration		
Share of Top 1% (by Employment)	28%	32%
Share of Top 10% (by Employment)	65%	69%
HHI	.035	.039
Sales Concentration		
Share of Top 1% (by Sales)	29%	42%
Share of Top 10% (by Sales)	69%	78%
HHI	.068	.070

Note: Unit of observation is an industry (N=445). Data on establishments/firm, MSA/firm, and employment concentration are from the LBD. Data on sales concentration are from the Economic Censuses. Sales concentration is for 1977 and 2012 (not 2013) and only include establishments with sales data matched to the LBD. The economic census for utilities and transportation starts in 1987 and for finance in 1992; we exclude these two censuses in the sales concentration calculations for 1977.

B Counties and Zipcodes as Markets

In the main text of the paper we used establishments and MSAs to measure the local market served by a firm. In this section we show the main results using zipcodes and counties as alternative measures of local markets. Figure B1 presents the weighted average across four digit industries of the change in log zipcode per firm (left panel) and county per firm (right panel), where the weights are the Sato-Vartia average of the employment share of each industry. The figure also presents the change in zipcode per firm and county per firm of an industry in the top and in the bottom quintile.

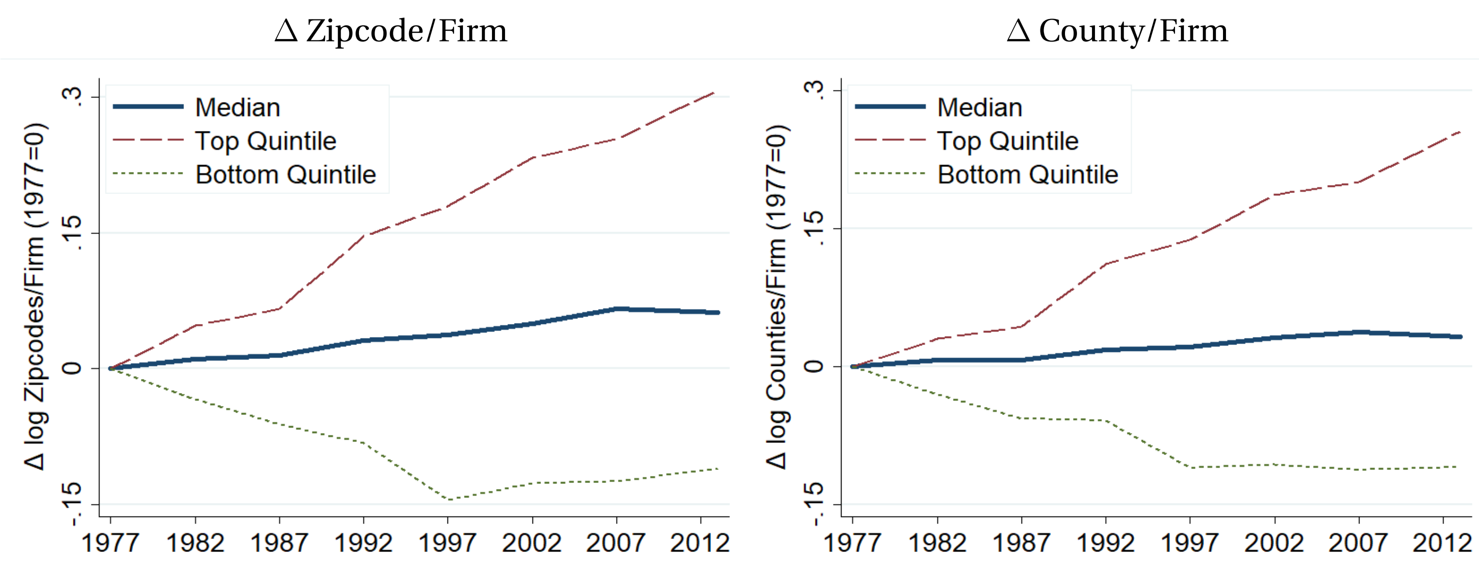
Table B1 shows the coefficients and standard errors from a regression of the change in log aggregate employment in the industry (column 1) or aggregate sales (column 2) on the change in log zipcode per firm (row 1) or county per firm (row 2), all from 1977

Table A3: MSA Level Summary Statistics, 1977 and 2013

	1977	2013
Employment Share of Top 10%		
by # Establishments in all MSAs	45%	53%
By Employment in all MSAs	65%	71%
Local Concentration		
Employment Share of Top Firm in MSA	31%	21%
Employment Based Local HHI	.302	.218

Note: Unit of observation is a MSA based on the 1980 Population Census (N=329). Top 10% in top panel defined by establishments in all MSAs or employment in all MSAs. Employment share of top 10% is the weighted average of the employment share of top 10% firms in an MSA-industry. The top firm in bottom panel is the largest firm by employment in the MSA-industry in that year. Employment share of the top firm is the weighted average of the employment share of the top firm in the MSA-industry. Local HHI is the weighted average of the employment-based HHI in the MSA-industry. Weights are employment share of each industry in the MSA in that year.

Figure B1: Δ Zipcodes and Counties per Firm, 1977-2013



Note: Unit of observation is an industry (N=445). Figure shows cumulative change of log zipcodes/firm or counties/firm of the average firm in the median industry, top quintile industry, and bottom quintile industry from 1977 to 2013, weighted by Sato-Vartia employment share of each industry.

to 2013.

Next, Table B2 shows the relationship between the change in employment in R&D

Table B1: Regression of Industry Growth on Δ Markets/Firm, 1977-2013

	Δ log Employment	Δ log Sales
Δ log Zipcodes/Firm	0.912	1.356
	(0.199)	(0.240)
Δ log Counties/Firm	1.130	1.982
	(0.275)	(0.325)

Note: Unit of observation is an industry (N=445). Table shows coefficient estimates and standard errors from weighted regressions of Δ log aggregate employment (column 1) and sales (column 2) in the industry on Δ log average zipcodes/firm (row 1) and counties/firm (row 2) of all firms in the industry. All variables in regression in column 1 are from 1977 to 2013. Sales growth are from 1977 to 2012 and growth in the number of markets per firm are from 1977 to 2013, except for utilities and transportation and finance where sales are from 1987 to 2012 and 1992 to 2012 and change in markets per firm are from 1987 to 2013 and 1992 to 2013, respectively. Weights are Sato-Vartia average of industry employment share in 1977 and 2013.

and headquarters in an industry and the change in the average number of zipcodes per firm (row 1) or counties per firm (row 2) in the industry. Column 1 shows the results for the sum of employment in R&D and headquarters, column 2 shows employment in RD centers alone, and column 3 shows employment in establishments classified as headquarters.

Table B2: Regression of Δ Employment in HQ/R&D on Δ Markets/Firm, 1977-2013

	Δ Emp R&D and HQ	Δ Emp R&D Only	Δ Emp HQ Only
Δ log Zipcodes/Firm	1.716	1.898	2.682
	(0.312)	(0.344)	(0.475)
Δ log Counties/Firm	2.477	2.079	2.949
	(0.436)	(0.305)	(0.421)

Note: Unit of observation is an industry (N=445). Table shows coefficient estimates and standard errors from weighted regressions of Δ log aggregate employment in R&D and headquarters (column 1), R&D only (column 2), and headquarters only (column 3) of all firms in the industry on Δ log zipcodes/firm (row 1) and counties/firm (row 2) of the average firm in the industry, all from 1977 to 2013. See text for details on how we identify R&D and headquarter establishments of firms in each industry. Weights are Sato-Vartia average of industry employment share in 1977 and 2013.

The next two tables show the correlation between the growth of top firms in an industry and the growth in the average number of zipcodes per firm and counties per firm. Table B3 shows the regression of the change in the number of zipcodes or counties per firm of the top 1% or top 10% of firms in an industry (top measured by number of zipcodes or counties served by firm) on the change in the average number of zipcodes or counties per firm in the industry. Table B4 shows the results from regressions of the employment and sales share of the top 1% and top 10% firms in an industry (this time measured by employment or sales) as well as the Herfindahl index on the same independent variables.

Table B3: Regression of Δ Markets/Firm of Top Firms on Δ Markets/Firm of All Firms

	Δ Markets/Firm of Top Firms	
	Top 1%	Top 10%
Δ log Zipcodes/Firm	2.538	2.267
	(0.108)	(0.047)
Δ log Counties/Firm	3.185	2.729
	(0.133)	(0.051)

Note: Unit of observation is an industry (N=445). Top firms defined by zipcodes per firm (column 1) or counties per firm (column 2). Entries are coefficient estimates and standard errors from weighted regressions of Δ log markets per firm of the top 1% firms (column 1) or top 10% firms (column 2) in the industry on Δ log average zipcodes/firm (row 1) or counties/firm (row 2) of the *average* firm in the industry, all from 1977 to 2013. Weights are Sato-Vartia average of industry employment share in 1977 and 2013.

C Markets per Firm and Share of Employment of Top Firms from 1977 to 2013

D Δ Establishments/Firm and Employment Share by Decile

In Table 4 we present the regression of the change in the log number of establishments per firm of the top 10% firms in an industry on the change in the log number of average number of markets per firm in the industry. Figure D1 shows the coefficients and 95% confidence interval of the same regression for all the deciles and not just the top decile, where the decile is defined by the number of establishments a firm owns. The left panel shows the elasticity with respect to the average number of estabishments per firm; the

Table B4: Regression of Δ Employment and Sales Concentration on Δ Markets/Firm

	Employment Concentration			Sales Concentration		
	Top 1%	Top 10%	HHI	Top 1%	Top 10%	HHI
Δ Zipcodes/Firm	0.810	0.392	0.125	0.382	0.276	0.070
	(0.072)	(0.027)	(0.016)	(0.084)	(0.030)	(0.026)
Δ Counties/Firm	1.043	0.482	0.161	0.518	0.365	0.091
	(0.102)	(0.039)	(0.023)	(0.115)	(0.042)	(0.035)

Note: Unit of observation is an industry (N=445). Entries are point estimates and standard errors from weighted regressions of the change in employment concentration (log share of top 1%, log share of top 10%, and HHI in columns 1-3) or sales concentration (log share of top 1%, log share top 10%, and HHI in columns 4-6) on the change in log markets/firm (MSA in row 1 and establishments in row 2) of the average firm in each 4-digit industry. Employment based concentration regressions use 1977 to 2013 for all variables. Sales based concentration regressions use the change from 1977 to 2012 for concentration and 1977 to 2013 for growth in markets per firm, except for utilities and transportation and finance where concentration changes are from 1987 to 2012 and 1992 to 2012 and change in markets per firm are from 1987 to 2013 and 1992 to 2013, respectively. Weights are Sato-Vartia average of industry employment share of each industry.

Table B5: Δ Share of Top 10% Firms by Employment or Sales: Number of Markets vs. Average Size

	Employment Share		Sales Share	
	Markets	Size	Markets	Size
Zipcodes	1.433	-0.433	1.116	-0.116
	(0.087)	(0.087)	(0.091)	(0.091)
Counties	1.227	-0.227	0.971	0.029
	(0.080)	(0.080)	(0.083)	(0.083)

Note: Unit of observation is an industry (N=445). Column 1 (“Markets”) shows point estimates and standard errors from a weighted regression of Δ log zipcodes or counties of top 10% firms (measured by employment) relative to all firms from 1977-2013 on Δ log employment share of top 10% firms from 1977-2013. Column 2 (“Size”) shows the results from regression of weighted Δ log employment per zipcode or county of top 10% firms relative to all firms from 1977 to 2013 on the same independent variable. Columns 3 and 4 show similar regressions using the Δ log sales share or Δ log sales per zipcode or county of the top 10% firms measured by sales. The change in sales are from 1977 to 2012, except for utilities and transportation and finance where the change are calculated from 1987 to 2012 and 1992 to 2012, respectively. Weights are Sato-Vartia average of the industry employment share.

right panel shows the elasticity with respect to the average number of MSAs per firm.

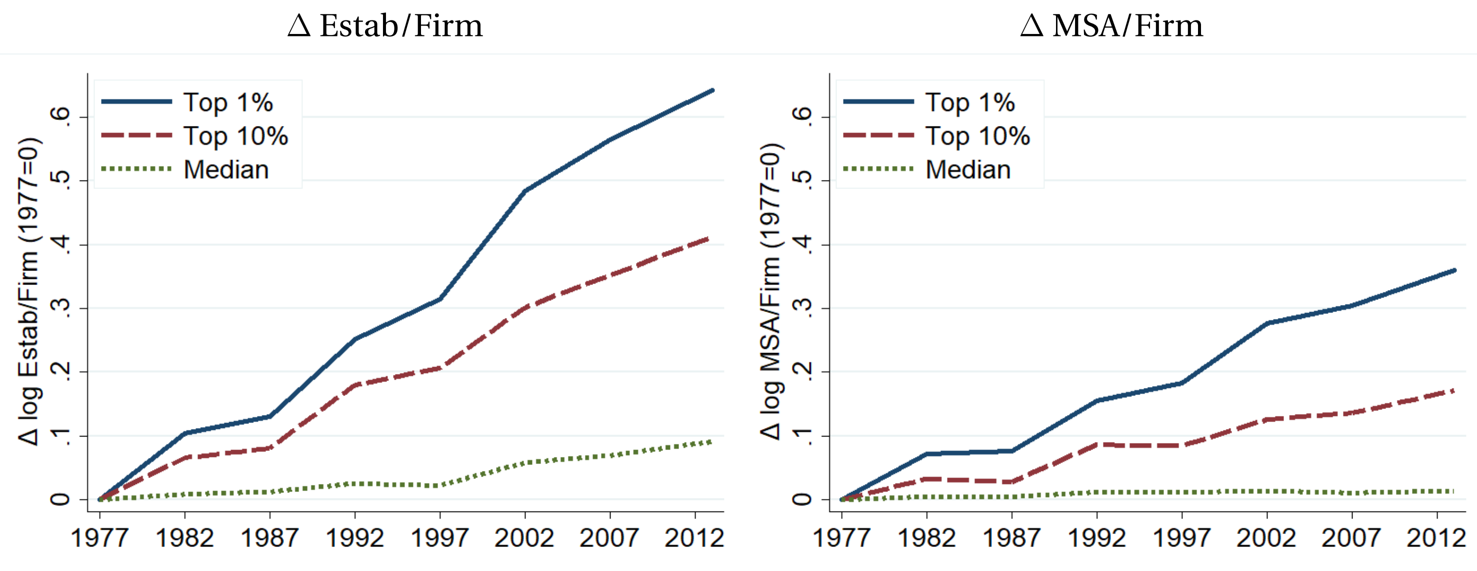
Figure D2 shows the coefficients and 95% confidence interval from regressions of

Table B6: Δ Market Size of Top 10% Firms

	Top 10% Firms	
	by Employment	*by* Estab/Firm
Δ County Size of Top Firms/All Firms	-0.364	-0.080
	(0.083)	(0.017)
Δ Zipcode Size of Top Firms/All Firms	-0.085	0.026
	(0.056)	(0.011)

Note: Unit of observation is an industry (N=445). Table shows weighted regression of Δ log market size of top 10% firms measured by employment (column 1) or establishments per firm (column 2) in the industry relative to market size of average firm in the industry on Δ log employment share of top 10% firms by employment in the industry (column 1) or Δ log establishments per firm of the top 10% firms measured by establishments in the industry (column 2). Market size is average total employment (in all industries) in a zipcode (row 1) or a county (row 2). All variables are from 1977 to 2013. Weights are Sato-Vartia average of industry employment in 1977 and 2013.

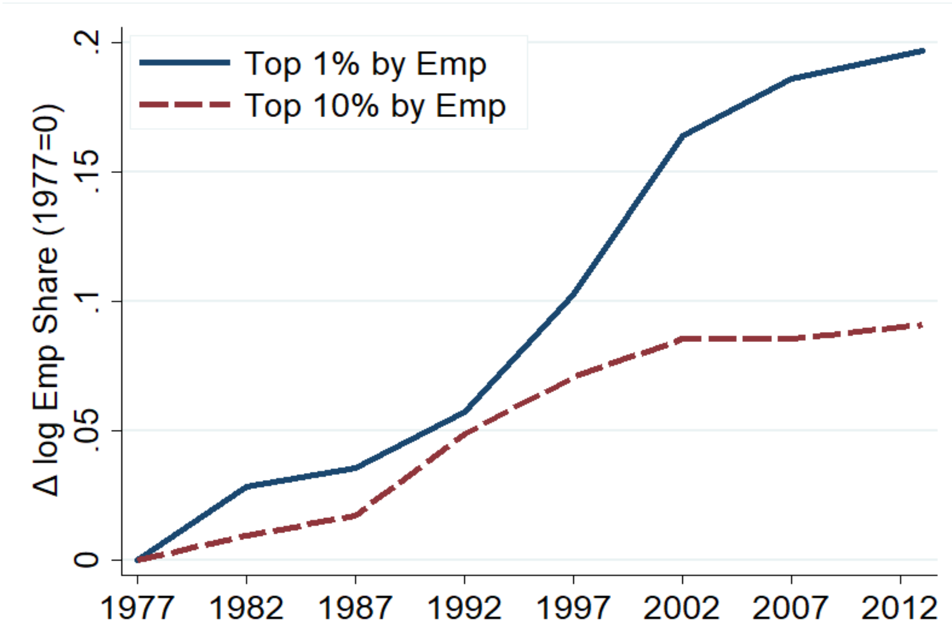
Figure C1: Δ Markets/Firm of Top Firms, 1977-2013



Note: Top firms defined by number of establishments (left panel) or MSAs (right panel). Figure shows cumulative average change of the log establishment/firm (left panel) and MSA/firm (right panel) of the top 1%, top 10%, and the average firm in each four digit industry from 1977 to 2013, weighted by Sato-Vartia employment share of each four-digit industry over these two years.

the change in the log employment share of each decile (defined by employment) on the change in the log average number of establishments (left panel) or average number of MSAs (right panel).

Figure C2: Δ Employment Share of Top Firms, 1977-2013



Note: Top firms defined by employment. Figure shows cumulative weighted average of the change of the log employment share of the top 1% and top 10% firms measured by employment in each four digit industry from 1977 to 2013, weighted by Sato-Vartia employment share of each four-digit industry over these two years.

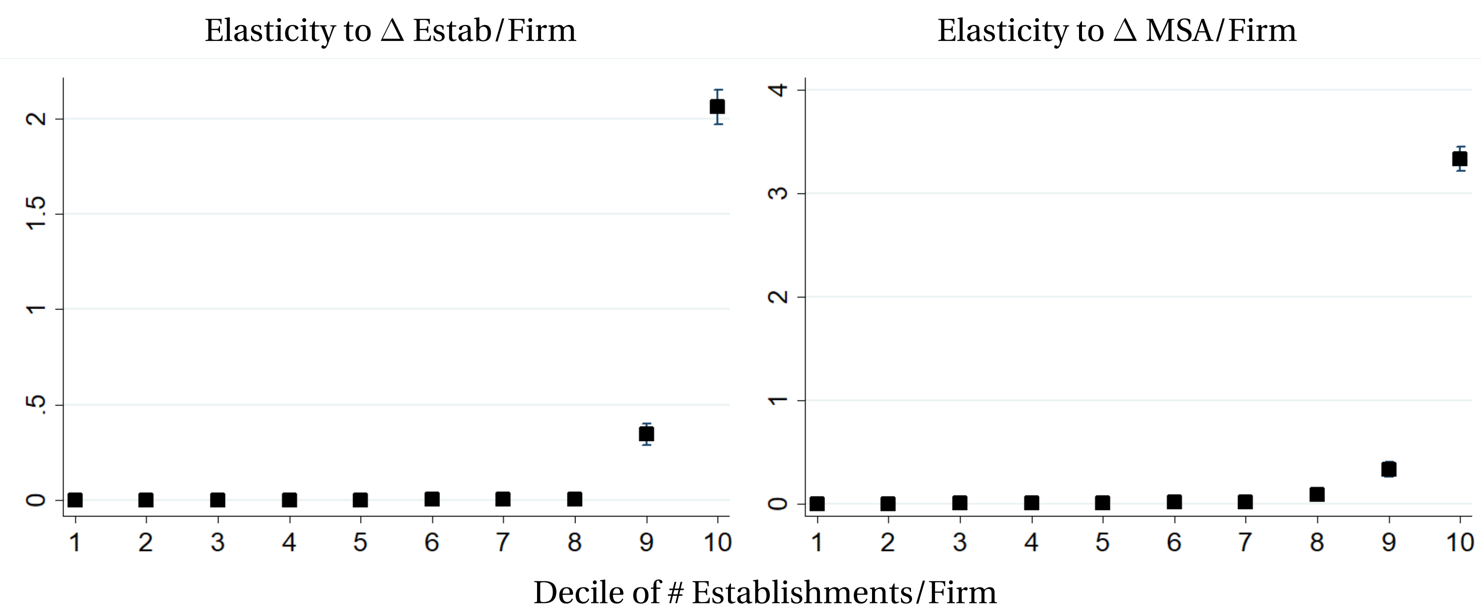
E Δ Employment and Sales *Within* Manufacturing

Using the variation across all four digit industries in the change in number of markets per firm, Table 4 shows that employment and sales increase by more in industries where the number of markets served by an average firm in the industry has increased by more. Table E1 presents similar evidence, this time using only the variation across industries *within* the manufacturing sector in the change in the average number of establishments per firm or MSAs per firm.

F Mergers and Acquisitions

In this section, we examine the importance of mergers and acquisitions. Figure C1 shows that the establishments per firm of the top 1% firms in the average increase increased by more than 0.6 log points between 1977 and 2013. When we exclude establishments of the top 1% firms in 2013 acquired through mergers and acquisitions,

Figure D1: Δ log Estab/Firm for each Decile of # Establishments, 1977-2013



Note: Figure shows point estimate and 95% confidence interval from regressions of the change in the log # establishments per firm in each decile of establishments per firm on the change in the log average number of establishments per firm (left panel) or the log average number of MSAs per firm (right panel).

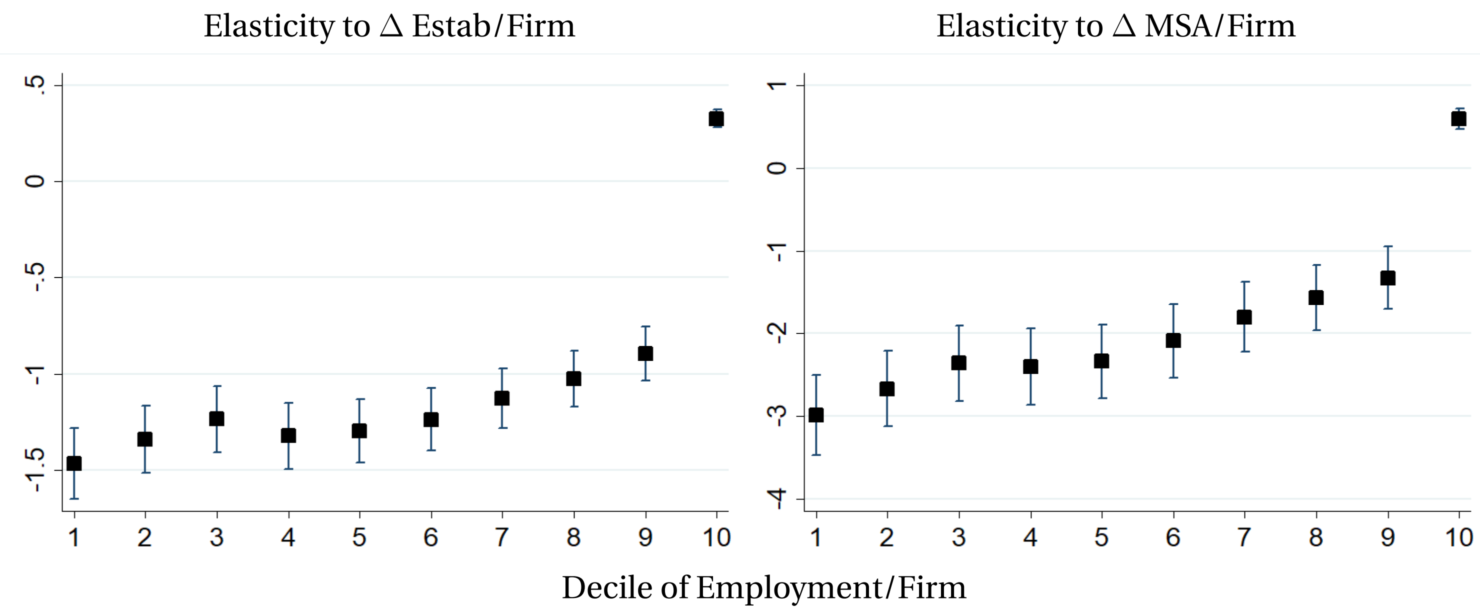
Table E1: Within Manufacturing Regression of Industry Growth on Δ Markets/Firm

	Δ log Employment	Δ log Sales
Δ log Estab/Firm	2.432	3.144
	(0.334)	(0.548)
Δ log MSA/Firm	2.421	3.559
	(0.369)	(0.589)

Note: Table shows coefficient estimates and standard errors from regressions of Δ log aggregate employment (column 1) and sales (column 2) in four-digit industries within manufacturing on Δ log average establishments/firm or MSA/firm in the industry, all from 1977 to 2013.

the increase is much lower, an increase of 0.19 log points between 1977 and 2013. The increase in the number of establishments of a top 10% firm, after excluding establishments acquired through mergers and acquisitions, is 0.025 log points between 1977 and 2013. The increase in the data, as shown in Figure C1 is about .4 log points. So it seems that mergers and acquisitions are an important part of the increase in the number of establishments of top firms in a typical industry.

Figure D2: Δ Employment Share of each Decile of Employment, 1977-2013



Note: Figure shows point estimate and 95% confidence interval from regressions of the change in the log employment share of each decile of employment on the change in the log average number of establishments per firm (left panel) or the log average number of MSAs per firm (right panel).

The next question is whether mergers and acquisitions is important in explaining the *differential* increase in the number of establishments per firm across industries. Remember that this is our metric of the industrial revolution in services. Table F1 probes for evidence of this. In this table, we measure employment and number of establishments of top firms in 2013 excluding establishments owned by a top firm in 2013 that was previously owned by another firm. We then calculate the change in the log number of establishments/firm of the top 10% firms measured by the number of establishments and the change in the employment share of the top 10% firms measured by employment.[31] We regress these two measures of the expansion of top firms on the change in the number of establishments per firm of all firms in the industry (including those where ownership changed). For comparison, the first row in Table F1 reproduces the estimate where we include all establishments owned by top firms in 2013.

As can be seen, the elasticity of the number of establishments of top firms and the

[31] The change in the number of establishments per firm and employment share omits establishments acquired through mergers and acquisitions. The definition of a top 10% firm includes such establishments.

Table F1: Regression of Δ Estab/Firm and Employment Share of Top Firms on Δ Estab/Firm of All Firms: Effect of Mergers and Acquisitions

	Top 10% Firms	
	Δ Estab/Firm	Δ Employment Share
Baseline (with mergers)	2.099 (0.046)	0.323 (0.023)
Without mergers	2.049 (0.060)	0.344 (0.064)

Note: Unit of observation is an industry (N=445). Entries in column 1 are coefficient estimates and standard errors from weighted regression of Δ log establishments per firm of the top 10% firms measured by # of establishments on the change in the average number of establishments per firm in the industry, both from 1977 to 2013. Column 2 show the weighted regression of the change in log employment share of the top 10% firms measured by employment on the same independent variable. Row 1 replicates the baseline results using all establishments of top firms. Row 2 excludes establishments acquired by a top 10% firm from another firm at any point prior to 2013 from the calculation of the top firm share in 2013. Weights in all regressions is the Sato-Vartia average of the employment share of the industry in 1977 and 2013.

employment share of top firms with respect to the average number of establishments when we exclude establishments acquired by top firms is virtually the same as in the baseline estimates where we include such establishments. Again, this is not to say that acquisitions does not matter for top firm growth. The point is simply that the effect of mergers and acquisitions on the growth of top firms is the same in all industries, and is not correlated with the change in average number of establishments per firm in the industry.

G Industry Classification

The LBD classifies the industry of an establishment by four digit SIC from 1977 to 2000 and by six digit NAICS from 2001 to 2013. Fort and Klimek (2018) use the original SIC and NAICS classifications in the LBD along with the micro-data of the Economic Censuses and Business Registers to classify all establishments in the LBD (including establishments prior to 2001 classified by SIC code) by 2002 NAICS code. When possible we use Fort and Klimek (2018)'s NAICS classification (FK-NAICS) to classify an establishment's industry. However, Fort and Klimek (2018) randomly assigned NAICS codes in some industries when there is one-to-many mapping from early vintages of SIC or NAICS codes to their time-consistent industry classification, or when there is very limited information about the establishment. We find that this random assignment causes employment and establishment counts by industry to change abruptly in some years. Furthermore, we find that in these years, many establishments switch between FK-NAICS codes. In these cases, we aggregate the FK-NAICS code to minimize large changes in establishment counts and employment across years, as well as large changes in industry classifications for a given establishment across years. Table G1 shows the share of FK-NAICS industries in each broad sector that we aggregated into "new" industries.

Table G1: % of Fort and Klimek (2018) NAICS Codes Aggregated into Broader Industries

All Industries	77.3%
Manufacturing	77.8%
Finance	83.7%
Other	84.0%
Utilities and Transportation	87.5%
Retail	67.0%
Wholesale	45.3%
Construction	85.7%

Note: Table shows the share of Fort and Klimek (2018)'s 2002 NAICS codes we aggregated into broader industries. There are a total of 1,115 2002 NAICS industries in the LBD.

We now examine the effect of alternative industry classifications on the main results. We consider four alternative classifications. First, we hold fixed the industry classification of the establishment given at the time the establishment appeared in the LBD for the first time. The second alternative is the four digit SIC codes, which are available from 1977 to 2000. The third is the six digit NAICS code, which are provided in the LBD data from 2001 to 2013. The fourth alternative is the original codes in Fort and Klimek (2018).

Table G2 shows regressions of the change in industry employment (column 1), employment in R&D and headquarters (column 2), establishments per firm of the top 10% firms defined by the number of establishments (column 3), and employment share of the top 10% firms defined by employment (column 4) on the change in the average number of establishments per firm with these alternative industry definitions.

Table G2: Regression of Δ Industry Employment, HQ/R&D Employment, Estab/Firm of Top 10%, and Employment Share of Top 10% on Δ Estab/Firm

	Δ log Employment		Top 10% Firms	
	Industry	HQ/R&D	Δ Estab/Firm	Δ Emp Share
Baseline Industry (1977-2013) w/ Industry Fixed at Birth	1.165 (0.188)	1.698 (0.270)	2.099 (0.046)	0.323 (0.023)
SIC (1977-2000)	1.429 (0.110)	1.374 (0.143)	1.362 (0.024)	0.071 (0.013)
NAICS (2001-2013)	1.312 (0.105)	1.452 (0.130)	1.261 (0.015)	0.081 (0.010)
FK-NAICS (1977-2013)	0.477 (0.073)	0.595 (0.102)	1.292 (0.021)	0.045 (0.009)

Note: Table shows coefficient estimates and standard errors from weighted regressions of Δ log aggregate employment in the industry (column 1), Δ log aggregate employment in headquarter and R&D establishments of firms in the industry (column 2), Δ log establishments per firm of top 10% firms (defined by # establishments) in the industry (column 3) , and Δ log employment share of the top 10% firms (defined by employment) in the industry (column 4) on the Δ log establishments per firm of the average firm in the industry, all from 1977 to 2013. Weights are Sato-Vartia average of industry employment share in 1977 and 2013. Observations are our baseline industries in row 1 with industries fixed for each establishment, four-digit SIC industries in row 2, six-digit NAICS industries in row 3, and six-digit industries defined by Fort and Klimek (2018) in row 4.

Next, Table G3 shows the results of the decomposition of the change in the employment share of the top 10% firms into the extensive and intensive margins, where a market is defined as an establishment, using the three alternative definitions of an industry.

H Effects Over 5-Year Periods

In this section, we produce the main results every five years. For simplicity, we only show the results using the variation in the average number of establishments per firm across four digit industries. Table H1 shows the relationship between the change in industry employment, employment in headquarters and R&D centers, establishments per firm of the top 10% firms, and the employment share of the top 10% firms. Table H2

Table G3: Δ Share of Top 10% Firms by Employment: Number of Markets vs. Average Size

	Markets	Size
Baseline (1977-2013)	1.472	-0.472
w/ Fixed Industry	(0.088)	(0.088)
SIC (1977-2000)	1.023	-0.023
	(0.053)	(0.053)
NAICS (2001-2013)	0.968	0.032
	(0.04)	(0.040)
FK-NAICS (1977-2013)	1.241	-0.241
	(0.065)	(0.065)

Note: Column 1 ("Markets") shows point estimates and standard errors from a regression of Δ log # Establishments of top 10% firms (measured by employment) relative to all firms from 1977-2013 on Δ log employment share of top 10% firms from 1977-2013. Column 2 ("Size") shows the results from regression of Δ log employment per establishment of top 10% firms relative to all firms from 1977 to 2013 on the same independent variable. Observations are our baseline industries in row 1 with industries fixed for each establishment, four-digit SIC industries in row 2, six-digit NAICS industries in row 3, and six-digit industries defined by Fort and Klimek (2018) in row 4.

shows the results of the decomposition of the employment share of the top 10% firms into the relevant extensive and intensive margins.

Table H1: Regression of Δ Industry Employment, HQ/R&D Employment, Estab/Firm of Top 10%, and Employment Share of Top 10% on Δ Estab/Firm Over 5-Year Periods

	Δ log Employment		Top 10% Firms	
	Industry	HQ/R&D	Δ Estab/Firm	Δ Emp Share
1977-1982	0.258	-0.682	2.036	0.085
	(0.185)	(0.374)	(0.054)	(0.047)
1982-1987	1.112	0.982	2.440	0.352
	(0.213)	(0.445)	(0.054)	(0.041)
1987-1992	0.676	0.927	1.843	0.179
	(0.141)	(0.240)	(0.050)	(0.025)
1992-1997	0.816	1.218	2.101	0.304
	(0.151)	(0.248)	(0.046)	(0.024)
1997-2002	0.839	1.446	2.171	0.325
	(0.175)	(0.290)	(0.047)	(0.025)
2002-2007	1.028	1.560	2.162	0.342
	(0.179)	(0.263)	(0.045)	(0.024)
2007-2013	1.040	1.729	2.099	0.323
	(0.182)	(0.269)	(0.046)	(0.023)

Note: Unit of observation is an industry (N=445). Table shows coefficient estimates and standard errors from weighted regressions of Δ log aggregate employment in the industry (column 1), Δ log aggregate employment in headquarter and R&D establishments of firms in the industry (column 2), Δ log establishments per firm of top 10% firms (defined by establishments) in the industry (column 3) , and Δ log employment share of the top 10% firms (defined by employment) in the industry (column 4) on the Δ log average establishments per firm in the industry, all from 1977 to 2013. Weights are Sato-Vartia average of industry employment share in 1977 and 2013.

I Summary Statistics by Sector

Table I1 shows the key statistics – change in log establishments per firm of the average firm and of the top 10% firms measured by number of establishments, change in the log employment share of the top 10% firms measured by employment, and change in total employment in the industry for each broad sector, where we take each broad sector as an industry.

Table H2: Δ Share of Top 10% Firms by Employment: Number of Markets vs. Average Size

	Markets	Size
1977-1982	0.389	0.611
	(0.070)	(0.070)
1982-1987	0.987	-0.013
	(0.076)	(0.076)
1987-1992	1.256	-0.256
	(0.094)	(0.094)
1992-1997	1.445	-0.445
	(0.093)	(0.093)
1997-2002	1.399	-0.399
	(0.098)	(0.098)
2002-2007	1.419	-0.419
	(0.098)	(0.098)
2007-2013	1.541	-0.541
	(0.096)	(0.096)

Note: Unit of observation is an industry (N=445). Column 1 ("Markets") shows point estimates and standard errors from a weighted regression of Δ log # Establishments of top 10% firms (measured by employment) relative to all firms from 1977-2013 on Δ log employment share of top 10% firms from 1977-2013. Column 2 ("Size") shows the results from a weighted regression of Δ log employment per establishment of top 10% firms relative to all firms from 1977 to 2013 on the same independent variable. Weights are Sato-Vartia average of industry employment share in 1977 and 2013.

Table I1: Δ Sector Characteristics, 1977-2013

	Δ log Estab/Firm		Δ log Emp Share	Δ log
	Average Firm	Top 10% by Estab.	Top 10% by Emp	Employment
Manufacturing	.035	.139	-.047	-.438
Finance	.161	.539	.015	.587
Other	.088	.386	.041	1.071
Util and Trans	.101	.337	-.006	.411
Retail	.165	.451	.104	.645
Wholesale	.093	.277	.161	.492
Construction	.008	.065	.059	.411

Note: Statistics are calculated from 1977 to 2013 for each broad sector, taking each sector as an industry.

J Missing Growth Measured by Employment For All Sectors

In Figure 12 we used data on sales to measure missing growth. The limitation of the numbers shown in Figure 12 is that we had to drop the two industries where the micro-data is not available throughout the entire period (the two industries are finance and utilities and transportation). In this section, we use employment data from the LBD to provide the same measure of missing growth. The advantage of using the LBD is that we can include all industries. The disadvantage is that the theoretically consistent measure of missing growth should be based on sales, and employment is proportional to sales only when the marginal product of labor is the same across all firms. With this in mind, Figure J1 shows missing growth from 1977 to 2013 by the size of the MSA in 1977 from entry into incumbent industries (left panel) and all industries (right panel). As can be seen, the qualitative picture is the same as when we use sales to measure missing growth. There is much more missing growth in smaller cities compared to larger cities. And when we aggregate missing growth across all MSAs, we get missing growth across all cities of 0.5% per year from 1977 to 2013.

K Proofs of Propositions in Section 4

In this section we provide the proofs of all propositions in the main text.

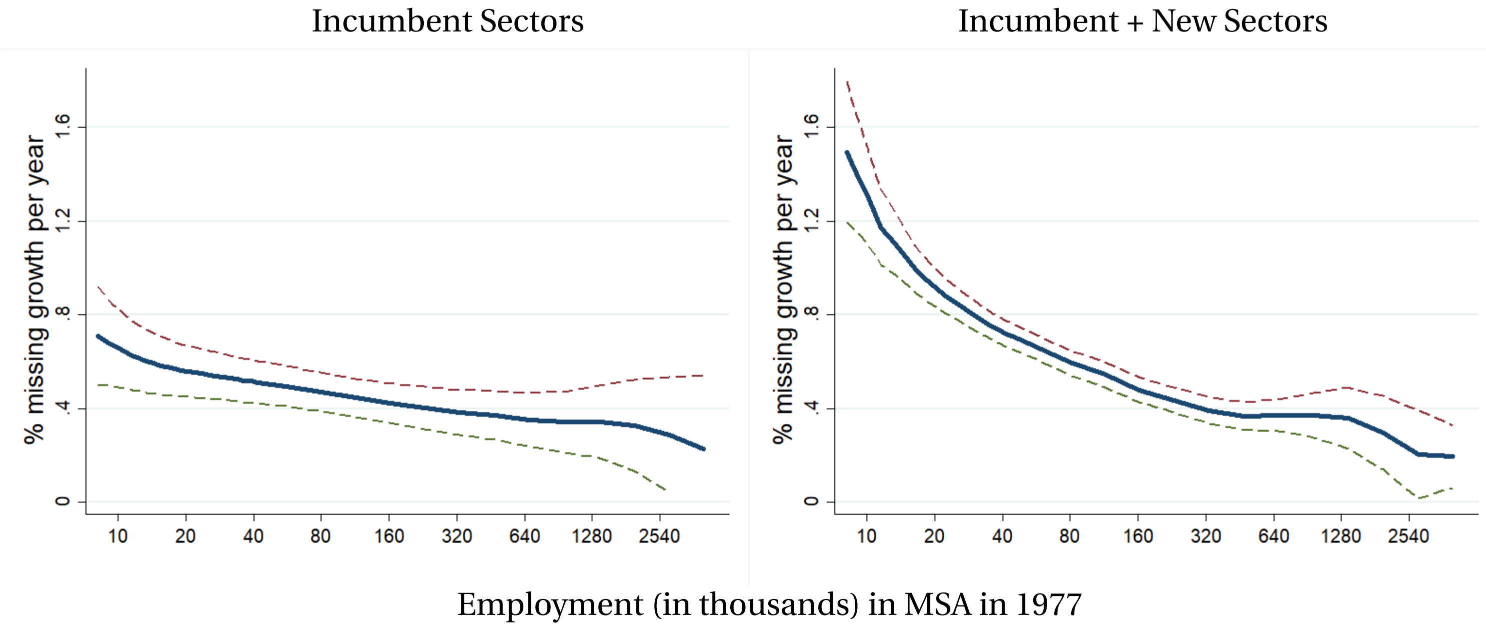
K1. Proof of Proposition 1

Firms will adopt the technology if $\Pi\left(hA_{ij}, h^{\eta}F_j, f, \Gamma\right) \geq \Pi\left(A_{ij}, F_j, f, \Gamma\right)$. This condition can be rewritten as the sum of the profits of the firm in new markets plus the increased profits in old markets being grater or equal than the increase in the firm-product fixed cost relative to local fixed costs, namely,

$$\underbrace{\int_{A_{ij}}^{hA_{ij}} \left(\left(\frac{hA_{ij}}{\alpha}\right)^{\sigma-1} - 1\right) \Gamma\left(d\alpha; f\right)}_{\text{Value of new markets}} + \underbrace{\int_{0}^{A_{ij}} \left(\frac{A_{ij}}{\alpha}\right)^{\sigma-1} \left(h^{\sigma-1} - 1\right) \Gamma\left(d\alpha; f\right)}_{\text{Increased value of old markets}} \geq \left(h^{\eta} - 1\right)\frac{F_j}{f}. \tag{A1}$$

We need to show that the benefits of adopting the new technology, the left-hand side

Figure J1: Local Missing Growth Calculated from Employment by MSA Size



Note: Unit of observation is a MSA (N=329). Figure shows coefficients and 95% confidence intervals from non-parametric regression of average annual missing growth from 1977 to 2012 in the MSA due to entry of top firms into incumbent sectors in the MSA (left panel) and all sectors in the MSA (right panel) on total employment in the MSA in 1977. Missing growth is calculated for each five year period. Incumbent sectors are present in MSA at the beginning and end of each five year period. New sectors are in the MSA at the end but not at the beginning of each five year period.

of condition (A1), is increasing in firm productivity. Taking the derivative of the left-hand side of condition (A1) with respect to A_{ij} yields:

$$\begin{aligned}\frac{\partial LHS}{\partial A_{ij}} &= \int_0^{hA_{ij}} (\sigma-1)\left(\frac{h}{\alpha}\right)^{\sigma-1} A_{ij}^{\sigma-2}\Gamma(d\alpha;f) - \int_0^{A_{ij}} (\sigma-1)\left(\frac{1}{\alpha}\right)^{\sigma-1} A_{ij}^{\sigma-2}\Gamma(d\alpha;f)\\ &= \underbrace{(\sigma-1)A_{ij}^{\sigma-2}\int_{A_{ij}}^{hA_{ij}}\left(\frac{h}{\alpha}\right)^{\sigma-1}\Gamma(d\alpha;f)}_{>0\text{, Larger value of new markets for top firms}}\\ &\quad \underbrace{+(\sigma-1)A_{ij}^{\sigma-2}\int_0^{A_{ij}}\left(\frac{1}{\alpha}\right)^{\sigma-1}\left(h^{\sigma-1}-1\right)\Gamma(d\alpha;f)}_{>0\text{, Larger value of existing markets for top firms}} > 0\end{aligned}$$

since, by Leibniz rule, the derivative of A_{ij} in the limit of the integral is equal to zero. Hence, the gains from adopting the new technology increase with a firm's productivity, while the costs (the right-hand side of condition A1) are fixed. This implies that there exists a threshold $H(F_j, f, \Gamma, h, \eta)$ such that if $A_{ij} \geq H(F_j, f, \Gamma, h, \eta)$, firm i adopts the new technology. The function $H(\cdot)$ is increasing in F_j and η, as simple inspection of (A1) indicates. Firms that adopt a better technology have larger establishments, since $L_{ijn} = (\sigma - 1) f \left(\frac{hA_{ij}}{\alpha_n}\right)^{\sigma-1}$, have larger sales given by $\int_0^{hA_{ij}} \left(\left(\frac{hA_{ij}}{\alpha}\right)^{\sigma-1}\right) \Gamma(d\alpha; f)$. Clearly, given Γ, firms that adopt a better technology h, which are the more productive firms, enter more locations since $\Gamma(hA_{ij})$ is increasing in h by definition.

K2. Proof of Proposition 2

The cross-derivative of the left-hand side of (A1) is given by

$$\frac{\partial^2 LHS}{\partial A_{ij} \partial h} = (\sigma - 1)\gamma(hA_{ij}) + (\sigma - 1)^2 A_{ij}^{\sigma-2} \int_0^{hA_{ij}} h^{\sigma-2} \left(\frac{1}{\alpha}\right)^{\sigma-1} \Gamma(d\alpha; f) > 0.$$

Since the right-hand side of condition (A1) does not depend on A_{ij}, this implies that more productive firms choose technologies with higher h. Note also that the right-hand side of equation (A1), $(h^\eta - 1)F_j/f$, is increasing in h for $\eta > 0$ and the slope grows with η for $h > 1$. The corresponding derivatives are given by

$$\frac{\partial \frac{(h^\eta - 1)F_j}{f}}{\partial h} = \eta h^{\eta-1} \frac{F_j}{f} > 0$$

and

$$\frac{\partial \frac{(h^\eta - 1)F_j}{f}}{\partial h \partial \eta} = \left[h^{\eta-1} + \eta h^{\eta-1} \log h\right] \frac{F_j}{f}.$$

Furthermore, as $\eta \to 0$, $h^\eta - 1 \to 0$, and the derivatives above converge to zero. Hence, since the left-hand side of (A1) is strictly positive for $h > 1$, there exists a threshold η_0 such that if $\eta < \eta_0$, low productivity firms also adopt a new technology, although with weakly lower h.

K3. Proof of Proposition 3

Given Γ, firms that adopt a better technology h, which are the more productive firms, enter more locations. This is simply implied by $\Gamma(hA_{ij})$ increasing in h. Furthermore, when the new technology is available, the difference between the number of markets of productive and unproductive firms increases. Namely,

$$\left.\frac{d\Gamma\left(h\left(A\right)A\right)}{dA}\right|_{h(A)=1}=\gamma\left(A\right)\left[h'\left(A\right)A+1\right]>\gamma\left(A\right)=\frac{d\Gamma\left(A\right)}{dA}$$

since $h'\left(A\right)>0$ by Proposition 2. Note also that, given Γ, firms that adopt a better technology have larger establishments, since $L_{ijn}=\left(\sigma-1\right)f\left(\frac{hA_{ij}}{\alpha_n}\right)^{\sigma-1}$. Furthermore, even though the new markets where the firm enters are less profitable, the increase in productivity due to the new technology implies that the *marginal* market has constant employment size. Employment size in the firm's marginal market when $hA_{ij}=\alpha_n$ is $w_n\left(\sigma-1\right)f$, which does not depend on h. The result is that more productive firms take a larger share of the market and concentration increases. Finally, note that in industries where the new technology is very good (η is low) there is more concentration since top firms will adopt a larger h. In those industries, less productive firms will also adopt a better technology, although with a lower h (see Proposition 2).

K4. Proof of Proposition 4

From equation (2), given E_n and w_n, the fixed cost does not affect establishment sizes directly. It does, however, determine entry into marginal markets and the size of the smallest establishment of the firm, which is given by $w_n\left(\sigma-1\right)fh^{-\varphi}$. For firms that choose $h>1$, this implies that the smallest establishment size of the firm falls. Hence, with the new technology, average establishment sizes of existing firms fall for φ large enough since the average will be dominated by the entry of smaller establishments.

K5. Proof of Proposition 5

The profits of a manufacturing firm i in industry M that invests in technology h are given by

$$\max_m\int\left(\frac{hA_{iM}}{\alpha}\right)^{\sigma-1}\left(\frac{a_{Mjm}}{w_m}\frac{w_n}{a_{iMn}}\right)^{\sigma-1}f\Gamma\left(d\alpha;f\right)-f-h^{\eta}F_M.$$

Hence, the the FOC with respect to h is

$$h_{iM}^{\eta-(\sigma-1)}=\frac{\max_m\left(\sigma-1\right)\int\left[\left(\frac{A_{iM}}{\alpha}\right)^{\sigma-1}\left(\frac{a_{iMm}}{w_m}\frac{w_n}{a_{iMn}}\right)^{\sigma-1}\right]f\Gamma\left(d\alpha;f\right)}{\eta F_M}.$$

Under our assumption that $\eta > \sigma - 1$, which is need for an internal solution and for the second order condition to be satisfied, the left-hand-side is increasing in h_{iM}.

Now consider a service firm i' in industry S, the profits of investing in technology h are

$$\int_0^{hA_{i'S}} \left(\left(\frac{hA_{iS}}{\alpha} \right)^{\sigma-1} - 1 \right) f\Gamma\left(d\alpha; f\right) - h^{\eta} F_S$$

and so the FOC is

$$h_{i'S}^{\eta-(\sigma-1)} = \frac{(\sigma-1) \int_0^{hA_{ij}} \left(\frac{A_{ij}}{\alpha} \right)^{\sigma-1} f\Gamma\left(d\alpha; f\right)}{\eta F_S}.$$

Now consider two firms with equal fixed costs $F_M = F_S$ and equal sales before their investment in h, then

$$\max_m \int \left(\frac{A_{ij}}{\alpha} \right)^{\sigma-1} \left(\frac{a_{ijm}}{w_m} \frac{w_n}{a_{iMn}} \right)^{\sigma-1} f\Gamma\left(d\alpha; f\right) = \int_0^{A_{i'j'}} \left(\left(\frac{A_{i'j'}}{\alpha} \right)^{\sigma-1} - 1 \right) f\Gamma\left(d\alpha; f\right)$$

and so

$$\begin{aligned}
\left(\frac{h_{i'S}}{h_{iM}} \right)^{\eta-(\sigma-1)} &= \frac{\int_0^{A_{i'S}} \left(\left(\frac{hA_{iS}}{\alpha} \right)^{\sigma-1} - 1 \right) f\Gamma\left(d\alpha; f\right) + \int_{A_{i'S}}^{h_S A_{i'S}} \left(\left(\frac{hA_{iS}}{\alpha} \right)^{\sigma-1} - 1 \right) f\Gamma\left(d\alpha; f\right)}{\max_m (\sigma-1) \int \left[\left(\frac{A_{iM}}{\alpha} \right)^{\sigma-1} \left(\frac{a_{iMm}}{w_m} \frac{w_n}{a_{iMn}} \right)^{\sigma-1} \right] f\Gamma\left(d\alpha; f\right)} \\
&= 1 + \frac{\int_{A_{i'S}}^{h_S A_{i'S}} \left(\left(\frac{hA_{iS}}{\alpha} \right)^{\sigma-1} - 1 \right) f\Gamma\left(d\alpha; f\right)}{\int_0^{A_{i'S}} \left(\left(\frac{hA_{iS}}{\alpha} \right)^{\sigma-1} - 1 \right) f\Gamma\left(d\alpha; f\right)} > 1.
\end{aligned}$$

This implies that, $h_{i'S} > h_{iM}$.

K6. Proof of Proposition 6

We know from Proposition 2 that $h_j\left(A_{ij}\right) > 1$ is increasing in A_{ij} and is decreasing in η_j. Consider the residents of a location n. Their preferences are given by

$$U_n = \left(\int_{j \in \mathcal{J}_n} Q_{jn}^{\frac{\rho-1}{\rho}} d_j \right)^{\frac{\rho}{\rho-1}}$$

where $\mathcal{J}_n$ is the set of industries present in n. Q_{jn} is consumption of varieties in industry j, which are aggregated according to

$$Q_{jn} = \left(\int_{i \in \mathcal{I}_{jn}} Y_{ijn}^{\frac{\sigma-1}{\sigma}} d_i \right)^{\frac{\sigma}{\sigma-1}},$$

where $\mathcal{I}_{jn}$ is the set of firms operating industry j in location n.

We can do two stage budgeting. Start with the varieties. Then, if the total income of an agent in n is w_n, the budget constraint of the agent is $\int_{j \in \mathcal{J}_n} \int_{i \in \mathcal{I}_{jn}} Y_{ijn} p_{ijn} d_i d_n = \int_{j \in \mathcal{J}_n} Q_{jn} P_{jn} = w_n$, where $Q_{jn} P_{jn}$ denotes expenditure in industry j and P_{jn} is the industry's ideal price index. Hence,

$$Y_{ijn} = Q_{jn} \left(\frac{p_{ijn}}{P_{jn}} \right)^{-\sigma}$$

where $P_{jn} = \left(\int_{i \in \mathcal{I}_{jn}} p_{ijn}^{1-\sigma} d_i \right)^{\frac{1}{1-\sigma}}$. Using equation 2 and the definition of $E_{nj} = Q_{jn}^{\frac{1}{\sigma}} P_{jn}$, then

$$L_{ijn} = \left(a_{ijn} h_j \left(A_{ij} \right) A_{ij} \right)^{\sigma-1} \left[\left(1 - \frac{1}{\sigma} \right) \frac{P_{jn}}{w_n} \right]^{\sigma} Q_{jn}$$

Note also that two stage budgeting implies

$$Q_{jn} = \frac{w_n}{P_n} \left(\frac{P_{jn}}{P_n} \right)^{-\rho},$$

and so

$$L_{ijn} = \left(a_{ijn} h_j \left(A_{ij} \right) A_{ij} \right)^{\sigma-1} \left(1 - \frac{1}{\sigma} \right)^{\sigma} \left(\int_{i \in \mathcal{I}_{jn}} p_{ijn}^{1-\sigma} d_i \right)^{\frac{\sigma-\rho}{1-\sigma}} w_n^{-\sigma} P_n^{\rho-1}.$$

Note that $p_{ijn} = \left(\sigma / \left(\sigma + 1 \right) \right) \left(w_n / \left(h_j \left(A_{ij} \right) a_{ijn} A_{ij} \right) \right)$ and so

$$\int_{i \in \mathcal{I}_{jn}} L_{ijn} d_i = \left(1 - \frac{1}{\sigma} \right)^{\sigma} \left(\sigma / \left(\sigma + 1 \right) \right)^{\sigma-\rho} \left(\int_{i \in \mathcal{I}_{jn}} \left(h_j \left(A_{ij} \right) a_{ijn} A_{ij} \right)^{\sigma-1} d_i \right)^{\frac{\rho-1}{\sigma-1}} w_n^{-\rho} P_n^{\rho-1}$$

which is increasing in $h_j \left(A_{ij} \right)$ if $\rho > 1$. Since this applies to every location it also applies to the whole industry. Note also that total sales are given by

$$P_{jn} Q_{jn} = w_n P_n^{\rho-1} P_{jn}^{1-\rho}$$

which increases if $\rho > 1$ since P_{jn} declines when all prices fall due to $h_j(A_{ij}) \geq 1.$

K7. A parametric example

It is useful to illustrate the intuition behind the cutoff productivity with a parametric example. Suppose that the density of markets with characteristic α is $\gamma(\alpha) = \Omega\alpha^{\beta}/f^{\sigma-1}$ for some $\beta > \sigma - 1$. This distribution implies that there are many markets where it is hard to enter, and the more so when β is larger. $\Omega > 0$ is related to the availability of good markets to enter and is determined in general equilibrium by the level of wages and real expenditures. Then total profits from product j are given by $\Pi(A_{ij}, F_j, f, \Gamma) = \tilde{a}\frac{\Omega}{f^{\sigma}}A_{ij}^{1+\beta} - F_j$ where $\tilde{a} = \left[\frac{\sigma-1}{(2+\beta-\sigma)(1+\beta)}\right]$. So active firms in industry j are those with productivity $A_{ij} \geq \underline{A}(F_j, f, \Gamma) \equiv \left(\frac{F_j f^{\sigma}}{\tilde{a}\Omega}\right)^{1/(1-\beta)}$. The productivity threshold is decreasing in Ω since having more profitable markets implies a lower entry productivity threshold.

Some firms will decide not to adopt the new technology as long as $\underline{A}(h^{\eta}F_j, f, \Gamma)/h > \underline{A}(F_j, f, \Gamma)$. This is not always the case. In this case it requires $\eta > 1 + \beta$, since

$$\underline{A}(h^{\eta}F_j, f, \Gamma)/h = h^{\frac{\eta}{1+\beta}-1}\left(\frac{F_j f^{\sigma}}{\tilde{\alpha}\Omega}\right)^{1/(1-\beta)} > \underline{A}(F_j, f, \Gamma),$$

if $\eta > 1 + \beta$, since $h > 1$. Namely, some firms do not adopt if the elasticity of fixed cost to h is larger than one plus the elasticity of the density of tougher markets (higher $1 + \beta$). More generally, we need the increase in fixed costs in the new technology to be large enough.