Superstar Firms through the Generations*

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Abstract

We study the landscape of the largest American companies over time. Among the top manufacturers today, in the 1950s, and in the 1910s, birth years always cluster around 1900, but the individual companies have changed. Among the top retailers and wholesalers today and in the past, the age distribution appears stationary. The data suggest that certain settings produce special generations of entrants that give rise to superstar firms for decades to come. We show that the persistent dominance of special cohorts cannot arise in a model with i.i.d. entrant draws. Instead, it can arise from the adoption of a new technology that exhibits higher returns to scale in the presence of learning by doing.

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1 Introduction

Production activities in the economy feature a substantial degree of skewness. The largest companies, sometimes referred to as "superstar firms," account for a considerable amount of output and play a major role in shaping macroeconomic outcomes (Berle and Means, 1932; Gabaix, 2011; Crouzet and Mehrotra, 2020; Autor et al., 2020; Braguinsky et al., 2023). Entrepreneurs often start their companies with the dream of building a superstar firm. Observers often wonder if they can succeed, or if the superstars tend to stay the same. Where do these superstar firms come from? Are new superstars born at the same pace over time? Is the dominance of existing superstars persistent over time?

Frameworks in economics imply different perspectives about the evolution of top firms. In one set of benchmark models, firms face idiosyncratic shocks and the lucky ones become superstars (Hopenhayn, 1992). The age distribution of superstars is stationary, and previous stars constantly get displaced. In another view, some generations of entrants may have a stronger edge (e.g., entrants during periods of major technological change), and capable early entrants may possess a lasting advantage (Jovanovic and Rousseau, 2005; Klepper, 1996). In this case, the superstars may remain the same, become older and older, until the next technological revolution. Understanding the profile of the superstar firms over time can shed light on the underlying economic mechanisms behind their eminence, and the extent to which earlier stars have been displaced by subsequent entrepreneurs.

In this paper, we collect information about the largest American companies in the present day and in the past. We document several facts about the superstar population. First, a special generation of firms have been prominent in manufacturing: the largest manufacturers today, as well as the largest in the mid-1900s and the early 1900s, were predominantly born around the turn of the 20th century. Accordingly, the largest manufacturers now are much older than those in the past. Second, even though the generation born around 1900 has remained prominent for a century, the particular companies have changed. Third, the picture appears quite different among the largest retailers and wholesalers, where the age distribution of the largest companies has been stable over time. Finally, few large services firms existed before the 1970s, and today's largest services firms were primarily born around the 1970s and 1980s. The services sector now has large firms that are very young, like the manufacturing sector in the early 20th century. Overall, the data suggest that occasionally a special generation of powerful entrants emerge, and such a cohort—though not necessarily the same companies—stand out for a long time. Meanwhile, in areas without these special cohorts, the age distribution of large firms appears stationary, and one generation gets constantly replaced by the next.

To trace out the identity of the largest American companies, we process the *Fortune* lists of top firms by sales revenue published since 1955. After 1995, the *Fortune* list covers the largest 1,000 companies by sales among all sectors. Before 1995, the main *Fortune* list covers the largest 500 industrial (i.e., manufacturing and mining) companies by sales; additional lists of top companies in other sectors are compiled on a more ad hoc basis. Top retailers (and wholesalers) have received relatively consistent coverage. In addition, there are sporadic tabulations of the largest companies in earlier time periods, such as the largest 500 industrials by assets in 1917 by Navin (1970). We then research the origin of each company. Whenever possible, we use information from company sources, such as websites, filings, and anniversary documents. Otherwise, we use historical documents or business history websites.

Among the top companies today (e.g., in 2018 as a recent example year before COVID), we observe substantial clustering of birth years around 1900 for industrials (mainly manufacturing with a few mining companies), and some clustering around the 1970s and 1980s for services as well as retail and wholesale. For top industrials, the cluster of birth years around 1900 turns out to be a persistent phenomenon. Among the largest industrials in 1955 (the first *Fortune* list) and those in 1917, birth years also cluster around 1900. Accordingly, the largest industrials now are much older than those in the past: for example, the median age among the largest industrials in 1955 is around 60, whereas that in 2018 is around 100.

For top retailers and wholesalers, those in the 1950s primarily date back to the late 19th century and the early 20th century (e.g., grocery chains and department stores), which have been displaced by discount retailers and specialty stores in recent years. After collecting additional data on the largest retailers and wholesalers in 1970 and in 1995, we confirm that the largest retailers and wholesalers have always stayed 60 to 70 years old on average. The stability of the age distribution of large retailers and wholesalers presents an interesting contrast with the continuously aging pattern of the largest industrials.

For top services companies, few very large ones existed before the 1970s and 1980s. Less than ten services firms appeared on historical *Fortune* tabulations of the largest non-industrial companies. The business size distribution data in Kwon, Ma, and Zimmermann (2024) also suggest that few services companies would qualify for the largest businesses in the economy until recently. Today, the large services firms were predominantly born around the 1960s to the 1980s. Therefore, the large services among *Fortune* 1,000 are fairly young, with a median age of 43. This pattern resembles the youth of the largest industrials in 1917. It is possible that the cohort of services firms born around the "Third Industrial Revolution" will follow a similar path of persistent dominance to the cohort of industrial firms born around the "Second Industrial Revolution," but it will require several more decades of time to verify whether this is the case.

For other sectors, the large companies in finance as well as transportation, communications, and utilities are fairly old on average, but their birth years do not display much clustering. Historical data on large firms in these sectors in previous decades are less consistently available, so we are less able to document how the large firms evolved over time in these domains.

Finally, even though the birth years of top industrials today and in the past many decades always cluster around the turn of the 20th century, the persistence of individual companies is not high. We perform a detailed comparison of the largest industrial firms (by sales) in the *Fortune* 1955 list and the *Fortune* 2018 list, to examine whether the same companies continue to prevail. First, we look at the fraction of the companies on the *Fortune* 1955 list that remain on the *Fortune* 2018 list. In this case, 21% of the companies on the *Fortune* 1955 list remain on the 2018 list, and the rank correlation is 0.39. Second, some of the companies on the *Fortune* 1955 list were subsequently acquired (e.g., Quaker Oats was acquired by PepsiCo). In this case, another 21% of the companies on the *Fortune* 1955 list "survived" on the *Fortune* 2018 list through their acquirers. Nonetheless, "survival" through acquirers may overstate the persistence since some firms were acquired following operating weakness (e.g., Union Carbide & Carbon was acquired by Dow Chemical following accidents and poor performance, National Steel Corporation was sold in bankruptcy to U.S. Steel). Furthermore, we look at the presence of "late bloomers" on the *Fortune* 2018 list. For example, for the 388 industrial firms among the *Fortune* 1,000 companies in 2018, 137 were born during the important era of the 1880s to the 1910s, but only 45 of them were among the top 388 industrial firms in 1955 (and another 17 were related to them through spinoffs or having acquired the top 1955 firms). The rest (and the majority) of this cohort on the *Fortune* 2018 list is represented by the "late bloomers."

A common question is whether the patterns among top firms are similar in other countries. From Chandler (1994), we are able to obtain the list of the largest 200 German industrial firms by assets in 1913 and 1953, and the largest 200 British industrial firms by market value of shares in the 1919 and 1948. We supplement these historical lists with their 2018 counterpart. Interestingly, the patterns among the largest German industrials are similar to those among the largest American industrials: they were very young in the early 20th century, and have become fairly old by 2018. The cohort from around 1900 continues to dominate. Meanwile, the largest British industrials behave quite differently: the age distribution looks rather stationary, and no particular cohort has lasting dominance. Curiously, these findings align with Chandler's remark that the German experience in the Second Industrial Revolution "is closer to that of the United States than to that of Britain." In his view, "in Germany as in the United States, but much more than in Britain, entrepreneurs did make the investment in production facilities and personnel large enough to exploit the economies of scale and scope" (Chandler, 1994).

We investigate firm dynamics models to understand the economic forces that can shape the empirical evidence we observe. We start with the canonical Hopenhayn (1992) model. In this benchmark model, superstars emerge from the good fortune of entrants who realize large permanent advantages at entry *and* accumulate large persistent advantages in productivity over their lifetime stemming from good luck and gains from learning. The permanent and persistent components of productivity generate a stationary hump-shaped age distribution of superstar firms. Very young firms are less represented as they have not had enough time to grow large, and very old firms are also less represented as they experience more attrition with age. This hump-shaped pattern in the benchmark model shows that we cannot use the clustering of birth years in a single cross section to detect special cohorts: such clustering of birth years could be just the natural hump in the age distribution among the top firms. Rather, we need to examine the birth years over time. If special cohorts exist, then the clustering of birth years will remain similar in calendar year for superstar firms at different points in time, and the age distribution of top firms will be non-stationary.

The stationary hump-shaped age distribution in the benchmark model can approximate the patterns we observe among large retailers and wholesalers. However, the benchmark model cannot match the evolution among the large industrials, where the cohort from the turn of the 20th century enjoys a lasting over-representation among the superstars many decades later. We also show that the benchmark model cannot match the key facts among the large industrials even with a period of rapid market size growth around 1900, which is one common intuition for what might make that era special. A period of rapid growth in market size creates more superstars, but these superstars are not persistent, and they die out a century later.

To introduce special cohorts into the model, we follow the narrative of Chandler (1994) and consider the adoption of a capital intensive modern technology that increases the returns to scale. In particular, the adoption cost of the capital intensive technology falls in the second half of the 19th century, and entrants can enjoy the lower adoption costs (whereas incumbents cannot due to their organizational rigidity). In addition, firms become more efficient over time through learning by doing. The capital intensive technology succeeds in seeding new superstar firms, but there is no special generation without learning by doing, as late adopters would be equally likely to enter the top firms. Productivity gains from additional experience, even when small, allow the early entrants to accumulate a lasting advantage over late adopters. We simulate the model with exponentially declining adoption costs for the modern technology starting in the mid-1800s, and obtain results that align with the empirical patterns among the large American industrials. Meanwhile, the absence of special cohorts among retailers and wholesalers can be due to the lack of high returns to scale technology, or the lack of learning by doing. The absence of special cohorts among British industrials can come from slower decline in the adoption cost of the modern technology, for example due to the insistence on family management according to Chandler (1994).

Overall, the presence of special cohorts implies that they have a particularly strong edge relative to both firms that came before and potential entrants afterwards.[1] In our model, the advantage of the special cohort relative to previous firms arises from declining adoption costs of the modern technology when this cohort entered. It could be that these entrants can seize the extraordinary opportunity while existing firms are less able to do so due to organizational rigidity (Christensen, 1997; Carroll and Hannan, 2000; Jovanovic, 2001; O'Reilly and Tushman, 2021); according to historical accounts, the emergence of large-scale production around 1900 required "new and improved processes of production developed for the first time in history," which were successfully implemented by entrants in U.S. and Germany but less so in Britain (Lamoreaux, 1988; Chandler, 1994). The advantage of the special cohort relative to subsequent cohorts comes from learning by doing. Firms' "learned capabilities" result from "solving problems of scaling up the processes of production, from acquiring knowledge of customers' needs and altering product and process to services needs, coming to know the availabilities of supplies and the reliability of suppliers, and in becoming knowledgeable in the ways of recruiting and training workers and managers" (Chandler, 1992). Levitt, List, and Syverson (2013) present empirical evidence of organizational learning. In a different setting, Ohyama, Braguinsky, and Murphy (2004) highlight the importance of learning in the adoption of modern technology for the Japanese cotton spinning industry. Our combination of technological change and learning by doing also echoes the work of Atkeson and Kehoe (2007), which uses these components to explain delayed productivity gains following the Second Industrial Revolution.

Will special generations for superstar firms emerge again? Will the cohort of services firms born in the 1970s/1980s stay dominant for a long time? Through the lenses of our model analyses, if new technologies emerge that exhibit high returns to scale, confer low adoption costs for new entrants, and require organizational learning, then "hysterisis" may occur among the top firms. The initial generation of entrants can have lasting staying power, although individual firms at the top can still shuffle substantially. The generation of services firms from the 1970s/1980s may satisfy these conditions, but it is also possible that the advantages from organizational learning are weaker in services than in industrials if production and distribution processes are less complicated in services.

Our work relates to three sets of literature. First, our study adds to the firm dynamics literature, which has provided many empirical and theoretical insights about the population of businesses both in steady state (Jovanovic, 1982; Hopenhayn, 1992; Klepper, 1996; Luttmer, 2010; Sterk, Sedláček, and Pugsley, 2021) and in response to business cycle shocks (Samaniego, 2008; Clementi and Palazzo, 2016; Lee and Mukoyama, 2018). We shed light on the evolution of the largest firms over a long period of time. The lasting influence of important cohorts, combined with the fluidity of individual companies at the top, presents

[1] In one extreme case, if entrants have no systematic edge over existing firms, then special cohorts will not exist. In another extreme case, if new technologies or business ideas are always implemented more effectively by new firms, then subsequent cohorts would continuously take over previous ones and special cohorts are also unlikely to exist.

an interesting picture. The presence of special cohorts in industrials, but not in retail and wholesale, is intriguing as well.[2] Analyses of cohort effects at the business cycle frequency find that companies born in recessions remain smaller than those born in booms (Moreira, 2016; Sedláček and Sterk, 2017). Some work postulates that periods of rapid technological and organizational change may create the most favorable opportunities for new entrants (Arrow, 1974; Jovanovic, 2001; Jovanovic and Rousseau, 2005; Bowen, Fresard, and Hoberg, 2023). Our findings resonate with this view, and our analyses shed light on the forces that can give rise to lasting cohort effects among top firms.[3]

Second, researchers and the general public have always been interested in the large companies in the economy (Berle and Means, 1932; Collins and Preston, 1961; Hannah, 1976; Prais and Reid, 1976; Autor et al., 2020). We provide new evidence about the generational effects among the largest companies in the U.S., U.K., and Germany, which requires collecting information about the large companies at different points over time. To our knowledge, two previous articles tabulated the overall age of *Fortune* 500 companies for 1995 (Harris, 1996) and 2009 (Stangler, 2009), and Luttmer (2011) examined the average age of companies with more than 10,000 employees in 2008. The persistence of individual companies among the *Fortune* lists has attracted abundant attention, and many articles have noted the constant shuffling among the top firms, with few companies remaining after several decades (Hannah, 1998; Louçã and Mendonça, 2002; Stangler and Arbesman, 2012). The persistence of special generations, combined with the displacement of individual companies, makes the story of superstar firms especially intriguing. The strong generational effects in some industries but not in others, combined with the similarity between American and German industrials, suggest that these patterns do not just result from economy-wide regulatory policies in the U.S. (e.g., antitrust enforcement).

Third, the literature on innovation has also been interested in the role of entrants versus incumbents (Aghion and Howitt, 1992; Aghion and Tirole, 1994; Klette and Kortum, 2004; Acemoglu et al., 2018). In some studies, entrants and incumbents are based on a product, and an entrant can be an existing firm arriving in a new product market. Schumpeter (1942) also seems vague about whether creative destruction is about new firms overtaking old firms, new producers of a product overtaking old producers, or new products overtaking old products. Our focus is the formation and evolution of firms, which connect to the

[2]Influential recent research in firm dynamics shows that overall startup rates among U.S. businesses have declined since the 1980s and firms are becoming older (Decker et al., 2016; Pugsley and Şahin, 2019; Hopenhayn, Neira, and Singhania, 2022; Karahan, Pugsley, and Şahin, 2024). Our evidence suggests that, at least for the prospective superstars, the startup rate may be uneven over time, with occasional emergence of important cohorts, and the largest firms become older before the next important cohort takes over.

[3]Our findings are also broadly in line with the management literature's view that organizations form with certain capabilities (such as processes that enhance efficiency and reliability), which can be durable but rigid, so a generation of important new firms may emerge when organizational structures experience a major and persistent change (Christensen, 1997; O'Reilly and Tushman, 2021).

literature on both firm dynamics and organizations. Garcia-Macia, Hsieh, and Klenow (2019) assess the contribution of innovation by incumbent firms and new firms from 1983 to 2013, and suggest that most growth comes from innovation and improvement by incumbent firms. To the extent that some generations of new firms are more powerful than others, it is possible that the turn of the 20th century could provide different results for such an analysis.

The rest of the paper is organized as follows. Section 2 describe the data collection. Section 3 presents the empirical facts. Sections 4 and 5 examine the predictions of firm dynamics models. Section 6 concludes.

2 Data

We begin with the list of the largest American companies by sales revenue published by *Fortune* since 1955. After 1995, *Fortune* combined companies from all industries and published an annual list of the largest 1,000 American companies by sales. Before 1995, *Fortune* published an annual list of the largest American industrial (i.e., manufacturing and mining) companies by sales, together with additional lists such as the 50 largest companies in other industries, for instance the largest merchandising firms by sales (retailers and wholesalers together in some years and retailers alone in others), the largest transportation companies by operating revenues, and the largest banks, life insurers, and utilities by assets. As a result, consistent tabulations of the largest firms by the size of sales is mainly available for industrials and mechandising, so our analyses focus more on these sectors. We note that historical *Fortune* lists available online (such as via CNN Money) do not necessarily display the actual name of the company at the time of the list, but use the name of their successors (e.g., Esmark for Swift and CBS for Westinghouse Electric on the 1955 list). We recover the actual name of the company at the time of each *Fortune* list from the archives of the print publications.

In addition to the *Fortune* lists, we study the 500 largest American industrials in 1917 compiled by Navin (1970). However, this list is based on firm size by assets, not by sales like the *Fortune* lists, because data on assets were more widely reported at that time.[4] Aside from these lists, it is difficult to know the identities of the largest companies, especially for the earlier decades.

We then collect information on the origin of the companies. Whenever possible, we use information from company sources, such as websites (e.g., "Our History" webpage), SEC filings (e.g., annual reports), and anniversary documents. Otherwise, we use Wikipedia and historical documents. For the 2018 *Fortune* 1,000 list, we can use data from company sources for 830 firms. For the 1955 *Fortune* 500 list, we can

[4] Navin (1970) wrote: "I, too, would have used sales had I been able, but very few companies reported their sales in 1917 whereas many companies reported their assets, and most reported their capitalization from which their assets could be estimated."

use data from company sources for 216 firms (e.g., a larger fraction of companies did not build a website before they were acquired or ceased to exist). If firm A acquired firm B, we use the origin year of firm A. If two or more firms joined as equals, we use the earliest origin among them. If a firm was formed as a subsidiary and later spun off, we prioritize using the origin year of the subsidiary; we create a flag if we cannot determine the origin year of the subsidiary and instead have to use the origin year of the parent company. Overall, we aim to use the beginning of the business operations (i.e., entry of the enterprise into production activities), and mimic the notion of entry in the firm dynamics literature. Our main results are similar if we drop the cases where the origin year is hard to determine (e.g., spinoffs or firms that trace back to consolidating a large number of small predecessors). For the *Fortune* list in 1995, Harris (1996) tabulates the founding years of the top 500 companies, which are exactly the same as founding year results from our research for 67% of the companies and within ten years apart for 82% of the companies. We also compare with firm age distribution among the largest employers in the census Business Dynamics Statistics (BDS) dataset in Section 3.1, but firm age in BDS data is left censored for those formed before 1976.

We do not use off-the-shelf data on incorporation year because it may not accurately represent the economic history of a company. First, firms sometimes reincorporate for legal reasons (e.g., when they move to another state or as a result of a merger), so age based on the incorporation year may not reflect the actual age. Second, the incorporation year omits the firm's early origins before incorporation. As a result, off-the-shelf data on incorporation year tend to contain many large firms that are excessively young. Commercial datasets like Dun & Bradstreet often use the incorporation year as the start year of a firm, and such a variable does not seem reliable for studying the history of companies.

We find the two-digit SIC code of the largest firms in a given year using SEC registration and CapitalIQ data for the recent list, and CRSP data for historical lists. When such data are not available for some companies in the historical lists, we fill in the firm's two-digit SIC code by reading the business description. We also separately record the two-digit SIC code that best describes a firm's business at founding, which we discuss further in Section 3.1.

3 Empirical Facts

This section presents the empirical patterns among the largest American companies at different points in time.

3.1 Birth Years of Superstars

We document the birth years of the largest firms over time. We use 2018 as an example for recent years (pre-COVID), 1955 (the first year of the *Fortune* list) as an example for the mid-20th century, and 1917 (one of the earliest years with company ranking) as another example for the early 20th century.

Superstars in 2018 We start by analyzing the largest companies in the 2018 *Fortune* list. In Figure 1, we plot the number of the *Fortune* 1,000 companies that originated in each decade. We present the plot for each main sector, based on the firm's industry in 2018. Among the 2018 *Fortune* 1,000 companies, there are 26 in construction, 168 in finance, 388 in industrials (355 in manufacturing and 33 in mining), 139 in services, 159 in retail and wholesale, and 120 in utilities. For industrials, we observe substantial clustering of birth years around the turn of the 20th century: many of today's largest industrials date back to that era. For services, we observe clustering of birth years around the 1960s to the 1980s. For retail and wholesale, the 1960s to the 1980s also have the highest number of birth years, and the early decades of the 20th century have a relatively high number as well. For finance, some large companies date back to the 19th century (e.g., banks) whereas others originated in the second half of the 20th century (e.g., asset management firms and nonbanks). For utilities, mining, and construction, there is no obvious pattern but these industries also have fewer very large firms.

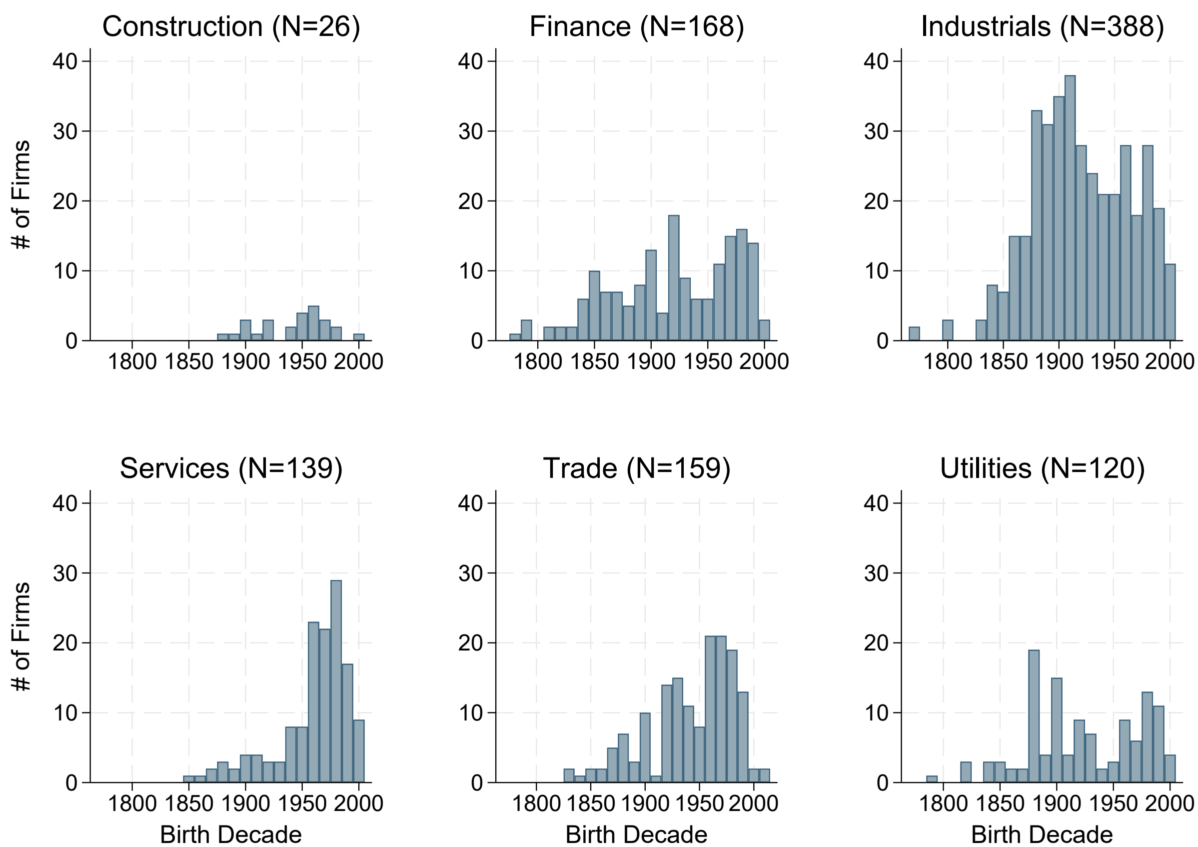
These patterns are robust to alternative ways to weight the distribution of birth years (e.g., by the number of firms and by the value of their sales or employment). In Figure IA1, we also plot the total sales of the firms born in each decade, for the 2018 *Fortune* 1,000 companies by main sector. In Figure IA2, we plot the total employment of the firms born in each decade. The results are similar to those using the number of firms born in each decade in Figure 1. Decades around 1900 are especially prominent for industrials, whereas the 1960s to 1980s are relatively more important for services, retail, and wholesale. In the following, we focus on distributions by the number of firms for parsimony; results are similar if we weight by sales or employment like in Figures IA1 and IA2.

In addition, Figure IA3 shows that the patterns are similar if we drop companies with complex histories: firms that involve mergers of equals (which complicate the main lineage), and firms that are spin-offs where we do not have information about the origin of the spun-off entity. The birth year distribution in this case (solid line with circles) is almost identical to that in our baseline (solid line with triangles).

Finally, the *Fortune* lists include companies incorporated in the U.S., operate in the U.S., and file financial statements with a government agency. This includes private companies and cooperatives that file a 10-K or a comparable financial statement with a government agency, and mutual insurance companies that file with state regulators. Excluded are private companies not filing with a government agency; companies

Figure 1: Birth Years of 2018 *Fortune* 1,000 Companies

This figure shows the number of birth years per decade for the 2018 *Fortune* 1,000 companies. Companies are assigned to main sectors based on their industries in 2018. The main sectors correspond to SIC codes 15-17 (construction), 10-14 and 20-39 (industrials), 40-49 (transportation, communications, and utilities), 50-59 (wholesale and retail trade), 60-67 (finance, insurance, and real estate), and 70-89 (services).

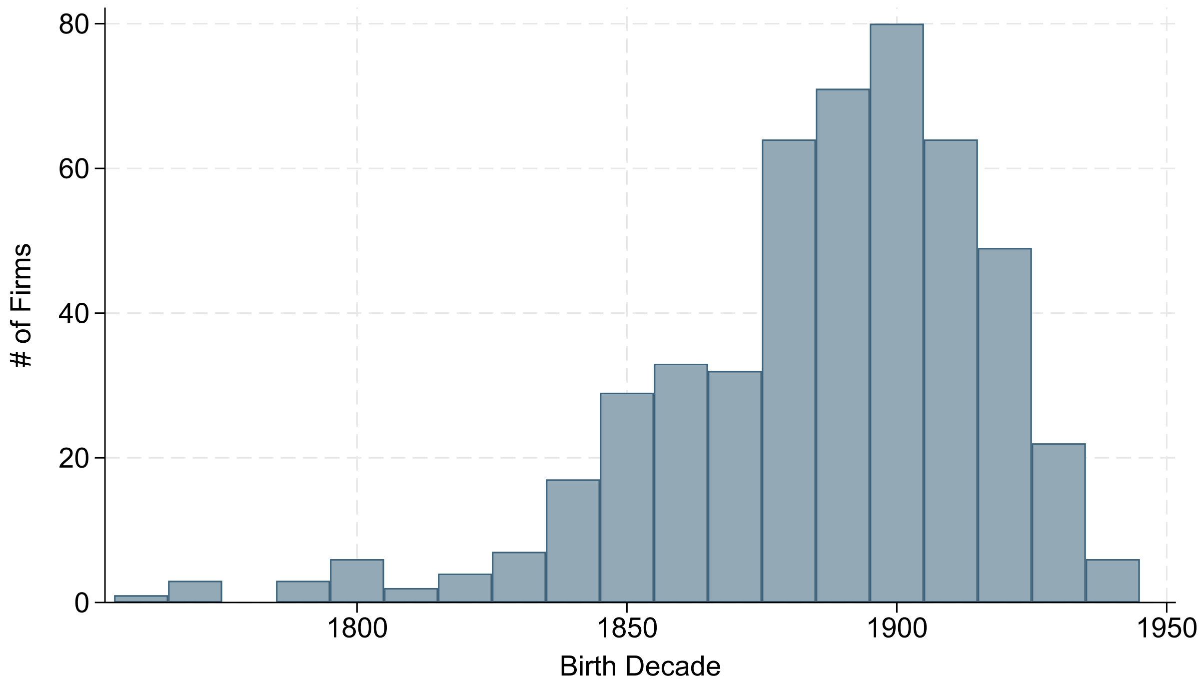


incorporated outside the U.S.; and U.S. companies consolidated by other companies, domestic or foreign. To expand coverage of private firms, we also process the *Forbes: America's Largest Private Companies* list for 2018, which covers 229 private firms with revenue over $2 billion based on analyses by *Forbes*. In Figure IA4, we combine the *Fortune* and *Forbes* lists and take the largest 1,000 by sales (which contain 171 companies from the *Forbes* private firm list not in the *Fortune* list). The birth year distribution using the combined list (solid line with circles) is similar to that using only the *Fortune* list (solid line with triangles).

As we explain further in Section 4.1, the clustering of birth years in a single cross section is not sufficient for thinking that some cohorts are special. In a benchmark model, the age distribution of top firms in the stationary equilibrium will feature a hump-shaped pattern: very young firms will be less represented as they have not had enough time to grow large, and very old firms will also be less represented as they experience more attrition with age. Therefore, we need to examine the birth years of superstar firms at

Figure 2: Birth Years of 1955 *Fortune* 500 Industrials

This figure shows the number of birth years per decade for the 1955 *Fortune* 500 industrials. Companies are assigned to main sectors based on their industries in 1955.



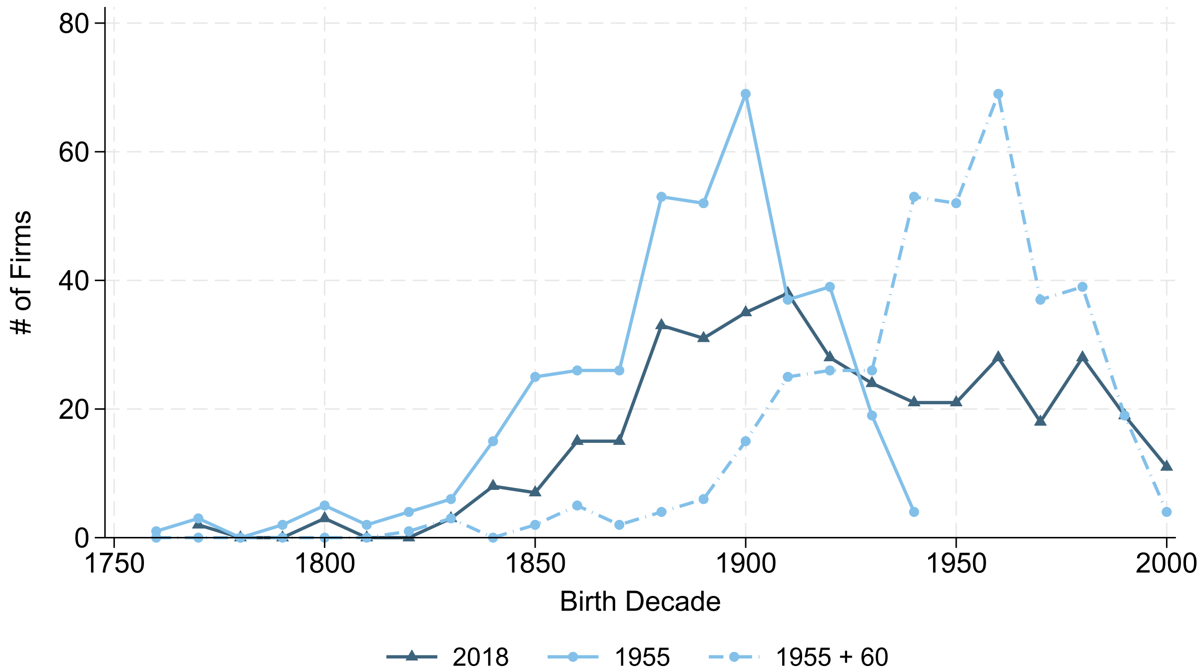
various points of time: if special cohorts exist, they should display lasting dominance over time, and the age distribution of top firms will not be stationary in that case. Accordingly, we also study the superstar firms in the past.

Superstars in 1955 We then analyze the largest firms around 1955. In 1955, *Fortune* provided the first list of the largest 500 industrial (i.e., manufacturing and mining) companies by sales. In Figure 2, we plot the birth years of the largest 500 industrials directly from the 1955 *Fortune* 500 list. Interestingly, the birth years of the largest industrials in 1955 still cluster around the turn of the 20th century. Accordingly, the age distribution of the largest industrials in 1955 is very different from that in 2018: the median age of the largest industrials in 1955 and 2018 is 57 and 98, respectively (the result is similar if we restrict to the 388 largest industrials in 1955 so we have the same number of firms as the 2018 list).

Figure 3 provides further visualization. Here we overlay the birth year distribution for the largest 388 industrials in the *Fortune* 2018 list (solid line with triangles) and the largest 388 industrials in the *Fortune* 1955 list (solid line with circles). Since there are 388 industrials in the *Fortune* 2018 list, we focus on the top 388 industrials in this comparison. The dashed line with circles shows what the birth year distribution in 2018 would look like if the age distribution of the top firms were stationary; in other words, it shifts

Figure 3: Largest Industrials in 1955 and 2018

The solid line with triangles shows the number of birth years per decade for the largest 388 industrial companies in the *Fortune* 2018 list (which contains 388 industrial firms). The solid line with circles shows the number of birth years per decade for the largest 388 industrial companies in the *Fortune* 1955 list. The dashed line with circles is the solid line shifted to the right for six decades (i.e., what the 2018 distribution would be like if the age distribution of the top firms were stationary).

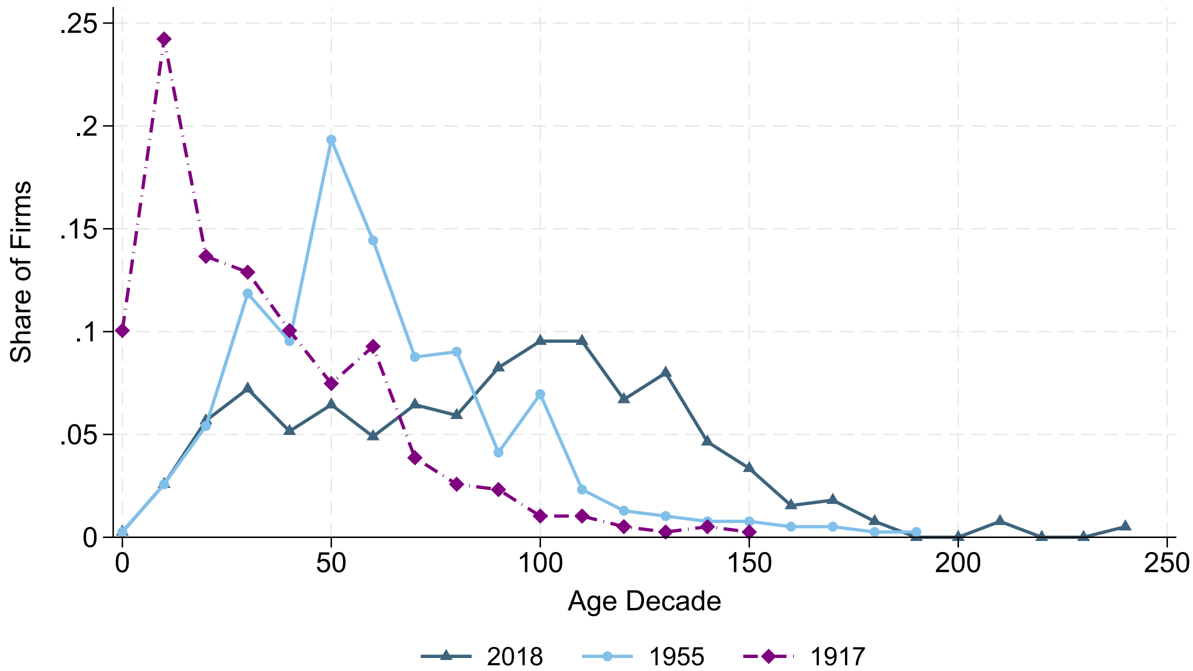


the birth year distribution in the 1955 list to the right by six decades. This plot shows that the birth year distribution for the largest industrials in 1955 and 1988 are similar in calendar time. Accordingly, the age distribution of the largest industrials is not stationary, which we can also see from Figure 4, where the special cohorts from around 1900 pull the age distribution to the right over time.

For retail and wholesale, the *Fortune* lists in the earlier decades separately tabulated the largest 50 merchandising firms by sales, which first appeared in 1956. Accordingly, we focus on the largest 50 retailers and wholesalers in the following analysis of this sector. In Figure 5, we plot the birth years of the largest 50 retailers and wholesalers in 1956. At that time, the largest retailers and wholesalers primarily date back to late 19th century and early 20th century, which include a number of grocery chains and department stores. That generation of retailers and wholesalers are much less prominent in the 2018 *Fortune* list: about 50% of the largest 50 retailers and wholesalers in 2018 were born after 1950. The median (mean) age of the largest 50 retailers and wholesalers in 1956 is 62 (64). In comparison, the median (mean) age of the largest 50 retailers and wholesalers in the 2018 *Fortune* list is 75 (79). Figure 6 shows that the age distribution of the largest 50 retailers and wholesalers is similar in 1956 and 2018. To further verify the

Figure 4: Age Distribution of the Largest Industrials

The solid line with triangles shows the age distribution for the largest 388 industrial companies (by sales) in the *Fortune* 2018 list (which contains 388 industrial firms). The solid line with circles shows the age distribution for the largest 388 industrial companies (by sales) in the *Fortune* 1955 list. The dashed line with diamonds shows the age distribution for the largest 388 industrial companies (by assets) in 1917 from Navin (1970).

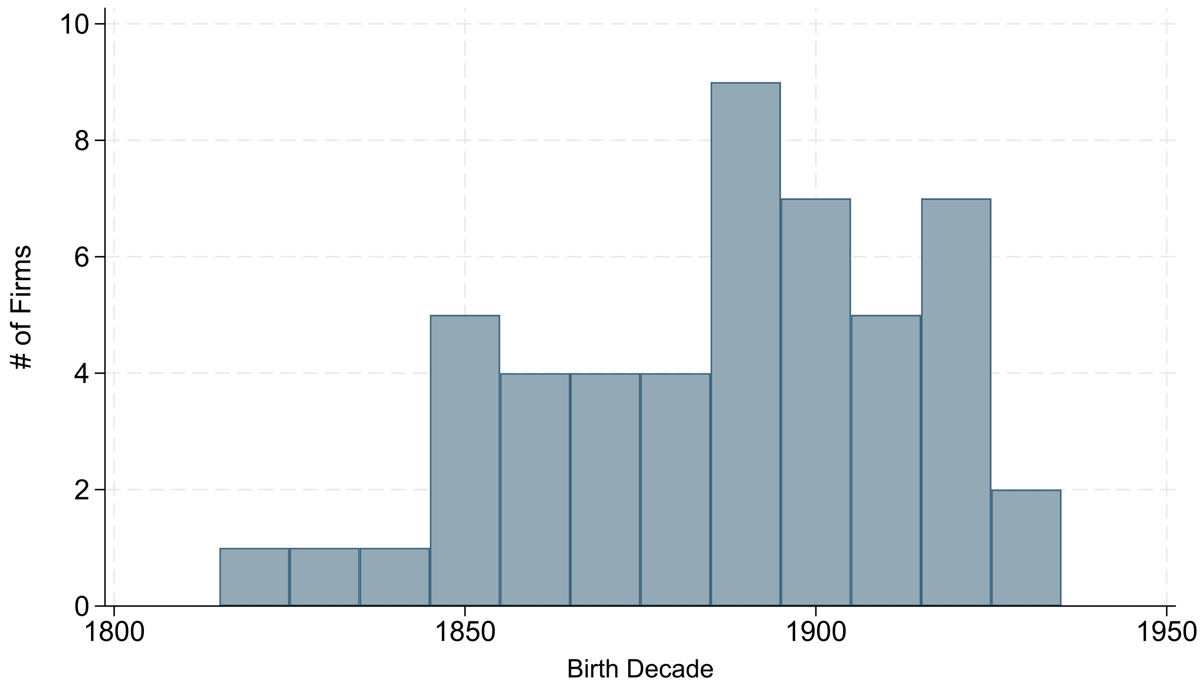


stability of the age distribution of the largest retailers and wholesalers, we also include in Figure 6 the age distribution of the largest 50 retailers and wholesalers in 1970 and 1995 (we use 1970 because after 1966 *Fortune* tabulated the largest 50 retailers and dropped the wholesalers, except for 1970 where the largest wholesalers are separately tabulated, and we use 1995 which is the first year *Fortune* tabulated the largest 1,000 companies combining all sectors). Overall, the patterns among top retailers and wholesalers are quite different from those among top industrials: later generations of large retailers and wholesalers have continuously displaced previous ones, whereas the generation of industrials from the turn of the 20th century remain prominent even today.

For services, there were few large firms in 1955. Since *Fortune* did not systematically tabulate industrial and non-industrial companies together before 1995, we need to examine the prevalence of large services firms in other ways. First, we study the tabulations of corporations by size and industry from Statistics of Income (SOI) published by the Internal Revenue Service (IRS), digitized by Kwon, Ma, and Zimmermann (2024). Starting in 1959, the SOI data provides tabulations of corporations by the size of sales and industry. We estimate the sales cutoff for the top 1,000 (and top 500) companies, and then estimate how many firms

Figure 5: Birth Years of 1956 *Fortune* Largest 50 Retailers and Wholesalers

This figure shows the number of birth years per decade for the largest 50 merchandising firms (i.e., retailers and wholesalers) in 1956 by sales.

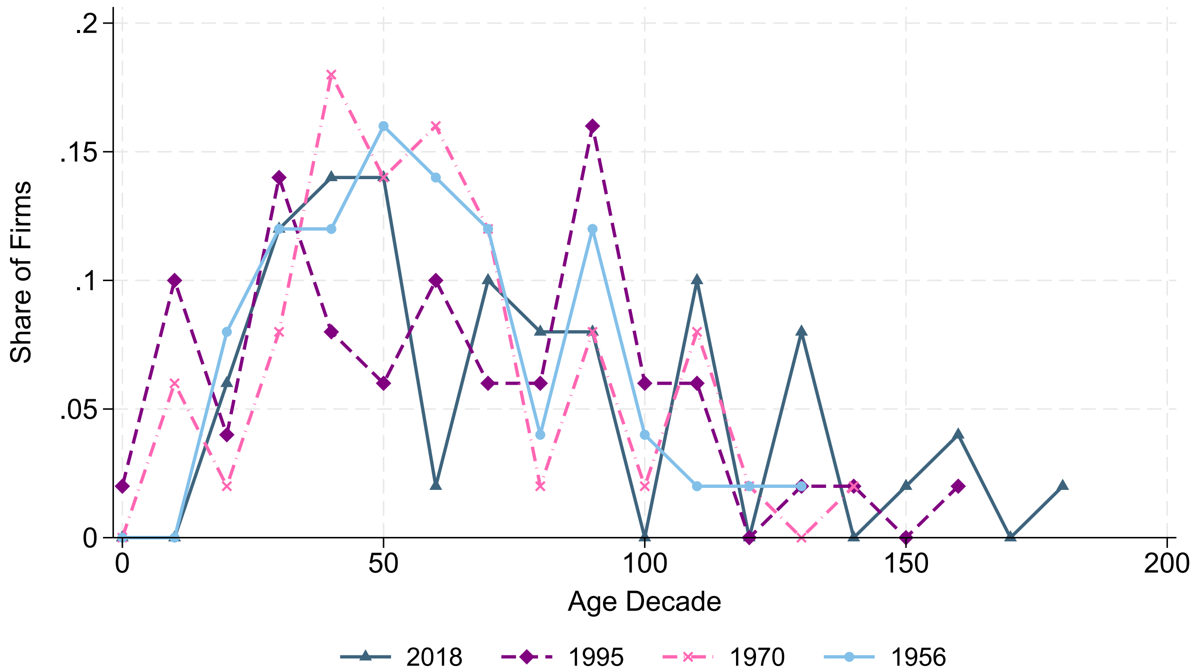


in services (as well as other industries) are above this threshold. Using 1960 as an example, the SOI data suggest that 18 firms (4 firms) among the top 1,000 (top 500) by sales are in the services industry. Second, in 1970, *Fortune* provided a one-off analysis of companies that had larger sales than the 500th industrial firm but were not included in any *Fortune* lists. They were able to find two firms in business services (Sperry & Hutchinson and Dun & Bradstreet), two hotels (Holiday Inns and Hilton Hotels), and a few in entertainment (Kinney National Service, Music Corporation of America, United Artists, Columbia Pictures, and MGM). Given the scarcity of large services companies, *Fortune* did not provide much information about them until 1995 when the top 1,000 companies combining industrials and non-industrials was tabulated in one list. By the 1995 list, the top 1,000 companies included 56 services firms, 31 of which were born after 1960. Overall, it appears that few large services firms existed until recently.

Largest industrials in 1917 Prior to the *Fortune* lists started in 1955, we have one additional tabulation of the largest 500 industrial companies by assets in 1917 from Navin (1970). In Figure 7, we plot the birth years of these largest industrials in 1917. Remarkably, we still see the cluster of birth years around the turn of the 20th century for the largest industrials in 1917. At this time, the median large industrial is only 30 years old, compared to 57 years old in the 1955 *Fortune* list and 98 years old in the 2018 *Fortune* list.

Figure 6: Age Distribution of the Largest Retailers and Wholesalers

The solid line with triangles shows the age distribution for the largest 50 retailers and wholesalers in the *Fortune* 2018 list. The dashed line with diamonds shows the age distribution for the largest 50 retailers and wholesalers in the *Fortune* 1995 list. The dashed line with crosses shows the age distribution for the largest 50 retailers and wholesalers in 1970. The solid line with circles shows the age distribution for the largest 50 retailers and wholesalers in 1956.

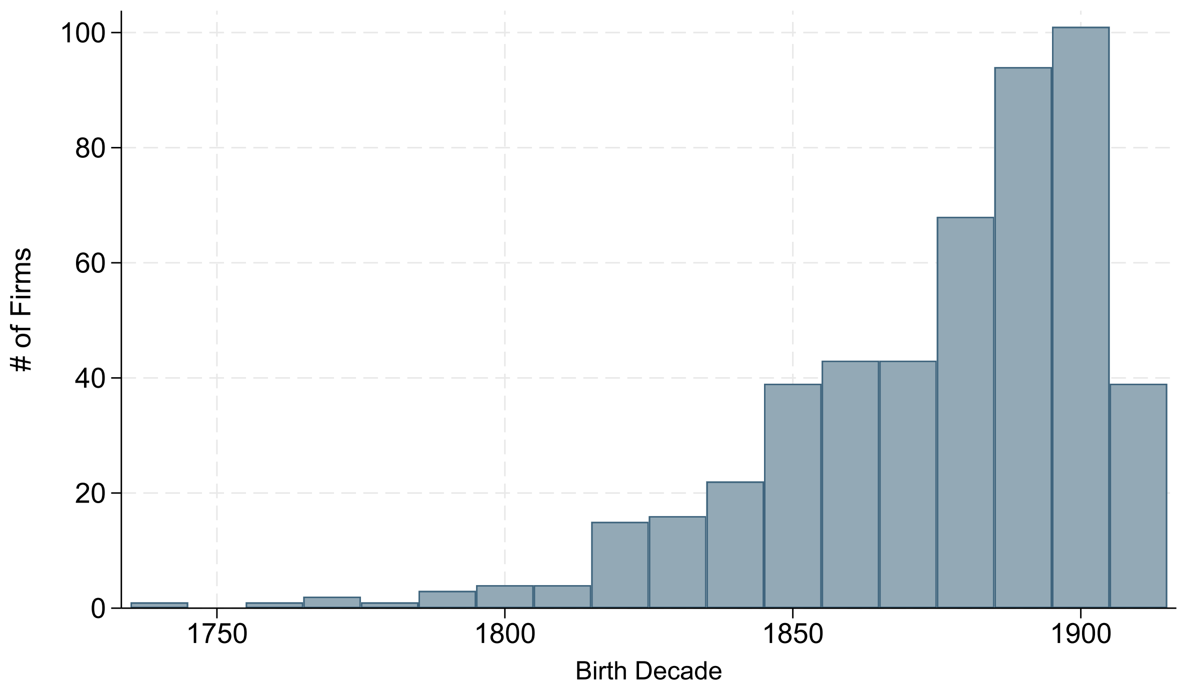


Additional information One possible question is whether firms at birth belonged to the same sectors as when we observe them in the top firm lists. We also collect information on the firm's business at the time of founding (which is typically simple). For instance, among the *Fortune* 2018 companies, 72% belong to the same two-digit SIC code when they formed and 87% belong to the same main sector. Results are similar for the largest companies in other years. Therefore, the patterns above are similar if we use firms' industry group at birth instead of at the time of the *Fortune* list. The stability of the business over time is consistent with previous findings among entrepreneurial firms (Kaplan, Sensoy, and Strömberg, 2009).

We also investigate the birth year distribution in the population of firms more generally. Comprehensive data on the age profile of all firm appear rather sparse. Census BDS data date back to the late 1970s, and the age of firms born before 1976 is left censored. In 2018, 7% of the firms in BDS data were born before 1976, 14% between 1976 and 1992, and 79% after 1992. In other words, the vast majority of the population of firms is fairly young. Panel A of Figure IA5 shows the age distribution of the population of firms in BDS by main sector (gray bars), and a similar pattern holds in all cases. We also look at the largest size category in BDS publications, namely firms with more than 10,000 employees, which has a total of 1,196

Figure 7: Birth Years of the Largest 500 Industrials in 1917

This figure shows the number of birth years per decade for the largest 500 American industrial companies in 1917 according to the list in Navin (1970). Companies are assigned to main sectors based on their industries in 1917.



firms in 2018. In this case, 67% were born before 1976, 20% between 1976 and 1992, and 13% after 1992. The patterns for each main sector are shown in Panel B of Figure IA5 (gray bars). Among the Fortune 1,000 firms, 75% were born before 1976, and 16% between 1976 and 1992; the comparison is shown in both panels of Figure IA5 (blue bars). In sum, the largest firms are understandably older than firms overall. For the large firms, the distribution by age group in our data for the *Fortune* 1,000 companies and that for the largest employers in BDS appear broadly similar. However, the left-censored BDS data do not provide information for the earlier decades. Accordingly, we do not know whether the early 20th century is particularly important for the formation of the largest employers in BDS, or whether the decades that are especially important for the formation of superstar firms had high business startup rate in general.

3.2 Persistence of Superstars

A natural question is whether the largest firms over time are the same companies. Given the evidence in Section 3.1, this question is especially salient for industrial firms, as the cohort from 1900 remains dominant for a very long time. Indeed, the prevalence of old firms among the recent *Fortune* list has led some observers to postulate that corporate giants are hard to topple (The Economist, 2023). We analyze the persistence of the top firms in the following.

Industrials We perform a detailed comparison of the largest industrial firms in the *Fortune* 1955 list and the *Fortune* 2018 list (both are ranked by the size of sales), to examine whether the same companies continued to prevail. Interestingly, even though the cohort born around 1900 has remained prominent among the largest industrials for a century (from the 1917 list to the 2018 list), the exact companies are not necessarily the same.

We compare the *Fortune* 1955 list and the *Fortune* 2018 list in several ways. Since there are 388 industrial firms in the *Fortune* 2018 list, we focus on the top 388 industrial firms in the *Fortune* 1955 list. First, we look at the fraction of the companies on the *Fortune* 1955 list that remain on the *Fortune* 2018 list. Overall, 21% of the companies on the *Fortune* 1955 list remain on the 2018 list. Table 1 presents more detailed information for firms born in each decade. Columns (1) to (4) show the number of firms born in each decade for the top 388 firms in the 1955 list and the 2018 list, respectively. Columns (5) and (6) show the number of top firms in the 1955 list that survived on the 2018 list, for firms born in each decade. For example, 37 of the top firms in the 1955 list were born in the 1910s, only 9 of which survived to the 2018 list, yet a total of 38 top firms in the 2018 list were born in that decade.

Second, we recognize that some of the companies on the *Fortune* 1955 list were subsequently acquired (e.g., Quaker Oats was acquired by PepsiCo). In this case, another 21% of the companies on the *Fortune* 1955 list "survived" on the *Fortune* 2018 list through their acquirers, and 42% in total either "survived" on the *Fortune* 2018 list as either the main entity or through their acquirers. Columns (7) and (8) of Table 1 shows these direct plus indirect survivors by birth decade. Finally, another 22% of the top firms in the 1955 list were acquired by foreign firms (which do not qualify for the *Fortune* 2018 list). "Survival" through acquirers may overstate the persistence since some firms were acquired following operating weakness (e.g., Union Carbide & Carbon was acquired by Dow Chemical following accidents and poor performance, National Steel Corporation was sold in bankruptcy to U.S. Steel).

Figure 8 plots the birth year distribution of the largest industrials in the *Fortune* 2018 list that were also among the largest 388 industrials in the *Fortune* 1955 list, either directly or through relatives (i.e., acquired a firm among the largest 388 industrials in the *Fortune* 1955 list or is a spinoff of a firm among the largest 388 industrials in the *Fortune* 1955 list). The birth year distribution for all of the largest industrials in the *Fortune* 2018 list is also shown. We see that among the largest industrials today which were born around 1900, many were not the ones that made top industrial firms in 1955. Some of these examples include Clorox, Coty, Cummins, Harley-Davidson, Harris, Lear, Nucor, Parker-Hannifin, VF, and Xerox. Table IA1 shows examples of the top ten firms in food and metal manufacturing for 1955 and 2018: the birth years are similar but the companies have changed. Overall, although the largest industrial firms in both 1955

Table 1: Persistence among the Largest Industrials

This table shows the number of firms in 1995 and 2018 by decade for the top 388 industrial companies. "Direct survivors" are top firms in 1955 that are still among the top firms in 2018. "Indirect survivors" are top firms in 1955 that have been acquired by a top firm in 2018.

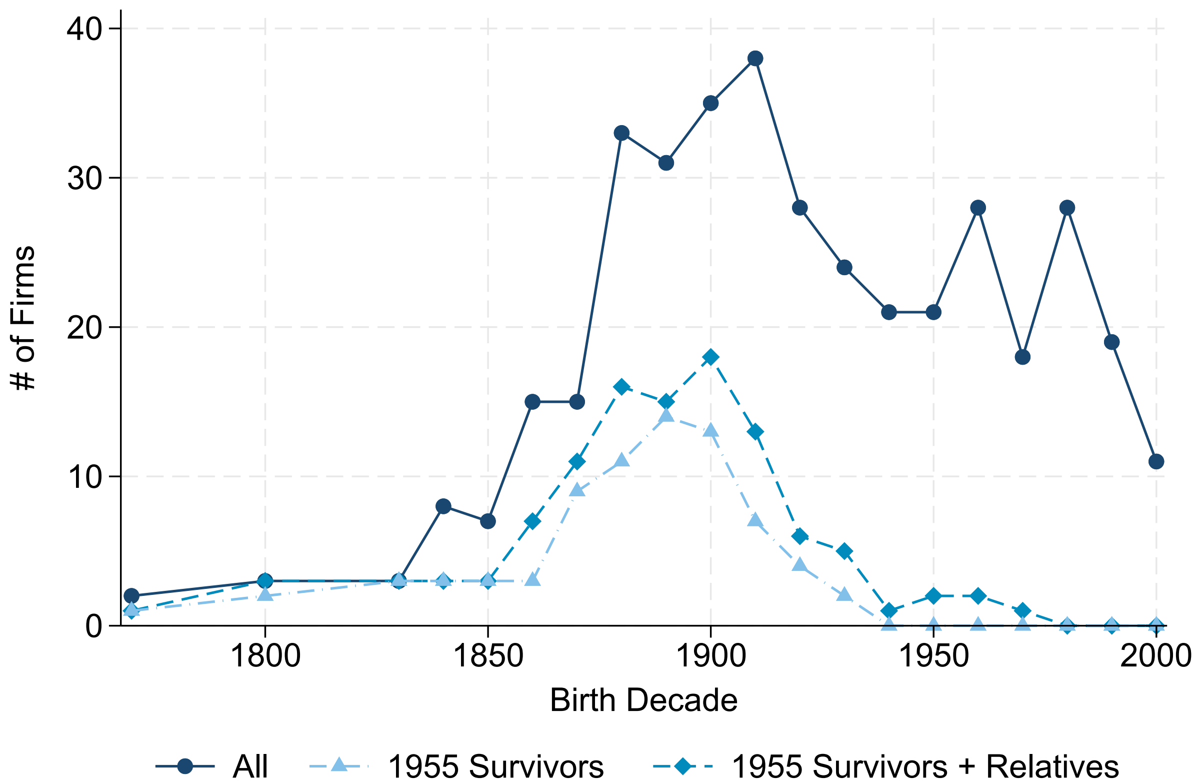
2018 List		1955 List		Direct Survivor		Direct & Indirect Survivor	
Decade of Birth (1)	Number (2)	Decade of Birth (3)	Number (4)	Decade of Birth (5)	Number (6)	Decade of Birth (7)	Number (8)
1760	0	1760	1	1760	0	1760	0
1770	2	1770	3	1770	1	1770	2
1780	0	1780	0	1780	0	1780	0
1790	0	1790	2	1790	0	1790	1
1800	3	1800	5	1800	2	1800	2
1810	0	1810	2	1810	0	1810	0
1820	0	1820	4	1820	0	1820	1
1830	3	1830	5	1830	3	1830	4
1840	8	1840	15	1840	3	1840	6
1850	7	1850	24	1850	3	1850	8
1860	15	1860	26	1860	4	1860	9
1870	15	1870	26	1870	9	1870	13
1880	33	1880	53	1880	12	1880	23
1890	31	1890	51	1890	16	1890	27
1900	35	1900	68	1900	13	1900	25
1910	38	1910	37	1910	9	1910	17
1920	28	1920	38	1920	3	1920	15
1930	24	1930	19	1930	3	1930	9
1940	21	1940	4	1940	0	1940	1
1950	21	1950		1950		1950	
1960	28	1960		1960		1960	
1970	18	1970		1970		1970	
1980	28	1980		1980		1980	
1990	19	1990		1990		1990	
2000	11	2000		2000		2000	

and 2018 predominantly come from the turn of the 20th century (e.g., firms born between 1880 and 1930 account for 64% and 42% of the largest industrials in 1955 and 2018, respectively), the exact companies do change over time.

Retail and wholesale For retailers and wholesalers, Section 3.1 shows that the largest companies in 1955 largely date back to the late 1800s, but the largest companies in 2018 largely date back to the 1960s to 1980s. Accordingly, the persistence of individual companies is necessarily limited. Indeed, only nine companies among the top 50 retailers and wholesalers in the 1955 remain among the 50 largest retailers and wholesalers in 2018: McKesson, Melville Shoe through its connection with CVS, Kroger, Walgreen, Macy's, Sears, J.C. Penney, Foot Locker, and Graybar. Another eight companies were acquired by Macy's, three by Albertsons, and three more by other top 50 retailers in 2018.

Figure 8: Overlap between the Largest Industrials in 2018 and 1955

This figure depicts the overlap between the largest 388 industrial companies in 2018 and 1955. The solid line with circles indicates the number of companies founded each decade within the largest 388 industrials in 2018. The dashed line with triangles represents the number of birth years per decade for firms on the 2018 list that were already among the largest 388 industrials in 1955. The dashed line with diamonds represents the number of birth years per decade for firms on the 2018 list that were either among the largest 388 industrials in 1955 or have relatives in the 1955 list (e.g., through a spinoff or acquisition).



3.3 Germany and United Kingdom

A common question is whether similar patterns exist among top firms in other countries. From Chandler (1994), we are able to obtain the list of the largest 200 German industrial firms by assets in 1913 and 1953, and the largest 200 British industrial firms by market value of shares in 1919 and 1948. We supplement these historical lists with their 2018 counterpart. For Germany, the newspaper *Die Welt* published a list of the largest 500 German firms by revenue in 2018. The list is based on annual reports or information provided by the companies at the request of the editors. We select the 225 industrials on that list and drop subsidiaries of other firms (for example, the original list includes both Volkswagen and Audi). For the U.K., we get the largest 200 industrials by market cap in 2018 from the list of public companies. We then research the history of these companies, following the same approach for U.S. firms.

Figure 9 shows the age distributions for the largest German (Panel A) and British (Panel B) industrials in the 1910s, around 1950, and in 2018. Interestingly, the patterns among the largest German industrials are similar to those among the largest American industrials (e.g., Figure 4). They were very young in the early 20th century, and have become fairly old by 2018. The cohort from the late 1800s continues to dominate. Meanwile, the largest British industrials behave quite differently. The age distribution looks rather stationary, and no particular cohort has lasting dominance. The historical British lists rely on size by market capitalization of shares (and therefore restrict to public firms) because consolidated financial accounts were not mandatory before 1948, so it is difficult to obtain reliable data on sales or assets for the early 20th century (Prais, 1976; Meeks and Whittington, 2023). For 2018, we compare the age distribution for the largest 200 industrials by market cap and by sales (using ORBIS data), and verify that the results are similar in Figure IA7: the largest British industrials in 2018 are fairly young whether we use size by market cap or by sales.

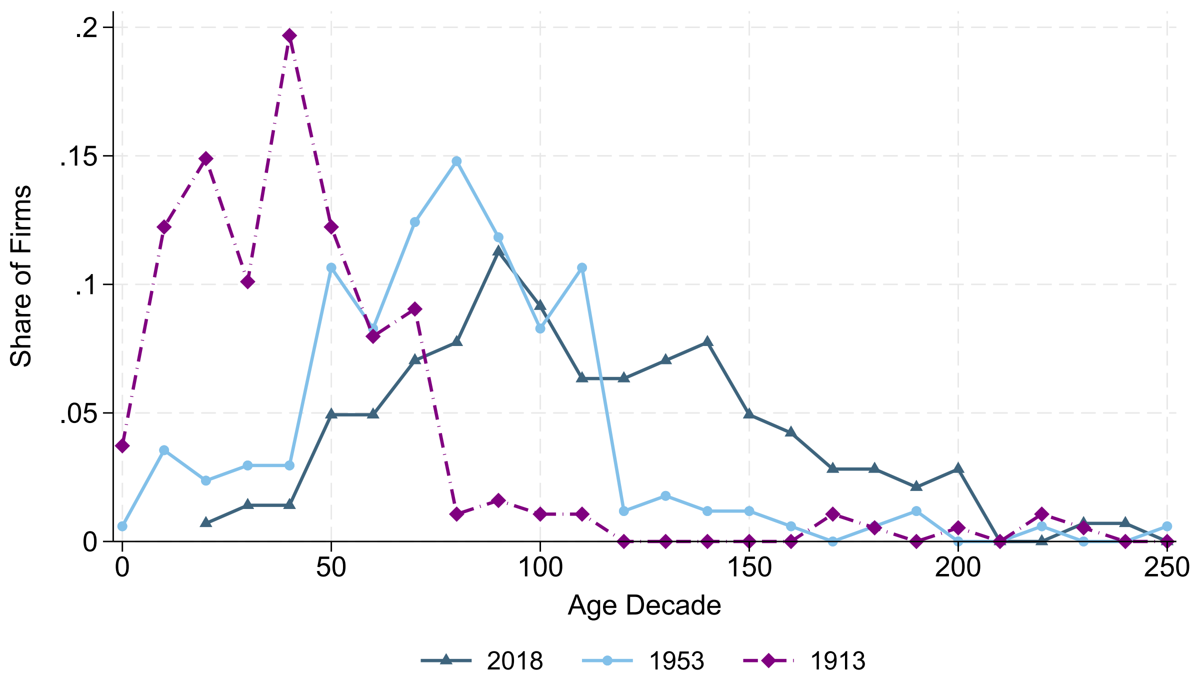
In his study of the largest American, German, and British firms, Chandler (1994) did not examine the birth year patterns among the top firms. He did remark that the German experience through the Second Industrial Revolution "is closer to that of the United States than to that of Britain." In particular, "in Germany as in the United States, but much more than in Britain, entrepreneurs did make the investment in production facilities and personnel large enough to exploit the economies of scale and scope, did build the product-specific international marketing and distribution facilities, and did recruit the essential managerial hierarchies." "The history of the modern industrial enterprise in Great Britain provides a counterpart to the story just told about its beginnings and evolution in the United States. In Britain fewer such firms appeared, and they grew in a slower and more evolutionary manner. British entrepreneurs failed to make the essential three-pronged investment in manufacturing, marketing, and management in a number of the capital-intensive industries of the Second Industrial Revolution."

According to Chandler's account, the cohort of firms from the Second Industrial Revolution is likely to have lasting staying power in the U.S. and in Germany, but not in the U.K. Our data indeed reveal such patterns. To better understand the conditions under which special cohorts may emerge, we proceed to analyze firm dynamics models in the next section.

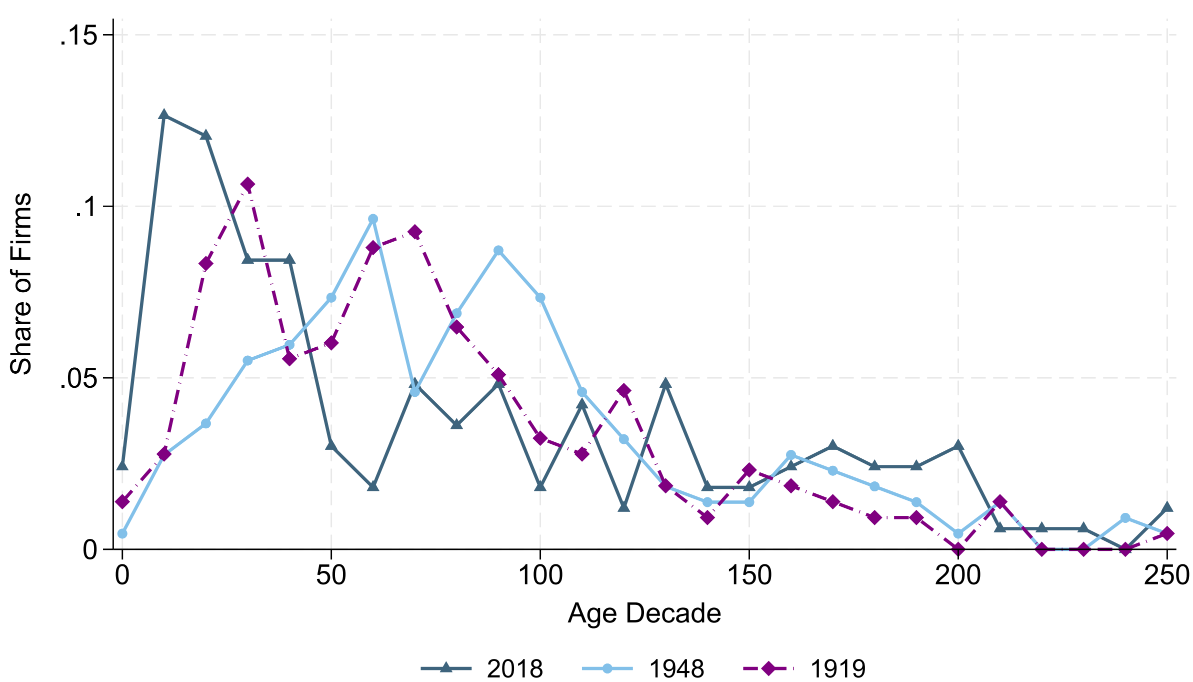
Figure 9: Age Distribution of the Largest German and British Industrials

Panel A shows the age distribution of the largest 200 German industrials by sales in 2018 (solid line with triangles), and by assets in 1953 (solid line with circles), and 1913 (dashed line with diamonds). Panel B shows the age distribution of the largest 200 British industrials (by market capitalization of shares) in 2018 (solid line with triangles), 1948 (solid line with circles), and 1919 (dashed line with diamonds).

Panel A. Age Distribution of the Largest German Industrials



Panel B. Age Distribution of the Largest British Industrials



4 Baseline Firm Dynamics Model

We examine models of firm dynamics to better understand the forces that can shape the landscape of top firms. We start with the canonical Hopenhayn (1992) model of equilibrium industry dynamics. This model has a well-known stationary equilibrium that can approximate the patterns in the retail and wholesale trade sector. Yet, even when subjected to entry shocks, it cannot replicate the special generation we observe among industrials. In the next section, we provide a parsimonious extension that mimics the special generation dynamics in the industrial sector.

4.1 Baseline

Each firm i of age $0 \leq a \leq \bar{a}$ operates a decreasing returns to scale technology $y_{iat} = z_{iat} n_{iat}^{\theta}$ in labor. Productivity $z_{iat} = e_i s_{iat}$ has a permanent component and a stochastic component. The permanent component, e_i, is drawn at birth from distribution G. The stochastic component, s_{iat}, evolves as an AR(1) process in logs over the firm's lifetime, i.e., $\log s_{iat} = \rho \log s_{ia-1t-1} + \sigma_\varepsilon \varepsilon_{it}$, with initial condition s_{i0} drawn at birth from distribution F. We assume there is some absorbing maximum age, $\bar{a}$, sufficiently large that the influence of initial condition s_{i0} is effectively zero.[5] Given these components, log productivity for a firm of age a, written as a moving average, is:

$$\log z_{iat} = \log e_i + \rho^a \log s_{i0} + \sum_{k=0}^{a-1} \rho^l \sigma_\varepsilon \varepsilon_{it-k}. \tag{1}$$

Here, ρ is the persistence of the AR(1) process for the stochastic component, σ_ε is its volatility, and ε_{it} is an i.i.d. standard normal random variable.

This setup models a firm's life cycle as driven by a mix of ex ante and ex post heterogeneity (Sterk, Sedláček, and Pugsley, 2021). The permanent type and initial condition terms in Equation (1) form an ex ante predictable life cycle. When the distribution of initial conditions, F, differs from the long-run distribution for $\log s_t$, as we will assume, the ex ante terms implicitly introduce age dependence to the stochastic component. A firm's log productivity gravitates as it ages toward its long run mean, $\log e_i$. Along the way, its realized life cycle may deviate from this ex ante path with the accumulation of persistent ex post shocks that are captured by the last term.

Firms pay a fixed cost c_f in units of labor to operate, and hire variable labor n_{it} in a competitive labor market. There are no adjustment costs. Firms sell their output in a competitive market at price p_t. Labor is

[5] After reaching the maximum age, $\log s_{i\bar{a}t+1} = \rho \log s_{i\bar{a}t} + \sigma_\varepsilon \varepsilon_{it+1}$.

the numeraire so $w_{it} = 1$. Firms discount the future using a constant discount rate r in *goods*, and face an exogenous probability of exit δ. They may also choose to exit endogenously and avoid paying any future fixed costs. We characterize a firm's problem recursively.

Recursive formulation Let $V_t(a, e_i, s_{iat})$ be the value of an age a firm in period t with permanent productivity component e_i and stochastic component s_{iat}. Then V_t satisfies the following Bellman equation:

$$V_t = \max_n \left\{p_t z_{iat} n^\theta - n - c_f\right\} + \max_{x\in\{0,1\}} \left\{\frac{1-\delta}{1+r} E_t\left[\frac{p_t}{p_{t+1}} V_{t+1}(a+1, e_i, s_{i,a+1,t+1})\right], 0\right\}, \qquad (2)$$

with productivity $z_{iat} = e_i s_{iat}$. Without adjustment costs, labor demand is a static problem. For any period t, we let $n_t(z)$ be the labor demand function and $y_t(z)$ the implied output. We let $x_t(a, e, s)$ be the exit policy function that solves Equation (2). These depend on calendar time only through the path of prices p_t, and we maintain time subscripts in anticipation of characterizing transition paths. The ratio $\frac{p_t}{p_{t+1}}$ converts the discounting in goods to the numeraire.

Potential entrants and free entry Potential entrants evaluate the expected value of entry considering the distribution $G(e)$ over permanent types and the distribution $F(s_0)$ over initial conditions. The expected value of a potential entrant in period t, W_t , is:

$$W_t = \iint_{e,s_0} V_t(e, 0, s_0) F(ds_0) G(de).$$

We assume there is an infinitely elastic supply of potential entrants when this expected value equals entry cost c_e in units of labor, i.e., the free entry condition:

$$W_t = c_e. \qquad (3)$$

Measuring firm heterogeneity Let $\mu_t(a, E, S')$ be the measure of age a firms with productivity components $e \in E$ and $s' \in S'$. Firms in t are surviving incumbents, $1 \leq a \leq \bar{a}$, or new entrants, $a = 0$, and M_t is the measure of entrants.

Product market clearing Sector demand is given by a CES function $D(p_t) = L_t p_t^{-\epsilon}$, where ϵ is the demand elasticity and L_t is the market size, which grows exogenously at rate η_t. Market clearing requires:

$$L_t p_t^{-\epsilon} = \sum_{0\leq a\leq \bar{a}} \iint_{e,s} y(es)\mu_t(a, de, ds). \qquad (4)$$

Adjusting for growth in market size With growth η_t in market size L_t, we introduce counterparts, denoted with $\bar{\cdot}$, to the measure over all firms and entrants that are normalized by market size L_t:

$$\bar{\mu}_t = \frac{\mu_t}{L_t} \qquad \bar{M}_t = \frac{M_t}{L_t}.$$

Market clearing (4) is simply:

$$p_t^{-\epsilon} = \sum_{0 \leq a \leq \bar{a}} \iint_{e,s} y(es)\bar{\mu}_t(a, de, ds). \tag{4a}$$

Evolution of firm heterogeneity Let $\bar{\mu}_t\left(a, E, S'\right)$ be the normalized measure of age a firms with productivity components $e \in E$ and $s' \in S'$. The law of motion for $\bar{\mu}_t$ is:

$$\bar{\mu}_t\left(a, E, S'\right) = \begin{cases} \bar{M}_t G(E) F(S') & a = 0 \\ \iint_{e \in E, s} (1-\delta)\left(1 - x_{t-1}\left(a-1, e, s\right)\right) P\left(S'|s\right) \frac{\bar{\mu}_{t-1}(a-1, de, ds)}{1+\eta_t} & 1 \leq a < \bar{a} \\ \iint_{e \in E, s} (1-\delta)\left(1 - x_{t-1}\left(\bar{a}, e, , s\right)\right) P\left(S'|s\right) \frac{\bar{\mu}_{t-1}(\bar{a}, de, ds)}{1+\eta_t} & a = \bar{a} \end{cases}. \tag{5}$$

The piecewise formulation in age, a, accounts in turn for entrants, aging incumbents, and incumbents that have reached their "maximum" age, $\bar{a}$.

Stationary industry equilibrium We first define the familiar stationary equilibrium featuring entry and exit with constant market size growth η. There is a constant price p, value function V with policy functions $n(es)$ and $x(a, e, s)$, measure $\bar{\mu} = \mu_t / L_t$ over all firms, and measure $\bar{M} = M_t / L_t$ of entrants, both normalized by market size, such that (i) V solves Bellman equation (2), (ii) free entry condition (3) is satisfied, (iii) the product markets clears (4a), and (iv) $\bar{\mu}$ and $\bar{M}$ solve the law of motion (5).

4.2 Results

Calibration We set the model period to be a year and calibrate the model to match a rich set of annual firm dynamics statistics. We target a set of moments, all conditional on firm age, that have remained stable. To hold the calibration constant as an illustration of the special generation shock, these targets are measured for all firms rather than a particular sector.

To implement this approach, we first calibrate several parameters outside the model: the time discount factor β to 0.96, and the curvature parameter of the production function θ to 0.64, which matches the labor share of total revenue. We also set the growth rate of market size η to 1 percent and the elasticity of

Table 2: Values for Internally Calibrated Parameters

c_e	c_f	δ	ρ	σ_ε	μ_0	σ_0	σ_a
17.649	5.337	0.005	0.972	0.032	0.142	0.138	0.078

demand ϵ to 0 so that demand equals market size L_t, but we note that the target moments are invariant to these latter two parameter choices. Following Karahan, Pugsley, and Şahin (2024), the remaining eight parameters governing firm dynamics are calibrated internally by matching a set of data moments. These eight parameters are: the entry cost c_e, the operating cost c_f, the exogenous exit rate δ, the persistence and standard deviation of the idiosyncratic shocks ρ and σ_ε, the parameters μ_0 and σ_0 governing the log-normal distribution F of its initial condition, and finally the dispersion σ_a of the log-normal distribution G of permanent types (its mean is normalized so $E[a] = 1$).

For targets, we choose a set of 23 moments that have remained stable throughout a 1979-2007 period measurable in the Census Bureau Business Dynamics Statistics. First, we target an average startup size of 6 employees, the average over our sample period. Second, we target the conditional growth rates of three-year old firms by their initial size. Specifically, we group three-year old firms into three size bins (0–49, 50–249, and 250+ employees), and compute the growth in average firm size for the firms in each initial size bin. Averaged over the sample period, these growth rates are 8.1, 1.2, and -3.0 percentage points for the 0–49, 50–249, and 250+ initial size groups, respectively. Finally, we target the exit rate of firms by age out to age 19 from Sterk, Sedláček, and Pugsley (2021), calculated on the LBD microdata for the 1979 to 1993 pooled birth cohorts of firms.

We then choose the 8 parameters by minimizing the weighted squared distance between the data and model counterparts for the 23 targets.[6] Using these parameters, Figure IA8 compares the model-implied statistics using the Karahan, Pugsley, and Şahin (2024) calibration with the data. Despite targeting 23 moments with only eight parameters, the model captures the key features of the U.S. firm dynamics very well. We report the internally calibrated model parameters in Table 2.[7]

We approximate the log-normal distribution over permanent types, G, using three equally spaced points in logs. To increase the fat-tailedness of the distribution of permanent types, we add a fourth gridpoint 4.5 times larger than the third, which is drawn with probability 0.0025.

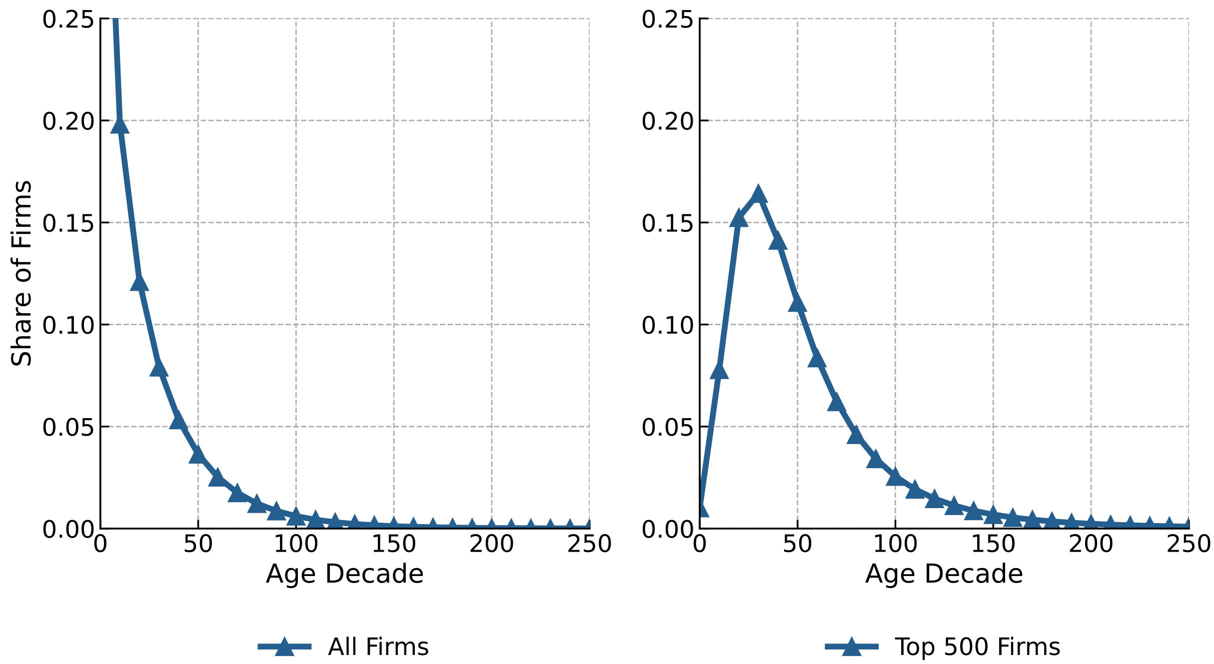
Firm age distribution Although firm decisions in this model do not depend explicitly on firm age, a firm age state variable, a, increases each period conditional on survival. Figure 10 plots the implied

[6]We weight the startup size and growth moments 10 percent each to ensure we fit these moments well, and we split the remaining 60 percent equally across the 19 exit rates.

[7]We adjust the exogenous exit rate from 1.8 percent in the Karahan, Pugsley, and Şahin (2024) calibration to 0.5 percent.

Figure 10: Stationary Firm Age Distribution in Baseline Model: Overall and Top Firms

This figure plots the firm age distribution of the stationary equilibrium in the baseline model. We use the parametrization from Karahan, Pugsley, and Şahin (2024) with exogenous exit $\delta = 0.005$ and market size growth rate $\eta = 0.01$. We approximate the top 500 firms using the top 0.5 percent, i.e., 500/100k.



stationary age distribution for a calibration of the baseline model. The left panel shows the age decade distribution among all firms, and the right panel conditions on the largest firms. Examining the process for productivity in Equation (1), both high permanent and persistent components are necessary to reach the set of superstar firms. As the ex-post persistent component takes some years to accumulate, the model naturally generates a hump-shaped pattern in the age distribution of the top firms.

By construction, in the stationary equilibrium, the firm age distribution, both overall and for the largest firms, will remain constant over calendar time. This feature approximates the empirical evidence in the retail and wholesale trade sector. In Section 3, Figure 6 shows that among the largest U.S. retailers and wholesalers, the hump-shaped pattern in firm age changes little from the 1956, 1970, 1995, and 2018 cross sections. However, it will not be able to match the empirical evidence on the industrial sector from Figure 4, where the age distribution among the top firms keeps shifting over time.

The hump-shaped pattern in the baseline model raises an additional point about identifying special generations in the data. The peak of the hump-shaped age distribution among the largest firms is a function of the time required to accumulate enough positive idiosyncratic shocks to become one of the largest firms. Empirically, we cannot use the clustering of birth years in a single cross section to detect special cohorts: such clustering of birth years could be just the natural hump in the age distribution among the top firms resulting from growth and selection. Rather, identifying special cohorts requires examining the distribution birth years over time. If special cohorts exist, the clustering of birth years will remain similar in *calendar year* for top firms in different time periods, and the *age* distribution of top firms will be non-stationary. These key features are not present in the baseline model.

4.3 Dynamic Effects of Shocks to Market Size

The stationary equilibrium of the baseline model, by definition, cannot match the non-stationary empirical patterns among the largest industrials shown in Figures 4 and 8. But even away from the stationary equilibrium, in response to a perfect foresight shock to market size, the model has difficulty matching the lasting presence of the special generation among the largest industrials and the dynamics of the special generation cohort in the data. To illustrate, we examine in the baseline model an equilibrium away from the stationary equilibrium from a shock that temporarily increases the number of entering superstars.

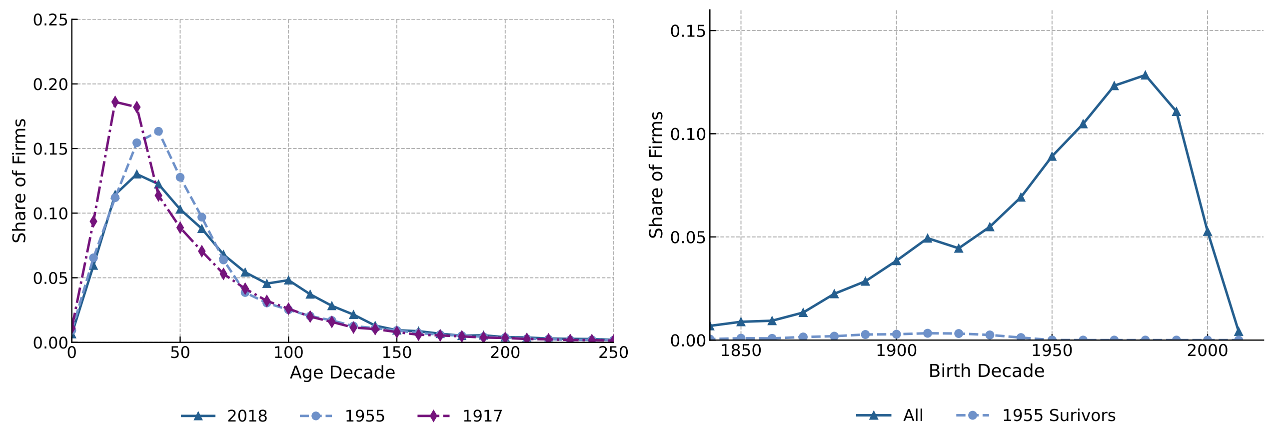
One intuition is that the disproportionate importance of a special generation of firms can arise from rapid growth in market size. Since fluctuations in market size are primarily accommodated through the entry margin (Hopenhayn, Neira, and Singhania, 2022; Karahan, Pugsley, and Şahin, 2024), a surge in the growth rate of market size would induce unusually large cohorts of entrants. In this account, the distribution over potential entrants remains the same, and additional superstars emerge through more "shots on goal." The importance of the rapid market growth birth cohort lingers until these firms eventually exit. To consider the short- and long-run effects of a shock to market size on the distribution of firms we examine the non-stationary equilibrium resulting from a perfect foresight shock to market size growth, η_t.

Non-stationary equilibrium with market size growth shock Given an initial measure $\bar{\mu}_{t-1}$, normalized by market size, the equilibrium with a perfect foresight market size growth shock, $\{\eta_{t+k}\}_{k=0}^{\infty}$, is a sequence of prices $\{p_{t+k}\}_{k=0}^{\infty}$, of value functions $\{V_{t+k}\}_{k=0}^{\infty}$ with corresponding policy functions $\{n_{t+k}, x_{t+k}\}_{k=0}^{\infty}$, market-size scaled measures over firms $\{\bar{\mu}_{t+k}\}_{k=0}^{\infty}$, such that for $k \geq 0$: (i) V_{t+k} solves Bellman equation (2), (ii) free entry condition (3) is satisfied, (iii) the product markets clears (4a), and (iv) $\bar{\mu}_{t+k}$ and $\bar{M}_{t+k}$ satisfy the law of motion (5).

Effects of a 40-year period of rapid growth Starting from the stationary equilibrium with 1 percent market size growth, i.e., $\eta = 0.01$, we consider the equilibrium path resulting from a 40-year doubling of this growth rate, i.e., $\eta_t = 0.02$ when $0 < t \leq 40$, which then returns to its baseline 1 percent growth rate thereafter. All other parameters remain the same as Section 4.2.

Figure 11: Top Firms in Baseline Model with Market Size Shock

Panel A is the firm age decade distribution of the largest 388 firms in 2018, 1955, and 1917 (i.e., simulated model counterpart to Figure 4). Panel B is the birth decade distribution of the top 388 firms in 2018 and the subset that were also among the top 388 firms in 1955 (i.e., simulated model counterpart to Figure 8). Model simulation uses parametrization from Karahan, Pugsley, and Şahin (2024) with exogenous exit $\delta = 0.005$. Market size growth rate $\eta = 0.01$ outside of 1880 to 1920, and $\eta = 0.02$ from 1880 to 1920. We simulate the model 120 times, each with an initial 100k firms drawn from the ergodic distribution, a 500-period burn-in, and then for 160 periods following the shock. Results are averaged over 120 simulations.



Panel A. Age Distribution of Top Firms

Panel B. Top Firms in 2018 and 1955

In Figure 11, we plot the results of such a perfect foresight market size growth in the baseline model. Panel A shows the age distribution of the top firms in 2018, 1955, and 1917, which is the model counterpart to Figure 4 for U.S. industrials in the data. The doubling of market size growth starting in 1880 does generate a period of larger (in number) cohorts of entering firms. Comparing the largest firms in 1917 and in 1955, the modal firm age shifts right and the mode remains a member of the rapid growth period cohort. The echo of the rapid growth cohort is visible even in 2018, but its relative importance is small. Moreover, in Panel B of Figure 11 we plot the birth decade distribution of top firms in 2018, which is the model counterpart to Figure 8, and find that there is too little persistence among the superstars between cross sections. In this model, few of the top firms in 1955 remain among the top firms in 2018.

Finally, a pickup in market size growth around 1900 is difficult to find in the data. Panel A of Figure IA9 plots the growth of real value added in manufacturing for each decade since 1850. The decades around the 1900s do not necessarily stand out, and the growth of the manufacturing sector was high for many decades until the 1960s. Panel B of Figure IA9 plots the growth of employment, and the 1900s are not necessarily special either.

In summary, a market size growth shock brings about more new firms, but there is nothing "special" about this generation beyond its cohort size. We observe more superstars only because there are more new firms, and conditional on their productivity, these superstars are no different than superstars from any other period. For a special generation to arise, there need to be not only more superstars, but these firms also need to possess a lasting advantage over firms from generations both before and *after*.

5 Firm Dynamics with Special Generations

The baseline model, even when away from its stationary distribution, has difficulty matching the features of the largest industrials in the past century. We next extend the baseline model to illustrate how a special generation emerges endogenously from the introduction of a modern technology with higher returns to scale. As hypothesized by Chandler (1994), this can occur when the technology is embodied in *new* firms and firms gradually become more efficient over time.

5.1 Incorporating Special Generations

We allow for special generations by extending the baseline model from Section 4 in two ways. First, we provide a modern technology that allows larger scale production, and *entrants* can utilize this technology if they are willing to pay an adoption cost. The adoption of this modern technology by entrants captures organizational frictions that make it difficult for incumbent firms to implement the modern technology. Second, we allow firms to learn from experience so that they become more efficient with their technology over time. With these extensions, a special generation emerges from a perfect foresight shock that permanently reduces the adoption cost of the modern technology. We describe each ingredient in turn.

A capital intensive modern technology The modern technology, $y_{iat} = z_{iat}k^{\alpha}_{iat}n^{\theta}_{iat}$, incorporates capital with elasticity α. We assume $\alpha + \theta < 1$ to maintain DRS. Further, we assume perfect rental markets for capital, with constant rental rate R expressed in goods.

The capital intensity of the modern technology effectively increases the returns to scale in labor. To see this, we can write an expression for the modern technology that maximizes out over capital to characterize production as a function of only labor:

$$y_{iat} = \max_{k} \left\{ z_{iat}k^{\alpha}_{iat}n^{\theta}_{iat} - Rk \right\} = \left(\chi z_{iat}n^{\theta}_{iat} \right)^{\frac{1}{1-\alpha}} ,$$

with $\chi \equiv \frac{\alpha^{\alpha}(1-\alpha)^{1-\alpha}}{R^{\alpha}}$. The capital intensive technology has two effects on scale. If the rental rate is not too high it boosts productivity of labor over the traditional technology, i.e., $\chi > 1$. Moreover, it unambiguously increases the returns to scale in labor. In effect, the span of control parameter increases from θ to $\frac{\theta}{1-\alpha}$. For the same z_{it}, even if $\chi = 1$, a firm operating the modern technology will be significantly larger.

Learning from experience All firms, regardless of technology, can become more efficient at production over time. Now, $z_{iat} = e_i \exp(\zeta a) s_{iat}$. This introduces a learning component to productivity that grows deterministically at rate ζ until maximum age $\bar{a}$. With learning, log productivity for a firm of age a, written as a moving average, is:

$$\log z_{iat} = \log e_i + \zeta a + \rho^a \log s_{i0} + \sum_{k=0}^{a-1} \rho^l \sigma_\varepsilon \varepsilon_{it-k}. \tag{6}$$

The value of a traditional firm is still characterized by Equation (2), with productivity, $z_{iat} = e_i \exp(\zeta a) s_{iat}$, now depending on firm age in addition to its permanent and stochastic components. We next formulate recursively the value of a firm using the modern technology.

Recursive formulation Let $V_t^M(a, e_i, s_{iat})$ be the value of an age a *modern* firm in period t with permanent productivity component e_i and stochastic component s_{iat}. Then V_t^M satisfies the following Bellman equation:

$$V_t^M = \max_n \left\{ p_t \left(\chi z_{iat} n^\theta \right)^{\frac{1}{1-\alpha}} - n - c_f \right\} + \max_{x \in \{0,1\}} \left\{ \frac{1-\delta}{1+r} E_t \left[\frac{p_t}{p_{t+1}} V_{t+1}^M \left(a+1, e_i, s_{i,a+1,t+1} \right) \right], 0 \right\}. \tag{7}$$

The characterization of firm value changes only through the modern technology, $y_{iat} = (\chi z_{iat} n^\theta)^{\frac{1}{1-\alpha}}$ with shifter χ and higher effective span of control, $\frac{\theta}{1-\alpha}$. Technology choice is irreversible, fitting with the narrative of Chandler (1994), so there is no link between V_t and V_t^M except at entry.

Potential entrants and technology adoption Potential entrants evaluate the expected value of entry incorporating the possibility of adopting the modern technology. Conditional on drawing a permanent e_i and initial s_{i0}, the firm can use c_M units of labor to implement the modern technology or use the traditional technology at no additional cost. The expected value, W_t, of a potential entrant in period t, becomes:

$$W_t = \iint_{e,s} \max_{m \in \{0,1\}} \left\{ V_t(e, 0, s_0), V_t^M(e, 0, s_0) - c_{Mt} \right\} F(ds_0) G(de). \tag{8}$$

For any period t, we let $m_t(E, S) \in \{0, 1\}$ be the indicator function in (8) that is equal to 1 if an entering firm with productivity components $e \in E$ and $s_0 \in S$ chooses to adopt the modern technology.

Firm heterogeneity and aggregation Let $\bar{\mu}_t^M(a, E, S')$ be the measure of modern age a firms with productivity components $e \in E$ and $s' \in S'$, also normalized by market size. Incorporating both traditional and modern firms in aggregate production, market clearing becomes:

$$p_t^{-\epsilon} = \sum_{0 \le a \le \bar{a}} \iint_{e,s} \Big(y_t(e \exp(\zeta a) s) \bar{\mu}_t(a,e,s) + y_t^M(e \exp(\zeta a) s) \bar{\mu}_t^M(a,e,s) \Big) \, de \, ds. \tag{4b}$$

Evolution of traditional and modern firms In light of the technology adoption, we adjust the law of motion in Equation (5) for the traditional firms as follows:

$$\bar{\mu}_t\left(a, E, S'\right) = \begin{cases} \bar{M}_t \iint_{e \in E, s' \in S'} (1 - m_t(e,s')) G(de) F(ds') & a = 0 \\ \iint_{e \in E, s} (1-\delta)\left(1 - x_{t-1}\left(a-1, e, s\right)\right) P\left(S' | s\right) \frac{\bar{\mu}_{t-1}(a-1, de, ds)}{1+\eta_t} & 1 \le a < \bar{a} \\ \iint_{e \in E, s} (1-\delta)\left(1 - x_{t-1}\left(\bar{a}, e, s\right)\right) P\left(S' | s\right) \frac{\bar{\mu}_{t-1}(\bar{a}, de, ds)}{1+\eta_t} & a = \bar{a} \end{cases} \tag{5a}$$

This accounts for the technology adoption choice at entry, i.e., when $a = 0$. We then define a new law of motion for the measure of *modern* firms, $\mu_t^M(a, E, S')$, which evolves as follows:

$$\bar{\mu}_t^M\left(a, E, S'\right) = \begin{cases} \bar{M}_t \iint_{e \in E, s' \in S'} m_t(e,s') G(de) F(ds') & a = 0 \\ \iint_{e \in E, s} (1-\delta)\Big(1 - x_{t-1}^M\left(a-1, e, s\right)\Big) P\left(S' | s\right) \frac{\bar{\mu}_{t-1}^M(a-1, de, ds)}{1+\eta_t} & 1 \le a < \bar{a} \\ \iint_{e \in E, s} (1-\delta)\Big(1 - x_{t-1}^M\left(\bar{a}, e, s\right)\Big) P\left(S' | s\right) \frac{\bar{\mu}_{t-1}^M(\bar{a}, de, ds)}{1+\eta_t} & a = \bar{a} \end{cases} \tag{5b}$$

Stationary industry equilibrium Allowing for the modern technology and learning, we define the stationary equilibrium. There is a constant price p, value functions V and V^M with policy functions $n(e \exp(\zeta a) s)$ and $x(a, e, s)$ as well as $n^M(e \exp(\zeta a) s)$ and $x^M(a, e, s)$, measures $\bar{\mu}$ and $\bar{\mu}^M$ over traditional and modern firms, respectively, and measure $\bar{M}$ of entrants, all normalized by market size, along with technology adoption policy $m(e, s)$, such that (i) V and V^M solves Bellman equations (2) and (7), (ii) free entry condition (3) is satisfied with expected value of an entrant W_t determined by (8), (iii) the product markets clears (4b), and (iv) $\bar{\mu}$, $\bar{\mu}^M$, $\bar{M}$, and $m(e, s)$ solve the two law of motions (5a) and (5b), respectively.

We note the baseline model is a special case where the adoption cost, c_M, is sufficiently high, so that it is never profitable to adopt the modern technology and with no learning from experience, $\zeta = 0$.

Special generation shock In the presence of learning $\zeta \ge 0$, the *special generation shock*, then, is a perfect foresight path for c_{Mt} that reduces the adoption cost enough to induce at least some entering firms to adopt the modern technology. Specifically, we consider a sequence that declines exponentially for τ years and remains constant thereafter. We next describe the equilibrium path resulting from such a shock.

Non-stationary equilibrium with special generation shock Given an initial measure $\bar{\mu}_{t-1}$ over firms, normalized by market size, and $\bar{\mu}^M_{t-1} = 0$, i.e., no incumbent modern firms, the equilibrium with a perfect foresight special generation shock from t to $t + \tau$ is a sequence of prices $\{p_{t+k}\}_{k=0}^{\infty}$, of value functions $\{V_{t+k}, V^M_{t+k}\}_{k=0}^{\infty}$ with corresponding policy functions $\{n_{t+k}, x_{t+k}, n^M_{t+k}, x^M_{t+k}\}_{k=0}^{\infty}$, market-size scaled measures over all firms $\{\bar{\mu}_{t+k}, \bar{\mu}^M_{t+k}\}_{k=0}^{\infty}$, and entrants with technology adoption policy $\{\bar{M}_{t+k}, m_{t+k}\}_{k=0}^{\infty}$, such that for $k \geq 0$: (i) V_{t+k} and V^M_{t+k} solve Bellman equations (2) and (7), respectively, (ii) free entry condition (3) is satisfied with expected value of an entrant W_t determined by (8), (iii) the product markets clears (4b), and (iv) $\bar{\mu}_{t+k}$, $\bar{\mu}^M_{t+k}$, and $\bar{M}_{t+k}$ satisfy the two law of motions (5a) and (5b), respectively.

5.2 Results

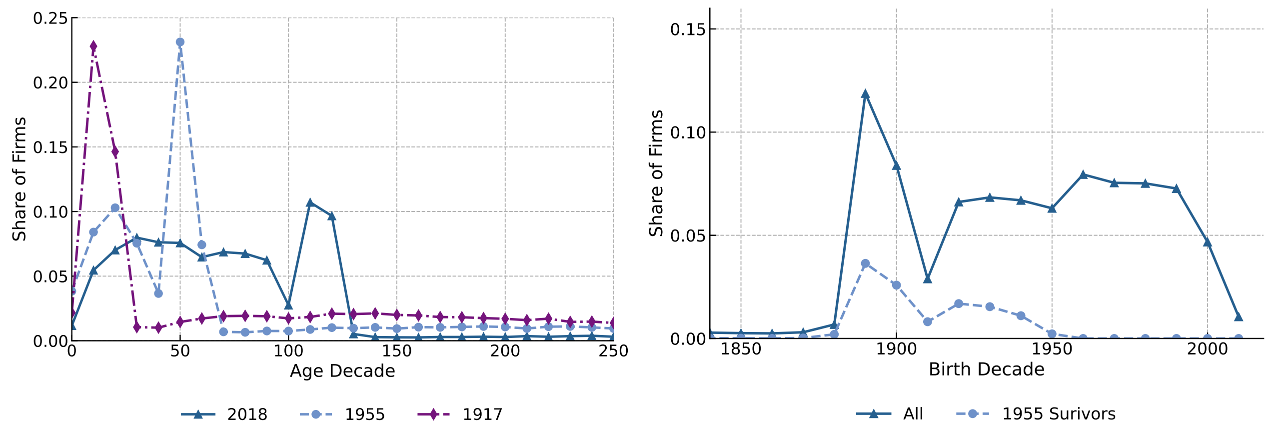
To examine the determinants of a special generation, we start with a stationary economy where firms learn gradually from experience so their efficiency improves at rate $\zeta = 0.003$, but with only the traditional technology, i.e., $c_M \to \infty$ (see Figure IA10). Next we introduce the adoption of the modern technology. We choose the capital elasticity to be $\alpha = 0.12$, which increases the effective span of control over labor, $\frac{\theta}{1-\alpha}$, to 0.72 from $\theta = 0.64$. We consider a special generation shock with a finite adoption cost, where c_{Mt} starts at 40,000 units of labor and shrinks geometrically over 40 years by 80 percent to roughly 8,000 units of labor, where it remains thereafter (Figure IA11). These adoption costs are significant. Even 8,000 units of labor is still 450 times larger than the entry cost.

We examine the equilibrium path in response to a special generation shock starting in 1860, which corresponds to the common dating of the start of the Second Industrial Revolution. Figure 12 plots the results. Panel A is the model counterpart to Figure 4 for U.S. industrials in the data. Like the data, the availability of the modern technology leaves a strong imprint on the age distribution that fades only very slowly with time. In the 1917 cross section, the largest firms are very young. These are the firms that were early adopters of the modern technology as its cost declined. This early cohort remains the most important among the top firms in 1955 and 2018. Panel B is the model counterpart to Figure 8, which shows that the largest firms in 2018 are disproportionately drawn from the cohort born around 1900, and a modest fraction of the largest firms in 2018 (from the special cohort around 1900 or otherwise) were also among the largest firms in 1955. Like in the data, the special generation shock in our model makes the cohort from around 1900 more persistent than the individual top firms within the cohort.

In general, the largest firms are those with highest productivity. Examining the moving average representation of productivity in equation (6), the highest productivity firms posses high permanent types, the accumulation of good ex post shocks through the stochastic component, and the accumulation of

Figure 12: Top Firms in Model with Modern Technology and Learning by Doing

Panel A is the firm age decade distribution of the largest 388 firms in 2018, 1955, and 1917 (i.e., simulated model counterpart to Figure 4). Panel B is the birth decade distribution of the top 388 firms in 2018 and the subset that were also among the top 388 firms in 1955 (i.e., simulated model counterpart to Figure 8). Model simulation uses parametrization from Karahan, Pugsley, and Şahin (2024) with exogenous exit $\delta = 0.005$ and market size growth rate $\eta = 0.01$. The modern technology has capital with elasticity $\alpha = 0.12$, and adoption costs exponentially decreasing from 40,000 to 8,000 in 40 periods starting from 1860. The learning rate ζ is 0.003. We simulate the model 120 times, each with an initial 100k firms drawn from the ergodic distribution, a 500-period burn-in, and then for 160 periods following the shock. Results are averaged over 120 simulations.



Panel A. Age Distribution of Top Firms

Panel B. Top Firms in 2018 and 1955

experience. The modern technology amplifies the scale of any firm that chooses to adopt it. What makes the special generation special is the advantage of firms within this cohort over both older pre Second Industrial Revolution firms *and* the advantage of these early modern firms over later modern firms. The advantage of the modern technology (once it is economical for the most productive firms to adopt it) over the traditional technology is self-evident. The advantage of the early modern firms over late modern firms arises from incumbent learning, however gradual. As Chandler (1994) explains: "The first movers were apt to be well down the learning curve in each of the industry's functional activities before challengers went into full operation."

Each productivity component is essential. The greater importance of the birth-decade cohort than the specific firms within it confirms the importance of the right mix of fundamentals (the permanent type) and good luck. The stochastic component of productivity, in the accumulation of ex post shocks $\sum_k \rho^k \varepsilon_{t-k}$, will mean revert to 0. The mean reversion of this ex post component induces the firm-level churning where only a fraction of the 1955 largest firms from the special generation remain in the 2018 list, despite the continued importance of the special generation. However, if dominance were only from accumulated and mean-reverting good luck, i.e., without a permanent advantage, it would be improbable to observe firms dominant in *both* 1955 and 2018. The high permanent type makes potential superstars in the special generation, even if not dominant early, more likely to survive long enough to eventually accumulate a sufficiently large ex post component to become dominant.

Dynamics of the special generation The patterns in Figure 12 result from the dynamics of the special generation cohort. The reduced adoption cost enables the most productive entrants to adopt the modern technology and operate permanently at much larger scale. As the adoption cost continues to fall, the share of entrants adopting the modern technology rises (Figure IA12). The introduction of these firms ultimately drives down the equilibrium price (Figure IA13).[8] As incumbent firms adjust their scale in response to the lower price and those that have become unprofitable exit, new firms enter to take their place and meet demand (Figure IA14). This temporary effect increases the size of the special generation cohort. Thus the special generation arises because of both the rising propensity to adopt the modern technology and the increase in the size of the cohort. Although the propensity to adopt the modern technology remains permanently higher when adoption costs reach the minimum, the early adopters in the special generation maintain their advantage as they learn to operate the technology more efficiently.

Importance of learning Efficiency gains from experience compound the permanent advantage of the early modern firms. Without learning, highly productive late modern entrants would be no different than similarly productive early entrants. Figure IA15 examines the same shock without learning, $\zeta = 0$. Even without learning, the echo of the early cohort is still visible, but the importance of this special generation fades quickly. The head start from the gradual learning gives the early entrants a much longer lasting advantage.

Importance of swift declines in adoption costs of the modern technology In Figure IA16, we show that the special generation also won't register if the decline of the modern technology adoption cost happens too slowly. Here, we stretch out the adoption cost decline to over 100 rather than 40 years. These variations could shed light on why special generations did not appear among British industrials. According to Chandler (1994), "What differentiated British entrepreneurial, later family-controlled, enterprises from those in the United States and Germany was that the entrepreneurs assembled smaller management teams, and until well after World War II they and their heirs continued to play a larger role in the making of middle and top-management decisions." The insistence on personal and family management could have contributed to higher effective costs of operating modern large-scale industrial enterprises. In the model, with a slow 100-year decline in the adoption cost of the modern technology, the adopters emerge too gradually and many of them too late to form a concentrated special generation from around 1900.

[8] In Figure IA13, the price initially rises for the following reason. In the early years of the shock, the adoption costs of the modern technology are still too high for almost all entrants to incur. Nonetheless, these entrants—with their traditional technology—still anticipate the eventual price declines from a wider range of subsequent entrants adopting the modern technology. The effect of future price declines on profits puts upward pressure on *current* prices through free entry.

Learning without a modern technology One might wonder whether adopting a higher returns to scale technology is even necessary when learning from experience generates persistence. Would a shock to the size of the entering cohort (as in the baseline model), combined with learning, be enough to match the patterns for the largest industrials? This turns out not to be the case. Figure IA17 plots the same shock to market size growth as in Section 4.3 Figure 11. As expected, learning can enhance the persistence of the rapid growth cohort among the top firms. However, it fails to capture the persistence of individual firms. Without the boost in scale from adopting the modern technology, the firms within the rapid growth cohort have no lasting advantage beyond the size of the cohort.

6 Conclusion

We study the largest American companies at different points in time and document several patterns. In industrials, we observe the persistent prominence of firms born around 1900, even though the particular companies have changed substantially over time. As a result, the average age of the largest industrials keeps increasing. In retail and wholesale, we observe the age distribution of the largest firms to be stationary. In services, very large firms became more common after the 1970s and the 1980s. These decades could have produced a special generation of entrants similar to the experience of industrials in the early 20th century, but this possibility will take more decades to verify.

The evidence suggests that certain settings produce special generations of entrants that give rise to superstar firms for decades to come, but these settings occur occasionally. Through the lenses of our model analyses, these settings occur if new technologies emerge that exhibit economies of scale, confer low adoption costs for new entrants, and require organizational learning. The combination of these forces leads to "hysterisis," and produces special cohorts that have a strong edge relative to both firms that came before and potential entrants thereafter. At the same time, the individual firms at the top can keep churning due to idiosyncratic shocks, so top firms are old yet the landscape is not stale. Taken together, our facts and analyses provide new perspectives on the dynamics of dominant firms.

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Internet Appendix: For Online Publication

Figure IA1: Sales by Birth Decade for 2018 *Fortune* 1,000 Companies

This figure shows the total sales of 2018 *Fortune* 1,000 companies by birth decade. Companies are assigned to main sectors based on their industries in 2018. The main sectors correspond to SIC codes 15-17 (construction), 10-14 and 20-39 (industrials), 40-49 (transportation, communications, and utilities), 50-59 (wholesale and retail trade), 60-67 (finance, insurance, and real estate), and 70-89 (services).

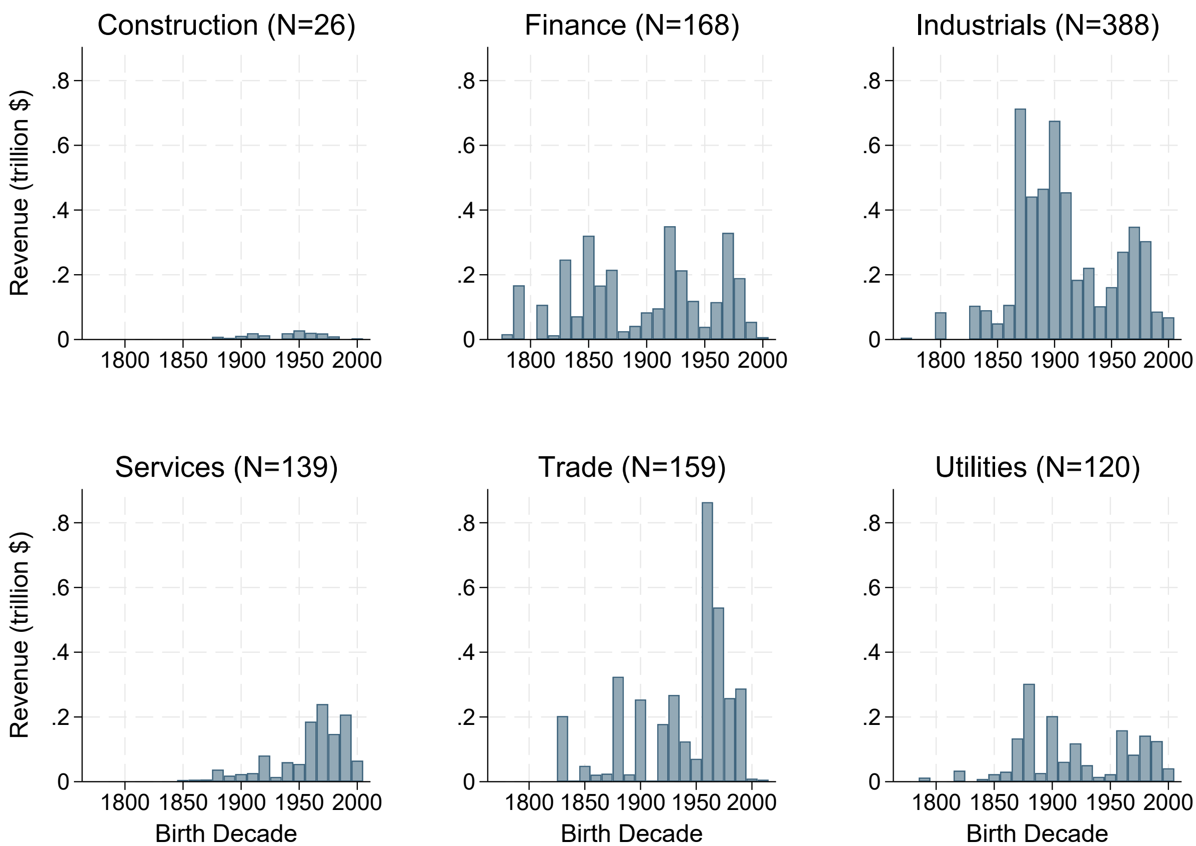


Figure IA2: Employment by Birth Decade for 2018 *Fortune* 1,000 Companies

This figure shows the total employment of 2018 *Fortune* 1,000 companies sales by birth decade. Companies are assigned to main sectors based on their industries in 2018. The main sectors correspond to SIC codes 15-17 (construction), 10-14 and 20-39 (industrials), 40-49 (transportation, communications, and utilities), 50-59 (wholesale and retail trade), 60-67 (finance, insurance, and real estate), and 70-89 (services).

Figure IA3: Birth Year Distribution Excluding Firms with Complex Histories

This figure shows the distribution of birth years per decade for the 2018 *Fortune* 1,000 companies, excluding firms that involve mergers of equals and firms that are spin-offs where we do not have information about the origin of the spun-off entity. The main sectors correspond to SIC codes 15-17 (construction), 10-14 and 20-39 (industrials), 40-49 (transportation, communications, and utilities), 50-59 (wholesale and retail trade), 60-67 (finance, insurance, and real estate), and 70-89 (services).

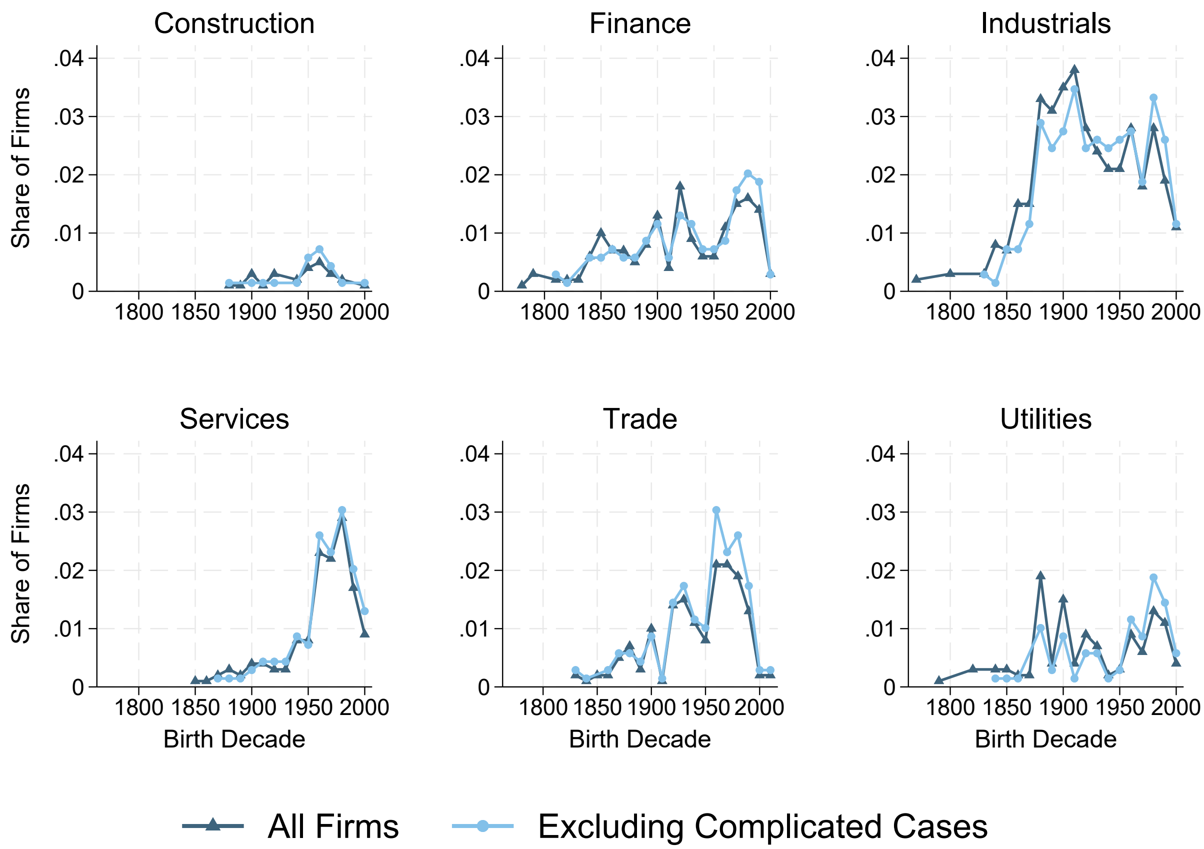


Figure IA4: Top 1,000 in 2018 with Private Firms from *Forbes* List

This figure shows the distribution of birth decade for the largest 1,000 firms by sales in the 2018 *Fortune* 1,000 list (solid line with triangles) and the combined list that also includes additional large private firms according to the 2018 *Forbes: America's Largest Private Companies* list (solid line with circles). The main sectors correspond to SIC codes 15-17 (construction), 10-14 and 20-39 (industrials), 40-49 (transportation, communications, and utilities), 50-59 (wholesale and retail trade), 60-67 (finance, insurance, and real estate), and 70-89 (services).

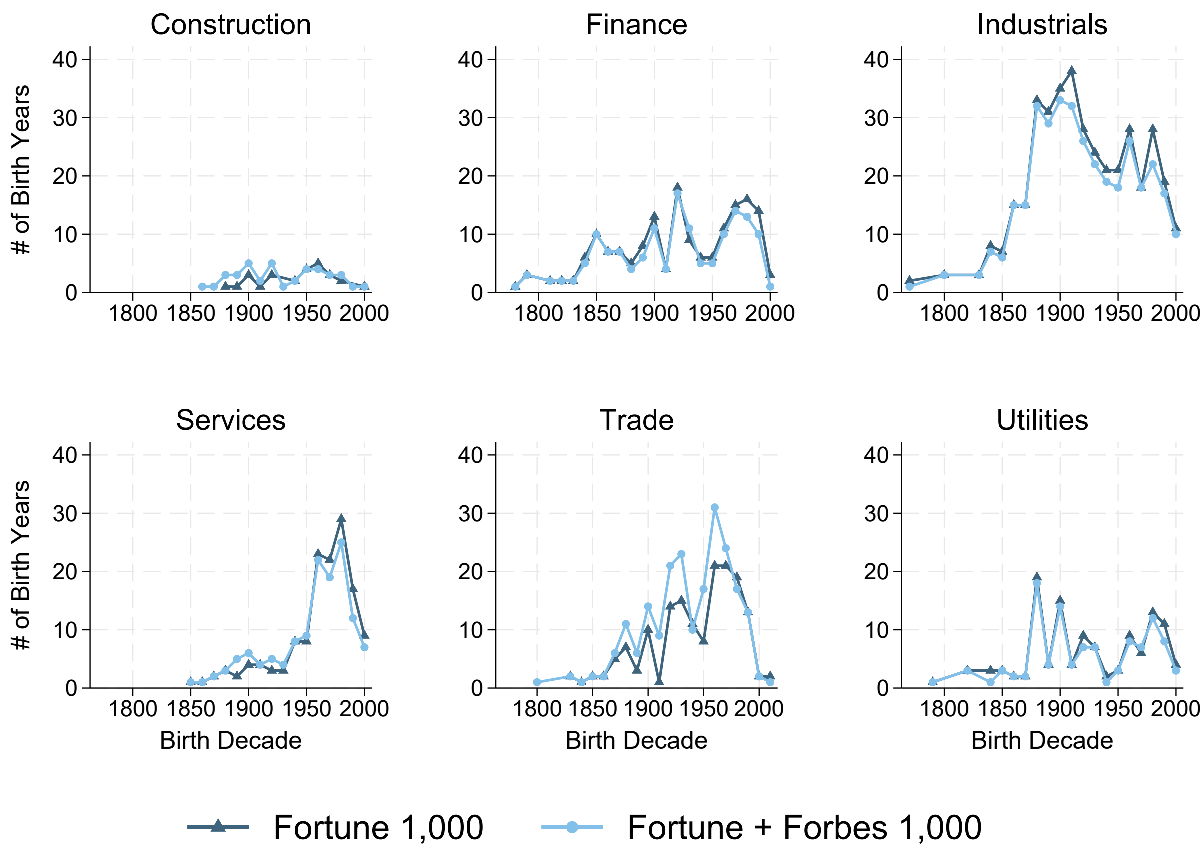


Figure IA5: Firm Age in BDS and *Fortune* 1,000

This figure compares the firm age distribution in the Business Dynamics Statistics with Fortune 1000 firms for all firms in the BDS (Panel A) and for firms in the BDS with more than 10,000 employees (Panel B). BDS suppresses the number of firms by age category in some sectors for the very largest firms. We impute values whenever possible and otherwise set the suppressed cells equal to zero. The main sectors correspond to SIC codes 15-17 (construction), 10-14 and 20-39 (industrials), 40-49 (transportation, communications, and utilities), 50-59 (wholesale and retail trade), 60-67 (finance, insurance, and real estate), and 70-89 (services).

Panel A. All BDS Firms

Panel B. BDS Firms with More than 10,000 Employees

Figure IA6: Sector Composition of the Largest 1,000 Firms

This figure plots the sector composition of the largest 1,000 firms in the U.S. economy by sales in 1960 and 2018. The 1960 composition is estimated using SOI tabulations by sales. First, we estimate a sales threshold for the largest 1,000 firms by sales. We then use sector-level tabulations to interpolate how many firms are above the estimated threshold. The 2018 composition directly uses the *Fortune* 2018 list. The main sectors correspond to SIC codes 15-17 (construction), 10-14 and 20-39 (industrials), 40-49 (transportation, communications, and utilities), 50-59 (wholesale and retail trade), 60-67 (finance, insurance, and real estate), and 70-89 (services).

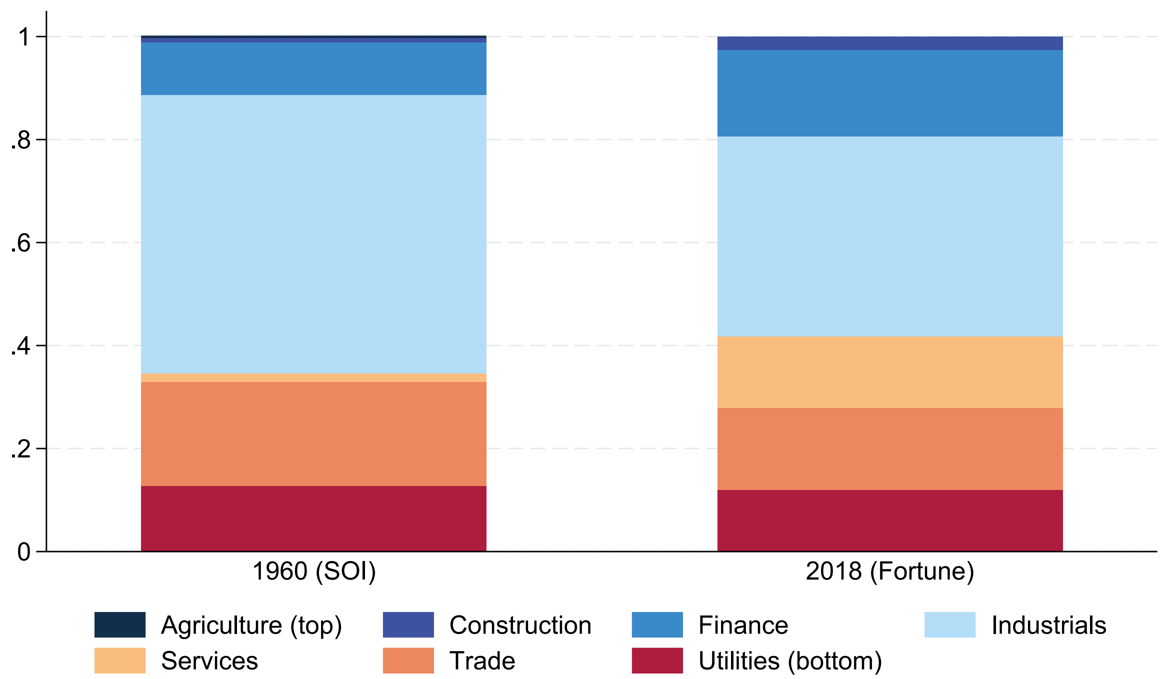


Figure IA7: Age Distribution of the Largest British Industrials in 2018 by Sales and by Market Cap

This figure shows the age distribution of the largest 200 British industrials by market capitalization of shares (solid line with circles) and by sales (solid line with triangles) in 2018.

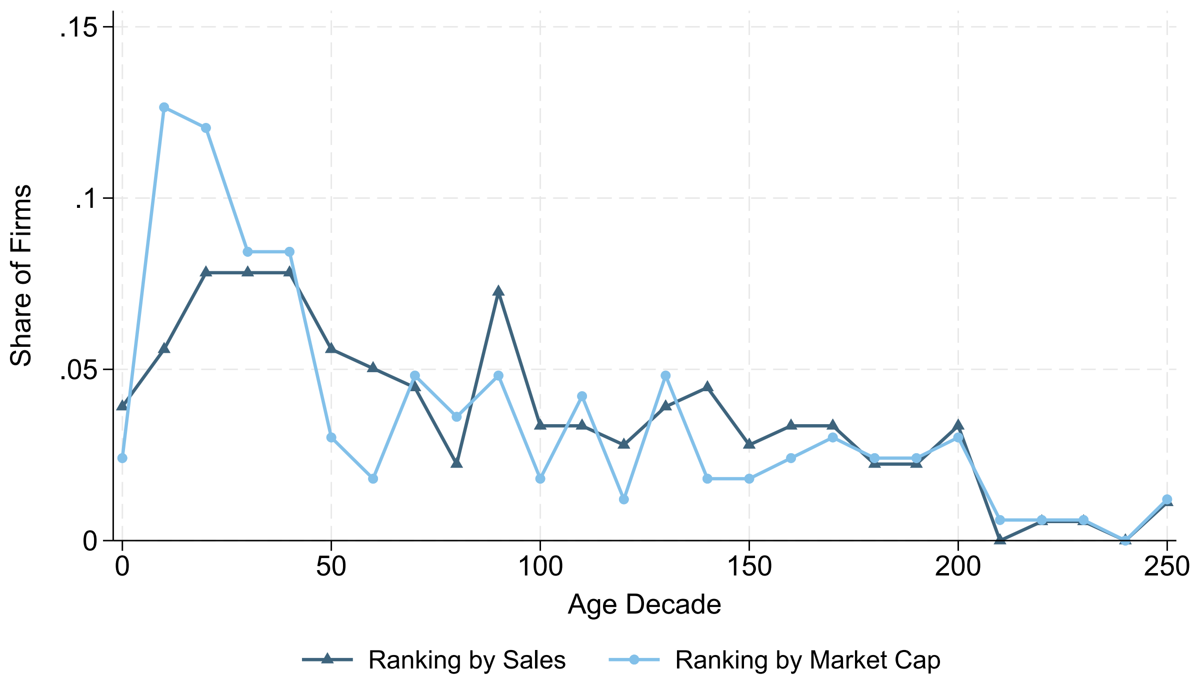
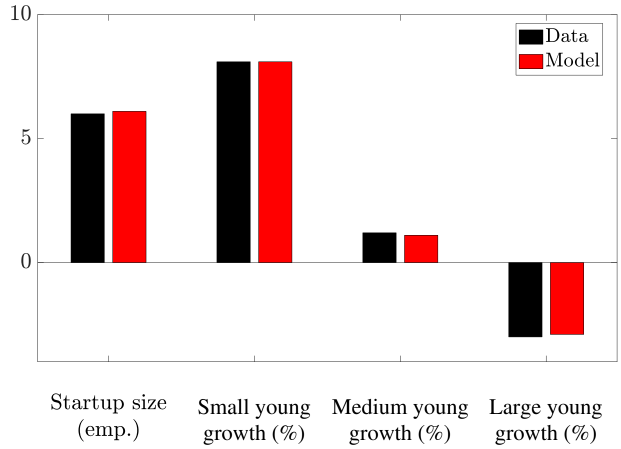


Figure IA8: Model Fit to Targeted Moments

This figure compares the model-implied statistics using the Karahan, Pugsley, and Şahin (2024) calibration with the data.



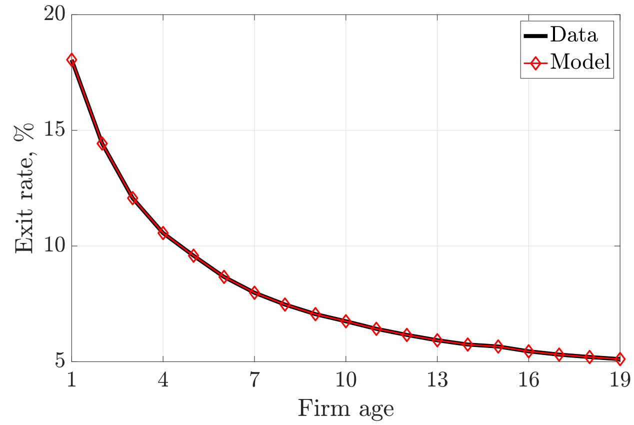
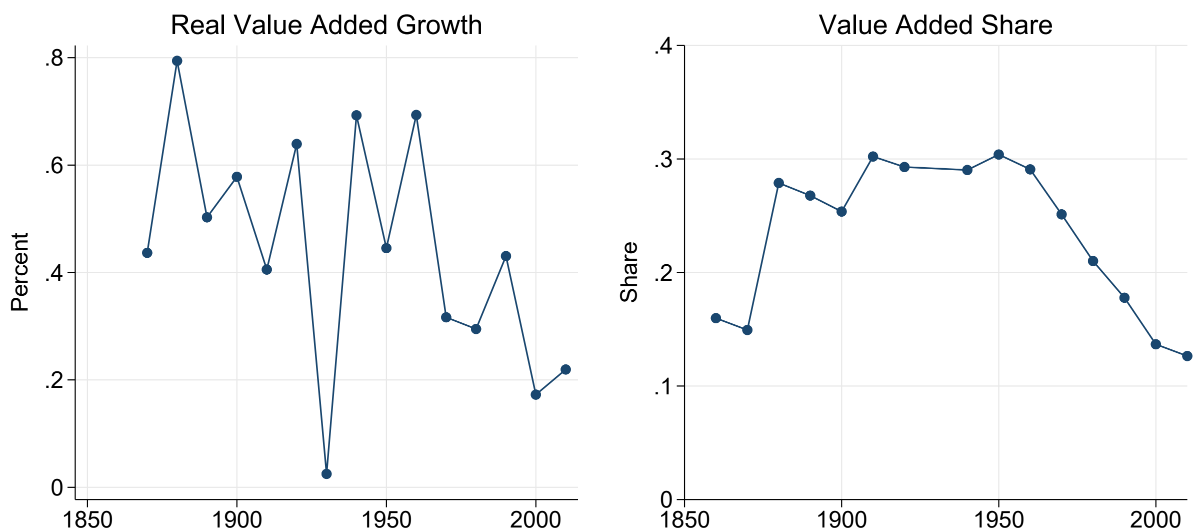


Figure IA9: Sector Trends

Panel A plots value added growth (left-hand side) and value added shares (right-hand side) of the manufacturing sector by decade. Panel B plots employment growth (left-hand side) and employment shares in total labor force (right-hand side) of the industrials (manufacturing and mining) and the trade (retail and wholesale) sector by decade. Historical data are from Carter et al. (2006) and historical national accounts provided by the Groningen Growth and Development Centre. Recent data are from the BEA.

Panel A. Manufacturing Value Added Growth and Share



Panel B. Employment Growth and Share

Figure IA10: Stationary Firm Age Distribution with Learning by Doing: Overall and Top Firms

This figure plots the firm age distribution of the stationary equilibrium with learning by doing. We use the parametrization from Karahan, Pugsley, and Şahin (2024) with exogenous exit $\delta = 0.005$ and market size growth rate $\eta = 0.01$. The learning rate ζ is 0.003. We approximate the top 500 firms using the top 0.5 percent, i.e., 500/100k.

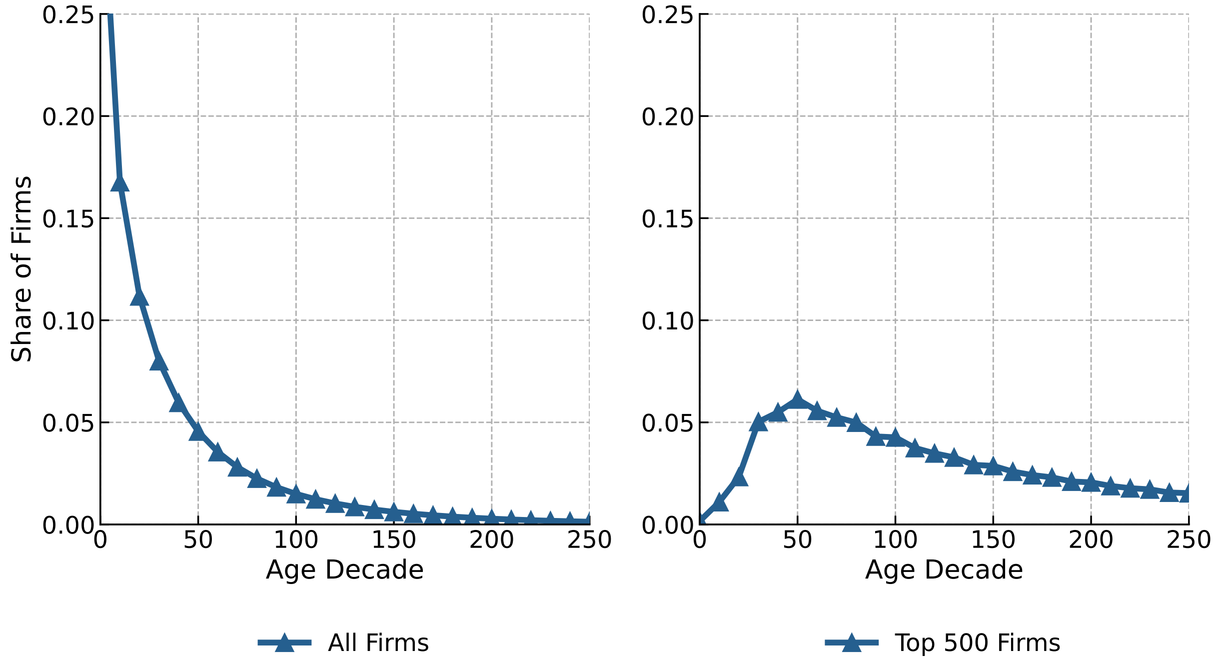


Figure IA11: Special Generation Shock

This figure illustrates the perfect foresight path of the adoption cost for the modern technology in units of labor starting in 1860.

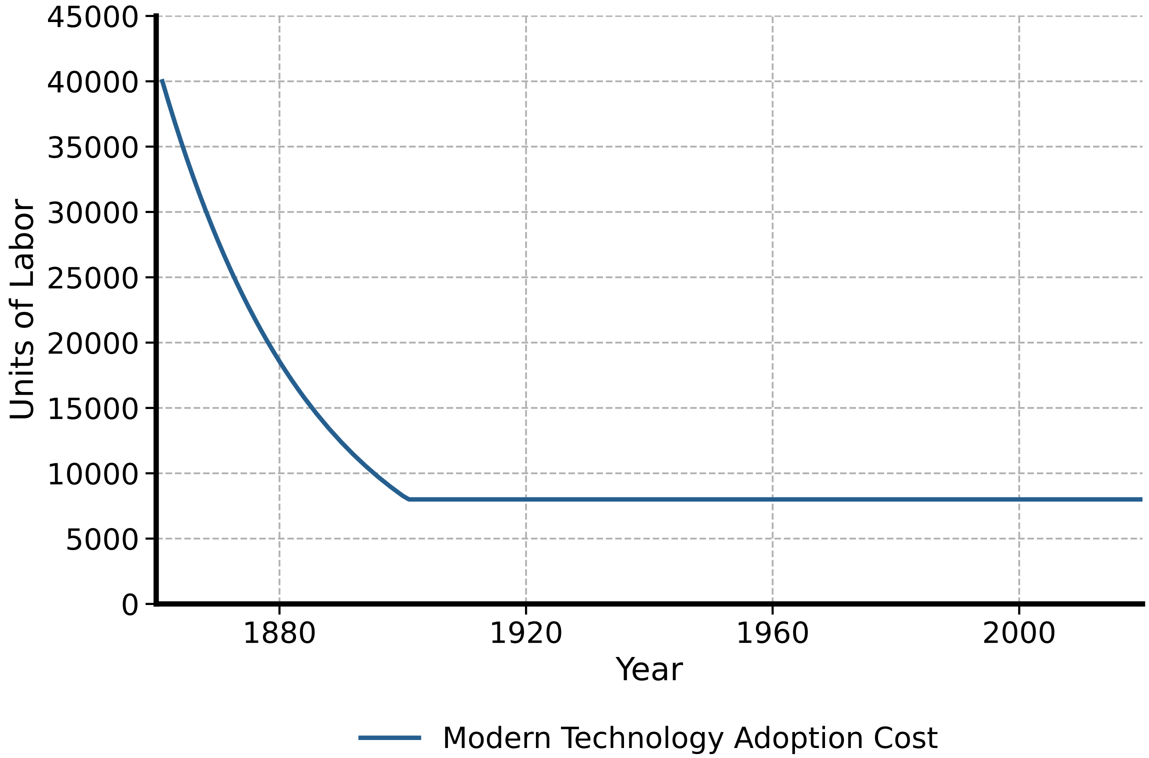


Figure IA12: Share of Entrants and All Firms using Modern Technology

This figure plots the share of entrants (left y-axis) and all firms (right y-axis) adopting modern technology. The purple dashed line represents the year when the relative price of output reaches its maximum. The pink dashed line represents the year when the relative price hits its minimum. We use the parametrization from Karahan, Pugsley, and Şahin (2024) with exogenous exit $\delta = 0.005$ and market size growth rate $\eta = 0.01$. The modern technology has capital with elasticity $\alpha = 0.12$, and adoption costs exponentially decreasing from 40,000 to 8,000 in 40 periods starting from 1860. The learning rate ζ is 0.003. We simulate the model 120 times, each with an initial 100k firms drawn from the ergodic distribution, a 500-period burn-in, and then for 160 periods following the shock. Results are averaged over 120 simulations.

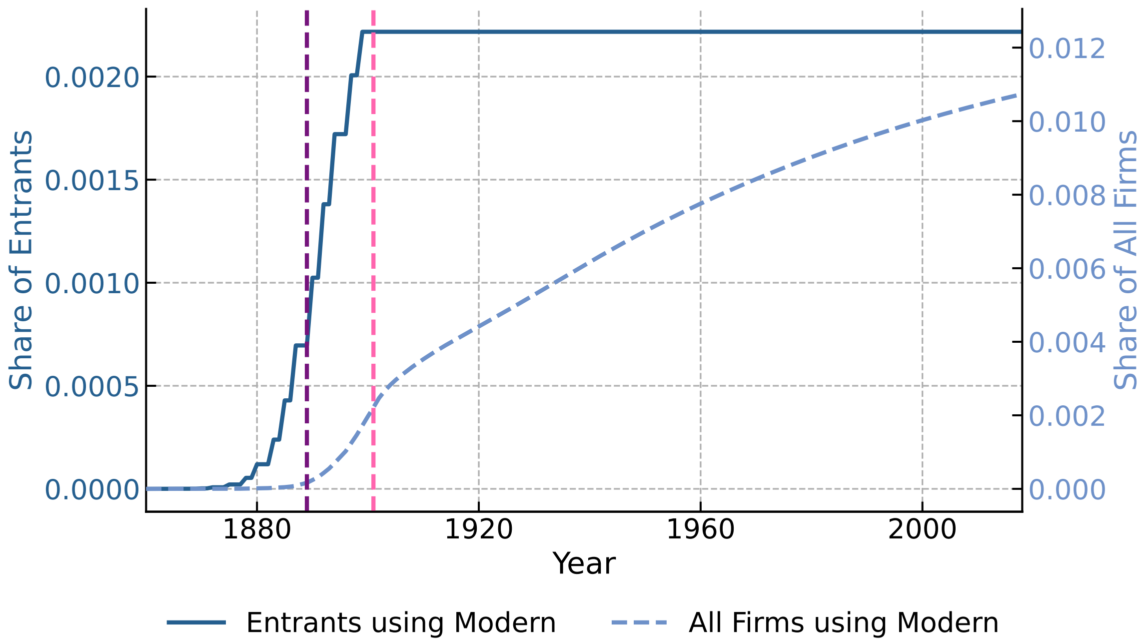


Figure IA13: Price of Output

This figure plots a price index for the relative price of output. We scale the initial relative price of output of 2.15, measured in units of labor, to be 1. The price index peaks at 1.04 in 1889 (purple dashed line), and maintains its minimum value of 0.95 from 1901 onwards (pink dashed line). We use the parametrization from Karahan, Pugsley, and Şahin (2024) with exogenous exit $\delta = 0.005$ and market size growth rate $\eta = 0.01$. The modern technology has capital with elasticity $\alpha = 0.12$, and adoption costs exponentially decreasing from 40,000 to 8,000 in 40 periods starting from 1860. The learning rate ζ is 0.003. We simulate the model 120 times, each with an initial 100k firms drawn from the ergodic distribution, a 500-period burn-in, and then for 160 periods following the shock. Results are averaged over 120 simulations.

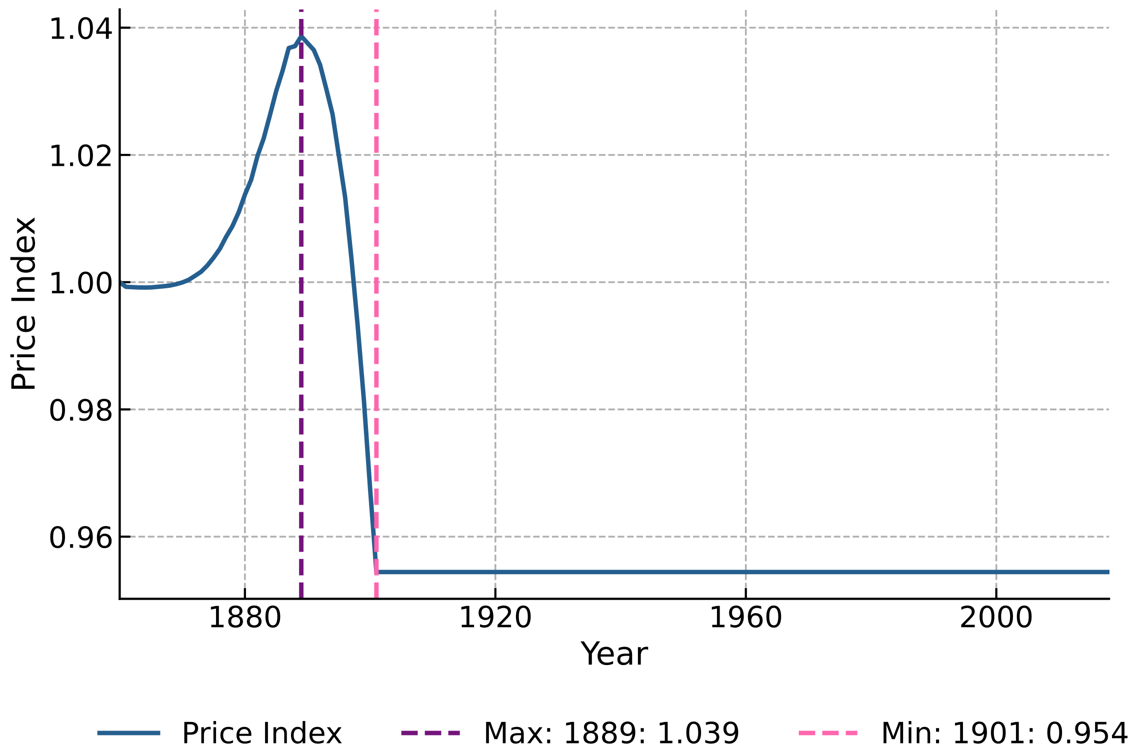


Figure IA14: Startup Rate and Exit Rate

This figure plots the startup rate and exit rate. The purple dashed line represents the year when the relative price of output reaches its maximum. The pink dashed line represents the year when the relative price hits its minimum. Model simulation uses parametrization from Karahan, Pugsley, and Şahin (2024) with exogenous exit $\delta = 0.005$ and market size growth rate $\eta = 0.01$. The modern technology has capital with elasticity $\alpha = 0.12$, and adoption costs exponentially decreasing from 40,000 to 8,000 in 40 periods starting from 1860. The learning rate ζ is 0.003. We simulate the model 120 times, each with an initial 100k firms drawn from the ergodic distribution, a 500-period burn-in, and then for 160 periods following the shock. Results are averaged over 120 simulations.

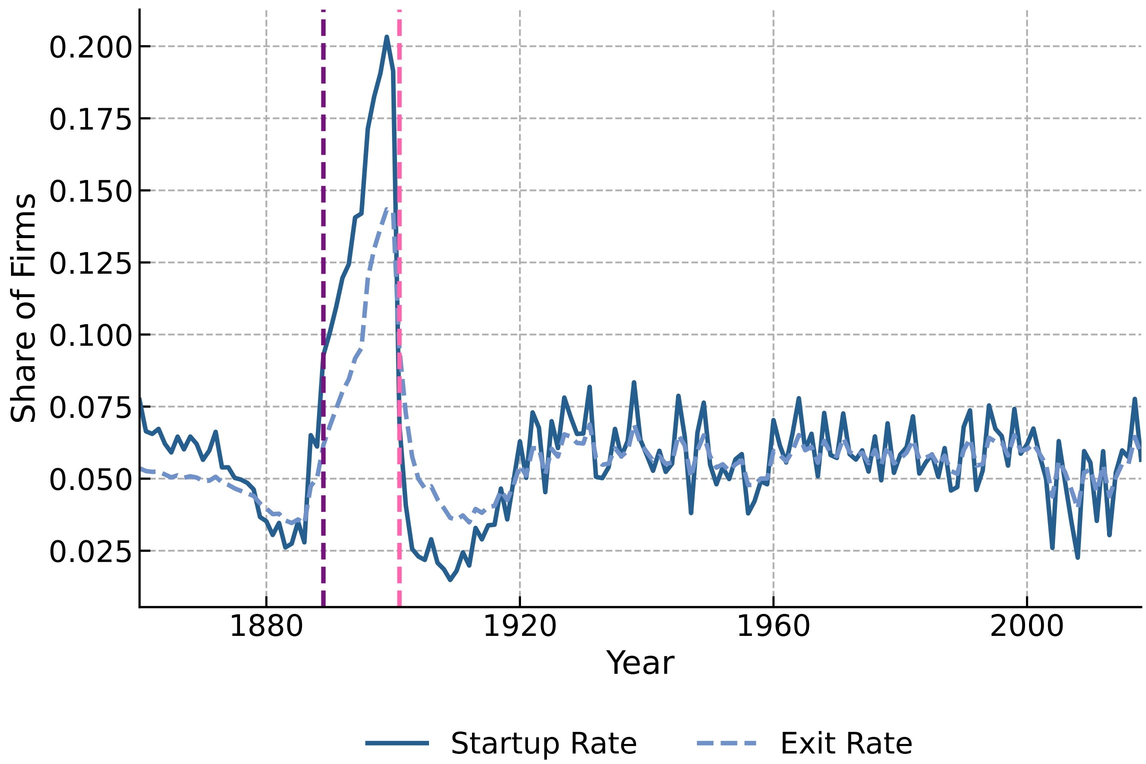
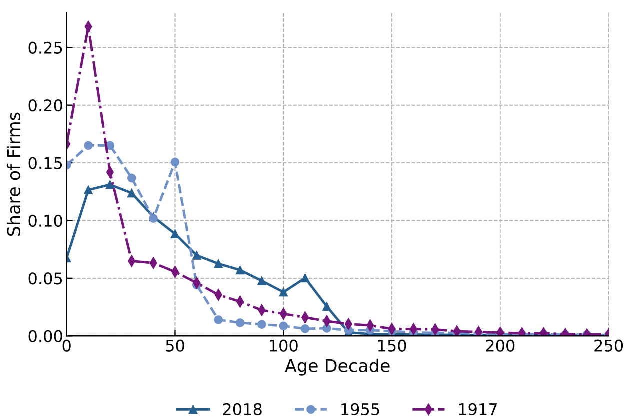
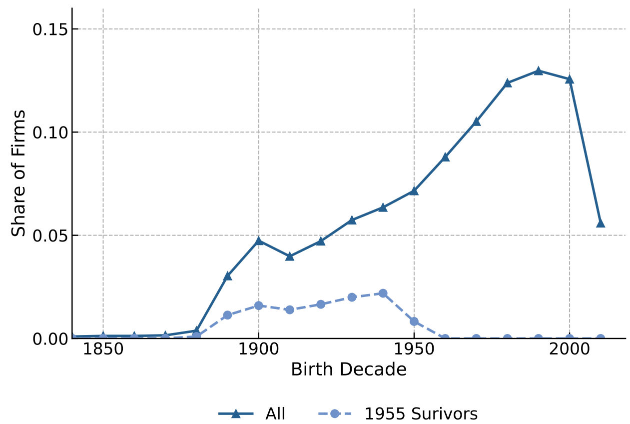


Figure IA15: Top Firms in Model with Modern Technology and No Learning by Doing

Panel A is the firm age decade distribution of the largest 388 firms in 2018, 1955, and 1917 (i.e., simulated model counterpart to Figure 4). Panel B is the birth decade distribution of the top 388 firms in 2018 and the subset that were also among the top 388 firms in 1955 (i.e., simulated model counterpart to Figure 8). Model simulation uses parametrization from Karahan, Pugsley, and Şahin (2024) with exogenous exit $\delta = 0.005$ and market size growth rate $\eta = 0.01$. The modern technology has capital with elasticity $\alpha = 0.12$, and adoption costs exponentially decreasing from 40,000 to 8,000 in 40 periods starting from 1860. We simulate the model 120 times, each with an initial 100k firms drawn from the ergodic distribution, a 500-period burn-in, and then for 160 periods following the shock. Results are averaged over 120 simulations.



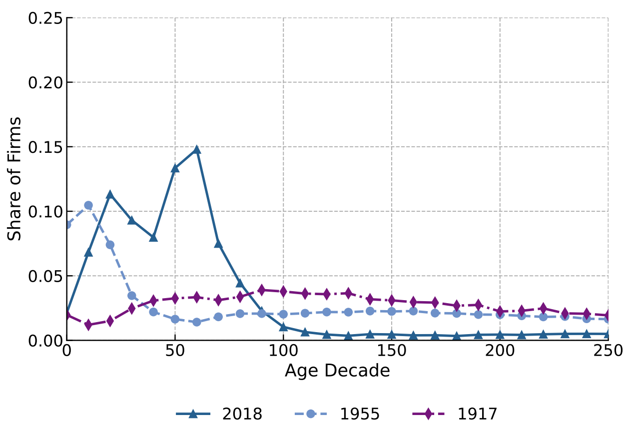
Panel A. Age Distribution of Top Firms



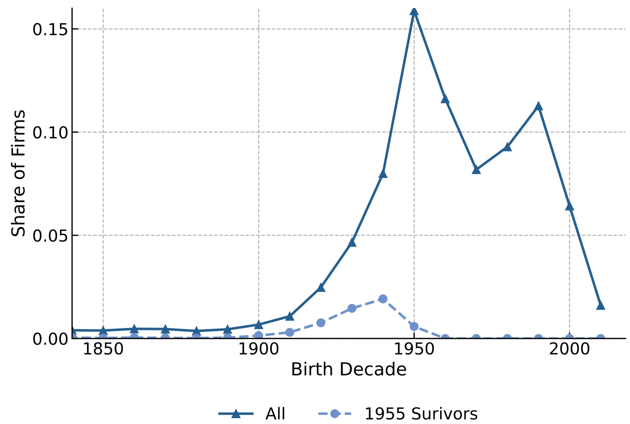
Panel B. Top Firms in 2018 and 1955

Figure IA16: Top Firms in Model with Slow Decline of Modern Technology Adoption Cost

Panel A is the firm age decade distribution of the largest 388 firms in 2018, 1955, and 1917 (i.e., simulated model counterpart to Figure 4). Panel B is the birth decade distribution of the top 388 firms in 2018 and the subset that were also among the top 388 firms in 1955 (i.e., simulated model counterpart to Figure 8). Model simulation uses parametrization from Karahan, Pugsley, and Şahin (2024) with exogenous exit $\delta = 0.005$ and market size growth rate $\eta = 0.01$. The modern technology has capital with elasticity $\alpha = 0.12$, and adoption costs exponentially decreasing from 40,000 to 8,000 in 100 periods starting from 1860. The learning rate ζ is 0.003. We simulate the model 120 times, each with an initial 100k firms drawn from the ergodic distribution, a 500-period burn-in, and then for 160 periods following the shock. Results are averaged over 120 simulations.



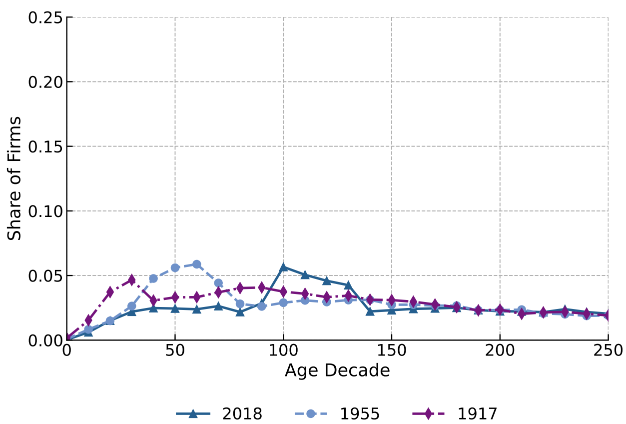
Panel A. Age Distribution of Top Firms



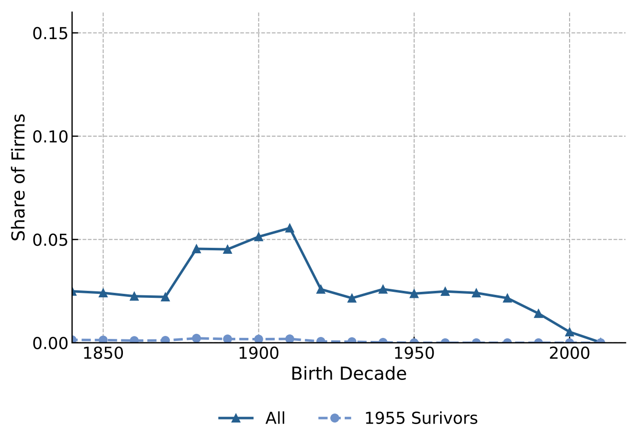
Panel B. Top Firms in 2018 and 1955

Figure IA17: Top Firms in Baseline Model plus Learning by Doing and Market Size Shock

Panel A is the firm age decade distribution of the largest 388 firms in 2018, 1955, and 1917 (i.e., simulated model counterpart to Figure 4). Panel B is the birth decade distribution of the top 388 firms in 2018 and the subset that were also among the top 388 firms in 1955 (i.e., simulated model counterpart to Figure 8). Model simulation uses parametrization from Karahan, Pugsley, and Şahin (2024) with exogenous exit $\delta = 0.005$. The learning rate is $\zeta = 0.003$. Market size growth rate $\eta = 0.01$ outside of 1880 to 1920, and $\eta = 0.02$ from 1880 to 1920. We simulate the model 120 times, each with an initial 100k firms drawn from the ergodic distribution, a 500-period burn-in, and then for 160 periods following the shock. Results are averaged over 120 simulations.



Panel A. Age Distribution of Top Firms



Panel B. Top Firms in 2018 and 1955

Table IA1: Examples for Persistence of Top Firms

This table lists top ten firms in food (Panel A) and metals (Panel B) manufacturing in 1955 and 2018 and their birth years. It also includes information about the outcomes of the top firms in 1955 by 2018. Outcomes with direct connections to 2018 Fortune *1,000* firms are displayed in bold, and outcomes with indirect connections to 2018 Fortune *1,000* firms are displayed in italics.

Panel A. Top 10 in Food: 1955 vs 2018

Top in 1955	**Birth Year**	**Outcome in 2018**	**Top in 2018**	**Birth Year**
Swift	**1855**	acquired, owned by JBS	PepsiCo	**1898**
Armour	**1867**	dissolved	Archer Daniels Midland	**1902**
National Dairy Products	**1898**	**Mondelez**	Tyson Foods	**1935**
General Foods	**1895**	*acquired, owned by Mondelez*	Coca-Cola	**1886**
Borden	**1857**	dissolved	Kraft Heinz	**1869**
Wilson & Co.	**1855**	dissolved	Mondelez	**1898**
General Mills	**1866**	**General Mills**	General Mills	**1866**
Cudahy Packing	**1887**	acquired, owned by Sigma Alimentos	Land O'Lakes	**1921**
Standard Brands	**1852**	*acquired, owned by Mondelez*	Kellogg	**1906**
Ralston Purina	**1894**	dissolved	Molson Coors Brewing	**1873**

Panel B. Top 10 in Metals: 1955 vs 2018

Top in 1955	**Birth Year**	**Outcome in 2018**	**Top in 2018**	**Birth Year**
U.S. Steel	**1872**	**U.S. Steel**	Nucor	**1905**
Bethlehem Steel	**1857**	dissolved	Arconic	**1888**
Republic Steel	**1886**	acquired, owned by Grupo Simec	Stanley Black & Decker	**1843**
Aluminum Co. of America	**1888**	**Alcoa, Arconic**	U.S. Steel	**1872**
American Can	**1901**	Primerica	Parker-Hannifin	**1917**
Continental Can	**1904**	dissolved	Alcoa	**1888**
Inland Steel	**1893**	acquired, owned by ArcelorMittal	Ball	**1880**
Armco Steel	**1899**	**AK Steel Holdings**	Corning	**1851**
American Metal Products	**1887**	*acquired, owned by Freeport-McMoRan*	Steel Dynamics	**1993**
Jones & Laughlin Steel	**1852**	acquired, owned by Grupo Simec	Crown Holdings	**1892**