Blueprint Labs

Discussion Paper #2023.05

Patenting with the Stars: Where are Technology Leaders Leading the Labor Market?

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March 2023

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February 2023

Abstract

This paper considers the potential labor market consequences of the innovative activity of the largest U.S. firms ('superstars') over eight decades. Superstars generate a large share of innovations, and their innovations are technologically distinct and differentially impactful relative to those of other firms. Leveraging a novel patent-level measure of innovations' labor-augmenting and labor-automating potential, we show that superstar innovations are more likely to augment labor compared to innovations pioneered by other firms, especially in recent decades. Workers of different skill types do not benefit equally, however: top firms' differential labor augmentation is largely limited to high-paid occupations. This suggests modern-day superstar firms' innovations contribute to the diverging labor market fortunes of high- and low-skilled workers. We highlight that the social value of augmenting innovations as measured by novelty and intellectual impact has risen while their market value has fallen—particularly for innovations which augment middle-skilled workers—suggesting that labor-augmenting innovations may be under-supplied by the market.

Keywords: Superstar Firms, Technological Change, Augmentation, Automation
JEL: E24, J11, J23, J24

*We thank Tania Babina, Guy Ben-Ishai, James Manyika, and participants of the Brookings Institution's AI authors' conference for helpful comments. We thank Max Porlein, and especially Jonathan Rojas and Rocky Xie for expert research assistance. We gratefully acknowledge support from the Brookings Institution and the Washington Center for Equitable Growth. Autor additionally acknowledges support from the Hewlett Foundation, Google, and the Smith Richardson Foundation.

Introduction

"[I] thought what was good for our country was good for General Motors, and vice versa. The difference did not exist. Our company is too big. It goes with the welfare of the country. Our contribution to the Nation is quite considerable." –Charles Erwin Wilson, 1953

The growth of so-called superstar firms in industrialized countries has attracted the attention of scholars and policymakers. Such firms account for a rising share of economic activity (Autor et al., 2020; Gutiérrez and Philippon, 2019), and recent work further suggests that corporate concentration has persistently increased over the past 100 years (Kwon et al., 2022). Why superstar firms have gained economic heft is a subject of ongoing debate. Globalization and technological changes may push sales toward the most productive firms in each industry, leading to rising market concentration (Sampath and Park, 2019; Autor et al., 2020; De Loecker et al., 2020; Ganapati, 2021; Kehrig and Vincent, 2021; Kwon et al., 2022). Alternatively or simultaneously, lax antitrust enforcement, or a combination of technological and regulatory forces, may enable firms to thwart competitors and amass market share (Barkai, 2020; Grullon et al., 2019; De Loecker et al., 2021). What is not contested is that the rise of superstar firms has the potential to affect overall productivity growth, the rate of innovation, and the distribution of national income among capital, labor, and profits (Baqaee and Farhi, 2019; Autor et al., 2020; Barkai, 2020; De Loecker et al., 2020, 2021; Kehrig and Vincent, 2021; Seegmiller, 2021; Berger et al., 2022). These concerns are evident in policy as well as scholarship. Recent U.S. congressional hearings examine the dominance of Amazon in retail, Apple in hardware and software, Facebook in social media, and Google in search and advertising. Motivating its inquiry, the Congressional Subcommittee on Antitrust, Commercial, and Administrative Law, writes that "[A]ny single action by one of these companies can affect hundreds of millions of us in profound and lasting ways" (U.S. Government Publishing Office, 2020).

In this paper, we trace a link from the innovative activity of superstar firms to their potential labor market consequences. We ask first whether the innovations of top firms (AKA, superstars) are technologically distinct and differentially impactful relative to those of other firms, and further whether the characteristics of top firm innovations have changed across cohorts. We next consider how the innovations of top firms may shape the demand for labor, both overall and by skill group. To address this question, we deploy the classification tools developed by Autor et al. (2022) to assess whether innovations pioneered by larger firms are differentially labor-augmenting versus labor-automating, for which skill groups, and how this augmentation-automation differential has evolved over eight decades. We finally consider the incentives that firms may face to produce labor-augmenting versus labor-automating innovations. To this end, we document the evolution of the *social* value of innovations, as measured by their intellectual impact, with the *private* value of innovations, as measured by their impact on firms' stock market valuations. Operationally, we classify superstar firms as publicly listed entities that occupy the top few percentiles (ranging from 1% to 10%) of market activity or innovative output in a given decade. Superstar firms are by definition large. Beyond that, we find that they punch above their economic weight in steering innovation. Simultaneously, we note that our measure of innovative output is limited to patents, and hence excludes innovations such as open-source software that have become increasingly important (Lerner and Tirole, 2005; Greenstein and Nagle, 2014).

Our paper is related to but distinct from recent work on the role of superstar firms in both innovation activity and labor market outcomes. Superstar firms are shown to be important innovators (Kogan et al., 2017; Grullon et al., 2019; Short, 2019), but it is unclear whether the content of superstar innovations meaningfully differs from that of other firms, or whether this relationship has changed over time. Understanding these facts can help to clarify whether superstar firms are merely large firms, or whether they are distinct in the quantity, impact, or technological focus of their innovations. These questions also shed light on the contribution of top firms to the marked shifts in the locus of innovative activity across decades documented by Kelly et al. (2021), including the advent of the digital revolution.

Work studying the labor market implications of the superstar firm phenomenon has mostly considered labor practices within these firms and the aggregate implications of superstars for labor allocation across firms. For example, much evidence indicates that superstar firms have lower labor shares (Autor et al., 2020; De Loecker et al., 2020; Kehrig and Vincent, 2021; Seegmiller, 2021) and that their rise contributes to the fall in the aggregate labor share. The ability of superstar firms to simultaneously choose wages and employment may also account for a substantial share of capital income in the U.S. economy (Seegmiller, 2021). This may in turn distort competition, leading to too little employment at the most productive firms (Baqaee and Farhi, 2019; Berger et al., 2022), an inefficient allocation of capital across firms, and a dampening of aggregate investment (De Loecker et al., 2021). Our contribution is to consider the labor market implications of the innovations pioneered by superstar firms. Logically, these labor market consequences of superstars' innovations have the potential to shape labor market outcomes as they are widely adopted, often in sectors distinct from where they originate.

Our analysis of this question is guided by a growing literature studying the labor market impacts of advancing technology at the level of job tasks (Autor et al., 2003; Acemoglu and Autor, 2011; Autor, 2013; Goos et al., 2014; Acemoglu and Restrepo, 2018; Autor et al., 2022). This research has recently distinguished between innovations that displace labor from existing tasks (Kogan et al., 2021; Mann and Püttmann, 2020; Webb, 2020; Acemoglu and Restrepo, 2021) and innovations that create new labor-using tasks (Lin, 2011; Acemoglu and Restrepo, 2018, 2019; Autor et al., 2022). In Autor et al. (2022), we document that employment and wage-bills expand in occupations exposed to augmentation innovations, which complement labor's outputs, and contract in occupations exposed to automation innovations, which replace labor inputs. Whereas that work considers the employment consequences of the entire spectrum of innovations patented between 1940 and 2018—abstracting from the role of specific firms—the current paper focuses tightly on the innovative activity of the superstars. We explore whether such firms are particularly consequential for the path of automation and augmentation; whether they have become more or less consequential across decades; whether the nature of their innovations plays an outsized role in either augmenting or automating labor, overall and by skill group; and how public versus private incentives for producing such innovations may align or diverge.

This paper is structured as follows. Section 1 outlines our data and identifies the changing set of top U.S. firms over 1940–2020. In section 2, we document the role of top firms in both the amount and direction of U.S. innovation, by characterizing superstar shares in total innovation outputs as well as the distinctive technology content of their patents. Section 3 presents our novel measure of the labor-augmenting potential of individual patents, building on Autor et al. (2022), and analyzes to what extent superstar innovations are more labor-augmenting or labor-automating, overall and by skill group. We study the social and market values of labor-augmenting innovations in section 4. Section 5 concludes.

1 Identifying Top U.S. Firms over Eight Decades

1.1 Data sources

To link superstar firms to innovations and innovations to potential labor market impacts, we combine numerous datasets reporting firm characteristics, their patenting output, and the substantive content their of patents. In particular, to measure firm market value, we use data on market capitalization of publicly listed U.S. firms from 1940 onward from the

Center for Research in Security Prices (CRSP). We combine this market value information with employment data for these firms starting in 1950 from Compustat. We additionally link firms to patenting activity using data from Google Patents. Lastly, we append the market value of each of these patents as indicated by stock market reactions, from Kogan et al. (2017). These data are also our source for linking patents to publicly traded firms.[1] These are the data we will use to identify top firms over 1940–2020, as described below.

To compare patenting by superstar firms to the complementary set, we construct a dataset enumerating all U.S. utility patents granted between 1940 and 2020 (including those granted to publicly listed and non-listed firms). We draw the 3-digit Cooperative Patent Classification (CPC) of each patent from Google Patents. We append the count of citations to each patent, constructed from Berkes (2018) over 1940–1975 (following Kelly et al. 2021), and from the United States Patent and Trademark Office (USPTO) PatentsView database over 1976–2020.[2] To capture the novelty and influence of these patents, we merge in patent 'breakthrough' scores from Kelly et al. (2021) where available (covering 1940–2002), discussed further below. We also use Kelly et al. (2021)'s aggregation of CPC 3-digit codes into broad technology classes, to measure the technology content of innovations.

Lastly, we use data from Autor et al. (2022) to construct individual patents' augmentation and automation potential, as outlined in Section 3.1.

1.2 Ranking firms

We identify top U.S. firms by ranking publicly listed firms on five different scales: average decadal market capitalization, average decadal employment, total decadal patent count, total decadal patent citations, and total decadal patent market value.

Tables 1A through 1E list the names of the top five firms in each decade between 1940 and 2020 according to each of these measures. The set of top firms has changed substantially in this time interval. In the 1940 and 1950s, the top firms were largely in the automotive sector (e.g. General Motors, Ford); electronics and telecommunications (e.g. AT&T); and

[1]In using patents to characterize innovation, we follow a vast literature originating with Griliches (1981); Jaffe et al. (1993); Hall et al. (2001), which uses patents to study knowledge spillovers, innovation networks, the value of innovation and its relationship to rent creation, public-private R&D complementarities, and innovation responses to taxation, among many other topics. See Hall and Harhoff (2012); Moser (2016) for recent reviews of (aspects of) this literature. Our data on the market value of patents are from Kogan et al. (2017), updated through 2020 by Noah Stoffman and available here.

[2]The PatentsView database is available for download here.

chemical manufacturing (e.g. Dow, Dupont), as well as oil. Only one company remains on the list for most of these eight decades on many measures: ExxonMobil. By the 2000s, the top five firms better represented software and electronics (e.g. IBM, Intel, Microsoft, Alphabet, Apple), finance (e.g. Berkshire Hathaway), pharmaceuticals (e.g. Johnson & Johnson, Pfizer), and retail (e.g. Walmart). This pattern underscores the shifting locus of corporate leadership. Since large firms are often (though not always) large investors in R&D, this pattern likely indicates a shift in the technology locus where leading U.S. firms are innovating, as we investigate below.

The largest firms as measured by employment are not always the most important innovators as measured by patent count, patent citations, or patent value, especially in later decades. For example, large staffing companies (Manpower, Kelly services) as well as postal services (UPS) and fast-food and retail chains (McDonald's, Yum China Holdings, Kroger, K-Mart) rank in the top five based on employment but largely do not appear as top firms according to innovation or, necessarily, market capitalization. This pattern hints that the potential impacts of superstar firms on the labor market should not be exclusively—or even necessarily primarily—understood through their own employment practices. Our findings are consistent with Philippon (2015), who ranks top-five firms by market capitalization and with Autor et al. (2020), who document that superstar concentration is evident primarily in sales rather than employment.[3]

Table 2 reports the correlations among firm ranks based on each of these five measures over the entire period. All rankings are statistically significantly positively correlated, but rank correlations among the two firm size measures (market capitalization and employment) and among the three innovation measures (patent counts, patent citations, and patent value) are substantially higher than rank correlations between measures of firm size and measures of firm innovation. Figure 1 highlights that the correlation of firm ranks based on employment and based on innovation has declined markedly over 1950–2000, falling from around 0.40 to around 0.20, even as the correlation between employment and market capitalization ranks has remained relatively constant around 0.70–0.80. Thus, the distinction between the identities of the largest firms based on employment or market capitalization and the top innovators extends beyond the top five firms documented above, and it has grown over time.

For the remainder of this paper, we primarily categorize 'top firms' as publicly listed firms

[3]While highly similar, our market capitalization rankings are not identical to Philippon (2015) because we calculate the decadal rank by first ranking market capitalization values within each year, and then taking the average rank over the decade to avoid assigning a higher weight to the end of each decade.

that are in the top 2 percentiles of market capitalization in a decade. Because the number of publicly listed firms has grown over time, this quantile approach is preferable to selecting a constant number of firms.[4] Our results are robust to instead using the top 1, 5, or 10 percent of publicly listed firms based on market capitalization, and to using other measures (i.e., employment and innovation outcomes) to define top firms. Market capitalization is our baseline measure, both because it is the standard in the literature on superstar firms (e.g. see Philippon 2015; Autor et al. 2020), and because it is not itself a measure of innovative activity, which we study as an outcome.[5]

1.3 Top firm turnover

To interpret the economic significance of membership in the set of top firms, it is valuable to know how stable that set is, and whether the rate of churn has risen or fallen over time. To provide context, we consider the probability that a firm that was in the top 1, 2, 5, or 10% for market capitalization in a particular decade remains in that same top percentage of firms in the next decade. Results are reported in Figure 2.[6]

Top firms in each decade are relatively likely to persist in the top category in subsequent decades. If firm ranks were, in the extreme case, drawn at random each decade, a top 2% firm would have only a one-in-fifty chance of staying in the top 2% the next decade. In reality, this probability is between 40 and 100%, depending on the time period. This persistence is, however, substantially lower now than six decades earlier, declining monotonically from the 1960s to the 2000s and then reversing course in the most recent decade. This reversal is consistent with findings reported in Short (2019) and Autor et al. (2020).

To provide a longer-run view of the persistence of top firms, Figure 3 plots the probability that firms in each decadal cohort of top firms (by market capitalization) are found among the subsequent set of decadal top firms for as many subsequent decades as available.[7]

[4] Appendix Table A1 lists the number of top firms for each measure and percentile cut-off we employ.

[5] Further, we do not observe employment in the 1940s, limiting the time window in which we can rank firms by employment.

[6] Throughout this section, we assume that when a top publicly listed firm delists it is no longer in the top set of firms. All our results are robust to not including instances of firm delisting in calculating probabilities of top firm persistence. Appendix Figures A1, A2, A3, and A4 report corresponding results for top employment, top patent count, top patent citation, and top patent value firms.

[7] Although not reported here, patterns are qualitatively identical for top 1%, top 5%, and top 10% firms. Appendix figures A5, A6, A7, and A8 show corresponding results for top 2% firms based on employment and innovation measures.

Logically, the probability of remaining among the top firms declines with time elapsed. But the persistence of superstardom is substantial. Approximately 30% of the top 2% firms from the 1940–1949 cohort (labeled as 1940s in the graph) are found in the top 2% of firms 70 years later. Simultaneously, consistent with the declining decade-to-decade persistence documented above, later cohorts of stars are falling faster than earlier cohorts: the top 2% market cap firms of the 1990s have only a 40% chance of surviving into a second decade, whereas it took the 1940s cohort of superstars closer to six decades to fall this far. Again, the last cohort has seen a reversal of this trend: around 65% of the 2000s superstars remain in the top 2% one decade later.[8]

We note that there is no universally agreed upon definition of superstar firms. For example, Manyika et al. (2018) classify superstars as the 10% firms earning the largest share of (estimated) economic profit among firms worldwide. Consistent with our findings below, these firms exhibit relatively higher levels of digitization, greater innovation-intensity, and more intangible assets than peers. They have also become increasingly profitable relative to the median firm. Approximately 55% of superstar firms by the Manyika et al. (2018) measure remained in the top decile over the course of a decade between the years 1995 and 2016. This retention rate appears comparable to what Figure 2 reports for the years 1990–2010, despite the difference in definition of superstar firms.

2 The Role of Top Firms in Innovation

Superstar firms are of interest to researchers and policymakers in part because of their importance in innovation (Kogan et al. 2017; Grullon et al. 2019; Short 2019). Our focus on top firms stems from the potential impacts of their innovations on labor market outcomes. These impacts may be disproportionately important if top firms generate a large share of innovation, if their innovations are particularly impactful, or if their innovations are distinct from those of other firms in terms of technological content.

[8] One concern with this pattern of results is that persistence may be artificially depressed by mergers and acquisitions (M&As): if a top firm is acquired by another firm, it will no longer appear in the top set. Reassuringly, Short (2019) finds that the decline in persistence documented in his related analysis is not driven by M&A activity. We also find that M&A activity cannot explain this decline, even at its peak in the late 1990s and early 2000s. For example, using our preferred measure of firms in the top 2% of market capitalization, accounting for acquisitions of top firms by other publicly listed firms would only raise top firm persistence from about 41% to 46% between the 1990s and 2000s, with little to no effect in other decades.

2.1 The disproportionate impact of top firms' innovations

We noted in the introduction that top firms play a disproportionate role in overall innovation. We substantiate that claim here. As a starting point, Figure 4 summarizes the contribution of top firms to three measures of innovative output: patent counts, patent citations, and breakthrough patents, as defined in Kelly et al. (2021).[9] Top firms account for a large share of total innovation, and even more so for influential and original innovations. The top two percent of firms by market capitalization account for 11.7% of all patents, 13.3% of all patent citations, and 19.9% of all breakthroughs.

Given that the firm size distribution is highly right-skewed, it is not entirely surprising that top firms account for a disproportionate share of all innovations. What is more surprising is that even accounting for the number of innovations they produce, their innovations are disproportionately impactful. We document this in Table 3 by regressing measures of the importance of each patent on an indicator variable for whether the patent was originated by a top 2% firm. We measure importance in two ways: first, in panel A, by the patent's count of citations (specifically, the inverse hyperbolic sine (IHS) of the citation count); second, in panel B, by a dummy variable equal to one if the patent belongs to the set of top 10% breakthrough for its cohort using the Kelly et al. (2021) measure of breakthrough innovations.[10] Top firm patents have a disproportionate number of citations and are substantially more likely than average to be breakthroughs. Estimates in column 1 show that top firm patents receive 9% more citations ($SE = 0.80$) and are 7.5 percentage points ($SE = 0.63$) more likely to belong to the set of top-10% breakthroughs. These findings are robust to controlling for year fixed effects (column 2 onward), and fixed effects for broad and detailed CPC technology classes (columns 3 and 4). Estimates in column 4 imply that compared to non-top firm patents, top firm patents in the same narrowly defined technology class receive 8.3% more citations, and are 3.4 percentage points more likely to be among the set of top-10% breakthroughs. These estimates are sizable, corresponding to around 0.12 of a standard deviation in inverse hyperbolic sine of citations, and 0.11 of a standard deviation

[9] This breakthrough measure scores each patent's impact by comparing its textual similarity to both the patents that follow it and the patents that precede it. Patents that have a high ratio of future textual similarity to past textual similarity are likely to have shaped the course of subsequent innovation and hence are classified as breakthroughs. Throughout, we use the baseline measure in Kelly et al. (2021) which classifies patents as breakthroughs when they are in the top 10% of the 10-year forward-to-backward textual similarity measure.

[10] Kelly et al. (2021) define a breakthrough patent as one that is both novel and impactful.

in the breakthrough probability.

2.2 The technology content of top firm innovation

Top firm innovations may be particularly impactful either because they make substantial incremental contributions to the current trajectory of innovation or, alternatively, because they change that trajectory. To explore the latter possibility—that top firms shape the trajectory of innovation—Figure 5 reports the technology composition of patents by broad technology class (as defined in Kelly et al. 2021) for all firms versus top firms (panels A and B, respectively).[11] In all decades, the distribution of top firms' innovations across technology classes differs from other firms. Furthermore, the technology focus of top firm innovations has changed more over time than that of their non-top counterparts. These contrasts are further documented in Figure 6, which shows the decadal difference over eight decades between the share of patents by broad class issued by top and non-top firms. In each decade, share differences sum to zero, such that positive values mean that top firms differentially patent in these technology classes as compared to non-top firms, and conversely for negative values. In the first post-WWII decades, top firms differentially innovated in chemistry and metallurgy, whereas top firms of later decades differentially innovated in instruments and information. Throughout the full 1940 through 2020 time interval, top firms differentially innovated in electricity and electronics, though the difference declines over time.[12]

The evolution of patenting shares by technology class among top firms documented in panel B of Figure 5 could emerge because earlier cohorts of top firms of *any* decade are patenting in these technologies ('within top firm effect'), or because more recent cohorts of top firms have a different locus of innovation than do older cohorts of top firms ('between top firm effect'). To distinguish these possibilities, we decompose the change in the patenting composition of top firms between 1940–1980 and 1980–2020 into four components: within-firm changes in patenting among firms that persist in the top category across decades; between-firm changes in patenting among firms that persist in the top category across decades; changes due to firms exiting the top category; and changes resulting from

[11] These patterns are presented as stacked area plots, showing the distribution of patents by broad technology class over time.

[12] Appendix Figure A9 shows that the innovation shifts among superstars are robust for the top 1%, 2%, 5%, and 10% firms on market capitalization.

new firms entering the top category.[13]

To quantify these components, we apply a Melitz and Polanec (2015) decomposition to the patenting shares S of broad technology classes c among top firms. We start by writing the overall share of top firm patents in a class in time τ as:

$$\mathrm{S}^c_\tau = \sum_j \frac{\mathrm{Npatents}_{j\tau}}{\mathrm{Npatents}_\tau} \times \frac{\mathrm{Npatents}_{cj\tau}}{\mathrm{Npatents}_{j\tau}} = \sum_j \omega_{j\tau} \mathrm{S}^c_{j\tau}, \tag{1}$$

where $\omega_{j\tau}$ denotes the weight of firm j, determined by its patent count among top firms in decade τ, and $\mathrm{S}^c_{j\tau}$ denotes the patenting share of technology class c within the firm. Following Melitz and Polanec (2015), we write the change in the share of a technology class between two decades as:

$$\begin{aligned}\Delta \mathrm{S}^c_\tau = \Delta \bar{\mathrm{S}}^c_{S,\tau} + \Delta \left[\sum_{j \in S} \left(\omega_{j\tau} - \bar{\omega}_{S,\tau} \right) \left(\mathrm{S}^c_{j\tau} - \bar{\mathrm{S}}^c_{S,\tau} \right) \right] \\ + \omega_{X,\tau_0} \left(\mathrm{S}^c_{S,\tau_0} - \mathrm{S}^c_{X,\tau_0} \right) + \omega_{E,\tau_1} \left(\mathrm{S}^c_{E,\tau_1} - \mathrm{S}^c_{S,\tau_1} \right).\end{aligned} \tag{2}$$

The first two terms reflect contributions to the patenting share of the technology class made by surviving superstar firms, denoted by subscript S. The last two terms reflect contributions by firms that exit or enter the top category, denoted by subscripts X and E respectively. Surviving superstar firms are defined here as those ranking as top firms in both τ_0 and τ_1, and exiting and entering firms as those respectively present in the top only in the first and second period. Surviving firms' contribution is further decomposed into a within-firm effect ($\Delta \bar{S}^c_{S,\tau}$), reflecting shifts in the innovation focus of top firms over time (measured as changes in the unweighted mean of patent shares across technology classes), and a between-firm reallocation component (in square brackets), which captures the covariance between shifts in the innovation focus of top firms and shifts in their overall innovative activity. Entering top firms make a positive share contribution in those technology classes where they have a greater innovation focus than incumbent top firms. Similarly, exiting top firms make a positive share contribution to technology classes where they are relatively less innovative than incumbent top firms.

Figure 7 plots the contributions of surviving, exiting, and entering superstar firms to the

[13] To avoid measurement error from choosing a single year for defining the set of top firms and patenting shares by technology class, we pool years 1940–1949 and years 1970–1979 for the 1940–1980 period difference; and years 1980–1989 and years 2010–2019 for the 1980–2020 period difference.

patenting-share changes in four broad-technology classes responsible for most of the top firm innovation shifts: instruments and information, electricity and electronics, chemistry and metallurgy, and manufacturing process.[14]

In general, within-firm changes in the locus of patenting account for a small share of the overall changes in top firm innovation over both periods: they account for little of the rise of patenting in instruments and information and in electricity and electronics over the 1980–2020 period; and similarly, they contribute little to the relative decline in chemistry, metallurgy, and manufacturing process patenting witnessed over the same period. The bulk of the change in superstar innovation focus documented in panel B of Figure 5 is due instead to reallocation of activity between ongoing superstar firms, alongside a complementary role played by the entry of new superstars in growing innovation domains.

3 The Labor Market Implications of Top Firm Innovations

Top firms account for a substantial share of all patenting, and these patents are disproportionately novel and impactful. Top firm patents also have distinct technological foci that drive the leading edge of major innovation eras. Due to both the scale of their innovative output and the influence of their patents on the direction of subsequent innovation, the impacts of innovations pioneered by top firms are likely to be broadly felt in the labor market. It is thus critical to understand whether these innovations tend to skew towards either labor-augmentation or labor-automation, for which skill groups, and how this has changed over time.

3.1 Measuring the augmentation and automation potential of individual patents

To study how innovation by top firms may shape labor demand, we construct a novel measure of the labor-augmenting potential of individual patents, leveraging data from Autor et al. (2022), who extract augmentation and automation technologies from patent texts. We briefly summarize these data here before presenting our patent-level augmentation measure.[15] Our focus on labor-augmenting versus labor-automation innovations is motivated

[14] Decompositions for all technology classes are reported in Appendix Figure A10.

[15] Further detail is reported in Autor et al. (2022).

by Autor et al. (2022), who show that labor-augmenting innovations spur the emergence of new work and boost occupational labor demand, whereas labor-automating innovations erode occupational labor demand. Focusing on how top firm innovations contribute to these potentially countervailing demand impacts provides insight into the question posed by our title: Where are technology leaders leading the labor market?

We leverage two conceptually distinct measures of innovation flows developed in Autor et al. (2022). The first captures *augmentation innovations* that may complement the output of occupations, creating new demands for occupational expertise and occupational services. This measure is constructed by calculating the textual overlap between patent texts and detailed occupation titles from the Census Alphabetical Index of Occupations and Industries (CAI) (US Census Bureau, 2018) to identify innovations that are aligned with occupational outputs in each decade. The second patent-based measure captures *automation innovations* that may substitute for the labor inputs of occupations. For this, Autor et al. (2022) follow Kogan et al. (2021) and Webb (2020) in identifying the textual overlap between the content of patents and the tasks that workers perform, as described by the Dictionary of Occupational Titles (DOT), using the 1939 DOT volume for task descriptions over 1940–1980 and the 1977 DOT volume for task descriptions over 1980–2018.[16] In constructing both measures, Autor et al. (2022) harness natural language processing (NLP) tools to map the text of U.S. utility patents to the domain of occupations between 1930 and 2018. Following Kogan et al. (2021), documents are represented as term-frequency inverse-document-frequency (TF-IDF) weighted averages of word embeddings, which are geometric representations of word meanings, to measure the distance between patent texts and occupational descriptions.

As detailed in Autor et al. (2022), a key textual distinction between these two sources is that the titles enumerated in the CAI primarily characterize what an occupation or industry produces—i.e., its outputs—while the task descriptions in the DOT enumerate the quotidian activities that a worker in that job performs, i.e., its task inputs. Consequently, patents linked to occupational titles from the CAI tend to capture technologies that increase the capabilities, quality, variety, or utility of the *outputs* of occupations, potentially generating new demands for worker expertise and specialization. Conversely, patents linked to DOT descriptions of occupational tasks tend to capture technologies that may replicate and replace workers in these tasks. In line with this expectation, Autor et al. (2022) find

[16]In related work, Felten et al. (2018, 2019) and Brynjolfsson et al. (2018) develop measures of the exposure of occupations to advances in artificial intelligence and machine learning.

starkly diverging predictive patterns of augmentation- versus automation-linked patents for occupational labor demand. In particular, occupations that are more exposed to augmentation patents experience significantly greater employment growth over multiple decades and are differentially likely to gain new occupational titles, whereas occupations that are more exposed to automation patents exhibit falling relative employment and are not more likely to gain new occupational titles.[17]

To crystallize these distinctions, Autor et al. (2022) enumerate example patents that are augmenting for computer systems analysts and computer scientists but are automating for other occupations. They show that patents that are *augmentation*-linked to computer systems analysts and computer scientists are most often *automation*-linked to occupations in technicians or clerical and administrative support—occupations that are particularly susceptible to software-based automation during this period of rapid digital innovation. These same patents may also automate the tasks of other occupations. For example, the patent "Method and apparatus for storing confidential information" (US patent number 8,613,105), is automation-linked to billing clerks and related financial records processing. The patent "Direct connectivity system for healthcare administrative transactions" (US patent number 9,020,826) is automation-linked to health record technologists and technicians. And the patent "System and method for securing data" (US patent number 10,541,811) is automation-linked to office machine operators, n.e.c., computer and peripheral equipment operators, and other telecom operators. The evidence in Autor et al. (2022) suggests these patents—all of which are classified as *augmenting* for computer systems analysts and computer scientists—serve to automate tasks in exposed occupations even while complementing computer scientists.

3.2 The role of top firms in labor-augmenting vs. labor-automating innovations

We use these patent-level data to measure the augmentation and automation potential of individual patents as follows. After determining decadal patent-occupation pair matches from the Census Alphabetical Index and Dictionary of Occupational Titles respectively, we estimate the labor-augmenting or labor-automating potential of each patent as the employment-

[17] Related results on task overlap and declining labor demand are also found in (Webb, 2020; Kogan et al., 2021).

share weighted sum of these augmentation or automation matches.[18] Specifically, let $I^k_{j,i\tau}$ be an indicator taking the value of 1 if occupation j in decade τ has been matched to patent i for type $k \in \{\text{Aug}, \text{Aut}\}$. Finally, denote $t(i)$ as the year of issuance for patent i. We then construct the patent-level augmentation or automation score:

$$\text{Score}_{it,k} = \sum_j I^k_{j,i\tau} \times \text{Emp Share}_{j,t(i)}$$

This allows us to construct the augmentation-automation gap for individual patents to capture the relative intensity of augmentation potential:

$$(\text{Aug-Aut})_{it} \equiv \text{Score}_{it,k=Aug} - \text{Score}_{it,k=Aut}$$

We analyze patterns in this patent-level measure over time, contrasting patents held by top versus non-top firms, using the following empirical specification:

$$(\text{Aug-Aut})_{it} = \sum_\tau \beta_\tau \times \text{TopFirm}_{it} + \gamma_t \ (+\text{tech}_{it}) + \varepsilon_{it}. \tag{3}$$

Here, the dependent variable is the augmentation-automation gap for each patent i issued in year t, and TopFirm_{it} is a dummy indicating that the patent was issued by a top firm. We control for year fixed effects (γ_t), as well as three-digit CPC technology class fixed effects (tech_{it}) in some specifications. Standard errors are clustered by patent issue-year. The coefficients of interest, β_τ, are positive if patents issued by top firms are relatively more labor-augmenting than those issued by non-top firms, and are negative if relatively more labor-automating. So that the sign and magnitude of this comparison may vary over time, we allow β_τ to take a separate slope in each decade.

Figure 8 shows that the estimated β_τ are positive in all time periods, meaning that top firm patents are on average relatively more labor-augmenting than patents issued by non-top firms.[19] This difference exhibits a U-shaped pattern between 1940 and the present: relative to other firms, top firm innovations were approximately 0.33 standard deviations more labor-

[18] We use employment shares in the year the patent is issued, and infer occupational employment shares for between-Census years by taking a log-linear interpolation of occupation employment in the nearest previous and future Censuses.

[19] Our measure captures the augmentation-automation skew of top firm patents *relative* to non-top firm patents in each decade. Because it is an ordinal rather than cardinal measure, it is not well-suited to capturing the *absolute* skew of overall patenting. (In fact, it's normalized to zero in each decade.)

augmenting in the 1940s, between 0.05 and 0.18 standard deviations more labor-augmenting over 1950–1980, and then became steadily more so over the next three decades, reaching 0.51 standard deviations in the most recent decade.

One channel through which top firms may increasingly differentially innovate in labor-augmenting technologies is their distinct technological locus, as documented above. Figure 8 shows this indeed accounts for a large part of the difference between top and non-top firms: adding detailed 3-digit technology class fixed effects to the comparison between top and non-top firms reduces the top/non-top difference in augmentation versus automation skew to less than 0.25 standard deviations at its maximum. This is particularly pronounced in recent decades: controlling for technology locus of top versus non-top firms accounts for around two-thirds of top firms' differential augmentation. Thus, a large part of what makes top firm innovations distinctive in their labor market impacts is that they are concentrated in technology classes that are particularly augmenting rather than being particularly augmenting for their innovation class.

3.3 Augmenting for whom?

Innovations may not have uniform effects across skill groups. We have so far focused on the *average* augmentation versus automation potential of innovations by weighting up employment in occupations that are augmented and automated by each patent and then taking the difference between them. This measure does not consider which *types* of jobs are affected—in particular, which skill groups are employed in each occupation. This distinction is potentially important, however, since a vast literature finds that recent waves of technological innovation have had uneven and, in some cases, unfavorable distributional effects (see Acemoglu and Autor (2011) for an overview).

In what follows, we explore these distributional consequences by analyzing patent-level augmentation-automation gaps for three broad occupational groups that are consistently defined over the entire 1940–2020 time period: high-paid occupations (comprised of managers, professionals, and technicians), middle-paid occupations (production, clerical and administrative, and sales occupations), and low-paid occupations (farming, health services, personal services, cleaning and protective services, construction, and transportation occupations). We obtain skill-specific augmentation and automation scores for occupations by calculating

$$\text{Score}^{s}_{it,k} = \frac{1}{N^{s}_{t(i)}} \sum_{j \in O(s)} \boldsymbol{I}^{k}_{j,i\tau} \times \text{Emp Share}_{j,t(i)}$$

for skill groups $s \in \{\text{low, middle, high}\}$. In this equation, $N^s_{t(i)}$ is the number of occupations in skill type s during time period of patent issuance, and $O(s)$ denotes the set of occupations belonging to occupation group s. $\boldsymbol{I}^k_{j,i\tau}$ and Emp $\text{Share}_{j,t(i)}$ are as defined before. This yields the following skill-specific patent-level augmentation-automation gap:

$$(\text{Aug-Aut})^s_{it} \equiv \text{Score}^s_{it,k=\text{Aug}} - \text{Score}^s_{it,k=\text{Aut}}$$

In contrast to the overall augmentation-automation gap measure outlined above, these occupation-specific gaps indicate to what extent a patent is labor-augmenting for low-, middle-, and high-paying occupations, which for brevity, we refer to as skill groups.

We then re-estimate equation (3) for each of these skill-specific measures to determine how the relative augmentation-automation skew of top firm innovations compares across skill groups. Estimates are plotted over time in Figure 9, both without (upper panel) and with (lower panel) technology class fixed effects.

We found above that top-firm innovations are on average relatively labor-augmenting. Figure 9 shows that this overall skew is primarily driven by the tendency of top firm innovations to augment workers in the highest paid occupations. Over the last four decades, the relative augmentation potential of top firm innovations for professional, technical, and managerial occupations has risen dramatically, from essentially zero in the 1980s, to 0.18 standard deviations in the 1990s, 0.34 standard deviations in the 2000s, and 0.57 standard deviations in the 2010s.

Top firm innovations are also *modestly* more augmenting for low- and middle-skill occupations throughout most of the eight decades of our sample. But the augmentation potential of top firm innovations has remained essentially unchanged for low- and middle-skill occupations over this entire time interval, while it has increased monotonically and substantially for high-skill occupations over four decades. Thus, in recent decades, the relative augmentation potential of top-firm innovations has skewed strongly towards the highest-skilled occupations.

These patterns are qualitatively similar, though less pronounced, when comparing the content of top versus non-top firms within technology classes, as shown in the lower panel of Figure 9. When we limit the variation to contrasts of top versus non-top firm patents within 3-digit technology classes, the relative augmentation potential of top firm innovations for high skill occupations has risen by approximately 0.20 standard deviations over the last four decades—implying that the distinct technological content of top firm innovation accounts for about one-third of their rising augmentation potential for high-skill occupations, while the rest is accounted for by differences in the technology classes where these patents are located. By contrast, across the last eight decades, top firm patents exhibit almost no excess augmentation potential for low- and middle-skill occupations relative to non-top firm patents within the same classes.

This recent rise in the augmentation skew of top firm patents towards high-skill occupations stands in contrast to trends in earlier decades. From the 1940s through the 1970s, there was a tendency toward *compression* in these skill-group differences, with top firm innovations becoming less labor-augmenting (compared to other firms' innovations) for high-skill groups in particular. This pattern sharply reverses after the 1980s, corresponding to the time period of the Information and Communications Technologies revolution.

4 Comparing the Social and Market Value of Labor-Augmenting Innovations

The fact that labor-augmenting innovations catalyze the emergence of new work, increasing occupational labor demand, suggests that these innovations have social value from the perspective of workers. This is particularly true if, as argued by Acemoglu et al. (2020) and Beraja and Zorzi (2022), existing economic distortions favor excessive automation. Here, we leverage our measure of individual patents' labor-augmenting potential to consider how social versus private incentives for producing such innovations may align or diverge. To make this comparison, we consider, first, whether patents with higher labor-augmentation content have distinct social value as measured by their intellectual impact; and, second, whether private incentives, as measured by market valuation of labor-augmenting patents, appear to align with social valuation.

To make these comparisons, we estimate the following model:

$$\mathrm{Y}_{it} = \sum_{\tau} \beta_\tau \times (\text{Aug-Aut})_{it} + \gamma_t \ \ (+\text{tech}_{it}) + \varepsilon_{it}. \tag{4}$$

The dependent variable in this equation, Y_{it}, is a measure of either the social or market value of patent i issued in year t; and $(\text{Aug-Aut})_{it}$ is the patent-level augmentation-automation gap as defined above. We control for year fixed effects (γ_t), and add dummies for patents' three-digit CPC technology class in some specifications to investigate the role of patents' technological content. Standard errors are clustered by patent issue-year t.

We use two measures to proxy for the social value of patents: the breakthrough patent indicator from Kelly et al. (2021) used in Table 3 above, indicating that a patent is both novel and impactful, and the patent's cohort-normalized citation count (specifically, the IHS of this count) to measure its broad intellectual importance. To capture firms' private incentives to provide innovations, we use the log of the revealed market valuation of each patent from Kogan et al. (2017), which is inferred from stock market reactions to patent announcements. The decade-specific parameters of interest, β_τ, reveal whether labor-augmenting patents are more likely to constitute scientific breakthroughs, have substantial intellectual importance, and receive higher market valuations from investors. We stress that this exercise cannot establish whether the market and social values (in money-metric terms) of labor-augmenting innovations are fully aligned at the margin; rather, it asks whether they are directionally aligned—that is, whether social and market indicators of the value of labor-augmenting innovations point in the same direction, and whether their movements positively covary across decades.

Estimates of equation (4), reported in Figure 10, reveal two key results. First, patents that are relatively labor-augmenting have seen consistently rising social value over the last half-century. In particular, they have over the last five decades become increasingly likely to constitute scientific breakthroughs: from 1980 forward, a one standard deviation increase in the labor-augmentation measure predicts a 4 to 9 percentage point increase in the probability that a patent constitutes a breakthrough. Given that only 10% of patents are classified as breakthroughs (Kelly et al., 2021), this is an economically large effect. The pattern for citations reinforces this finding: labor-augmenting patents receive up to 18% more citations in recent decades compared to labor-automating patents (for a standard deviation increase in the labor-augmentation measure), though there is some decline in the 2010s. In the first three post-WWII decades, by contrast, labor-augmenting innovations received significantly lower citation counts than labor-automating innovations. Thus, labor-augmenting innovations appear to be growing in their novelty, influence, and intellectual impact.

While the revealed social value of labor-augmenting patents appears to be rising, our second key result is that the *market* value of labor-augmenting innovations has not witnessed a concomitant rise. Rather, investors appear to value labor-augmenting patents either similarly to, or less than, labor-automating patents. In fact, labor-augmenting patents carry a (relative) market penalty in the 1980s and 1990s. Outside of these decades, the market does not place either a premium or penalty on them. Given that firms' private incentives to invest in labor-augmenting innovations do not appear to have tracked the rising social value of these innovations, such innovations may be (increasingly) under-supplied by the market.

Figure 10 demonstrates that these patterns remain evident when we add fixed effects for detailed technology classes (panel B), though magnitudes are slightly muted. Even among innovations within narrow technological fields, labor-augmenting patents have risen in social value, seen in their differentially high citation counts and breakthrough probabilities. Conversely, similar comparisons of market valuations indicate that within narrow technology classes, labor-augmenting innovations were differentially valued by investors from the 1940s through the 1970s, but that this distinction has since disappeared.

Is the potentially rising misalignment between social and market incentives for the generation of labor-augmenting innovations evident among all skill groups? We explore this question by re-estimating equation (4) while including patents' labor-augmenting potential separately by the type of labor they augment. That is, we estimate

$$\mathrm{Y}_{it} = \sum_{\tau,s} \beta_{\tau}^{s} \times (\text{Aug-Aut})_{it}^{s} + \gamma_t \ (+\text{tech}_{it}) + \varepsilon_{it}, \tag{5}$$

where the dependent variables are market and social value as defined before and $(\text{Aug-Aut})_{it}^{s}$ is the skill-specific augmentation-automation gap for each patent.

Figure 11 presents estimates of β_{τ}^{s} for market valuations of labor-augmenting patents. Strikingly, these valuations have polarized: the revealed value of patents that are augmenting for high-skilled jobs has risen, whereas the value of patents that are augmenting for middle-skilled jobs has declined substantially, with less of a change for low-skill augmenting patents. This is particularly evident in panel B, where we contrast patents within narrow technology classes. Since the 1960s, the market value of patents that augment skilled jobs has risen by 13 percentage points (per standard deviation), with most of this rise occurring post-1980. By contrast, the value of low-skill augmenting patents has barely budged over this period, while the revealed market value of middle-skill-augmenting patents rose in the 1960s and 1970s before sharply declining over the last four decades.

We finally repeat this analyses for the social value of patents as measured by both breakthroughs (Figure 12) and patent citations (Figure 13). Consistent with our estimates above for overall labor-augmentation, we find that the social value of innovations that augment high-skill occupations has risen in recent decades, commensurate with their rising market value. The pattern for middle-skill augmenting innovations is just the opposite, however. The market value of these patents has declined sharply over the last four decades, even as their probability of constituting scientific breakthroughs and receiving higher levels of citations has risen. This suggests that firms' private incentives for producing innovations that augment middle-skill occupations may have deteriorated relative to the social value of producing such technologies. Recent work by Acemoglu et al. (2020) and Brynjolfsson (2022) considers why economic and policy incentives facing firms and researchers may tend to favor technologies for automation over augmentation.

5 Conclusions

Innovations pioneered by large firms are disproportionately intellectually novel and impactful, and further, are technologically distinct from those developed by other firms—contributing to secular shifts in patenting across broad technology classes over time. These stylized facts motivate our study of the labor market implications of top firm innovation, focusing on their potential to augment and automate labor, both overall and by occupational skill group.

We document that top firms play a growing role in labor augmentation in recent decades relative to other firms, largely because of the shifting technological locus of their innovations: top firms have increasingly and disproportionately patented in information and communication technologies, which appear to be relatively labor-augmenting on average. However, these innovations do not augment all skill groups equally. Top firms' labor-augmenting innovations have increasingly targeted high-paid managerial, professional, and technical occupations, without becoming differentially labor-augmenting for low- and middle-skill occupations. In combination with their large and disproportionately impactful innovative output, these results suggest that modern-day superstar firms contribute to the diverging labor market fortunes of high- and low-skilled workers.

We also provide suggestive evidence for why the innovations of top firms are increasingly skewed towards augmenting high-skilled labor: while both the social and market value of labor-augmenting innovations have risen for innovations targeting high-skill occupations, the market value (though not social value) of labor-augmenting innovations targeting middle-skill workers has steeply declined. This pattern suggests that innovations augmenting the work performed by low- and particularly middle-skill occupations may be increasingly undersupplied by the market.

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Figures

Figure 1: Correlations between firms' employment ranks
and their ranks based on innovation outputs and market valuations

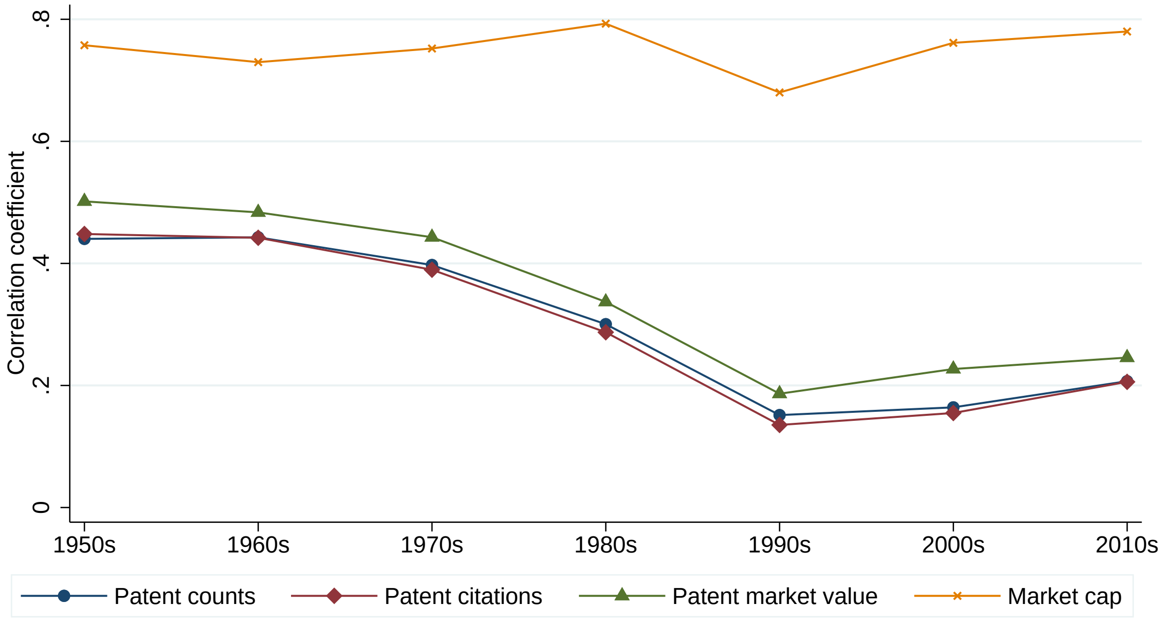


Figure 2: Probability of staying in set of top market value firms, decade by decade

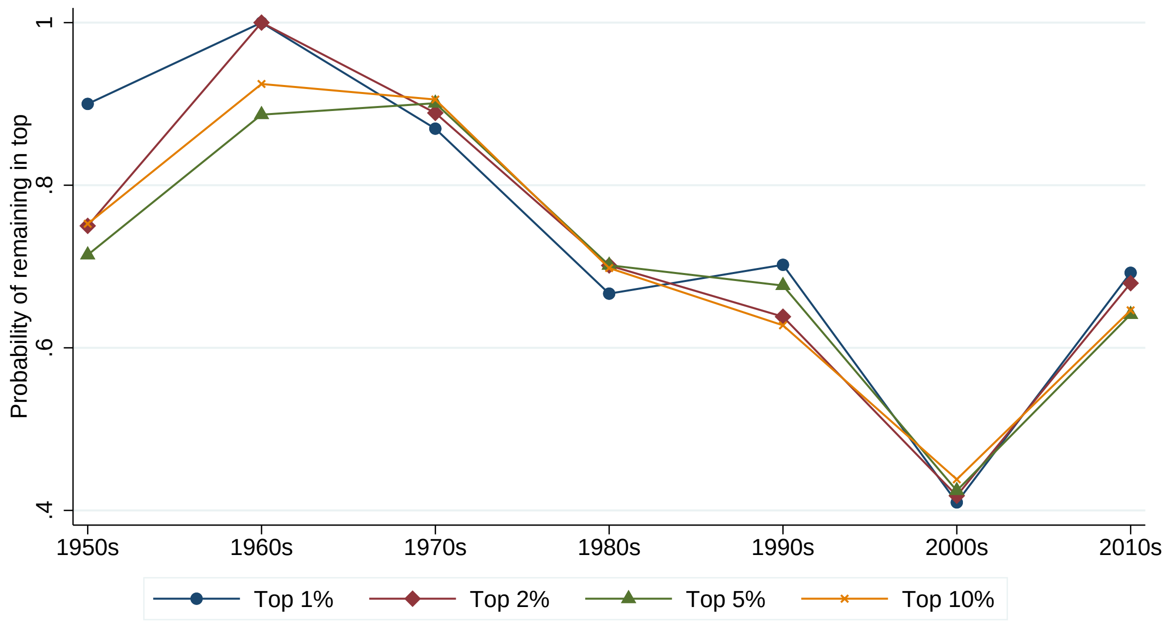


Figure 3: Cohort-specific probability of staying in set of top market cap firms over time

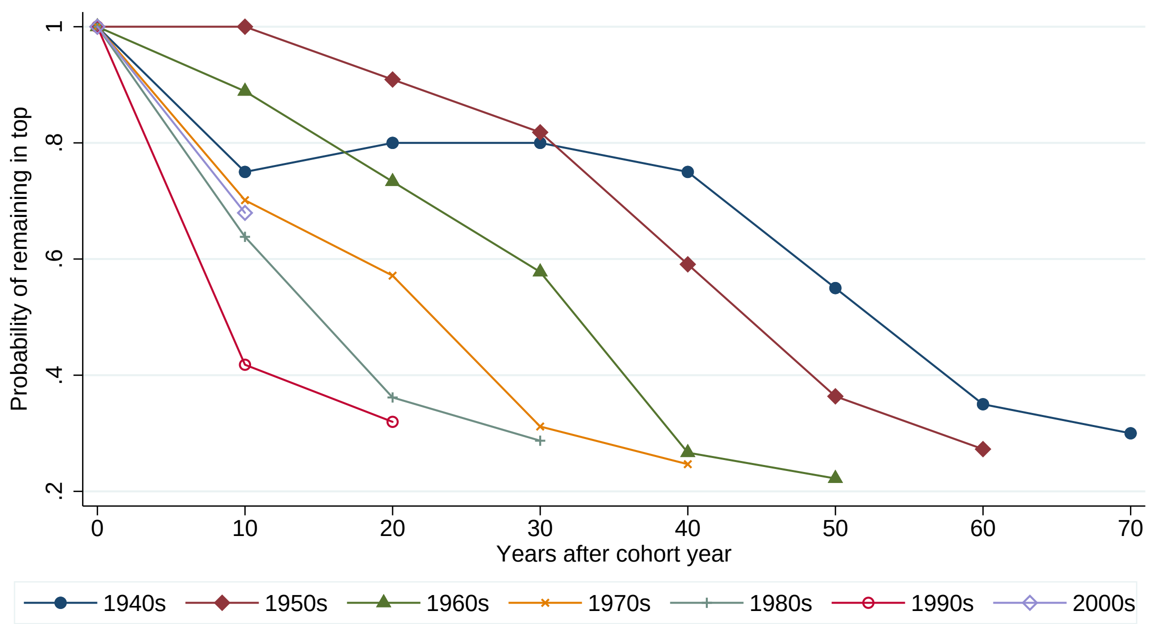


Figure 4: Shares of top 2% of publicly listed firms in total innovation

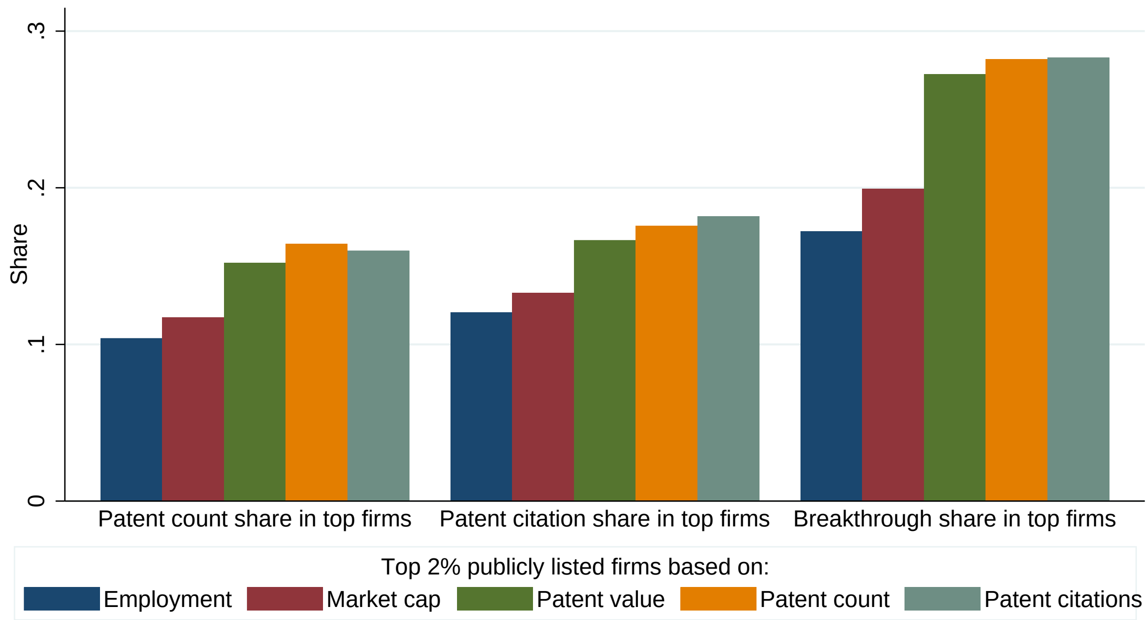
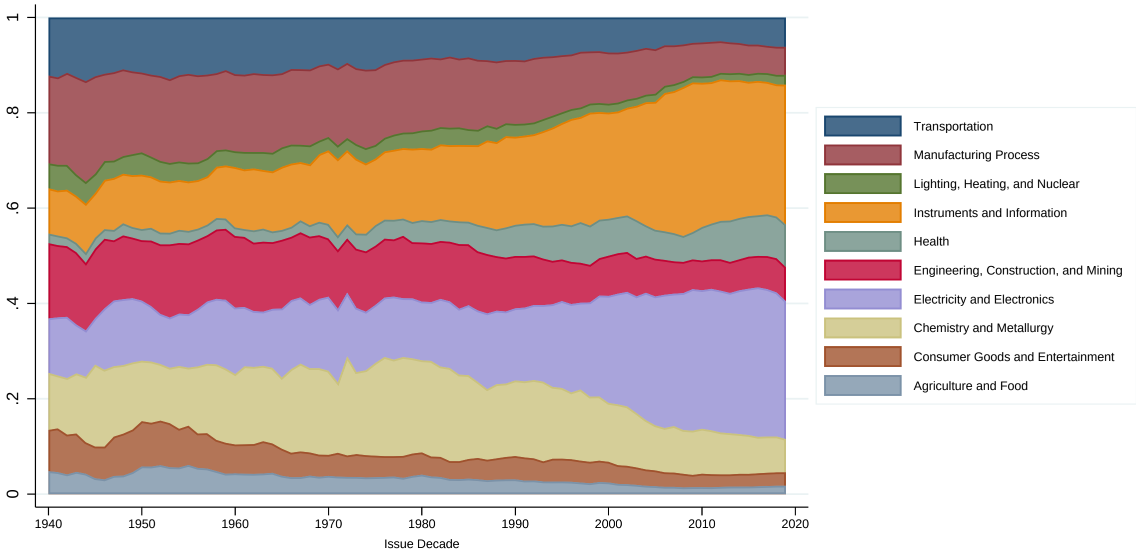
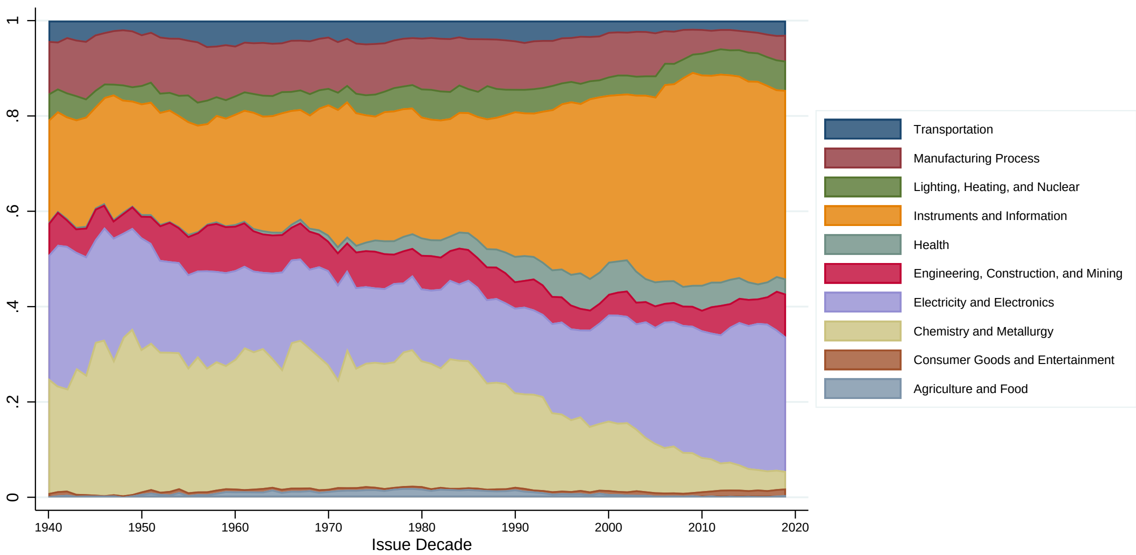


Figure 5: Patenting across broad tech classes

A. All firm patents

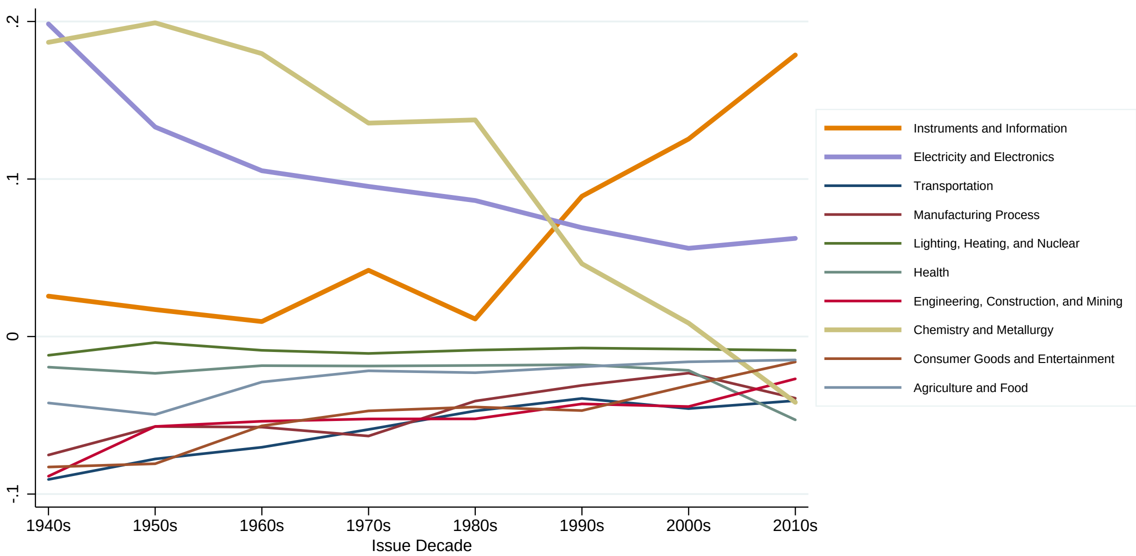


B. Top firm patents



Figures are stacked area plots. Top firms are the top 2% of publicly listed firms on market capitalization.

Figure 6: Difference in decadal patenting shares by broad tech class for top versus non-top firms



Top firms are the top 2% of publicly listed firms on market capitalization.

Figure 7: Difference in patenting-shares decomposition for top firms

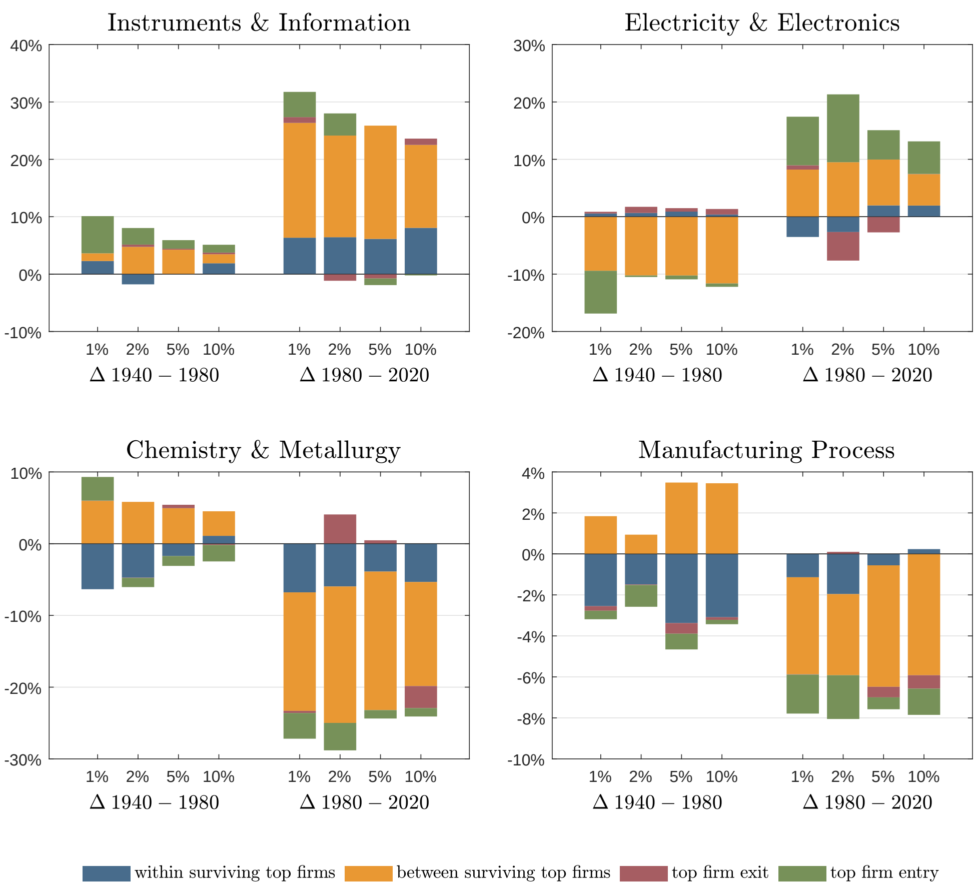


Figure shows the decomposition of top firms' patenting share changes over 1940–1980 and 1980–2020. Top firms are those in the top 1, 2, 5 or 10% of market capitalization in any year of the respective decade.

Figure 8: Labor-augmenting potential of top versus non-top firm patents

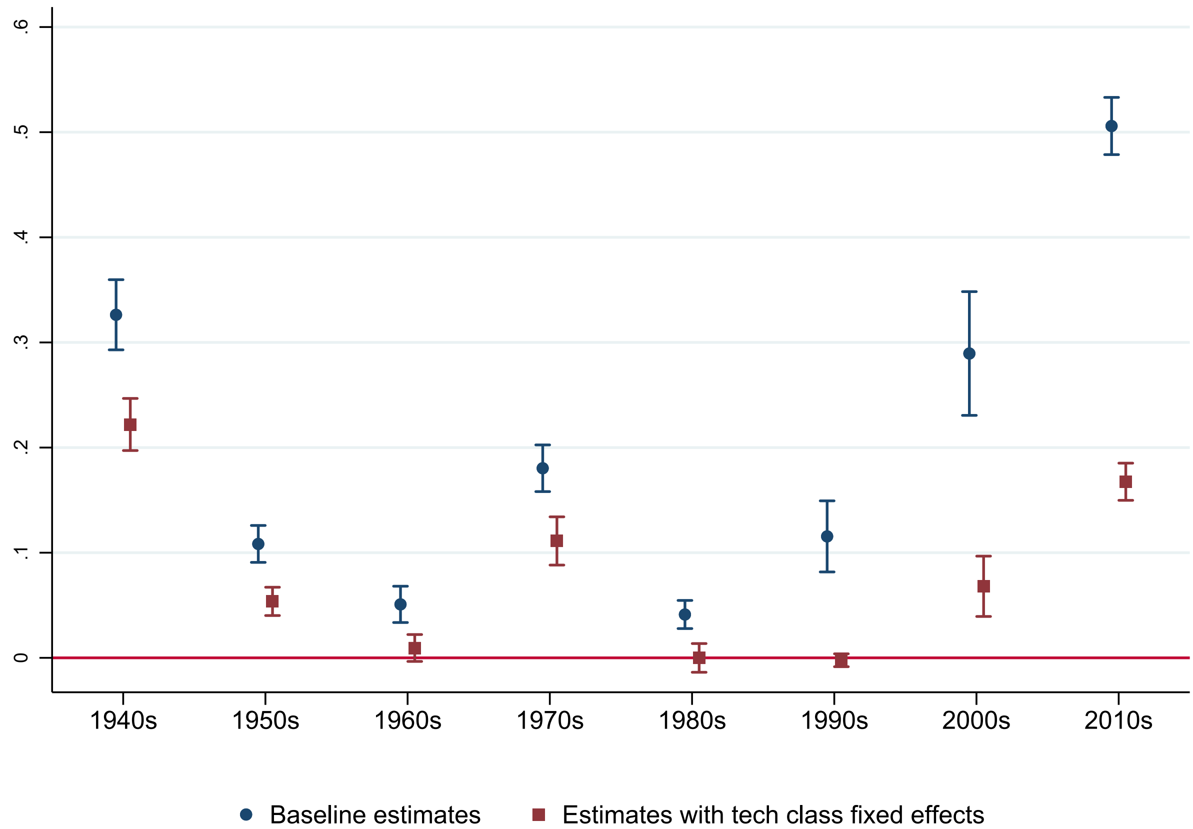
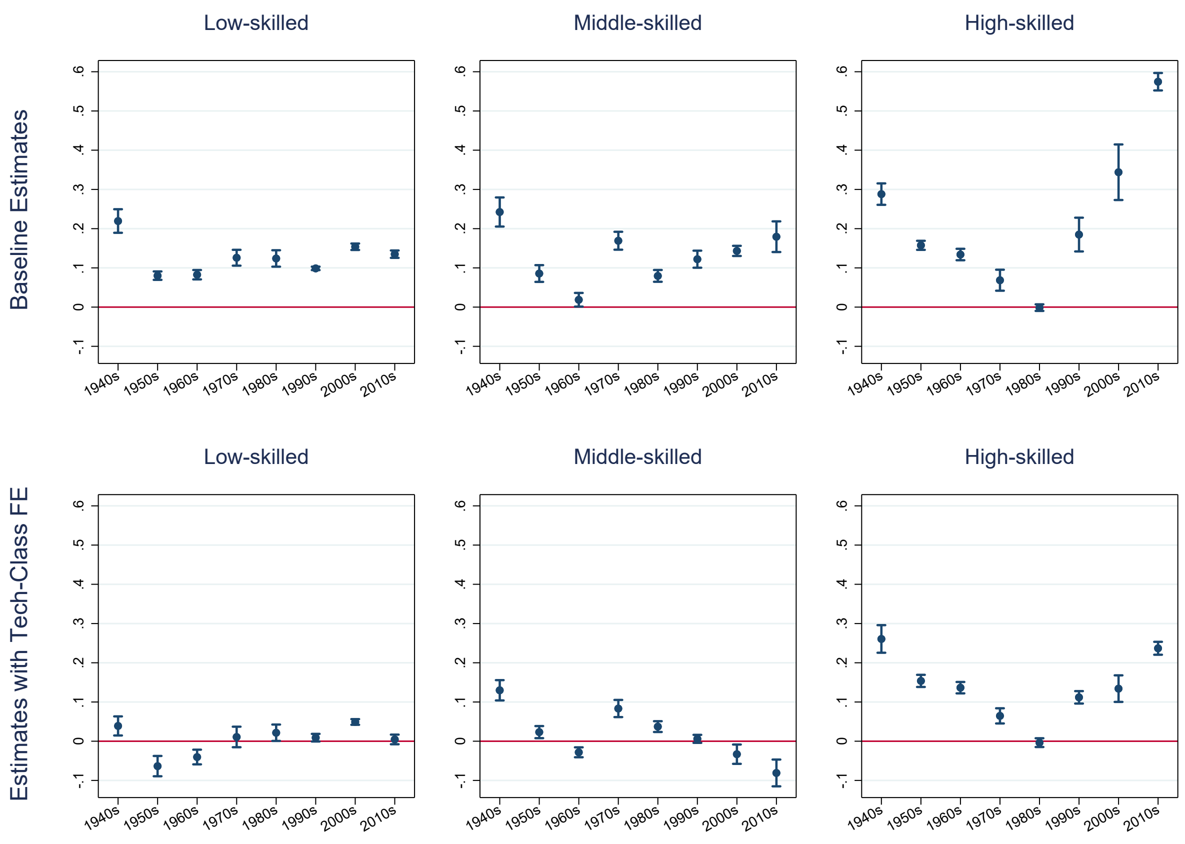


Figure presents the estimated β_τ from equation (3). The augmentation-automation gap is standardized yearly. Both specifications include year fixed effects. Standard errors are clustered by patent issue-year (78 clusters) and 95% confidence intervals are displayed.

Figure 9: Labor-augmenting potential of top vs. non-top firm patents by occupational skill group



The augmentation-automation gap is standardized yearly within each skill group. Both specifications include year fixed effects. Standard errors are clustered by patent issue-year (78 clusters) and 95% confidence intervals are displayed.

Figure 10: The social and market values of labor-augmenting patents

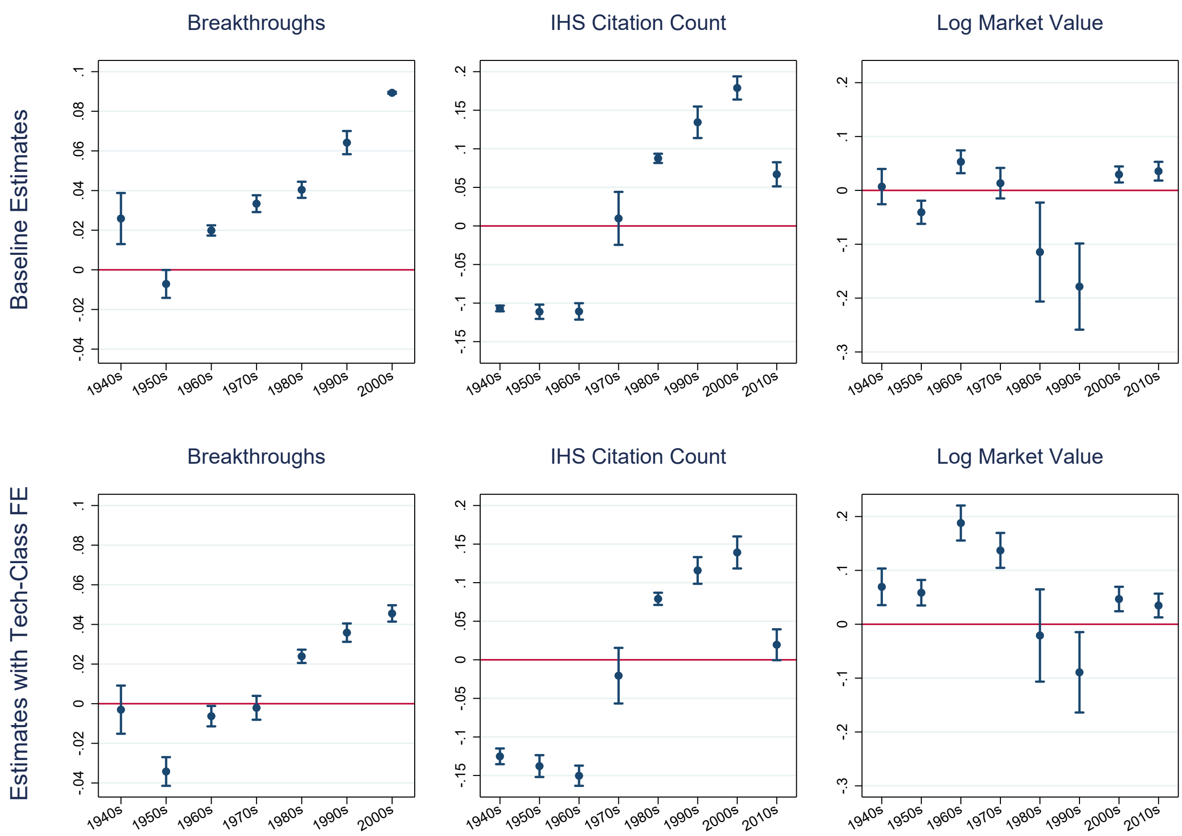


Figure presents the estimated β_τ from equation (4), capturing the decade-specific effect of a one standard deviation increase in patents' augmentation-automation gap on a dummy for breakthroughs, patents' inverse hyperbolic sine citation count, and their log market value. The augmentation-automation gap is standardized yearly. All specifications include year fixed effects. Standard errors are clustered by patent issue-year (78 clusters) and 95% confidence intervals are displayed. Breakthrough data up to 2002.

Figure 11: The market value of labor-augmenting patents by occupational skill group

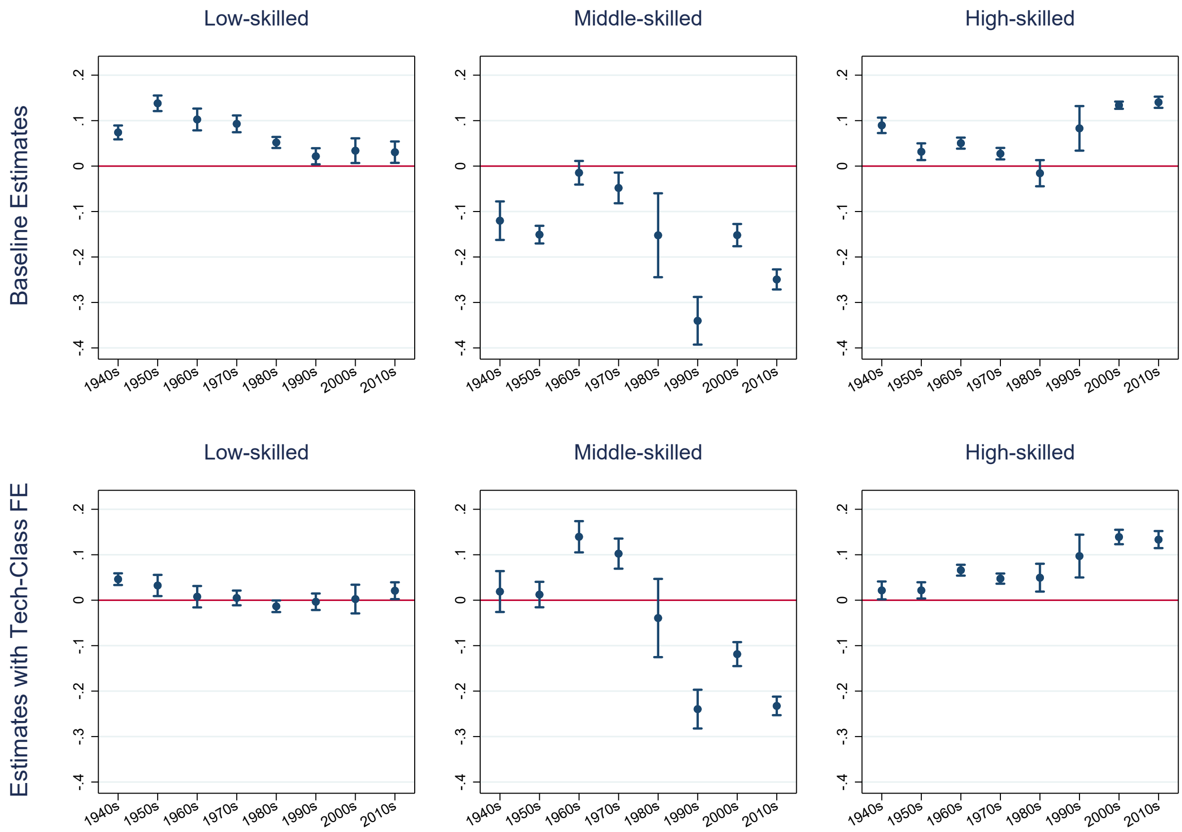


Figure presents the estimated β_τ^s from equation (5), capturing the decade- and occupation-specific effect of a one standard deviation increase in patents' augmentation-automation gap on their log market value. The augmentation-automation gap is standardized yearly within each skill group. Both specifications include year fixed effects. Standard errors are clustered by patent issue-year (78 clusters) and 95% confidence intervals are displayed.

Figure 12: The social value of labor-augmenting patents by occupational skill group, as measured by breakthroughs

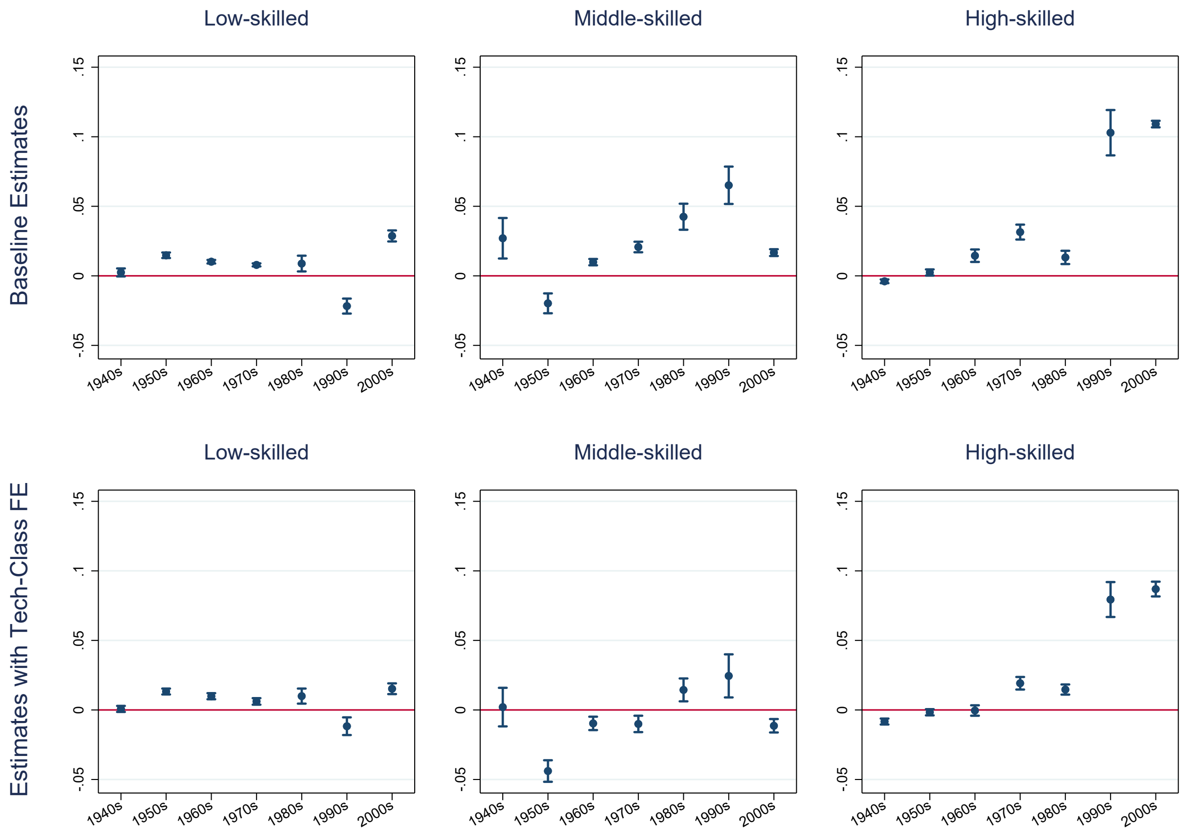


Figure presents the estimated β_τ from equation (5), capturing the decade- and occupation-specific effect of a one standard deviation increase in patents' augmentation-automation gap on a dummy for breakthroughs. The augmentation-automation gap is standardized yearly within each skill group. Both specifications include year fixed effects. Standard errors are clustered by patent issue-year (63 clusters) and 95% confidence intervals are displayed. Breakthrough data up to 2002.

Figure 13: The social value of labor-augmenting patents by occupational skill group, as measured by inverse hyperbolic sine citation count

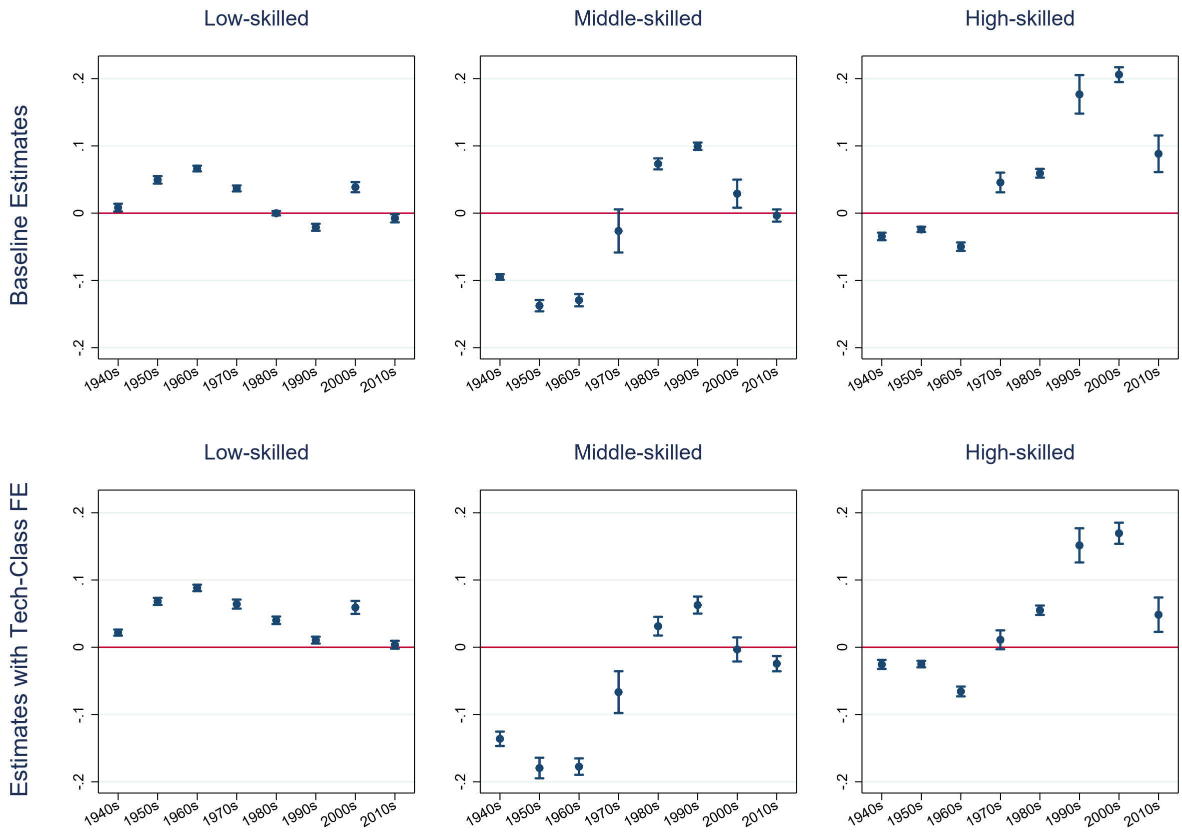


Figure presents the estimated β_τ from equation (5), capturing the decade- and occupation-specific effect of a one standard deviation increase in patents' augmentation-automation gap on their inverse hyperbolic sine citation count. The augmentation-automation gap is standardized yearly within each skill group. Both specifications include year fixed effects. Standard errors are clustered by patent issue-year ($n = 78$) and 95% confidence intervals are displayed.

Tables

Table 1A: Top 5 publicly listed firms by market capitalization, 1940s–2010s

1940s	AMERICAN TELEPHONE & TELEG CO GENERAL MOTORS CORP DU PONT E I DE NEMOURS & CO STANDARD OIL CO N J GENERAL ELECTRIC CO	**1980s**	INTERNATIONAL BUSINESS MACHS COR EXXON CORP AMERICAN TELEPHONE & TELEG CO GENERAL ELECTRIC CO GENERAL MOTORS CORP
1950s	AMERICAN TELEPHONE & TELEG CO GENERAL MOTORS CORP STANDARD OIL CO N J DU PONT E I DE NEMOURS & CO GENERAL ELECTRIC CO	**1990s**	GENERAL ELECTRIC CO COCA COLA CO A T & T CORP MERCK & CO INC WAL MART STORES INC
1960s	AMERICAN TELEPHONE & TELEG CO GENERAL MOTORS CORP INTERNATIONAL BUSINESS MACHS COR STANDARD OIL CO N J TEXACO INC	**2000s**	EXXON MOBIL CORP GENERAL ELECTRIC CO MICROSOFT CORP WAL MART STORES INC PFIZER INC
1970s	INTERNATIONAL BUSINESS MACHS COR AMERICAN TELEPHONE & TELEG CO EXXON CORP GENERAL MOTORS CORP EASTMAN KODAK CO	**2010s**	APPLE INC MICROSOFT CORP BERKSHIRE HATHAWAY INC DEL EXXON MOBIL CORP ALPHABET INC

Table 1B: Top 5 publicly listed firms by employment, 1950s–2010s

1940s	*no data*	**1980s**	SEARS ROEBUCK & CO FORD MOTOR CO DEL KELLY SERVICES INC INTERNATIONAL BUSINESS MACHS COR AMERICAN TELEPHONE & TELEG CO
1950s	AMERICAN TELEPHONE & TELEG CO GENERAL MOTORS CORP FORD MOTOR CO GENERAL ELECTRIC CO UNITED STATES STEEL CORP	**1990s**	KELLY SERVICES INC WAL MART STORES INC SEARS ROEBUCK & CO FORD MOTOR CO DEL K MART CORP
1960s	GENERAL MOTORS CORP AMERICAN TELEPHONE & TELEG CO MANPOWER INC FORD MOTOR CO DEL GENERAL ELECTRIC CO	**2000s**	WAL MART STORES INC KELLY SERVICES INC MCDONALDS CORP UNITED PARCEL SERVICE INC INTERNATIONAL BUSINESS MACHS COR
1970s	AMERICAN TELEPHONE & TELEG CO GENERAL MOTORS CORP FORD MOTOR CO DEL SEARS ROEBUCK & CO GENERAL ELECTRIC CO	**2010s**	WALMART INC KELLY SERVICES INC UNITED PARCEL SERVICE INC YUM CHINA HOLDINGS INC KROGER COMPANY

Table 1C: Top 5 publicly listed firms by patent counts, 1940s–2010s

1940s	GENERAL ELECTRIC CO AMERICAN TELEPHONE & TELEG CO WESTINGHOUSE ELECTRIC CORP RADIO CORP AMER DU PONT E I DE NEMOURS & CO	**1980s**	GENERAL ELECTRIC CO INTERNATIONAL BUSINESS MACHS COR GENERAL MOTORS CORP DOW CHEMICAL CO WESTINGHOUSE ELECTRIC CORP
1950s	GENERAL ELECTRIC CO AMERICAN TELEPHONE & TELEG CO GENERAL MOTORS CORP STANDARD OIL CO N J WESTINGHOUSE ELECTRIC CORP	**1990s**	INTERNATIONAL BUSINESS MACHS COR MOTOROLA INC EASTMAN KODAK CO GENERAL ELECTRIC CO GENERAL MOTORS CORP
1960s	GENERAL ELECTRIC CO GENERAL MOTORS CORP AMERICAN TELEPHONE & TELEG CO WESTINGHOUSE ELECTRIC CORP DU PONT E I DE NEMOURS & CO	**2000s**	INTERNATIONAL BUSINESS MACHS COR MICRON TECHNOLOGY INC INTEL CORP HEWLETT PACKARD CO GENERAL ELECTRIC CO
1970s	GENERAL ELECTRIC CO GENERAL MOTORS CORP AMERICAN TELEPHONE & TELEG CO INTERNATIONAL BUSINESS MACHS COR WESTINGHOUSE ELECTRIC CORP	**2010s**	INTERNATIONAL BUSINESS MACHS COR MICROSOFT CORP QUALCOMM INC INTEL CORP ALPHABET INC

Table 1D: Top 5 publicly listed firms by patent citations, 1940s–2010s

1940s	GENERAL ELECTRIC CO AMERICAN TELEPHONE & TELEG CO RADIO CORP AMER WESTINGHOUSE ELECTRIC CORP DU PONT E I DE NEMOURS & CO	**1980s**	INTERNATIONAL BUSINESS MACHS COR GENERAL ELECTRIC CO AMERICAN TELEPHONE & TELEG CO MINNESOTA MINING & MFG CO GENERAL MOTORS CORP
1950s	GENERAL ELECTRIC CO AMERICAN TELEPHONE & TELEG CO GENERAL MOTORS CORP STANDARD OIL CO N J RADIO CORP AMER	**1990s**	INTERNATIONAL BUSINESS MACHS COR MOTOROLA INC JOHNSON & JOHNSON A T & T CORP GENERAL ELECTRIC CO
1960s	GENERAL ELECTRIC CO GENERAL MOTORS CORP DU PONT E I DE NEMOURS & CO AMERICAN TELEPHONE & TELEG CO DOW CHEMICAL CO	**2000s**	INTERNATIONAL BUSINESS MACHS COR MICROSOFT CORP INTEL CORP HEWLETT PACKARD CO JOHNSON & JOHNSON
1970s	GENERAL ELECTRIC CO INTERNATIONAL BUSINESS MACHS COR AMERICAN TELEPHONE & TELEG CO GENERAL MOTORS CORP DU PONT E I DE NEMOURS & CO	**2010s**	JOHNSON & JOHNSON INTERNATIONAL BUSINESS MACHS COR A T & T INC ALPHABET INC AMAZON COM INC

Table 1E: Top 5 publicly listed firms by patent market value, 1940s–2010s

1940s	AMERICAN TELEPHONE & TELEG CO GENERAL MOTORS CORP DU PONT E I DE NEMOURS & CO STANDARD OIL CO N J GENERAL ELECTRIC CO	**1980s**	INTERNATIONAL BUSINESS MACHS COR EXXON CORP AMERICAN TELEPHONE & TELEG CO GENERAL ELECTRIC CO AMOCO CORP
1950s	GENERAL MOTORS CORP STANDARD OIL CO N J AMERICAN TELEPHONE & TELEG CO DU PONT E I DE NEMOURS & CO GENERAL ELECTRIC CO	**1990s**	MICROSOFT CORP GENERAL ELECTRIC CO INTEL CORP INTERNATIONAL BUSINESS MACHS COR MERCK & CO INC
1960s	AMERICAN TELEPHONE & TELEG CO INTERNATIONAL BUSINESS MACHS COR GENERAL MOTORS CORP STANDARD OIL CO N J GENERAL ELECTRIC CO	**2000s**	MICROSOFT CORP GENERAL ELECTRIC CO INTEL CORP CISCO SYSTEMS INC EXXON MOBIL CORP
1970s	INTERNATIONAL BUSINESS MACHS COR AMERICAN TELEPHONE & TELEG CO GENERAL MOTORS CORP EASTMAN KODAK CO EXXON CORP	**2010s**	APPLE INC AMAZON COM INC MICROSOFT CORP EXXON MOBIL CORP FACEBOOK INC

Table 2: Correlations between ranks for publicly listed firms

	Correlations for firm ranks based on:				
	Market cap	Employment	Patent count	Patent citations	Patent value
Market cap	1				
Employment	0.782***	1			
Patent count	0.466***	0.391***	1		
Patent citations	0.466***	0.382***	0.992***	1	
Patent value	0.509***	0.423***	0.992***	0.986***	1

Averages over 1940–2018 with $N = 26,156$ for all pairwise correlations between market cap and patent counts, citations and value; averages over 1950–2018 with $N = 24,029$ for all pairwise correlations with employment. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 3: Top firm patents have higher intellectual impact

	(1)	(2)	(3)	(4)
	A. Dep. Var.: 100 × IHS patent citation count			
Top firm patent	9.04***	8.73***	10.38***	8.26***
	(0.80)	(0.88)	(0.49)	(0.38)
N	7,923,009	7,923,009	7,923,009	7,923,009
R^2	0.00	0.02	0.05	0.06
	B. Dep. Var.: 100 × Dummy for patent being a breakthrough			
Top firm patent	7.46***	7.80***	4.54***	3.37***
	(0.63)	(0.58)	(0.40)	(0.26)
N	4,295,173	4,295,173	4,295,173	4,295,173
R^2	0.01	0.03	0.09	0.16
Year FE		X	X	X
Broad Class FE			X	
CPC3 Class FE				X

Top firms are in the top 2% of market capitalization. The number of observations is the number of patents issued over 1940–2018 for panel A, and over 1940–2002 for panel B. Standard errors clustered by patent issue-year reported in parentheses. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Appendix

Figure A1: Probability of staying in set of top employment firms, decade by decade

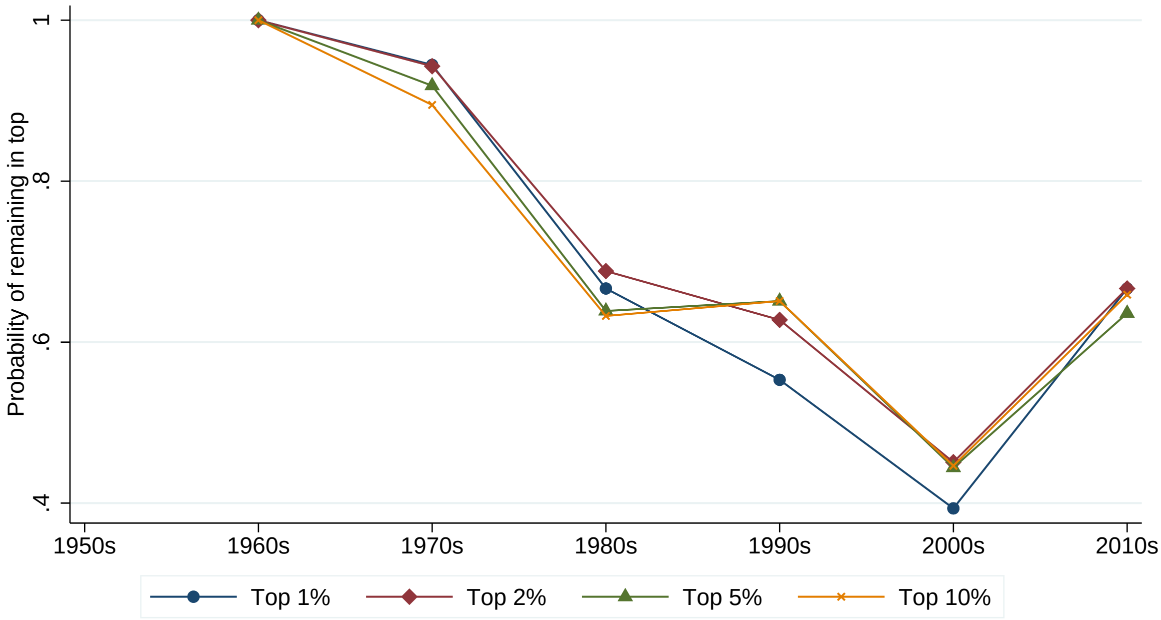


Figure A2: Probability of staying in set of top patent count firms, decade by decade

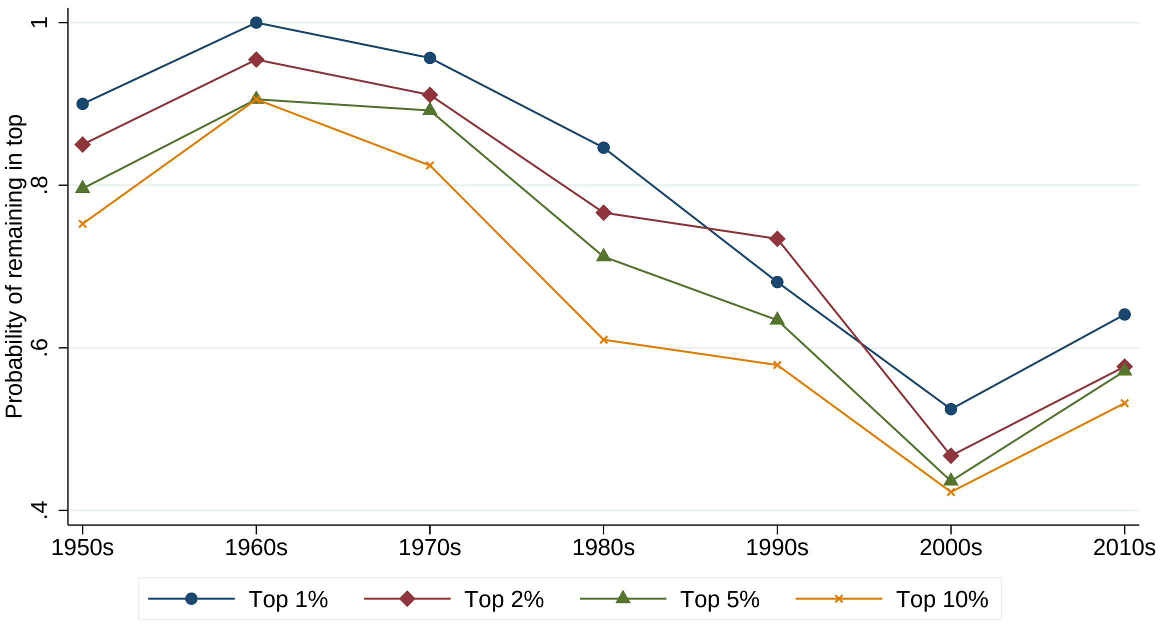


Figure A3: Probability of staying in set of top patent citation firms, decade by decade

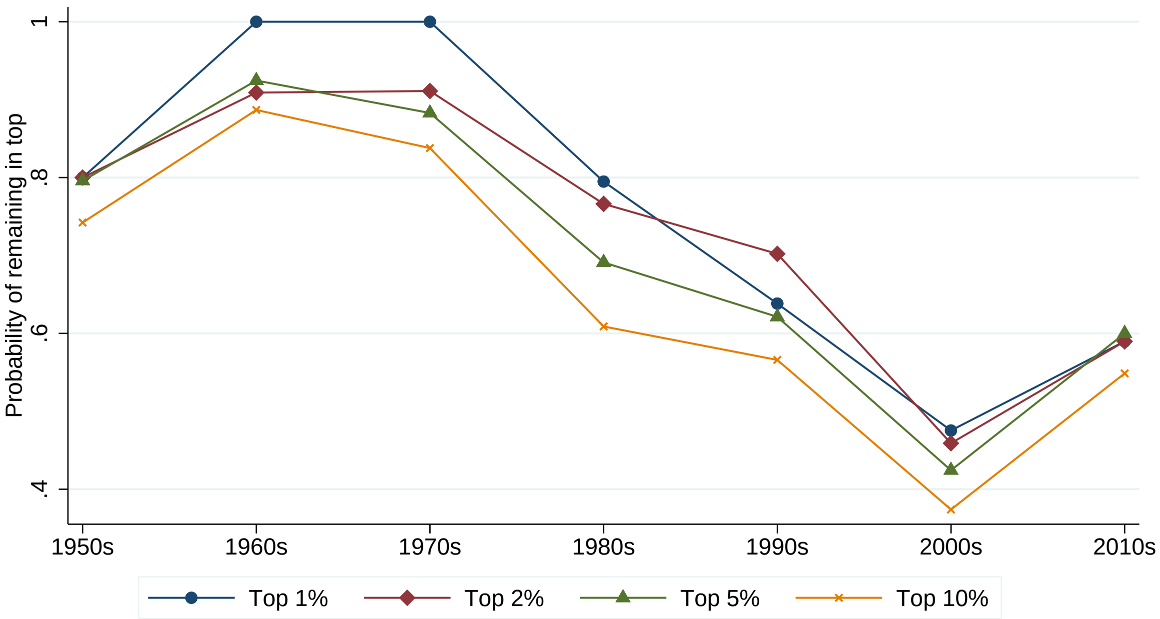


Figure A4: Probability of staying in set of top patent value firms, decade by decade

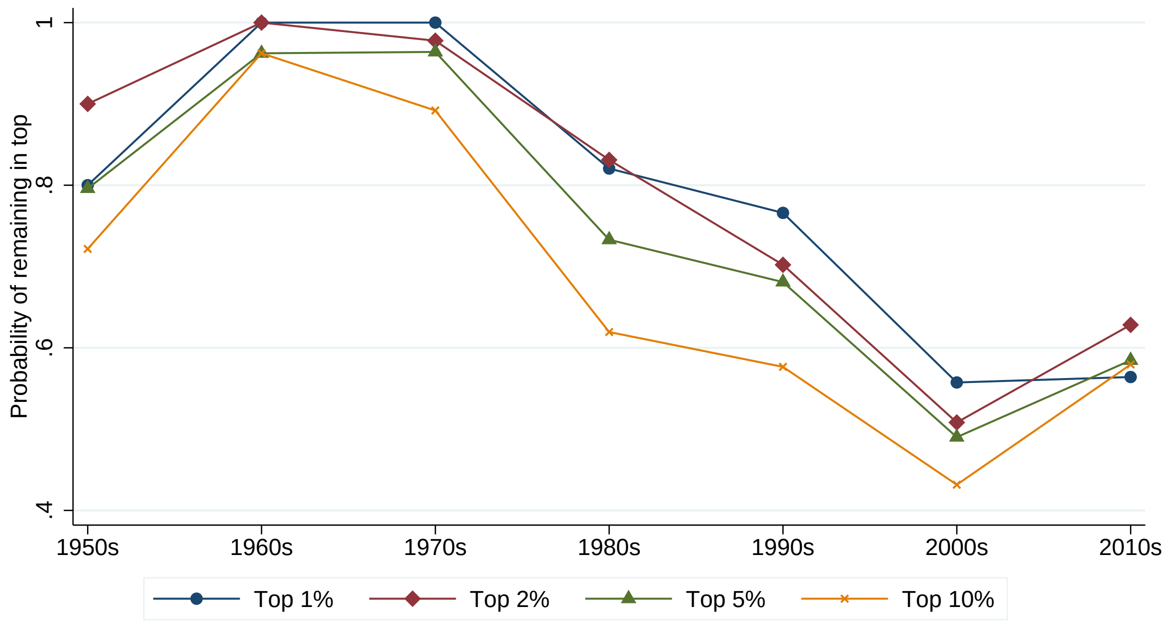


Figure A5: Cohort-specific probability of staying in set of top employment firms over time

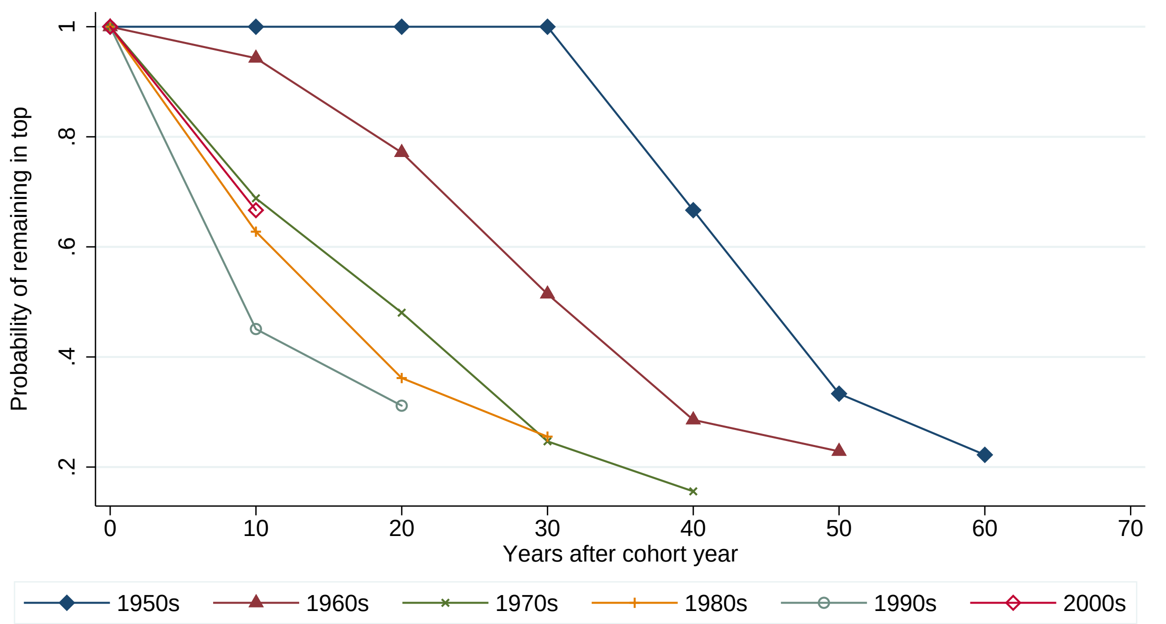


Figure A6: Cohort-specific probability of staying in set of top patenting firms over time

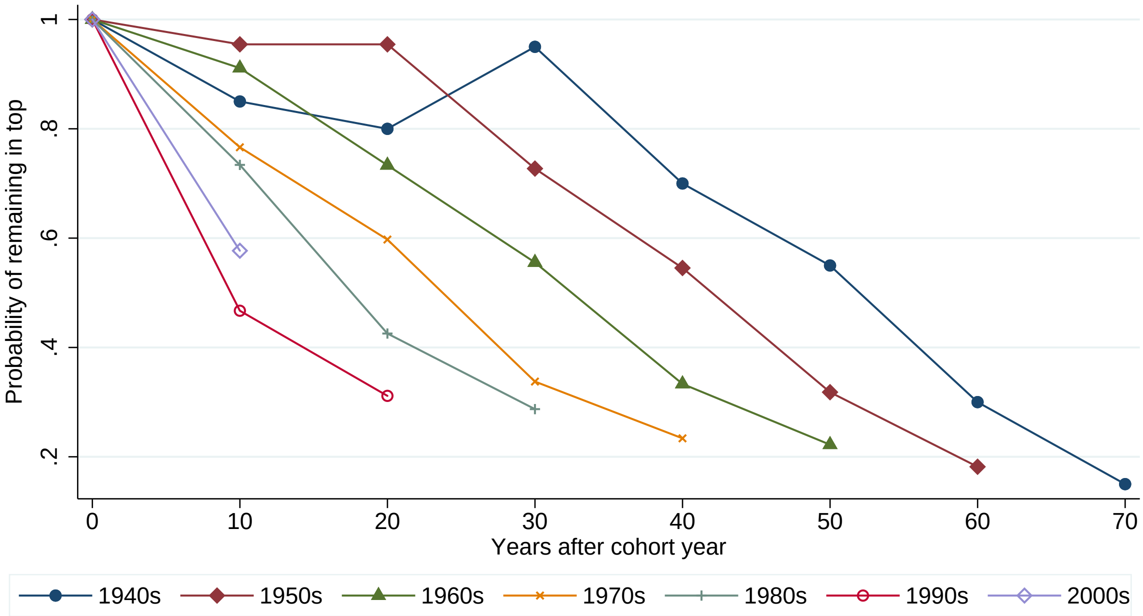


Figure A7: Cohort-specific probability of staying in set of top patent citation firms over time

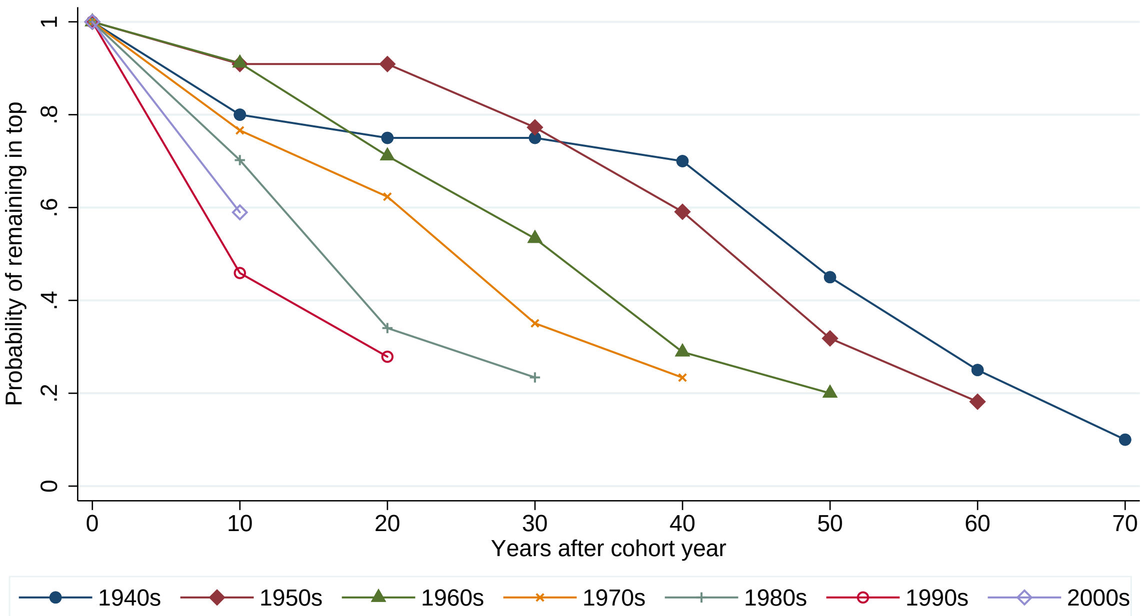


Figure A8: Cohort-specific probability of staying in set of top patent value firms over time

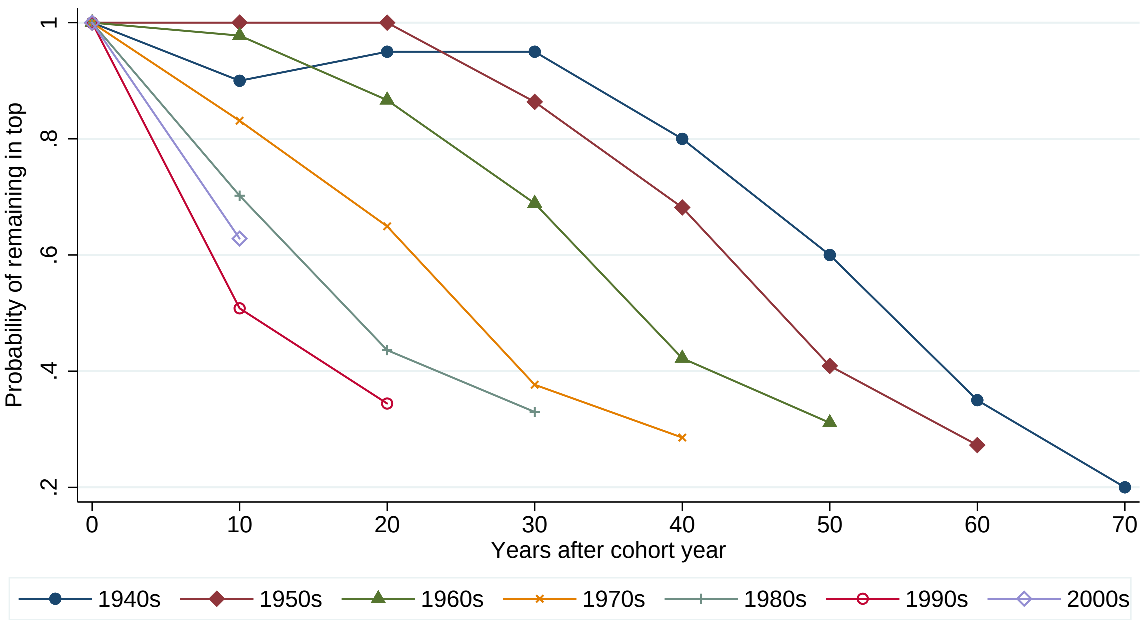
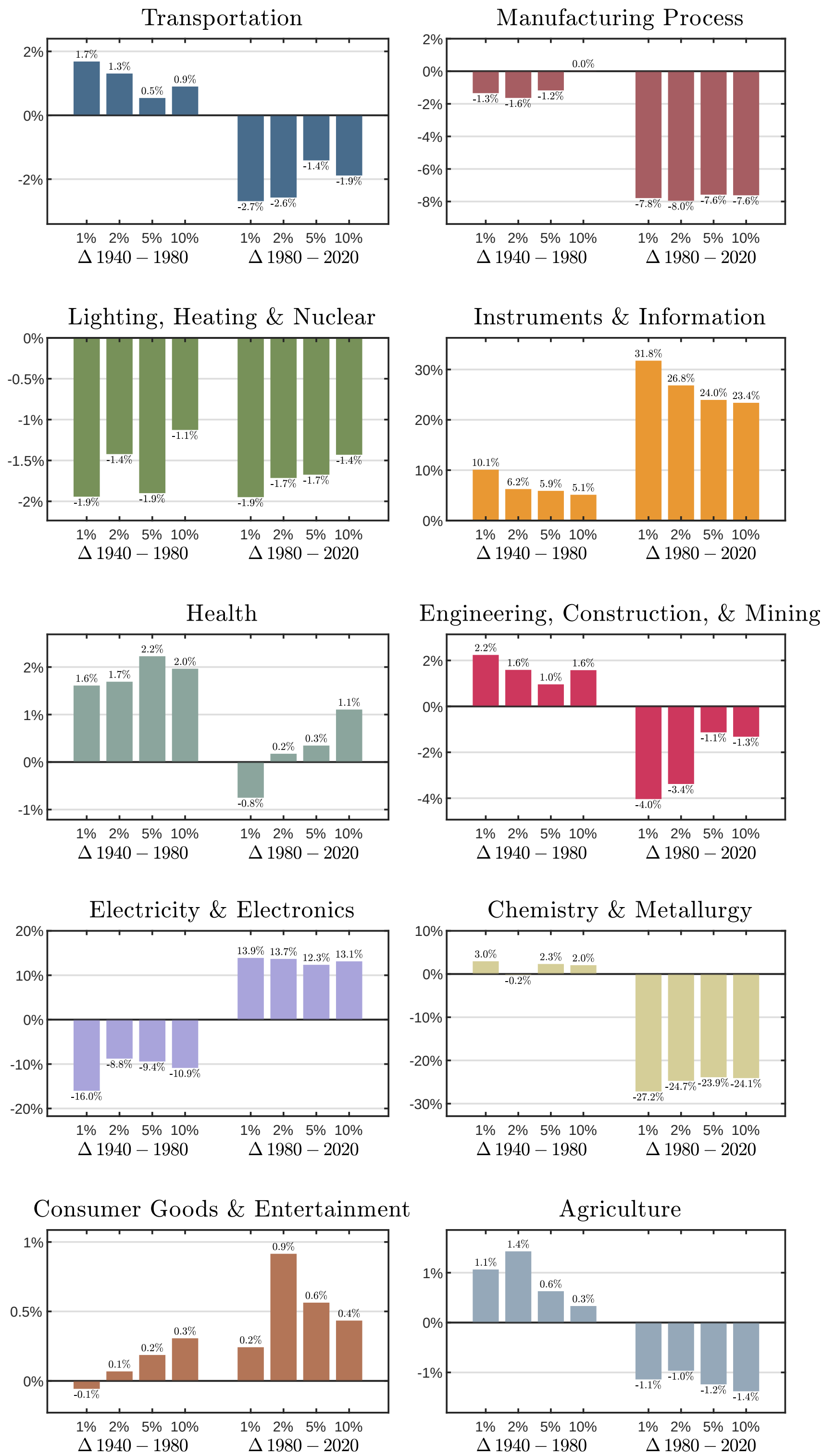
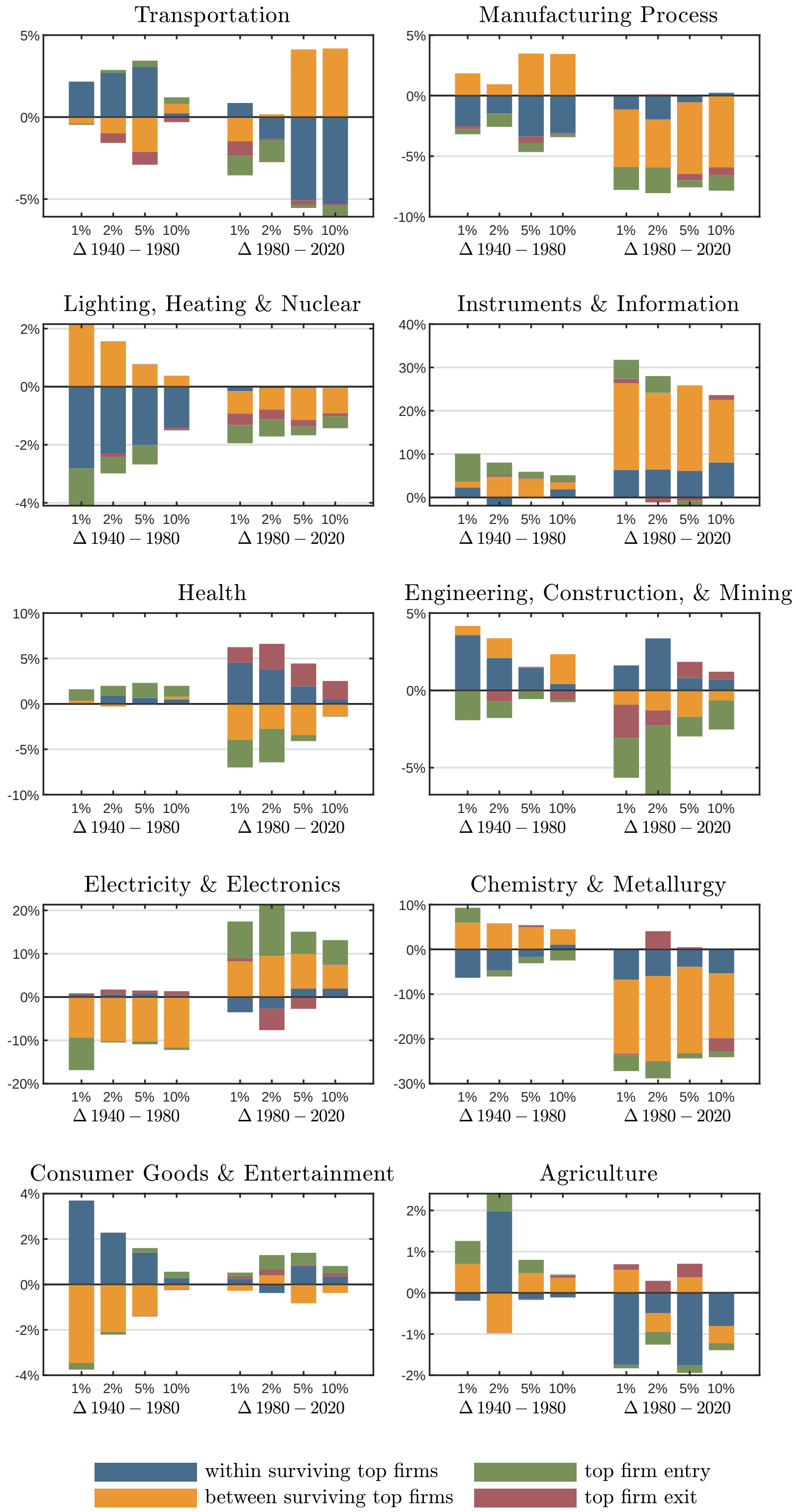


Figure A9: Changes in patenting shares by broad technology class for top firms



Top firms are the top 1, 2, 5, or 10% in market capitalization.

Figure A10: Decomposition of changes in patenting shares by broad technology class for top firms



Top firms are the top 1, 2, 5, or 10% in market capitalization.

Table A1: Number of top firms by decade based on different measures and percentile cut-offs

	Ranking based on employment:				Ranking based on other measures:			
Decade	Top 1%	Top 2%	Top 5%	Top 10%	Top 1%	Top 2%	Top 5%	Top 10%
1940s					10	20	49	97
1950s	5	9	21	41	11	22	53	106
1960s	18	35	86	171	23	45	111	222
1970s	39	77	191	381	39	77	191	382
1980s	47	94	235	470	47	94	235	482
1990s	61	122	304	607	61	122	305	608
2000s	39	78	195	390	39	78	196	391
2010s	35	69	173	345	35	69	173	345

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