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100 Years of Rising Corporate Concentration

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Abstract

We collect data on the size distribution of all U.S. corporate businesses for 100 years. We document that corporate concentration (e.g., asset share or sales share of the top 1%) has increased persistently over the past century. Rising concentration was stronger in manufacturing and mining before the 1970s, and stronger in services, retail, and wholesale after the 1970s. Furthermore, rising concentration in an industry aligns closely with investment intensity in research and development and information technology. Industries with higher increases in concentration also exhibit higher output growth. The long-run trends of rising corporate concentration indicate increasingly stronger economies of scale.

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1 Introduction

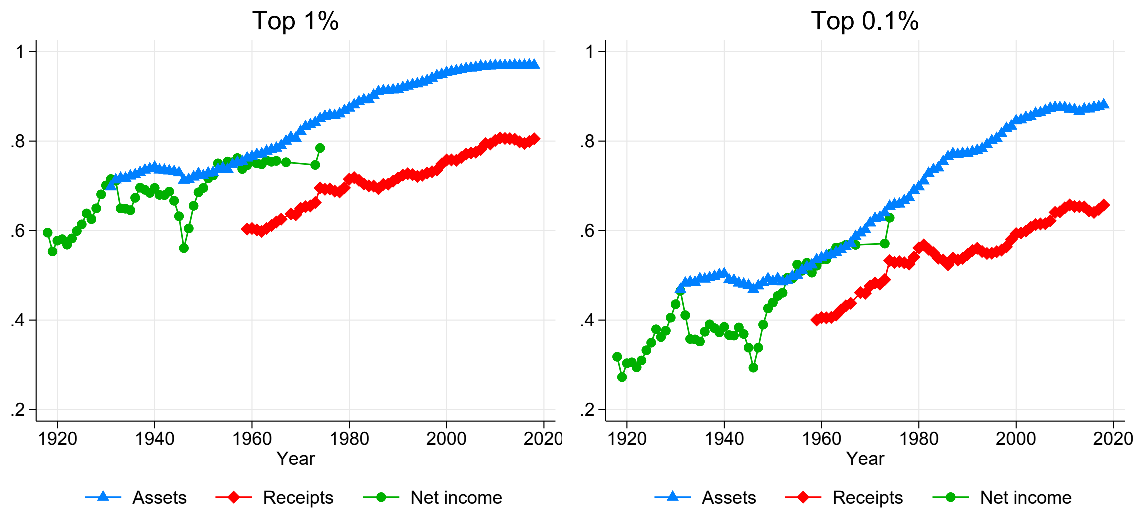
The role of large businesses in the economy is an important question for researchers, policymakers, and the public. The finding of rising concentration among U.S. industries since the 1980s (as shown by Autor et al. (2020) and others using comprehensive census data covering this period) has attracted particular attention. Recent discussions of this evidence often focus on the special features of today's world. In the archives of history, however, lives an old conjecture that rising concentration is a feature, if not a law, of industrial development. In fact, both Marx (1867) and Marshall (1890) wrote that technological progress increases economies of scale and raises concentration in production. Lenin (1916) gathered census statistics in the early 1900s to back up the conviction that "the enormous growth of industry and the remarkably rapid concentration of production…are one of the most characteristic features of capitalism." After the National Bureau of Economic Research (NBER) was established in 1920 to provide "exact and impartial determinations of facts," one of its first publications also noted the spread of mass production at that time, as well as a general view that "each generation believes itself to be on the verge of a new economic era" but what appears to be new often represents recurring themes in history (Committee on Recent Economic Changes, 1929).

In this paper, we collect new data covering the population of U.S. corporate businesses for 100 years, from 1918 to 2018. We document that corporate concentration (e.g., asset share or sales share of the top 1% businesses) in the U.S. has been rising steadily over the past century. Among different sectors, rising concentration was stronger in manufacturing and mining before the 1970s, and stronger in services, retail, and wholesale after the 1970s. We then perform detailed analyses about the mechanism behind these long-run trends. First, we observe evidence in line with stronger economies of scale. We document that rising concentration in an industry coincides with higher investment intensity in R&D and IT; it is also accompanied by higher output growth. Second, globalization since the 1970s does not appear sufficient to account for the evidence by itself, but having access to broad markets (domestically or internationally) could have supported the influence of economies of scale. Third, antitrust policies do not appear to be the primary determinant of economy-wide corporate concentration. Overall, the data shows that increasing concentration in production activities has been a feature of the U.S. economy for at least a century, and long-run forces are important for this historical development.

Data We collect long-run data on the business size distribution in the U.S. by digitizing historical publications of the Statistics of Income (SOI) and the associated Corporation Source Book from the Internal Revenue Service (IRS). Since 1918, the SOI has been reporting annual statistics of the population of corporate businesses by size bins, including the number of businesses and their financial information (e.g., assets, sales, net income). We use these size bins to calculate top businesses' shares in the aggregate, the main sectors (roughly one-digit SICs), and the subsectors (roughly two-digit SICs). Our data captures production activities in the U.S. (similar to the gross output convention in the national accounts). Correspondingly, we analyze concentration of production, namely the extent to which a small fraction of businesses account for a large share of production assets or output. In other words, our focus is the role of large businesses in the production activities of the U.S. economy, not market concentration for a given product (which requires defining markets based on consumption activities) or market power.

Figure 1: Top 1% and 0.1% Shares: All Corporate Businesses

This figure shows the shares of the top 1% (left panel) and the top 0.1% (right panel) corporate businesses. The blue line with triangles shows the share of assets accounted for by top businesses sorted on assets. The red line with squares shows the share of receipts (sales) accounted for by top businesses sorted on sales. The green line with circles shows the share of net income accounted for by top businesses sorted on net income (restricting to those with positive net income).



Basic results For the aggregate economy, the data reveals a persistent rise in the shares accounted by the top 1% or 0.1% businesses. Figure 1 shows top shares for three types of size bins. In earlier years (from 1918 to 1975), the SOI provided size bins sorted by net income (green line with circles). In later years (from 1959 onwards), the SOI provided size bins sorted by sales (red line with diamonds). The longest and most comprehensive size bin tabulations are sorted by assets, available since 1931 (blue line with triangles). The long-run increase in corporate concentration is reflected by all three series. For instance, since the early 1930s, the asset shares of the top 1% and top 0.1% have increased by 27 percentage points (from 70% to 97%) and 40 percentage points (from 47% to 88%), respectively.

At the industry level, we also observe a general rise in corporate concentration among the main sectors (where all three types of series are available) and the subsectors (where only size bins by assets are available). However, the timing differs across industries. For example, for manufacturing and mining, concentration increased more substantially in the earlier decades (before the 1970s). In contrast, for services, retail, and wholesale, rising concentration occurred primarily in the later decades (after the 1970s). The overall trends are similar if we use a fixed number of top businesses (e.g., top 500), but a fixed number can be less comparable across different levels of aggregation and different time periods over the long run. The results are also similar if we examine the relative concentration within the largest businesses (e.g., the top 1% within the top 10%).[1]

Finally, the SOI data also provides information about other characteristics of corporate businesses over the past century, such as profitability. Profitability (i.e., net income/sales) does not display secular

[1]A possible concern about the baseline top 1% share is that when small firms enter the number of firms increases, which may mechanically increase the top 1% share. The relative concentration measure (the top 1% within the top 10%) is robust to this concern as we discuss more in Section 2 and it is 98% correlated with our baseline top 1% share.

trends, unlike concentration. It plunged during the Great Depression, rebounded during the 1940s, then declined gradually until the 1980s, and increased slightly afterwards.

Mechanisms Why did corporate concentration increase persistently over the past century? We analyze several mechanisms and find substantive evidence for the role of economies of scale. Early work by Stigler (1958) suggests that higher prominence of larger companies in the business size distribution is a straightforward reflection of economies of scale. We extend beyond this general argument and document further empirical facts about several key features that accompany rising corporate concentration.

First, we find that the timing and the degree of rising concentration in an industry align closely with rising investment intensity in R&D and IT, measured using additional data from the Bureau of Economic Analysis (BEA). These types of investment are commonly viewed to embody greater scalability (Haskel and Westlake, 2017; Crouzet and Eberly, 2019; Lashkari, Bauer, and Boussard, 2022) and entail greater upfront spending (Sutton, 1991, 2001). They can be directly involved in technological changes that enhance economies of scale, or required to achieve scale production when other forces (e.g., customer preferences, transportation improvements) increase the benefits of scale. Overall, to the extent that production processes with more scalability are associated with more R&D and IT, we can use the intensity of R&D and IT as a general indicator of firms exploiting economies of scale. Importantly, this measure can be constructed across different industries, which allows us to perform systematic analyses.

Among the main sectors, the concentration trends are consistent with industrial technologies enabling mass production in manufacturing in the early 20th century (Chandler, 1994), while modern IT started to transform services, retail, and wholesale more recently (Hsieh and Rossi-Hansberg, 2022). Among the subsectors, the turning points in concentration trends also coincide with key developments in economies of scale. For instance, concentration in restaurants began to increase around the 1960s as prominent restaurant chains emerged. Concentration in several manufacturing subsectors accelerated in the 1940s as production capacity developed for World War II stimulated more large-scale production for commercial use. Although the particular drivers of economies of scale can be heterogeneous across industries, investment intensity in R&D and IT appears effective as a general reflection of the relevance of scale; in the data, it comoves closely with top business shares. We confirm the relationship statistically via regressions of the top 1% asset shares in an industry on the fraction of its investment in R&D and IT, using both levels and changes over the medium term (e.g., twenty years). We also include specifications with year fixed effects to absorb aggregate trends, which further isolates the timing alignment between rising concentration in an industry and technological intensity.

To further document the role of technological innovations in the production process, we show that our technological intensity measure, and moreover rising concentration, increase with the prevalence of breakthrough patents. We use the long-run data on breakthrough patents constructed by Kelly et al. (2021), available mainly for manufacturing subsectors plus mining, construction, and agriculture. In addition, we use the patent data to address a possible concern about reverse causality regarding our previous analysis: maybe large businesses report more comprehensively their spending on R&D and IT, and shocks that happen to benefit large firms (even randomness) could increase concentration as well as the industry-level investment intensity in R&D and IT. The patent data verifies that influential technologies play a role, and the results are similar even if we control for the number of patents in case large firms also have a higher propensity to file patents.

Second, we also find that increases in concentration are positively associated with industry growth. Over the medium term (e.g., twenty years), industries that experience higher increases in concentration are also the ones that experience higher growth in real gross output. Correspondingly, their output shares in the economy expand as well. We check that the results are robust when we use the persistent component of industry growth (e.g., predicted by industry developments in the past), which addresses the concern that random shocks to large firms can affect both changes in concentration and contemporaneous industry growth.

We use a simple model to illustrate that production processes with greater economies of scale can account for the empirical facts. Following Hsieh and Rossi-Hansberg (2022), firms with heterogeneous productivity can choose a new production technology with higher upfront spending and lower marginal costs, or an old technology with lower upfront spending and higher marginal costs. Productive firms will find it worthwhile to pay the higher upfront spending and obtain scalability; other firms will not find it appealing to do so, but they can still exist when products are imperfect substitutes. Greater scalability of the new technology will increase concentration (e.g., top 1% share) as large firms expand relative to small firms; industry output will also increase. Meanwhile, profitability can follow other forces that drive markups.

We then analyze two other mechanisms.[2] A natural question is whether trade and globalization can explain our baseline facts. International trade for the U.S. (relative to GDP) did not expand substantially in the first half of the 20th century, and globalization only started to accelerate around the 1970s. In our data, rising concentration in manufacturing was stronger before the 1970s. During the period of globalization, rising concentration was stronger in services instead, and services have smaller trade volumes than goods. The timing suggests that international trade does not account for the entire long-run evidence. Additionally, in a simple model following Melitz (2003), if the reduction of barriers to international trade is the only force, then sales concentration among U.S. businesses would not increase when exports are excluded from sales. In the data, sales concentration increases significantly even when exports are excluded from sales. Nonetheless, although trade and globalization alone cannot fully explain the long-run evidence, having broad markets (domestically or internationally) could increase the appeal of economies of scale.

Another question is whether regulatory policies and antitrust enforcement drive our main facts. For instance, regulatory restrictions on interstate banking could have a direct impact on the size of banks (and we indeed observe rising concentration in banking when these restrictions were lifted). In most other sectors, we are not aware of such policies that align with the patterns of rising concentration in our data. For antitrust policies, the past century witnessed several regimes of antitrust enforcement (Lamoreaux, 2019). However, rising corporate concentration has been a secular trend throughout different antitrust regimes. We do not observe a significant relationship between corporate concentration in our data and standard aggregate antitrust enforcement measures, such as the number of antitrust cases filed by the

[2]We have not focused on the random growth mechanism because standard random growth frameworks do not easily explain systematic differences across industries (Sutton, 1997). In addition, these frameworks generally focus on a stationary size distribution, while the empirical evidence suggests that the business size distribution is not necessarily stationary for a reasonably long period of time.

Department of Justice (DOJ) or the budget of the DOJ's antitrust division. While we do not find evidence that antitrust shapes the economy-wide business size distribution, it could have a more visible impact on the market for a particular product (which is closer to the domain of antitrust analyses). Additionally, since concentration does not necessarily have a clear relationship with market power (Syverson, 2019), we do not speak to the strength of market power or the effectiveness of policies targeting market power.

Additional checks We perform several additional checks for the concentration trends. First, we cross-check our results with census data, which reports sales shares of the top 4, 8, 20, and 50 firms by sales for manufacturing industries in census years since 1947 and other industries since the 1980s. For the degree of concentration over time, we rely on the longer census data for manufacturing industries at the four-digit SIC level (Peltzman, 2014; Keil, 2017). We take the average concentration ratios in each census year and observe a persistent upward trend, especially for the value-weighted average. For the degree of concentration in the cross section, we use more recent data from 2012 (with both manufacturing and non-manufacturing industries) and compare top shares in census data (sales share of top businesses by sales) with those interpolated from SOI data (assets share of top businesses by assets). The two sets of data are closely aligned, with a correlation of around 0.8.

Second, to check that our SOI data reliably captures firms at the very top, we perform a comparison of aggregate top business shares with Compustat data. In particular, we calculate the total sales (assets) among the top 500 Compustat firms by sales (assets) as a share of total corporate sales (assets), and compare the result with the top 500 shares estimated from the SOI. Compustat data misses large private companies and has other caveats, but the level of top 500 shares is generally similar in Compustat and SOI data (the former is slightly lower as we would expect).

Third, our main analyses use comprehensive information by size bins for corporate businesses (both C-corporations and S-corporations). For noncorporate businesses (partnerships and nonfarm sole proprietorships), we only have size bins by receipts for some years. In these years, we can construct the receipt share of top businesses (e.g., top 0.1%) by receipts among all businesses (corporates plus noncorporates), and we find similar trends of rising concentration. For other years, we can construct a lower bound estimate for top businesses' shares with the assumption that the top 0.1% businesses (corporates plus noncorporates) only have corporate businesses. We find similar results using this method too, with slightly less rising concentration after the 1980s possibly because some large noncorporate businesses begin to emerge and our assumption becomes too conservative.

Finally, while we focus on production activities by businesses in the U.S., in recent years some U.S. firms may have shifted their production assets to foreign subsidiaries for a variety of reasons. We show that results are similar if we include the international assets of U.S. companies, using data from the BEA on Activities of U.S. Multinational Enterprises (available since the 1980s).

1.1 Literature Review

Our work contributes to knowledge about the long-run evolution of the U.S. economy. First, we collect new data covering the population of U.S. corporate businesses for 100 years. Second, we document that a key feature over the past century is rising corporate concentration, and this theme has influenced different industries over time. Third, we analyze possible mechanisms behind the long-run trends. Our data shows that mechanisms for rising corporate concentration (proposed by us or by other researchers) need to explain not only the recent trends, but also the long-run developments over the past century. Results from our analyses suggest that the persistent rise of corporate concentration likely reflects increasingly stronger economies of scale. Certainly, each decade may have special features that are also important to analyze, and many studies investigate the special features of our times (e.g., low interest rates, demographics, regulation); our focus is the long-run evolution. In the following, we explain in more detail the relationship between our work and several branches of the literature.

Concentration An influential body of work documents rising industry concentration in the U.S. since around the 1980s using census data.[3] Some studies focus on the role of technology (Autor et al., 2020; Ganapati, 2021; Hsieh and Rossi-Hansberg, 2022); others raise concerns about weak competition policies (Baker, 2019; Covarrubias, Gutiérrez, and Philippon, 2020). For the latter question, recent work also suggests that the more relevant realm of analyses is not industry concentration, but concentration in the market for a particular product or location (Rossi-Hansberg, Sarte, and Trachter, 2021; Benkard, Yurukoglu, and Zhang, 2021; Amiti and Heise, 2021), which does not appear to be increasing in recent decades in U.S. data.[4] Our focus is concentration in production activities in the U.S. and the economy-wide business size distribution; our results speak to the impact of larger versus smaller businesses in the economy and mechanisms related to production activities (e.g., economies of scale). Our focus is not product market concentration or competition policies.

Some analyses of the business size distribution examine a small number of "giant" or "dominant" firms (e.g., top 20) in the aggregate economy (Collins and Preston, 1961; Stonebraker, 1979; White, 2002; Gutiérrez and Philippon, 2020). They tend to find less pronounced increases in the shares of this set of firms. We capture a broader set of top businesses (e.g., top 0.1% in recent years has nearly 6,000 businesses), and our evidence suggests that the rise of corporate concentration is not limited to a few giant companies (which tend to attract the most public attention). Consistent with the conjecture of White (2002), the increasing prevalence of larger enterprises in the right tail of the size distribution appears related to changes in technology.

Finally, the SOI data we use focuses on financial metrics rather than employment. Comprehensive information on firm size by employment is only available from census data since the 1970s to our knowledge. In these recent decades, employment concentration among U.S. firms exhibits a slight increase. The changes are smaller than increases in concentration by financial metrics, since large firms generally achieve more output with less labor (Autor et al., 2020; Hubmer and Restrepo, 2021).[5] Given the relative stability of the employment distribution, some models have focused on obtaining

[3]For analyses of recent decades using data on public companies, see also DeAngelo, DeAngelo, and Skinner (2004) and Grullon, Larkin, and Michaely (2019). For earlier time periods, studies such as Peltzman (2014) examined the Manufacturing Census, as we discussed in the cross-checks above.

[4]For instance, as large firms expand into more locations or product lines, market concentration for a given location or a given product may decrease. This phenomenon can coexist with large firms accounting for more output in the economy (higher concentration in economy-wide production activities).

[5]Interestingly, Lenin (1916) also observed that "Concentration of production, however, is much more intense than the concentration of workers, since labour in the large enterprises is much more productive."

stationarity for the firm size distribution, as reviewed by Luttmer (2010). Our work (as well as other work using census data) suggests that the business size distribution based on production assets or output does not appear to be stationary.

Economies of scale Stigler (1958) suggests that the evolution of the business size distribution is the most straightforward way to reflect economies of scale. A number of studies further suggest that technology is associated with scalability (Chandler, 1994; Haskel and Westlake, 2017; Crouzet and Eberly, 2019; Hsieh and Rossi-Hansberg, 2022; Lashkari, Bauer, and Boussard, 2022), so a natural test is to examine whether technological intensity is related to corporate concentration. We collect additional data on the investment intensity in R&D and IT as a general measure of technological forces related to economies of scale. We find that this measure aligns closely with the timing and the degree of rising concentration across different industries in the past century. We also find that industries with higher increases in concentration witness higher output growth. These analyses provide further evidence that increasingly stronger economies of scale likely underlie the persistent rise of corporate concentration. One might ask why technological and other forces have been evolving in the direction of stronger economies of scale. One possibility is that businesses always seek to expand, and technology has been enhancing the replication of production processes as Brynjolfsson et al. (2008) highlight; moreover, such replication is easier to implement within a firm, in line with the insight of Coase (1937).

Other topics The long-run trends we document also relate to several other questions in understanding macro outcomes. First, many studies analyze financial frictions among large versus small businesses; as Crouzet and Mehrotra (2020) point out, the aggregate impact of financial frictions across the firm size distribution depends on the degree of concentration in production activities. Relatedly, Gabaix (2011) highlights that shocks to large firms can drive aggregate fluctuations; such effects are likely stronger when concentration in production activities is higher. Second, although we focus on concentration in production activities rather than product market competition, some postulate that economies of scale may increase market power (Eeckhout, 2021; Eeckhout and Veldkamp, 2021). In the data, estimated markups do not display a secular increase over the past century (De Loecker, Eeckhout, and Unger, 2020; Traina, 2018); combined with our findings, the evidence suggests that stronger economies of scale may not always raise market power. Analyzing the conditions under which economies of scale increase market power is an interesting topic for future research.

2 Data

Our primary data source is the Statistics of Income (SOI) and the associated Corporation Source Book published annually by the IRS. The SOI originated from the Revenue Act of 1916, which requires the IRS to report statistics based on the tax returns filed each year. Statistics on the size of corporate businesses were included for the first time in 1918. The SOI is a key source for the national income and product accounts (NIPA), and the data we use captures production activities in the U.S. like the national accounts. For the early years (before 2000), we digitize historical SOI publications; for some years between 1965 and 1980, we are able to use data from the Electronic Records Archives of the

National Archives. For recent years (after 2000), we use data from the SOI website. We summarize the key elements of our data construction below, and provide more details in Internet Appendix IA2. We have made the cleaned series available online at `https://businessconcentration.com`.

Every year, the SOI tabulates a variety of statistics for the population of corporate businesses, including the number and financial information of corporate businesses by size bins, which allows us to investigate the business size distribution. Table 1 shows examples for the aggregate economy (Panel A) and for one industry (Panel B) from the SOI in 1945. The primary size bins that we use are based on total assets, since these size bins are reported continuously for the longest period of time and have the most detailed breakdowns by industry. Size bins are also available based on receipts (sales) after 1959 and net income from 1918 to the 1970s. The data of corporate businesses by size includes both C-corporations and S-corporations, and the information comes from corporate tax returns (Form 1120 or 1120-S). For noncorporates (partnerships and nonfarm sole proprietorships), size bins were presented in some years in separate SOI publications. We transcribe this data whenever available and perform detailed checks including noncorporate businesses in Section 3.2.[6]

We have processed tabulations of businesses by size bins for the aggregate economy, main sectors (roughly at the one-digit SIC code level), and subsectors (roughly at the two-digit SIC code level). The industry classification system switched from SIC to NAICS in 1997, and we harmonize the industries to maintain consistency as explained in Internet Appendix IA2. The SOI assigns a single industry code to each business based on the industry that represents the largest percentage of its total receipts.[7] The IRS ceased to publish the sector-level tabulations after 2013 due to an update in its privacy guidelines (IRS Publication 1075), but the aggregate tabulations continue to be available. Information at the individual firm level is confidential and not available in our SOI data.

For each level of aggregation, we use two methods to calculate top business shares (e.g., top 1% share) from size bins marked by dollar thresholds. The first method is to interpolate the top 1% using Pareto distributions, following standard methods used to calculate household top income shares from income bins with a similar format. Blanchet, Fournier, and Piketty (2017) provide a detailed description of the generalized Pareto interpolation method, which refines and standardizes top share interpolations in earlier work (e.g., Piketty and Saez, 2003).[8] The second method is to directly add up the top bins such that the number of businesses in these bins approximates 1%.[9] These two methods produce similar

[6]It is challenging to construct reliable economy-wide measures of corporate concentration before our SOI data started in 1918, since limited information exists to our knowledge about the denominator (total corporate assets or sales), the numerator (the largest businesses and their assets or sales), as well as the number of businesses.

[7]Since we are interested in the business size distribution, we do want to keep a business as a whole instead of separating it into different pieces. The SOI industry classification is in line with this objective (and ensuring that a business is not counted multiple times in different industries), although the industry classification may have some imperfections.

[8]While earlier work typically assumes that Pareto coefficients are constant for the entire distribution or within bin thresholds, the generalized Pareto interpolation of Blanchet, Fournier, and Piketty (2017) relaxes this assumption. The method first calculates the inverted Pareto coefficient $b(p_i)$ for each threshold where p_i is the fraction of firms with assets (receipts/net income) more than y_i, and $b(p_i)$ is the ratio between the average assets (receipts/net income) above y_i and the threshold y_i. It then derives a continuous curve of inverted Pareto coefficients, conditional on the information from the tabulation. We find that the estimated inverted Pareto coefficients tend to decline in firm size, consistent with the right tail thinning out (Rossi-Hansberg and Wright, 2007).

[9]If the total number of businesses is N and the number of businesses in the top k bins add up to less than $0.01N$ (whereas the top $k + 1$ bins add up to more than $0.01N$), then we take all the businesses in the top k bins and add

Table 1: Raw Data from Statistics of Income (1945)

This figure shows examples of raw data from the SOI for the year 1945. Panel A is a screenshot of the tabulation by asset size bins for the aggregate economy. Panel B is a screenshot of the tabulation by asset size bins for one industry.

Panel A. Example of Aggregate Tabulation

[Total assets classes and money figures in thousands of dollars]

Total assets classes [38]	Number of returns [32]	Total assets—Total liabilities [38]	Total compiled receipts [6]	Compiled net profit or net loss	Net income or deficit [2]
AGGREGATE					
Under 50	177, 788	3, 647, 660	9, 030, 941	267, 783	267, 621
50 under 100	61, 431	4, 378, 846	8, 650, 707	376, 597	376, 379
100 under 250	60, 308	9, 526, 342	16, 659, 649	837, 872	837, 120
250 under 500	27, 583	9, 666, 507	15, 828, 823	914, 465	913, 563
500 under 1,000	17, 669	12, 436, 856	17, 397, 634	1, 196, 416	1, 193, 741
1,000 under 5,000	22, 057	47, 907, 402	42, 250, 752	3, 450, 003	3, 427, 380
5,000 under 10,000	3, 948	27, 591, 380	17, 749, 140	1, 719, 313	1, 704, 217
10,000 under 50,000	3, 197	65, 334, 850	39, 917, 400	3, 900, 112	3, 868, 073
50,000 under 100,000	427	29, 834, 282	15, 626, 460	1, 521, 776	1, 508, 085
100,000 and over	542	231, 137, 144	69, 524, 822	7, 035, 344	6, 917, 796
Total	374, 950	441, 461, 268	252, 636, 330	21, 219, 681	21, 013, 975

Panel B. Example of Industry-Level Tabulation

Total assets classes [55]	Number of returns with balance sheets [42]	Cash [43]	Notes and accounts receivable less reserve	Inventories	Investments [56]	Capital assets [46] less reserves	Total assets—Total liabilities [48]	Accounts and notes payable [57]
SERVICE: BUSINESS SERVICE—								
0	2, 419	11, 723	11, 877	1, 264	4, 076	9, 901	41, 710	9, 258
50	519	9, 009	11, 138	1, 170	4, 203	8, 186	36, 246	8, 416
100	433	13, 848	20, 844	1, 964	10, 960	15, 292	66, 950	15, 679
250	173	12, 547	16, 526	2, 122	11, 386	13, 542	60, 054	15, 626
500	99	11, 875	20, 417	2, 614	16, 166	11, 856	66, 486	17, 827
1,000	92	31, 130	45, 472	8, 058	56, 072	37, 504	185, 880	41, 630
5,000	7	6, 589	17, 685	1, 044	13, 450	4, 913	47, 822	11, 048
10,000	5	9, 951	15, 301	1, 936	18, 255	26, 171	75, 814	8, 786
50,000	---	---	---	---	---	---	---	---
100,000	---	---	---	---	---	---	---	---
Total	3, 747	106, 672	159, 260	20, 171	134, 570	127, 365	580, 964	128, 271

results, as shown in Figure IA1. The raw correlation is over 0.99. The benefit of the first method is we do not have missing values for the small fraction of industry-years where the top bin has more than 1% businesses; the benefit of the second method is we can calculate other attributes of the top 1% businesses (e.g., profits). We use the first method as the default, and use the second method when we need to measure other attributes of top businesses.

We focus on the top 1% or top 0.1% (similar to Crouzet and Mehrotra (2020), Hsieh and Rossi-Hansberg (2022), among others) instead of the top N businesses (with a fixed N) for several reasons. First, the share of the top N businesses is not easily comparable across different levels of aggregation (e.g., main sectors versus subsectors). The number of businesses also differs considerably across industries. Second, over the past century the number of businesses in the U.S. economy has increased substantially, so the top N businesses (with a fixed N) can be too conservative. Table 2 shows the number of corporations

$(0.01N - \sum_{i=1}^{k} n_i)/n_{k+1}$ fraction from the $k+1$th bin (where n_i denotes the number of businesses in bin i). In other words, we take all businesses in the top k bins and fill in the residual from the $k+1$th bin.

Table 2: Number of Corporate Businesses

This table shows the number of corporate businesses (in thousands) for the beginning of each decade, for the aggregate economy and the main sectors. The main sectors largely correspond to SIC codes 01-09 (agriculture), 10-14 (mining), 15-17 (construction), 20-39 (manufacturing), 40-49 (transportation, communications, and utilities), 50-59 (wholesale and retail trade), 60-67 (finance, insurance, and real estate), and 70-89 (services).

	Number of Corporations (000)									
Sector	1920	1930	1940	1950	1960	1970	1980	1990	2000	2010
All	314	463	473	629	1,141	1,665	2,710	3,717	5,045	5,814
Agriculture	9	10	8	8	17	37	81	126	141	137
Construction	10	19	16	28	72	139	272	407	598	718
Finance	79	137	143	172	334	406	493	609	748	892
Manufacturing	78	92	86	116	166	198	243	302	321	281
Mining	18	12	10	9	13	14	26	40	33	40
Services	17	38	41	55	121	281	671	1,029	1,791	2,273
Trade	79	131	140	209	356	518	800	1,023	1,182	1,226
Utilities	21	22	22	26	44	67	111	160	210	246

in the aggregate and in the main sectors for each decade, and the *SOI Bulletin* publications provide extensive descriptions of the business population (Harris and Szeflinski, 2007). Finally, analyzing top percentiles is also the standard approach in research on household income and wealth inequality (Piketty and Saez, 2003; Saez and Zucman, 2016; Kuhn, Schularick, and Steins, 2020; Smith et al., 2019). To make sure the results of top 1% shares are not affected by small and extraneous firms coming in or out of the sample (therefore changing the total number of firms), we present the top 1% as a share of the top 10% as well, which should not be affected when the right tail is Pareto.[10] We also provide robustness checks using the top 500 businesses in the aggregate and in each main sector in Section 3.2.

For businesses with subsidiary affiliates, the SOI reports consolidated affiliates as one entity.[11] We follow IRS publications to refer to an entity in the SOI tabulations as a "business" (see Petska and Wilson (1994), Harris and Szeflinski (2007), and other *SOI Bulletin* publications). We explain consolidation rules in detail in Internet Appendix IA2 and provide a summary here. First, the consolidation threshold was 95% ownership of an affiliate before 1954 and 80% afterwards. The consolidated filing privilege is granted to all affiliated domestic corporations except regulated investment companies (RICs), real estate investment trusts (REITs), tax-exempt corporations, Interest Charge Domestic International Sales Corporations (IC-DISCs), and S-corporations. Second, consolidation was mandatory from 1918 to 1921 and voluntary after 1922, with the exception of 1934 to 1941 when consolidated filings were not allowed for most corporations. In recent decades at least, eligible firms generally elect to consolidate

[10] Specifically, if small and extraneous firms come in (out) of the data, the total number of firms in the top 1% will increase (decrease). Thus the top 1% share can increase (decrease), as the small firms have little impact on the total value of the denominator while the numerator will include more/less firms. To make sure our results are not affected by this issue, we can calculate top x% as a fraction of top y% (e.g., top 1% as a share of top 10%). One can show that for Pareto distributions, this relative share only depends on x/y and the tail coefficient k. In other words, top 1%/top 10% = top $0.01N$/top $0.1N$ is invariant to the total number of firms N.

[11] For instance, the SOI in 2013 (as well as in other years) writes: "A consolidated return filed by the common parent company was treated as a unit and each statistical classification was determined on the basis of the combined data of the affiliated group."

(Mills, Newberry, and Trautman, 2002), given more favorable treatments when consolidated (e.g., when consolidated the sales among affiliates do not generate taxes, and gains and losses across affiliates can be netted). Before 1964, there was often a small surtax on consolidated returns. In Internet Appendix IA2, we use SOI data to show the prevalence of consolidated filings over time, and examine the impact on our concentration estimates. We observe a decrease in the prevalence of consolidated filings between the early 1930s and the early 1940s, and then an increase between the 1960s and the 1980s (returning to the level observed in the early 1930s). Overall, the trend of rising concentration remains within each regime of consolidation filings.

For accounting methods, firms report their balance sheets (assets and liabilities) in Section L of Form 1120 and are instructed to use “the accounting method regularly used in keeping the corporation's books and records" (see Form 1120 instructions). In other words, the accounting methods for balance sheet items in Form 1120 (and correspondingly the SOI) largely follow what companies do for financial statements, with some possible differences (e.g., foreign affiliates, consolidation thresholds, special purpose vehicles). Mills, Newberry, and Trautman (2002) and Boynton and Mills (2004) provide detailed discussions about the relationship between total assets in the SOI data and in firms' annual reports. As we show in Section 3, these reporting differences are unlikely to drive the main time trends we observe (given the high consistency among concentration trends by assets, receipts, and net income). For net income, the SOI uses tax depreciation but the concentration series by net income is not our primary focus. Section 3.3 also compares net income in SOI and NIPA (where the BEA makes adjustments to use economic depreciation instead), and we find the results are similar in the aggregate.

Finally, like the national accounts, the SOI focuses on production activities by businesses in the U.S. (e.g., receipts in the SOI are similar to the convention of gross output in the national accounts). This is the natural realm for our analyses of concentration in production activities in the U.S. economy. For assets, the SOI data includes businesses incorporated in the U.S.[12] For receipts, the SOI data includes U.S. corporations and foreign corporations with U.S. business activities (only income connected with conducting businesses in the U.S. is included); they cover exports but few imports. We will discuss issues related to trade activities between U.S. and other countries in detail in Section 5.1. We also perform checks relating to foreign affiliates of U.S. businesses in Section 3.

3 100 Years of Corporate Concentration

In this section, we present the basic results of top businesses' shares in the historical SOI data. We show the results for the aggregate economy and for different sectors in Section 3.1. We present additional checks of the concentration trends in Section 3.2. We discuss long-run trends of other outcomes (e.g., profitability) in Section 3.3.

[12] Affiliates of foreign companies incorporated in the U.S. are treated as regular corporations (they also do not count towards imports in the national accounts).

3.1 Top Business Shares over 100 Years

We study the population of corporate businesses every year. We present results for the aggregate economy, the main sectors, and the subsectors. Analyses at the industry level mainly aim to group firms that share similar production activities (e.g., chemical plants have different production processes from hotels). We do not stipulate that industry classifications map into product markets; as mentioned before, our focus is concentration in the production activities in the economy, not concentration in the market for a particular product or location.

Aggregate Figure 1 in the Introduction already previewed the trends for the aggregate economy. Figure 2 presents two more aggregate trends: the share of the top 1% businesses among the top 10% (left panel) and the share of the top 0.1% businesses among the top 1% (right panel). These additional series show the evolution of the far right tail of the size distribution. As discussed in Section 2, they also address the possible concern that some small businesses in the bottom of the size distribution may not be very active, or they may affect the number of firms and correspondingly the top 1% share. Like before, the blue line with triangles shows the share of assets accounted for by top businesses sorted on asset size; the SOI has consistently tabulated business characteristics by asset size bins since 1931. The red line with squares shows the share of receipts (i.e., sales revenue) accounted for by top businesses sorted on receipt size; the SOI only started tabulating businesses by receipt size bins in 1959. The green line with circles shows the share of net income accounted for by top businesses sorted on net income (restricting to those with positive net income); the SOI tabulated businesses by net income bins in the early years, but stopped doing so after 1975. We observe consistent results across these three types of size tabulations. Top shares by assets and by receipts have correlations over 0.9, and top shares by net income have correlations of around 0.7 with the other two series.

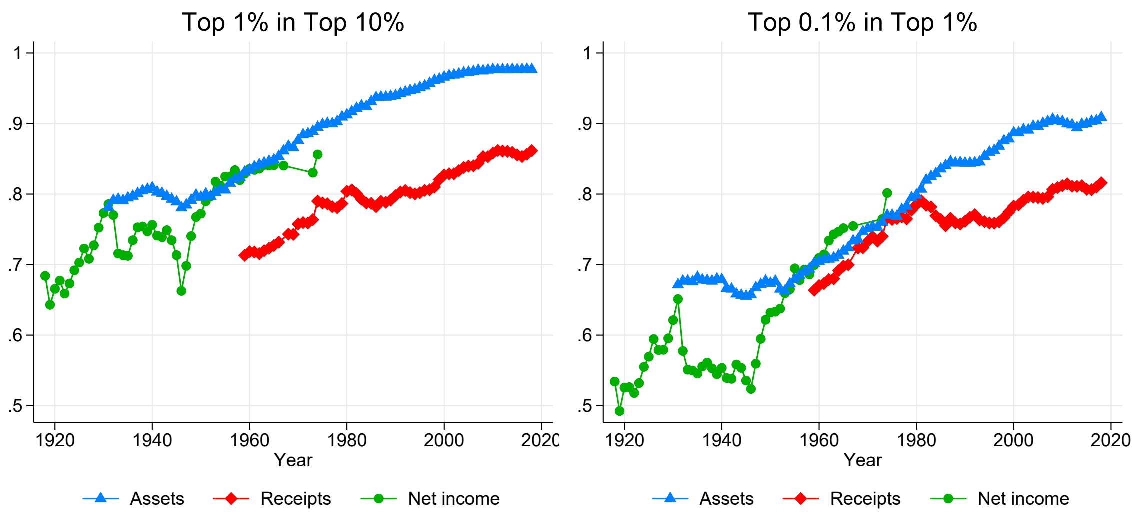
Interestingly, the secular trend of rising corporate concentration differs from the evolution of the top 1% and 0.1% household income and wealth shares in the U.S., which decreased between the 1920s and the 1970s and increased afterwards (Piketty and Saez, 2003; Saez and Zucman, 2016). In principle, whether corporate concentration and household inequality are linked depends on several factors. First, it depends on the extent to which the large businesses' revenues and profits disproportionately benefit a small number of individuals (e.g., due to concentrated equity ownership (Kuhn, Schularick, and Steins, 2020) or high executive compensation (Frydman and Saks, 2010)), rather than households more generally (e.g., if all households hold the market portfolio). Second, household inequality is also driven by redistribution policies (e.g., taxation), education, and many other forces.

Main sectors and subsectors We present results for the main sectors (around the one-digit SIC level) in Figure 3 and the subsectors (around the two-digit SIC level) in Figure 5. For the main sectors, we can obtain size bins by assets, receipts, and net income. For the subsectors, tabulations are most comprehensive for size bins by assets (and this sorting also has the longest time series as shown before). Accordingly, we use the asset share of the top 1% corporate business by assets as the main series in industry-level analyses.

Figure 3, Panel A, shows that concentration (as represented by the top 1% share) has been rising over the past century in most of the main sectors. The series by assets, receipts, and net income display

Figure 2: Aggregate Trends

This figure shows the shares of the top 1% corporate businesses among the top 10% corporate businesses (left panel) and the top 0.1% corporate businesses among the top 1% corporate businesses (right panel). The blue line with triangles shows the share of assets accounted for by top businesses sorted on assets. The red line with squares shows the share of sales accounted for by top businesses sorted on sales. The green line with circles shows the share of net income accounted for by top businesses sorted on net income (restricting to those with positive net income).



consistent patterns. Figure 3, Panel B, focuses on concentration by assets, and shows that the results are similar for the share of the top 1% in the top 10%. Indeed, the share of the top 1% businesses in the top 10% is more than 0.98 correlated with the top 1% share, and all of our subsequent results about the top 1% hold for this series as well. Figure 3 also indicates that the timing for rising concentration varies across industries. The rise in concentration is stronger in earlier years for manufacturing, mining, and utilities (which also includes communications and transportation), and stronger in later years in services and trade (retail and wholesale). Panel A of Figure IA2 further visualizes the differences in timing. For each main sector, the solid blue circles show the change in the top 1% asset share between the 1930s and the 1970s, and the hollow red diamonds show the change between the 1970s and the 2010s. Table 3 provides a tabulation of the average top 1% asset shares in each decade.[13]

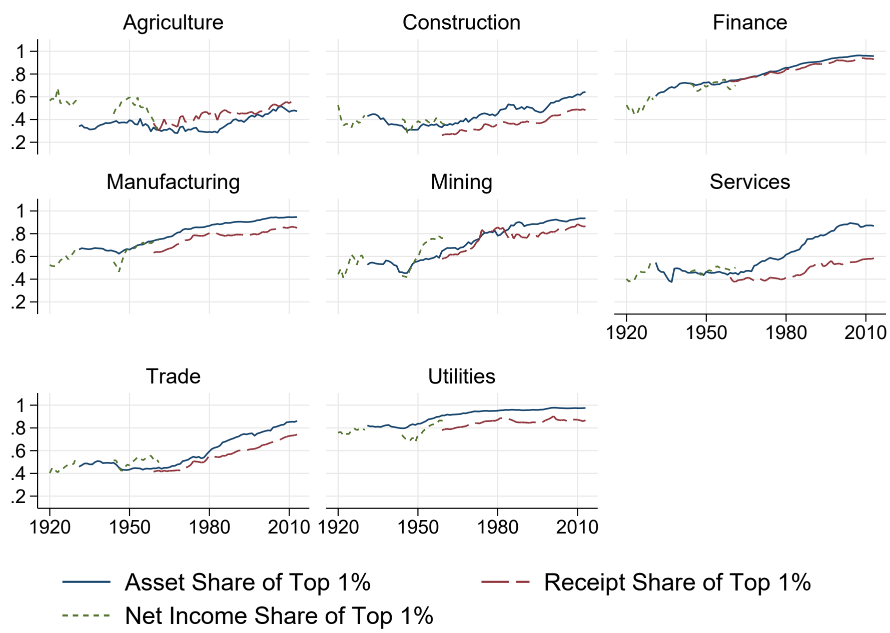
Figure 4 delineates the asset shares (Panel A) and receipt shares (Panel B) across the full distribution by size (top 0.1%, top 0.1% to 1%, top 1% to 10%, top 10% to 50%, and bottom 50%). First, this figure shows that most of the expansion of the top share is driven by the top 0.1%. Nonetheless, our data by size bins measures the top 1% shares more accurately; sometimes the top 0.1% has too few businesses, so we need to rely more on interpolation (e.g., size bins by receipts are less granular at the main sector level and Panel B shows that the interpolated top 0.1% shares by receipts have one-off jumps when the granularity of the top bin changes). Accordingly, we use the top 1% share as the main variable in our analysis, bearing in mind that much of its expansion can be driven by the top 0.1%. Second, Figure

[13] The level of top business shares can be higher in the aggregate than in most industries because some industries have more large firms and more concentrated industries may also have more large firms. For the *change* in aggregate top business shares, rising concentration in different industries in general, higher growth of industries with larger firms, and higher growth of industries with more concentration can all play a role.

Figure 3: Top 1% Shares: Main Sectors

This figure shows the share of the top 1% corporate businesses among the main sectors. In Panel A, the solid blue line shows the share of assets accounted for by top businesses sorted on assets. The dashed red shows the share of sales accounted for by top businesses sorted on sales. The dotted green line shows the share of net income accounted for by top businesses sorted on net income (restricting to those with positive net income). In Panel B, the solid blue line repeats the share of the top 1% businesses by assets in total corporate assets, and the dashed red line shows the share of the top 1% businesses by assets in the top 10% businesses by assets. The main sectors largely correspond to SIC codes 01-09 (agriculture), 10-14 (mining), 15-17 (construction), 20-39 (manufacturing), 40-49 (transportation, communications, and utilities), 50-59 (wholesale and retail trade), 60-67 (finance, insurance, and real estate), and 70-89 (services).

Panel A. By Assets, Receipts, and Net Income



Panel B. By Assets

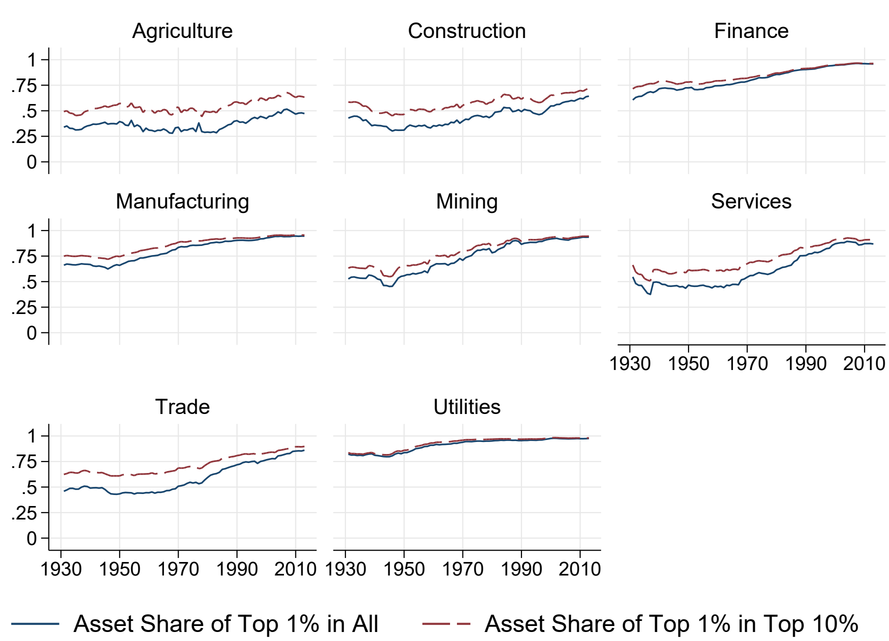


Table 3: Top 1% Asset Shares: Average by Decade

This table shows the average asset share of the top 1% businesses in each decades for the aggregate economy and the main sectors. The main sectors largely correspond to SIC codes 01-09 (agriculture), 10-14 (mining), 15-17 (construction), 20-39 (manufacturing), 40-49 (transportation, communications, and utilities), 50-59 (wholesale and retail trade), 60-67 (finance, insurance, and real estate), and 70-89 (services).

	Asset Share of Top 1%								
	1930s	1940s	1950s	1960s	1970s	1980s	1990s	2000s	2010s
All	0.72	0.73	0.74	0.79	0.85	0.90	0.93	0.96	0.97
Agriculture	0.33	0.37	0.36	0.31	0.32	0.33	0.41	0.48	0.47
Construction	0.42	0.33	0.34	0.37	0.43	0.50	0.49	0.58	0.63
Finance	0.66	0.72	0.72	0.76	0.82	0.88	0.92	0.96	0.96
Manufacturing	0.67	0.65	0.70	0.77	0.85	0.89	0.91	0.94	0.95
Mining	0.54	0.50	0.59	0.68	0.78	0.85	0.89	0.92	0.93
Services	0.46	0.46	0.46	0.47	0.57	0.68	0.80	0.88	0.87
Trade	0.49	0.47	0.44	0.46	0.54	0.66	0.74	0.80	0.86
Utilities	0.82	0.81	0.87	0.92	0.95	0.96	0.96	0.97	0.97

4 also shows the expansion of the top businesses primarily decreases the shares of businesses in the middle of the distribution, and the bottom 50% is too small in value terms in any case.

For subsectors, Figure 5 shows the asset share of the top 1% businesses (as mentioned earlier, we do not have comprehensive data for size bins by receipts or net income at this level). Similarly, the persistent rise in concentration is common in many industries, but the timing can differ.[14] Panel B of Figure IA2 shows the change in the top 1% asset share between the 1930s and the 1970s and the change between the 1970s and the 2010s for each subsector. We investigate the timing in detail in subsequent sections to analyze the relevant mechanisms behind rising corporate concentration.

Finally, while most industries experienced noticeable increases in concentration over time, the ranking in the cross section remains stable. For instance, the rank correlation between top 1% asset shares in the 1930s and those in the 2010s is over 0.9 among main sectors and around 0.7 among subsectors. This phenomenon suggests that industries differ persistently in the degree of economies of scale in production. Meanwhile, the cross-industry dispersion of the top 1% asset share has decreased over time, as the top shares are bounded from the above for industries that were already concentrated in the early decades.

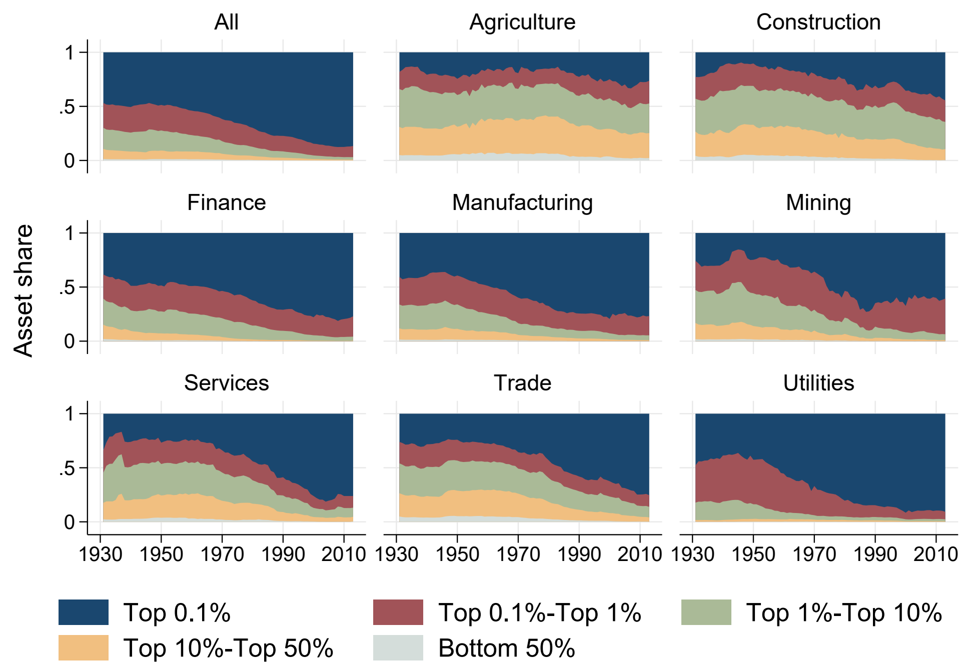
Employment concentration The SOI data provides information for business size by financial metrics such as assets, receipts, and net income; it does not provide information about employment. Does employment concentration among U.S. firms also increase over time? Since 1979, the Business Dynamics Statistics (BDS) database from the Census Bureau tabulates the number of firms and their employment by employment bins. We can therefore calculate the employment shares of top firms by employment size in the BDS data. Autor et al. (2020) perform detailed analyses of employment concentration using census data since the 1980s for a wide range of industries. We are not aware of

[14]For all subsector analyses, we exclude "Holding Companies and Others," which includes RICs and REITs as these industries are the exceptions where consolidated filings are not allowed.

Figure 4: Full Distribution

Panel A shows the asset shares across the entire distribution: top 0.1% by assets (dark blue), top 0.1% to top 1% by assets (red), top 1% to top 10% by assets (green), top 10% to top 50% by assets (yellow), and bottom 50% by assets (gray). Panel B shows the receipt shares across the entire distribution: top 0.1% by receipts (dark blue), top 0.1% to top 1% by receipts (red), top 1% to top 10% by receipts (green), top 10% to top 50% by receipts (yellow), and bottom 50% by receipts (gray).

Panel A. By Assets



Panel B. By Receipts

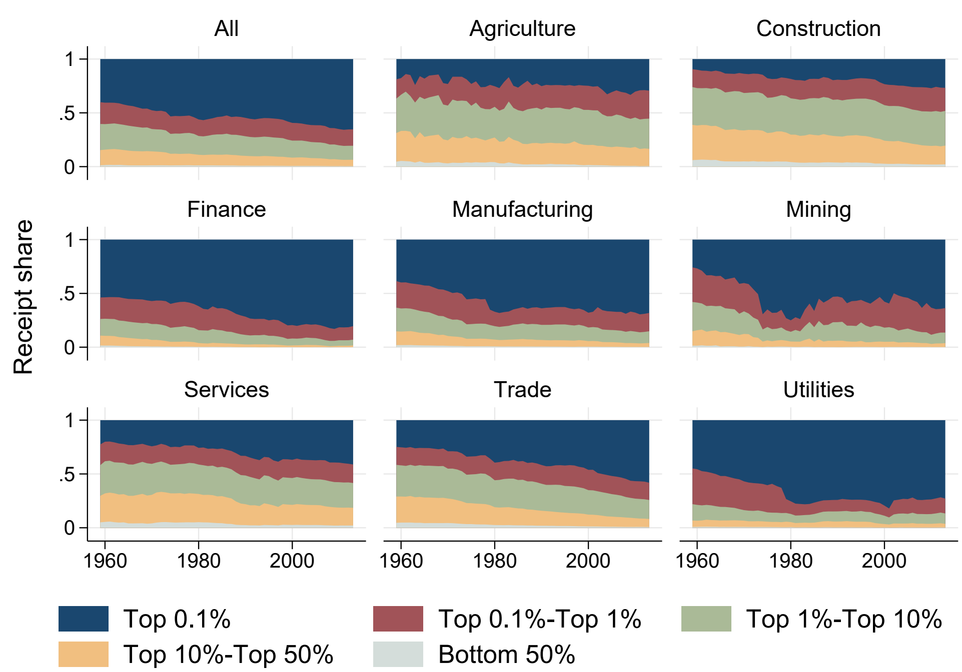


Figure 5: Top 1% Asset Shares: Subsectors

This figure shows the asset share of the top 1% corporate businesses by assets in the subsectors. The solid blue line shows the share among all corporate businesses and the dashed red line shows the share among the top 10% corporate businesses.

earlier data on firm size distribution by employment.

Figure IA3 plots the aggregate share of the top 1% firms by employment in total employment using BDS data; results are similar using census SUSB data (available since around 1990). We observe two features. First, the level of employment concentration is lower relative to the level of concentration measured by financial outcomes; this is also the case for the comparison of employment concentration and sales concentration in Autor et al. (2020). Top firms appear to be less labor-intensive, and they account much more for financial outcomes (e.g., sales and assets). Second, employment concentration displays a slight increase in the sample period (e.g., the top 1% share rose from 55% in 1979 to around 60% in the 2010s); the magnitude is relatively modest and can be less visible as shown in Luttmer (2010). Autor et al. (2020) also document that industry-level employment concentration increased in this period, but less than sales concentration. As they wrote, the evidence suggests that top firms may produce more with fewer workers and exhibit "scale without mass." Hubmer and Restrepo (2021) also highlight that large firms become more capital intensive and less labor intensive.[15]

[15]We can also use the BDS data to calculate employment concentration at the industry level and check its correlations with our main concentration measures. A caveat about the BDS data is the industry classification is based on establishments,

3.2 Robustness Checks

We perform a number of checks for our concentration measures to ensure their reliability.

Comparison with census data We cross-check our data with census data, which reports sales shares of the top 4, 8, 20, and 50 firms by sales, for manufacturing industries in census years since 1947 and other industries after 1982. First, for the degree of concentration over time, we rely on the longer time series of census concentration ratios in manufacturing industries at the four-digit SIC level (analyzed in Pryor (2001), Peltzman (2014), Lamoreaux (2019) among others). For this data, we can take the average of census concentration ratios across these detailed industries, but cannot sort all firms in manufacturing as a whole. Figure IA5, Panel A, displays the value-weighted average (solid blue line) and the equal-weighted average (dashed red line). We observe a persistent increase in the sample period, especially for the value-weighted average.[16]

Second, for the degree of concentration across industries, we compare census concentration ratios in 2012 (with both manufacturing and non-manufacturing industries) with our estimates using SOI data. The census data in 2012 is available in two-digit to six-digit NAICS industries. The most granular SOI industries in 2012 map into roughly four-digit NAICS codes, and here we can interpolate the asset shares of the top 4, 8, 20, and 50 businesses by assets (in these granular industries the SOI data mainly reports size bins by assets). Figure IA5, Panel B, shows an example of the cross-sectional relationship between the top 20 sales shares in census data (x-axis) and the top 20 assets shares in SOI data (y-axis). We observe a high degree of consistency in the cross section, with a correlation of about 0.8. Results are similar using the top 4, 8, or 50 firms as well.[17]

Comparison with Compustat We also present a comparison with aggregate top business shares using Compustat data in Figure IA4. This comparison helps us check that businesses in the SOI data are similar to those in financial statements (e.g., consolidation is performed properly in the SOI); it also verifies that the SOI data reliably captures firms at the very top. In Panel A, we calculate the total assets of the top 500 firms by assets in Compustat and compute their share in total corporate assets (from SOI data). We compare this series with the imputed share of the top 500 businesses by assets in total corporate assets using SOI data (the imputation can be imperfect in the later years when the top bin contained much more than 500 businesses). In Panel B, we calculate the total sales of the top 500 firms by sales in Compustat and compute their share in total corporate receipts (from SOI data). We compare this series with the imputed share of the top 500 businesses by receipts in total corporate receipts using

and a firm is included in an industry if it has an establishment in the industry; accordingly, some firms are counted multiple times in different industries, which can complicate the concentration estimates. Nonetheless, the industry-level top 1% employment share using BDS data is about 0.6 correlated with the top 1% asset share in our SOI data, which suggests a reasonable degree of consistency.

[16] Peltzman (2014) tabulates the equal-weighted average of the change in CR4 between 1963 and 1982, which is close to zero. This is consistent with the milder increase in the equal-weighted averages in Figure IA5, Panel A. In addition, the rise in concentration in this period seems stronger among a broader set of firms (e.g., CR20 compared to CR4).

[17] Since the SOI data has asset concentration, the level is on average higher than the level of sales concentration reported in census data. In Section 3.1 we also observe that the concentration series by assets tends to have a higher level than that by sales (whereas the concentration series by employment has a lower level). In general, large businesses appear to have more assets and less labor.

SOI data. The Compustat data has two limitations. First, Compustat mainly covers public firms and misses large private companies. Second, total assets and sales in Compustat generally include global activities; after around 1998, activities of foreign subsidiaries can be separated using Compustat data on geographical segments, but the segment data is less reliable (e.g., a segment can include North America as a whole) and unavailable for many companies. The first issue will lead to a downward bias in top business shares calculated using Compustat data, while the second issue will lead to an upward bias.

Figure IA4 shows that the level of the aggregate top 500 shares is similar using SOI data (solid blue line) and Compustat data (dashed red line). Both display an upward trend since Compustat data became comprehensive in the 1960s (though the trend in the Compustat data needs to be viewed with caution given the data coverage issues discussed above). Overall, the results suggest broad consistency at the aggregate level; our SOI data is reliable for capturing the firms at the very top (even though we rely more on imputation for this small set of firms), and a business in the SOI data should be largely similar to a firm in Compustat. Since the limitation of Compustat's coverage becomes more severe at the industry level, we restrict this comparison to the aggregate series.

Including noncorporate businesses The SOI tabulations by size bins that we use cover corporate businesses (both C-corporations and S-corporations). As shown in Figure IA6, in the aggregate, corporates' share in business receipts hovered around 80% in the early decades, peaked at 90% in the 1980s, and decreased gradually to 80% since then; these trends are consistent with several studies showing that noncorporate businesses have become more important since the Tax Reform Act of 1986 (Clarke and Kopczuk, 2017; Kopczuk and Zwick, 2020). Among the main sectors, noncorporates account for a larger share of receipts for industries such as agriculture, construction, and services, especially in earlier years. In our baseline results, rising concentration was stronger in manufacturing and mining before the 1980s, and the share of corporate businesses was high and stable in these sectors during that period; rising concentration was stronger in services and retail/wholesale after the 1980s, and the share of corporate businesses was also high and stable in these sectors during that period. In other words, the settings with the most substantial increases in concentration do not have major shifts in the prevalence of corporates versus noncorporates, so changes in the legal form of businesses should not play a major role for our key results.

We also perform checks for top business shares including noncorporate businesses (partnerships and sole proprietorships) in Figure IA7. In some years, we have tabulations of noncorporate businesses by size bins based on receipts. In these years, we can directly calculate top businesses' receipt shares among all businesses (corporates and noncorporates): we rank all businesses by size of receipts and compute the share accounted for by the top 1% or 0.1% businesses among all businesses. Otherwise, we have information about the number of noncorporate businesses and their total receipts (using the dataset compiled by Lamoreaux (2006) and we extend it to recent years with additional SOI publications). We can construct lower bound estimates of top business shares among corporate plus noncorporate businesses, with the assumption that the top 0.1% businesses are primarily corporates.[18] We then

[18]This assumption seems reasonable based on our data as well as census SUSB tabulations of firms by legal form and employment size. The top 1% appears to have more noncorporates (e.g., there are some large partnerships), so we focus on the top 0.1% for this estimate.

calculate the total number of corporate businesses (N_{corp}) and noncorporate businesses ($N_{noncorp}$) each year, take the total receipts by the top $0.1\%(N_{corp} + N_{noncorp})$ *corporate* businesses, and look at their share in the total receipts by all businesses. Figure IA7 shows that the top 0.1% receipt shares calculated among all businesses (purple diamonds) are similar to those calculated among corporates (blue circles) in our baseline results; the former has a slightly higher level and both series are rising over time with the same trends. The lower bound estimate of the top 0.1% receipt share (dashed red line) is close to the actual value before the 1980s, but it seems to underestimate the top business share by the early 2000s, possibly because some larger businesses are organized as partnerships in recent decades (so our assumption that the top 0.1% among all businesses only has corporates becomes too conservative). Taken together, the patterns of rising concentration are similar when noncorporates are included.

Top N businesses with fixed N Another metric for concentration is the share of the top N businesses with a fixed N. As discussed in Section 2, this metric is not easily comparable for different levels of aggregation; it is also possibly too conservative for a long period of time as the business population has expanded substantially over a century. Nonetheless, we perform robustness checks using the share of the top 500 businesses. The aggregate share of the top 500 businesses is already presented in the comparison with Compustat in Figure IA4. We also show the share of the top 500 businesses at the main sector level in Figure IA8. Panel A presents the shares of the top 500 corporate businesses by assets in the total assets of corporate businesses, and Panel B presents the shares of the top 500 corporate businesses by receipts in the total receipts of corporate businesses (solid blue line) and corporate plus noncorporate businesses (dashed red line). We restrict to corporate businesses in Panel A since we mainly have data on the receipts of noncorporate businesses.

In Figure IA8, we still observe rising concentration in manufacturing and mining in earlier decades, and in services and trade (retail and wholesale) in more recent decades. For the top 500 share among corporate businesses (solid blue line in both panels), we observe some declines in earlier decades, especially for agriculture, construction, and services. The reason is that corporate businesses became more common in these sectors from the 1950s to the 1980s (as shown above), which increased the denominator when we calculate the top share among corporate businesses. In the case of the top $x\%$ in our baseline results, the numerator adjusts too (i.e., the number of businesses in the top $x\%$ changes) so the prevalence of corporate businesses does not make much difference. In the case of the top 500 businesses, however, the numerator does not adjust so the top share falls when the corporate sector expands. This problem is not relevant if we divide the top 500 by corporate plus noncorporate businesses (the dashed red line in Panel B), and the share of the top 500 businesses shows a slight increase in agriculture, construction, and services in the earlier decades. Overall, the main patterns of rising concentration remain similar.

Including international assets of U.S. companies While we focus on production activities by businesses in the U.S., in recent years some U.S. firms may have shifted their production assets to foreign subsidiaries for a variety of reasons (Auerbach, 2021). We perform checks that include the assets of U.S. businesses' foreign affiliates, using Activities of U.S. Multinational Enterprises compiled by the BEA. Since the early 1980s, the BEA data records the assets of foreign affiliates and information about their U.S. parents (e.g., the number of U.S. parents by industry). According to the number of U.S. parents with foreign activities reported in this data, less than 1% businesses are multinational in all main sectors.

We perform checks including international assets under two assumptions. A stronger assumption is that all international assets belong to the top 1% businesses. This assumption seems reasonable as the average assets for U.S. parents with foreign affiliates are almost always larger than the average assets of the top 1% businesses in every main sector. A weaker assumption is that the top 1% businesses' share of international assets is the same as their share of domestic assets. It is unlikely that businesses outside of the top 1% account for a larger proportion of the international assets. In Figure IA9, the solid blue line shows the original top 1% asset share; the dashed red line shows the adjusted top 1% asset share where we allocate all international assets to the top 1% businesses; the dash-dotted green line shows the adjusted top 1% share where we allocate international assets to the top 1% businesses and the rest according to their shares in domestic assets. The concentration trends including international assets are similar to our original results. Indeed, the two adjusted series are not easily distinguishable from the original series (international assets are less than 20% of domestic assets in most industries except manufacturing and services after the 2000s, and the ratio of international assets to the top 1% businesses' domestic assets has remained stable).

3.3 Additional Outcomes

Finally, we present several additional outcomes to provide further context of corporate activities during our sample period.

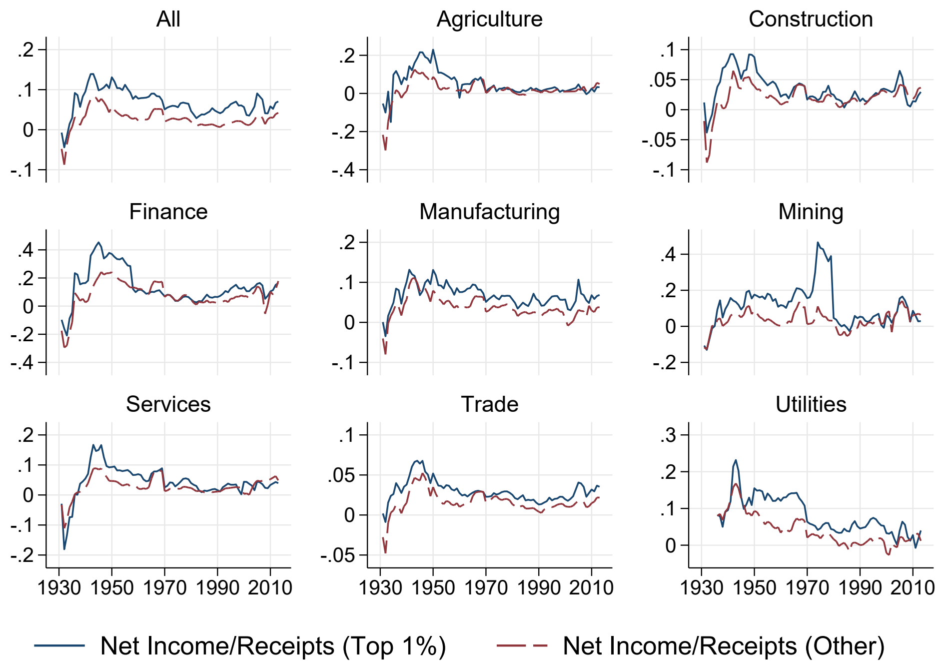
Profitability The SOI data provides a variety of financial information for businesses in each size bin. Using this information, Figure 6 shows the profitability ratio (i.e., net income before tax over sales) for the top 1% businesses by assets (solid blue line) and the rest (dashed red line). Several patterns emerge from this figure. First, the profitability ratio has fluctuated substantially over time; it does not exhibit a persistent long-run trend. Profitability in almost all sectors was low during the Great Depression; it then rebounded sharply in the 1940s, declined until the 1980s, and increased slightly afterwards. These trends are in line with the analyses of corporate profits since 1945 by Barkai and Benzell (2018). Second, profitability is higher among the top 1% businesses than among the remaining businesses, but the difference between these two groups does not display noticeable changes over time.

Because net income is affected by depreciation and tax rules for depreciation have changed over time, we also cross-check profitability in the SOI with that in the national accounts. The BEA begins with data from the SOI and then makes capital consumption adjustments so that corporate profits are calculated using economic depreciation (estimated by the BEA). Figure IA10 shows corporate profits according to SOI and BEA, both normalized by total receipts from SOI. The result shows that aggregate corporate profits from these two sources are similar.

Overall, the data shows that corporate profitability has fluctuated over the past 100 years; it has not followed the same persistent trend as corporate concentration. Estimating markups is more challenging, as shown by the ongoing discussions in the literature (Hall, 2018; Traina, 2018; De Loecker, Eeckhout, and Unger, 2020; Foster, Haltiwanger, and Tuttle, 2021). Nonetheless, existing estimates using different

Figure 6: Profitability

This figure shows the profitability ratio (net income before tax over total receipts) for the top 1% businesses by assets (solid blue line) and the rest (dashed red line). Here we need to use the adding up bins method discussed in Section 2 to calculate net income and receipts for these two groups.



methods also do not find that markups increased before the 1980s.

Balance sheet characteristics We also examine whether changes in the balance sheet characteristics of larger and smaller businesses might play a role in the rising concentration trends we observe (we focus on nonfinancial industries here since the balance sheet structure of financial services is substantially influenced by regulations). First, on the asset side, one concern is that maybe smaller firms lease more assets over time, so their book assets (which do not include most leases) will shrink relative to those of larger firms (this concern primarily relates to concentration by assets but it should not be a major issue for concentration by sales). In Figure IA11, Panel A, we plot the ratio of fixed assets on firms' balance sheets relative to their total assets, since leasing mainly applies to fixed assets. We do not observe different long-run trends for the ownership of fixed assets among the top 1% businesses by assets and the rest. Second, on the liability side, one might wonder whether financing availability contributes to the long-run changes in concentration. It is well recognized that the degree of financial frictions is difficult to measure, but we can provide some information about the financing structure of larger and smaller businesses over time. Figure IA11, Panel B, plots the ratio of book equity over assets, which reflects the fraction of financing that comes from equity versus debt and other liabilities. This ratio has declined over time (correspondingly debt financing has increased) for both the top 1% businesses and the rest. This evidence is consistent with the finding by Graham, Leary, and Roberts (2015) among Compustat firms that nonfinancial firms' leverage has secularly increased over the past century. Overall, it does not appear that rising concentration is likely driven by financial frictions becoming more severe over time, and therefore restricting more businesses to be small. Perhaps another possibility is that if financial constraints are relaxed over time, then outperforming firms can raise financing more easily and stand out from the crowd. While it is difficult to directly test the role of financial frictions, such mechanisms alone do not seem to explain the differences in the timing of rising concentration across different industries (e.g., manufacturing versus services and retail); in other words, financial frictions probably need to be combined with another mechanism to account for results across different industries.

Investment rate Recent work postulates that the decline in corporate investment rates in the past few decades is linked to rising concentration (Gutiérrez and Philippon, 2017). In Figure IA12, we plot the long-run relationship between the investment rate (investment spending over asset stock using BEA fixed asset tables) and corporate concentration (top 1% asset share). We include investment rates calculated using fixed assets alone (dashed red line) and fixed assets plus intellectual property (dash-dotted green line); even though annual investment spending in the BEA data started in 1901, the fixed asset stock only began in 1947. The investment rate in fixed assets shows a decline in many sectors, but the decline is less evident when intellectual property is included, in line with findings in Crouzet and Eberly (2021). Overall, Figure IA12 suggests that, over the long run, there does not appear to be a strong association between changes in investment rates and concentration.

Labor share Several studies use census data across different industries to document that falling labor shares since the 1980s are associated with concurrent increases in concentration (Autor et al., 2020; Barkai, 2020; Ganapati, 2021). Over the long run, the labor share in most industries did not appear to decline before the 1980s (Elsby, Hobijn, and Şahin, 2013), even though we observe a secular increase in corporate concentration. As Hubmer (2021) points out, the long-run evolution of the labor share could be affected by other forces such as preferences, which are beyond the focus of our study. Accordingly, at the moment we do not dive into the long-run relationship between the labor share and concentration.

Entry rate Recent work also uses census data to document declining firm entry rates since the 1980s (Decker et al., 2014a,b). We use the census BDS data (available since 1978) to calculate firm entry rates (i.e., the share of new firms) across industries, and examine the relationship with concentration trends. Figure IA13 shows that rising concentration is generally correlated with decreasing entry rates. However, this relationship can be consistent with multiple mechanisms. For instance, stronger economies of scale (e.g., due to changes in production technology) can increase concentration and reduce entry. Changes in regulatory policies may also increase concentration and reduce entry. Accordingly, while there is evidence that rising concentration and declining entry appear correlated in recent decades, this correlation per se may not provide enough information for the underlying mechanisms.

4 Economies of Scale

We now investigate the mechanisms behind the long-run evolution of top business shares. We study the role of economies of scale in this section, and examine other mechanisms in Section 5.

A longstanding observation suggests that stronger economies of scale will increase concentration in various economic domains (Demsetz, 1973; Rosen, 1981; Frank and Cook, 1996; Kaplan and Rauh, 2013). For firms, following the Second Industrial Revolution, mass production became increasingly common, leading to the emergence of large-scale modern industrial enterprises. Chandler (1994) provides detailed narratives of the propagation of economies of scale in U.S. manufacturing industries in the late 1800s and early 1900s. He highlights that production processes with economies of scale entail high fixed costs and low marginal costs, so firms need to achieve large enough production volume (throughput) to cover the fixed costs. Over time, economies of scale could have become stronger in other industries as well (e.g., retail and services), especially with the advancement in IT and new business models (Brynjolfsson et al., 2008; Hsieh and Rossi-Hansberg, 2022; Aghion et al., 2022; Lashkari, Bauer, and Boussard, 2022). For example, computers have made it easier to operate large retail chains and improve supply chain management (Holmes, 2001; Basker, 2007).

The measurement of economies of scale also has a long intellectual history. Stigler (1958) offers an in-depth discussion in an article titled "The Economies of Scale," which builds on comments by Milton Friedman at a 1955 NBER conference on "Business Concentration and Price Policy." Stigler (1958) suggests that examining the evolution of the business size distribution is perhaps the most straightforward method to reflect the extent of economies of scale (whereas calculating the costs of different sizes of businesses encounters "formidable obstacles").[19] In particular, he suggests to "classify the firms in an industry by size, and calculate the share of industry output coming from each class over time. If the share of a given class falls, it is relatively inefficient, and in general is more inefficient the more rapidly the share falls." Under this view, our baseline facts in Section 3.1 might be already considered evidence of economies of scale. In addition, we document further empirical facts in Section 4.1 that rising concentration in an industry is associated with higher technological intensity, as well as higher output growth. We then present a simple model in Section 4.2, which illustrates that new technologies enhancing the scalability of production can lead to the empirical results that we observe in both Section 3 and Section 4.1.

4.1 Empirical Findings

We use two approaches to further delineate the relevance of economies of scale. First, we study the relationship between the trajectories of corporate concentration and technological intensity. Production activities that are more technologically intensive are commonly viewed to require more resources to set up; once put to work, they can support a larger volume of production. Second, we study the relationship between industry concentration and output. When economies of scale are stronger, we may also expect higher output.

[19] For instance, measuring the cost structure would require data on upfront costs as well as fixed and marginal operating costs. Such information is difficult to obtain (e.g., based on companies' financial reports). De Loecker, Eeckhout, and Unger (2020) argue that selling, general & administrative expenses (SG&A) represent fixed operating costs and cost of goods sold (COGS) represent variable operating costs, whereas Traina (2018) argues that SG&A costs are not necessarily fixed. Aside from this issue, upfront investment spending (e.g., building facilities) is recorded as capital expenditures and is not included in SG&A or COGS.

Industry concentration and technological intensity We start by analyzing a general measure of technological intensity using the share of R&D and IT (computer equipment and software) spending in total investment (fixed assets plus intellectual property). This measure can be constructed for each industry-year from the BEA's fixed asset tables (available since 1901).[20] Importantly, we can obtain this general measure for all industries and use it to conduct systematic analyses.

R&D and IT are commonly viewed to require upfront fixed outlays while enhancing the scalability of production (Brynjolfsson et al., 2008; Haskel and Westlake, 2017; Crouzet and Eberly, 2019; Lashkari, Bauer, and Boussard, 2022). This general measure for the relevance of scale can encompass two possibilities. First, IT and R&D can be directly involved in technological changes that enhance economies of scale. For instance, industrial R&D played an important role in the development and commercialization of chemical products, and IT played an important role for the rise of large supermarket chains. Second, it is also possible that other forces increase the benefits of scale production (e.g., lower transportation costs that expand market size, shifts in consumer preferences that favor speed and convenience), and scale production entails more IT and R&D. For example, hotel chains formed partly because long-distance travel became more common and customers looked for reliable and standardized services, and restaurant chains formed partly because eating out became more common and customers looked to save time during work days and travels. Managing such chains requires more IT and at times also more R&D (e.g., to ensure quality stability). In both cases, to the extent that production processes with more scalability are associated with more IT and R&D, this general measure of technological intensity can reflect firms exploiting economies of scale.

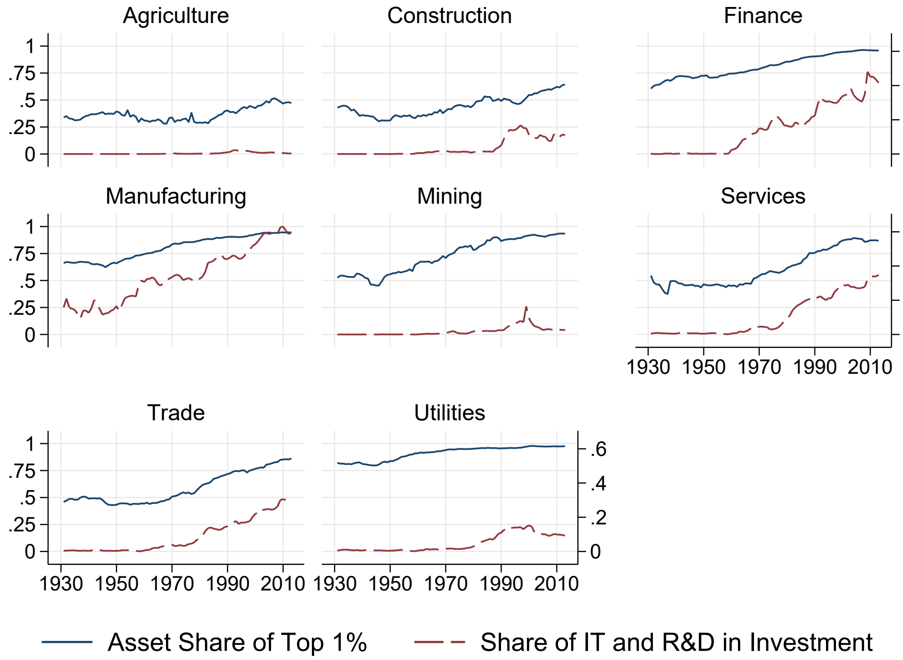
Figure 7 visualizes the relationship between concentration and technological intensity: the solid blue line shows the top 1% asset share in each industry (using our SOI data) and the dashed red line shows the investment share in IT and R&D (using BEA data). Panel A presents the results for the main sectors and Panel B presents the results for subsectors (the subsectors are close to the industries in the BEA fixed asset tables and the mapping is presented in Internet Appendix IA2). Interestingly, these two series display a strong comovement in most industries. Among the main sectors, the rise of both concentration and technological intensity were stronger in earlier decades for manufacturing, and stronger in recent decades for services, retail and wholesale. These trends align with the view that industrial technologies propagated mass production in manufacturing in the early 20th century, while modern information and communications technologies (ICT) started to transform services, retail, and wholesale more recently. Among the subsectors, we also find that the turning points in concentration trends coincide with key developments in the economies of scale in production. For instance, concentration in restaurants started to increase around the 1960s, when prominent restaurant chains began to emerge. Concentration in retail started to rise around the 1970, as discount retailers expanded across the country. Concentration in several manufacturing subsectors (e.g., food, apparel, chemicals) accelerated in the 1940s as industrial production developed for the second world war stimulated more mass production for commercial use. These turning points are also marked by a rise in technological intensity. Overall, we observe that industries with rising concentration witness rising technological intensity around the same time.

[20] This measure focuses on the composition of investment, whereas the investment rate variable in Section 3.3 captures the total quantity of investment.

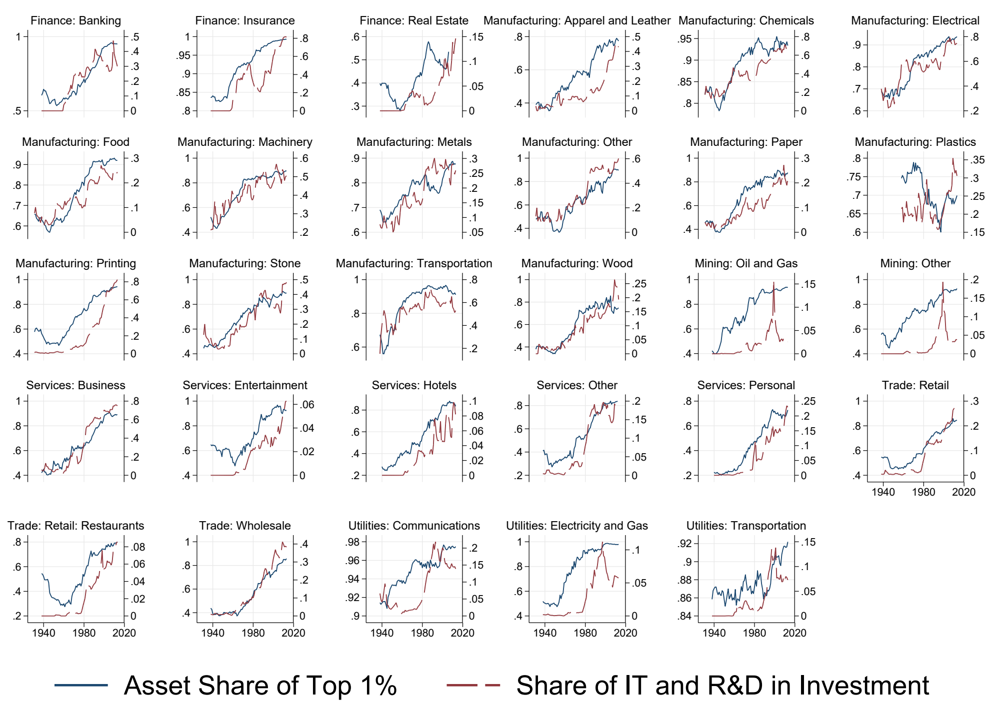
Figure 7: Concentration and Technological Intensity

This figure shows the top 1% asset share (solid blue line) and the investment intensity in IT and R&D using BEA data (dashed red line). The left axis is the top 1% asset share and the right axis is the investment share in IT and R&D.

Panel A. Main Sectors



Panel B. Subsectors



Tables 4 and 5 confirm the comovement between the two series plotted in Figure 7 in regressions, for the main sectors and the subsectors respectively. We present results for all industries in Panel A and for nonfinancial industries in Panel B, since finance subsectors could have been affected by banking deregulation around the 1980s; the concept of R&D also applies less well to financial services (indeed our results in these technological intensity analyses are stronger for nonfinancial industries). We use Driscoll and Kraay (1998) standard errors. In columns (1) and (2), we present raw regressions of top 1% asset shares on the investment intensity in IT and R&D. In columns (3) and (4), we present regressions of changes of these two series over the medium term (e.g., twenty years); this specification removes fixed differences in the level of concentration or technological intensity among different industries, and focuses on the changes within an industry over time. We also include time fixed effects in columns (2) and (4) which absorb common time trends. For instance, the specification in column (4) zooms into the timing alignment between these two series as visualized in Figure 7: at a given point in time, those industries that experience more increases in concentration are also the ones that experience more increases in technological intensity. Overall, although the BEA data contains some noise (which may attenuate our results), this general measure of technological intensity displays a strong relationship with industry concentration in our long-run data.[21] Bessen (2020) analyzes census concentration ratios from 1997 to 2012, and finds a positive relationship with IT intensity as well.

We perform two sets of robustness checks for the regressions in Tables 4 and 5. First, we address the concern that changes in the number of corporate businesses may affect the top 1% share. In columns (1) to (4) of Table IA1, we repeat the regressions in columns (3) and (4) of Tables 4 and 5, controlling for the log change in the number of businesses. Our main results are similar; the coefficient on changes in the number of businesses is small and insignificant, which further verifies that these changes are not a main driver of rising concentration in our data. Second, Table IA2 shows that our main results are similar if we normalize investment in IT & R&D by business receipts in each industry (instead of total investment spending); in this case the numerator uses BEA data and the denominator uses SOI data (we use this variable as a robustness check since normalizing across different datasets may introduce more noise).

We also perform additional analyses using long-run data on breakthrough patents constructed by Kelly et al. (2021), which is mainly available for manufacturing and mining subsectors plus agriculture, construction, and utilities. We use the patent data to further flesh out the role of technological innovations in production activities. In addition, one might raise a reverse causality concern about our results above using investment in R&D and IT: maybe large businesses report more comprehensively their spending on R&D and IT, and shocks that happen to benefit large firms (even randomness) could increase concentration as well as the industry-level investment intensity in R&D and IT. The breakthrough patent data can help us isolate important technologies, and we can control for the number of patents in case large firms are also more likely to register patents.

Specifically, Kelly et al. (2021) identify breakthrough patents by comparing the similarity of a patent to patents that came before and after it: a patent represents a breakthrough if it is very distinct from patents that came before, but followed by subsequent patents that are similar. They match patents

[21] For instance, the value is sometimes zero in the early years. The BEA data also shows large swings in a few industries, which could arise from changes in underlying data sources according to BEA staff.

Table 4: Rising Concentration and Technological Intensity: Main Sectors

This table shows industry-level regressions of the asset share of the top 1% businesses on the investment intensity in IT and R&D. For both left hand side and right hand side variables, we use their levels in columns (1) and (2) and their changes over twenty years in columns (3) and (4). Year fixed effects are included in columns (2) and (4). Panel A shows results for all industries. Panel B shows results for nonfinancial industries. Standard errors are Driscoll and Kraay (1998) with twenty lags. R^2 does not include fixed effects.

Panel A. All Industries

	Asset Share of Top 1%			
	Level		Change (Δ_{20})	
	(1)	(2)	(3)	(4)
Share of IT and R&D in Investment	0.873***	0.671***		
	(0.070)	(0.080)		
Δ_{20}Share of IT and R&D in Investment			0.412***	0.265***
			(0.114)	(0.074)
Year Fixed Effect	No	Yes	No	Yes
Obs	664	664	504	504
R^2	0.33	0.18	0.13	0.05

Panel B. Nonfinancial Industries

	Asset Share of Top 1%			
	Level		Change (Δ_{20})	
	(1)	(2)	(3)	(4)
Share of IT and R&D in Investment	0.855***	0.642***		
	(0.082)	(0.082)		
Δ_{20}Share of IT and R&D in Investment			0.504***	0.378***
			(0.114)	(0.092)
Year Fixed Effect	No	Yes	No	Yes
Obs	581	581	441	441
R^2	0.30	0.17	0.16	0.08

to industries using the probabilistic mapping between patent technology classifications and industry classifications. We normalize the number of patents by population as in the original study; results are similar if we use alternative normalization such as real GDP.

Panel A of Table 6 shows that higher intensity of breakthrough patents is correlated with stronger increases in concentration. This relationship remains similar when we control for the number of patents in the even columns; indeed, breakthrough patents show much stronger results than the number of patents. Panel B shows breakthrough patents are also positively correlated with our general technological intensity measure (investment intensity in R&D and IT). In other words, our general measure of technological intensity at least partly reflects technological innovations captured by breakthrough patents (R&D and IT can be involved in both the development and the commercialization of the technological innovations measured by breakthrough patents). If we regress rising concentration on increases in the general technological intensity measure together with the breakthrough patent intensity, then

Table 5: Rising Concentration and Technological Intensity: Subsectors

This table shows industry-level regressions of the asset share of the top 1% businesses on the investment intensity in IT and R&D. For both left hand side and right hand side variables, we use their levels in columns (1) and (2) and their changes over twenty years in columns (3) and (4). Year fixed effects are included in columns (2) and (4). Panel A shows results for all industries. Panel B shows results for nonfinancial industries. Standard errors are Driscoll and Kraay (1998) with twenty lags. R^2 does not include fixed effects.

Panel A. All Industries

	Asset Share of Top 1%			
	Level		Change (Δ_{20})	
	(1)	(2)	(3)	(4)
Share of IT and R&D in Investment	0.522***	0.287***		
	(0.091)	(0.085)		
Δ_{20}Share of IT and R&D in Investment			0.101*	0.065**
			(0.053)	(0.026)
Year Fixed Effect	No	Yes	No	Yes
Obs	2,228	2,228	1,648	1,648
R^2	0.27	0.11	0.01	0.01

Panel B. Nonfinancial Industries

	Asset Share of Top 1%			
	Level		Change (Δ_{20})	
	(1)	(2)	(3)	(4)
Share of IT and R&D in Investment	0.487***	0.246***		
	(0.102)	(0.091)		
Δ_{20}Share of IT and R&D in Investment			0.164***	0.138***
			(0.051)	(0.023)
Year Fixed Effect	No	Yes	No	Yes
Obs	2,007	2,007	1,487	1,487
R^2	0.24	0.09	0.02	0.02

both are significant: these two measures have some overlap, but each offers unique information. Finally, the last four columns in Table 6 suggest that the results are somewhat stronger in the subsample before the 1980s, which is the time period when rising concentration among manufacturing-related industries was strongest. Autor et al. (2020) examine the relationship between rising concentration and increases in the amount of patents in detailed manufacturing industries from 1982 to 2012, and find a positive relationship as well.

Industry concentration and industry output In Tables 7 and 8, we document that industries with higher increases in concentration also experience higher growth in real output. Correspondingly, their output shares in the economy increase as well (columns (3) and (6)). The industry-level real output data comes from the BEA, which is available since 1947 (slightly shorter than our concentration series). Figure 8 visualizes the relationship by plotting the change in concentration over twenty years and the change in an industry's share in total real gross output in the same period. Broadly speaking, manufacturing

Table 6: Technological Innovations Measured by Breakthrough Patents

Panel A shows industry-level regressions of changes in the asset share of the top 1% businesses on log changes in breakthrough patents in the industry (over twenty years). Panel B shows industry-level regressions of changes in the investment share in IT and R&D on log changes in breakthrough patents in the industry (over twenty years). Breakthrough patent data comes from Kelly et al. (2021) and the number of breakthrough patents is normalized by population. The even columns control for log changes in the number of patents in the industry. Industries include manufacturing subsectors, mining subsectors, agriculture, construction, and utilities, due to the coverage of the breakthrough patent data. Standard errors are Driscoll and Kraay (1998) with twenty lags. R^2 does not include fixed effects.

Panel A. Relationship with Concentration

	Δ_{20}Asset Share of Top 1%							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ_{20}Log Breakthrough Patents	0.012	0.006	0.017***	0.021***	0.028**	0.015***	0.018***	0.020***
	(0.012)	(0.008)	(0.005)	(0.005)	(0.012)	(0.004)	(0.003)	(0.003)
Δ_{20}Log # of Patents		0.033		-0.039***		0.066**		-0.039***
		(0.026)		(0.009)		(0.027)		(0.011)
Year Fixed Effect	No	No	Yes	Yes	No	No	Yes	Yes
Sample Period	Full				Pre-1980			
Obs	849	849	849	849	458	458	458	458
R^2	0.01	0.04	0.03	0.05	0.05	0.13	0.03	0.04

Panel B. Relationship with Investment Intensity in IT and R&D

	Δ_{20}Investment in IT + R&D							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ_{20}Log Breakthrough Patents	0.023***	0.016**	0.008	0.004	0.024***	0.016***	0.017***	0.013**
	(0.004)	(0.007)	(0.009)	(0.013)	(0.003)	(0.003)	(0.004)	(0.006)
Δ_{20}Log # of Patents		0.044***		0.047**		0.042***		0.051**
		(0.017)		(0.022)		(0.011)		(0.023)
Year Fixed Effect	No	No	Yes	Yes	No	No	Yes	Yes
Sample Period	Full				Pre-1980			
Obs	849	849	849	849	458	458	458	458
R^2	0.06	0.10	0.01	0.03	0.07	0.12	0.03	0.06

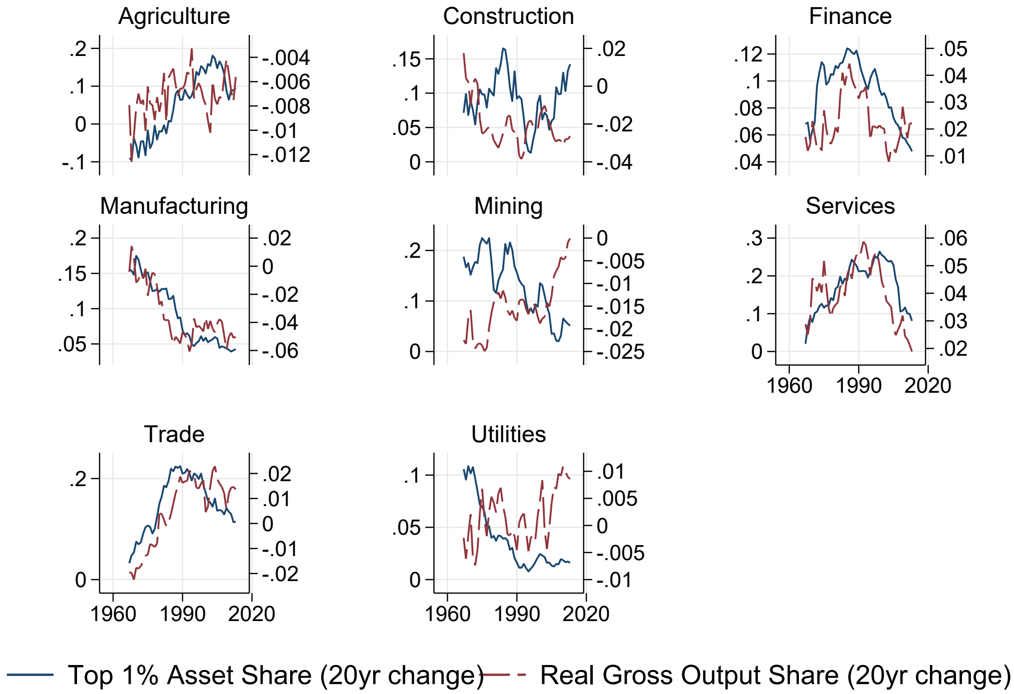
industries witnessed major increases in concentration and expansion in output in the first half of the 20th century; services and retail/wholesale witnessed rising concentration and expanding output towards the end of the 20th century. Our results also resonate with findings in Ganapati (2021) who analyzes industry-level data from the census in recent decades and documents a positive correlation between changes in CR4 and real output growth.

One possible concern is that positive idiosyncratic shocks to large firms may lead to both increases in concentration and more industry output in a given period of time. To address this concern, in Table IA3 we also present regressions of changes in concentration over a decade on industry growth in that decade *fitted by industry growth in the past decade*. In this case, we use industry growth in the past decade to capture persistent changes the industry has been experiencing, and the effective measurement windows for the left-hand-side and the right-hand-side of the regression are different; the results are similar.

Figure 8: Concentration and Industry Output Share

This figure shows changes in the top 1% asset shares over twenty years (solid blue line) and changes in the industry's share in total real gross output (dashed red line). The left axis is changes in top 1% asset shares and the right axis is changes in the industry's share in total real gross output.

Panel A. Main Sectors



Panel B. Subsectors

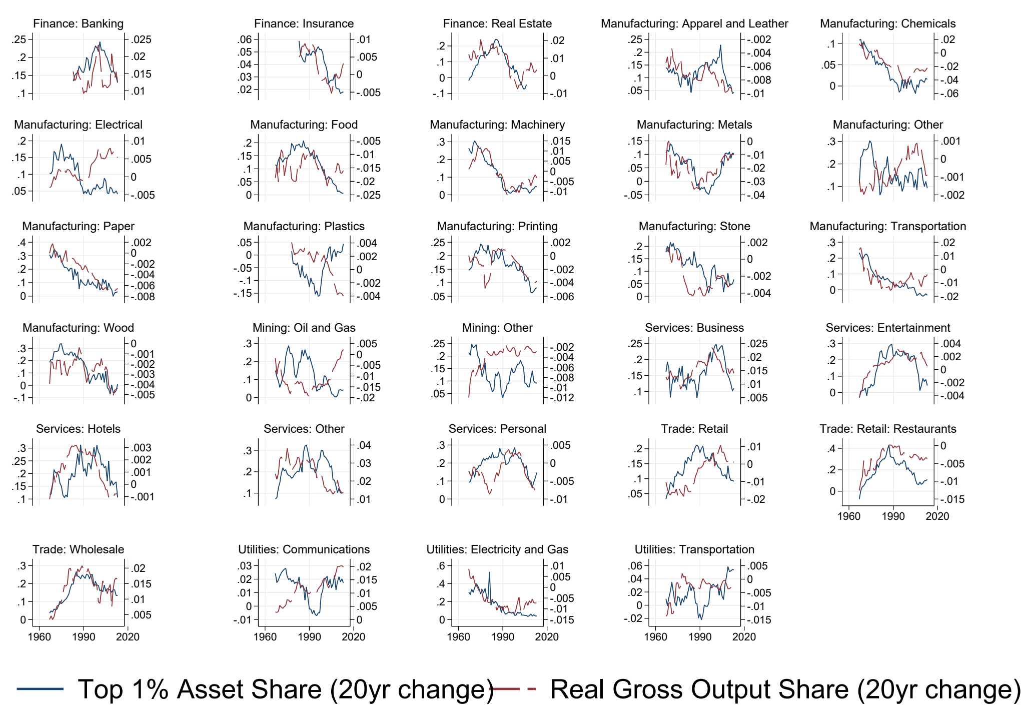


Table 7: Rising Concentration and Industry Growth: Main Sectors

This table shows industry-level regressions of changes in the asset share of the top 1% businesses over twenty years on industry growth over twenty years. In columns (1), (2), (4) and (5), industry growth is measured as log changes in real gross output. In columns (3) and (6), industry growth is measured as change in the industry's share in total real gross output of private industries. Columns (1) to (3) show results for all industries. Columns (4) to (6) show results for nonfinancial industries. Standard errors are Driscoll and Kraay (1998) with twenty lags. R^2 does not include fixed effects.

	Δ_{20}Asset Share of Top 1%					
	All Industries			Nonfinancial Industries		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ_{20}Log Real Gross Output	0.048*	0.054**		0.058*	0.069**	
	(0.025)	(0.024)		(0.030)	(0.028)	
Δ_{20}Real Gross Output Share			0.907***			1.095***
			(0.310)			(0.364)
Year Fixed Effect	No	Yes	No	No	Yes	No
Obs	376	376	376	329	329	329
R^2	0.03	0.04	0.11	0.04	0.05	0.14

Table 8: Rising Concentration and Industry Growth: Subsectors

This table shows industry-level regressions of changes in the asset share of the top 1% businesses over twenty years on industry growth over twenty years. In columns (1), (2), (4) and (5), industry growth is measured as log changes in real gross output. In columns (3) and (6), industry growth is measured as change in the industry's share in total real gross output of private industries. Columns (1) to (3) show results for all industries. Columns (4) to (6) show results for nonfinancial industries. Standard errors are Driscoll and Kraay (1998) with twenty lags. R^2 does not include fixed effects.

	Δ_{20}Asset Share of Top 1%					
	All Industries			Nonfinancial Industries		
Δ_{20}Log Real Gross Output	0.067***	0.046**		0.068***	0.045**	
	(0.017)	(0.021)		(0.016)	(0.020)	
Δ_{20}Real Gross Output Share			2.385***			2.428***
			(0.680)			(0.600)
Year Fixed Effect	No	Yes	No	No	Yes	No
Obs	1,312	1,312	1,312	1,210	1,210	1,210
R^2	0.06	0.03	0.08	0.06	0.03	0.08

Additionally, columns (5) to (8) of Table IA1 show that the results in Tables 7 and 8 are also robust to controlling for the change in the number of businesses (the coefficient on this control variable is small and insignificant). Taken together, industries that experience higher increases in concentration on average tend to be those that are experiencing faster growth, which is also consistent with technological changes contributing to rising concentration in the long-run.[22]

[22]It is difficult to consistently measure productivity at the industry level over our entire sample period. Productivity measurement may also face other complications (e.g., Solow's paradox, adjustment for product quality, difference between physical productivity and revenue productivity, dependence on assumptions about the production function).

4.2 Simple Model

We present a simple model to formalize how production processes with economies of scale can give rise to the empirical facts we observe. We analyze the impact of a production technology that decreases marginal costs but requires higher upfront spending, which leads to greater economies of scale. The structure follows the spirit of the model in Hsieh and Rossi-Hansberg (2022).[23] We outline the model below and provide the details in Internet Appendix IA3.1.

On the production side, firms pay an entry cost κ and then draw an idiosyncratic productivity a_i, which has a power law distribution. Depending on the realization of a_i, the firm can stay or exit. Importantly, firms that stay choose between two possible technologies. First, they can access an old technology, which requires upfront spending ϕ and offers per-unit productivity a_i: after paying ϕ, firms have access to a constant-returns-to-scale technology so they can hire L units of input to produce $a_i \cdot L$ units of output. Second, they can access a new technology with greater economies of scale, which requires upfront spending $\Phi(h)$ and offers higher per-unit productivity $A(a_i, h)$: they can use L units of input to produce $A(a_i, h) \cdot L$ units of output. The parameter $h \geq 1$ is an index of the scalability of the new technology.

On the demand side, we assume a standard nested CES structure. A firm i in industry k faces demand $y_{i,k} = Y_k \cdot (p_{i,k}/P_k)^{-\sigma}$, where $p_{i,k}$ is the firm's price, and P_k is the aggregate price index for industry k. Finally, we assume an exogenous markup μ (as in Covarrubias, Gutiérrez, and Philippon (2020)), which illustrates that the new technology does not necessarily change profitability. The long-run profitability of a firm in the model is given by the exogenous level of markup (which can be driven by the degree of price competition, regulations, and other forces).

The model generates the following main results.

1. Adoption of the new technology: Firms with productivity a_i below a threshold a^* will exit. For the remaining firms, the most productive firms with productivity a_i above a threshold a^{**} will adopt the new technology, and firms with productivity a_i between a^* and a^{**} will adopt the old technology.

2. Technology and concentration: As the scalability of the new technology h increases, concentration (e.g., sales shares of the top 1%) also increases.

3. Industry output: As h increases, the industry's output share in the economy also increases.

4. Profitability remains exogenous: Per-period profits/sales are given by $\frac{\mu}{1+\mu}$, which only depends on the exogenous markup μ.

These results show that the rise of the scalable technology (e.g., IT and R&D) has several effects. First, the development of the scalable technology sets firms further apart. Firms that use the new scalable technology become larger, but not all firms will find it optimal to use this technology given the high

[23] This setup is also in line with the idea of upfront spending serving as endogenous sunk costs (Sutton, 1991, 2001).

upfront spending, so some will stay with the traditional technology and stay small.[24] In this case, the impact of the scalable technology is not necessarily to increase the average firm size, but to "polarize" the size of businesses, as we observe in Figure 4. Second, the development of the scalable technology can also contribute to an expansion of the industry size. Finally, the size of total profits will increase for firms that adopt the new technology, whereas their profitability (profits/sales) is given by the markup and can be shaped by other forces that affect the markup. In particular, firms that use the scalable technology and incur higher upfront spending are ultimately compensated through greater sales and total profits, not necessarily through a higher per-unit markup. We also provide a dynamic extension in Internet Appendix IA3.2.

Taken together, the model's predictions summarized above are consistent with the empirical facts we document. In addition to the development of the scalable technology (i.e., comparative statics with respect to h considered here), in Section 4.1 we also mentioned that other forces may increase the appeal of using the scalable technology (e.g., market expansion); we provide further analyses of such forces in Section 5.1 by studying the impact of lower barriers to trade. Besides economies of scale, economies of scope could play a role in the formation of large firms as well (Chandler, 1994; Hoberg and Phillips, 2022). Direct measures of scope (e.g., the variety of products each business has) is difficult to construct in the long-run historical data. To the extent that higher technological intensity may also facilitate economies of scope, our results above could be consistent with the economies of scope interpretation.

5 Other Mechanisms

In this section, we investigate additional mechanisms that may affect corporate concentration. These mechanisms are not mutually exclusive with economies of scale, and some could complement it. We discuss both the conceptual relevance of these mechanisms and the extent to which we can find empirical support. We examine trade and expansion of markets in Section 5.1, and antitrust and regulation in Section 5.2.

5.1 Trade and Expansion of Markets

If the U.S. consisted of isolated villages, then the size of businesses would face natural limits. Many observers postulate that the initial formation of large U.S. companies in the 19th century was influenced by the integration of domestic markets thanks to railroads, steamships, and telegraphs (Chandler, 1994). It is also natural to ask whether the further expansion of markets in the 20th century, such as globalization, drives the concentration trends in our data.

To understand the role of trade and market expansion, we start with a simple theoretical framework in the spirit of Melitz (2003). We then discuss the empirical impact of trade and market expansion, both domestically and internationally. Our results suggest that changes in trade barriers alone are not

[24] In this simple model, whether a firm finds it appealing to adopt the new versus the old technology is driven by a firm's productivity. In practice, whether a firm chooses a scalable business model may also depend on the owner's preferences, managerial capacity, or financing availability.

sufficient for the rise of corporate concentration we observe. Nonetheless, it is possible that lower trade barriers and broader markets can strengthen economies of scale.

Conceptual framework We extend the basic model presented in Section 4.2 to an environment with two economies. We summarize the main elements here and provide details in Internet Appendix IA3.3. The two economies can represent the U.S. and foreign countries for international trade, or the east coast and the west coast for domestic trade. We use "exports" to refer to goods sold outside of the local economy and "imports" to refer to goods purchased from outside. For simplicity, both economies have the same aggregate demand and the same CES setup. Following Melitz (2003), we assume that there is a standard iceberg cost $\tau > 1$ (which raises the marginal cost of exports by a factor τ), as well as a fixed cost of exporting ϕ_x. The key parameter for trade barrier is therefore τ.

Since our data captures concentration in production activities in the U.S., when the two economies in the model are interpreted as the U.S. and abroad, we are interested in the share of top U.S. firms in total U.S. production; when the two economies are interpreted as east coast and west coast, we are interested in the share of top firms in both economies in the total production of the two economies. In the baseline analysis, we consider businesses' sales including exports.[25] When the two economies represent U.S. and abroad, we also examine "concentration excluding exports," namely top U.S. businesses' domestic sales over all U.S. businesses' domestic sales.

Initially, we assume that all firms use the same constant-returns-to-scale technology, and only differ in their idiosyncratic productivity a_i. In other words, we shut down technologies with economies of scale and focus on trade barriers only. We obtain two key predictions. First, the top business share is hump-shaped in trade barriers τ. For sufficiently high barriers to trade (τ sufficiently large), lowering barriers to trade increases concentration: when τ starts from a high level and falls, relatively more efficient firms export and top businesses' shares increase. However, when τ is already low, then further decreases in τ will primarily make mediocre firms export (top firms already export); in this case, concentration can decrease rather than increase. Second, when the two economies are interpreted as the U.S. and abroad, then U.S. "concentration excluding exports" remains unchanged. In other words, if changes in international trade barriers represent the only force, then we may expect U.S. "concentration excluding exports" to be stable, which we will examine empirically later.

Then, we analyze a setting where trade barriers coexist with the technology with economies of scale laid out in Section 4.2 (i.e., the new technology has $h > 1$). In this case, when trade barriers fall (smaller τ), a higher fraction of firms will adopt the new technology with greater scalability, and concentration can increase. In other words, having broader markets can amplify economies of scale. In addition, in this case even "concentration excluding exports" can increase.

Taken together, a reduction in trade barriers can increase concentration by itself; it can also strengthen the influence of economies of scale. However, changes in trade barriers alone (without technologies with greater scalability) would not affect "concentration excluding exports."

[25] If the focus is instead product market concentration, then the relevant metric needs to use the sales of U.S. producers minus exports in the numerator and the sales of U.S. producers plus imports minus exports as the denominator. See Amiti and Heise (2021) for an analysis of manufacturing products between 1992 and 2012.

International trade For international trade, we can examine "concentration excluding exports" in the data to understand whether changes in trade barriers alone are sufficient for explaining rising concentration. In Figure IA14, the solid blue line shows the share of the top 1% businesses by receipts in total receipts, and the dashed red line shows the estimated "concentration excluding exports." To be conservative, we subtract all exports from the receipts of the top 1% businesses, and divide this value by total receipts minus exports. We see that "concentration excluding exports" increases substantially as well, which suggests that changes in trade barriers may not be the only force affecting rising concentration.

In addition, historical data suggests that trade barriers did not decrease much before the 1970s. For instance, exports and imports relative to GDP did not expand substantially in the first half of the 20th century, and then they began to increase considerably around 1970 (Wen and Reinbold, 2020). Rising concentration in our data started much earlier. In particular, international trade is especially relevant for manufacturing, but rising concentration in manufacturing was most substantial before the 1970s.

Domestic trade For domestic trade, we cannot directly separate "exports" in the data (i.e., sales to other regions in this case) and isolate "concentration excluding exports." Nonetheless, we can rely on some historical evidence on the integration of domestic markets to understand the evolution of domestic trade. For manufacturing industries, prior studies suggest that the integration of domestic markets took place largely in the late 19th century. According to historical studies by Kim (1995), "goods market integration seems to have been realized by the latter half of the nineteenth century." For instance, prices of similar goods converged across regions. Moreover, regional specialization in manufacturing increased in between 1860 and early 1900s but did not increase afterwards. High regional specialization in production suggests that goods were made in centralized locations and shipped nationally. Overall, it can be difficult to directly test the impact of domestic trade barriers; however, trade barriers alone do not easily account for the full set of evidence presented earlier (e.g., timing of rising concentration in different industries and the relationship with technological intensity). Nonetheless, having a large domestic market in the U.S. could help strengthen the influence of economies of scale.

In summary, our analyses suggest that rising concentration does not appear to be driven by changes in trade barriers alone, but having access to large markets could in principle strengthen the influence of economies of scale. In the U.S., broad markets were already available by the early 20th century. Globalization since the 1970s does not seem to play an essential role in the long-run trends of rising corporate concentration. For manufacturing-related industries, rising concentration largely took place before this era; for services-related industries, rising concentration is stronger in recent decades, but globalization may not be first-order for this development (as international trade in services is smaller in volume).

5.2 Antitrust and Regulation

Antitrust Topics related to concentration are frequently mentioned in discussions of antitrust policies and enforcement (Peltzman, 2014; Philippon, 2019; Baker, 2019). As explained earlier, our data captures concentration on the production side, and our focus is not market concentration for a given product or location. In addition, even market concentration may not have a clear relationship with competitiveness (higher concentration can be associated with less competition or with more depending on the setting), as Syverson (2019) highlights. De Loecker, Eeckhout, and Unger (2020) emphasize that market power should be measured through markups. Therefore, we do not aim to use our evidence to speak to the strength or weakness of market power, and correspondingly the success or failure of antitrust policies.

However, we can analyze the following question: if we are interested in the role of large firms in the economy (e.g., the share of assets and sales in the economy that belong to larger firms), do antitrust policies have a major impact? Over the past century, corporate concentration increased steadily while antitrust policies shifted through several different regimes. By and large, antitrust enforcement is thought to be tougher before the 1980s and more relaxed afterwards (Peltzman, 2014; Stucke and Ezrachi, 2017; Phillips Sawyer, 2019). As shown in Section 3, rising concentration was present for a long period of time before the 1980s. In manufacturing and mining in particular, the rise of top businesses' shares primarily occurred before the 1980s.

To perform further statistical analyses, we use a standard measure of antitrust enforcement, the annual number of antitrust cases brought by the Department of Justice (DOJ), collected by Posner (1970) and Gallo et al. (2000).[26] We also examine the budget for the DOJ antitrust division. As Gallo et al. (2000) write, "although DOJ prosecutions provide only a partial picture of all antitrust enforcement effort, omitting FTC, state, and private enforcement efforts, DOJ enforcement efforts constitute an important, if not the dominant, component of American antitrust enforcement." In Figure IA15, the solid blue line shows the annual number of DOJ cases, and the dashed red line shows the annual budget of the DOJ antitrust division (per million dollar of GDP). The two series are about 0.6 correlated. Both series are indeed relatively high between the 1940s and the 1970s, followed by a decline in the 1980s. The timing largely aligns with changes in political and judicial philosophies, such as an active DOJ with ample resources after Roosevelt appointed Thurman Arnold to the antitrust division in 1938, and a quieter DOJ with diminished resources in the Reagan era. More generally, in Panel A of Table IA4, we examine the average annual DOJ cases and antitrust division budget through presidential cycles. We see that they decrease somewhat when Republications have presidential or congressional control, and decrease significantly when Republicans control the presidency as well as both chambers of congress.

In Panel B of Table IA4, we turn to changes in concentration. We continue to use the four-year presidential cycles given that DOJ resources and activities are affected by the political environment. We use the change in the top 1% asset share in each cycle on the left hand side. On the right hand side, we examine the average DOJ cases and annual antitrust division budget during each cycle; we also examine the variables capturing Republicans' political control used in Panel A. Overall, we do not observe that changes in corporate concentration display significant relationships with DOJ activities or political environments. One possible concern is that stronger antitrust enforcement or Democratic control can occur in response to more corporate consolidation, which could induce a positive bias in the relationship between DOJ activities and concentration. At a minimum, the long-run data suggests that top business shares have increased through different antitrust regimes. Rising concentration also occurred at different points in time in different industries, and we are not aware that antitrust policies have systematically targeted different industries over time.

[26] If there is a series of investigations related to the same issue, they are consolidated into one case.

In summary, the data does not show evidence that antitrust is the main determinant of the economy-wide business size distribution throughout the past 100 years. As mentioned before, our focus is the economy-wide business size distribution among U.S.-based production, rather than concentration in antitrust markets. Antitrust enforcement could have affected market shares in narrowly defined product markets (Affeldt et al., 2021), even though it does not appear to be the main determinant of the economy-wide business size distribution.

Finally, we do not focus on analyzing mergers for three reasons. First, the prevalence of mergers can be affected by a number of mechanisms, including economies of scale, antitrust, and other regulations. Second, Holmstrom and Kaplan (2001) collect data on aggregate merger volume as a percentage of GDP from 1968 to 1999 and do not find a strong trend over these decades. Third, it is difficult to obtain comprehensive long-run merger data at the industry level or the firm level.[27]

Other regulations Several other types of government regulation may also affect the size of businesses. An important case is the restriction on interstate banking before the 1980s, which limited the size of banking operations (Savage, 1993). For the subsector "Finance: Banking", we do observe that top business shares increased from the 1980s until around the early 2000s, although it can be difficult to establish causation with only one sector-level time series. For another case, in the late 1920s and the 1930s, around half of the states passed laws imposing special taxes on chain stores, which decreased the share of sales by chain stores in those states (Ross, 1986). The anti-chain movement largely ended by the 1940s (Ross, 1986), which perhaps cleared way for the later rise of prominent national chains in retail. Interestingly, the most influential restaurant and retail chains took off only around the 1960s, and top business shares in these industries in our data also began to rise around then. Therefore, the decline of anti-chain regulations appears to be a necessary but not sufficient condition for the rise of retail chains. Finally, a number of policies subsidize small businesses though not explicitly punishing or restricting larger businesses (Hurst and Pugsley, 2011).

Overall, government regulations certainly can affect the size of businesses. However, as illustrated by the examples above, such regulations are very heterogeneous and often idiosyncratic. Accordingly, it is difficult to perform a systematic analysis of all potentially relevant regulations. To explain our main findings, such policies need to have shifted in favor of large firms over the past 100 years. Furthermore, they need to have been particularly important for the growth of large firms in manufacturing rather than in services in the early 20th century, and then switched focus in the later decades. At the moment, we are not aware of such a pattern in regulatory policies.

6 Conclusion

We collect new data on the size distribution of U.S. corporate businesses and document that corporate concentration (e.g., shares of the top 1% or top 0.1% businesses) has been rising persistently for the past 100 years. The rise was stronger in manufacturing and mining in earlier decades, and

[27] For large mergers studied in merger waves such as the conglomerate boom, many appear to represent firms in the top 0.1% buying firms in the top 1%, so the impact of such a merger on the top 1% share may not be substantial.

stronger in services, retail, and wholesale in later decades. We find that the timing and the degree of rising concentration in an industry align closely with investment intensity in IT and R&D. Moreover, industries with higher increases in concentration also exhibit higher output growth. Overall, the long-run historical trends we document point to increasingly stronger economies of scale. These long-run trends also have implications for several macroeconomic questions, such as the aggregate effects of shocks to larger versus smaller firms (Gabaix, 2011) and the aggregate effects of financial frictions across the firm size distribution (Crouzet and Mehrotra, 2020).

The top 1% or 0.1% businesses that we study capture a broad set of firms in the right tail of the size distribution, not just a small number of "giant" firms (White, 2002; Gutiérrez and Philippon, 2020). Our evidence suggests that larger companies contributing to an increasingly higher share of the economy is a general phenomenon, not limited to a few giant companies (which tend to attract the most public attention). Our results certainly do not rule out that some large firms may have gained market shares by unduly exerting power and influence (Cunningham, Ederer, and Ma, 2021; Kamepalli, Rajan, and Zingales, 2021), but the evidence suggests that economies of scale is important for understanding the long-run development of the U.S. economy. Finally, even if rising concentration comes from economies of scale, its social implications are much more difficult to pin down. As Stigler (1958) writes in his article on "The Economies of Scale," "the socially optimum firm is fundamentally an ethical concept, and we question neither its import its elusiveness."

An intriguing question is whether rising corporate concentration will be an enduring trend in the future. Some have conjectured that it can be an inevitable phenomenon, as mentioned at the beginning of the Introduction. Understanding this question requires more insights about whether ongoing developments in technology and the organization of businesses will increase fixed costs and reduce marginal costs in production, or ultimately facilitate decentralization. This issue returns to the fundamental inquiry about the boundaries of the firm posed by Coase (1937). More analyses of the evolution of firms' production processes may provide knowledge that can guide our outlook for the decades to come.

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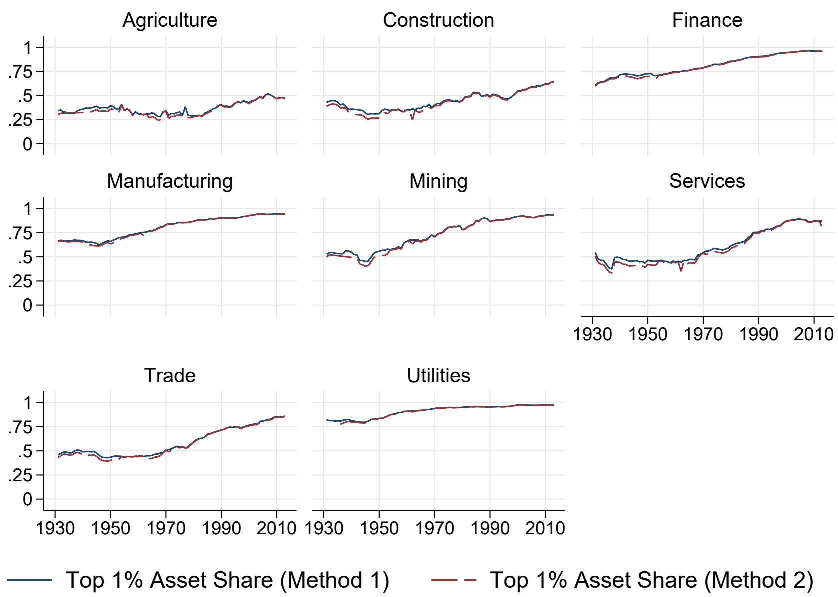
Internet Appendix: For Online Publication

IA1 Additional Figures and Tables

Figure IA1: Comparison of Two Methods for Calculating Top Shares

This figure shows the top 1% asset shares calculated using two methods explained in Section 2. The solid blue line shows the results of interpolating Pareto distributions (method 1). The dashed red line shows the results of adding up top bins (method 2).

Panel A. Main Sectors



Panel B. Subsectors

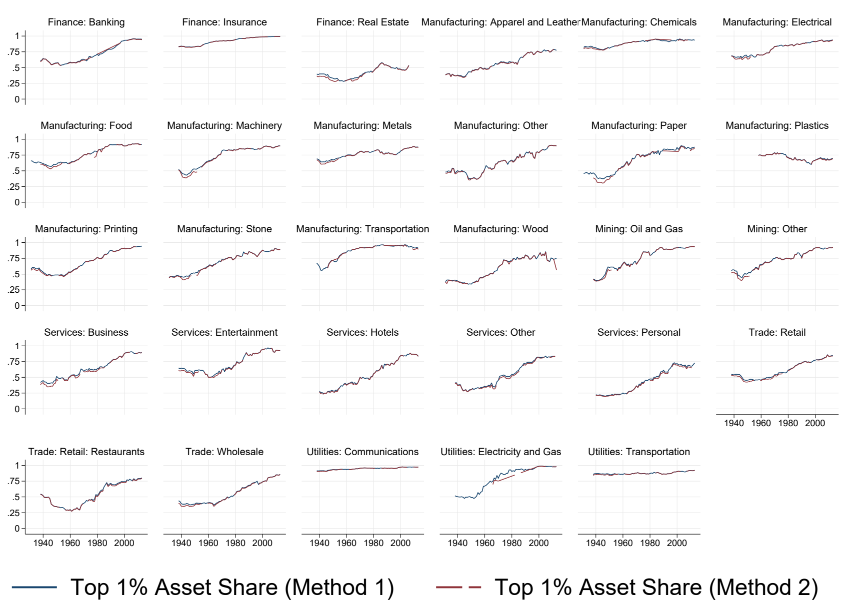
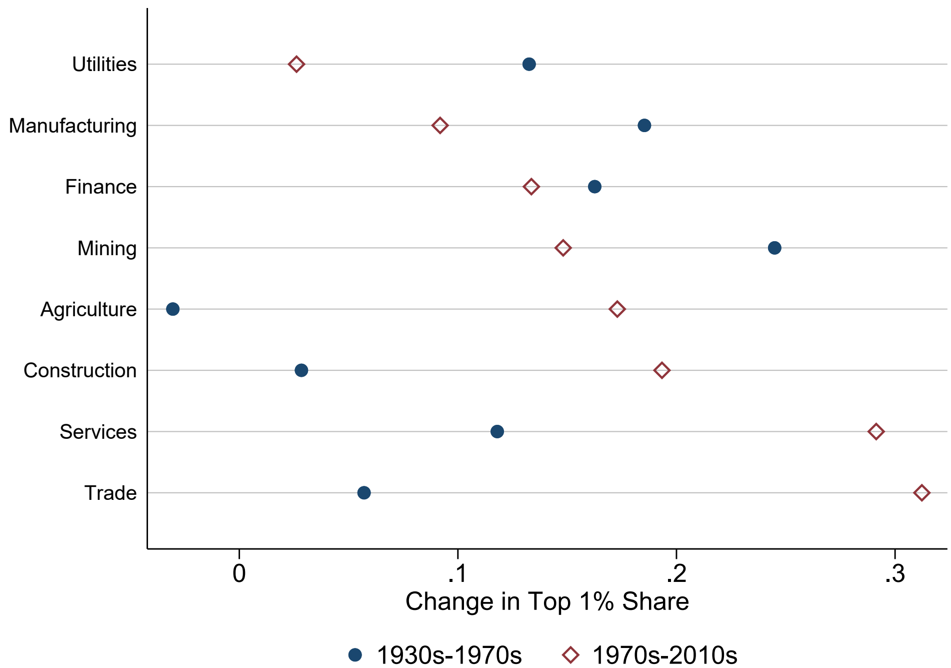


Figure IA2: Rising Concentration in Earlier and Later Decades

This figure shows the change in the top 1% asset share between 1930s to 1970s (solid blue circle) and between 1970s and 2010s (hollow red diamond), for main sectors in Panel A and subsectors in Panel B. The industries are sorted by the change in the top 1% asset share between 1970s and 2010s.

Panel A. Main Sectors



Panel B. Subsectors

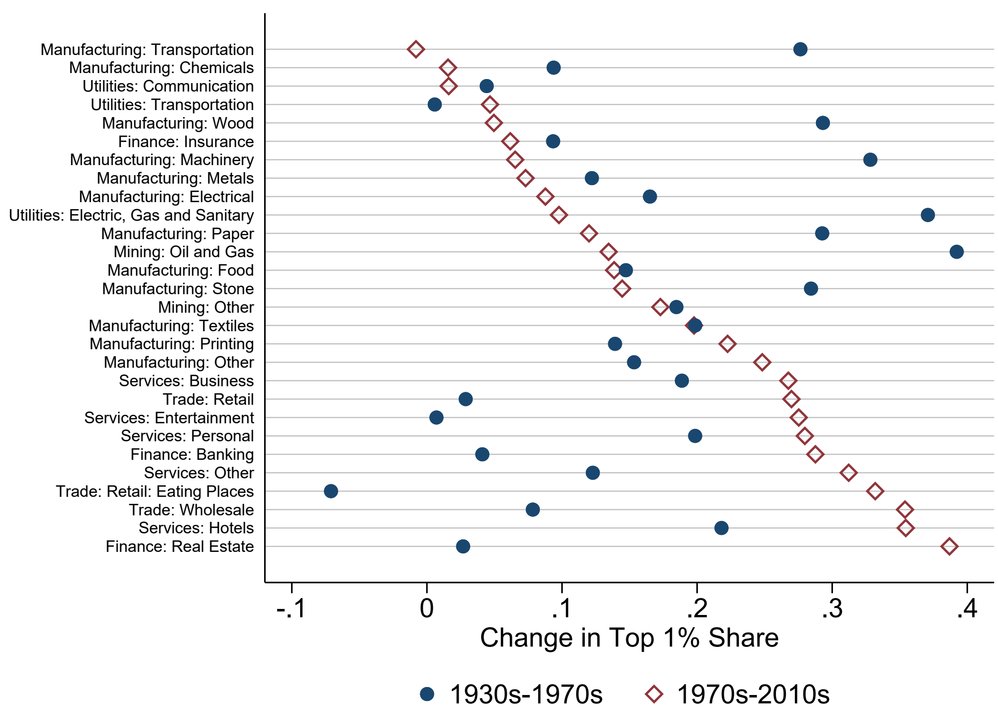


Figure IA3: Employment Concentration in Census Business Dynamic Statistics

This figure shows the aggregate employment share of the top 1% and top 0.1% firms by employment using census Business Dynamic Statistics.

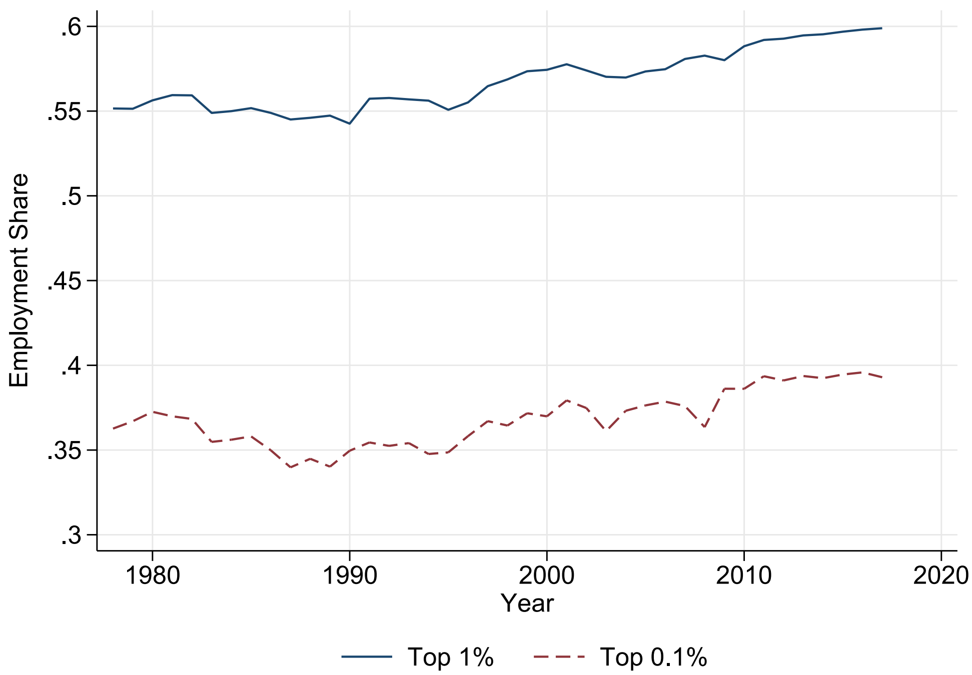
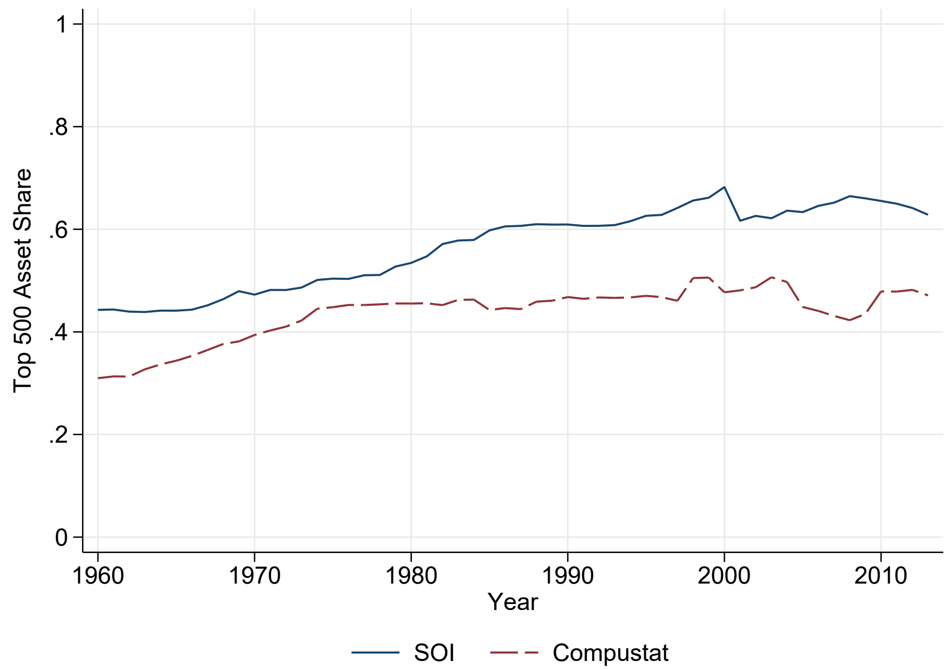


Figure IA4: Comparison with Compustat

This figure compares the share of the top 500 businesses calculated using our SOI data and using Compustat data. Panel A shows the imputed share of the top 500 business by assets in total corporate assets using SOI data (solid blue line) and the share of the top 500 by assets in Compustat in total corporate assets (dashed red line). Panel B shows the imputed share of the top 500 business by receipts in total corporate receipts using SOI data (solid blue line) and the share of the top 500 by sales in Compustat in total corporate receipts (dashed red line).

Panel A. Top 500 Share by Assets



Panel B. Top 500 Share by Receipts

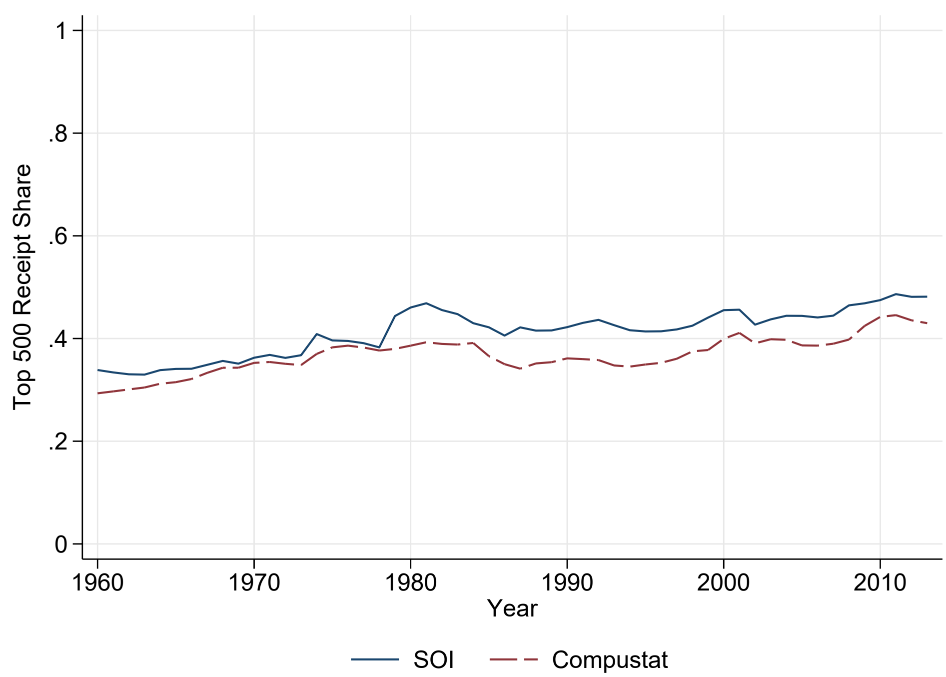
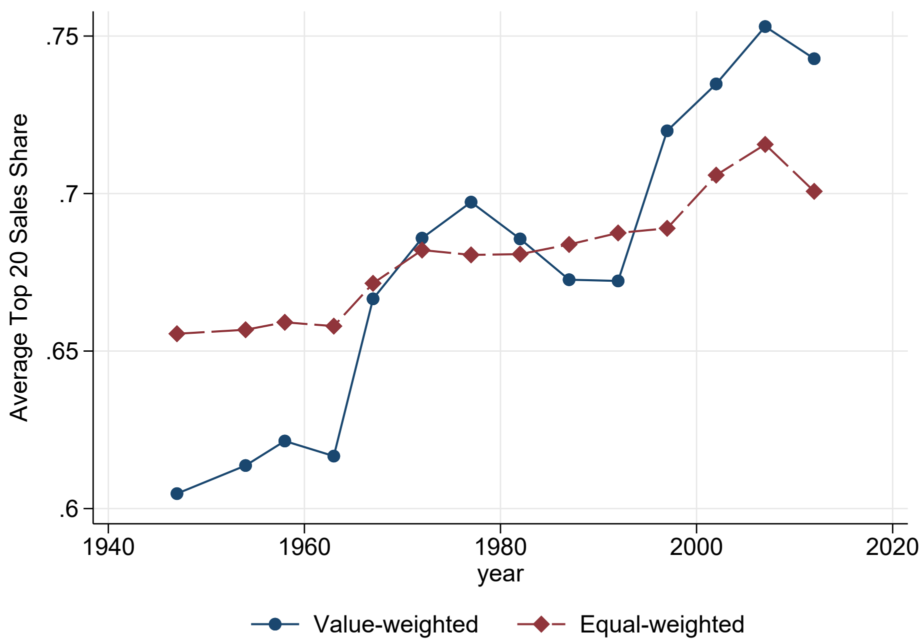


Figure IA5: Concentration Ratios in Census Data

Panel A shows the time series of the value-weighted average (solid blue line with circles) and equal-weighted average (dashed red line with diamonds) of sales concentration of the top 20 firms by sales from the Manufacturing Census. The data uses four-digit SIC industries until 1992 and six-digit NAICS industries after 1997. Panel B shows the 2012 cross section of the sales share of the top 20 firms by sales in census data on the x-axis and assets share of the top 20 businesses by assets in SOI data on the y-axis. Each dot is a six-digit SOI industry, which largely map into four-digit NAICS. Solid blue dots indicate manufacturing industries and hollow red dots inducate non-manufacturing industries.

Panel A. Time Series of Top 20 Share in Manufacturing Census



Panel B. Cross Section of Top 20 Share in 2012 Census

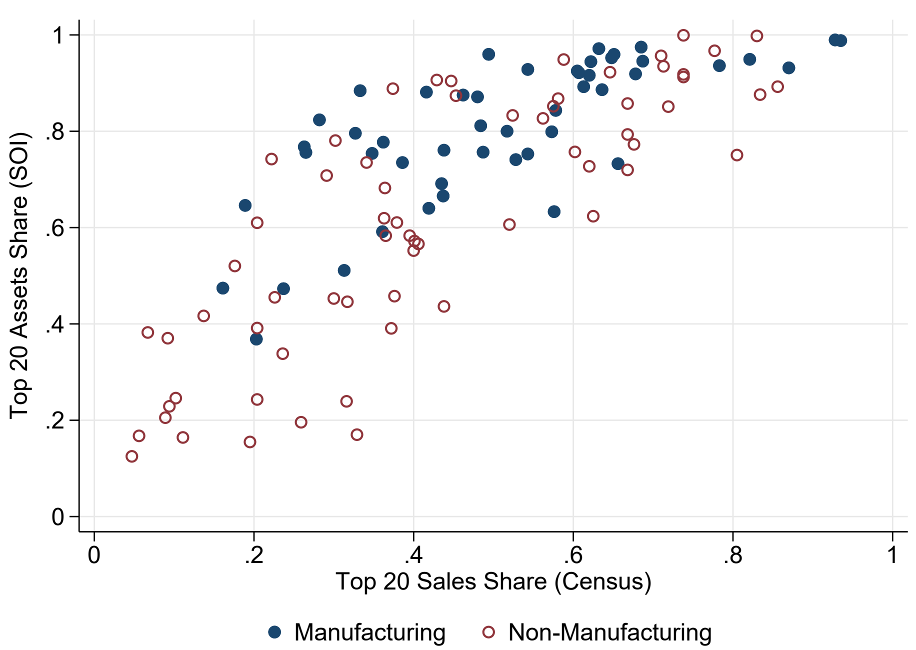


Figure IA6: Share of Corporate Businesses in Total Business Receipts

This figure shows the share of corporate businesses in the total value of business receipts (receipts by corporate businesses, partnerships, and nonfarm proprietors), for the aggregate and the main sectors.

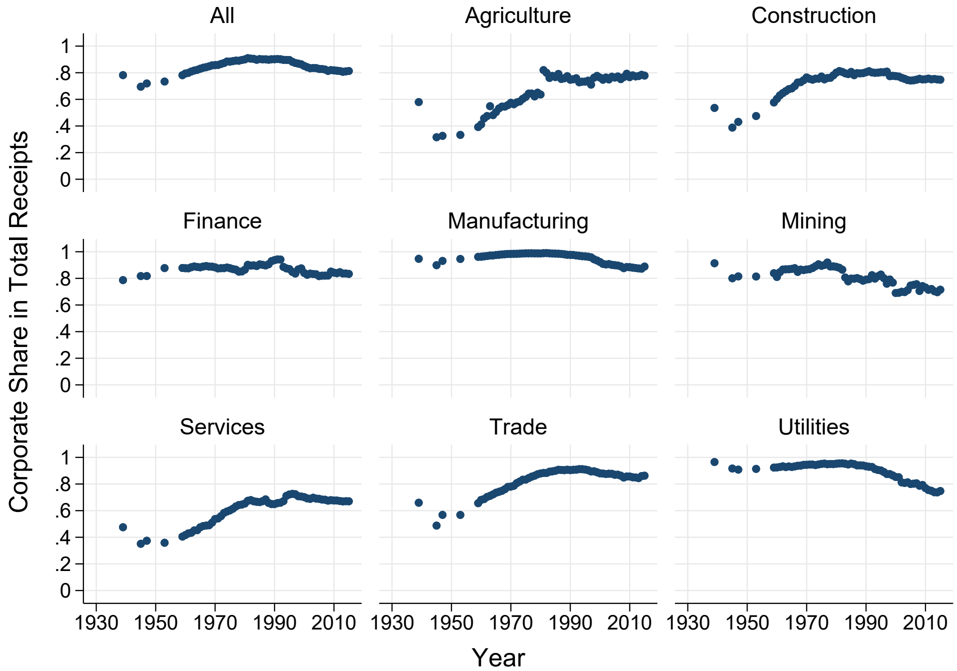


Figure IA7: Top 0.1% Receipt Share: Including Noncorporate Businesses

This figure shows robustness checks for top businesses' shares including noncorporate businesses. The blue circles show the receipt share of the top 0.1% corporates by receipts among all corporate businesses, and the purple diamonds show the receipt share of the top 0.1% businesses by receipts among all businesses (corporate and noncorporate) for years when size bins for noncorporates are available. The dashed red line shows the lower bound estimate of the receipt share of the top 0.1% businesses among both corporate and noncorporate businesses, where we assume that the top 0.1% businesses among all businesses consist entirely of largest corporates. In other words, we take the total receipts by the top $0.1\%(N_{corp}+N_{noncorp})$ corporate businesses, and divide by the total receipts by all corporate and noncorporate businesses. The top 0.1% receipt shares among all businesses (purple diamonds) are not available for finance in recent decades due to data errors in the SOI publications.

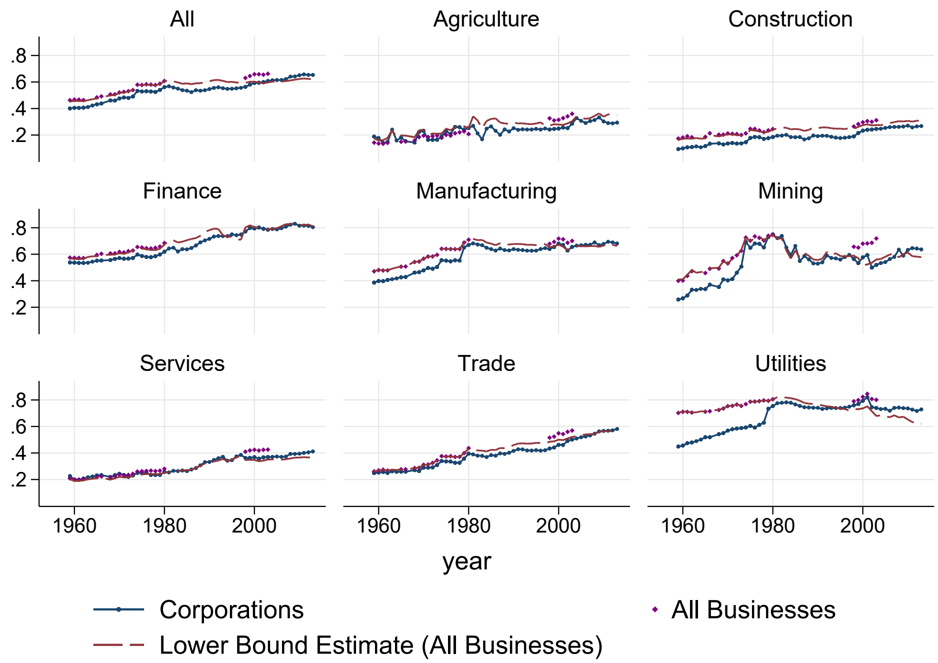
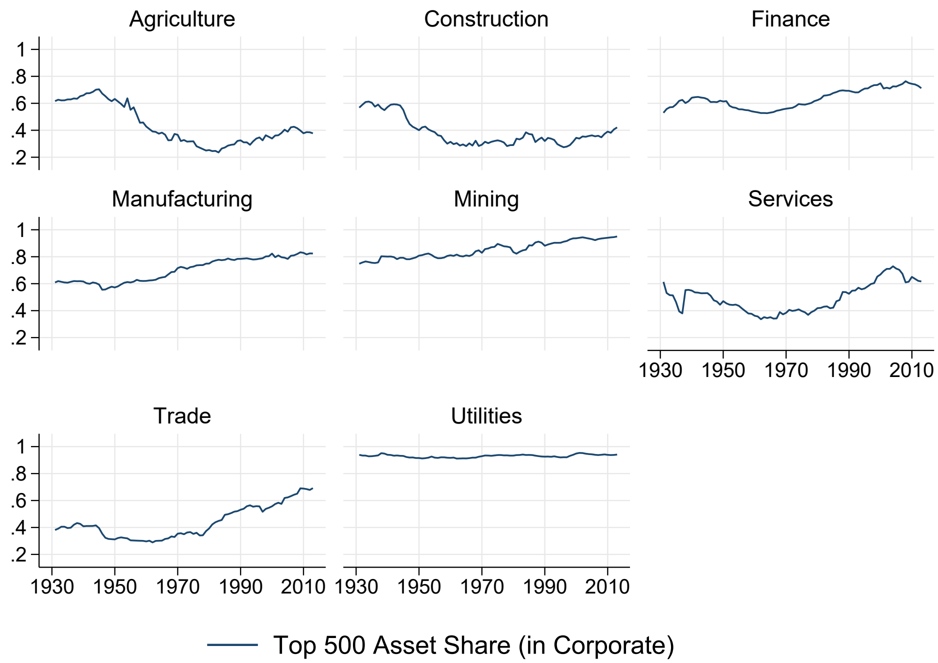


Figure IA8: Share of Top 500 Businesses: Main Sectors

Panel A shows the asset share of the top 500 corporate businesses by assets in the main sectors. Panel B shows the asset share of the top 500 corporate businesses in total receipts of all corporate businesses (solid blue line) and total receipts of corporate plus noncorporate businesses (dashed red line).

Panel A. Asset Shares



Panel B. Receipt Shares

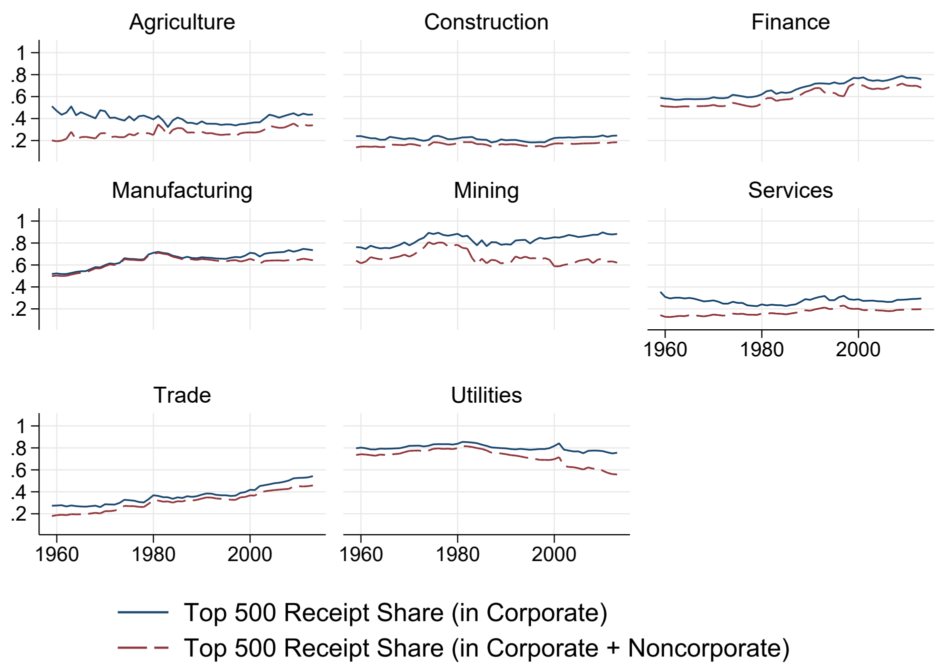


Figure IA9: Including International Assets

This figure shows estimated top 1% asset shares including international assets using Activities of U.S. Multinational Enterprises from the BEA. The solid blue line shows the original top 1% asset shares using SOI data. The dashed red line shows the top 1% asset shares when all international assets are assigned to the top 1% businesses. The dash-dotted green line shows the top 1% asset shares when international assets are assigned to the top 1% and the bottom 99% businesses according to their domestic asset shares (using SOI data).

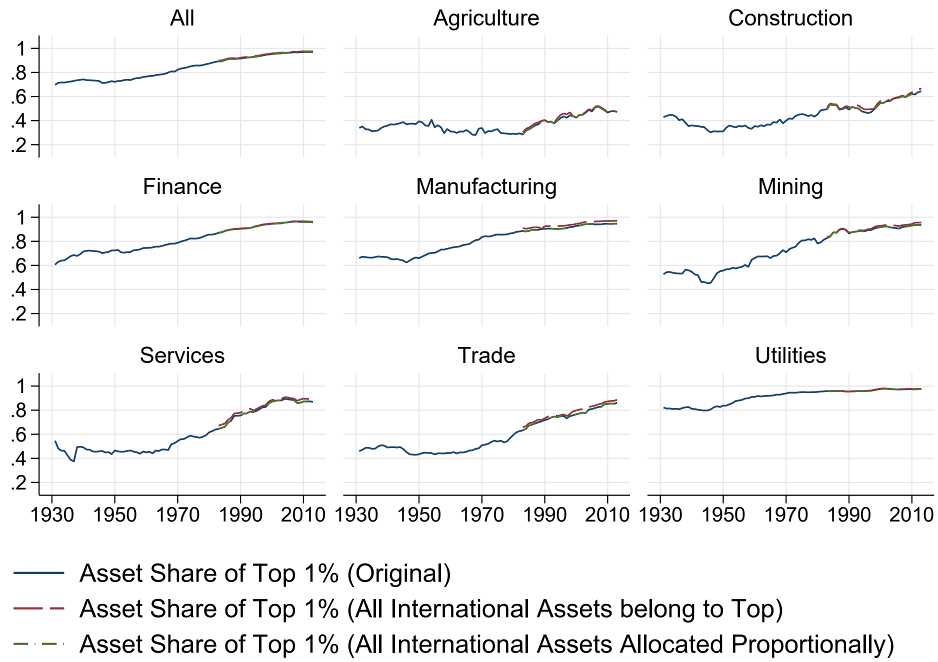


Figure IA10: Profitability in SOI and BEA

The solid blue line shows net income (before tax) in SOI normalized by total receipts in SOI. The dashed red line shows net income (corporate profit before tax with inventory valuation and capital consumption adjustments) from BEA normalized by total receipts in SOI.

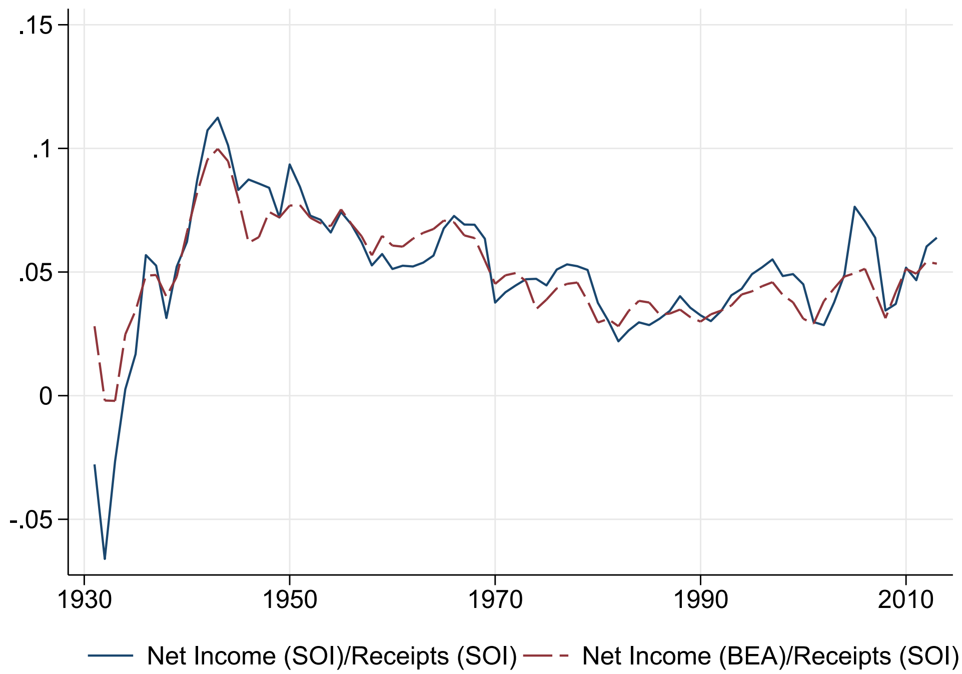
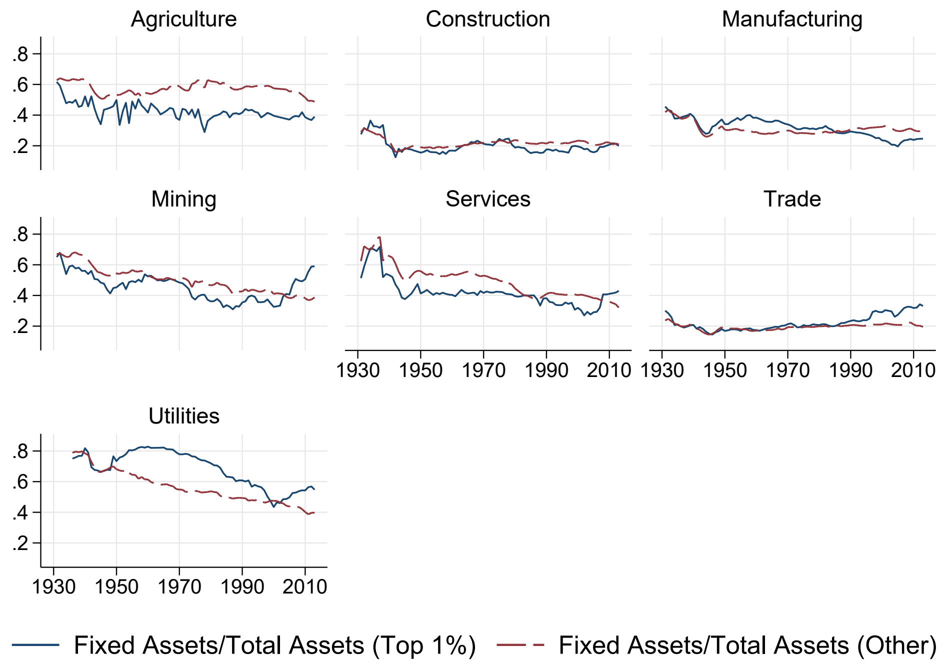


Figure IA11: Balance Sheet Characteristics

Panel A shows the ratio of fixed assets to total assets and Panel B shows the ratio of equity to total assets for nonfinancial industries among the main sectors. The solid blue line shows the result for the top 1% businesses by assets and the dashed blue line shows the result for the rest.

Panel A. Fixed Assets/Total Assets



Panel B. Equity/Total Assets

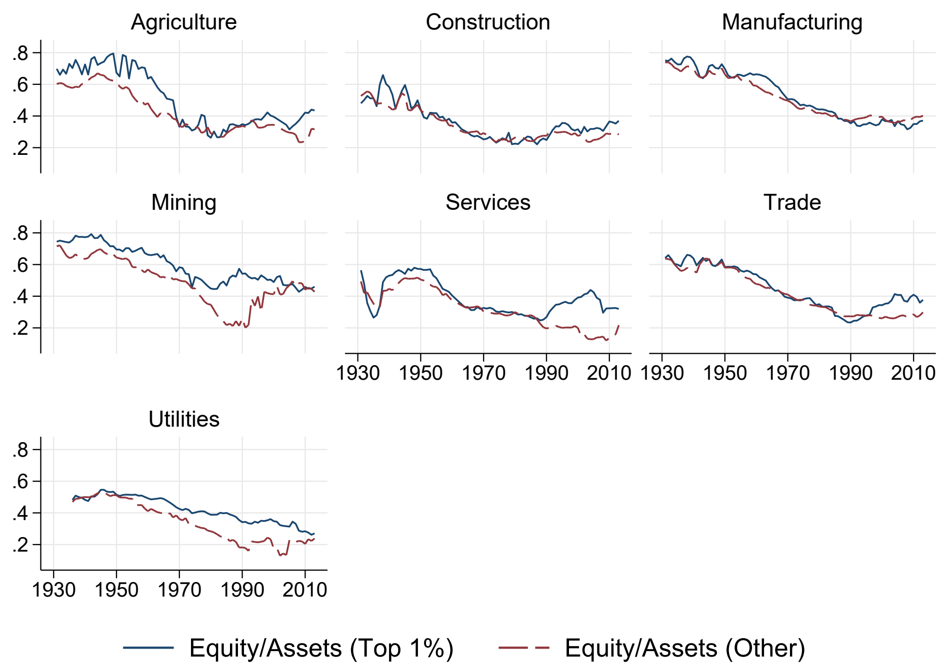


Figure IA12: Investment Rate

This figure shows the investment rate (investment over capital stock) from the BEA fixed asset tables. The dashed red line shows the investment rate of fixed assets (equipment and structures). The dash-dotted green line shows the investment rate of fixed assets plus intellectual property. The solid blue line is the asset share of the top 1% corporate businesses by asset size from SOI. The left axis is the top 1% asset share, and the right axis is the investment rate.

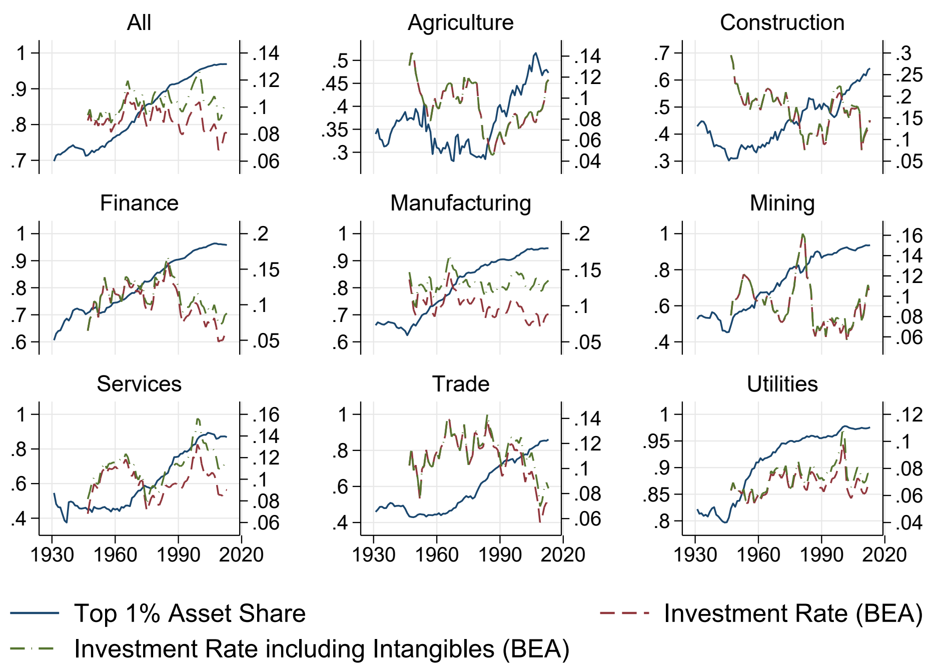
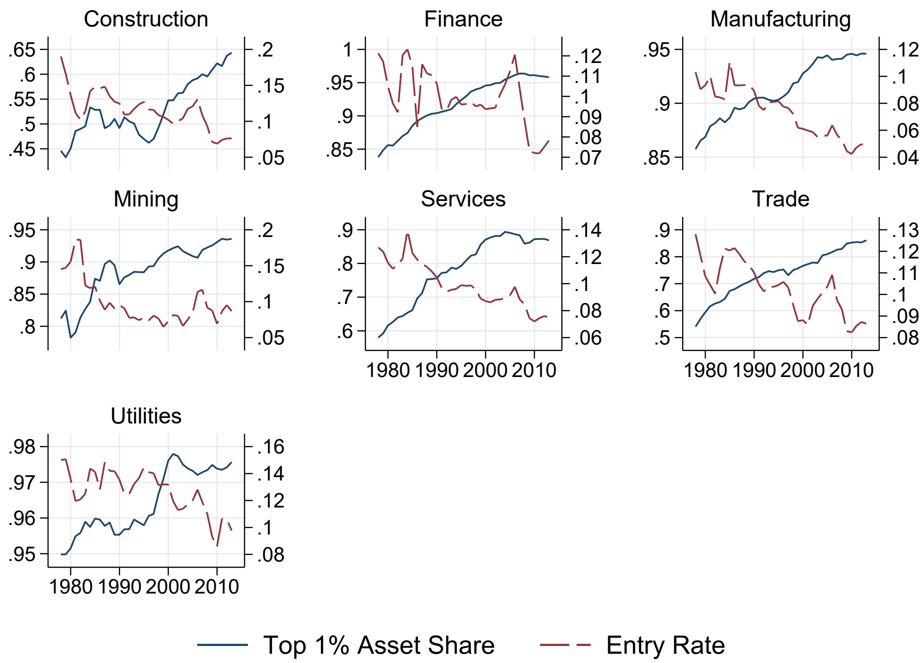


Figure IA13: Entry Rate

This figure shows the entry rate (the share of new firms) from census BDS (dashed red line). The solid blue line repeats the asset share of the top 1% corporate businesses by asset size from SOI. The left axis is changes in the top 1% asset share, and the right axis is changes in industry entry rates.

Panel A. Main Sectors



Panel B. Subsectors

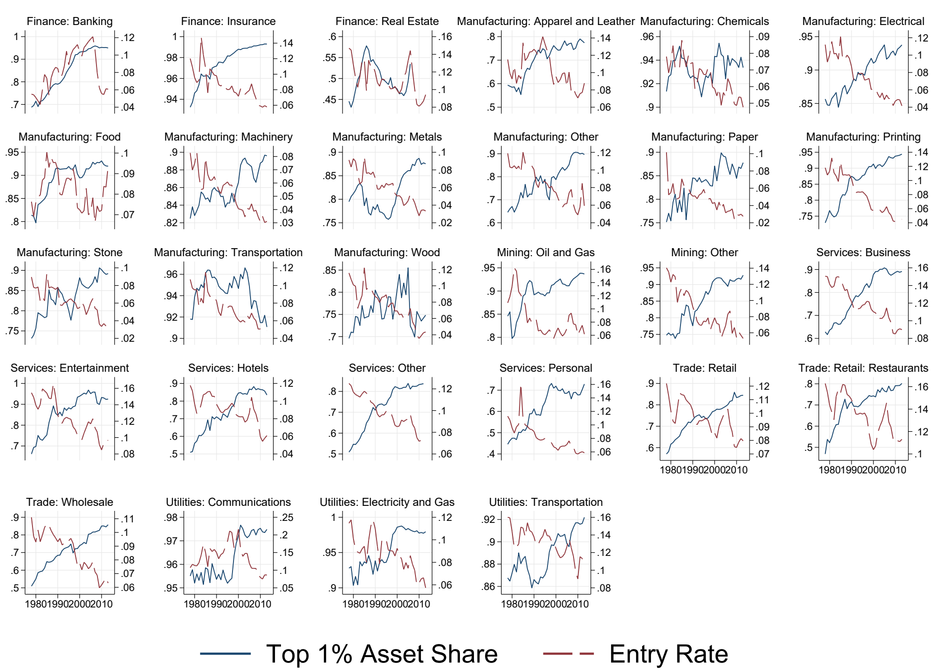


Figure IA14: Sales Concentration Excluding Exports

The solid blue line shows the baseline aggregate sales concentration, which measures the share of the top 1% businesses by receipts in total receipts. The dashed red line shows aggregate sales concentration excluding exports, where we remove all exports from the receipts of the top 1% businesses to be conservative. In other words, we calculate (top 1% receipts − exports)/(total receipts − exports).

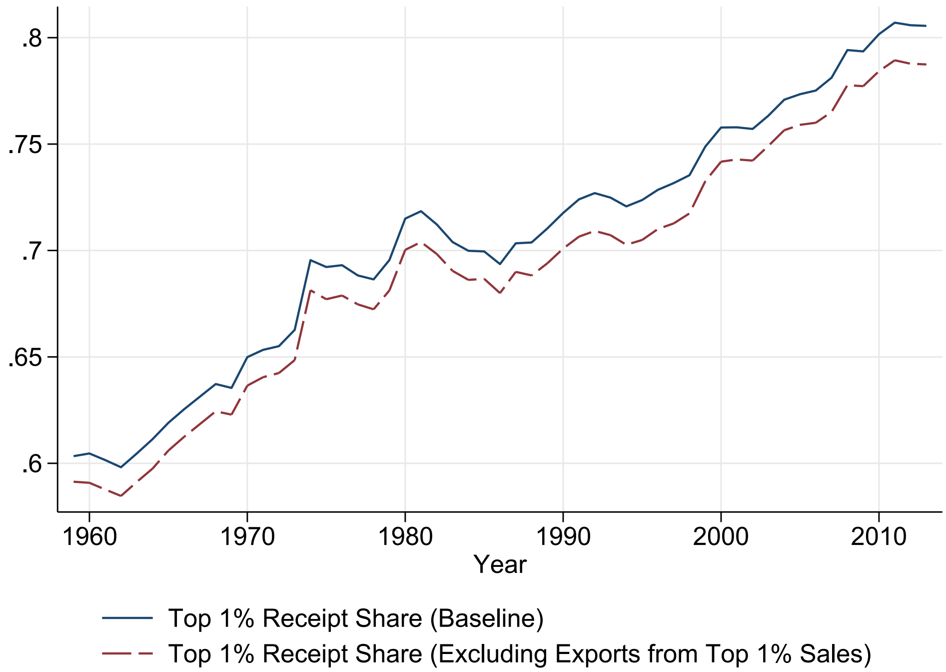


Figure IA15: DOJ Antitrust Activities

The solid blue line shows the annual number of antitrust cases institute by the DOJ. The dashed red line shows the DOJ antitrust division budget normalized by GDP in million dollars.

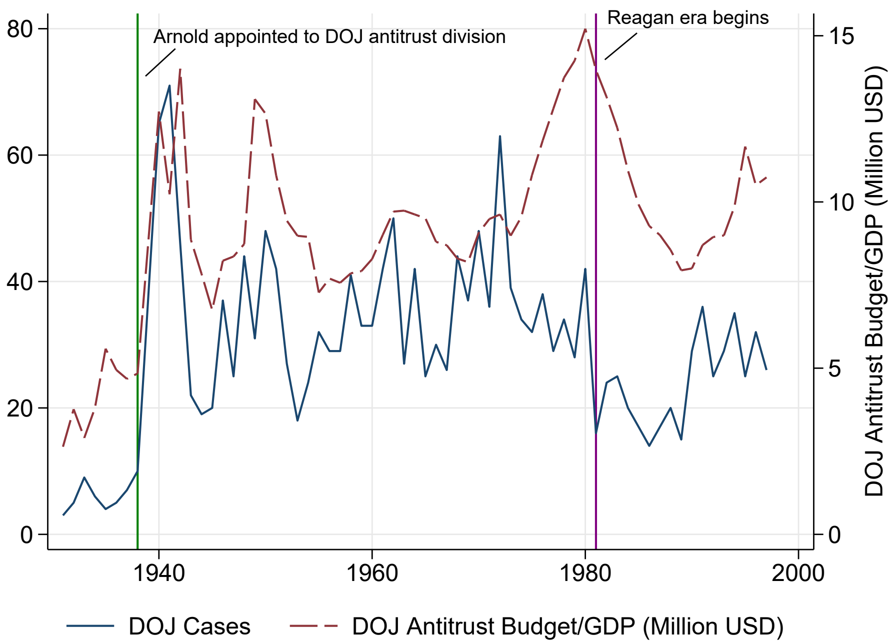


Table IA1: Robustness Check Controlling for the Number of Businesses

This table shows industry-level regressions of the asset share of the top 1% businesses on the investment intensity in IT and R&D in columns (1), (2), (5), and (6), which are the same as columns (3) and (4) in Tables 4 and 5 except we also control for the log change in the number of corporate businesses in the industry. The table shows industry-level regressions of changes in the asset share of the top 1% businesses over twenty years on industry growth over twenty years in columns (3), (4), (7), and (8), which are the same as columns (1) and (2) in Tables 7 and 8 except we also control for the log change in the number of corporate businesses in the industry. Year fixed effects are included in columns (2) and (4). Panel A shows results for main sectors. Panel B shows results for subsectors. Standard errors are Driscoll and Kraay (1998) with twenty lags. R^2 does not include fixed effects.

Panel A. Main Sectors

	Δ_{20}Asset Share of Top 1%							
	All Industries				Nonfinancial Industries			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ_{20}Share of IT and R&D in Investment	0.402***	0.214***			0.496***	0.327***		
	(0.111)	(0.059)			(0.111)	(0.069)		
Δ_{20}Log Real Gross Output			0.058***	0.062***			0.078***	0.092***
			(0.012)	(0.016)			(0.015)	(0.019)
Δ_{20}Log # of Businesses	-0.007	-0.036	-0.018	-0.028	-0.007	-0.043	-0.025	-0.043
	(0.017)	(0.030)	(0.027)	(0.030)	(0.017)	(0.031)	(0.029)	(0.034)
Year Fixed Effect	No	Yes	No	Yes	No	Yes	No	Yes
Obs	504	504	376	376	441	441	329	329
R^2	0.14	0.09	0.05	0.06	0.16	0.14	0.07	0.10

Panel B. Subsectors

	Δ_{20}Asset Share of Top 1%							
	All Industries				Nonfinancial Industries			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ_{20}Share of IT and R&D in Investment	0.098*	0.063**			0.162***	0.135***		
	(0.056)	(0.028)			(0.058)	(0.034)		
Δ_{20}Log Real Gross Output			0.047***	0.038**			0.041***	0.033**
			(0.012)	(0.016)			(0.012)	(0.015)
Δ_{20}Log # of Businesses	0.018	0.006	0.028*	0.014	0.027	0.009	0.034*	0.019
	(0.023)	(0.026)	(0.017)	(0.017)	(0.022)	(0.028)	(0.020)	(0.021)
Year Fixed Effect	No	Yes	No	Yes	No	Yes	No	Yes
Obs	1,646	1,646	1,311	1,311	1,485	1,485	1,209	1,209
R^2	0.02	0.01	0.08	0.03	0.05	0.02	0.09	0.04

Table IA2: Robustness Check for Rising Concentration and Technological Intensity

This table shows industry-level regressions of the asset share of the top 1% businesses on IT and R&D investment in an industry (BEA data) normalized by business receipts (SOI data). For both left hand side and right hand side variables, we use their levels in columns (1) and (2) and their changes over twenty years in columns (3) and (4). Year fixed effects are included in columns (2) and (4). Panel A shows results for all industries. Panel B shows results for nonfinancial industries. Standard errors are Driscoll and Kraay (1998) with twenty lags. R^2 does not include fixed effects.

Panel A. Main Sectors

	Asset Share of Top 1%			
	Level		Change (Δ_{20})	
	(1)	(2)	(3)	(4)
IT and R&D Investment/Business Receipts	9.987***	8.307***		
	(0.986)	(1.224)		
Δ_{20}IT and R&D Investment/Business Receipts			3.253***	1.929***
			(0.964)	(0.312)
Year Fixed Effect	No	Yes	No	Yes
Obs	664	664	504	504
R^2	0.37	0.21	0.12	0.04

Panel B. Subsectors

	Asset Share of Top 1%			
	Level		Change (Δ_{20})	
	(1)	(2)	(3)	(4)
IT and R&D Investment/Business Receipts	3.414***	1.030***		
	(1.057)	(0.398)		
Δ_{20}IT and R&D Investment/Business Receipts			0.459**	0.191**
			(0.218)	(0.090)
Year Fixed Effect	No	Yes	No	Yes
Obs	2,227	2,227	1,646	1,646
R^2	0.14	0.02	0.01	0.00

Table IA3: Robustness Check for Rising Concentration and Industry Growth

This table shows industry-level regressions of changes in the asset share of the top 1% businesses over ten years on industry real gross output growth over ten years predicted by the growth over the past ten years. Columns (1) and (2) show results for all industries. Columns (3) and (4) show results for nonfinancial industries. Panel A shows results for main sectors, and Panel B shows results for subsectors. Standard errors are Driscoll and Kraay (1998) with twenty lags. R^2 does not include fixed effects.

Panel A. Main Sectors

	Δ_{10}Asset Share of Top 1%			
	All Industries		Nonfinancial Industries	
	(1)	(2)	(3)	(4)
Δ_{10}Log Real Gross Output	0.096**	0.095***	0.128***	0.123***
	(0.038)	(0.031)	(0.049)	(0.037)
Year Fixed Effect	No	Yes	No	Yes
Obs	376	376	329	329
R^2	0.01	-0.01	-0.02	-0.01

Panel B. Subsectors

	Δ_{10}Asset Share of Top 1%			
	All Industries		Nonfinancial Industries	
	(1)	(2)	(3)	(4)
Δ_{10}Log Real Gross Output	0.126**	0.105**	0.120**	0.098**
	(0.052)	(0.047)	(0.055)	(0.046)
Year Fixed Effect	No	Yes	No	Yes
Obs	1,312	1,312	1,210	1,210
R^2	0.03	-0.03	0.04	-0.01

Table IA4: Antitrust Enforcement

Panel A presents time series regressions of DOJ antitrust enforcement activities on political control. The outcome variables are the average annual DOJ antitrust cases (Annual Cases) and the average annual DOJ antitrust division budget normalized by GDP (Annual Budget) in each presidential cycle. The independent variables include an indicator for Republican presidential control (Republican President), the number of years with Republican control of the House as well as the Senate (Republican Congress), and the number of years with Reduplication control of both the presidency and congress (Republican Trifecta). Standard errors are Newey-West. Panel B presents panel regressions of changes in concentration in each main sector or subsector on DOJ antitrust enforcement activities and political control. The outcome variable is the change in the top 1% asset share in each industry during each presidential cycle. The independent variables include the average annual DOJ antitrust cases and the average annual DOJ antitrust division budget (normalized by GDP) in each presidential cycle. The independent variables also include variables for Republican control. Standard errors are Driscoll and Kraay (1998) with five lags.

Panel A. DOJ Antitrust Enforcement and Political Control over Presidential Cycles

	Annual Cases		Annual Budget	
	(1)	(2)	(3)	(4)
Republican President	-3.946		-1.248	
	(5.251)		(1.165)	
Republican Congress	-0.325*		-0.055	
	(0.176)		(0.040)	
Republican Trifecta		-0.472***		-0.112***
		(0.164)		(0.035)
Obs	19	19	23	23
R^2	0.21	0.30	0.18	0.35

Panel B. Changes in Concentration over Presidential Cycles

	Change in Top 1% Asset Share							
	Main Sectors				Subsectors			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Annual DOJ Cases	-0.0000				-0.0004			
	(0.0005)				(0.0006)			
Annual DOJ Antitrust Budget		0.0022				-0.0003		
		(0.0015)				(0.0017)		
Republican President			0.0107*				0.0108	
			(0.0056)				(0.0069)	
Republican Congress			0.0001				-0.0000	
			(0.0002)				(0.0001)	
Republican Trifecta				0.0000				-0.0001
				(0.0002)				(0.0001)
Obs	136	160	160	160	446	533	533	533
R^2	0.00	0.03	0.03	0.00	0.01	0.00	0.02	0.00

IA2 Appendix: Data Construction

IA2.1 SOI Data

We digitize data from historical publications of the Internal Revenue Service (IRS). The IRS has a longstanding tradition of collecting detailed statistics for individuals and businesses going back to the Revenue Act of 1916. The Statistics of Income (SOI) was first published in 1918 (with data for 1916). Initially the SOI included only basic statistics on corporations, but over the years the section on corporations has become increasingly detailed, with more cross-tabulations and variables. In addition to data on receipts and net income, the SOI also contains data on balance sheets, which derives from (end-of-fiscal-year) balance sheets submitted by corporations with their tax returns. Using micro data from these submissions, the SOI provides tabulations of businesses by size of net income and sector since 1918 (which ended in the 1970s), by size of assets and sector since 1931, and by business receipts and sector since 1959. We use these size tabulations to study trends in corporate concentration over the long run. As discussed in Section 2, the tabulations by size are mainly available for corporate businesses (both C-corporations and S-corporations), and we provide additional checks for concentration estimates including noncorporate businesses in Section 3.2.

The SOI publications are accompanied by the Corporation Source Book, which is a series of initially unpublished volumes containing tabulations with more detailed classifications compared to the published reports. The Corporation Source Book is digitally available through the IRS and the Electronic Records Division at the U.S. National Archives and Records Administration from 1964. The advantage of the Corporation Source Book data is that it includes more granular sector data and additional income and balance sheet items. We use the Corporation Source Book whenever available.

The earliest SOI publications were based on the analysis of all submitted corporate tax returns. In later years, the SOI used estimates from sample data. Starting in 1951, the IRS began to use a stratified probability sample to provide estimates for the whole population. In these samples the IRS varied the sampling rate by size (measured using the size of total assets or the size of net income) to guarantee reliable totals. Accordingly, the sample usually included the universe of businesses in the top bins. Therefore, the transition to sample data should not be accompanied by large effects on corporate concentration.

Industry classification The SOI assigns a single industry code to each business based on the industry that represents the largest percentage of its total business receipts. For studies using long-run data by industry, a common task is to address changes to the industry classification systems over time. We harmonize the different industry classification systems to construct consistent industries. The SOI industry classification can be broadly separated into three periods. Between 1931 and 1937, the IRS followed its own industry classification. In 1938, the IRS adopted the newly created SIC industry classification system (with a few small modifications), and followed its various vintages until 1997. In 1998, the IRS began to use NAICS codes. Broad industrial groupings remained relatively stable within these three periods, which allows us to build consistent definitions for main sectors (roughly at the level of one-digit SIC codes) and subsectors (roughly at the level of two-digit SIC codes).

Table IA5, Panel A, presents how our main sectors correspond to Industrial Divisions in the SIC classification system and NAICS codes. Panel B shows the construction of the subsectors. These subsectors are also designed to maximize the comparability with industries in BEA data (including the BEA fixed asset tables and NIPA accounts), since our analyses also rely on BEA data to measure various outcomes. If we are not mapping into industries in BEA data, then we can further break down several subsectors. Among "Construction," we can have "Construction: Buildings" (SIC 15, NAICS 236), "Construction: Heavy Construction" (SIC 16, NAICS 237), and "Construction: Special Trade" (SIC 17, NAICS 238). Among Mining, we can have "Mining: Metal" (SIC 10, NAICS 2122), "Mining: Coal" (SIC 12, NAICS 2121), and "Mining: Non Metallic" (SIC 14, NAICS 2123). Among "Manufacturing: Apparel and Leather," we can have "Manufacturing: Textiles" (SIC 22 and 23, NAICS 313, 314, and 315) and "Manufacturing: Leather" (SIC 31 and NAICS 316). Among "Trade: Retail," we can have "Trade: Retail: Apparel" (SIC 56, NAICS 448), "Trade: Retail: Automotive" (SIC 55, NAICS 441 and 447), "Trade: Retail: Building Materials" (SIC 52, NIACS 444), "Trade: Retail: Food" (SIC 54, NAICS 445), "Trade: Retail: Furniture" (SIC 57, NAICS 442), "Trade: Retail: General Merchandise" (SIC 53, NAICS 452) and "Trade: Retail: Miscellaneous" (SIC 59, NAICS 446, 451, 453, and 454). Among "Services: Other," we can have "Services: Repair" (SIC 75 and 76, NAICS 532 and 811) and "Services: Miscellaneous" (SIC 89, NAICS 561, 61, 62, and 813).

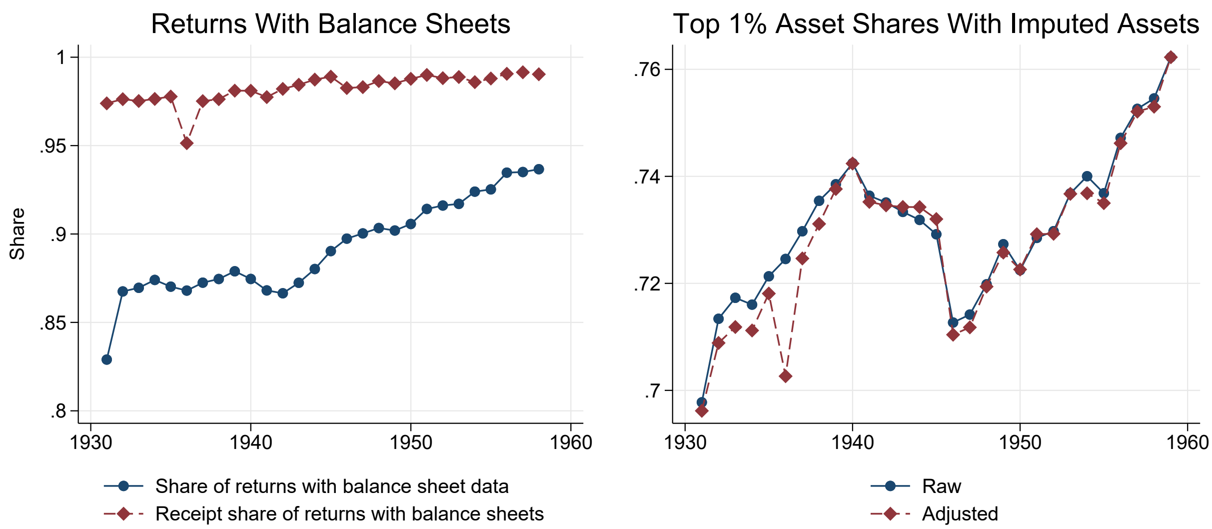
Bin deletions For certain size bins at the industry level, financial data is suppressed to avoid disclosing information of individual businesses. This problem rarely arises in the main sector data, but becomes more common at the subsector level. For some of the early SOI issues, we can manually back out the missing values using adding up constraints from the hierarchical industry and bin structure (similar in spirit to Eckert et al., 2020). In later years, additional precautions have been introduced by the IRS to preserve taxpayer confidentiality by deleting information from additional size and industry bins when necessary. In these cases, we join the deleted bins (and all bins in between) into one large bin, and back out the financial data using the difference of the total and all other bins. While this approach generally works well and does not create problems for the calculation of concentration indices, in a handful of cases the number of size bins is reduced too much to calculate consistent and robust top shares. We linearly interpolate data for these years.

Accounting We discuss several aspects of accounting in the SOI. First, as discussed in Section 2, the SOI primarily focuses on domestic assets and sales, like national accounts. We provide additional checks about the potential influence of international assets in Section 3.2. Second, net income in SOI data is calculated using tax depreciation. Nonetheless, net income is not a focus of our analyses; Figure IA10 also shows that net income calculated using SOI data (tax depreciation) and BEA data (where the BEA translates tax depreciation into economic depreciation) are similar, at least in the aggregate. Third, accounting methods could have changed over time (e.g., last in, first out versus first in, first out for inventory accounting). There are many changes over time in the accounting rules for companies' financial statements as well, and we do not think these changes have a first-order impact on the key outcomes we study.

Not all companies submit information about their balance sheets together with their tax returns. Reports without balance sheets are usually from corporations without assets (liquidations, dissolutions, acquisitions), foreign corporations doing business in the United States, and a small number of corporations that fail to supply balance sheet information. Until the SOI of 1958-59, these filings are included in all tabulations "by net income," but excluded from tables pertaining to balance sheet information. Starting in 1959-60, the IRS included businesses with zero assets in the balance sheet tabulations and imputed data for businesses with missing balance sheets using information from the returns of businesses with both income statements and balance sheets in the same industry. Taken together, before 1959, the omission of businesses without missing balance sheet information in the

Figure IA16: Returns without Balance Sheets

The right panel shows share of returns submitted with balance sheet information and the receipt share accounted for by these returns. The left panel shows how concentration changes if we impute assets for firms without balance sheet information using information on their receipts and assuming that they have the same assets-to-receipts ratios as the industry as a whole.



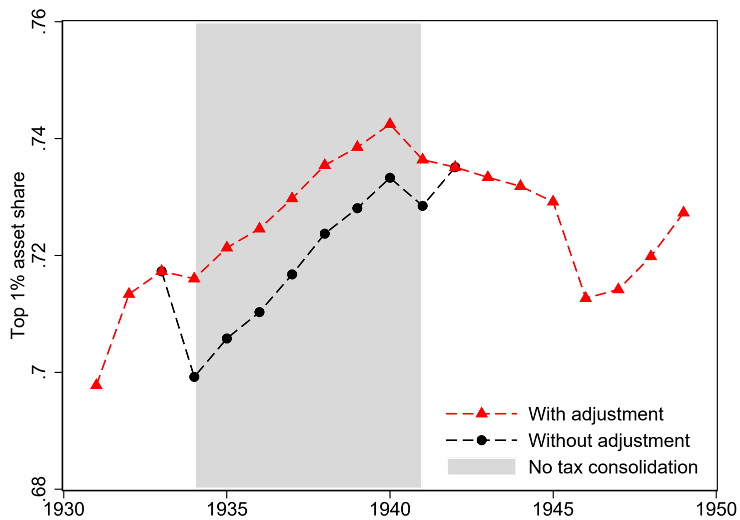
SOI asset bin tabulations could affect the number of businesses in our calculations (for the asset share of top businesses). The left panel of Figure IA16 shows the share of returns in each year with balance sheet information and the receipt share accounted for by these returns. For example, in 1950 about 10 percent of returns representing 1.2 percent of total receipts did not include balance sheet data. The figure also shows that both the share of returns without balance sheet data and their receipt share has declined over time. We can provide robustness checks by either assuming that the businesses with missing balance sheets fall in the smallest asset size bin, or imputing the asset size bins they belong to using information on their receipts (assuming they have the same assets-to-receipts ratios as the industry as a whole). The right panel of Figure IA16 compares our baseline concentration estimate to a concentration estimate with imputed assets for returns without balance sheets. The two series are similar. We also find the same degree of consistency at the industry level (results not shown).

Consolidation The IRS allows corporations to file consolidated returns if at least 80 percent of the equity of an affiliate is owned within the group. Corporations that chose to file consolidated returns in one year are generally also required to file consolidated returns in the subsequent years. The consolidation privilege is granted to all affiliated domestic corporations except regulated investment companies (RICs), real estate investment trusts (REITs), tax-exempt corpo-rations, Interest Charge Domestic International Sales Corporations (IC-DISCs), and S-corporations. Life insurance companies can file consolidated returns with other life insurance companies without restrictions. In recent years at least, eligible firms generally elect to consolidate (Mills, Newberry, and Trautman, 2002), given more favorable treatments when consolidated (e.g., when consolidated the sales among affiliates do not generate taxes, and gains and losses across affiliates can be netted).

Rules on consolidation for tax purposes have had several changes over time. Streuling (1971) offers

Figure IA17: Consolidation Adjustment

This figure shows the top 1% asset share between 1931 and 1950 with and without adjustment for changes in consolidation.



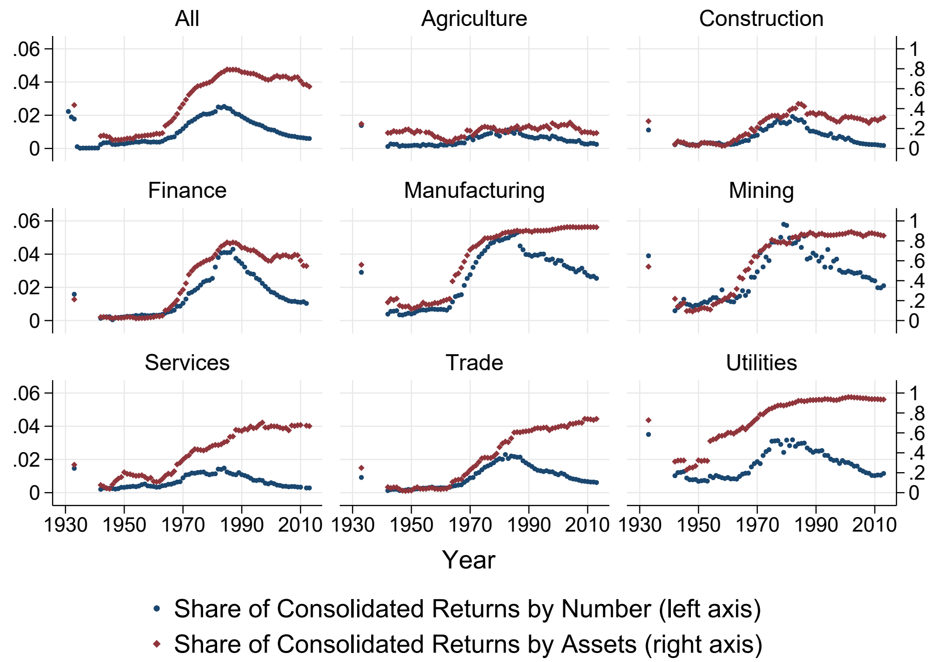
a detailed discussion of the various Revenue Acts that led to the changes. First, the 80% ownership requirement applicable today dates back to 1954. Prior to 1954, the ownership threshold was 95%. Second, consolidated returns were often taxed at higher rates before the 1960s. In 1932 and 1933, consolidated returns were subject to an additional tax of 0.75 percent. In 1934 and 1935, the additional tax increased to 1 percent. No additional tax was imposed between 1936 and 1941, but the consolidation privilege was significantly limited (see below). Between 1942 and 1963, corporations filing consolidated returns were subject to a surtax on the group of two percentage points. The Revenue Act of 1964 eventually repealed the two percent surtax for consolidated returns, so surtaxes no longer applied since 1964. Finally, consolidation was mandatory between 1918-1921 and voluntary after 1922. Then between 1934 and 1941, there was a change in procedure whereby all corporations (except for railway companies that were affiliated with each other) were not allowed to file consolidated returns. This change led to an upward shift in the number of returns and a downward shift in concentration. While this policy change only induced a relatively modest decline in the top 1% asset share for the whole economy (see black line in Figure IA17), its effects in sectors with many consolidated returns (particularly Utilities and Manufacturing: Chemicals) were more sizable.

We adjust the 1934-1941 concentration estimates for all sectors using two approaches. First, if we have data before 1934 and after 1942, then we scale the 1934-1941 data to the 1933 and 1942 benchmarks and divide the remaining level difference equally over the 1934-1941 period. This allows us to rescale the data to the correct level, while preserving the time trends of the 1934-1941 period. Second, for some subsectors, our concentration estimates only begin in 1938 (with the introduction of SIC industry codes). For these sectors, we assume that concentration did not change between 1941 and 1942 and rescale earlier years accordingly. The effects of our adjustment can be seen in Figure IA17. The black dashed line shows 1% asset shares without adjustment and the red dashed line shows the adjusted series.

One possible concern is that changes in the prevalence of consolidation may affect the concentration trends we observe. We make three observations. First, we digitize data on the share of consolidated

Figure IA18: Prevalence of Consolidation

This figure shows the prevalence of consolidation over time. The blue circles show the share of consolidated returns in the total number of returns, and the red diamonds show the share of assets from consolidated returns in total assets.



returns in total returns using information about consolidated returns in the SOI. Figure IA18 shows the share of consolidated returns in the total number of returns (blue circles), and the share of assets from consolidated returns in total assets (red diamonds). We observe a decrease in the prevalence of consolidated returns between the early 1930s and the 1940s. Then the prevalence of consolidated returns increased from the mid-1960s to the 1980s, roughly returning to the prevalence of consolidated returns in the early 1930s. Meanwhile, top 1% asset shares were much higher in the 1980s relative to the 1930s. After the 1980s, the prevalence of consolidated returns decreased in number (though not much in their shares of total assets), while top 1% shares continued to rise.

Second, within each subperiod of consolidation rules (1934 to 1941, 1942 to 1954, 1954 to 1964, and after 1964), we generally observe rising top 1% asset shares, as shown in Figure IA19. Here we present the final top 1% asset shares in our data, using manufacturing and aggregate series as examples. The only modification to the raw results from the SOI is the adjustment for the 1934 to 1941 period as explained above.

Finally, the consolidation rules apply to all sectors and the consolidation trends are largely similar across sectors, but the concentration trends display differences in the timing of rising concentration. In the analyses of the mechanisms behind rising concentration in Section 4, we use time fixed effects to isolate the timing differences in rising concentration across industries (see Tables 4 to 8); these time fixed effects should absorb the impact of changes in consolidation rules which apply to all industries.

Figure IA19: Top 1% Asset Shares under Different Consolidation Rules

This figure shows the top 1% asset shares for manufacturing (blue circles) and for the aggregate economy (red diamonds). The dash-dotted red lines mark the 1934 to 1941 period where consolidated filings were not allowed; the concentration estimates in this period use our adjustment explained above. The dashed gray line marks 1954, where the consolidation threshold changed from 95% ownership in affiliates to 80% ownership. The blue line marks 1964, where the surtax on consolidated returns ended.

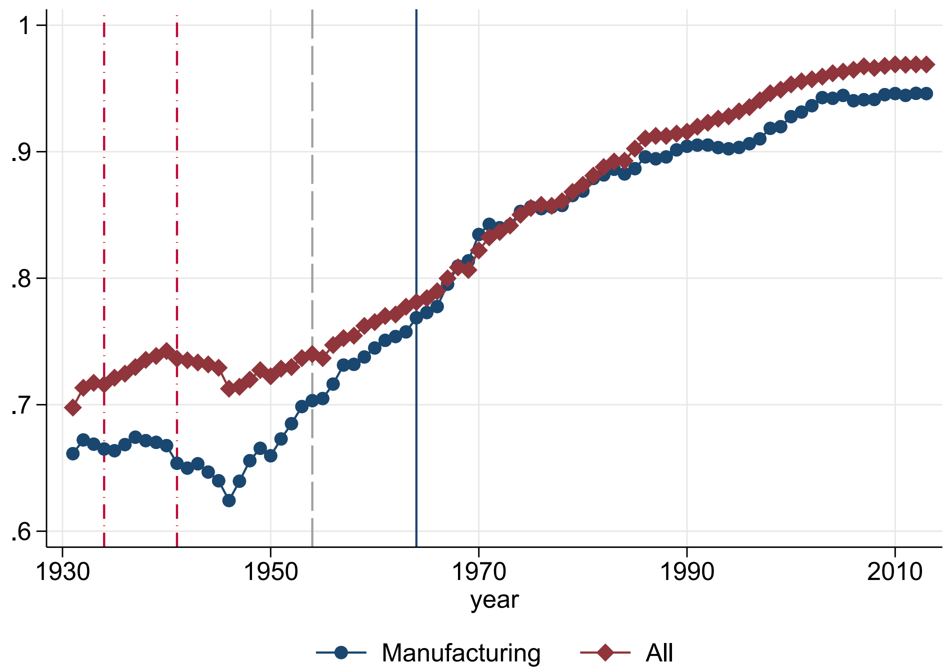


Table IA5: Industry Harmonization of SOI Data

This table shows the mapping between historical SOI industries and our main sectors and subsectors. SOI industries are classified by economic activity using the ESIC (Enterprise Standard Industrial Classification) until 1997 and NAICS industry codes afterwards. The SOI sometimes departs from the ESIC and NAICS classification systems in order to reflect particular provisions in the Internal Revenue Code. However, the SOI industries are generally very similar to SIC and NAICS industries, so we illustrate them using SIC codes (in the second column) and NAICS codes (in the third column). Panel A shows the list of main sectors in our data (the first column) and the correspondence with SIC industry divisions and NAICS industry codes. Panel B shows the list of subsectors in our data (the first column) and the correspondence with SIC industry groups and NAICS codes.

Panel A. Main Sectors

Main Sector	SIC Industry Division	NAICS Codes
Agriculture	Agriculture, Forestry, Fishing (01-09)	11
Mining	Mining (10-14)	21
Construction	Construction (15-17)	23
Manufacturing	Manufacturing (20-39)	31-33, 511
Utilities	Transportation and Public Utilities (40-49)	22, 48-49, 513, 515, 517, 562
Trade	Wholesale and Retail Trade (50-59)	42-45, 722
Finance	Finance, Insurance, and Real Estate (60-67)	52, 531, 533, 55
Services	Services (70-89)	512, 514, 516, 518, 519, 532, 54, 561, 61, 62, 71, 721, 81

Panel B. Subsectors

Subsector	SIC Industry Group	NAICS Codes
Finance: Banking	Banking (60), Credit Agencies Other than Banks (61), Security and Commodity Brokers (62)	522, 523
Finance: Holding Companies and Other	Holding and Other Investment Companies (67)	525, 55
Finance: Insurance	Insurance (63)	524
Finance: Real Estate	Real Estate (65)	531, 533
Manufacturing: Apparel and Leather	Textile Mill Products (22), Apparel (23), Leather (31)	313, 314, 315, 316
Manufacturing: Chemicals	Chemicals and Allied Products (28)	324, 325
Manufacturing: Electrical	Electronic (36), Measuring, Analyzing, and Controlling Instruments (38)	334, 335
Manufacturing: Food	Food and Kindred Products (20), Tobacco Products (21)	311, 312
Manufacturing: Machinery	Industrial and Commercial Machinery (35)	333
Manufacturing: Metals	Primary Metal (33), Fabricated Metal Products (34)	331, 332
Manufacturing: Other	Miscellaneous Manufacturing (39)	339
Manufacturing: Paper	Paper and Allied Products (26)	322
Manufacturing: Plastics	Rubber and Plastics Products (30)	326
Manufacturing: Printing	Printing, Publishing, and Allied Industries (27)	323
Manufacturing: Stone	Stone, Clay, Glass, and Concrete Products (32)	327
Manufacturing: Transportation	Transportation Equipment (37)	336
Manufacturing: Wood	Lumber and Wood Products (24), Furniture and Fixtures (25)	321, 337
Mining: Oil and Gas	Oil and Gas Extraction (13)	211, 213
Mining: Other	Metal Mining (10), Coal and Lignite Mining (12), Nonmetallic Minerals (14)	212
Services: Business	Business Services (73)	54, 514, 516, 518, 519
Services: Entertainment	Motion Pictures (78), Amusement and Recreation (79),	512, 71
Services: Hotels	Hotels and Other Lodging Places (70)	721
Services: Other	Auto Repair (75), Miscellaneous Repair Services (76), Health Serivces (80), Legal Services (81), Educational Services (82), Miscellaneous Services Not Elsewhere Classified	532, 561, 61, 62, 811, 813
Services: Personal	Personal Services (72)	812
Trade: Retail	Retail Trade (52-57), 59	44-45
Trade: Retail: Restaurants	Eating and Drinking Places (58)	722
Trade: Wholesale	Wholesae Trade (50-51)	42
Utilities: Communications	Communications (48)	513, 515, 517
Utilities: Electricity and Gas	Electric, Gas, and Sanitary Services (49)	22, 562
Utilities: Transportation	Transportation (40-47)	48, 49

Partnerships and sole proprietorships We also collect data for noncorporate businesses (partnerships and sole proprietorships) from historical SOI publications. For the years 1957 to 1980 and 1998 to 2003, we are able to obtain tabulations of noncorporate businesses by size bins based on business receipts for the main sectors. For a detailed list of the sources see Table IA6.[28] Otherwise, we have information about the number of noncorporate businesses and their total receipts (using the dataset compiled by Lamoreaux (2006) extended to recent years using data from Table 3 of the Integrated Business Statistics on the IRS Website).[29]

Data on partnerships comes from Form 1065, which partnerships need to file with the IRS for informational purposes. The partnership data includes all groups conducting business for profit unless classified as corporations, trusts, or estates for tax purposes. This data includes partnerships, syndicates, joint ventures and other unincorporated organizations. Data on sole proprietorships is based on the business schedule of owners' individual tax returns. Properly identifying the number of sole proprietorships from individual tax returns has always been a challenge for IRS statisticians. Since 1981, when a return has more than one business schedule, data from the schedules is combined to simplify statistical processing. This implies that the statistics effectively report the number and business receipts of proprietors, rather than those of individual proprietorships. However, the ratio between the number of companies and the number of owners is claimed to be relatively small (between 1 - 1.1, Lamoreaux, 2006). Prior to 1981, the SOI counting of sole proprietorships differed over the years, in particular when individuals filed multiple business schedules per individual return. In some years, the reporting unit was the number of C Schedules filed with the return, and in some other years the SOI only counted those businesses that operated in different industries as separate businesses, or restricted the overall number of businesses per owner.

Tax returns and schedules of partnerships, sole proprietorships, and corporations use different terms to describe items that are similar in nature. The historical SOI publications adopted common naming conventions across business organizations. For sole proprietorships, business receipts are defined as total receipts from sale and services, less rebates, returns, and allowances plus other business income. For partnerships, business receipts are defined as gross receipts from sales and services, less rebates, returns. For corporations, business receipts are defined as gross sales plus gross receipts from operations, less rebates, returns and allowances. For more detail on the noncorporate data, see the original documents on the IRS website (Table IA6) and the documentation of Lamoreaux (2006).

[28] We exclude the main sector "Finance" for the years 1998–2003 due to an inconsistency in the tabulations for partnerships. Unfortunately the column on "gross receipts" has data errors and the values presented there do not represent gross receipts.

[29] Lamoreaux (2006) reports total receipts for noncorporates while the SOI size tabulations are based on business receipts. We use the ratio of total receipts to business receipts of corporations to adjust the noncorporate total receipt data and make it comparable with the business size tabulations.

Table IA6: Sources for Noncorporate Tabulations

This table shows the sources for the tabulations of noncorporate businesses.

Year	Source	Business type and notes
1957	U.S. Business tax returns, July 1957-June 1958, pages 8ff. & 12ff	All; Only "All Industries"
1958	U.S. Business tax returns, July 1958-June 1959, pages 22ff. & 36ff.	All
1959	U.S. Business tax returns, July 1959-June 1960, pages 18ff. & 46ff.	All
1960	U.S. Business tax returns, July 1960-June 1961, pages 24ff. & 56ff.	All
1961	U.S. Business tax returns, July 1961-June 1962, pages 24ff. & 54ff.	All
1962	U.S. Business tax returns, 1962, pages 34ff. & 120ff.	All
1964	U.S. Business tax returns, July 1964-June 1965, pages 87ff.	Partnerships
1965	U.S. Business income tax returns, 1965, pages 39ff. & 129ff.	All
1966	U.S. Business income tax returns, 1966, pages 37ff. & 130ff.	All
1967	U.S. Business income tax returns, 1967, pages 41ff. & 165ff.	All
1968	U.S. Business income tax returns, 1968, pages 36ff. & 143ff.	All
1969	U.S. Business income tax returns, 1969, pages 34ff. & 115ff.	All; IRS scan incomplete.
1970	U.S. Business income tax returns, 1970, pages 38ff. & 123ff.	All
1971	U.S. Business income tax returns, 1971, pages 35ff. & 123ff.	All
1972	U.S. Business income tax returns, 1972, pages 18ff. & 123ff.	All
1973	U.S. Business income tax returns, 1973, pages 23ff. & 144ff.	All
1974	U.S. Business income tax returns, 1974, pages 30ff. & 145ff.	All
1975	U.S. Business income tax returns, 1975, pages 22ff. & 220ff.	All
1976	U.S. Business income tax returns, 1976, pages 34ff. & 259ff.	All
1977	Sole Proprietorships returns, 1977, pages 42ff.	Sole proprietorships
1977	Partnership returns, 1977, pages 29 & 47	Partnerships
1978	Sole Proprietorships returns, 1978, pages 27ff.	Sole proprietorships
1978	Partnership returns, 1978, pages 27ff.	Partnerships
1979	Sole Proprietorships returns, 1979-1780, pages 34ff.	Sole proprietorships
1979	Partnership returns, 1979, pages 29ff.	Partnerships
1980	Sole Proprietorships returns, 1979-1780, pages 165ff.	Sole proprietorships
1980	Partnership returns, 1980, pages 33ff.	Partnerships
1998	IRS Website, Integrated Business Data, Table 2	All; Inconsistency in “Finance” data
1999	IRS Website, Integrated Business Data, Table 2	All; Inconsistency in “Finance” data
2000	IRS Website, Integrated Business Data, Table 2	All; Inconsistency in “Finance” data
2001	IRS Website, Integrated Business Data, Table 2	All; Inconsistency in “Finance” data
2002	IRS Website, Integrated Business Data, Table 2	All, Inconsistency in “Finance” data
2003	IRS Website, Integrated Business Data, Table 2	All; Inconsistency in “Finance” data

IA2.2 BEA Data

Investment composition from BEA fixed asset tables. The BEA fixed asset tables report the investment composition by industry on an annual basis since 1901. There are 39 types of equipment, 31 types of structures, and 25 types of intellectual property. We include asset codes starting with “EP1" (computing equipment), “ENS" (software), and “RD" (R&D) in the numerator, and investment in all categories in the denominator. We match BEA sectors to our main sectors and subsectors, following Table IA7. We drop 5210 Federal Reserve Banks in BEA fixed asset tables.

Industry output from national accounts. We also use industry gross output from the BEA. Tables IA8 and IA9 show the mapping between industries in NIPA and our main sectors and subsectors. We do not reassign different components of "Information" and we do not reassign “Waste management and remediation services" to “Utilities: Electric, Gas and Sanitary Services" because detailed breakdown for these industries was not available from 1947 to 1962.

Table IA7: Industry Mapping with BEA Fixed Asset Tables

This table shows the mapping between BEA industries and main sectors and subsectors in our data.

BEA Industry Name	BEA Code	Main Sector	Subsector
Farms	110C	Agriculture	
Forestry, fishing, and related activities	113F	Agriculture	
Oil and gas extraction	2110	Mining	Mining: Oil and Gas
Mining, except oil and gas	2120	Mining	Mining: Other
Support activities for mining	2130	Mining	Mining: Oil and Gas
Utilities	2200	Utilities	Utilities: Electric, Gas and Sanitary Services
Construction	2300	Construction	
Wood products	3210	Manufacturing	Manufacturing: Wood
Nonmetallic mineral products	3270	Manufacturing	Manufacturing: Stone
Primary metals	3310	Manufacturing	Manufacturing: Metals
Fabricated metal products	3320	Manufacturing	Manufacturing: Metals
Machinery	3330	Manufacturing	Manufacturing: Machinery
Computer and electronic products	3340	Manufacturing	Manufacturing: Electrical
Electrical equipment, appliances, and components	3350	Manufacturing	Manufacturing: Electrical
Motor vehicles, bodies and trailers, and parts	336M	Manufacturing	Manufacturing: Transportation
Other transportation equipment	336O	Manufacturing	Manufacturing: Transportation
Furniture and related products	3370	Manufacturing	Manufacturing: Wood
Miscellaneous manufacturing	338A	Manufacturing	Manufacturing: Other
Food, beverage, and tobacco products	311A	Manufacturing	Manufacturing: Food
Textile mills and textile product mills	313T	Manufacturing	Manufacturing: Apparel and Leather
Apparel and leather and allied products	315A	Manufacturing	Manufacturing: Apparel and Leather
Paper products	3220	Manufacturing	Manufacturing: Paper
Printing and related support activities	3230	Manufacturing	Manufacturing: Printing
Petroleum and coal products	3240	Manufacturing	Manufacturing: Chemicals
Chemical products	3250	Manufacturing	Manufacturing: Chemicals
Plastics and rubber products	3260	Manufacturing	Manufacturing: Plastics
Wholesale trade	4200	Trade	Trade: Wholesale
Retail trade	44RT	Trade	Trade: Retail
Air transportation	4810	Utilities	Utilities: Transportation
Railroad transportation	4820	Utilities	Utilities: Transportation
Water transportation	4830	Utilities	Utilities: Transportation
Truck transportation	4840	Utilities	Utilities: Transportation
Transit and ground passenger transportation	4850	Utilities	Utilities: Transportation
Pipeline transportation	4860	Utilities	Utilities: Transportation
Other transportation and support activities	487S	Utilities	Utilities: Transportation
Warehousing and storage	4930	Utilities	Utilities: Transportation
Publishing industries (including software)	5110	Manufacturing	Manufacturing: Printing
Motion picture and sound recording industries	5120	Services	Services: Entertainment
Broadcasting and telecommunications	5130	Utilities	Utilities: Communication
Information and data processing services	5140	Services	Services: Business
Federal Reserve banks	5210		
Credit intermediation and related activities	5220	Finance	Finance: Banking
Securities, commodity contracts, and investments	5230	Finance	Finance: Banking
Insurance carriers and related activities	5240	Finance	Finance: Insurance
Funds, trusts, and other financial vehicles	5250	Finance	Finance: Holding Companies and Other
Real estate	5310	Finance	Finance: Real Estate
Rental and leasing services	5320	Finance	Services: Other
Legal services	5411	Services	Services: Business
Computer systems design and related services	5415	Services	Services: Business
Miscellaneous professional, scientific, and technical services	5412	Services	Services: Business
Management of companies and enterprises	5500	Finance	Finance: Holding Companies and Other
Administrative and support services	5610	Services	Services: Other
Waste management and remediation services	5620	Services	Services: Other
Educational services	6100	Services	Services: Other
Ambulatory health care services	6210	Services	Services: Other
Hospitals	622H	Services	Services: Other
Nursing and residential care facilities	6230	Services	Services: Other
Social assistance	6240	Services	Services: Other
Performing arts, spectator sports, museums, and related activities	711A	Services	Services: Entertainment
Amusements, gambling, and recreation industries	7130	Services	Services: Entertainment
Accommodation	7210	Services	Services: Hotels
Food services and drinking places	7220	Trade	Trade: Retail: Eating Places
Other services, except government	8100	Services	Services: Personal

Table IA8: Industry Mapping with NIPA: Pre-1997

This table shows the mapping between industries in NIPA before 1997 (first column) and main sectors and subsectors in our data (second and third columns).

NIPA Industry Name	Main Sector	Subsector
Private industries		
Agriculture, forestry, fishing, and hunting	Agriculture	
Mining	Mining	
Oil and gas extraction		Mining: Oil and Gas
Mining, except oil and gas		Mining: Other
Support activities for mining		Mining: Oil and Gas
Utilities	Utilities	Utilities: Electric, Gas and Sanitary Services
Construction	Construction	
Manufacturing	Manufacturing	
Wood products		Manufacturing: Wood
Nonmetallic mineral products		Manufacturing: Stone
Primary metals		Manufacturing: Metals
Fabricated metal products		Manufacturing: Metals
Machinery		Manufacturing: Machinery
Computer and electronic products		Manufacturing: Electrical
Electrical equipment, appliances, and components		Manufacturing: Electrical
Motor vehicles, bodies and trailers, and parts		Manufacturing: Transportation
Other transportation equipment		Manufacturing: Transportation
Furniture and related products		Manufacturing: Wood
Miscellaneous manufacturing		Manufacturing: Other
Food and beverage and tobacco products		Manufacturing: Food
Textile mills and textile product mills		Manufacturing: Apparel and Leather
Apparel and leather and allied products		Manufacturing: Apparel and Leather
Paper products		Manufacturing: Paper
Printing and related support activities		Manufacturing: Printing
Petroleum and coal products		Manufacturing: Chemicals
Chemical products		Manufacturing: Chemicals
Plastics and rubber products		Manufacturing: Plastics
Wholesale trade	Trade	Trade: Wholesale
Retail trade	Trade	Trade: Retail
Transportation and warehousing	Utilities	Utilities: Transportation
Information	Utilities	Utilities: Communication
Finance and insurance	Finance	
Federal Reserve banks, credit intermediation, and related activities		Finance: Banking
Securities, commodity contracts, and investments		Finance: Banking
Insurance carriers and related activities		Finance: Insurance
Funds, trusts, and other financial vehicles		Finance: Holding Companies and Other
Real estate	Finance	Finance: Real Estate
Rental and leasing services and lessors of intangible assets	Finance	Services: Other
Professional, scientific, and technical services	Services	Services: Business
Management of companies and enterprises	Finance	Finance: Holding Companies and Other
Administrative and waste management services	Services	Services: Other
Educational services, health care, and social assistance	Services	Services: Other
Arts, entertainment, and recreation	Services	Services: Entertainment
Accommodation	Services	Services: Hotels
Food services and drinking places	Trade	Trade: Retail: Eating Places
Other services, except government	Services	Services: Personal

Table IA9: Industry Mapping with NIPA: Post-1997

This table shows the mapping between industries in NIPA after 1997 (first column) and main sectors and subsectors in our data (second and third columns).

NIPA Industry Name	Main Sector	Subsector
Private industries		
Agriculture, forestry, fishing, and hunting	Agriculture	
Mining	Mining	
Oil and gas extraction		Mining: Oil and Gas
Mining, except oil and gas		Mining: Other
Support activities for mining		Mining: Oil and Gas
Utilities	Utilities	Utilities: Electric, Gas and Sanitary Services
Construction	Construction	
Manufacturing	Manufacturing	
Wood products		Manufacturing: Wood
Nonmetallic mineral products		Manufacturing: Stone
Primary metals		Manufacturing: Metals
Fabricated metal products		Manufacturing: Metals
Machinery		Manufacturing: Machinery
Computer and electronic products		Manufacturing: Electrical
Electrical equipment, appliances, and components		Manufacturing: Electrical
Motor vehicles, bodies and trailers, and parts		Manufacturing: Transportation
Other transportation equipment		Manufacturing: Transportation
Furniture and related products		Manufacturing: Wood
Miscellaneous manufacturing		Manufacturing: Other
Food and beverage and tobacco products		Manufacturing: Food
Textile mills and textile product mills		Manufacturing: Apparel and Leather
Apparel and leather and allied products		Manufacturing: Apparel and Leather
Paper products		Manufacturing: Paper
Printing and related support activities		Manufacturing: Printing
Petroleum and coal products		Manufacturing: Chemicals
Chemical products		Manufacturing: Chemicals
Plastics and rubber products		Manufacturing: Plastics
Wholesale trade	Trade	Trade: Wholesale
Retail trade	Trade	Trade: Retail
Transportation and warehousing	Utilities	Utilities: Transportation
Information	Utilities	Utilities: Communication
Finance, insurance, real estate, rental, and leasing	Finance	
Federal Reserve banks, credit intermediation, and related activities		Finance: Banking
Securities, commodity contracts, and investments		Finance: Banking
Insurance carriers and related activities		Finance: Insurance
Funds, trusts, and other financial vehicles		Finance: Holding Companies and Other
Real estate and rental and leasing		Finance: Real Estate
Professional, scientific, and technical services	Services	Services: Business
Management of companies and enterprises	Finance	Finance: Holding Companies and Other
Administrative and waste management services	Services	Services: Other
Educational services, health care, and social assistance	Services	Services: Other
Arts, entertainment, and recreation	Services	Services: Entertainment
Accommodation	Services	Services: Hotels
Food services and drinking places	Trade	Trade: Retail: Eating Places
Other services, except government	Services	Services: Personal

IA3 Model Details

In the following we provide more details about the model in Section 4.2.

IA3.1 Static Case

IA3.1.1 Setup

We use the standard nested CES demand structure, so a firm i in industry k faces demand:

$$y_{i,k} = Y_k \cdot \left(\frac{p_{i,k}}{P_k}\right)^{-\sigma}, \tag{IA1}$$

where $p_{i,k}$ is the price, and $P_k^{1-\sigma} = \int_0^{N_k} p_{i,k}^{1-\sigma} di$ is the aggregate price index for industry k, with N_k being the mass of firms in industry k. The aggregate demand for industry k is given by:

$$Y_k = \bar{Y} \left(\frac{P_k}{\bar{P}}\right)^{-\epsilon}, \tag{IA2}$$

with the aggregate price index $\bar{P}^{1-\epsilon} = \int_0^1 P_{k,t}^{1-\epsilon} dk$. Appendix IA3.1.4 shows the detailed CES aggregator that justifies the above demand function.

Firms pay an entry cost κ to enter the market (as in Autor et al. (2020), Covarrubias, Gutiérrez, and Philippon (2020), among others). After entry, each firm i observes its idiosyncratic productivity, a_i. Depending on the realization of its idiosyncratic productivity, a firm has three options:

1. **Exit immediately.**

2. **Operate with old technology:** Invest ϕ and operate a constant-returns-to-scale technology with per-unit productivity a_i (or per-unit cost of $1/a_i$). In other words, the firm uses L units of input (normalized to unit cost) to produce $a_i L$ units of output.

3. **Operate with new technology:** Invest $\Phi(h)$ and operate a constant-returns-to-scale technology with per-unit productivity $A(a_i, h)$ (or per-unit cost of $1/A(a_i, h)$). In other words, the firm uses L units of input (normalized to unit cost) to produce $A(a_i, h)L$ units of output.

This choice between new (old) technology with higher (lower) upfront costs and lower (higher) marginal costs is similar to the spirit of the model in Hsieh and Rossi-Hansberg (2022). For simplicity of illustration, firms that decide to stay will operate in perpetuity under the same per-period productivity (a_i for the old technology and $A(a_i, h)$ for the new technology), with profits in each period discounted at a constant rate R.[30]

The parameter $h \geq 1$ is an index of the scalability of the new technology. We examine how the development of the new technology affects concentration by comparing the equilibrium outcomes under $h = 1$ (where the two technologies are one and the same) with those under $h > 1$. We assume that

[30]This shortcut allows us to illustrate the role of technological innovation on rising concentration without fully specifying a dynamic model.

a) $\Phi(h) \geq \phi$: the new technology requires a greater upfront investment than the old technology, and b) $A(a_i, h) \geq a_i$: the new technology enables firms to produce each unit more efficiently. Furthermore, we assume $\Phi'(h), \frac{\partial A}{\partial h} > 0$. For tractability, we assume a simple functional form for Φ and A: $\Phi(h) = h^\eta \phi$ and $A(a_i, h) = h \cdot a_i$, with $\eta > 1$.

Denote the time-0 profit of a firm with idiosyncratic productivity a_i using the old and new technology as $\pi_t(a_i)$ and $\pi'_t(a_i)$ respectively. Then, the net present value of each technology is given by:

$$\begin{aligned} \Pi(a_i) &= \underbrace{\sum_{t=1}^{\infty} \frac{1}{R^t} \pi_t(a_i)}_{\text{Discounted Profit}} - \underbrace{\phi}_{\text{Investment}} , \\ \Pi'(a_i) &= \underbrace{\sum_{t=1}^{\infty} \frac{1}{R^t} \pi'_t(a_i)}_{\text{Discounted Profit}} - \underbrace{\Phi(h)}_{\text{Investment}} . \end{aligned} \tag{IA3}$$

To solve for equilibrium entry, profits, and concentration, we make some simplifying assumptions. First, we assume exogenous markups (as in Covarrubias, Gutiérrez, and Philippon (2020)).

Assumption IA1 (Exogenous markups). *Firms adopt an exogenous markup μ: a firm with constant returns to scale technology a_i has unit cost $\frac{1}{a_i}$ and set $p_i = \frac{1+\mu}{a_i}$.*

We make this assumption to demonstrate that trends in concentration do not have to be accompanied by trends in profitability. The use of an exogenous markup allows us to flexibly allow any movements in markups. Even if we allow markups to be endogenously set at the profit-maximizing level $\mu^* = \frac{1}{\sigma-1}$, all of our conclusions remain.

Second, we assume free entry to pin down the number of firms N_k.

Assumption IA2 (Free entry). *The entry cost is equal to the ex ante expected net present value of the firm:*

$$\kappa = E_{a_i \sim F}\left[\max\left\{0, \Pi(a_i), \Pi'(a_i)\right\}\right]. \tag{IA4}$$

Finally, we assume that the new technology requires a sufficiently high upfront cost, such that it does not completely dominate the pre-existing technology for all firms. Under our functional form assumption, the above assumption translates to the following condition:

Assumption IA3 (Non-domination of technology). *Let $\Phi(h) = h^\eta \phi$ be the investment cost function. We assume $\eta > \sigma - 1$.*

IA3.1.2 Solution

Under the above assumptions, the exogenous markup assumption pins down the demand for firm with the old technology: the firm in industry k with unit cost $\frac{1}{a_i}$ charges a price of $\frac{1+\mu}{a_i}$, and thus faces demand:

$$y_{i,k} = Y_k \cdot \left(\frac{1+\mu}{a_i}\frac{1}{P_k}\right)^{-\sigma}. \tag{IA5}$$

This pins down the input choice $L^*_{i,k}$ at:

$$L^*_{i,k} = \frac{1}{a_i} y_{i,k} = \frac{1}{a_i} Y_k \cdot \left(\frac{1+\mu}{a_i} \frac{1}{P_k} \right)^{-\sigma}. \tag{IA6}$$

The expressions for the firm that adopts the new technology follows similarly. Then, one can derive the following expression for Π and Π':

$$\begin{aligned} \Pi(a_i) &= \frac{R}{R-1} \cdot \frac{\mu}{(1+\mu)^\sigma} Y_k \cdot P_k^\sigma a_i^{\sigma-1} - \phi, \\ \Pi'(a_i) &= \frac{R}{R-1} \cdot \frac{\mu}{(1+\mu)^\sigma} Y_k \cdot P_k^\sigma (h \cdot a_i)^{\sigma-1} - \phi \cdot h^\eta. \end{aligned} \tag{IA7}$$

Given the above assumptions, one can show that there will be three groups of firms in equilibrium: 1) the most productive firms adopt the new technology, 2) the next productive firms operate with the old technology, and 3) the least productive firms exit immediately.

Proposition IA1. *In equilibrium, there exists two thresholds a^* and a^{**}, defined by:*

$$\begin{aligned} \Pi(a^*) = 0 \iff \phi &= \frac{R}{R-1} \frac{\mu}{(1+\mu)^\sigma} Y_k \cdot P_k^\sigma (a^*)^{\sigma-1}, \\ \Pi(a^{**}) = \Pi'(a^{**}) \iff a^{**} &= \left(\frac{h^\eta - 1}{h^{\sigma-1} - 1} \right)^{1/(\sigma-1)} a^*. \end{aligned} \tag{IA8}$$

In equilibrium, firms with $a_i < a^*$ exit, firms with $a^* \leq a_i \leq a^{**}$ use the old technology, and firms with $a_i \geq a^{**}$ use the new technology. The thresholds a^* and a^{**} depend positively on the markup μ and negatively on the discount rate R.

Second, let $S_t(a_i)$ be the per-period revenue, and $\tilde{\pi}_t(a_i) = \frac{\max\{\pi_t(a_i), \pi'_t(a_i)\}}{S_t(a_i)}$ be the profitability of the firm with idiosyncratic productivity a_i in equilibrium. We can derive the following expressions for firms that choose to operate.

Proposition IA2. *Let dF^* be the (normalized) distribution of a_i conditional on $a_i \geq a^*$, and let A^* be given by:*[31]

$$A^* = \left(\int_{a^*}^{a^{**}} a^{\sigma-1} dF^*(a) + h^{\sigma-1} \int_{a^{**}}^{\infty} a^{\sigma-1} dF^*(a) \right)^{\frac{1}{\sigma-1}}. \tag{IA9}$$

Then,

$$S_t(a_i) = \begin{cases} \left(\frac{a_i}{A^*}\right)^{\sigma-1} \frac{P_k \cdot Y_k}{N_k} & a^* \leq a_i \leq a^{**}, \\ \left(\frac{h \cdot a_i}{A^*}\right)^{\sigma-1} \frac{(P_k \cdot Y_k)}{N_k} & a^{**} \leq a_i. \end{cases} \tag{IA10}$$

Furthermore, $\tilde{\pi}_t(a_i) = \frac{\mu}{1+\mu}$: the profitability of a firm corresponds one-to-one with the exogenous markup μ. In particular, it does not depend on the technology index h.

Proposition IA2 implies that profitability can be distinct from how technology affects concentration.

[31] In other words, A^* is the $\sigma - 1$ norm of the productivity of firms in operation; it can be loosely interpreted as the "average" productivity.

Finally, using the Pareto distribution assumption, we can derive the expression for industry concentration, as measured by sales. To be in line with our empirical results, we calculate the share of the top 1% firms in total sales. For simplicity, we assume that the parameters are such that the top 1% firms all belong to the group of firms that operate with the new technology.[32]

Then, the concentration measure is given by:

$$\zeta_{1\%} = \frac{h^{\sigma-1} \int_{\alpha a^*}^{\infty} a_i^{\sigma-1} dF^*(a)}{\int_{a^*}^{a^{**}} a_i^{\sigma-1} dF(a) + h^{\sigma-1} \int_{a^{**}}^{\infty} a_i^{\sigma-1} dF^*(a)}, \tag{IA11}$$

where α is a constant that only depends on the Pareto parameter k. Note that for aggregate sales to be finite, we need $k > \sigma - 1$. We can then obtain the concentration ratio.

Proposition IA3. *The concentration ratio (top 1% sales share) is given by:*

$$\zeta_{1\%} = C \cdot \frac{h^{\sigma-1}}{1 + (h^{\sigma-1} - 1)^{\frac{k}{\sigma-1}} (h^{\eta} - 1)^{1-\frac{k}{\sigma-1}}}, \tag{IA12}$$

where C is a constant independent of h.

IA3.1.3 Comparative Statics

We consider a marginal increase in h from 1 (where the two technologies coincide) to $h > 1$. By taking the comparative statics of Equation (IA12) and Proposition IA2, we obtain the following result.

Proposition IA4. *A rise in h leads to greater industry concentration, as measured by the top 1% sales share. Meanwhile, there is no change in the per-period profitability $\tilde{\pi}$, which depends on the exogenous markup μ.*

Next, we shall examine the predictions for industry output given a marginal increase in $h = 1 + \nu$ in one industry k. Due to the continuous CES setup, each industry is marginal and has no impact on the aggregate output, so the growth in industry output is the same as the growth in industry share.

Proposition IA5. *Assume $\sigma > \epsilon > 1$ (the cross-industry elasticity is weaker than the within-industry elasticity) and $\eta > \sigma - 1$ is sufficiently small.*[33] *Then, a rise in h leads to a rise in the industry's output and its share in the economy.*

The first assumption is standard: it is easier for a consumer to substitute within a given industry than to substitute across industries. The second assumption requires that the rise in investment associated with the new technology is not prohibitively expensive. This reflects two opposing consequences of technological improvement on output: first, it increases the output for firms that use the new technology. This is the primary intuition behind the link between higher concentration and higher industry output. On the other hand, technological improvement crowds out the output of firms that do not use the new technology. This effect is typically second-order relative to the first effect, provided that the new technology does not require a prohibitive amount of investment.

In summary, our model provides a simple illustration in which technological development results in higher concentration as firms that use the new technology increase their output relative to other firms. Industry output also increases. Meanwhile, profitability does not have to change.

[32] This holds as long as $1 - F^*(a^{**}) > 0.01$.

[33] Alternatively, one can assume that the technological improvement is sufficiently marginal, i.e. $\nu \mapsto 0$.

IA3.1.4 Details and Proofs

CES setup Recall the standard nested CES setup: let k be the index for the industry (ranging from 0 to 1), and let $i \in [0, N_k]$ be the index for a firm in industry k. The standard nested CES model assumes that the goods are aggregated using the following aggregator:

$$Y_k^{\frac{\sigma-1}{\sigma}} = \int_0^{N_k} y_{i,k}^{\frac{\sigma-1}{\sigma}} di. \tag{IA13}$$

The industry goods are also aggregated into a final consumption bundle:

$$\bar{Y} = \int_0^1 Y_k^{\frac{\epsilon-1}{\epsilon}} dk. \tag{IA14}$$

The demand system then implies that there exists an industry price index:

$$P_k^{1-\sigma} = \int_0^{N_k} Y_{k,t} \left(\frac{p_{i,k}}{P_k}\right)^{-\sigma}, \tag{IA15}$$

and an aggregate price index:

$$\bar{P}^{1-\epsilon} = \int_0^1 P_{k,t}^{1-\epsilon} dk. \tag{IA16}$$

Given these price indices, industry and firm demands are given by:

$$\begin{aligned} Y_k &= \bar{Y}\left(\frac{P_k}{\bar{P}}\right)^{-\epsilon}, \\ y_{i,k} &= Y_{k,t}\left(\frac{p_{i,k}}{P_k}\right)^{-\sigma}. \end{aligned} \tag{IA17}$$

Proofs For notational simplicity, we solve for the case as $R \mapsto \infty$: the general case of R follows identically.

Proof of Proposition IA4. To show that Equation (IA12) is increasing in h, we take the following approach. Recall that $\frac{a^{**}}{a^*} = \left(\frac{h^\eta - 1}{h^{\sigma-1}-1}\right)^{\frac{1}{\sigma-1}}$ is both larger than 1 and increasing in h. Denoting $H = h^{\sigma-1} - 1$, the above implies that

$$D(H) = \left(\frac{a^{**}}{a^*}\right)^{(\sigma-1)-k}$$

is smaller than 1 and is a decreasing function in H. Setting $F(H) = \frac{H+1}{1+H\cdot D(H)}$, it suffices to show that F is an increasing function of H. Differentiation yields:

$$\frac{\partial F}{\partial H} > 0 \iff 1 + H \cdot D(H) - (H+1) \cdot \left(D(H) + H\frac{\partial D(H)}{\partial H}\right) = 1 - D(H) - HD'(H) > 0,$$

which holds as we have already shown that $D(H) < 1$ and $D'(H) < 0$.

□

Proof of Proposition IA5. The three equations are given as follows:

$$
\begin{aligned}
\phi &= \frac{\mu}{1+\mu} \cdot \left(\frac{a^*}{A^*}\right)^{\sigma-1} \frac{P_k Y_k}{N_k}, \\
P_k &= \frac{1+\mu}{N^{\frac{1}{\sigma-1}}} \frac{1}{A^*}, \\
\frac{\kappa}{\phi} &= (1 - F(a^*)) \left(\left(\frac{A^*}{a^*}\right)^{\sigma-1} - 1\right).
\end{aligned}
\tag{IA18}
$$

The first equation is the zero-profit condition for the least profitable firm that stays in operation (which determines a^*). The second is by definition the aggregate price index for industry j. The final is the free-entry condition. Note that:

$$P_j Y_j \propto P_j^{1-\epsilon}. \tag{IA19}$$

Thus, for industry output to grow in h, it thus suffices to show that $P_j(h)$ is decreasing in h. Combining the first two equations gives:

$$C = \frac{\mu}{(1+\mu)^{\sigma}} (a^*)^{\sigma-1} P_j^{\sigma-\epsilon}, \tag{IA20}$$

where C is a constant. Given our assumption $\sigma > \epsilon$, it thus suffices to show that a^* is rising with h. The third equation then implies that holding everything constant, we have that a^* rises if and only if $\frac{A^*}{a^*}$ rises with h.

We can compute:

$$
\begin{aligned}
(A^*)^{\sigma-1} &= \int_{a^*}^{\infty} a^{\sigma-1} dF^*(a) + (h^{\sigma-1} - 1) \int_{a^{**}}^{\infty} a^{\sigma-1} dF^*(a) \\
&= E_*[a^{\sigma-1}] \cdot \left(1 + (h^{\sigma-1} - 1) \left(\frac{a^{**}}{a^*}\right)^{(\sigma-1)-k}\right),
\end{aligned}
\tag{IA21}
$$

where E_* is the expectation relative to F^*, which is a truncated Pareto distribution. By the properties of the distribution, $E_*[a^{\sigma-1}] = (a^*)^{\sigma-1} \cdot D$, where D is a constant (a function of the power-law parameter).

Therefore, A^*/a^* is increasing in h if and only if $(h^{\sigma-1} - 1) \left(\frac{a^{**}}{a^*}\right)^{(\sigma-1)-k}$ is increasing in h. As the expression makes clear, there are two countervailing forces: an increase in h makes firms more productive ($h^{\sigma-1} - 1$), but fewer firms adopt the technology, as the greater returns to scale technology only selects for the most efficient firms. We plug in:

$$a^{**}/a^* = \left(\frac{h^{\eta} - 1}{h^{\sigma-1} - 1}\right)^{\frac{1}{\sigma-1}}, \tag{IA22}$$

to get that $(h^{\sigma-1} - 1) \left(\frac{a^{**}}{a^*}\right)^{(\sigma-1)-k}$ evaluates to:

$$(h^{\eta} - 1)^{1-\frac{k}{\sigma-1}} (h^{\sigma-1} - 1)^{\frac{k}{\sigma-1}}, \tag{IA23}$$

with the log-derivative given by:

$$\left(1-\frac{k}{\sigma-1}\right)\frac{\eta\cdot h^{\eta-1}}{h^{\eta}-1}+\frac{k}{\sigma-1}\frac{(\sigma-1)h^{\sigma-2}}{h^{\sigma-1}-1}. \tag{IA24}$$

Recall that we have $k>\sigma-1$ (the moments need to be well-defined) and $\eta>\sigma-1$ (for there to be differential adoption of the technology). As $h\mapsto 1$, the second term dominates (and goes to ∞), which leads to the expression in Equation (IA24) being positive, as desired. Alternatively, note that $\frac{\eta\cdot h^{\eta-1}}{h^{\eta}-1}$ is increasing in η (and consequently the first term is decreasing in η, and for $\eta\mapsto\sigma-1$, Equation (IA24) converges to:

$$\frac{(\sigma-1)h^{\sigma-1}}{h^{\sigma-1}-1}>0, \tag{IA25}$$

as desired.

□

IA3.2 Dynamic Model

We now present a dynamic extension of the model.

IA3.2.1 Setup

We use the CES framework as before, with the per-period demand given by:

$$y_{i,t}=Y\cdot\left(\frac{p_{i,t}}{P_t}\right)^{-\sigma}, \tag{IA26}$$

where $P^{1-\sigma}=\int_0^N p_i^{1-\sigma}di$ and N is the mass of operating firms. As before, we assume that firms employ an exogenous markup μ.

Now, however, the supply side is modified to allow for dynamics. In each time period t, a new technology (A_t) arises, which enables firms with idiosyncratic productivity a_i to produce at constant returns to scale at efficiency $A_t(a_i)$ (where A_t is an increasing function).[34] A firm has to invest ϕ_t once to acquire the technology. The investment needs to be maintained (from the first period onwards) by paying a per-period cost f_t, which can be interpreted as a type of fixed operating costs (e.g., capital depreciation, overhead).

New firms have to pay an entry cost κ_t before choosing to enter. Once they enter, they discover their idiosyncratic productivity a_i, and choose whether to exit or operate by investing ϕ_t.[35] We assume these firms have idiosyncratic productivity a_i drawn from F_t, which we assume to be fixed to the firm. The production function is then linear, i.e. constant-returns-to-scale, as is the case for the basic version of the model: firms with idiosyncratic productivity a_i operating under a technology A_s at time t produce $A_t(a_i)\cdot L$ units of the output using L units of the input.

[34] This notation assumes that the idiosyncratic productivity for each period satisfies a monotonicity property: if incumbent firm X is more productive than incumbent firm Y under the old technology, then it remains the case if both adopt the new technology. This simplification rules out technological leap-frogging.

[35] Here we rule out the adoption of an older technology for simplicity.

The per-period profit of the firm then is given by:

$$\pi_{i,t}(a,s) = \frac{\mu}{(1+\mu)^\sigma} Y \cdot P_t^\sigma A_s(a_i)^{\sigma-1} - f_s. \tag{IA27}$$

The price index $P^{1-\sigma}$ now depends on the composition of the technology of the firms in operation. Let $N_{t,s}$ be the mass of firms operating at time t that use the technology introduced at time s, with $N_t = \sum_{s\leq t} N_{s,t}$. Furthermore, denote the distribution of idiosyncratic productivity of those firms as $F_{t,s}$. Then, the aggregate price index is given by:

$$P_t^{1-\sigma} = \sum_{s\leq t} N_{t,s} \cdot \int \left(\frac{1+\mu}{A_s(a)}\right)^{1-\sigma} dF_{t,s}(a). \tag{IA28}$$

If we continue to set $\bar{Y} = YP_t$ (industry aggregate remains constant), then we have the following simplification. Combining the previous two equations, we obtain the following expressions for per period profit π_t and sales S_t:

$$\begin{aligned} \pi_t(a,s) &= \frac{\mu}{1+\mu}\frac{\bar{Y}}{N_t}\left(\frac{A_s(a)}{A_t^*}\right)^{\sigma-1} - f_s, \\ S_t(a,s) &= \left(\frac{A_s(a)}{A_t^*}\right)^{\sigma-1}\frac{\bar{Y}}{N_t}, \end{aligned} \tag{IA29}$$

where

$$A_t^* = \left(\sum_{s\leq t}\frac{N_{t,s}}{N_t}\int A_s^{\sigma-1}(a)dF_{t,s}(a)\right)^{\frac{1}{\sigma-1}}. \tag{IA30}$$

IA3.2.2 Solving the Model

We make the following simplifying assumptions. First, we assume $f_t = f$ (constant). Second, we observe that there is a one-to-one correspondence between the mass of future entrants $N_{t,t}$ and the future trajectory of entry cost κ_t. Consequently, we can alternatively specify a sequence of the mass of future entrants $N_{t,t}$, which would imply a series of future entry costs.

Finally, to simplify the dynamic optimization problem each firm faces, we assume that each firms are myopic optimizers: they only seek to optimize the current period profits. We think of a period as roughly one decade (so this assumption is not unrealistic). We note that the dynamic problem faced by a firm with idiosyncratic productivity a_i using technology at time s is the same *regardless* of when the firm has entered the market. We parametrize the sequence of new technologies in the following way: $A_t(a_i) = h^t \cdot a_i$, and $\phi_t = h^{\eta \cdot t}\cdot\phi$, with F_t being the Pareto distribution with tail index k. In line with the one-to-one equivalence between $N_{t,t}$ and κ_t, we specify $N_{t,t} = \bar{N}$.

The following describes the algorithm that specifies the general equilibrium. For each generation $g = 1, 2, ...t$, there are firms that use technology vintage $g \leq s \leq t$. The set of firms belonging to generation g that use technology s is given by those with idiosyncratic productivity belonging to a collection of intervals $T_{g,s} = \cup_i(\ell^i_{g,s}, u^i_{g,s})$. The equilibrium is fully specified by $T_{g,s}$, which we continue to update with the introduction of a new technology.

Let $\Psi_t = (A_t^*)^{\sigma-1} \cdot N_t$. For companies using technology of vintage s, their per-period profits are given by:

$$\frac{\mu}{1+\mu} \frac{\bar{Y}}{\Psi_t} \cdot (h^s a)^{\sigma-1} - f. \tag{IA31}$$

On the other hand, the current period profit of adopting the new technology is given by:

$$\frac{\mu}{1+\mu} \frac{\bar{Y}}{\Psi_t} \cdot (h^t a)^{\sigma-1} - f - \phi \cdot h^{\eta \cdot t}. \tag{IA32}$$

Thus, for each firm using technology vintage $s < t$, the exit threshold $\beta_{t,s}$ is given by:

$$\begin{aligned}
&\max \left\{ \frac{\mu}{1+\mu} \frac{\bar{Y}}{\Psi_t} \cdot (h^t a)^{\sigma-1} - f - \phi \cdot h^{\eta \cdot t}, \frac{\mu}{1+\mu} \frac{\bar{Y}}{\Psi_t} \cdot (h^s a)^{\sigma-1} - f \right\} < 0 \\
\iff\ & a < \left(\frac{1+\mu}{\mu} \frac{\Psi_t}{\bar{Y}} \right)^{\frac{1}{\sigma-1}} \min \left\{ (f + \phi \cdot h^{\eta t})^{\frac{1}{\sigma-1}} h^{-t}, f^{\frac{1}{\sigma-1}} \cdot h^{-s} \right\} = \beta_{t,s}.
\end{aligned} \tag{IA33}$$

Furthermore, the adoption threshold $\gamma_{t,s}$ is given by:

$$\begin{aligned}
&\frac{\mu}{1+\mu} \frac{\bar{Y}}{\Psi_t} \cdot (h^t a)^{\sigma-1} - f - \phi \cdot h^{\eta \cdot t} > \frac{\mu}{1+\mu} \frac{\bar{Y}}{\Psi_t} \cdot (h^s a)^{\sigma-1} - f \\
\iff\ & a > \left(\frac{1+\mu}{\mu} \frac{\Psi_t}{\bar{Y}} \right)^{\frac{1}{\sigma-1}} \cdot \left(\phi \cdot \frac{h^{\eta t}}{h^{t(\sigma-1)} - h^{s(\sigma-1)}} \right)^{\frac{1}{\sigma-1}} = \gamma_{t,s}.
\end{aligned} \tag{IA34}$$

Finally, for each generation g, we record the minimum productivity of that generation at time g. In other words, at time g when the generation g firms enter, $T_{g,g} = (\alpha_g, \infty)$.[36] For a given value of Ψ_t, we have:

$$\alpha_t = \left(\frac{1+\mu}{\mu} \frac{\Psi_t}{\bar{Y}} \left(f + \phi \cdot h^{\eta \cdot t} \right) \right)^{\frac{1}{\sigma-1}} \cdot h^{-t}. \tag{IA35}$$

Finally, the collection $T_{g,s}$ for all g and s imply the true value of Ψ_t, given by the following formula:

$$\Psi_t = (A_t^*)^{\sigma-1} N_t = \sum_{g \le t} \frac{k}{k+1-\sigma} \alpha_g^k N_{g,g} \left(\sum_{g \le s \le t} h^{s(\sigma-1)} \sum_i \left((\ell_{g,s}^i)^{-(k+1-\sigma)} - (u_{g,s}^i)^{-(k+1-\sigma)} \right) \right) \tag{IA36}$$

Definition IA1. *A (myopic) dynamic equilibrium is given by the collection of* $\{\Psi_t, \alpha_t, N_{t,t}, T_{g,s}^t\}$ *for each* $t \ge 1$*, such that* $T_{g,s}^t$ *satisfy:*

$$\begin{aligned}
T_{g,s}^t &= \left(T_{g,s}^{t-1} \cap (\beta_{t,s}, \infty) \right) \cap (0, \gamma_{t,s}) \text{ for } g, s < t \\
T_{g,t}^t &= \left(T_{g,s}^{t-1} \cap (\beta_{t,s}, \infty) \right) \cap (\gamma_{t,s}, \infty) \text{ for } g < t \\
T_{t,t}^t &= (\alpha_t, \infty),
\end{aligned} \tag{IA37}$$

where $\beta_{t,s}$*,* $\gamma_{t,s}$*, and* $\alpha_{t,s}$ *are given by Equations* (IA33), (IA34)*, and* (IA35)*, with* Ψ_t *conditional on* $T_{g,s}^t$ *given*

[36] By the property of the power law, α_g is a sufficient statistic to compute Ψ_t.

by Equation (IA36).

Thus, we compute the dynamic equilibrium given the following algorithm:

1. Initialize the equilibrium for $t = 1$. Here, note that Ψ_1 takes a relatively simple form:

$$\begin{aligned}\Psi_1 &= \bar{N}\frac{k}{k+1-\sigma}h^{\sigma-1}\alpha_1^{\sigma-1} \\ \alpha_1^{\sigma-1} &= \frac{1+\mu}{\mu}\frac{\Psi_t}{\bar{Y}}(f+\phi h^{\eta})h^{-(\sigma-1)},\end{aligned} \tag{IA38}$$

   which implies:

$$\bar{N}_1 = \frac{k+1-\sigma}{k}\frac{\mu}{1+\mu}\frac{\bar{Y}}{f+\phi h^{\eta}}, \tag{IA39}$$

   and α_1 can be set to a constant 1.

2. Subsequently, for $t > 1$: have a record of $T_{g,s}$ for $g, s < t$.
   (a) Posit a value for Ψ_t.
   (b) Update the implied $T_{g,s}$ for $g, s < t$: compute the exit and adoption thresholds $\beta_{t,s}$ and $\gamma_{t,s}$ using Equations (IA33) and (IA34).
      i. For each $g, s < t$, set $T_{g,s}^{new} = (T_{g,s} \cap (\beta_{t,s}, \infty)) \cap (0, \gamma_{t,s})$.
      ii. Set $T_{g,t}^{new} = (T_{g,s} \cap (\beta_{t,s}, \infty)) \cap (\gamma_{t,s}, \infty)$.
      iii. Set $T_{t,t} = (\alpha_t, \infty)$ for α_t defined in Equation (IA35).
   (c) For $g < t$: compute the total remaining number of (non-exiting) firms as a share of the total number of firms at time $t-1$.
   (d) Verify that this exit share is equal to the target, and adjust proposed Ψ_t.

3. Finally, we compute the implied $N_{t,t}$ using Equation (IA36).

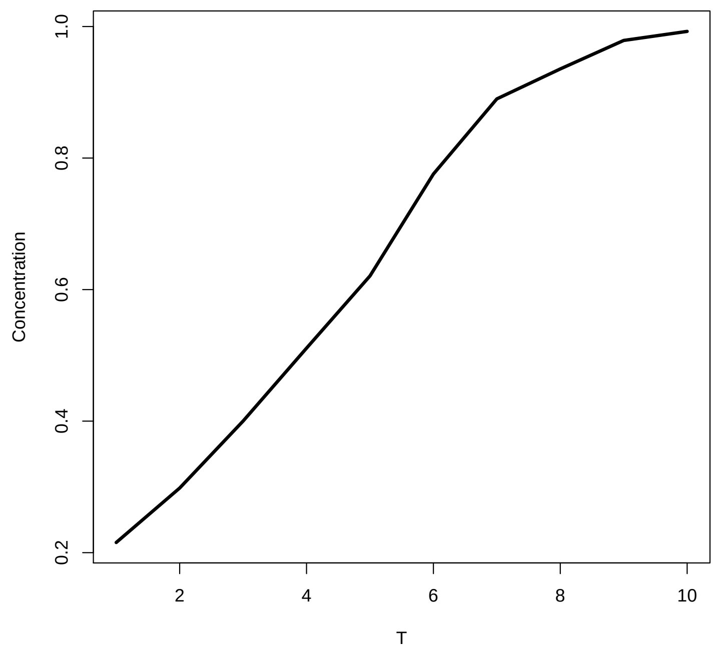
4. Record the new $T_{g,s}$ for $g, s \leq t$, the productivity thresholds α_g for $g = 1, ...t$, and finally the mass of entering firms: $N_1, N_2, ...N_t$.

Figure IA20 provides a numerical illustration where we set each time period to be one decade (each time period corresponds to the introduction of the new generation of technology). We set $h = 1.4$ to roughly correspond to the growth in aggregate output in a decade, and $\mu = 0.2$ as the average markup. We set the idiosyncratic productivity threshold α_t such that 30% of existing firms exit in each decade.[37] The figure shows the resulting concentration dynamics, as measured by the top 1% sales share. In the model, With the introduction of each generation of technology that has increasing stronger economies of scale, concentration rises over time.

[37] We set the remaining parameters to the following values: $\bar{Y} = 1000$, $\phi = 3$, $\eta = 4$, $\sigma = 3$, $f = 2$, $k = 3$.

Figure IA20: Simulated Concentration Dynamics

This figure presents a numerical illustration of concentration (measured as top 1% sales share) over time in the dynamic model. Each period is set to be one decade.



IA3.3 Trade Analyses

We now modify the basic framework in Section 4.2 and Appendix IA3.1 to analyze the impact of changes in trade barriers as well as possible interactions with economies of scale. For simplicity, we consider the symmetric case of two economies, "home" and "abroad." Each economy has the same aggregate demand and the same CES setup, where firms face demand $\bar{Y} \cdot \left(\frac{p_i}{P}\right)^{-\sigma}$ with an exogenous markup μ domestically. Following Melitz (2003), we assume that there is a standard iceberg cost $\tau > 1$, which raises the marginal cost by a factor of τ for products shipped abroad, as well as a fixed cost of exporting ϕ_x. We assume that exporting firms pass on the iceberg costs to consumers, i.e. $p_{i,exp} = \tau p_i = \tau \frac{1+\mu}{a_i}$. Given the symmetry of the two economies, we do not use additional notations to label each economy.

IA3.3.1 Homogeneous Technology

We start with homogeneous technology: all firms use the same constant-returns-to-scale technology but differ in their idiosyncratic productivity a_i (which corresponds to the case of $h = 1$ in the baseline model in Section 4.2). In other words, we examine the impact of changes in trade barriers alone, and shut down technology with economies of scale. For simplicity, we also assume that firms are only active for one period: the conclusions of our model remain unchanged in the standard specification.[38] Then,

[38]The only difference this additional assumption introduces is the addition of a term involving the discount rate R, with all of the conclusions remaining unchanged.

the per-period profits are reduced to a single period profit: $\Pi(a_i) = \pi(a_i) - \phi$.

Given the aggregate price index P, total profits of operating firms that do not export are given by:

$$\pi_{\text{no export}}(a_i) = \bar{Y}P^{\sigma}\left\{\left(\frac{1+\mu}{a_i}\right)^{-\sigma}\cdot\frac{\mu}{a_i}\right\} - \phi, \tag{IA40}$$

whereas total profits of operating firms that export are given by:

$$\pi_{\text{export}}(a_i) = \bar{Y}P^{\sigma}\left\{\left(\frac{1+\mu}{a_i}\right)^{-\sigma}\cdot\frac{\mu}{a_i} + \underbrace{\left(\frac{\tau(1+\mu)}{a_i}\right)^{-\sigma}\cdot\frac{\tau\mu}{a_i}}_{\text{export profits}}\right\} - \phi - \phi_x. \tag{IA41}$$

From the operating constraint and the exporting constraint, one can implicitly define two thresholds, given by:

$$\begin{aligned} \bar{Y}P^{\sigma}\left(\frac{1+\mu}{a^*}\right)^{-\sigma}\frac{\mu}{a^*} &= \phi \\ \bar{Y}P^{\sigma}\left(\frac{1+\mu}{a_{exp}}\right)^{-\sigma}\frac{\mu}{a_{exp}}\cdot\tau^{1-\sigma} &= \phi_x, \end{aligned} \tag{IA42}$$

where a^* is the minimum productivity threshold required to operate profitably, and a_{exp} is the minimum productivity required for exporting to be profitable. Combining the two equations yields:

$$\frac{a_{exp}}{a^*} = \tau\left(\frac{\phi_x}{\phi}\right)^{\frac{1}{\sigma-1}} \tag{IA43}$$

Intuitively, fewer firms export ($\frac{a_{exp}}{a^*}$ is high) when τ is high (greater iceberg costs) or ϕ_x (fixed cost of exporting) is high. We shall assume (for convenience) that either cost is sufficiently high such that $a_{exp} \geq a^*$.

Given the relative cutoffs a^* and a_{exp}, there are three types of firms.

1. Firms that export: their sales are given by $\bar{Y}P^{\sigma}(1+\mu)^{1-\sigma}\cdot a_i^{\sigma-1}(1+\tau^{1-\sigma})$.

2. Firms that do not export: their sales are given by $\bar{Y}P^{\sigma}(1+\mu)^{1-\sigma}\cdot a_i^{\sigma-1}$.

3. Imports from firms abroad: their sales (in the domestic market) are given by $\tau^{1-\sigma}\bar{Y}P^{\sigma}(1+\mu)^{1-\sigma}\cdot a_i^{\sigma-1}$.

In other words, among active firms, exporters have revenues proportional to $(1+\tau^{1-\sigma})a_i^{\sigma-1}$, where $a_i \geq a_{exp}$, non-exporters have revenues proportional to $a_i^{\sigma-1}$, where $a_{exp} \geq a_i \geq a^*$, and importers have revenues proportional to $\tau^{1-\sigma}a_i^{\sigma-1}$, where $a_i \geq a_{exp}$. We maintain our assumption that the idiosyncratic productivity is Pareto-distributed with $P(a \geq x) \propto x^{-k}$, with $k \geq \sigma - 1$.

Following our empirical exercise, we measure concentration in production activities. In other words, we consider total production by domestic firms *including* exports made by domestic exporters and excluding imports from foreign firms. Assume for simplicity that the cutoff for the concentration ratio is such that the non-exporting firms are not part of the top 1%. In this case, it suffices (given that the most productive firms export) to consider the sales (including exports) of the firms for which $a \geq a^* \cdot (0.01)^{-\frac{1}{k}}$. Then, the expressions for the top 1% sales share with and without exports are given by the following respectively:

$$\begin{aligned} \zeta_{1\%,\text{with exports}} &= \frac{(1+\tau^{1-\sigma}) \cdot (0.01)^{1-\frac{\sigma-1}{k}}}{1+\tau^{1-\sigma} \cdot \left(\frac{a_{exp}}{a^*}\right)^{-(k-(\sigma-1T))}} = \frac{(1+\tau^{1-\sigma}) \cdot (0.01)^{1-\frac{\sigma-1}{k}}}{1+\tau^{-k}\left(\frac{\phi_x}{\phi}\right)^{1-\frac{k}{\sigma-1}}} \\ \zeta_{1\%,\text{without exports}} &= (0.01)^{1-\frac{\sigma-1}{k}} \end{aligned} \tag{IA44}$$

One can then derive the following comparative static of the top 1% sales share with respect to trade barrier τ.

Proposition IA6. *The top share is hump-shaped in τ: for sufficiently high barriers to trade (τ sufficiently high), lowering barriers to trade increases concentration. Furthermore, "concentration excluding exports" remains the same as barriers to trade change.*

IA3.3.2 Incorporating Scalable Technology

Next, we augment the basic trade model and include the two types of technologies specified in our main model (Section 4.2 and Appendix IA3.1). In other words, firms with idiosyncratic productivity a_i can choose to invest in the standard technology above or alternatively in a new technology that requires $\phi \cdot h^\eta > \phi$ of spending but provides per-unit productivity $a_i \cdot h > a_i$.

For ease of analysis, we assume that technological innovations that affect the scalability of the new technology (the parameter h) is shared across both markets. In this case, there are two dimensions of firm optimization: 1) whether to export or not, and 2) whether to adopt the new technology. There are three possible equilibria:

1. The least efficient firms neither export nor adopt the new technology. Mediocre firms export but with old technology. Efficient firms export with new technology.

2. The least efficient firms neither export nor adopt the new technology. Mediocre firms adopt the new technology but do not export. Efficient firms export with new technology.

3. The least efficient firms neither export nor adopt the new technology. The rest export with new technology.

Which of the three possibilities ends up occurring depends on the relative cost of the new technology (indexed by η) and the cost of export (ϕ_x). For convenience, we shall assume the following regarding the relative values of η and ϕ_x, which guarantees the third possibility, the simplest case to analyze. Nonetheless, the general conclusions and comparative statics remain largely unchanged if we relax the assumption.

Assumption IA4. *Let h, η, ϕ_x and τ satisfy the following:*

$$\frac{h^{\sigma-1}-1}{h^\eta - 1} \cdot (1+\tau^{\sigma-1}) \geq \frac{\phi}{\phi_x} \geq \frac{h^{\sigma-1}-1}{h^\eta-1}\tau^{1-\sigma}h^{1-\sigma} \tag{IA45}$$

Proposition IA7. *Under the above assumption, there are two types of firms in the economy: firms with idiosyncratic productivity $a^{**} \geq a \geq a^*$ that neither export nor adopt the new technology, and firms with idiosyncratic productivity $a \geq a^{**}$ who do both. The two thresholds satisfy:*

$$\frac{a^{**}}{a^*} = \left(\frac{(h^\eta - 1) + \frac{\phi_x}{\phi}}{(1+\tau^{1-\sigma})h^{\sigma-1} - 1} \right)^{\frac{1}{\sigma-1}}. \tag{IA46}$$

First, in the presence of heterogeneous technology and economies of scale, changes in the barriers to trade now has an effect on both standard top sales concentration, as well as the export-excluded top sales concentration.

Corollary IA1. *Consider a reduction in barriers to trade (τ), then more firms (as a share of total firms) will adopt the new technology: $\frac{a^{**}}{a^*}$ falls. Assuming as before that the new technology is sufficiently marginal (i.e. $h = 1 + \nu$) and barriers to trade (τ) sufficiently high, then the top business share will increase.*

Corollary IA2. *Sales concentration excluding exports decreases with τ and increases with h.*

Contrary to the case with homogeneous technology (Proposition IA6), here lower trade barriers can increase concentration even when one excludes exports. This is because lower trade barriers lead to greater adoption of the scalable technology. Meanwhile, holding trade barriers fixed, the increase in economies of scale (higher h) raises concentration (as before) as well as "concentration excluding exports."

Corollary IA3. *Consider a marginal increase in the scalability of the new technology: $h = 1 + \nu$ with $\nu \mapsto 0$. The top business share will increase, along with total exports and imports as a share of gross output.*

Corollary IA1 and Corollary IA3 illustrate that trade and the scalable technology are complements. Lower barriers to trade encourage firms to adopt the scalable technology, while enhancement in the scalable technology increases the ability of efficient firms to reach foreign markets and increase the trade volume.

The above analyses are framed primarily as international trade ("home" and "abroad," "exports" and "imports"). The same framework can be used to think about the integration of domestic markets. In this case, we can think of "home" and "abroad" as say "east coast" and "west coast." Concentration in the U.S. would be the sales share of top businesses in these two economies in the total sales of these two economies. When the two economies are symmetric, this is the same as the top business share in each economy, so the expressions for concentration are the same as before. The only difference for the case of domestic trade is that we cannot easily measure "exports" and "imports" (i.e., trade across different U.S. regions), and we cannot calculate "concentration excluding exports" in the data.

IA3.3.3 Proofs

Proof of Proposition IA6. Using standard power-law identities,[39] we obtain that the sales share of the top 1% is given by:

$$\frac{(1+\tau^{1-\sigma}) \cdot (0.01)^{1-\frac{\sigma-1}{k}}}{1 + \tau^{1-\sigma} \cdot \left(\frac{a_{exp}}{a^*}\right)^{-(k-(\sigma-1T))}} = \frac{(1+\tau^{1-\sigma}) \cdot (0.01)^{1-\frac{\sigma-1}{k}}}{1 + \tau^{-k}\left(\frac{\phi_x}{\phi}\right)^{1-\frac{k}{\sigma-1}}}. \tag{IA47}$$

[39]Specifically, $\int_\alpha^\infty k(a^*)^k a^{-(k+1)} \cdot a^{\sigma-1} da = \frac{k}{k+1-\sigma}(a^*)^{\sigma-1}\left(\frac{\alpha}{a^*}\right)^{-k+\sigma-1}$.

Taking the comparative static with respect to τ, we have that the share is increasing in τ iff:

$$\begin{aligned}
&0 < k \cdot \frac{\left(\frac{\phi_x}{\phi}\right)^{1-\frac{k}{\sigma-1}} \tau^{-k-1}}{1+\tau^{-k}\left(\frac{\phi_x}{\phi}\right)^{1-\frac{k}{\sigma-1}}} - \frac{(\sigma-1)\tau^{-\sigma}}{1+\tau^{1-\sigma}} \\
\iff &\left(1+\tau^{-k}\left(\frac{\phi_x}{\phi}\right)^{1-\frac{k}{\sigma-1}}\right)(\sigma-1)\tau^{-\sigma} < \left(k\cdot\left(\frac{\phi_x}{\phi}\right)^{1-\frac{k}{\sigma-1}} \tau^{-k-1}\right)(1+\tau^{1-\sigma}) \\
\iff &(\sigma-1)\left(\frac{\phi_x}{\phi}\right)^{\frac{k}{\sigma-1}-1} < k\cdot\tau^{-(k-(\sigma-1))} + (k-(\sigma-1))\cdot\tau^{-k}.
\end{aligned} \tag{IA48}$$

Note that the left hand side of the last expression is fixed in τ, while the right hand side is a strictly decreasing function in τ that eventually converges to 0. Furthermore, at the minimum value of $\tau = \left(\frac{\phi_x}{\phi}\right)^{-\frac{1}{\sigma-1}}$, one has that the right hand side evaluates to: $k\cdot\left(\frac{\phi_x}{\phi}\right)^{\frac{k}{\sigma-1}-1} + (k-(\sigma-1))\cdot\left(\frac{\phi_x}{\phi}\right)^{\frac{k}{\sigma-1}}$, which is greater than the left hand side. Thus, by the single-crossing condition, we have that the original top share is hump-shaped in τ.

□

Proof of Proposition IA7. First, we consider firms that are on the cutoff of exporting:

$$\bar{Y}P^{\sigma}\left(\frac{1+\mu}{a}\right)^{-\sigma}\frac{\mu}{a}\cdot\tau^{1-\sigma} = \phi_x. \tag{IA49}$$

These firms then adopt the new technology iff the extra revenue justifies the higher cost of the technology:

$$(h^{\sigma-1}-1)\cdot\left(1+\tau^{1-\sigma}\right)\cdot\bar{Y}P^{\sigma}\left(\frac{1+\mu}{a}\right)^{-\sigma}\frac{\mu}{a} = (h^{\sigma-1}-1)\cdot\left(1+\tau^{\sigma-1}\right)\phi_x \geq (h^{\eta}-1)\phi. \tag{IA50}$$

In other words, we would like to assume:

$$\frac{h^{\sigma-1}-1}{h^{\eta}-1}\cdot(1+\tau^{\sigma-1})\phi_x \geq \phi. \tag{IA51}$$

Second, we consider firms that are on the cuttoff of adopting the new technology:

$$(h^{\sigma-1}-1)\bar{Y}P^{\sigma}\left(\frac{1+\mu}{a}\right)^{-\sigma}\frac{\mu}{a} = (h^{\eta}-1)\phi. \tag{IA52}$$

For these firms to export, the increase in revenue is given by:

$$\tau^{\sigma-1}\cdot h^{\sigma-1}\bar{Y}P^{\sigma}\left(\frac{1+\mu}{a}\right)^{-\sigma}\frac{\mu}{a}, \tag{IA53}$$

which must be balanced by the extra cost ϕ_x.

Thus, for the marginal adopters of the new technology to export, we must have:

$$\tau^{\sigma-1} \cdot h^{\sigma-1} \bar{Y} P^{\sigma} \left(\frac{1+\mu}{a}\right)^{-\sigma} \frac{\mu}{a} = \tau^{\sigma-1} \cdot h^{\sigma-1} \cdot \frac{h^{\eta}-1}{h^{\sigma-1}-1} \phi \geq \phi_x, \tag{IA54}$$

or in other words:

$$\phi \geq \frac{h^{\sigma-1}-1}{h^{\eta}-1} \tau^{1-\sigma} h^{1-\sigma} \phi_x. \tag{IA55}$$

□

Proof of Corollary IA3. The top 1% sales share is given by:

$$\frac{\left(1+\tau^{1-\sigma}\right) h^{\sigma-1} \cdot (0.01)^{1-\frac{\sigma-1}{k}}}{1+\left(\left(1+\tau^{1-\sigma}\right) h^{\sigma-1}-1\right) \cdot \left(\frac{a^{**}}{a^{*}}\right)^{-(k-(\sigma-1))}} = \frac{\left(1+\tau^{1-\sigma}\right) h^{\sigma-1} \cdot (0.01)^{1-\frac{\sigma-1}{k}}}{1+\left(\left(1+\tau^{1-\sigma}\right) h^{\sigma-1}-1\right)^{\frac{k}{\sigma-1}} \cdot \left((h^{\eta}-1)+\frac{\phi_x}{\phi}\right)^{1-\frac{k}{\sigma-1}}}, \tag{IA56}$$

and the total export share of this economy is given by:

$$\frac{\tau^{1-\sigma} h^{\sigma-1} \cdot \left(\frac{(h^{\eta}-1)+\frac{\phi_x}{\phi}}{(1+\tau^{1-\sigma})h^{\sigma-1}-1}\right)^{1-\frac{k}{\sigma-1}}}{1+\left(\left(1+\tau^{1-\sigma}\right) h^{\sigma-1}-1\right)^{\frac{k}{\sigma-1}} \cdot \left((h^{\eta}-1)+\frac{\phi_x}{\phi}\right)^{1-\frac{k}{\sigma-1}}} = \frac{\tau^{1-\sigma} h^{\sigma-1} \cdot \left(\frac{a^{**}}{a^{*}}\right)^{-k+(\sigma-1)}}{1+\left(\left(1+\tau^{1-\sigma}\right) h^{\sigma-1}-1\right) \cdot \left(\frac{a^{**}}{a^{*}}\right)^{-k+(\sigma-1)}}. \tag{IA57}$$

We consider the impact of a marginal increase in h from 1 to $1+\epsilon$. We have: $\frac{a^{**}}{a^{*}} = \left(\frac{(h^{\eta}-1)+\frac{\phi_x}{\phi}}{(1+\tau^{1-\sigma})h^{\sigma-1}-1}\right)^{\frac{1}{\sigma-1}} \approx \left(\frac{\phi_x}{\phi}\right)^{\frac{1}{\sigma-1}} \tau$, which is independent of h.

Then, both the top business share and the export share of output are approximately proportional to a rational function in $h^{\sigma-1}$ of the form:

$$\frac{h^{\sigma-1}}{A \cdot h^{\sigma-1}+B}, \tag{IA58}$$

where $A = \left(1+\tau^{1-\sigma}\right)\left(\frac{a^{**}}{a^{*}}\right)^{-k+(\sigma-1)}$, $B = 1-\left(\frac{a^{**}}{a^{*}}\right)^{-k+(\sigma-1)}$ As $a^{**} \geq a^{*}$ and $k > \sigma-1$, $A, B > 0$, which implies that the above function is increasing in h.

Finally, the imports from foreign firms are equal (via symmetry) to the net exports of exporting firms (as a share of GDP).

□

Proof of Corollary IA1. It suffices to show that $\frac{(h^{\eta}-1)+\frac{\phi_x}{\phi}}{(1+\tau^{1-\sigma})h^{\sigma-1}-1}$ is increasing in τ. This follows trivially from the observation that as $\sigma > 1$, the denominator is decreasing in τ and the original expression is thus increasing in τ.

The expression for concentration is given by the following:

$$\frac{\left(1+\tau^{1-\sigma}\right) h^{\sigma-1} \cdot (0.01)^{1-\frac{\sigma-1}{k}}}{1+\left(\left(1+\tau^{1-\sigma}\right) h^{\sigma-1}-1\right)^{\frac{k}{\sigma-1}} \cdot \left((h^{\eta}-1)+\frac{\phi_x}{\phi}\right)^{1-\frac{k}{\sigma-1}}}. \tag{IA59}$$

To see the comparative static of the above expression as a function of τ, it is convenient to denote $A(\tau) = 1 + \tau^{1-\sigma}$, which is a decreasing function of τ. Factoring out terms that are independent of τ, we see that it suffices to determine the comparative static of

$$\frac{A(\tau)}{1 + (A(\tau)h^{\sigma-1} - 1)^{\frac{k}{\sigma-1}} \cdot B}, \tag{IA60}$$

with respect to $A(\tau)$. Taking the log-derivative of the above expression with respect to A yields:

$$\begin{aligned}
&(1 + (Ah^{\sigma-1} - 1)^{\frac{k}{\sigma-1}} \cdot B) - A \cdot \frac{k}{\sigma - 1} \cdot h^{\sigma-1} \cdot (Ah^{\sigma-1} - 1)^{\frac{k}{\sigma-1}-1} \cdot B \\
&\quad = 1 + (Ah^{\sigma-1} - 1)^{\frac{k}{\sigma-1}-1} \cdot B \cdot \left((Ah^{\sigma-1} - 1) - A\frac{k}{\sigma - 1}h^{\sigma-1} \right).
\end{aligned} \tag{IA61}$$

Note that as $\tau \mapsto \infty$ and $h \mapsto 1$, the above term converges to $1 > 0$. Consequently, the above expression is increasing in A as $h \mapsto 1$ and τ is sufficiently large. As $A(\tau)$ is a decreasing function in τ, this means that the original expression for concentration, under the above assumptions, is decreasing in τ, as desired.

□

Proof of Corollary IA2. When we exclude exports from the original expression, we have the following expression for "concentration excluding exports":

$$\frac{h^{\sigma-1} \cdot (0.01)^{1-\frac{\sigma-1}{k}}}{1 + (h^{\sigma-1} - 1) \cdot \left(\frac{a^{**}}{a^*}\right)^{-(k-(\sigma-1))}}. \tag{IA62}$$

Naturally, since τ does not enter the expression except indirectly through $\frac{a^{**}}{a^*}$, which is increasing in τ, we obtain that the top business share is also increasing in τ. The comparative statics with respect to h follow the same logic as the case without trade.

□

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