100 Years of Rising Corporate Concentration*

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Abstract

We collect data on the size distribution of U.S. corporate businesses for nearly 100 years. We document that corporate concentration (e.g., asset share or sales share of the top 1%) in the U.S. economy has been increasing persistently over the past century. Across different industries, rising concentration was more pronounced in manufacturing, mining, and utilities before 1970s, and more pronounced in services, retail, and wholesale after 1970s. We find that the timing and the degree of rising concentration in an industry align closely with the investment intensity in research and development and information technology. In addition, industries with higher increases in concentration also exhibit higher output growth. The evidence suggests that the long-run trends of rising corporate concentration reflect increasingly stronger economies of scale.

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1 Introduction

The role of large firms in the U.S. economy has always attracted the attention of researchers, policy makers, and the public. In recent years, one of the most widely analyzed facts about the U.S. economy is the rise of corporate concentration since the 1980s. Some studies view the phenomenon as a result of technology (Autor, Dorn, Katz, Patterson and Van Reenen, 2020; Bessen, 2020; Ganapati, 2021; Hsieh and Rossi-Hansberg, 2021; De Loecker, Eeckhout and Mongey, 2021), and this period has witnessed significant advancement of information technology (IT). Others view it as a syndrome of anti-competitiveness (Wu, 2018; Philippon, 2019; Baker, 2019), and this period follows changes in antitrust policies since the Reagan era (Peltzman, 2014; Stucke and Ezrachi, 2017).

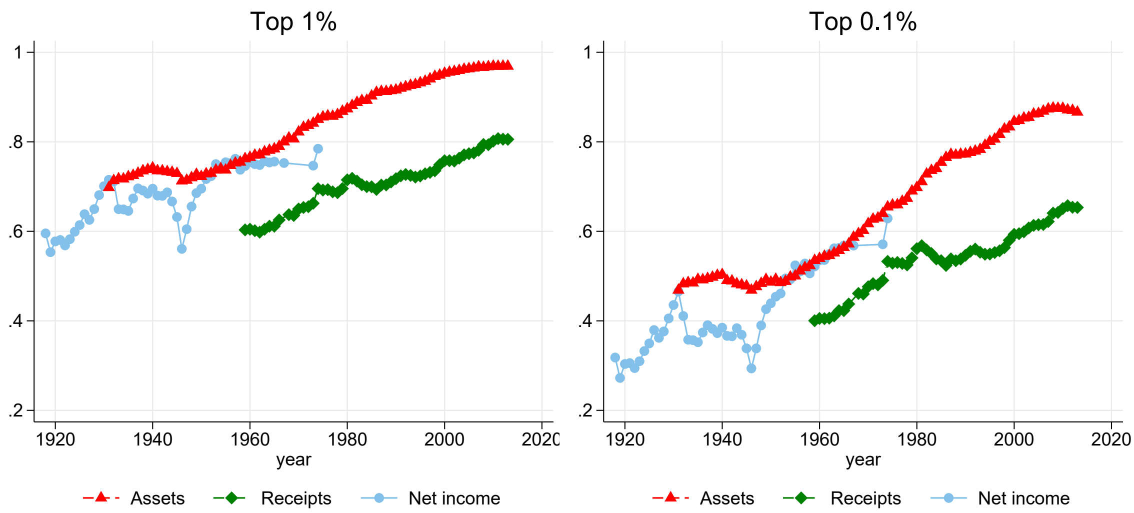
Are the recent decades special? What has been the long-run evolution of corporate concentration in the U.S. economy? In this paper, we collect historical data covering U.S. corporate businesses for nearly 100 years. We find that corporate concentration (e.g., asset share or sales share of the top 1% and the top 0.1%) has been increasing steadily over the past century. This rise is present in the economy as a whole and in most sectors, but the timing differs across sectors. We show that rising concentration in an industry coincides with increasing investment intensity in research and development (R&D) and IT; it is also accompanied by higher output growth. Meanwhile, profitability fluctuated in the past century without a secular trend, and antitrust went through different regimes. Overall, we find that the persistent rise of corporate concentration over the long run is most likely a reflection of increasingly stronger economies of scale.

Data. We collect data on the size distribution of U.S. corporate businesses by digitizing historical publications of the Statistics of Income (SOI) and the associated Corporate Source Book from the Internal Revenue Service (IRS). Every year, the SOI provides statistics for businesses across different size bins, including the total number of businesses and their financial information (e.g., assets, sales). We can then use these size bins to calculate top businesses' shares. In earlier years (from 1918 to 1975), the SOI provided size bins sorted by net income. In later years (from 1959 onwards), the SOI provided size bins sorted by receipts (i.e., sales). The longest and most comprehensive size bin tabulations are sorted by assets, available since 1931. For the aggregate economy, these three methods show consistent trends. Across different industries, size bins by assets have the most granular coverage, and we digitize corresponding industry-level data for main sectors (roughly one-digit SICs) and subsectors (roughly two-digit SICs). Our data thus captures concentration (i.e., the extent to which a small fraction of businesses account for a large share of economic outcomes) in the aggregate and in broad industries, which reflects the skewness of the business size distribution and the prominence of large businesses in the economy.

Main 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 the three types of size bins explained above. The red line with triangles shows the share of assets accounted for by top businesses sorted on assets. The green line with squares shows the share of sales accounted for by top businesses sorted on sales. The light blue 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 long-run increase in corporate concentration is reflected by all three series. For instance, since 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 87%), respectively.

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

This figure shows the shares of top 1% (left panel) and top 0.1% (right panel) corporate business. The red line with triangles shows the share of assets accounted for by top businesses sorted on assets. The green line with squares shows the share of sales accounted for by top businesses sorted on sales. The light blue 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).



At the industry level, we also observe a secular rise in corporate concentration. However, the timing differs across industries. For example, for manufacturing, mining, and utilities, the asset share of the top 1% increased more substantially in the earlier decades (before 1970s). In contrast, for retail, wholesale, and services, the increased occurred primarily in the later decades (after 1970s).

Finally, the SOI data also provides information about other characteristics, such as profitability. The data shows that profitability (i.e., net income/sales) does not display a secular trend in the past century. Profitability was very low during the Great Depression, and very high during the 1940s. It then declined gradually until 1980s and increased slightly since then. In other words, we do not observe the same long-run trends for corporate concentration and profitability.

Mechanisms. Why does corporate concentration increase persistently over the past century? We find two sets of evidence for the role of economies of scale.

First, we document 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 data from the fixed asset tables compiled by the Bureau of Economic Analysis (BEA). These types of investment are commonly viewed to embody greater economies of scale (Haskel and Westlake, 2017; Crouzet and Eberly, 2019). They can be directly involved in technological changes that enhance economies of scale, or required to achieve scale production when other forces (e.g., improvements in transportation or distribution) increase the benefits of scale (Stigler, 1958; Chandler, 1994). They also tend to raise upfront spending and fixed outlays (Sutton, 1991, 2001). Accordingly, we use the investment intensity in R&D and IT as a general indication of firms exploiting economies of scale, which allows us to conduct systematic analyses across different industries.

Among the main sectors, the concentration trends are consistent with industrial technologies enabling mass production in manufacturing since the early 20th century (Chandler, 1994), while modern IT started to transform services, retail, and wholesale more recently (Hsieh and Rossi-Hansberg, 2021). Among the subsectors, the turning points in concentration trends also coincide with key developments in economies of scale. For instance, concentration in restaurants started to increase around 1960s, the time when prominent restaurant chains began to emerge. 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. Although the particular drivers of economies of scale are heterogeneous across industries, the investment intensity in IT and R&D appears reasonably effective as a general reflection of the relevance of scale, and it comoves with top business shares. We confirm the relationship statistically via regressions of top 1% asset shares in an industry on the fraction of its investment in IT and R&D, using both levels and changes over the medium term (e.g., twenty years). We also include specifications with time fixed effects to absorb aggregate concentration trends, and isolate the alignment of the timing between rising concentration and increasing technological intensity across industries.

Second, we find that increases in concentration are also positively associated with industry growth. In particular, 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 and value added. Correspondingly, their shares in the economy expand as well. This evidence also appears consistent with the role of economies of scale. We use a simple model to show that the emergence of technologies with greater economies of scale can account for the long-run empirical facts: industries with increasing concentration have higher investment in R&D and IT as well as higher growth, while profitability does not exhibit persistent long-run trends.

The impact of regulatory environments (e.g., antitrust policies and enforcement) could be less straightforward to pin down in our data. To the extent that such regulations target market power, concentration does not necessarily have a clear relationship with market power, and analyses about market power require the definition of particular markets (Syverson, 2019). Accordingly, our data may not reflect the intensity or effectiveness of these regulations. Empirically, regulatory environments are also more challenging to measure, especially at the industry level. Aggregate time series such as the annual number of antitrust cases filed by the Department of Justice (DOJ) does not have a significant relationship with corporate concentration in our data. Overall, although aggregate regulatory environments have witnessed substantial changes in the past century (Lamoreaux, 2019), the data suggests that rising corporate concentration at the economy level has been a secular trend throughout different regulatory regimes.

Additional Checks. We perform several additional checks for the concentration trends. First, the size bins reported by the SOI cover corporate businesses (both C-corporations and S-corporations). For noncorporate businesses (e.g., partnerships), the SOI reports total receipts but size bins are not reported with sufficient consistency or granularity. Research shows that noncorporate businesses have become more prominent since 1980s (Clarke and Kopczuk, 2017; Kopczuk and Zwick, 2020), but corporate businesses still account for over 80% of the aggregate value of business receipts in recent decades. To include noncorporate businesses, we can make the assumption that top 0.1% businesses (corporate plus noncorporate) are all corporate businesses, and calculate their share in total receipts of both corporate and noncorporate businesses. This assumption seems reasonable according to the tabulation of firms by legal form and size (employment bins) from the Census Statistics of U.S. Businesses (SUSB), available since 2007.[1] We continue to find an increase in the receipt shares of the top 0.1% businesses (from around 40% when size bins by receipts started in 1960s to over 60% by 2010s), and the results are similar to top 0.1% shares using only corporates.

We also cross-check our results with data from the Manufacturing Census, which provides sales shares of top 4, 8, 20, and 50 firms at the four-digit SIC level for Census years since 1947 (Peltzman, 2014; Keil, 2017). We observe an upward trend in the average top firm shares reported by the Manufacturing Census as well, and the increase is especially pronounced

[1]According to SUSB data, it appears less innocuous to assume that top 1% businesses (among both coporate and noncorporate) only have corporate businesses.

for the value-weighted average. In addition, since top 8 to 20 firms largely map into top 1% in four-digit manufacturing SIC codes, we also compare our results for manufacturing subsectors with Manufacturing Census data aggregated to the same level; we find a high degree of similarity, with a raw correlation of around 0.7.

Another check using Census data is to compare our results of top firms' asset shares with top firms' employment shares calculated from the Business Dynamics Statistics (BDS). Since 1978, the BDS tabulates the number of firms and employment by employment bins. We can therefore calculate the employment shares of top 1% firms by employment size in the BDS data. The result is about 0.7 correlated with top 1% asset shares in our SOI data, which shows a high level of consistency. Naturally, the level of top firm employment shares tends to be lower than top firm asset shares. The trends over time are nonetheless similar.

Finally, the SOI data we use focuses on domestic assets and sales, similar to national accounts data. We use Activities of U.S. Multinational Enterprises compiled by the BEA (available since 1980s) to check the potential influence of international activities. According to the number of U.S. parents with foreign activities reported in this data, less than 1% businesses are multinational. 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 in every main sector are almost always larger than the average assets of top 1% businesses). A weaker assumption is that top 1% businesses' share of international assets is the same as their share of domestic assets; it seems unlikely that businesses outside of the top 1% account for a larger share of international assets compared to domestic assets. Under both assumptions, we find that the concentration trends (e.g., top 1% asset shares) including international assets are similar to our original results.

Literature Review. Our work contributes to knowledge about the long-run evolution of the U.S. economy. It is most closely related to two sets of literature. First, an influential body of work documents rising concentration among U.S. firms since 1980s (Autor et al., 2020; Covarrubias, Gutiérrez and Philippon, 2020). For earlier time periods, previous work examined the Manufacturing Census (Peltzman, 2014), as we discussed in the cross-checks above. Overall, our data suggests that rising corporate concentration in recent decades is not necessarily special; rather, it appears to be the continuation of long-run trends that have persisted for nearly a century. While a number of factors can be relevant for recent decades, including various limits to competition (Philippon, 2019; Grullon, Larkin and Michaely, 2019; Akcigit and Ates, 2019; Cunningham, Ederer and Ma, 2021; De Loecker, Eeckhout and Mongey, 2021) and low interest rates (Liu, Mian and Sufi, 2021), our results show that persistent long-term forces are important for understanding corporate concentration.

Some of the analyses on corporate concentration examine a small number of "giant" or "dominant" firms in the aggregate economy, such as the top 20 or 200 firms in the U.S. (Collins and Preston, 1961; Stonebraker, 1979; White, 2002; Gutiérrez and Philippon, 2020). They tend to find less pronounced increases in the asset or sales shares of this set of firms over time. The top 1% or 0.1% that we study capture a broader set of businesses in the right tail of the size distribution. Accordingly, our evidence suggests that the general 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 change in the right tail of the size distribution (with an increasing prevalence of larger enterprises) appears to be related to changes in technology.

Second, several studies investigate the role of technology and economies of scale in shaping the landscape of firms. Chandler (1994) provides detailed narratives for economies of scale in manufacturing industries in the late 19th century and early 20th century. Hsieh and Rossi-Hansberg (2021) focus on the dissemination of economies of scale among services industries in recent decades, given the advancement in IT and management practices. Crouzet and Eberly (2019) suggest that intangible capital can increase scalability. The evidence of the secular rise in corporate concentration over the past century is suggestive of the role of economies of scale. We then construct an intuitive measure of technological forces related to economies of scale, using the investment intensity in IT and R&D. We find that this measure aligns closely with the timing and the degree of rising concentration across different industries in the past century. Furthermore, we find that industries experiencing higher increases in concentration also witness higher output growth. Taken together, the results point to increasingly stronger economies of scale over time, and these developments account for the long-run trends of rising corporate concentration.

The long-run trends we document also connect to several other questions in understanding macroeconomic outcomes. First, as Crouzet and Mehrotra (2020) point out, the degree of corporate concentration affects the aggregate impact of financial frictions across the firm size distribution. Relatedly, Gabaix (2011) highlights that shocks to large firms can drive aggregate fluctuations; such effects are likely stronger when corporate concentration is higher. Second, for the widely discussed issue of market power, higher concentration per se does not imply stronger market power (Syverson, 2019); rising concentration in the aggregate economy can also coexist with stable or falling concentration at the local level or product level (Rossi-Hansberg, Sarte and Trachter, 2021; Hoberg and Phillips, 2021; Neiman and Vavra, 2021; Benkard, Yurukoglu and Zhang, 2021), as large firms expand into more domains. Some suggest that economies of scale could increase market power (Eeckhout, 2021). Empirically, estimated markups do not display a secular increase over the past century (De Loecker, Eeckhout and Unger, 2020; Traina, 2018), but the model by Eeckhout and Veldkamp (2021) shows that certain drivers of economies of scale (e.g., data) could increase markups.

Organization. The rest of the paper proceeds as follows. Section 2 explains our data collection. Section 3 presents the basic results on corporate concentration in the past century and a number of robustness checks. Section 4 investigates the economic mechanisms behind the long-run concentration trends. Section 5 concludes.

2 Data

Our primary data source is the Statistics of Income (SOI) and the associated Corporation Source Book published annually by the IRS. The historical documents are available since 1918. Every year, the SOI tabulates the number of corporate businesses by size, which allows us to investigate the size distribution. Table 1 shows examples for the aggregate (Panel A) and one sector (Panel B) from the SOI in 1945. We have digitized data for the aggregate economy, main sectors (roughly at the one-digit SIC code level), and subsectors (roughly at the two-digit SIC code level).[2] The industry classification system switched from SIC to NAICS in 1997 and we harmonize the industries to maintain consistency. We provide details about data construction in Appendix IA2. 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. Additional size bins are available based on receipts (sales) for later years and net income for earlier years.

We use two methods to calculate the top 1% share from size bins marked by dollar thresholds (such as the examples in Table 1). The first method is to interpolate the top 1% using Pareto distributions. Blanchet, Fournier and Piketty (2017) provide a detailed description of the interpolation method, which refines and standardizes top share interpolations in earlier work (for example Piketty and Saez, 2003). This method is now standard practice for calculating household top income shares using data on household income brackets with a similar format (Alstadsæter, Johannesen and Zucman, 2019; Piketty, Yang and Zucman, 2019; Blanchet, Chancel, Flores and Morgan, 2020). The second method is to directly add up the top brackets such that the number of businesses in these brackets approximates 1%.[3] These two methods produce similar 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 bracket has more than 1% businesses; the benefit

[2] The SOI assigns a single industry code to each business based on the industry that represents the largest percentage of its total receipts.

[3] If the total number of businesses is N and the number of businesses in the top k brackets add up to less than $0.01N$ (whereas the top $k+1$ brackets add up to more than $0.01N$), then we take all the businesses in the top k brackets and add $(0.01N - \sum_{i=1}^{k} n_i)/n_{k+1}$ fraction from the $k+1$th bracket (where n_i denotes the number of businesses in bracket i). In other words, we take all businesses in the top k brackets and fill in the residual from the $k+1$th bracket.

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 for an example sector.

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 By Industry 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

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 0.1%) instead of the top N businesses (with a fixed N) for several reasons. First, the number of businesses differs substantially across industries, which makes top N not always comparable across industries. The share of top N businesses is also not necessarily comparable across different levels of aggregation (e.g., main sectors versus subsectors). Second, the number of businesses in the U.S. economy has increased significantly over the past century. Finally, the focus on top percentiles is also the standard in research on household income and wealth inequality (Piketty and Saez, 2003; Saez and Zucman, 2016; Kuhn, Schularick and Steins, 2020; Smith, Yagan, Zidar and Zwick, 2019). Overall, our main interest is to study the right tail of the firm size distribution, rather than a small number of "giant" firms (White, 2002; Gutiérrez and Philippon, 2020); the SOI data is also especially suited for the former question. 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 also present top 1% as a share of top 10%. The top 1% share in top 10% will not be affected when the right tail is Pareto, and Figure IA1 shows that Pareto provides a close fit of our data.[4]

The SOI is one of the key sources for the national income and product accounts (NIPA) (see Concepts and Methods of the U.S. National Income and Product Accounts). Accordingly, aggregate statistics from SOI and NIPA are generally very similar (the BEA makes adjustments to SOI results when producing national accounts, but these adjustments appear quantitatively small in aggregate). The SOI is also the source for the Flow of Funds and Quarterly Financial Report (QFR) of the U.S. Census Bureau (Crouzet and Mehrotra, 2020). The underlying data for the SOI comes from corporate income tax returns (Form 1120 or 1120-S). It covers both C-corporations and S-corporations in the economy. We perform detailed checks about the impact of noncorporate businesses in Section 3.2.

For businesses with subsidiary affiliates, the SOI reports consolidated affiliates as one entity.[5] 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 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 where consolidated filings were not allowed for most corporations. In recent decades 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). Before 1964, there was often a small surtax on consolidated returns. In Appendix IA2, we use SOI data to show the prevalence of

[4] 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), given the small firms have little aggregate impact (i.e., the numerator in the top 1% share will include more/less firms while the denominator stays similar). 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. Correspondingly, this ratio should not be affected by small and extraneous firms changing N (unless the number of firms changes very drastically such as by a factor of ten, which did not happen in the data).

[5] 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."

consolidated filings over time, and examine the impact on our concentration estimates. We observe a decrease in the prevalence of consolidated filings between early 1930s and early 1940s, and then an increase between 1960s and 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, the SOI uses tax depreciation for net income, 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 find the results are similar at the industry level. For total assets reported in Form 1120, firms 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 reported in the SOI and in 10K filings. 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).

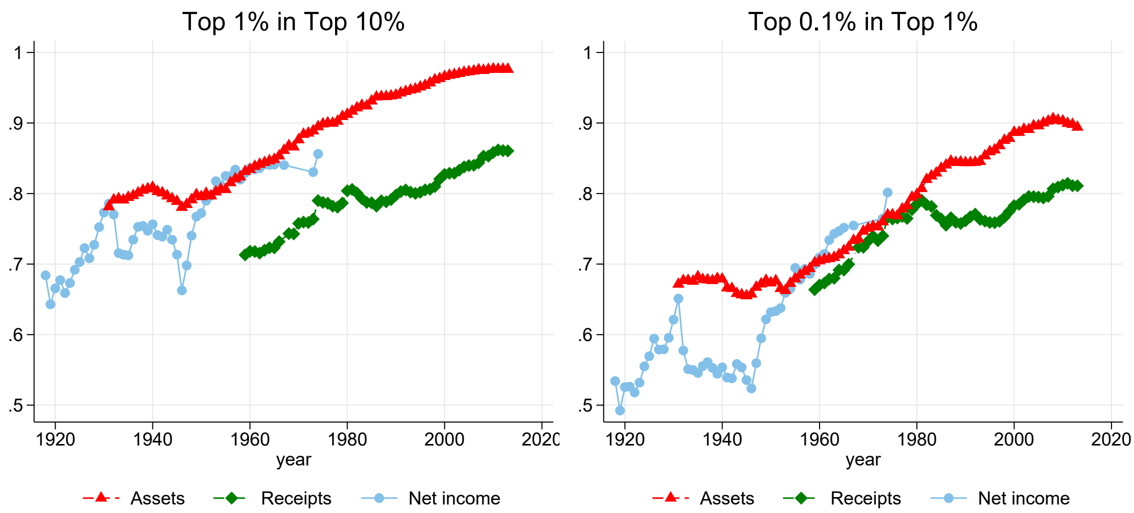
Finally, like the national accounts, the SOI focuses on domestic assets and sales. Accordingly to Activities of U.S. Multinational Enterprises compiled by the BEA, a small number of businesses have foreign activities (e.g., affiliates, assets, sales), which are less than 0.5% in manufacturing and mining and less than 0.1% in other major sectors. Total foreign assets and sales by value can be relatively large compared to domestic activities for several sectors (e.g., mining for both assets and sales, manufacturing and services for assets). These activities are most likely carried out by the largest companies (primarily among the top 1%), so the concentration ratios can be higher when foreign activities are also taken into account. We perform checks to include foreign assets 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 that we digitized. 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.

Figure 2: Aggregate Trends

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



3.1 Top Business Shares over 100 Years

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). The results are similar. 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 may affect the number of firms and correspondingly the top 1% share. Like before, the red 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 (where this line begins). The green 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 since 1959 (where this line begins). The light blue 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 early years but stopped doing so after 1975 (where this line stopped). We observe consistent results across these three types of tabulations. Top shares by assets and by receipts have correlations over 0.9, and top shares by net income have correlations around 0.7 with the other two series.

Interestingly, this time trend of persistently rising corporate concentration looks very different from the time trend of top 1% and 0.1% household income and wealth shares in the U.S., which decreased from 1920s to 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 then present results for main sectors (around the one-digit SIC level) in Figure 3 and subsectors (around the two-digit SIC level) in Figure 4. The tabulations by industry are most comprehensive for size bins by assets, and this sorting also has the longest time series as shown in Figures 1 and 2. The industry classification in the SOI changed from the SIC system to the NAICS system around 1997 and we match the industries to ensure consistency, as explained in Appendix IA2.

Figure 3 shows that concentration (as represented by the top 1% asset share) has been rising in the past century in most of the main sectors (the solid blue line). The trends are similar for the share of the top 1% businesses in the top 10% (the dashed red line). 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. The timing for rising concentration, nonetheless, varies somewhat across industries. The rise in concentration is more pronounced in earlier years for manufacturing, mining, and utilities (including communications and transportation), and more pronounced in later years services and trade (retail and wholesale). Table 2 also provides a tabulation of the average top 1% asset shares in each decade.

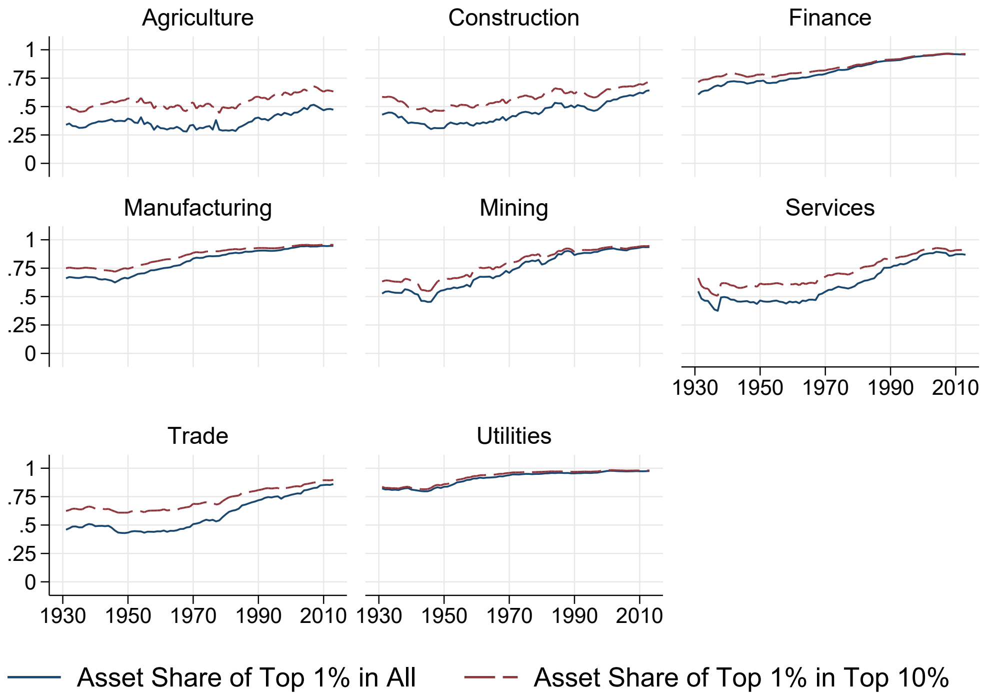
Figure 4 shows similar trends for subsectors: the persistent rise in concentration is common in many industries, but the timing can differ.[6] We investigate the timing in detail in Section 4. In addition, different subsectors started with varying degrees of top 1% asset shares in early 20th century (with median around 50% and interquartile range around 40% to 65%). By 2010s, top 1% asset shares in most subsectors have converged to a high level, arriving at over 80% in more than three quarters of the subsectors and over 90% in half of them (the median became 90% and the interquartile range around 84% to 93%).

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

[6]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 3: Top 1% Asset Shares: Main Sectors

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



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 top 1% asset shares has decreased over time, as discussed above. Top shares are bounded from above for industries that were already concentrated since the early decades, but have more room to increase for industries that were less concentrated in early decades.

3.2 Robustness Checks

We perform a number of checks for our concentration estimates, which we present below.

Including noncorporate businesses. The SOI tabulations by size bins that we use cover corporate businesses (both C-corporations and S-corporations). These tabulations by size are not available with the same consistency and granularity for noncorporate businesses. We can, however, obtain from the SOI the total number of noncorporate businesses each year and their *total receipts*; we use the dataset compiled by Lamoreaux (2006) and extend it to recent years with additional SOI publications. Figure IA2 shows that corporate busi-

Table 2: Top 1% Asset Shares: Average by Decade

This table shows the average asset share of top 1% businesses in each decades for the aggregate economy and the main sectors.

	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

Figure 4: Top 1% Asset Shares: Subsectors

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

nesses generally account for the vast majority of the aggregate value of business receipts. 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. The 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). We perform checks for including noncorporate businesses in Figure IA3. According to the Census Survey of U.S. Businesses (SUSB) tabulations of firms by industry and size (employment count) available since 2007, it seems reasonable to assume that in most industries at least the top 0.1% businesses are primarily corporates. We then perform the check as follows. We 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 corporate and noncorporate businesses. In other words, we assume that the top 0.1% businesses contain only corporates. Figure IA3 shows that the estimates including noncorporates (dashed red line) still display a general rise in concentration over time. They are also similar to top 1% receipt shares among corporates only (solid blue line).

Comparisons with Manufacturing Census. We also cross-check our data with concentration ratios (e.g., CR8, CR20) reported in the Manufacturing Census every five years since 1947 (analyzed in Pryor (2001), Peltzman (2014), Lamoreaux (2019) among others).[7] The data is available for four-digit SIC industries in manufacturing (roughly equivalent to six-digit NAICS industries when industry codes changed in 1997). Figure IA4 displays the average (equal-weighted and value-weighted) CR20 (Panel A) and CR8 (Panel B) in the Manufacturing Census, which shows a persistent increase in the sample period, especially for the value-weighted average.[8]

Figure IA5 provides a rough comparison between Manufacturing Census and our data. We match the two sets of data bearing in mind three main differences. First, given the Manufacturing Census data is at the four-digit SIC level, we take the value-weighted average to map it to the manufacturing subsector in our data (at the two-digit SIC level). Second, concentration ratios in the Manufacturing Census focus on a fixed number of top firms (e.g., four, eight, twenty), but the total number of firms varies across industries and over time. As a result, although these concentration ratios could be informative for regulatory monitoring, they do not translate into the same fraction of firms across industries and over time. There are about 20 firms in the top 1% in the larger four-digit manufacturing industries and 8 firms in the top 1% in the smaller ones. Thus we compare sales shares of top 1% businesses in each manufacturing subsector in our data with both CR20 (Panel A) as well as CR8 (Panel B). Third, concentration ratios in the Manufacturing Census are based on size sorted by sales. For detailed industries, the SOI tabulations only have size bins sorted by assets. Therefore, the SOI data in Figure IA5 represent the sales share of the top 1% by assets (not

[7]The data for non-manufacturing industries only began in 1982.

[8]Peltzman (2014) Table 2 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 IA4. In addition, the rise in concentration in this period seems stronger among a broader set of firms (e.g., CR20 compared to CR4).

by sales). Despite these caveats, Figure IA5 shows the two estimates are generally closely aligned, with a raw correlation about 0.7.

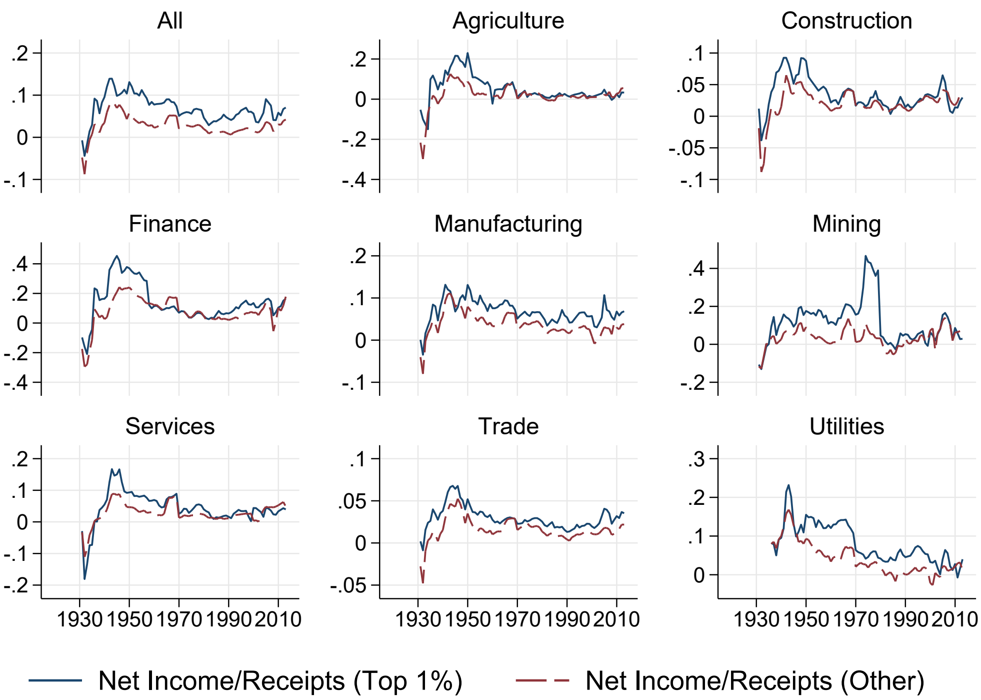
Comparisons with Census Business Dynamics Statistics (BDS). Another check using Census data is to compare our results of top firms' asset shares with top firms' employment shares calculated from the BDS. Since 1979, the BDS tabulates the number of firms and their employment by employment bins. We can therefore calculate the employment shares of the largest 1% firms by employment size in the BDS data. One caveat about the BDS data is the industry classification is based on establishments, and a firm is included in an industry when 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 result is about 0.7 correlated with top 1% asset shares in our main SOI data. Naturally, the level of top firm employment shares is generally smaller than top firm asset shares, but the trends over time are similar.

Including international activities. Like national accounts, the SOI data we use focuses on domestic activities. We use Activities of U.S. Multinational Enterprises compiled by the BEA to check the potential influence of international activities. Since early 1980s, this dataset presents information about foreign affiliates (e.g., total assets and sales) and their U.S. parents (e.g., number of U.S. parents and their total assets). 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 top 1% businesses in every main sector. A weaker assumption is that top 1% businesses' share of international assets is the same as their share of domestic assets. It seems unlikely that businesses outside of the top 1% account for a larger share of international assets compared to domestic assets. Under these assumptions, we allocate the entirety or a fraction of international assets to top 1% businesses and plot the modified top 1% asset shares in Figure IA6. 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 top 1% businesses; the dash-dotted green line shows the adjust top 1% share where we allocate international assets to top 1% businesses and the rest according to their shares in domestic assets. We find that the concentration trends including international assets are similar to our original results under both assumptions. 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

Figure 5: Profitability

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



after 2000s, and the ratio of international assets to 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. Figure 5 shows the profitability ratio, namely net income over sales, for top 1% businesses (solid blue line) and the rest (dashed red line); business size is sorted by assets. Several patterns emerge from this figure. First, the profitability ratio has fluctuated over time; it does not exhibit a persistent long-run trend. Profitability in almost all sectors was low during the Great Depression; it rebounded sharply in the 1940s, declined until 1980s, and then increased slightly since then. These trends are in line with 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 has 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) instead of tax depreciation (original SOI data on profits). Figure IA7 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 very 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 much 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 methods also do not find that markups increased between 1950s and 1980s. Accordingly, markups are also unlikely to exhibit secular trends over the long run.

Investment rate. Recent research postulates that the decline in corporate investment rates in recent years is linked to rising concentration (Gutiérrez and Philippon, 2017). In Figure IA8, we plot the long-run relationship between the investment rate (investment spending over asset stock using data from 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). The investment rate in fixed assets shows a decline in many sectors, but the decline is less pronounced when intellectual property is included, in line with findings in Crouzet and Eberly (2021). Overall, Figure IA8 suggests that, over the long run, there does not appear to be a strong association between changes in concentration and in investment rates.

Labor share. Several studies use Census data across different industries to document that falling labor shares since 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 1980s (Elsby, Hobijn and Şahin, 2013), even though we observe a secular increase in corporate concentration. The long-run evolution of the labor share could be affected by various changes in labor market conditions, 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 1980s (Decker, Haltiwanger, Jarmin and Miranda, 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 IA9 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 Mechanism

We now investigate the economic forces associated with the persistent rise in corporate concentration observed in the past 100 years. As Figures 3 and 4 indicate, although the overall upward trend in concentration is general, the timing varies across different industries. The rise in concentration occurred earlier in some industries and later in others. We utilize this information to decipher possible mechanisms behind the results. In Section 4.1, we find that rising concentration aligns closely with a higher intensity of investment commonly associated with economies of scale (e.g., R&D, IT). It is also accompanied by higher industry output growth. In Section 4.2, we discuss antitrust policies and enforcement.

4.1 Economies of Scale

A longstanding observation suggests that stronger economies of scale will increase concentration in various economic domains (Demsetz, 1973; Rosen, 1981; Chandler, 1994; Frank and Cook, 1996; Kaplan and Rauh, 2013; Hsieh and Rossi-Hansberg, 2021). For firms, following the Industrial Revolution and 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 due to new technologies as well as the advent of railroad and steamship that allowed firms to sell to broad markets. 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., services and retail), especially with the advancement in IT and new business models (Hsieh and Rossi-Hansberg, 2021; Aghion, Bergeaud, Boppart, Klenow and Li, 2021). For example, computers can make it easier to operate large retail chains and improve supply chain management (Holmes, 2001; Basker, 2007).

Since the particular driver of economies of scale can differ across industries, we rely on a general proxy that aims to capture common indications of economies of scale.[9] We use data on investment composition from the BEA's fixed asset tables (available since 1901), and calculate the share of IT (computer equipment and software) and R&D spending in total investment (fixed assets plus intellectual property). Investment in IT and R&D can be directly involved in generating technological changes that enhance economies of scale. It is also typically required to commercialize new technologies or achieve scale production more generally, even when other forces increase the benefits of scale production (e.g., new technologies that come from other industries, lower transportation costs that expand market size), as highlighted by Chandler (1994).[10] Such spending also tends to be associated with fixed upfront outlays. Accordingly, we use this measure as a broadly applicable reflection of firms exploiting economies of scale, which allows us to conduct systematic analyses among different industries.

Figure 6 plots the top 1% asset share in solid blue line and the investment share in IT and R&D in each industry in the dashed red line. Panel A shows the result for the main sectors and Panel B shows the result for subsectors (which are close to the sectors in the BEA fixed asset tables and the mapping is presented in 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 more pronounced in earlier decades for manufacturing, and more pronounced in recent decades for services, retail and wholesale. These general trends are consistent with the view that industrial technologies propelled mass production in manufacturing since 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 1960s, when prominent restaurant chains began to emerge. Concentration in retail started to rise around 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. In general, we observe

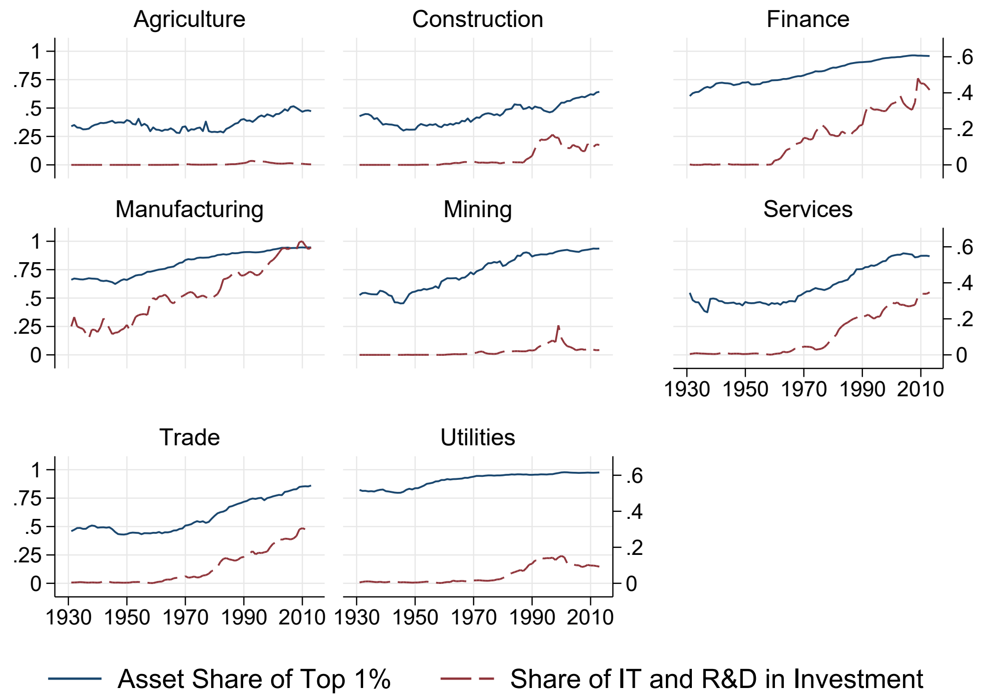
[9]The most direct measure of economies of scale would require data on upfront costs as well as fixed and marginal operating costs. Such information is difficult to obtain (e.g., based on companies' financial reports). For instance, De Loecker, Eeckhout and Unger (2020) argue that selling, general & 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.

[10]In other words, we do not argue that the investment intensity in IT and R&D is necessarily the primitive driver of economies of scale. This is an outcome (Cohen and Levin, 1989; Sutton, 2001), while the primitive driver could be different types of inventions (e.g., assembly lines, computers, internet).

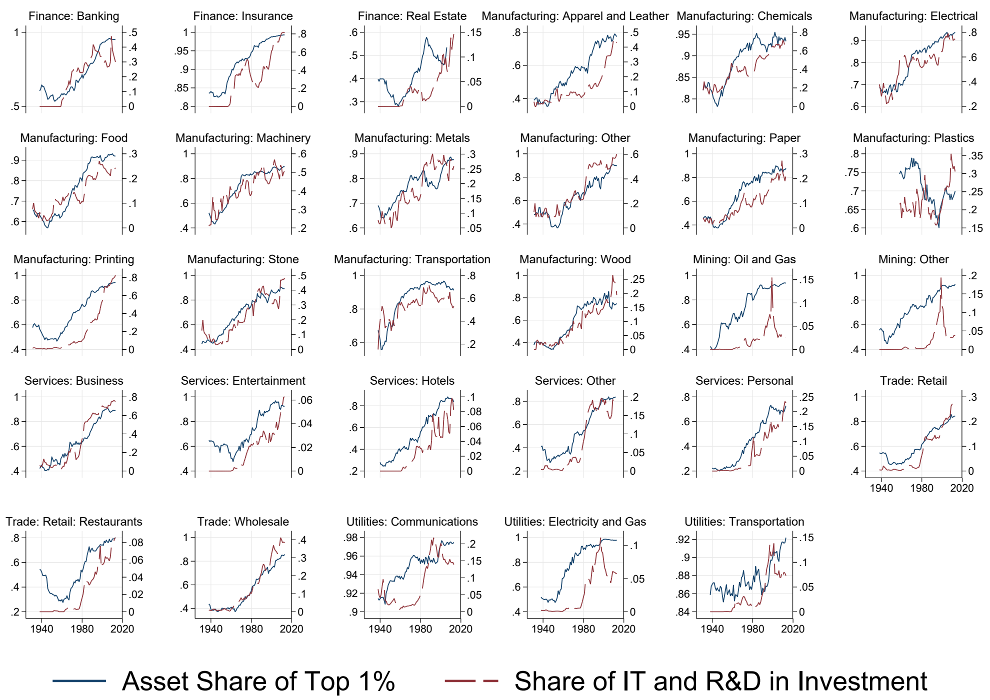
Figure 6: Concentration and Technological Intensity

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

Panel A. Main Sectors



Panel B. Subsectors



that industries that witness rising concentration in earlier (later) decades also witness rising technological intensity around the same time. Bessen (2020) analyzes Census concentration ratios from 1997 to 2012 and finds a positive relationship with IT intensity as well.

Tables 3 and 4 confirm the comovement between the two series plotted in Figure 6 in regression form. Table 3 examines the main sectors and Table 4 examines the subsectors. We present results for all industries in Panel A and for nonfinancial industries in Panel B. We use Driscoll and Kraay (1998) standard errors. We start with raw regressions of top 1% asset shares on the investment intensity in IT and R&D in columns (1) and (2). We then show regressions of changes of these two series over the medium term (e.g., twenty years) in columns (3) and (4). In particular, we also include time fixed effects to demonstrate the visual message in Figure 6 about the timing alignment between these two series. For instance, the specification in column (4) shows that aside from the overall rise in concentration over time, in a given time period those industries that experience more increases in concentration are also the ones that experience more increases in technological intensity.[11]

Moreover, in Tables 5 and 6, we find that when an industry experiences higher increases in concentration, it also experiences higher growth in real value added (columns (1) and (2)) and real gross output (columns (4) and (5)). Correspondingly, its share in the economy also increases (columns (3) and (6)). The industry-level real output and value added data comes from the BEA, available since 1947 (somewhat shorter than our concentration series). Figure 7 visualizes the relationship by plotting the change in concentration over twenty years and the change in an industry's share in total real value added in the same period (Figure IA10 does the same for real gross output). These results 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. Taken together, industries that experience higher increases in concentration on average tend to be those that grow faster, rather than those that stagnate. This evidence is also consistent with technological changes contributing to rising concentration in the long-run.[12]

To formalize how technologies with economies of scale can lead to the empirical facts we observe, we present a simple model in Appendix IA3, which follows the spirit of the model in Hsieh and Rossi-Hansberg (2021). We analyze the introduction of a new technology that decreases marginal costs but requires higher upfront costs, which leads to greater economies

[11]The subsector results in Table 4, Panel B, are strong for nonfinancial subsectors but slightly weaker when finance subsectors are included because the BEA data on IT investment intensity has large swings for the finance subsectors (although IT investment in the finance industry overall is smooth). These swings could arise from changes in underlying data sources according to BEA staff.

[12]We have found it difficult to consistently measure productivity at the industry level over the entire sample period. Productivity measurement may also face other complications (e.g., Solow's paradox, adjustment for product quality, dependence on assumptions about the production function).

Table 3: Rising Concentration and Technological Intensity: Main Sectors

This table shows industry-level regressions of the asset share of top 1% businesses on 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

of scale.[13] In the model, firms with higher idiosyncratic productivity (which can benefit more from the new technology) invest and adopt the new technology, while the remaining firms continue to use the old technology. Accordingly, firms that adopt the new technology increases their scale of production, resulting in higher concentration; industry output also increases.[14] Finally, we assume exogenous markup (as in Covarrubias, Gutiérrez and Philippon (2020)), which illustrates that the introduction of the new technology does not necessarily increase 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,

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

[14]Oh and Wachter (2021) study an asset pricing model where the distribution of stock returns is log-normal, in which case the concentration of market capitalization would rise to a high level. Our model focuses on the differences in the cross sectional level of productivity, not changes (corresponding to returns). Our results also suggest that the rise in corporate concentration does not appear to be random, but closely associated with reflections of technology (e.g., investment intensity in IT and R&D).

Table 4: Rising Concentration and Technological Intensity: Subsectors

This table shows industry-level regressions of the asset share of top 1% businesses on 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

regulations, and other forces).

In addition to economies of scale, economies of scope may also play a role in the formation of large firms (Chandler, 1994; Hoberg and Phillips, 2021). Direct measures of scope (e.g., the variety of products each business had) is difficult to construct in the long-run historical data. To the extent that higher intensity of IT and R&D may also facilitate economies of scope, our results above could be consistent with the economies of scope interpretation.

Finally, expanding market size (e.g., globalization) can also increase the benefits of greater economies of scale. As Chandler (1994) highlights, mass production is more attractive when firms can sell products to large markets; conversely, it may not be attractive when the market is small (e.g., in a small economy). For the impact of globalization, long-run data on the degree of globalization is primarily available in manufacturing industries to our knowledge. Our results suggest that, at the least, rising concentration is not entirely confined to time periods typically associated with substantial expansion in globalization.

Table 5: Rising Concentration and Industry Growth: Main Sectors

This table shows industry-level regressions of the asset share of top 1% businesses over twenty years on industry growth over twenty years. In columns (1) and (2), industry growth is measured as log changes in real value added. In columns (3), industry growth is measured as change in the industry's share in total real value added of private industries. In columns (4) and (5), industry growth is measured as log changes in real gross output. In columns (6), industry growth is measured as change in the industry's share in total real gross output of private industries. 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

	Δ_{20}Asset Share of Top 1%					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ_{20}Log Real Value Added	0.072***	0.081***				
	(0.017)	(0.017)				
Δ_{20}Real Value Added Share			1.018***			
			(0.374)			
Δ_{20}Log Real Gross Output				0.048*	0.054**	
				(0.025)	(0.024)	
Δ_{20}Real Gross Output Share						0.900***
						(0.310)
Year fixed effect	No	Yes	No	No	Yes	No
Obs	376	376	376	376	376	376
R^2	0.07	0.09	0.14	0.03	0.04	0.11

Panel B. Nonfinancial Industries

	Δ_{20}Asset Share of Top 1%					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ_{20}Log Real Value Added	0.083***	0.094***				
	(0.019)	(0.019)				
Δ_{20}Real Value Added Share			1.184***			
			(0.411)			
Δ_{20}Log Real Gross Output				0.058*	0.069**	
				(0.030)	(0.029)	
Δ_{20}Real Gross Output Share						1.089***
						(0.364)
Year fixed effect	No	Yes	No	No	Yes	No
Obs	329	329	329	329	329	329
R^2	0.08	0.10	0.16	0.04	0.05	0.14

Nonetheless, having a large domestic market in the U.S. and access to global markets should be conducive to the influence of economies of scale. For companies exploiting economies of scale in response to higher demand more generally, measuring industry demand is also challenging, but our results provide two pieces of suggestive evidence. First, aggregate rising concentration appears weakest during 1930s to 1940s. It is possible that the Great Depression (and the corresponding collapse in demand) made it difficult to operate businesses with high fixed costs and low marginal costs. Second, we find above that increasing concentration is systematically correlated with higher industry output growth. This relationship can be

Table 6: Rising Concentration and Industry Growth: Subsectors

This table shows industry-level regressions of the asset share of top 1% businesses over twenty years on industry growth over twenty years. In columns (1) and (2), industry growth is measured as log changes in real value added. In columns (3), industry growth is measured as change in the industry's share in total real value added of private industries. In columns (4) and (5), industry growth is measured as log changes in real gross output. In columns (6), industry growth is measured as change in the industry's share in total real gross output of private industries. 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

	Δ_{20}Asset Share of Top 1%					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ_{20}Log Real Value Added	0.075***	0.056***				
	(0.014)	(0.018)				
Δ_{20}Real Value Added Share			2.212***			
			(0.849)			
Δ_{20}Log Real Gross Output				0.067***	0.047**	
				(0.017)	(0.020)	
Δ_{20}Real Gross Output Share						2.398***
						(0.671)
Year fixed effect	No	Yes	No	No	Yes	No
Obs	1,312	1,312	1,312	1,312	1,312	1,312
R^2	0.08	0.04	0.07	0.06	0.03	0.08

Panel B. Nonfinancial Industries

	Δ_{20}Asset Share of Top 1%					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ_{20}Log Real Value Added	0.077***	0.057***				
	(0.012)	(0.017)				
Δ_{20}Real Value Added Share			2.190***			
			(0.728)			
Δ_{20}Log Real Gross Output				0.068***	0.046**	
				(0.015)	(0.019)	
Δ_{20}Real Gross Output Share						2.439***
						(0.592)
Year fixed effect	No	Yes	No	No	Yes	No
Obs	1,210	1,210	1,210	1,210	1,210	1,210
R^2	0.08	0.04	0.06	0.06	0.03	0.09

consistent with higher industry demand increasing the attractiveness of exploiting economies of scale in production.

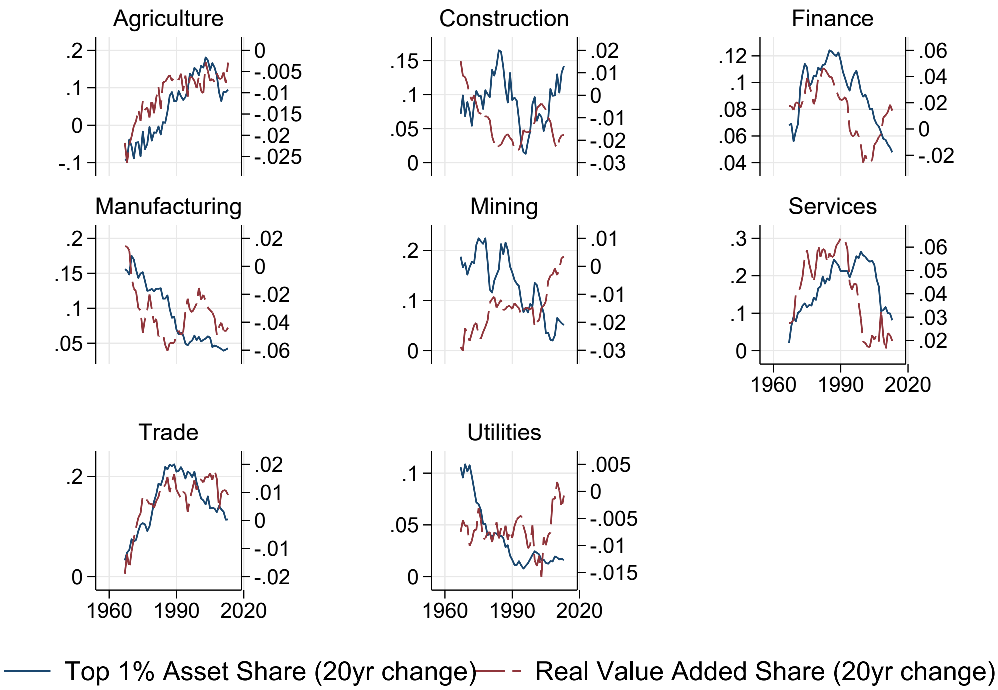
4.2 Antitrust

Another key topic in the discussion of corporate concentration is antitrust policies and enforcement (Peltzman, 2014; Philippon, 2019; Baker, 2019). We start by acknowledging that our data is not necessarily suitable for evaluating anti-competitiveness issues. As

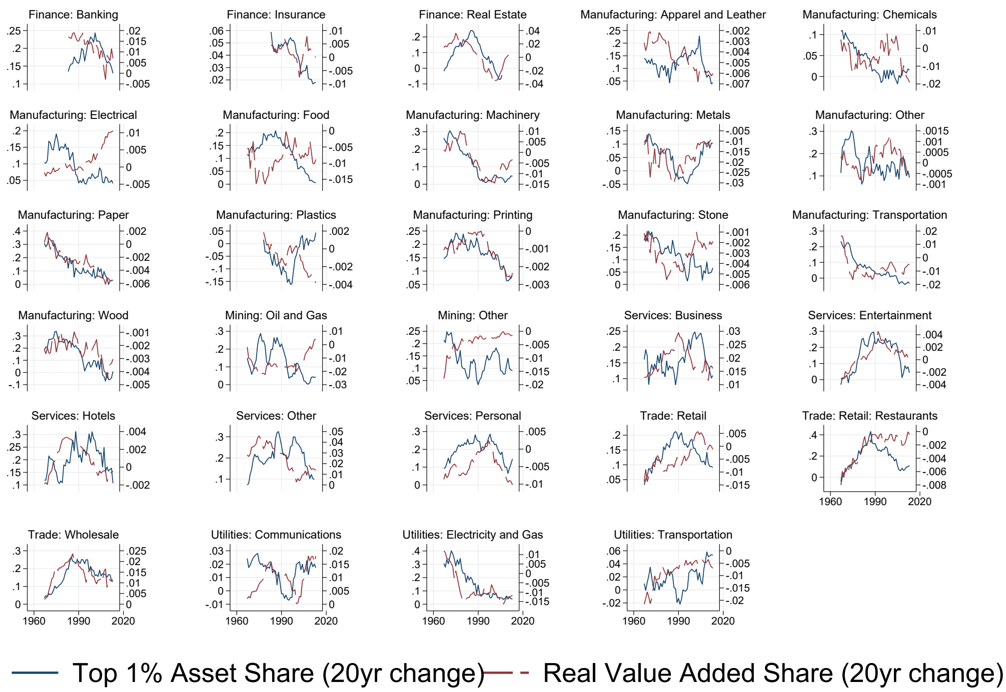
Figure 7: Concentration and Industry Value Added Share

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

Panel A. Main Sectors



Panel B. Subsectors



Syverson (2019) highlights, there is no definitive relationship between concentration and competitiveness (higher concentration can be associated with less competition or with more depending on the setting). In addition, anti-competitive issues require specific definitions of markets, while our data documents the role of large businesses in the aggregate economy and in broad industries. Higher concentration in the aggregate economy could coexist with increased competition in local markets as national firms expand into more locations and compete with local incumbents (Rossi-Hansberg, Sarte and Trachter, 2021); firms may also expand by increasing the variety of their products (Hoberg and Phillips, 2021; Benkard et al., 2021). Nonetheless, one could ask whether the corporate concentration trends we observe have any empirical associations with antitrust policies, which we examine below.

Researchers often view the 1980s as a watershed moment for U.S. antitrust policies in our sample period (Peltzman, 2014; Stucke and Ezrachi, 2017; Phillips Sawyer, 2019). Antitrust enforcement is thought to be tougher before this period and more relaxed afterwards. As shown in Section 3, aggregate concentration trends in our data do not display a turning point around 1980s.

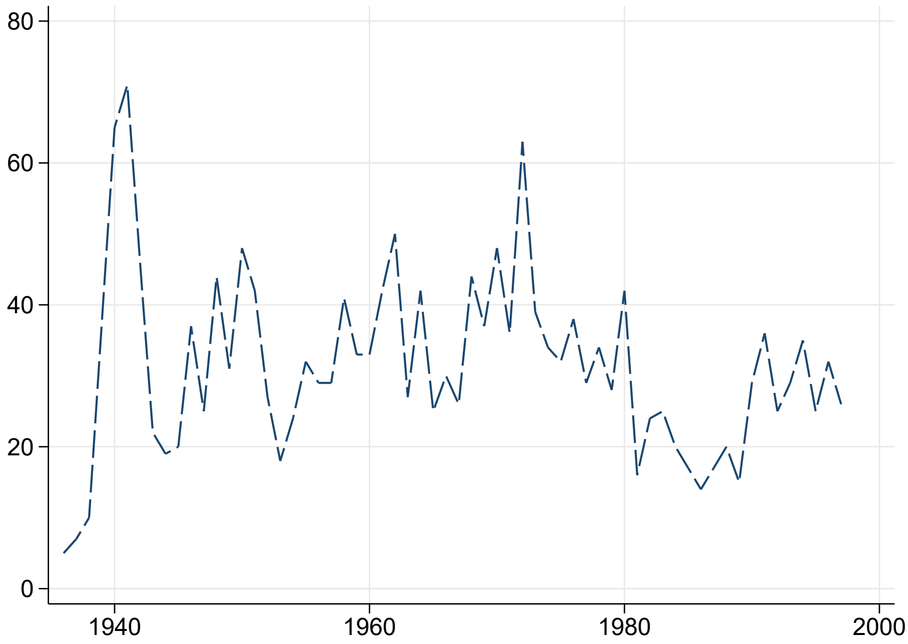
We also analyze data on the annual number of antitrust cases brought by the Department of Justice (DOJ), collected by Posner (1970) and Gallo, Dau-Schmidt, Craycraft and Parker (2000). Measurement of antitrust enforcement is admittedly challenging. As Gallo, Dau-Schmidt, Craycraft and Parker (2000) wrote, "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." Figure 8, Panel A, shows the time series of the number of cases (if there is a series of investigations related to the same issue, they are consolidated into one case). The number of cases was high between 1940s and 1970s, and it did appear to decrease after 1980s. Figure 8, Panel B, compares total DOJ cases in a five-year period and the rise in top 1% shares over that period. The raw correlation between cumulative DOJ cases and increases in top 1% asset shares over five-year periods is around 0.06. At the main sector level, the correlation between is also around 0.06. An obvious caveat is that DOJ cases may be more common during time periods of more corporate consolidation (which can be driven by many factors), leading to positive correlations between DOJ cases and increases in concentration. At a minimum, the data suggests that top business shares have experienced increases through different regimes of antitrust policies and enforcement.

Results in Section 3 also suggest that the timing of rising concentration differs by industry. Less data is available to measure antitrust enforcement by industry. Overall, the data does not show evidence that antitrust is the main determinant of the general corporate

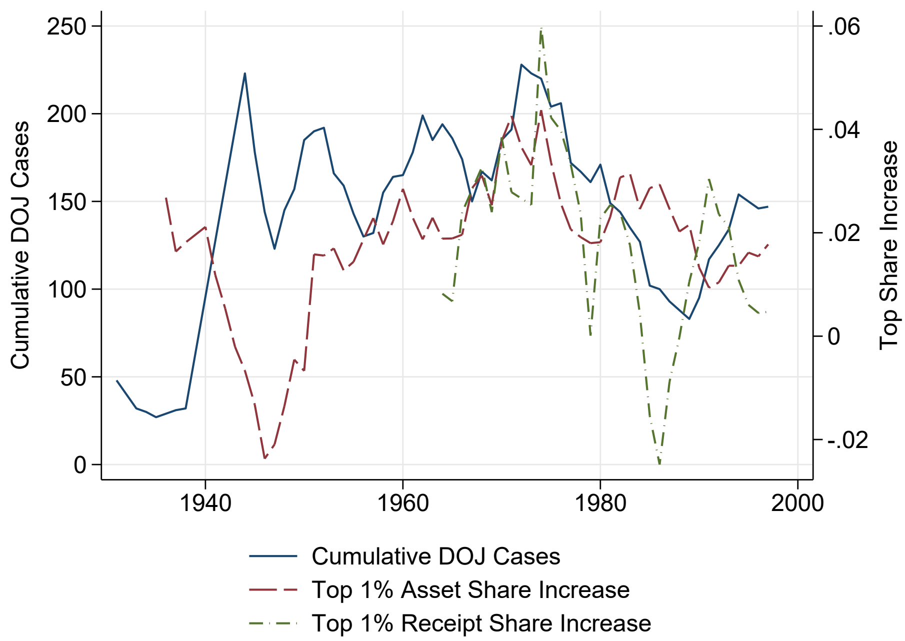
Figure 8: Antitrust Cases Instituted by the DOJ

Panel A shows the time series of antitrust cases institute by the DOJ. Panel B shows the cumulative DOJ cases over the past five years and changes in aggregate top 1% shares.

Panel A. Time Series of DOJ Cases



Panel B. DOJ Cases and Changes in Concentration



concentration trends throughout the past 100 years. However, it is possible that changes in antitrust policies could have had stronger effects on concentration in certain time periods (Philippon, 2019; Covarrubias, Gutiérrez and Philippon, 2020).

Finally, we do not focus on analyzing mergers as mergers arise for a number of reasons, including both economies of scale and anti-competitive motives. In addition, Holmstrom and Kaplan (2001) collect data on merger volume as a percentage of GDP from 1968 to 1999 and do not find a strong trend over these decades.

5 Conclusion

We collect historical data on the size distribution of corporate businesses in the U.S. and document that corporate concentration (i.e., shares of top 1% or top 0.1% businesses) has been rising persistently for nearly 100 years. The rise was more pronounced in manufacturing in earlier decades and more pronounced 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 the investment intensity in IT and R&D. In addition, 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). Accordingly, our evidence suggests that larger companies contributing to an increasingly higher share of the economy is a general phenomenon; this general rise of corporate concentration is 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, 2020), but the evidence suggests that economies of scale is important for understanding the long-run development of the U.S. economy.

An intriguing question is whether rising corporate concentration will inevitably persist in the future. Will economies of scale increase perpetually? Understanding this question requires more insights about whether ongoing developments in technology 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 function may provide knowledge that can guide our outlook for the decades to come.

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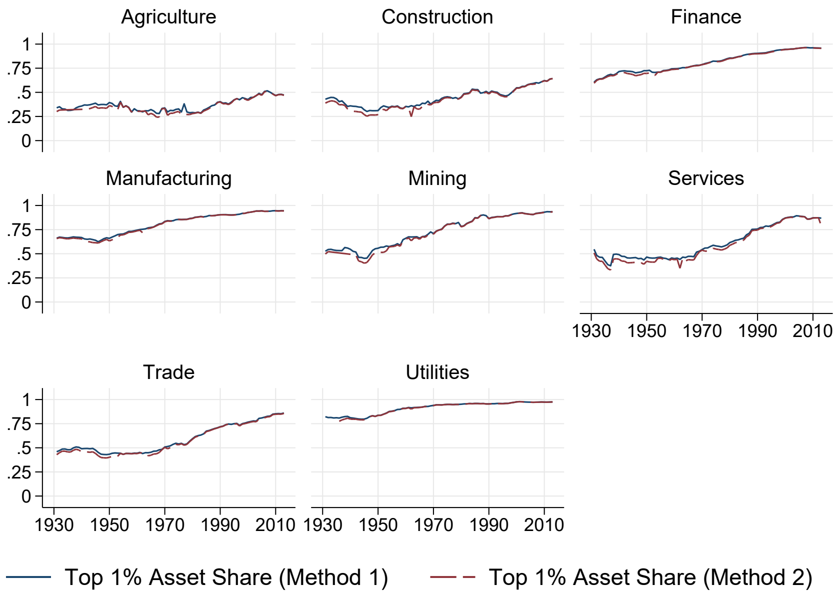
Internet Appendix

IA1 Appendix 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 a Pareto distribution (method 1). The dashed red line shows the results of adding up top brackets directly (method 2).

Panel A. Main Sectors



Panel B. Subsectors

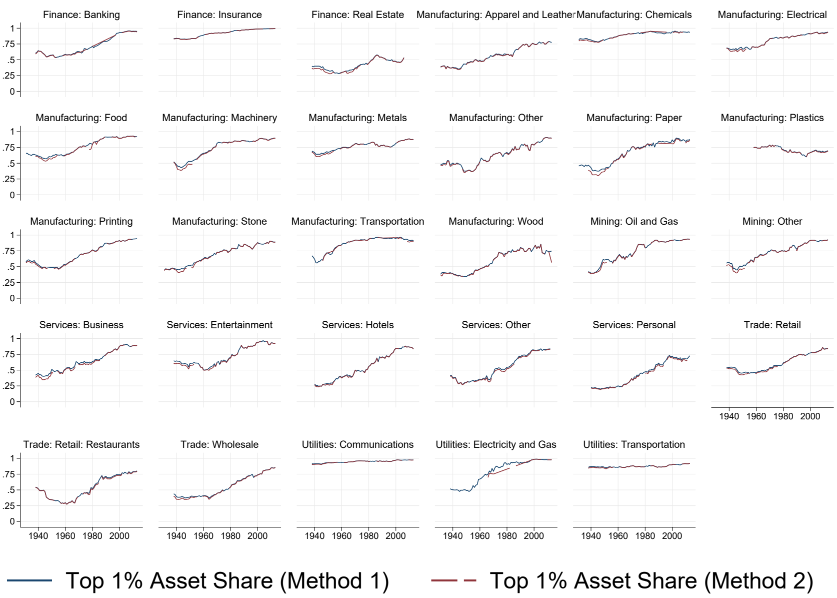


Figure IA2: Share of Corporate Businesses in Aggregate Business Receipts

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

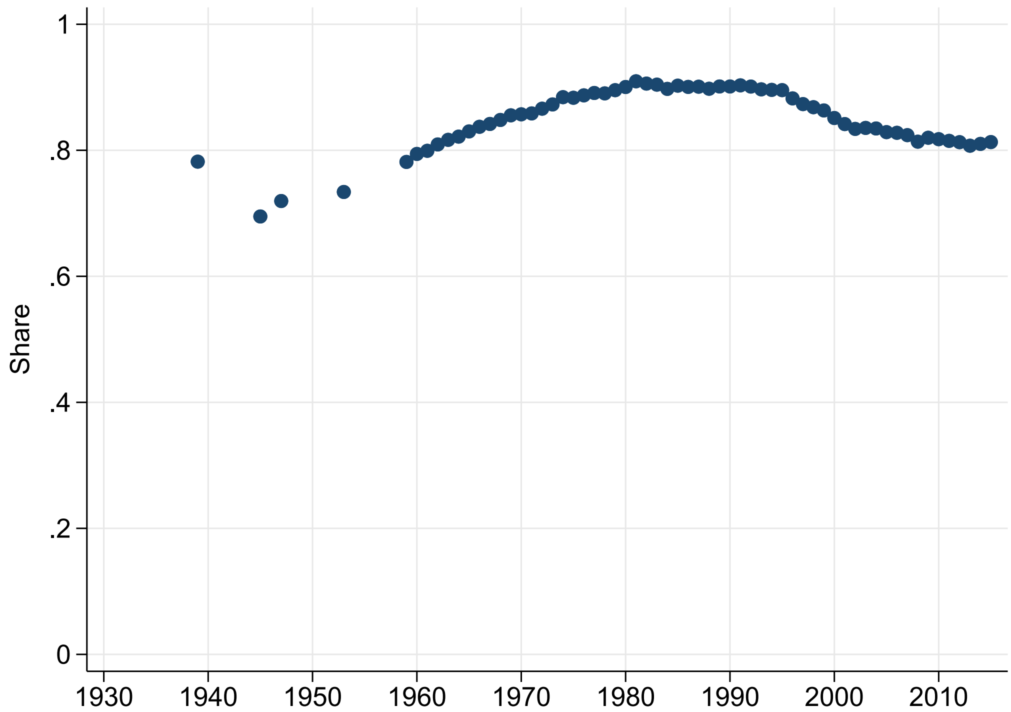


Figure IA3: Top 0.1% Receipt Share: Including Noncorporate Businesses

This figure shows robustness checks for top businesses' shares including noncorporate businesses. The solid blue line shows the receipt share of top 0.1% corporates by receipts among all corporate businesses. The dashed red line shows the receipt share of top 0.1% businesses among both corporate and noncorporate businesses, where we assume that 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. We have to assume that the top businesses are all corporates because we only have consistent information about the total receipts of noncorporate businesses each year (not tabulations by size bins).

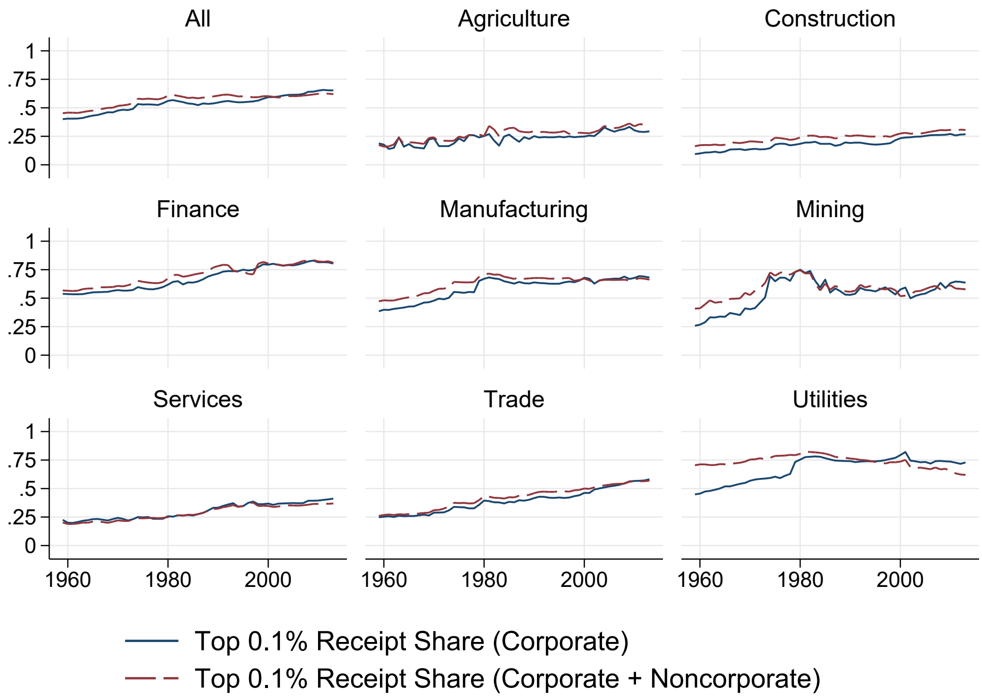
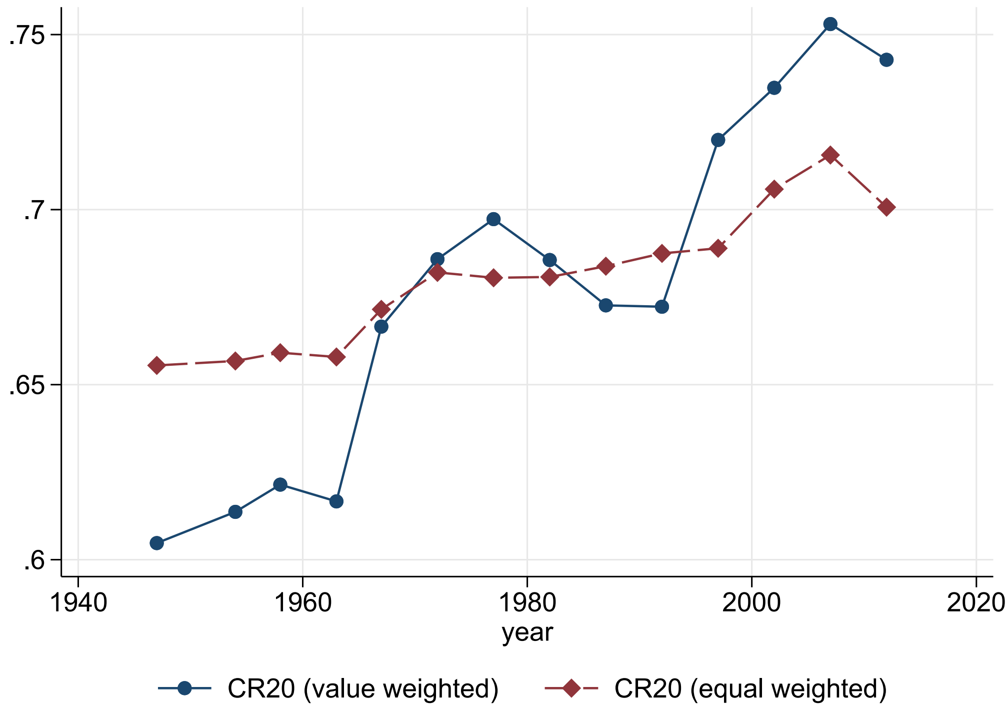


Figure IA4: Concentration Ratios in Manufacturing Census

This figure shows value-weighted average (solid blue line with circles) and equal-weighted average (dashed red line with diamonds) concentration ratios in the Manufacturing Census. Panel A shows CR20 and Panel B shows CR8. The data used four-digit SIC industries until 1992 and six-digit NAICS industries after 1997.

Panel A. CR20



Panel B. CR8

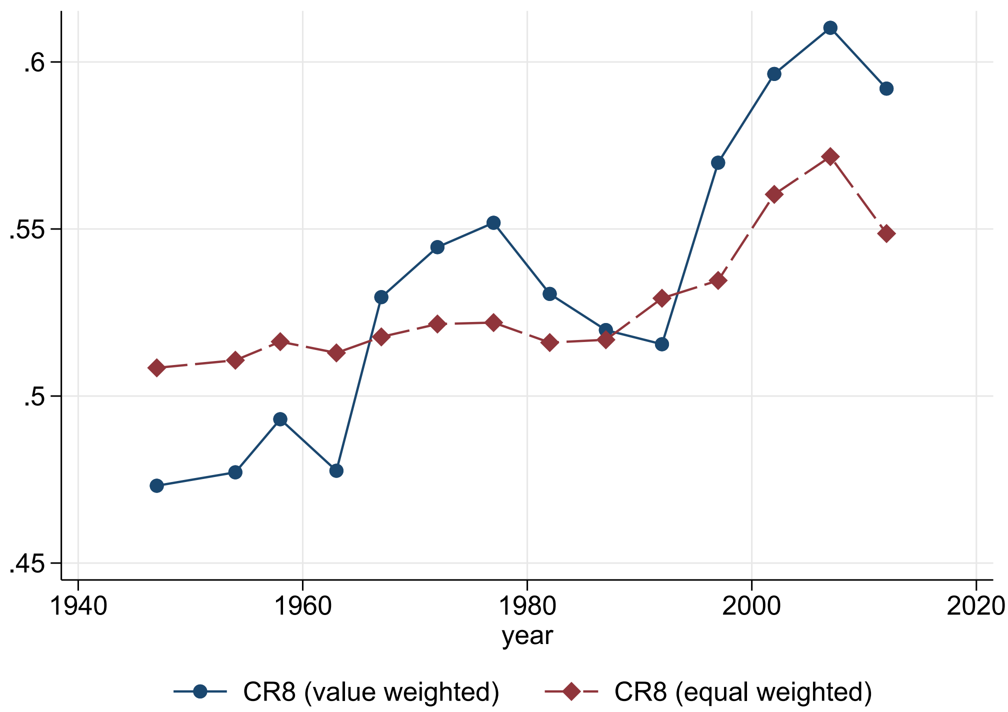
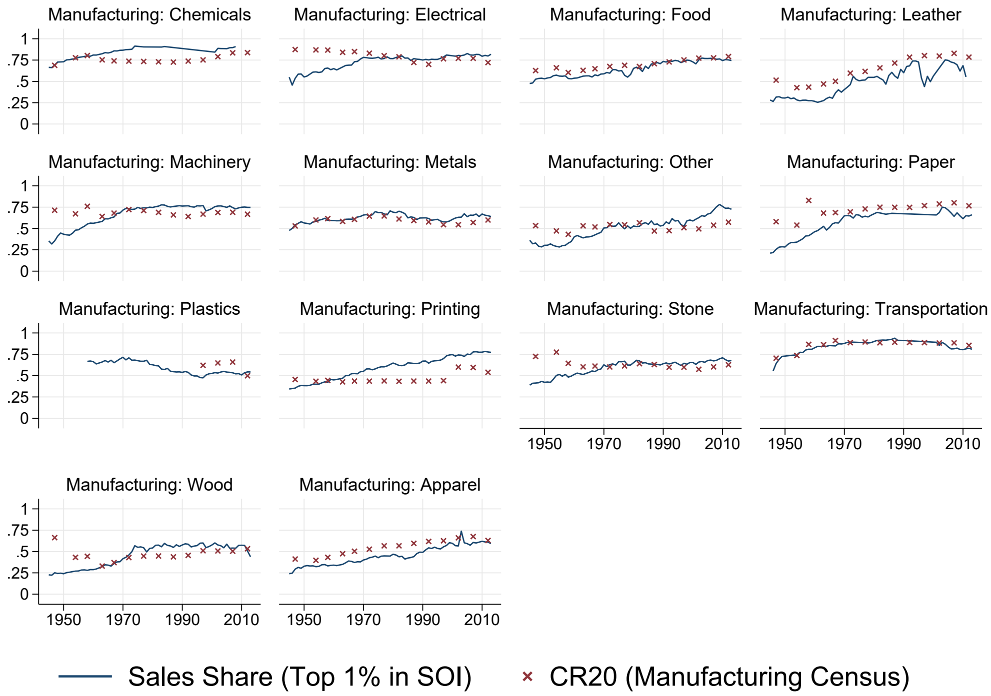


Figure IA5: Concentration in Manufacturing Census and SOI

This figure shows concentration ratios for each manufacturing subsector. The solid blue line shows the sales shares of top 1% corporate businesses (ranked by total assets) in each manufacturing subsector from the SOI. The red crosses show the value-weighted average of CR20 (Panel A) and CR8 (Panel B) in each subsector from the Manufacturing Census.

Panel A. Comparison with CR20



Panel B. Comparison with CR8

Figure IA6: 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 top 1% and bottom 99% businesses according to their domestic asset shares (using SOI data).

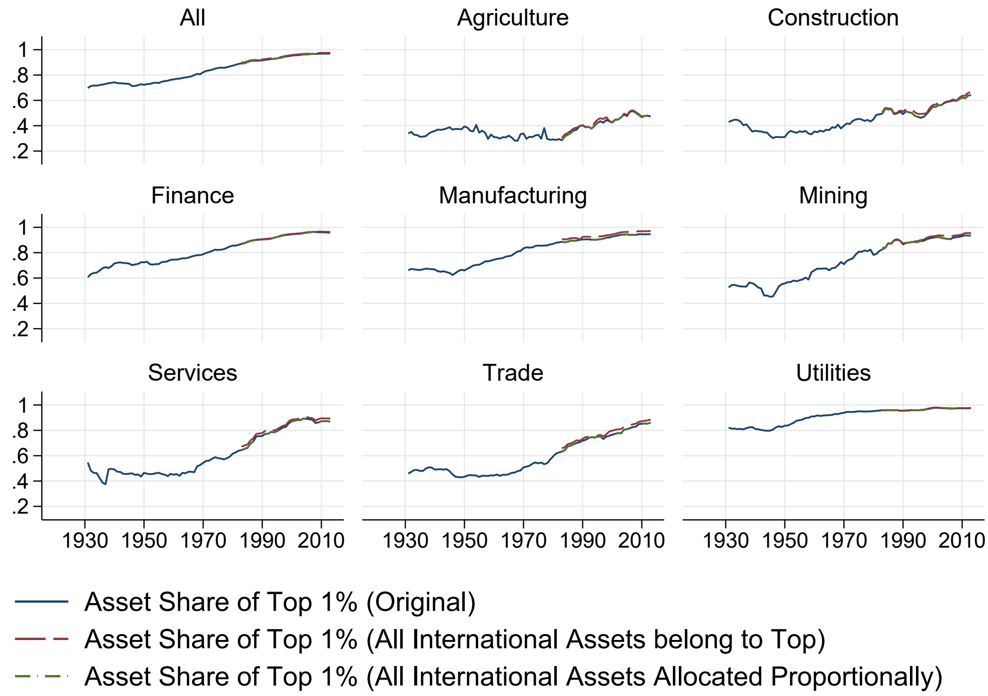


Figure IA7: Profitability in SOI and BEA

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 IA8: 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 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.

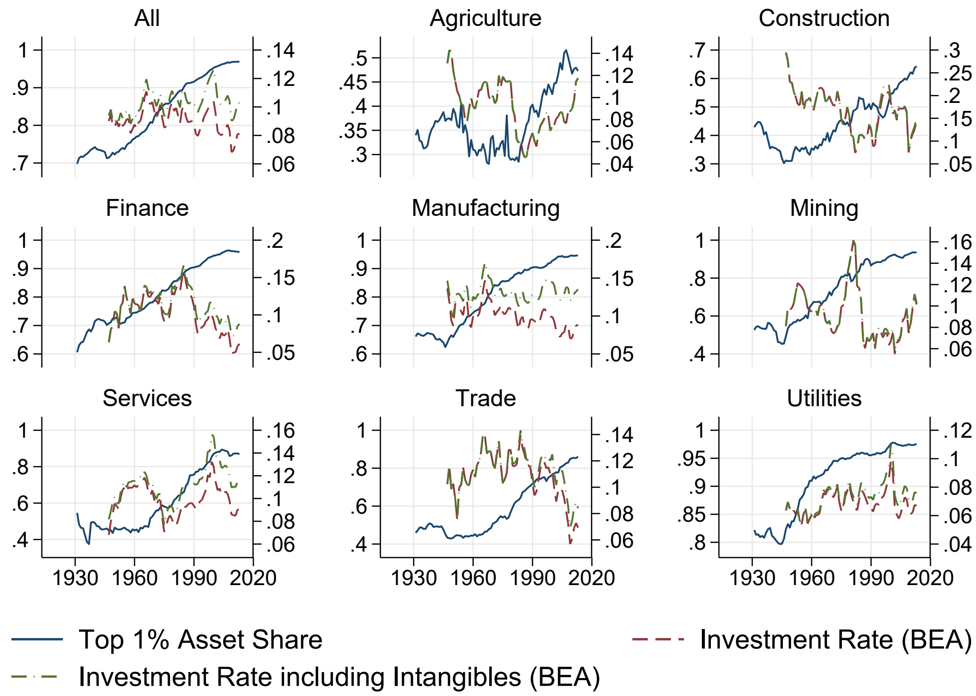
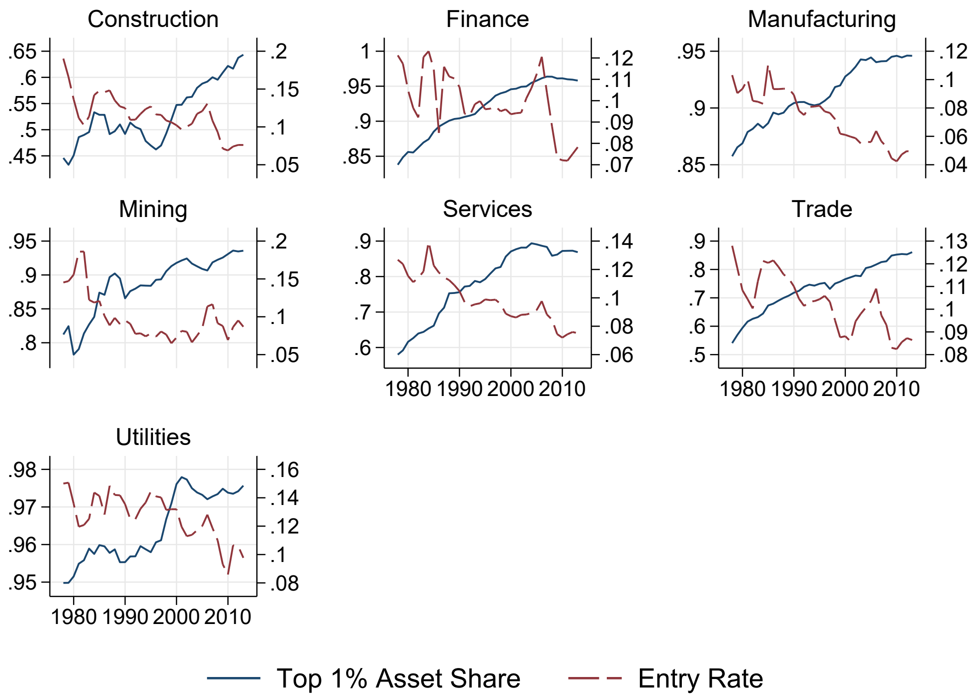


Figure IA9: Entry Rate

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 top 1% corporate businesses by asset size from SOI. The left axis is changes in top 1% asset share, and the right axis is changes in industry entry rates.

Panel A. Main Sectors



Panel B. Subsectors

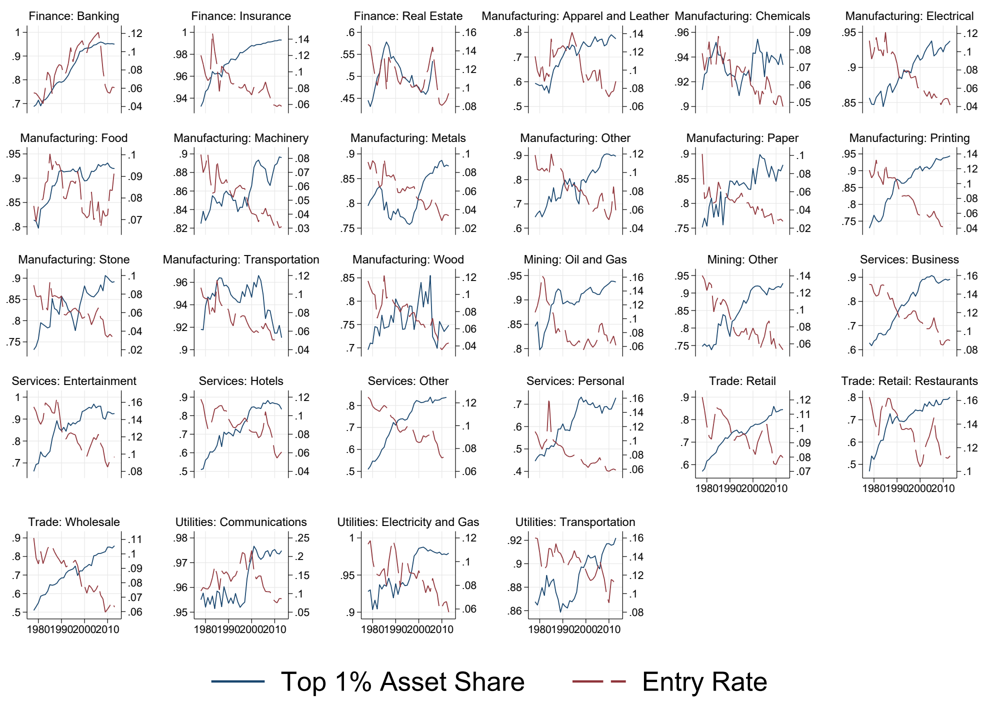
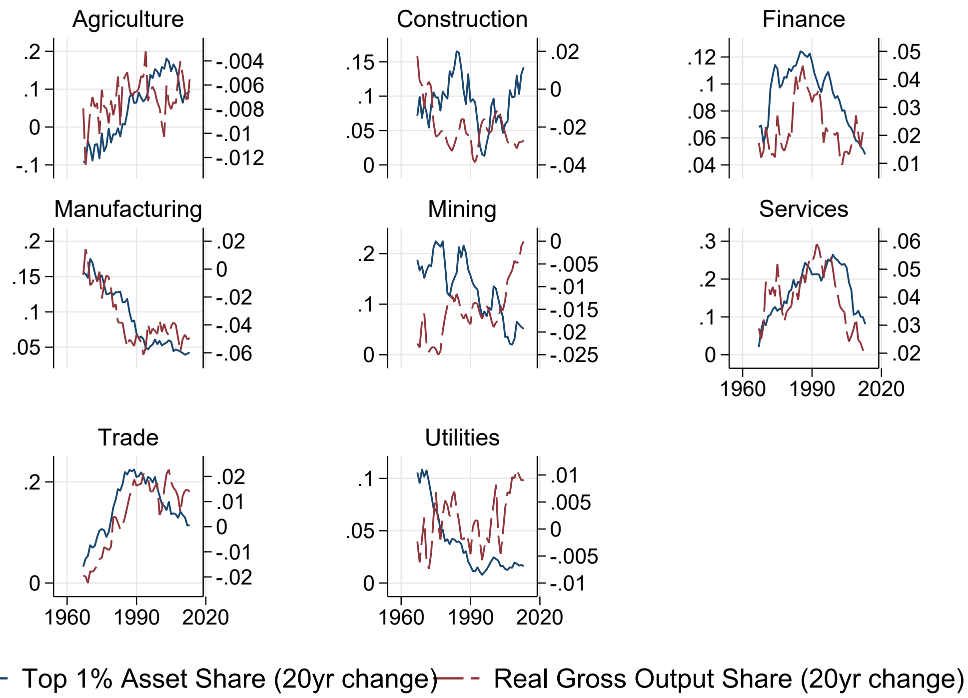


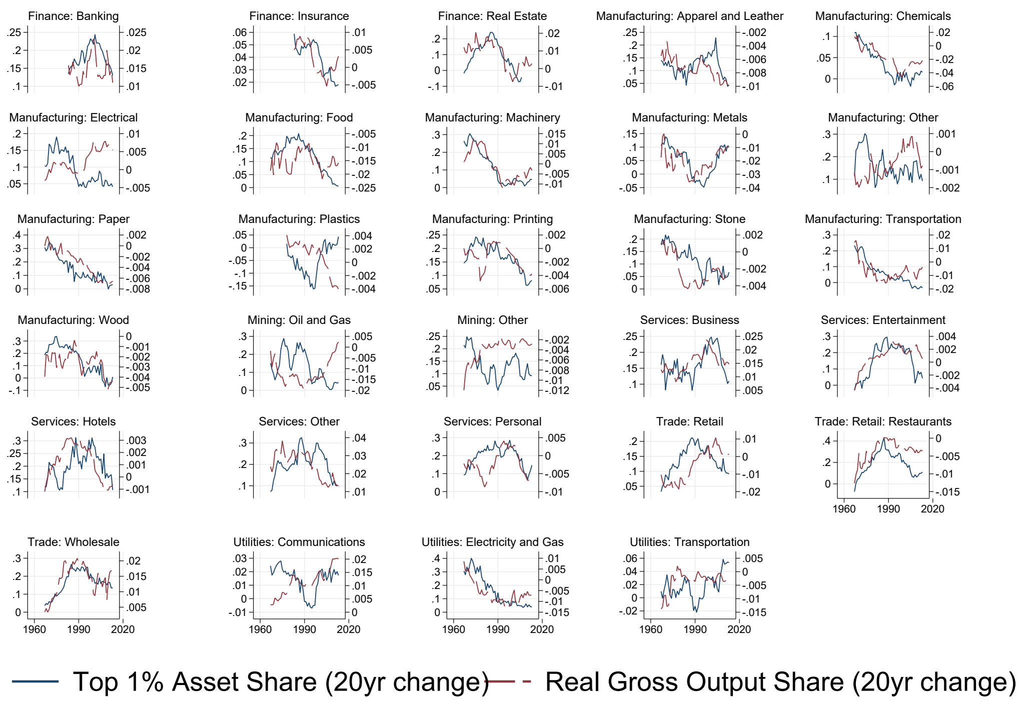
Figure IA10: Concentration and Industry Output Share

This figure shows changes in 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



IA2 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, and 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 brackets. Therefore, the transition to sample data should not be accompanied by large effects on corporate concentration.

Finally, 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. For example, in 1934 about 12 percent of tax returns representing 2.5 percent of total receipts did not include a balance sheet. 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 SOI asset bin tabulations could affect the number of businesses in our calculations (for the asset share of top businesses). We can provide robustness checks by either assuming that the businesses with missing balance sheet information fall in the smallest asset size bin, or using information on their receipts to impute which asset size bins they belong to (assuming they have the same assets-to-receipts ratios as the industry as a whole).

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 to classify industries. 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 IA1, 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 main analyses 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).

Bracket 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 or the minor industry 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 bracket structure (similar in spirit to Eckert, Fort, Schott and Yang, 2020). In later years, additional precautions have been introduced by the IRS to preserve taxpayer confidentiality by deleting information from additional size and industry brackets whenever necessary. In these cases, we join the deleted brackets (and all brackets in between) into one large bracket, and back out the financial data using the difference of the total and all other brackets. While this approach generally works very well and does not create problems for the calculation of concentration indices, in a handful of cases the number of size brackets 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 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 and Figure IA7 shows 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 key outcomes we study.

Consolidation. The IRS allows corporations to file consolidated returns if at least 80 percent of the equity of each 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).

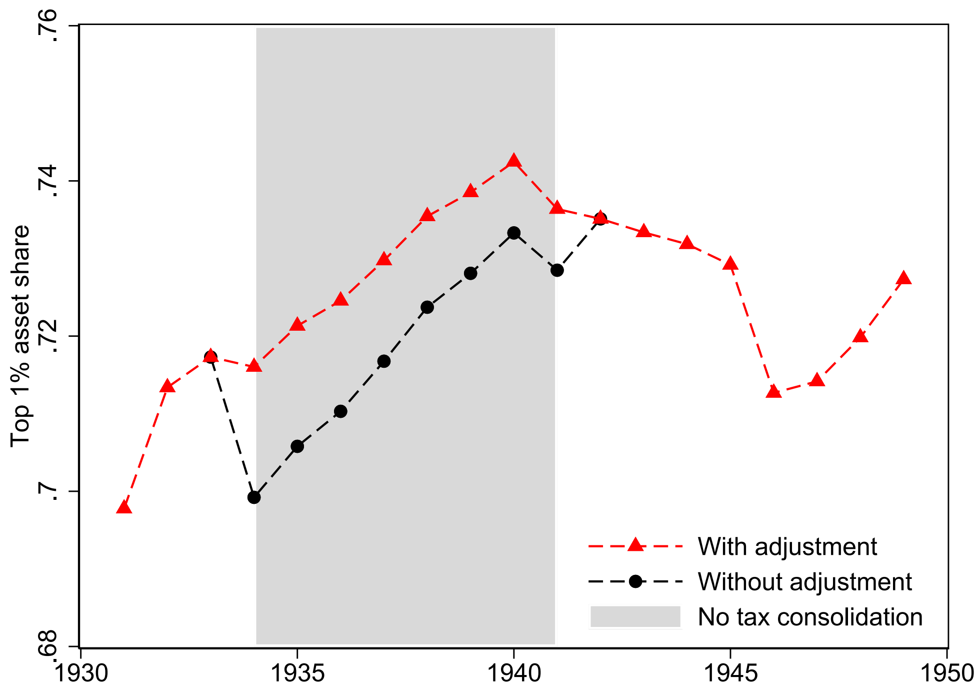
Rules on consolidation for tax purposes have had several changes over time. Streuling (1971) offers a detailed discussion of the various Revenue Acts that led to the changes. First, the 80% ownership requirement applicable today dates back to 1954. Prior to 1954, the ownership threshold was 95%. Second, 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 IA11), its effects in sectors with many consolidated returns (particularly Utilities and Manufacturing: Chemicals) were more sizeable.

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 IA11. The black dashed line shows 1% asset shares without adjustment and the red dashed line shows the adjusted series.

Figure IA11: Consolidation Adjustment

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



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 returns in total returns using information about consolidated returns in the SOI. Figure IA12 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 early 1930s and 1940s. Then the prevalence of consolidated returns increased from mid-1960s to 1980s, roughly returning to the prevalence of consolidated returns in early 1930s. Meanwhile, top 1% asset shares were much higher in 1980s relative to 1930s. After 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 IA13. 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 3 to 6); these time fixed effects should absorb the impact of changes in consolidation rules which apply to all industries.

Figure IA12: 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.

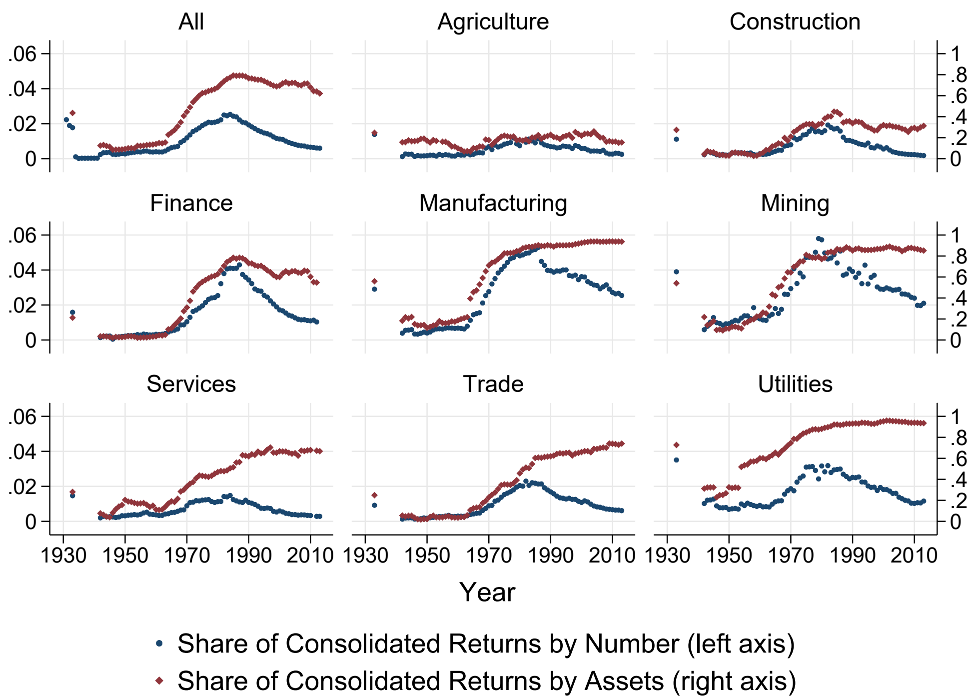


Figure IA13: Top 1% Asset Shares under Different Consolidation Rules

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.

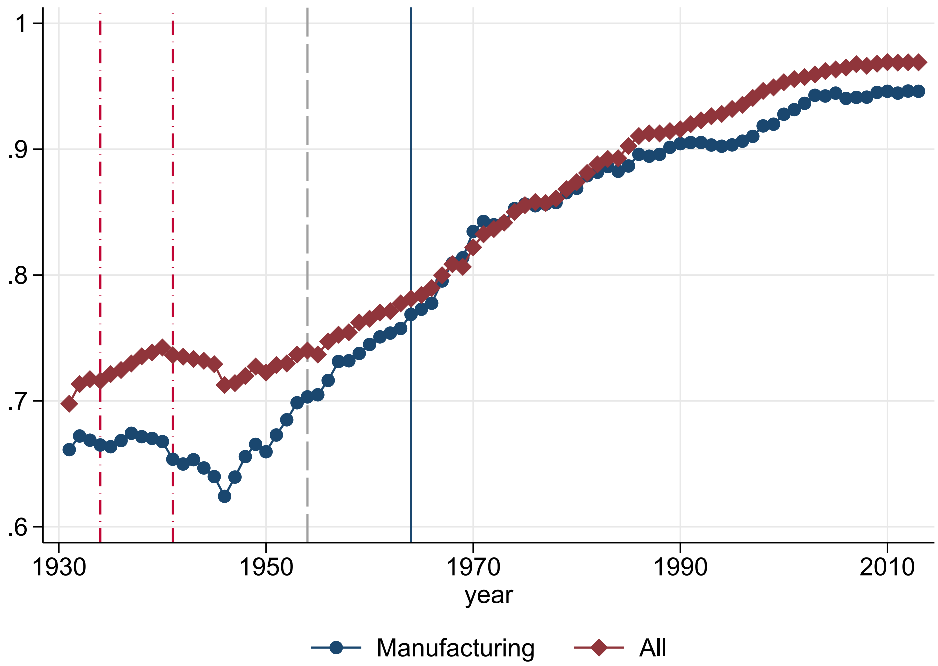


Table IA1: Industry Harmonization of SOI Data

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

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 IA2. We drop 5210 Federal Reserve Banks in BEA fixed asset tables.

Industry output from national accounts. We also use industry value added and gross output from the BEA. Tables IA3 and IA4 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 IA2: 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 IA3: 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 IA4: 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: Technology and Concentration

In this section, we provide a stylized model that illustrates how technologies with economies of scale can generate the empirical facts we observe (about concentration, output, and profitability). Following the spirit of Hsieh and Rossi-Hansberg (2021), we consider the existence of a traditional technology and the introduction of a new technology that decreases marginal costs but requires greater upfront investment. We show that technological improvement of this form will increase concentration and industry output. In addition, by allowing markups to be exogenous (e.g., Covarrubias, Gutiérrez and Philippon (2020)), we clarify that the introduction of the new technology does not need to be accompanied by higher profitability.

IA3.1 Static Case

IA3.1.1 Setup

We assume a standard nested CES demand structure. In other words, an individual 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. Finally, 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 IA3.1.5 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 the idiosyncratic productivity, firms have three options:

1. **Exit immediately.**

2. **Operate with old technology:** Invest ϕ and operate with per-unit productivity a_i.

3. **Operate with new technology:** Invest $\Phi(h)$ and operate with lower per-unit costs and therefore higher per-unit productivity $A(a_i, h)$.

This approach of 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 (2021). 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.[15]

The parameter $h \geq 1$ is an index of technological innovation. We examine the impact of technological innovation on 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 a) $\Phi(h) \geq h$: 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 $\Phi'(h), \frac{\partial A}{\partial h} > 0$: the greater the technological innovation, the greater the required upfront investment as well as the productivity boost. 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:

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

IA3.1.2 Assumptions

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 1 (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 2 (Free entry). *The entry cost is equal to the ex ante expected net present value of the firm:*

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

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

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

IA3.1.3 Solution

Under the above assumptions, one can derive the following expression for Π and Π':

$$\begin{aligned}\Pi(a_i) &= \frac{R}{R-1} \cdot \frac{\mu}{(1+\mu)^\sigma} Y_k \cdot P_k^\sigma a_i^{\sigma-1} - \phi, \\ \Pi'(a_i) &= \frac{R}{R-1} \cdot \frac{\mu}{(1+\mu)^\sigma} Y_k \cdot P_k^\sigma (h \cdot a_i)^{\sigma-1} - \phi \cdot h^\eta.\end{aligned} \tag{IA5}$$

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

$$\begin{aligned}\Pi(a_i^*) = 0 &\iff \phi = \frac{R}{R-1} \frac{\mu}{(1+\mu)^\sigma} Y_k \cdot P_k^\sigma (a_i^*)^{\sigma-1}, \\ \Pi(a_i^{**}) = \Pi'(a_i^{**}) &\iff a^{**} = \left(\frac{h^\eta - 1}{h^{\sigma-1} - 1} \right)^{1/(\sigma-1)} a^*.\end{aligned} \tag{IA6}$$

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

$$A^* = \left(\int_{a^*}^{a^{**}} a^{\sigma-1} dF^*(a) + h^{\sigma-1} \int_{a^{**}}^{\infty} a^{\sigma-1} dF^*(a) \right)^{\frac{1}{\sigma-1}}. \tag{IA7}$$ [16]

Then,

$$S_t(a_i) = \begin{cases} \left(\frac{a_i}{A^*}\right)^{\sigma-1} \frac{P_k \cdot Y_k}{N_k} & a^* \leq a_i \leq a^{**}, \\ \left(\frac{h \cdot a_i}{A^*}\right)^{\sigma-1} \frac{(P_k \cdot Y_k)}{N_k} & a^{**} \leq a_i. \end{cases} \tag{IA8}$$

[16] 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.

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.

Particularly, Proposition 2 implies that profitability can be distinct from how technological innovation affects concentration.

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 top 1% firms in total sales. For simplicity, we assume that the parameters are such that the top 1% of firms all belong to the group of firms that operate with the new technology.[17]

Then, the concentration measure is given by:

$$\zeta_{sales} = \frac{h^{\sigma-1} \int_{\alpha a^*}^{\infty} a_i^{\sigma-1} dF^*(a)}{\int_{a^*}^{a^{**}} a_i^{\sigma-1} dF(a) + h^{\sigma-1} \int_{a^{**}}^{\infty} a_i^{\sigma-1} dF^*(a)}, \tag{IA9}$$

where α is a constant that only depends on the Pareto parameter k, so the numerator has the top 1% firms. Note that for aggregate sales to be finite, we need $k > \sigma - 1$. The concentration ratio takes the following simple functional form:

Proposition 3. *The concentration ratio (top 1% sales share) is given by:*

$$\zeta_{sales} = C \cdot \frac{h^{\sigma-1}}{1 + (h^{\sigma-1} - 1)^{\frac{k}{\sigma-1}} (h^{\eta} - 1)^{1-\frac{k}{\sigma-1}}}, \tag{IA10}$$

where C is a constant independent of h.

IA3.1.4 Comparative Statics

We examine the effect of technological innovation by considering a marginal increase in h from 1 (where the two technologies coincide) to $h > 1$. By taking the comparative statics of Equation (IA10) and Proposition 2, we obtain the following result.

Proposition 4. *A rise in h (technological improvement) leads to greater industry concentration, as measured by the top 1% sales share. On the other hand, there is no change in the per-period profitability $\tilde{\pi}$, which depends on the exogenous markups μ.*

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

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

Proposition 5. *Assume $\sigma > \epsilon > 1$ (the cross-industry elasticity is weaker than the within-industry elasticity) and $\eta > \sigma - 1$ is sufficiently small.*[18] *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 improvement results in higher concentration as firms that use the new technology increase their output relative to other firms. Industry output also increases. Meanwhile, by separating out an exogenous markup μ (which can be shaped by a variety of forces), the model clarifies that technological improvement is not necessarily accompanied by changes in profitability.

IA3.1.5 Details and Proofs

A. 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:

$$Y_k^{\frac{\sigma-1}{\sigma}} = \int_0^{N_k} y_{i,k}^{\frac{\sigma-1}{\sigma}} di. \tag{IA11}$$

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

$$\bar{Y} = \int_0^1 Y_k^{\frac{\epsilon-1}{\epsilon}} dk. \tag{IA12}$$

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

$$P_k^{1-\sigma} = \int_0^{N_k} Y_{k,t} \left(\frac{p_{i,k}}{P_k}\right)^{-\sigma}, \tag{IA13}$$

[18] Alternatively, one can assume that h is sufficiently small, i.e., the technological improvement is sufficiently marginal.

and an aggregate price index:

$$\bar{P}^{1-\epsilon} = \int_0^1 P_{k,t}^{1-\epsilon} dk. \tag{IA14}$$

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

$$\begin{aligned} Y_k &= \bar{Y}\left(\frac{P_k}{\bar{P}}\right)^{-\epsilon}, \\ y_{i,k} &= Y_{k,t}\left(\frac{p_{i,k}}{P_k}\right)^{-\sigma}. \end{aligned} \tag{IA15}$$

B. Proofs

Proof of Proposition 4

To show that Equation (IA10) 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. This means that $D = \left(\frac{a^{**}}{a^*}\right)^{(\sigma-1)-k}$ is a) smaller than 1 and b) decreasing in h. Set $H = h^{\sigma-1} - 1$. It suffices to show $Conc(H) = \frac{H+1}{1+HD(H)}$ is increasing in H. Differentiation yields that $dConc(H)/dH > 0 \iff 1 + HD(H) - (H+1)(D(H) + HD'(H)) = 1 - D(H) - HD'(H) > 0$. As we showed that $D(H) < 1$ and $D'(H) < 0$, so this is satisfied.

Proof of Proposition 5

The three equations are given as follows:

$$\begin{aligned} \phi &= \frac{\mu}{1+\mu} \cdot \left(\frac{a^*}{A^*}\right)^{\sigma-1} \frac{P_k Y_k}{N_k}, \\ P_k &= \frac{1+\mu}{N^{\frac{1}{\sigma-1}}} \frac{1}{A^*} \\ \frac{\kappa}{\phi}, &= (1 - F(a^*))\left(\left(\frac{A^*}{a^*}\right)^{\sigma-1} - 1\right). \end{aligned} \tag{IA16}$$

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. We are a change in h (technological improvement) with everything else constant. Note that:

$$P_k Y_k \propto P_k^{1-\epsilon}. \tag{IA17}$$

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

$$C = \frac{\mu}{(1+\mu)^\sigma}(a^*)^{\sigma-1} P_k^{\sigma-\epsilon}, \tag{IA18}$$

where C is constant. Given our assumption $\sigma > \epsilon$, it suffices to show that a^* is rising with

h, which we will show using the third equation. Holding everything constant, we have that a^* rises if and only if $\frac{A^*}{a^*}$ rises with h.

We can compute:

$$(A^*)^{\sigma-1} = \int_{a^*}^{\infty} a^{\sigma-1} dF^*(a) + (h^{\sigma-1} - 1) \int_{a^{**}}^{\infty} a^{\sigma-1} dF^*(a)$$
$$= E_*[a^{\sigma-1}] \cdot \left(1 + (h^{\sigma-1} - 1)\left(\frac{a^{**}}{a^*}\right)^{(\sigma-1)-k}\right), \tag{IA19}$$

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:

$$a^{**}/a^* = \left(\frac{h^{\eta} - 1}{h^{\sigma-1} - 1}\right)^{\frac{1}{\sigma-1}}, \tag{IA20}$$

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

$$(h^{\eta} - 1)^{1-\frac{k}{\sigma-1}} (h^{\sigma-1} - 1)^{\frac{k}{\sigma-1}}, \tag{IA21}$$

with the log-derivative given by:

$$\left(1 - \frac{k}{\sigma - 1}\right) \frac{\eta \cdot h^{\eta-1}}{h^{\eta} - 1} + \frac{k}{\sigma - 1} \frac{(\sigma - 1)h^{\sigma-2}}{h^{\sigma-1} - 1}. \tag{IA22}$$

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 (IA22) 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 (IA22) converges to:

$$\frac{(\sigma - 1)h^{\sigma-1}}{h^{\sigma-1} - 1} > 0, \tag{IA23}$$

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:

$$y_{i,t} = Y \cdot \left(\frac{p_{i,t}}{P_t}\right)^{-\sigma}, \tag{IA24}$$

where $P^{1-\sigma} = \int_0^N p_i^{1-\sigma} di$ and N is the mass of operating firms.

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).[19] 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.[20] We assume these firms have idiosyncratic productivity a_i drawn from F_t, which we assume to be fixed to the firm.

Again, as before, we assume that firms employ an exogenous markup μ. This implies that the per-period profit of a firm with idiosyncratic productivity a_i operating under a technology A_s at time t is given by:

$$\pi_{i,t}(a, s) = \frac{\mu}{(1+\mu)^{\sigma}} Y \cdot P_t^{\sigma} A_s(a_i)^{\sigma-1} - f_s. \tag{IA25}$$

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:

$$P_t^{1-\sigma} = \sum_{s\leq t} N_{t,s} \cdot \int \left(\frac{1+\mu}{A_s(a)}\right)^{1-\sigma} dF_{t,s}(a). \tag{IA26}$$

If we continue to set $\bar{Y} = Y P_t$ (industry aggregate remains constant), then we have the

[19] This functional 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 this remains the case if both adopt the new technology. This simplification rules out technological leap-frogging.

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

following simplification. Combining the previous two equations, we obtain:

$$\begin{aligned}\pi_t(a,s) &= \frac{\mu}{1+\mu}\frac{\bar{Y}}{N_t}\left(\frac{A_s(a)}{A_t^*}\right)^{\sigma-1} - f_s,\\ Sales_t(a,s) &= \left(\frac{A_s(a)}{A_t^*}\right)^{\sigma-1}\frac{\bar{Y}}{N_t},\end{aligned} \tag{IA27}$$

where

$$A_t^* = \left(\sum_{s\leq t}\frac{N_{t,s}}{N_t}\int A_s^{\sigma-1}(a)dF_{t,s}(a)\right)^{\frac{1}{\sigma-1}}. \tag{IA28}$$

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 provide an illustration using the following case: $A_t(a_i) = h^t \cdot a_i$, 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 numerical 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:

$$\frac{\mu}{1+\mu}\frac{\bar{Y}}{\Psi_t}\cdot(h^s a)^{\sigma-1} - f. \tag{IA29}$$

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

$$\frac{\mu}{1+\mu}\frac{\bar{Y}}{\Psi_t}\cdot(h^t a)^{\sigma-1} - f - \phi\cdot h^{\eta\cdot t}. \tag{IA30}$$

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

$$\begin{aligned} &\max\left\{\frac{\mu}{1+\mu}\frac{\bar{Y}}{\Psi_t}\cdot(h^t a)^{\sigma-1} - f - \phi\cdot h^{\eta\cdot t}, \frac{\mu}{1+\mu}\frac{\bar{Y}}{\Psi_t}\cdot(h^s a)^{\sigma-1} - f\right\} < 0 \\ \iff\ & a < \left(\frac{1+\mu}{\mu}\frac{\Psi_t}{\bar{Y}}\right)^{\frac{1}{\sigma-1}} \min\left\{(f+\phi\cdot h^{\eta t})^{\frac{1}{\sigma-1}} h^{-t}, f^{\frac{1}{\sigma-1}}\cdot h^{-s}\right\} = \beta_{t,s}. \end{aligned} \tag{IA31}$$

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

$$\begin{aligned} &\frac{\mu}{1+\mu}\frac{\bar{Y}}{\Psi_t}\cdot(h^t a)^{\sigma-1} - f - \phi\cdot h^{\eta\cdot t} > \frac{\mu}{1+\mu}\frac{\bar{Y}}{\Psi_t}\cdot(h^s a)^{\sigma-1} - f \\ \iff\ & a > \left(\frac{1+\mu}{\mu}\frac{\Psi_t}{\bar{Y}}\right)^{\frac{1}{\sigma-1}}\cdot\left(\phi\cdot\frac{h^{\eta t}}{h^{t(\sigma-1)} - h^{s(\sigma-1)}}\right)^{\frac{1}{\sigma-1}} = \gamma_{t,s}. \end{aligned} \tag{IA32}$$

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, $T_{g,g} = (\alpha_g, \infty)$.[21] For a given value of Ψ_t, we have:

$$\alpha_t = \left(\frac{1+\mu}{\mu}\frac{\Psi_t}{\bar{Y}}\left(f+\phi\cdot h^{\eta\cdot t}\right)\right)^{\frac{1}{\sigma-1}}\cdot h^{-t}. \tag{IA33}$$

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

$$\Psi_t = (A_t^*)^{\sigma-1}N_t = \sum_{g\le t}\frac{k}{k+1-\sigma}\alpha_g^k N_{g,g}\left(\sum_{g\le s\le t} h^{s(\sigma-1)}\sum_i\left((\ell_{g,s}^i)^{-(k+1-\sigma)} - (u_{g,s}^i)^{-(k+1-\sigma)}\right)\right) \tag{IA34}$$

Definition 1. *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:*

$$\begin{aligned} T_{g,s}^t &= \left(T_{g,s}^{t-1}\cap(\beta_{t,s},\infty)\right)\cap(0,\gamma_{t,s}) \text{ for } g,s<t \\ T_{g,t}^t &= \left(T_{g,s}^{t-1}\cap(\beta_{t,s},\infty)\right)\cap(\gamma_{t,s},\infty) \text{ for } g<t \\ T_{t,t}^t &= (\alpha_t,\infty), \end{aligned} \tag{IA35}$$

where $\beta_{t,s}$*,* $\gamma_{t,s}$*, and* $\alpha_{t,s}$ *are given by Equations (IA31), (IA32), and (IA33), with* Ψ_t *conditional on* $T_{g,s}^t$ *given by Equation (IA34).*

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

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

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

$$\begin{aligned}\Psi_1 &= \bar{N}\frac{k}{k+1-\sigma}h^{\sigma-1}\alpha_1^{\sigma-1} \\ \alpha_1^{\sigma-1} &= \frac{1+\mu}{\mu}\frac{\Psi_t}{\bar{Y}}(f+\phi h^{\eta})h^{-(\sigma-1)},\end{aligned} \tag{IA36}$$

which implies:

$$\bar{N}_1 = \frac{k+1-\sigma}{k}\frac{\mu}{1+\mu}\frac{\bar{Y}}{f+\phi h^{\eta}}, \tag{IA37}$$

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 (IA31) and (IA32).

      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 (IA33).

   (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 (IA34).

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 IA14 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.[22] 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.

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

Figure IA14: 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.