Industry Shakeouts after an Innovation Breakthrough*

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Abstract

Conventional wisdom suggests that after a technological breakthrough, the number of active firms first surges, and then sharply declines, in what is known as a "shakeout". This paper challenges that notion with new empirical evidence from across the U.S. economy, revealing that shakeouts are the exception, not the rule. I develop a statistical strategy to detect breakthroughs by isolating sustained anomalies in net firm entry rates, offering a robust alternative to narrative-driven approaches that can be applied to all industries. The results of this strategy, which reliably align with well-documented breakthroughs and remain consistent across various validation tests, uncover a novel trend: the number of entry-driven breakthroughs has been declining over time. The variability and frequent absence of shakeouts across breakthrough industries are consistent with breakthroughs primarily occurring in industries with low returns to scale and with modest learning curves, shifting the narrative on the nature of innovation over the past forty years in the U.S.

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1 Introduction

In 1970, the computer manufacturing industry was dominated by the massive mainframes of IBM and Honeywell – machines so large they filled entire rooms, yet so limited they could only perform batch processing. Then, in 1975, the release of the Altair 8800 marked an innovation breakthrough. This unassuming device, no bigger than a breadbox, was the first to harness a microprocessor, unleashing a wave of new firms eager to capitalize on the breakthrough. Companies like Lenovo and Apple soon emerged as industry leaders, while incumbents like IBM and Honeywell eventually exited the computer manufacturing industry. As computing became cheaper and more accessible, the initial surge of entrants gave way to a sharp decline in firm numbers, a decline known as a "shakeout."

Conventional wisdom on industry dynamics after an innovation breakthrough has long associated breakthroughs with this rise and fall in firm numbers, due to a set of empirical case studies (Gort and Klepper, 1982; Horvath et al., 2001). Existing economic models have attributed the documented shakeouts to various factors, such as the failure of exiters to innovate, the arrival of negative information, and the rate of demand growth (Hopenhayn, 1993; Jovanovic and MacDonald, 1994; Klepper and Simons, 2000; Horvath et al., 2001; Wang, 2008). These studies have contributed to the conventional view that rising concentration, on both the extensive and intensive margins, is a hallmark – and perhaps an inevitable outcome – of technological progress and industry maturity (Autor et al., 2020; Akcigit and Ates, 2021; Ma, Yongwook, and Zimmerman, 2024).

However, the question remains as to whether shakeouts are truly representative of breakthroughs across the entire economy. The empirical evidence is limited, because it relies on a narrow set of industries, and because breakthroughs are detected through anecdotal accounts or patent data. The set of industries studied in the literature represents less than 5% of the approximately one thousand industries in the Census, even though the Census industries have comparable product market scopes. Anecdotal approaches are prone to selection bias, focusing on prominent consumer-facing products and potentially overlooking sectors in which innovation may be less visible or conventionally defined, such as service industries that rely on management, logistics, or communication technologies (Hsieh and Rossi-Hansberg, 2023). Meanwhile, patent-based approaches skew the detection of breakthroughs toward a few manufacturing sectors, in which innovations are more likely to be patentable (Hall and Harhoff, 2012; Levin et al., 1987; Cohen et al., 2000; Graham et al., 2009).

This paper is the first to offer evidence, across the entire US economy, on whether industries shake out after an innovation breakthrough, and give stylized facts generalizable across the economy about industry dynamics after a breakthrough. I find that shakeouts are the exception, not the rule: the majority (three-fifths) of the industries that experience an innovation breakthrough do not eventually shake out. This result, which passes a large array of robustness checks, qualifies the conventional view that rising concentration is a hallmark of technological progress and industry maturity. While this paper does not address concentration on the intensive margin (employment or sales), it is meaningful to study the concentration on the extensive margin (number of producers), because it reflects the potential for firm entry and thus industry competition (Sutton, 1991; Syverson, 2004).

To select a representative set of breakthrough industries from across the economy, I develop a statistical breakthrough detection strategy. The core intuition is to isolate sustained periods during which an industry's net entry rates are statistical outliers: periods in which entry trends cannot be attributed to other factors, whether economy-wide or sector-wide. Using firm-level data from the Longitudinal Business Database, I filter out statistical noise in the net entry rate and isolate sustained periods when an industry crosses a threshold (e.g., the top 5% of net entry rates across time and across industries). By design, the strategy focuses on breakthroughs for which industries respond on the extensive margin, aligning with literature that documents shakeouts following periods of high net entry. Notably, the strategy successfully detects salient breakthroughs: some of which, like computer systems design and internet publishing, do not exhibit shakeouts. Though the strategy is not immune to Type I and Type II errors, I demonstrate this strategy's systematic accuracy in detecting industry events that resemble historically prominent breakthroughs.

The strategy reveals a new fact: breakthroughs have been declining over time, driven by a reduction in the variance of net entry rates. This finding contributes to the business dynamism literature, which has documented a long-term decline in entry rates (Akcigit and Ates, 2021; Decker, Haltiwanger, Jarmin, Miranda, 2016). While previous work has emphasized the fall in entry levels, my analysis uncovers a related phenomenon: the decreasing volatility.

I present five novel stylized facts on industry dynamics following an innovation breakthrough, leveraging a much larger and more representative sample than previous studies. The first two facts pertain to the prevalence of industry shakeouts. First, I document significant heterogeneity in post-breakthrough outcomes: some industries follow the classic shakeout pattern, others deviate from it, and many fall in between. To capture this variation, I introduce a Shakeout Index, which quantifies the extent of shakeouts across industries. This index categorizes industries into quintiles, with the top two quintiles experiencing shakeouts and the bottom three avoiding them. This leads to my second fact: contrary to conventional wisdom, the majority of industries do not undergo a shakeout following an innovation breakthrough.

The remaining three facts highlight the stark differences between breakthrough and non-breakthrough industries, reinforcing the validity of the statistical detection procedure and providing key insights for understanding why some industries experience shakeouts while others do not. Third, labor reallocates significantly towards breakthrough industries, while non-breakthrough industries face a declining share of labor within the broader economy. Fourth, within breakthrough industries, labor shifts enormously towards firms that entered after the breakthrough, in contrast to non-breakthrough industries. Finally, the variation in shakeout patterns across industries is driven by the exit of post-breakthrough entrants, rather than by firms that entered before the breakthrough.

The breakthrough detection strategy is validated through historical evidence, extensive robustness checks, and counterfactual tests. First, I confirm that the selected industries correspond closely to well-documented breakthroughs. Next, I compare these industries to the ones selected in two prominent studies, Kalyani, Bloom, Lerner, Melo, and Tahoun (2024) and Kelly, Papanikolaou, Seru, and Taddy (2021). Despite differences in sectoral focus, the key result holds: shakeouts remain uncommon. I also perform various robustness checks, such as restricting the selected sample to those industries assigned a new NAICS code, those industries with declining prices, as well as adjusting parameters in the detection procedure. The primary finding—that most breakthrough industries do not experience shakeouts—remains robust across all these subsamples and parameter adjustments. Finally, I conduct counterfactual tests to demonstrate the null outcome if the procedure were flawed: randomly selected industry-year pairs and salient industries affected by demand shocks (but no large innovations) diverge from the patterns documented in breakthrough industries.

Although there is no universally accepted classification for an innovation breakthrough, this paper demonstrates that a useful classification is rooted in both empirical and theoretical considerations. The salient and non-salient breakthroughs selected by the statistical strategy universally manifest the shock as an event that improved the competitive advantage of new firms, resulting in a sustained reallocation of resources – distinct from other industries –

toward these new firms and their industry. This combination of consistent empirical outcomes and theoretical alignment establishes the proposed strategy as a reliable and effective tool for generating stylized facts about industry dynamics after breakthroughs.

Finally, I construct a qualitative model to illustrate two key mechanisms, consistent with anecdotal evidence, that drive the presence and absence of shakeouts in industries following a breakthrough. The first mechanism is industry-specific returns to scale, which reflect the technology's capacity to support large-scale production. Industries with high returns to scale are more likely to experience pronounced shakeouts. The second mechanism is the productivity gap between older firms and younger firms, often explained by incremental innovation or learning-by-doing (Klette and Kortum, 2004; Irwin and Klenow, 1994), and sometimes referred to as the learning curve. Industries with large productivity gaps between older and younger firms exhibit pronounced shakeouts, while industries with small productivity gaps avoid shakeouts.

The rest of the paper is organized as follows. Section II describes the empirical strategy for breakthrough detection, including the data set I use. Section III presents my main findings about industry shakeouts and dynamics after an innovation breakthrough, organized in five facts. Section IV demonstrates that the breakthrough detection strategy is systematically reliable. Section V presents a qualitative model to explain the variance in shakeouts. Section VI concludes. The appendix includes more details on my data and a number of additional empirical exercises that establish the robustness of my results, as well as the proofs of the propositions in section V.

2 Empirical Strategy for Breakthrough Detection

To select industries that have experienced a breakthrough from across the entire US economy, I develop a statistical breakthrough detection procedure.

2.1 Data

My data set is the microdata from the US Census Longitudinal Business Database (LBD), which contains annual firm-level data of all the industries in the economy from 1978 to 2019.

The LBD is based on administrative employment records of every nonfarm private establishment in the US economy. The variables I use are the establishment's ID, the ID of the firm that owns the establishment, first and last years of positive employment for the establishment, first and last years of positive employment for the firms, firm-level employment, and vintage-consistent 6-digit 2017 NAICS [North American Industry Classification System] codes from 1978 to 2019. The vintage were first developed by Fort and Klimek (2018), and updated by Chow et al. (2021). I restrict the sample to observations from 1978 to 2019, where years after 2019 are omitted to avoid the Covid 19 shock.

To define firm entry and exit, I use firm-to-establishment relationships within the LBD and the dates of positive employment for the establishments. First I define the establishment entry (exit) date as the first (last) year the establishment is observed with positive employment. An establishment is considered active in a given year if the year is between the entry date and the exit date, inclusive. This definition of active is consistent with the Business Dynamic Statistics produced by Chow et al. (2021). Firm entry and exit is defined in relation to the NAICS 6 industry: firm entry year is the entry year of the first establishment owned by the firm in the NAICS 6 industry, and firm exit year is the exit year of the last establishment owned by the firm in that industry. Hence, even if a firm has existing establishments in operation, a firm is treated as an entrant in any NAICS 6 industry if it opens an establishment in that industry for the first time. A firm is considered active in a given year if the year is between the firm entry date and the exit date (relative to a particular NAICS 6 industry), inclusive. For each industry, I count the number of active firms in each year to get a time path of the number of firms from 1978-2019.

2.2 Breakthrough Detection Strategy

I develop a statistical procedure that classifies an industry as a breakthrough industry if it undergoes at least one sustained period of exceptionally high net entry of firms, after filtering out other potential causes of net entry. This procedure can be applied to industries across the economy.

2.2.1 Overview of Detection Strategy

This process is formalized in math in the following section. First, I filter out statistical noise in the net firm entry rate. For each 6-digit NAICS industry i, I calculate the net firm entry rate in year t by dividing the change in the number of firms in year t from year $t-1$ by the number of firms in year $t-1$. To reduce noise from economy and sector-wide shocks, I remove year and sector fixed effects, yielding a smoothed cross-sectional deviation. To further filter out fluctuations from business cycles or other short-term events, I smooth the entry rates by averaging over a five-year window, from $t-2$ to $t+2$.

Then, I isolate industries and sustained periods of time where the filtered net entry rates are outliers. Using the smoothed, fixed-effects-adjusted net entry rate, I isolate periods where an industry's net entry rate falls within a threshold, say the top 10%, relative to all industries across the entire observation window (1978-2019). These sustained periods of exceptional net entry are defined as five consecutive years during which the entry rate consistently exceeds this 10% threshold. When such a period is isolated, the industry is classified as experiencing a breakthrough.

If an industry experiences multiple breakthroughs over time, the process restarts. Once an industry surpasses the threshold, exits, and then re-enters the threshold zone, this subsequent re-entry is treated as a new breakthrough. After an industry is classified as a breakthrough industry, I begin tracking it from the breakthrough year, which is designated as age 1. If a second breakthrough occurs, the time index resets, and the industry is tracked from age 1 once again. Importantly, after joining the selected sample, no industries exit, as I continue following them through subsequent breakthroughs.

Figure 1 illustrates the breakthrough detection procedure by contrasting a selected industry on the left panel, Software Publishers, with a non-selected industry on the right panel, Vehicle Manufacturing. The thick red line indicates the five-year period during which the industry's net entry rate crosses the 10% threshold. Although the industry remains above the threshold beyond this period, it does not affect the selection procedure, as the breakthrough is defined by the initial crossing of the threshold.

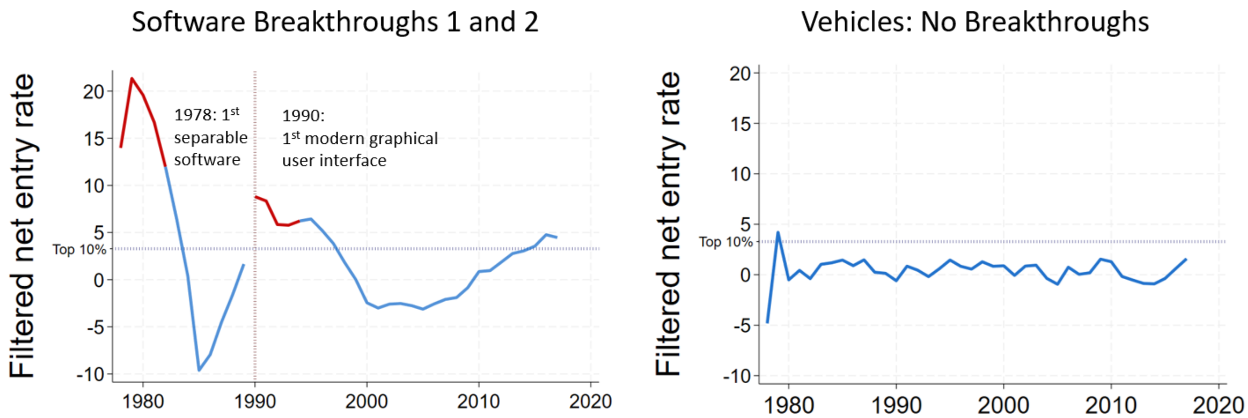

Figure 1. The unit of observation is a Naics 4 digit industry (using public BDS tabulations). The left panel shows Software Publishers (NAICS 5112) and the right panel shows Motor Vehicle Manufacturing (NAICS 3361).

Two breakthroughs were detected in Software Publishers, in 1978 and 1990. In 1978, the software industry experienced the commercial emergence of standalone software packages, separate from hardware. Firms that entered during the five-year selection window following 1978 included later-to-be-prominent companies such as Oracle, Adobe, Symantec, VisiCorp, and Lotus. After dipping below the threshold, the Software Publishers industry re-entered it in 1990. This coincided with the release of Microsoft's Windows 3.0, which introduced a novel graphical user interface (GUI) that founded the gaming industry. Firms that entered during the five-year selection window included id Software (creator of the first-person shooter genre), Rogue Entertainment, and Epic Games (creator of Fortnite). In contrast, while the vehicle manufacturing industry crossed the threshold in 1979, it did not remain above the threshold long enough to be selected.

By design, my approach detects breakthroughs where the industry exhibits a response on the extensive margin – where firm entry is substantial.[1] I will refer to these breakthroughs as entry-driven breakthroughs. This approach is grounded in the literature, which suggests that after a significant invention, new firms rapidly enter the market to capitalize on the profit opportunity, causing the number of firms to surge. As the examples in Section 2.3 will show, these breakthroughs can be initiated by incumbents, and incumbents may also respond to them. Breakthroughs that do not prompt an extensive margin response, such as those in industries with high entry barriers, would not be captured by this method. However, this limitation does not affect the focus of my study, which specifically addresses shakeouts

[1] For example, as the right panel of Figure 1 suggests, while the shift to electric vehicles represents a major innovation in vehicle manufacturing, it did not elicit a notable response from potential entrants.

in industries with entry-driven breakthroughs.

The breakthrough detection strategy reliably selects industry-wide events that can be robustly considered innovation breakthroughs. First, Appendix X provides a table of selected industries and breakthrough years, supported by corresponding anecdotal evidence. Second, while this procedure may be subject to Type I and Type II errors, I will demonstrate in Sections III and IV that it is an effective tool for analyzing industry dynamics following a breakthrough. Since there is no universally agreed-upon classification for an industry-wide breakthrough, I use a threshold-based approach to classify such events. Given that a breakthrough is generally understood as a significant transformative innovation, I will show in Section III (Facts 3-5) that the industries selected by this procedure exhibit substantial long-term transformations, distinct from non-selected industries. A faulty detection strategy (the null outcome) would select industries that exhibit patterns that are indistinguishable from the rest of the economy, or that diverge from the universal patterns of salient entry-driven breakthrough industries. In Section IV, I reinforce the procedure's validity by showing that there are large long-run disparities between the breakthrough industries and randomly selected industries, as well as industries known to have experienced demand shocks (but no innovation).

2.2.2 Formalization of the Breakthrough Detection Procedure

The breakthrough detection procedure is formalized in five steps:

1. **Filter out Noise in Net Entry Rates:** For each industry i in year t, calculate the net entry rate $r_{it} = \frac{N_{it} - N_{i(t-1)}}{N_{i(t-1)}}$, where N is the number of active firms. Then:

   (a) **Remove Fixed Effects:** To control for year and sector influences, estimate year and sector fixed effects (β_t and β_s), yielding the residual ε_{it}:

   $$r_{it} = \alpha + \beta_t I_t + \beta_s I_s + \varepsilon_{it}$$

   (b) **Apply Smoothing:** Smooth the residuals over a 5-year moving average to obtain $\hat{\varepsilon}_{it}$:

   $$\hat{\varepsilon}_{it} = \frac{1}{5} \sum_{k=-2}^{2} \varepsilon_{i(t+k)}$$

(c) **Append Initial Observations:** Include the years 1978 and 1979 in the dataset as follows (robustness to excluding these years is discussed in Appendix X):

$$\tilde{\varepsilon}_{it} = \begin{cases} \hat{\varepsilon}_{it} & \text{for } t \geq 1980 \\ \varepsilon_{it} & \text{for } t = 1978, 1979 \end{cases}$$

2. **Isolate Outliers:** Define E as the set of industry-year pairs (i, t) where $\tilde{\varepsilon}_{it}$ lies in the γth percentile of all pooled $\tilde{\varepsilon}_{it}$ values, where γ can take values such as 90 or 95.

3. **Define Breakthroughs:** A breakthrough for industry i is defined as a sequence of years $t, ..., t+T$ such that $\{(i,t),(i,t+1),\ldots,(i,t+T)\} \subset E$, where T can take values such as 5 or 6.

2.3 Illustration of Detection Procedure

Recall that an industry is classified as a breakthrough industry if its filtered net entry rate exceeds a threshold for a sustained period. This section illustrates that procedure for a threshold of 10% and a period of 5 years. The year of selection corresponds to the first year that the industry crosses this threshold.

I first highlight four salient breakthrough industries. Figure 2 shows the filtered net entry rate in the top row and the corresponding number of firms in the bottom row. In Computer Manufacturing, 1975 marked the release of the Altair 8800, the first computer powered by a microprocessor, which laid the groundwork for significantly reducing the size of personal computers. In Computer Systems Design, 1978 marked the release of Oracle's RDBMS, the first modern data storage system, which introduced a model that enabled scalable and efficient data management, laying the foundation for complex enterprise IT solutions.[2]

[2]Notable entrants in the following five years (the period used for breakthrough detection) included Electronic Data Systems, Microsoft with MS-DOS, and Ingres Database.

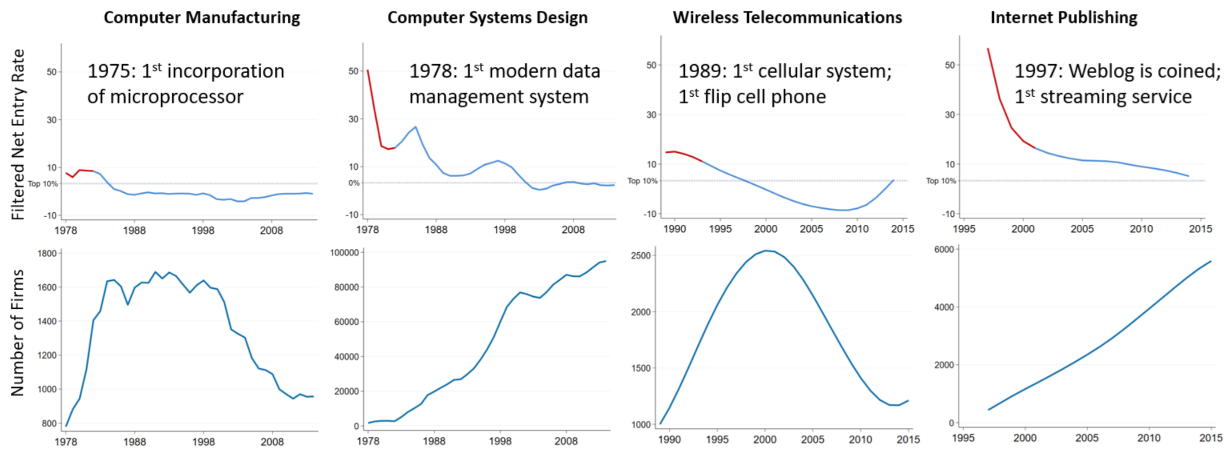

Figure 2. The unit of observations are 4-digit (using public BDS tabulations) and 6-digit industries. Figure shows the time path of the filtered net entry rate for four breakthrough industries: NAICS 3341 (Computer and Peripheral Equipment Manufacturing) from 1978-2015, NAICS 5415 (Computer Systems Design and Related Services) from 1978-2015 (disclosure of 6-digit industry TBD), NAICS 517312 (Wireless Telecommunications, Except Satellite) from 1989-2015, and NAICS 519130 (Internet Publishing and Broadcasting) from 1997-2015.

In Wireless Telecommunications, 1989 marked the first cellular system, Qualcomm's CDMA, and the first flip phone, Motorola's MicroTAC. In Internet Publishing, 1997 marked the launch of Weblogs and RealPlayer, the first online media sharing content and streaming platform, respectively.[3] The bottom row shows that while Computer Manufacturing and Wireless Telecommunications experienced shakeouts, Computer Systems Design and Internet Publishing did not. Appendix X provides a full list of breakthrough industries, their emergence years, and corresponding innovations.

Figure 3 illustrates four less salient innovation breakthroughs coinciding with the selected industry-year pairs. The top row shows the time path of the filtered net entry rate and the bottom row shows the corresponding number of firms. In Credit Intermediation, firms such as Ameriquest, Discover Financial Services, MBNA, and The Blackstone Group entered following the release of the first US debit card. In Waste Management Services, the first large-scale recycling facility for commingled materials (MRF) began operation in 1993. In Snack Foods, twin-screw extrusion technology enabled the production of snacks with distinct textures, shapes, and flavors that older methods could not achieve, leading to the emergence of modern snacks like Doritos, Cheetos, and Ritz Crackers. In Mobile Food Services, social media platforms like Twitter, Facebook, and Instagram served as a breakthrough in how

[3]Notable entrants in the following five years included Metacafe (precursor of Youtube), Napster, and SixDegrees.com (precursor of Myspace).

the industry operated and attracted customers: broadcasting their locations, menus, and schedules in real-time; and attracting a larger customer base through promotion of foodie culture.

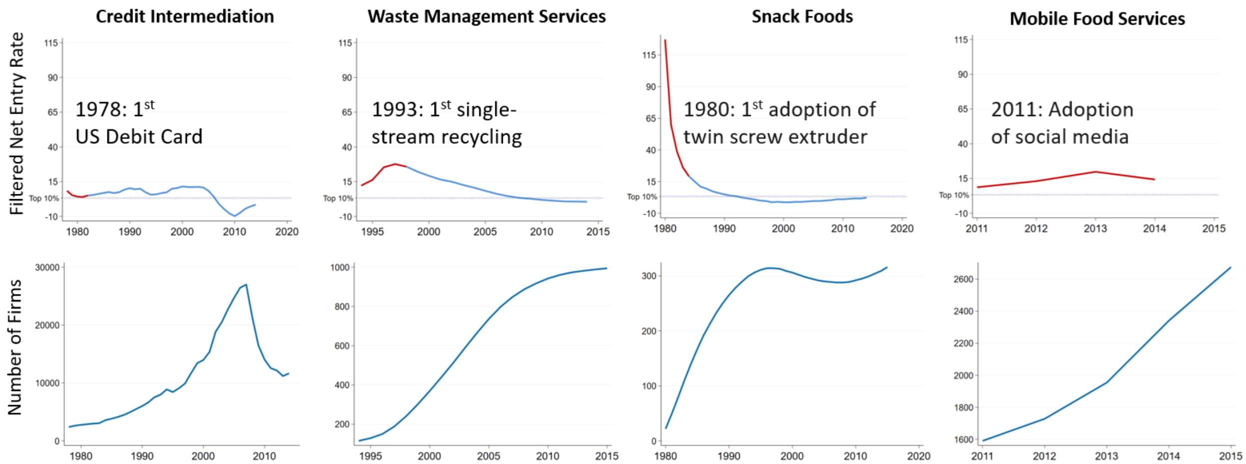

Figure 3. The unit of observations are 4-digit (using public BDS tabulations) and 6-digit industries. Figure shows three selected breakthrough industries: NAICS 5223 (Activities Related to Credit Intermediation) from 1978-2015 (disclosure TBD), NAICS 562998 (All Other Miscellaneous Waste Management Services) from 1994-2015, NAICS 311919 (Other Snack Food Manufacturing, Except Roasted Nuts and Peanut Butter) from 1980-2015, and NAICS 722330 (Mobile Food Services) from 2011-2015.

The main results in Section III are based on a 5% threshold to minimize Type I errors (the results are robust to a 10% threshold as well). Using the 5% threshold over a 5-year period, the procedure selects, on average, 0.5% (standard deviation 0.52) of the 1,012 industries in the sample each year. In total, 172 industries were selected between 1978 and 2014, with 191 potential breakthroughs detected, as some industries experienced multiple breakthroughs. Figure 4 displays the percentage of industries classified as having undergone a potential breakthrough in each year.

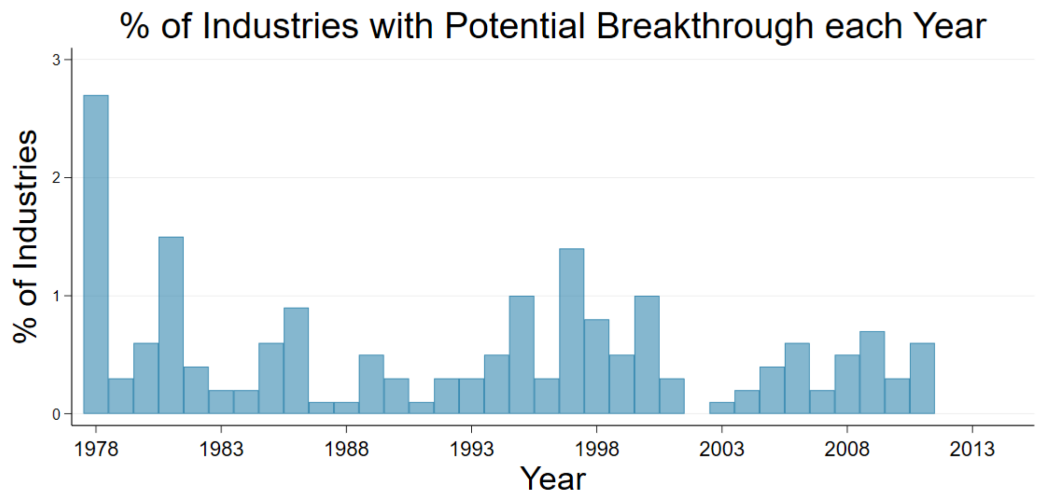

Figure 4. The unit of observation is a 6-digit industry (172 industries and 191 breakthroughs are selected out of 1012 industries). Figure shows the percentage of industries classified as a breakthrough industry each year, based on industries from the Longitudinal Business Database (LBD). Note that given that the data spans from 1978 to 2019 and the procedure employs five-year periods, the breakthough industry selection years range from 1978 to 2014. See text for details on how I classify an industry as a breakthrough industry and how I detect the year of the breakthrough.

2.4 New fact: Entry-driven breakthroughs have been decreasing

The breakthrough detection strategy reveals a new fact: entry-driven breakthroughs have been decreasing in the US over the past forty years. As Figure 4 illustrates, the number of industries selected for potential breakthroughs has declined over time, as shown by the decreasing height of the bars. This decline is linked to a decrease in the variance of net entry rates across industries. The detection strategy identifies an industry as a breakthrough if it exhibits outlier behavior in net entry rates for a sustained period, specifically if it falls within the right tail of the distribution.

In Figure 5, the left panel shows that the standard deviation of industry-level raw net entry rates has declined significantly—from approximately 6% in 1978 to around 2% in 2010. The horizontal line indicates that the top 10% threshold in 1978 would have been just one standard deviation. The right panel compares the distribution of filtered net entry rates in 1978 and 2010. In 1978, the right tail extends well beyond the 10% threshold, while in 2010, the tail is much shorter. While the decline in entry levels has been documented in prior work (Akcigit and Ates, 2021; Decker, Haltiwanger, Jarmin, Miranda, 2016), the decrease in variance has not been previously reported.

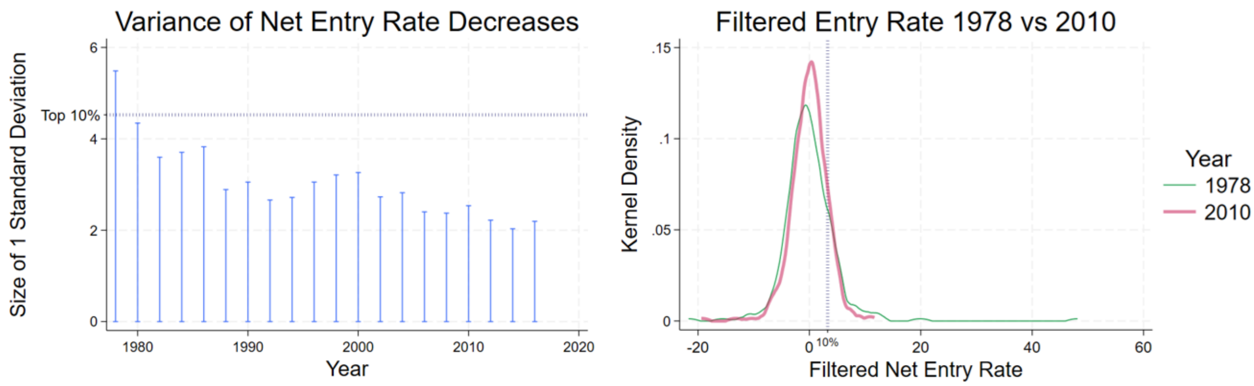

Figure 5. The unit of observation is a 4-digit industry (using public BDS tabulations) (N =288). The left panel shows the industry-level raw net entry rates and the right panel shows the filtered net entry rate. The figure illustrates the decline in the variance of the net entry rate using public Business Dynamic Statistics data.

3 Empirical Findings about Breakthrough Industries and Shakeouts

This section contains the main results of the paper. I present five novel stylized facts about shakeouts and industry dynamics after an innovation breakthrough. Facts 1 and 2 show that while there is considerable heterogeneity in the time path of the number of firms, most of the breakthrough industries do not shake out. Facts 3 to 5 show the impact of the breakthroughs on the aggregate economy and the breakthrough industries: labor in the economy re-allocates towards the breakthrough industries; labor in the breakthrough industries re-allocates towards the firms that entered after the breakthrough (in contrast to the non-breakthrough industries), and firms that entered after the breakthrough drive the shakeouts, rather than the firms that entered before.

3.1 Fact 1: Breakthrough industries display enormous shakeout heterogeneity

Some industries exhibit the classic textbook shakeout. However, others defy this pattern, showing a monotonic increase in the number of firms following a breakthrough. Many industries fall somewhere in between, displaying dynamics that blend elements of both shakeout and sustained firm growth.

I examine the path of the number of active firms for the selected breakthrough industries. By definition, the number of firms will rise for the first five years. After that, the number of firms can either continue to increase, stall, or decline. However, depending on the breakthrough date, the observation period for each industry varies. Therefore, I group the selected industries based on the length of the observation period into five-year panels.

However, the raw levels of active firms is highly heterogeneous across different industries. Some industries contain many firms on average, while others have relatively few. To compare the path of firms across industries, I normalize the annual number of active firms in each industry to a scale between 0 and 1. Specifically, I define the normalized number of firms in industry i in year t as

$$\text{Normalized Firms}_{it} = \frac{\text{Firms}_{it} - \text{Min Firms}_i}{\text{Max Firms}_i - \text{Min Firms}_i}$$

In the equation above, Min Firms_i is the minimum number of firms observed after the breakthrough (but before the next breakthrough) in industry i. Similarly, Max Firms_i is the maximum number of firms observed after the breakthrough. The intuition of the normalization is that the numerator serves as the offset factor, ensuring the minimum is 0, and the denominator serves as the normalization factor, ensuring the maximum is 1.

The left panel of Figure 6 shows the normalized number of firms averaged across seven panels of breakthrough industries. The legend highlights panels observed for 15-20 years, 25-30 years, and 40-42 years. Define the industry-level variable age to be the number of years after the breakthrough. A black vertical line at age 5 indicates that, by definition, the industries have high net entry rates up to age 5, making the increase in the number of firms up to age 5 mechanical. After age 5, the normalized number of firms, on average, exhibits a small decline or minor shake out. Appendix X shows the normalized number of firms split by major sector, which on average do not shake out, with the exception of manufacturing, which does on average shake out, consistent with the literature.

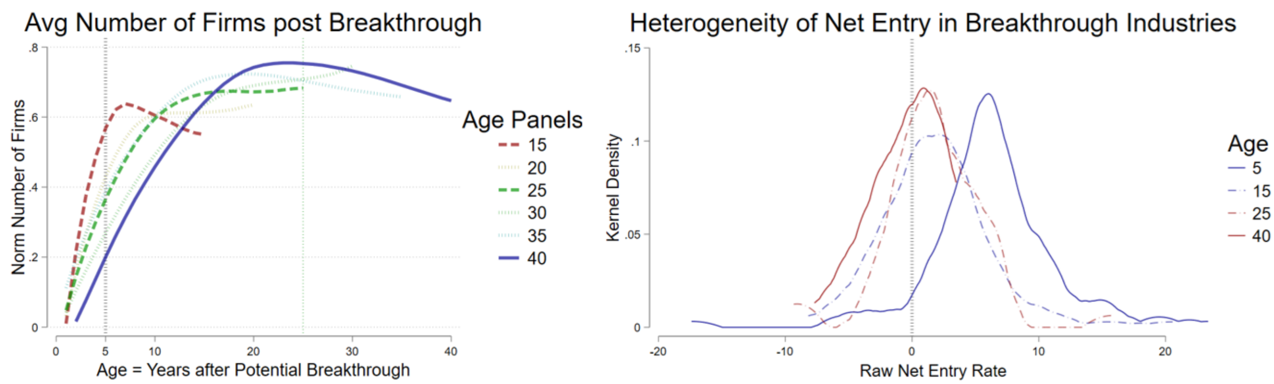

Figure 6. In the panel on the left, the unit of observation is a 6-digit industry (191 industries). The figure displays the smoothed, normalized number of firms, applied to facilitate compliance with Census data disclosure requirements (see Appendix X for the non-smoothed public data version). In the panel on the right, the unit of observation is a 4-digit industry (using public BDS tabulations). The x-axis represents the raw net entry rate – specifically, the net entry rate observed directly from the data, before any adjustments from my statistical procedure. Each point corresponds to an industry's raw net entry rate at one of four specific ages: 5, 15, 25, or 40. Future versions of the draft will display 6-digit Census industries to be consistent with the left panel.

While we know that, on average, industries exhibit small shakeouts, the average masks significant heterogeneity. The right panel in Figure 6 shows the distribution of the net entry rate (smoothed, with time fixed effects removed) of the selected industries at ages 5, 15, 25, and 40. Each point represents the net entry rate of an industry at a certain age. The net entry rate at age 5 is mechanically high, but the level varies widely across industries. As the industries move up in age, the distribution of net entry rates shifts to the left. By age 40, the distribution of net entry rates is strictly to the left of the distribution at age 5, but only the left tail of the distribution crosses the 0% threshold, which is necessary for the number of firms to decline.

3.2 Fact 2: Most of the breakthrough industries do not shake out

I show next that in approximately four-fifths of the breakthrough industries, the number of firms does not experience a significant decline within forty years of the breakthrough. Fact 1 showed considerable heterogeneity in the path of the number of firms across industries: some industries exhibit no shakeouts while others experience varying degrees of firm exits. To quantify the prevalence and intensity of shakeouts, I construct a Shakeout Index, which scores each industry on a continuum based on the degree to which its path of firm numbers resembles the classic shakeout pattern.

The Shakeout Index is centered on the percentage decline in the number of firms between the industry's peak (global maximum) and the lowest point observed after the peak (local minimum), where both extremes occur after the breakthrough and before any subsequent breakthrough in the same industry. Denoted as $\%\ \text{Decline}_i$ in equation 1, this measure captures the core intensity of firm exits. To provide additional differentiation among industries with similar percent declines, the index adjusts for decline duration ($\text{Decline Duration}_i$) and cumulative entry rate ($\text{Cumulative Entry Rate}_i$). The $\text{Decline Duration}_i$ captures the speed of the decline, distinguishing industries that decline faster (thus scoring higher on the index) from those that decline more gradually. The $\text{Cumulative Entry Rate}_i$ is particularly useful for distinguishing industries without shakeouts: it measures the total firm entry as a proportion of the initial firm count, lowering the index score in cases where persistent entry offsets decline. Together, these adjustments enable the index to reflect variations in shakeout intensity more accurately.

The Shakeout Index for each industry i is calculated as follows:

$$\text{Shakeout Index}_i = \frac{1}{\text{Cumulative Entry Rate}_i} \cdot \frac{\%\ \text{Decline}_i}{\text{Decline Duration}_i} \tag{1}$$

where each component is adjusted based on industry-specific benchmarks to ensure the Shakeout Index falls within the interval (0,1). See Appendix X for the mathematical formalization of the Index.

Figure 7 plots the normalized number of firms, as defined in Fact 1, averaged within each quintile of the Shakeout Index at age t (years after the breakthrough). The Shakeout Index effectively captures the trajectory of firm numbers: industries in Quintile 5 exhibit the steepest declines; while moving down the quintiles, the final point on the normalized firm count rises along the y-axis, indicating progressively smaller declines. A pronounced shakeout, consistent with the conventional view, is evident only in Quintile 5, the top quintile of the Index. Quintile 4 exhibits a smaller decline in the number of firms after about 20 years, closely resembling the average path presented in Fact 1. Quintiles 2 and 3 show a leveling-off in firm growth after 10–20 years but no shakeout, whereas Quintile 1 maintains a steady expansion in the number of firms.

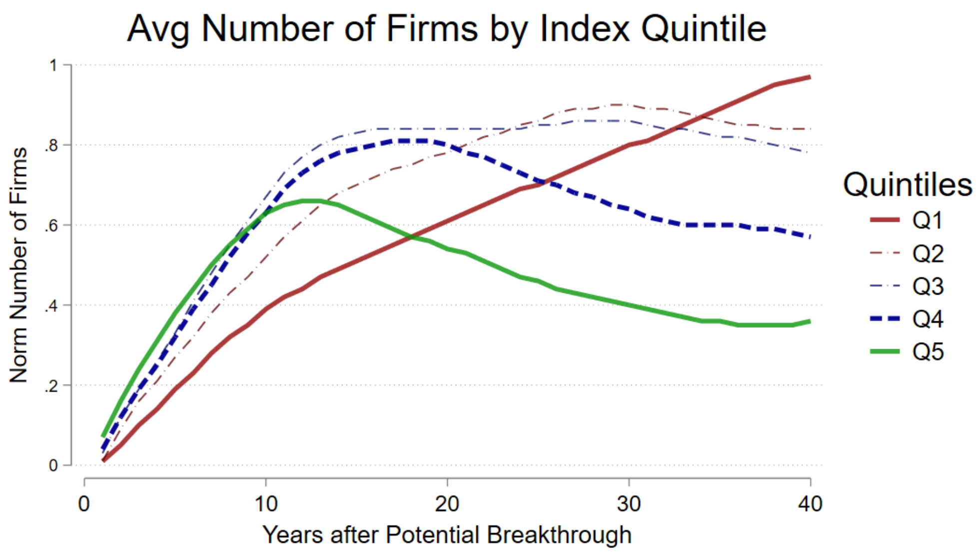

Figure 7. The unit of observation is a 6-digit industry ($N = 191$). The figure displays the smoothed, normalized number of firms, applied to facilitate compliance with Census data disclosure requirements (see Appendix X for the non-smoothed public data version). The plot shows the normalized number of firms, averaged across five panels of breakthrough industries based on their score on the Shakeout Index.

3.3 Fact 3: Labor reallocates toward breakthrough industries

Building on Facts 1 and 2, which documented the prevalence and heterogeneity of shakeouts among breakthrough industries, Fact 3 examines the broader economic impact of these breakthroughs on reallocation across the economy. This analysis, based on employment data from the Longitudinal Business Database (LBD), reveals that breakthrough industries absorb a growing share of the labor force over time, underscoring the persistent influence of breakthroughs. In contrast, non-breakthrough industries lose their share of the labor force over time. The distinct trajectories of breakthrough versus non-breakthrough industries supports the reliability of the statistical detection procedure.

For any year t, define the employment share EmpShare_{it} of industry i as a proportion of total national employment TotEmp_t:

$$\text{EmpShare}_{it} = \text{Emp}_{it}/\text{TotEmp}_t \tag{2}$$

where Emp_{it} is the employment in industry i in year t.

To ensure comparability across industries with varying observation periods, I group industries into observation panels based on age intervals (e.g., 10-15, 15-20 years post-breakthrough). I then aggregate the employment shares by industry age (the difference between the current year and the breakthrough year) within each panel to obtain the total employment share for each group. Figure 8 shows that, across all panels, breakthrough industries steadily absorb a growing share of the economy's labor force over time, signaling a consistent reallocation of resources towards these industries.

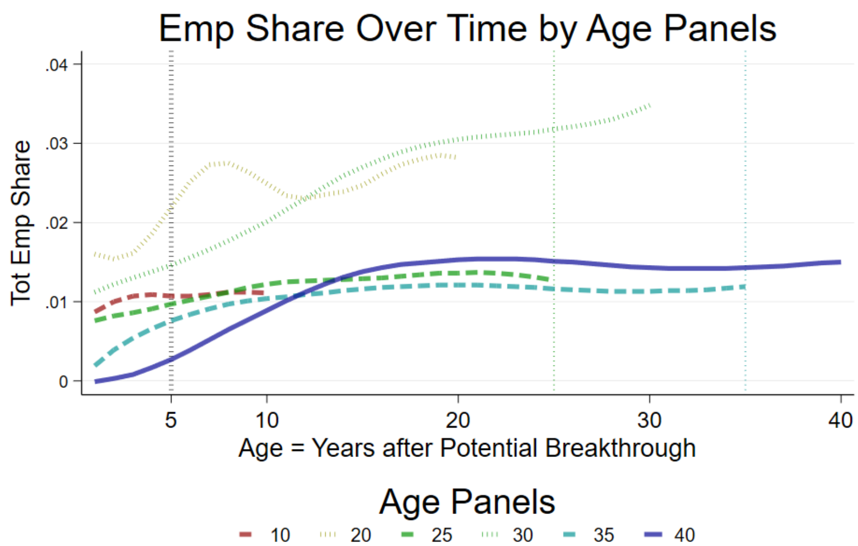

Figure 8. The unit of observation is a 6-digit industry ($N = 191$) across the 1978-2019 observation window. The figure displays the smoothed, normalized number of firms to meet Census data disclosure requirements (see Appendix X for non-smoothed version). The plot shows industry employment as a share of total national employment, averaged by age across seven panels of breakthrough industries.

The employment trajectory following a breakthrough functions similarly to an impulse response with a lasting, non-transitory effect. If the breakthrough impact were temporary, we would expect the employment share of these industries to either stabilize or revert to pre-breakthrough levels over time. Instead, the continued growth in employment share underscores the persistent nature of the shock.

In contrast, non-breakthrough industries experience a declining share of the economy's labor force, indicating a gradual reallocation of resources away from them (see Appendix X). This result is immediate, as breakthrough and non-breakthrough industries are mutually exclusive subsets of the economy, and the labor absorbed by breakthrough industries thus reflects a corresponding reduction in labor share for non-breakthrough industries.

3.4 Fact 4: Labor in breakthrough industries reallocates toward entrants

In Fact 3, I demonstrated that breakthrough industries absorb a growing share of labor in the broader economy, emphasizing the large-scale, long-term economic importance of these industries. Building on that foundation, Fact 4 investigates within these breakthrough industries, showing that labor re-allocates from pre-existing (or "incumbent") firms towards new entrants – those firms established after the breakthrough event. This dynamic provides critical insight into the internal shifts that accompany a breakthrough: the industry is transformed as entrants outcompete the incumbent firms for labor.

Within a breakthrough industry, entrants are defined as those that entered after the breakthrough date, while incumbents are defined as those that entered before. In cases of multiple breakthroughs, firms entering after an earlier breakthrough but before a subsequent one are considered entrants for the earlier breakthrough's observation period and incumbents for the later one. Recall that a firm is regarded as active in a NAICS 6-digit industry if it operates at least one establishment within that industry; this distinction allows a firm to be active in the US economy before "entering" as a new entrant within a specific industry.

I group industries by five-year observation panels to consistently compare them across observation periods, similarly to the process in Fact 3. This grouping controls for differing observation lengths, as potential breakthroughs span the period from 1978 to 2014. Within each panel g, I calculate the employment share of entrants as follows:

$$\text{EmpShare}_{egt} = \text{EmpTot}_{egt}/\text{TotEmp}_{gt} \tag{3}$$

where Emp_{egt} represents total employment among entrants e within panel g at age t, and TotEmp_{gt} is the total employment within the same panel and year.

The left panel of Figure 9 shows that in breakthrough industries, entrants capture an increasing share of industry employment over time. The employment share of entrants starts at zero at the breakthrough date (age 0) but rises steadily: by age 5, entrants account for approximately 60% of total industry employment, by age 20 they capture around 85%, and by age 40, their share exceeds 90%. This trend underscores the entrants' growing dominance over incumbents within the industry, as they increasingly attract labor resources over time, a phenomenon not observed in non-breakthrough industries.

As a comparison, I create a control group using non-breakthrough industries, for which I classify firms that entered after 1980 as "entrants" and those active before 1980 as "incumbents." The left panel of Figure 9 also shows that, while the employment share of entrants in non-breakthrough industries increases over time, it remains much smaller, rising to 30% by 1985, 55% by 2000, and 70% by 2019. This discrepancy underscores the distinctive impact of breakthroughs on labor reallocation. The "Non" line in the plot illustrates that non-breakthrough industries do not see the same level of entrant dominance as breakthrough industries.

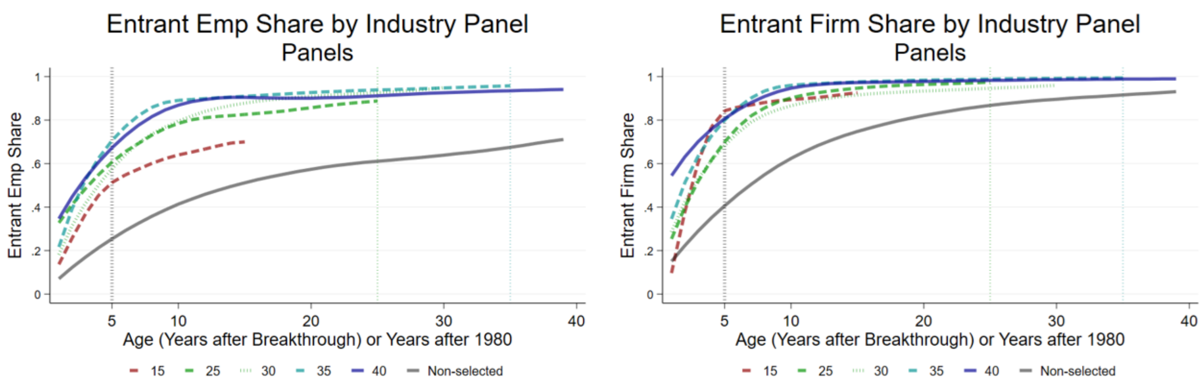

Figure 9. The unit of observation is a 6-digit industry ($N = 191$). The figure displays the smoothed, normalized number of firms, applied to facilitate compliance with Census data disclosure requirements. Figure shows the growth in employment share of entrants within breakthrough industries over time. The employment share of entrants is displayed as a percentage of total industry employment, averaged across seven panels of breakthrough industries grouped by observation length (in 5-year intervals).

Notably, this effect cannot solely be attributed to the entry explosion typical of breakthrough industries. The right panel of Figure 9 shows that the proportion of firms that are entrants, or the "entrant firm share," converges to around 90% in both breakthrough and non-breakthrough industries, indicating similar churn patterns. However, the gap in employment share remains significantly larger for breakthrough industries, suggesting that entrant firms in these industries outcompete incumbents on the intensive margin, drawing substantially more labor resources. This focus on entrants in breakthrough industries highlights the persistence of breakthrough impacts and provides insights into the mechanisms by which these industries evolve, justifying the procedure's focus on breakthrough industries for understanding long-term industry dynamics.

3.5 Fact 5: Inter-industry shakeout differences are driven by entrants

Industry dynamics after an innovation breakthrough are driven entirely by the entry and success of new firms that enter after the breakthrough, referred to as "entrants." These post-breakthrough entrants determine both the prevalence and magnitude of shakeouts in breakthrough industries. In contrast, incumbents – those firms that were active before the breakthrough – do not influence these industry dynamics. The nature of the shakeout is uncorrelated with incumbent exits, as incumbents exhibit similar survival rates regardless of whether the industry undergoes a shakeout.

As documented in Facts 1 and 2, the Shakeout Index measures how closely each industry's firm trajectory aligns with a typical shakeout pattern. One might expect that incumbent survival rates would vary by shakeout index quintile—perhaps higher in low-shakeout industries (Q1) than in those with substantial shakeouts (Q5). However, the data reveals no such correlation: incumbents decline at comparable rates across all quintiles, suggesting that post-breakthrough industry structure hinges on entrants' performance rather than incumbent persistence.

Figure 10 demonstrates this distinction. The left panel shows that entrant dynamics closely align with the Shakeout Index: industries in the top quintile (Q5) experience marked declines in entrants, reflecting a classic shakeout, while lower quintiles (Q1, Q2, Q3) exhibit stable or rising entrant numbers, indicating minimal to no shakeout. In fact, the left panel closely resembles the breakdown shown in Fact 2 Figure 7. In contrast, incumbent survival rates remain largely independent of shakeout magnitude. The right panel demonstrates that both high and low shakeout quintiles (Q1 and Q5) display comparable survival rates for incumbents, with approximately 20% surviving after twenty years and just over 10% after forty years. The middle quintiles (Q2, Q3, Q4) show similar declines, underscoring that incumbent exit rates do not correlate with shakeout intensity.[4]

[4] While the normalized number of incumbent firms theoretically starts at 1, they sometimes start slightly lower due to firm reorganizations within the Longitudinal Business Database (LBD). When an active firm splits into multiple entities, the newly formed entities typically receive new identifiers (Jarmin and Miranda, 2002). However, existing establishments maintain their original entry year, showing continuity before the breakthrough date.

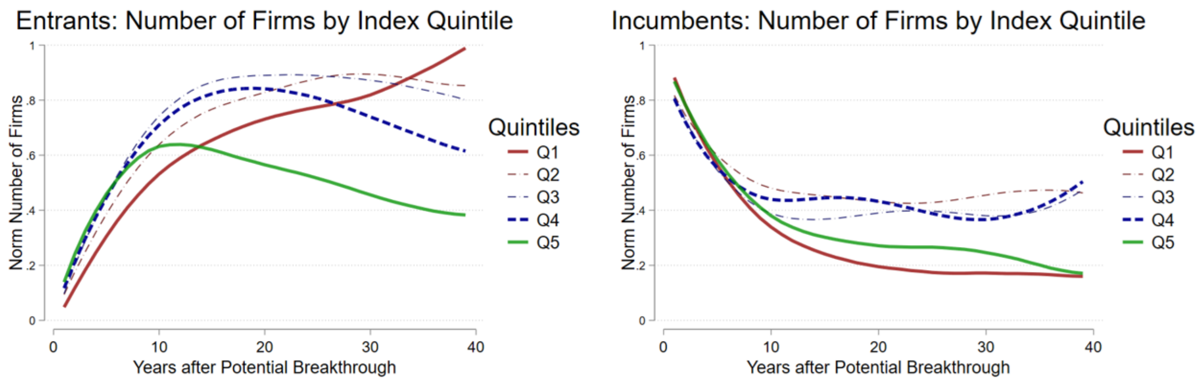

Figure 10. The unit of observation is a 6-digit industry ($N = 191$). The figure displays the smoothed, normalized number of firms, applied to facilitate compliance with Census data disclosure requirements. The left panel displays the normalized number of entrant firms (those that entered after the breakthrough date); the right panel displays the normalized number of incumbent firms (those that entered before the breakthrough date). Each quintile is based on the Shakeout Index score, ranging from the bottom quintile (Q1) to the top quintile (Q5).

Facts 4 and 5 together illustrate the critical role of new entrants in determining the impact of breakthroughs on industry structure, strengthening the broader narrative on how technological shocks redefine industry landscapes.

4 Reliability of the Breakthrough Detection Procedure

The breakthrough detection procedure is reliable at selecting breakthroughs: that is, at selecting industry-wide shocks that align with the properties of salient innovation breakthroughs. The procedure is validated through historical evidence, robustness checks, and counterfactual tests, which demonstrate that the selected industries should indeed be understood as having undergone an innovation breakthrough. While there may be marginal Type I errors (incorrectly selecting non-breakthrough industries) or Type II errors (failing to select true breakthrough industries), this section shows that the errors are minimal and do not affect the key finding about the prevalence of shakeouts among breakthrough industries.

4.1 Validation with Existing Literature

The breakthrough industries detected by my procedure aligns with those selected by other prominent methods, such as Kalyani, Bloom, Lerner, Melo, Tahoun (2024) (henceforth referred to as KBLMT) and Kelly, Papanikolaou, Seru, Taddy (2021) (henceforth referred to as KPST). Appendix X provides a detailed comparison of the commonly selected industries.

While more of the industries selected by KBLMT display shakeouts, many do not. The left panel of Figure 11 shows the distribution of industries selected by KBLMT split by Shakeout Index quintile, with the quintile relative to the scores in their sample. The figure implies that one-fifth of those industries do not experience shakeouts. While this share of shakeout-avoidant industries is smaller than in my sample of breakthrough industries, this result emphasizes that there exists KBLMT industries that do not experience shakeouts. Notably, some of these industries do not exhibit the post-breakthrough firm explosion typical of entry-driven breakthroughs, particularly in quintiles Q4 and Q5 (compared to Fact 2 Figure 7). Despite the differences in selection criteria, when I restrict the sample to commonly selected industries by KBLMT and my procedure, around half of the industries do not experience shakeouts, as evidenced by the right panel of Figure 11. Further drafts of this paper will incorporate robustness checks with KPST (2021).

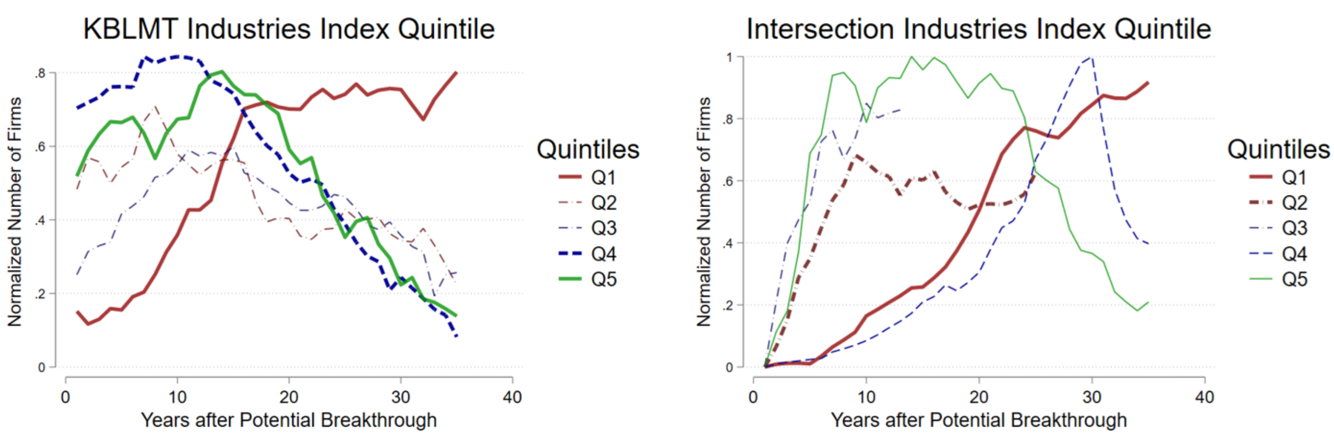

Figure 11. Unit of observation is a 4-digit industry (using public BDS tabulations), which is the level of aggregation of the data in KBLMT (2024). The left panel ($N = 51$) shows the path of the normalized number of firms in KBLMT's selected industries, split by the industries' score on the Shakeout Index, where the quintiles are relative to KBLMT's sample (not my sample). The right panel ($N = 15$) shows the commonly selected industries between KBLMT and this paper, split by the industries' score on the Shakeout Index, where the quintiles are relative to the sample of commonly selected industries.

The key distinction that drives the selection and shakeout differences in Figure 11 above is sector representation. The left panel of Figure 12 shows that KBLMT's sample is concentrated in manufacturing, with over 70% of selected industries coming from this sector, while my method selects a broader range of industries, including those in health, education, and finance. In contrast, fewer than 10% of the industries I select are from manufacturing. Importantly, even though KBLMT focuses on manufacturing sectors, their selected industries exhibit fewer shakeouts on average compared to mine, regardless of the sector, as the right panel of Figure 12 shows. This suggests that their results are being influenced by the sectors they focus on, particularly manufacturing.

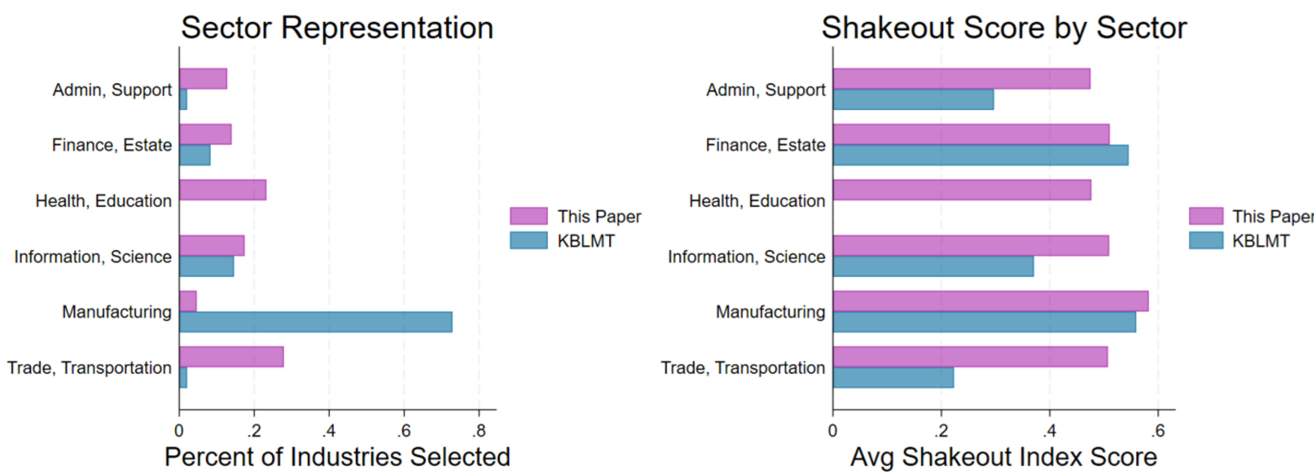

Figure 12. Unit of observation is a 4-digit industry (using public BDS tabulations), which is the level of aggregation of the data in KBLMT (2024). The left panel shows the distribution of major sectors among the industries selected via the statistical procedure in this paper ($N = 97$) at the 10% threshold versus the anecdotal method in KBLMT ($N = 51$). The right panel shows the average shakeout score of the major sectors among the industries selected.

To further explore sectoral representation, I compute the sector-weighted shakeout score for the industries selected by both KBLMT and my approach, followed by two counterfactual shakeout scores. Let Freq_s represent the proportion of selected industries in sector s. The sector-weighted shakeout score is then the weighted average of each sector's mean shakeout score, where weights correspond to Freq_s:

$$\text{Sector-weighted Score} = \sum_s \text{Shakeout Score}_s * \text{Freq}_s \tag{4}$$

Using my method, the sector-weighted shakeout score is 0.50, while the KBLMT approach yields a slightly higher score of 0.52, indicating that, on average, the industries selected by

KBLMT experience more shakeouts.

Next, I compute two counterfactuals. In the first, I apply the sector frequencies generated by my selection procedure to the sector-specific shakeout scores from KBLMT's selected industries. This allows for a direct comparison of the impact that sector composition has on the overall shakeout results:

$$\text{Counterfactual Sector-weighted Score} = \sum_s \text{Shakeout Score}_s^{\text{KBLMT}} * \text{Freq}_s^{\text{Li}} \tag{5}$$

This calculation yields a counterfactual score of 0.27, significantly lower than the 0.50 score from my method, which suggests that if KBLMT had the broader sectoral representation in my selection, their industries would experience far fewer shakeouts. Conversely, when I apply KBLMT's sector frequencies to the sector-specific shakeout scores from my selected industries, the sector-weighted score rises to 0.56, implying that my sample would exhibit more shakeouts if it were more concentrated in manufacturing, as in KBLMT's selection. This counterfactual indicates that the differences in shakeout outcomes between the two methods are largely driven by sectoral composition. The sector differences underscore the broader applicability of my breakthrough detection procedure, which captures industries beyond manufacturing and thus offers a more comprehensive picture of industry dynamics after a technological breakthrough.

4.2 Robustness Checks

I test the robustness of the breakthrough selection procedure by varying several parameters, including net entry rate smoothing, observation start years, selection thresholds, and industry scope. In all cases, the main result remains unchanged: most breakthrough industries do not experience shakeouts. First, the result is robust to different smoothing windows. While the main analysis smooths over five years, the result holds for no smoothing and windows of 2-3 years. Second, I vary the observation window, starting from different years (1979, 1980, 1990, and 2000), and the result remains consistent. Third, the result remains robust when adjusting the selection threshold between 5% and 10%, as well as when redefining the threshold relative to the annual cross-section instead of the entire 40-year period (see Appendix X).

To further test the robustness of my findings, I examine two specific subsamples: industries assigned new NAICS codes and those with post-breakthrough price declines. First, Census officials assign new NAICS codes to signal the emergence of a new or distinctly different product market, which could be attributed to a technological breakthrough. However, even when restricting my selected industries to those that have been assigned new NAICS codes, most do not experience shakeouts (see Appendix X). To assess whether demand-driven shifts influence the occurrence of shakeouts following breakthroughs, I conduct a robustness check using price trends, as prior literature suggests that price declines often accompany breakthroughs due to productivity improvements. If demand shifts were the main factor preventing shakeouts, then restricting the sample to industries with post-breakthrough price declines should yield much more shakeouts, as these industries would be less affected by demand. However, even within this subset, around half of the industries do not exhibit shakeouts, suggesting that demand shifts alone do not explain the observed variation in shakeout patterns. Furthermore, the nearly identical average shakeout scores between breakthrough industries with and without price declines reinforces the conclusion that factors beyond demand shocks contribute to shakeout outcomes.

I conduct several experiments to illustrate what the null outcome would look like if the breakthrough detection strategy were systematically flawed. A faulty strategy would incorrectly classify industries as breakthroughs even if their patterns were indistinguishable from those of the broader economy and did not resemble the distinct growth patterns seen in salient breakthrough industries. In the first experiment, I randomly select industry-year pairs, using the same number of selected industries as in the original procedure. Specifically, I generate random numbers, set a seed for reproducibility, and sort by these random values to ensure an unbiased selection process. The left panel of Figure 13 shows that these randomly selected industries exhibit stable employment shares as a proportion of the total economy, in contrast to the sustained growth pattern seen in Figure 8.[5]

In the second experiment, I focus on industries known for experiencing substantial idiosyncratic demand shocks: Residential Building Construction, Petroleum and Coal Products Manufacturing, and Gasoline Stations. These shocks stemmed from post-war demographic shifts, such as the baby boom and increased immigration in the construction sector, and from

[5]To generate the random industry-year sample, I used Stata's rnormal() function to assign each observation a random value and sorted them in ascending order. Setting the seed (set seed 12345) ensures reproducibility by fixing the order of random values generated, which allows the selection process to be replicated exactly. Industry-year pairs were then chosen to match the number used in the breakthrough detection sample.

the 1979 oil crisis in the latter two. Crucially, none of the variations of my breakthrough detection procedure selected these industries, supporting the robustness of the approach. As shown in the right panel of Figure 13, these industries exhibit declining or stable employment shares over time, regardless of the observation period, contrasting with the sustained employment growth in the breakthrough industries seen in Figure 8.

To reinforce this point, the bottom row of Figure 13 compares employment shares for both salient and non-salient breakthrough industries selected by my procedure. Each panel includes examples of industries known for 'shakeout' behavior (e.g., Software Publishers, Credit Intermediation) as well as non-shakeout industries (e.g., Computer Systems Design, Waste Collection). Vertical lines mark the timing of breakthroughs for certain industries, with a 1978 breakthrough implied for industries lacking a marked date. The patterns observed in non-salient breakthroughs align closely with those in salient breakthrough industries, reinforcing the accuracy of my procedure, while contrasting sharply with demand shock and random industries.

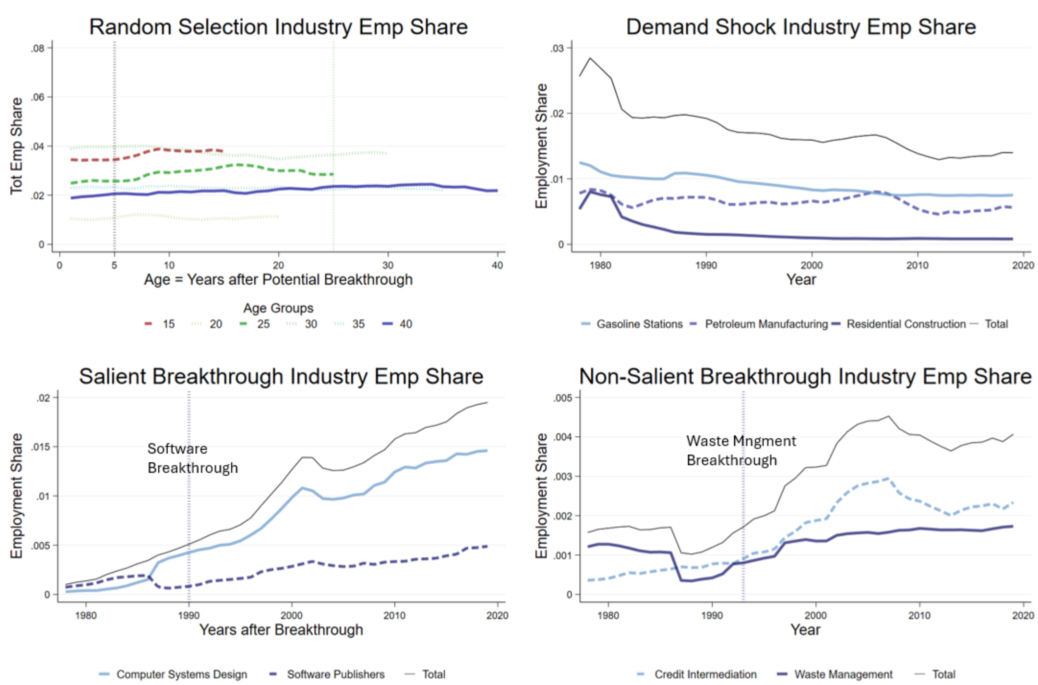

Figure 13. The unit of observation is a 4-digit industry (6-digit industry with Census data TBD). The top left panel shows employment share among a random selection of 97 industries, which is the number of industries selected by my procedure at the 10% threshold. The y-axis is scaled to match Figure 8. The top right panel shows the employment share of Residential Building Construction (NAICS 2361), Petroleum and Coal Products Manufacturing (NAICS 3241), and Gasoline Stations (NAICS 4471). The bottom left panel shows Computer Systems Design and Related Services (NAICS 5415) and Software Publishers (NAICS 5112). The bottom right panel shows Credit Intermediation (NAICS 5223) and Waste Collection (NAICS 5621).

In future drafts, I will extend this analysis to entrants and incumbents within these industries, as well as use the six-digit NAICS industries within the LBD to address potential aggregation issues.

Finally, in Appendix X I display the long-run behaviour of the subsample of industries selected by KBLMT (KPST to be included in a future draft) that are inconsistent with the set of industries selected by this paper. The industries that are inconsistent with the ones selected by my procedure display long-run employment behaviour indistinguishable from the rest of the economy, contrary to salient breakthrough industries.

5 A Qualitative Model to Explain Shakeout Differences

My aim in this section is to propose a simple theory of industry dynamics that explains why some industries experience shakeouts after a breakthrough, while others do not. The model must not only align with the breakthrough anecdotes but also be consistent with the empirical facts in the previous section. To do so, I need to propose a framework where the number of firms is an equilibrium outcome, and the industry response to a breakthrough can be either non-monotonic (with an initial rise in firm numbers followed by a decline) or monotonic (with firm numbers consistently increasing). This approach utilizes standard heterogeneous-firm models, while incorporating the possibility of divergent industry behavior depending on key parameters. The primary objective is to use this theory to precisely define what constitutes an innovation breakthrough and to shed light on the underlying drivers of industry shakeouts. In doing so, the model offers an abstract but useful description of the breakthrough anecdotes that resulted in shakeouts versus those that did not.

5.1 Environment

This model examines an industry over three periods: before, during, and after a breakthrough occurs, providing insight into the number of active firms as an equilibrium outcome driven by the industry price level and average productivity.[6] The production function specifies

[6] The model can be extended to a multi-period setting without altering the solution (see Appendix X). The model also provides insight into the timing of shakeouts: due to evidence of large learning-by-doing within 40-years (Irwin and Klenow, 1994), the 40 year observation window used in my empirical strategy should be sufficient to observe shakeouts.

firm output as a function of labor input and firm-specific productivity, with industry-specific returns to scale governed by the parameter α. Consumer demand is derived from a CES preference structure, where the elasticity of substitution σ shapes industry demand based on the price level. Market clearing ensures that industry output equals consumer demand, implying that the number of active firms N_t is determined by the equilibrium price level and the average productivity of firms.

5.1.1 Production

In period t, firm i produces output according to $y_{it} = z_{it} l_{it}^{\alpha}$, where l_{it} denotes labor input and z_{it} represents firm-specific productivity. Firms choose labor l_{it} to maximize profits, taking wages w and the industry price level P_t as given. Labor supply is elastic, resulting in constant wages, which I normalize to 1.[7] The parameter α captures the degree of returns to scale, which differentiates industries: industries like computer manufacturing exhibit large returns to scale, while others, like computer design, exhibit small returns to scale. Each period, incumbent firms incur a fixed overhead cost c. Profit maximization leads to the optimal labor choice as a function of firm-specific productivity: $l_{it} = (\alpha P_t z_{it})^{\frac{1}{1-\alpha}}$.

Firms are heterogeneous in productivity. Let $\mu_t(z)$ denote the distribution of active firms' productivity in period t. The industry's average productivity is defined as:

$$\tilde{z}_t \equiv \left(\int z_t^{\frac{1}{1-\alpha}} \mu_t(z)\, dz \right)^{1-\alpha} \tag{6}$$

5.1.2 Demand

Suppose economy-wide output $\mathcal{Y}$ and price level $\mathcal{P}$ are constant over time. Let σ be the inter-industry elasticity of substitution associated with CES preferences over industries. For

[7] Assuming elastic labor supply is innocuous due to the industry's small size relative to the economy. While the results extend to scenarios with an upward-sloping labor supply curve, this assumption simplifies the analysis, allowing us to focus on supply-side factors like technological change in understanding the industry dynamics.

period t, consumer demand for the industry Y_t given the price P_t is:

$$Y_t = \left(\frac{P_t}{\mathcal{P}}\right)^{-\sigma} \mathcal{Y}, \ \sigma > 1 \tag{7}$$

5.1.3 Market Clearing

Market clearing implies industry supply $Y_t = N_t \int y(z)\, \mu_t(z)\, dz$ equals demand, leading to the conclusion that the number of active firms N_t is an equilibrium outcome of price level P_t and average productivity $\tilde{z}_t$:

$$P_t^{\sigma + \frac{\alpha}{1-\alpha}} = \mathcal{Y}\mathcal{P}^{\sigma} \left(\alpha^{\frac{\alpha}{1-\alpha}} N_t \tilde{z}_t^{\frac{1}{1-\alpha}}\right)^{-1} \tag{8}$$

5.2 The Learning Curve: Old firms are Better than Young firms

Prominent business academics such as Christensen (1997) and Henderson (2005) have observed that incumbents often do not immediately respond to new entrants adopting revolutionary technologies. This reluctance is partly because these new entrants, despite leveraging breakthrough technologies, initially lack the productivity and market share to pose a significant threat to incumbents' dominant positions. Building on this idea, I examine the productivity gap between older and younger firms, which is well-documented in the economics literature as being driven by incremental innovation and learning-by-doing (Klette and Kortum, 2004; Irwin and Klenow, 1994).

This productivity gap between older and younger firms aligns with real-world breakthroughs, such as the microcomputer revolution of the late 1970s. Before the introduction of the Altair 8800 in 1975, the industry was dominated by established mainframe producers who had advanced along the learning curve. New entrants adopting microprocessor technology initially lagged in productivity, but the long-term potential of the breakthrough led to a surge in entry. While these younger firms temporarily lowered average industry productivity, they eventually improved, driving down prices and leading to exits and an industry shakeout.

I start with the standard assumption that there is an infinite pool of potential entrants, each facing a fixed entry cost c_e, which is thereafter sunk. Upon entry, firms operate for up to two periods. In the first period, firms are young and draw their productivity from the distribution f_y. In the second period, firms are old and may achieve higher productivity, based on their productivity draw from the superior distribution $f_o > f_y$ (first order stochastic dominance).[8] Firms exit if their productivity is insufficient at either stage.[9]

Both young and old firms exit at the beginning of the period if their operating values are negative. All old firms exit at the end of the period. The value of continuing operations for young and old firms is, respectively:[10]

$$\text{Young value: } v_{yt}\left(P_t, z\right) = \max \left\{ 0,\ \underbrace{\pi\left(P_t, z\right)}_{\text{young profits}} + \underbrace{\int_z v_{ot+1}\left(P_{t+1}, z\right) f_o\left(z\right) dz}_{\text{exp. old value}} \right\} \tag{9}$$

$$\text{Old value: } v_{ot}\left(P_t, z\right) = \max\left\{0, \pi\left(P_t, z\right)\right\} \tag{10}$$

As in standard heterogeneous-firm models, there exists a productivity threshold z^*_{yt} for young firms and z^*_{ot} for old firms where the value of operations is zero.

Figure 14 summarizes the two stages of firm productivity over time, illustrating the transition from the young to the old stage.

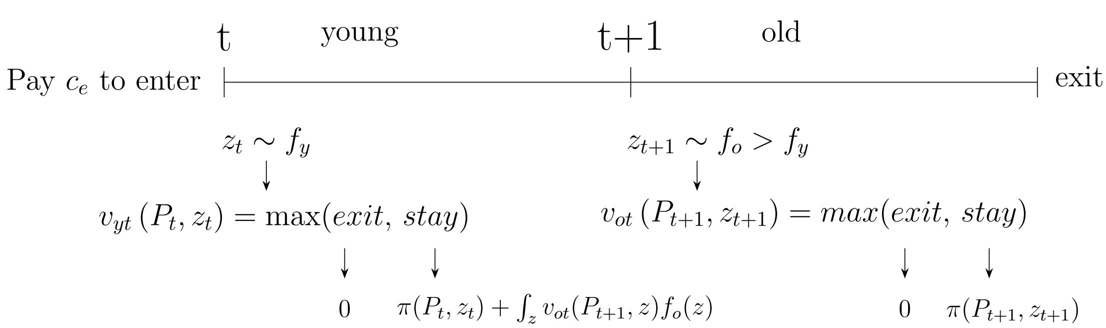

Figure 14. Timeline of firm productivity stages

Entry occurs until the value of entry equals the fixed entry cost, as described by the entry

[8] However, the condition $E(f_o) > E(f_y)$ is sufficient.

[9] We can have a continuous productivity process as in Hopenhayn (1992) without altering the core implications.

[10] A discount factor of 1 and a hazard rate $\delta = 0$ between young and old stages are assumed without loss of generality. The model can extend to a multi-period setting with exogenous hazard rate δ.

indifference condition:

$$\text{Entry value: } v_{et} = \int v_{yt}\left(P_t, z\right) f_{yt}^{\{s,b\}}\left(z\right) = c_e \tag{11}$$

Let N_y and N_o represent the number of young and old firms, respectively. The total number of firms in period t is:

$$N_t = N_{yt} + N_{ot} \tag{12}$$

The industry's average productivity $\tilde{z}_t$ is the weighted average of the young and old firms' average productivities $\tilde{z}_{yt}$ and $\tilde{z}_{ot}$:

$$\tilde{z}_t = \left(\frac{N_{yt}}{N_t}\tilde{z}_{yt}^{\frac{1}{1-\alpha}} + \frac{N_{ot}}{N_t}\tilde{z}_{ot}^{\frac{1}{1-\alpha}}\right)^{1-\alpha} \tag{13}$$

5.3 Definition of a Breakthrough

A breakthrough is defined as a one-time unanticipated shock that enhances the potential productivity of firms entering after the breakthrough, once they age and become older firms. Firms that entered before the breakthrough are unaffected by the shock. This definition parallels the impact of the microcomputer breakthrough, where microprocessor technology benefited younger firms entering after the breakthrough, but these firms only achieved higher productivity as they aged.

Refer to the timeline in Figure 15. Before the breakthrough ($t = -1$), active firms operate with a technology represented by f^s. The breakthrough introduces a new technology f^b such that $f_o^b > f_o^s$ (first order stochastic dominance): that is, for cohorts of firms entering after the breakthrough, the potential productivity in old age is higher. Firms that enter before the breakthrough are not affected.[11] The equilibrium before the breakthrough is characterized by the number of active firms N_{-1}, the price level P_{-1}, and the average productivity $\tilde{z}_{-1}$. During the breakthrough ($t = 0$ reflecting the short-run), active firms consist of old incumbent firms distributed according to f_o^s and young breakthrough entrants distributed according to f_y^b, which imply an equilibrium $N_0, P_0, \tilde{z}_0$. After the breakthrough ($t = 1$ reflecting the long

[11] I assume that the breakthrough only affects firms entering after its occurrence. This assumption simplifies the model without altering its key implications, enabling a more straightforward analytic solution.

run), both old and young firms are distributed according to the breakthrough productivity, with old firms now operating with f_o^b, which is superior to f_o^s.

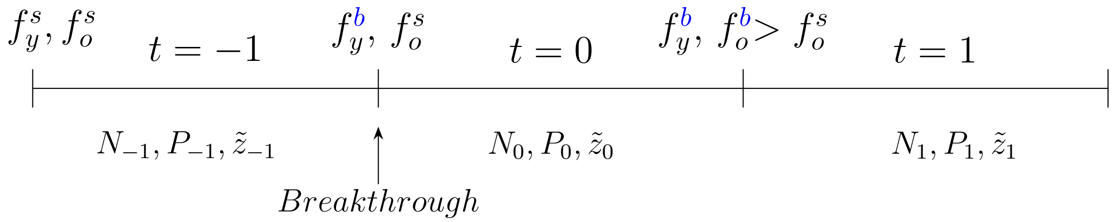

Figure 15. Timeline of industry before, during, and after the breakthrough: illustrating the productivity distributions of young and old firms. f_y^s and f_o^s are the productivity distributions of pre-breakthrough firms, while f_y^b and f_o^b are the productivity distributions of post-breakthrough firms.

To address the dynamic effects of a technological breakthrough without explicitly modeling the full transition path, this paper adopts a repeated static equilibria approach, which simplifies the analysis while preserving key economic insights. Rather than solving for each intermediate period's equilibrium, forward-looking firms internalize the long-run steady-state prices, following similar methods used in Atkeson and Kehoe (1999). By employing a backward induction strategy from the long-run equilibrium, the model captures the essential effects of the breakthrough on firm behavior while maintaining tractability.

5.4 A Simple Analytic Solution for the Dynamics of the Breakthrough

In this section, I first demonstrate the existence of an equilibrium where the industry experiences a shakeout following a technological breakthrough: the number of firms rises and then falls. I show that the size of the shakeout depends on the industry-specific returns to scale and the productivity gap between old and young firms. I then demonstrate the existence of an equilibrium where no shakeout occurs: the number of firms rises, but then does not eventually fall, after a breakthrough shock, due to the absence of an old-young productivity gap.

5.4.1 An Equilibrium where Shakeouts Occur

Suppose that economy-wide output $\mathcal{Y}$ and price level $\mathcal{P}$ remain constant. Assume that, in this setting, the young productivity distributions before and after the breakthrough are identical:

$$f_y^s(z) = f_y^b(z) = \begin{cases} \underline{z} \text{ w.p. } \gamma \\ 0 \text{ w.p. } 1-\gamma \end{cases}$$

In contrast, the breakthrough raises productivity in old age (for cohorts entering after the breakthrough):

$$f_o^s(z) = \begin{cases} \underline{z} \text{ w.p. } \lambda \\ 0 \text{ w.p. } 1-\lambda \end{cases} < f_o^b(z) = \begin{cases} z_h >> \underline{z} \text{ w.p. } \lambda \\ 0 \text{ w.p. } 1-\lambda \end{cases}$$

First, I show that the number of firms rises at the breakthrough, $N_0 > N_{-1}$. To establish this, observe that prices fall post-breakthrough relative to pre-breakthrough levels, specifically $P_1 < P_{-1}$. This is derived by equating the entry values in Periods -1 and 1, as in equation (11):

$$P_1 = \left(\frac{\gamma + \lambda}{\gamma + \lambda \left(\frac{z_h}{\underline{z}} \right)^{\frac{1}{1-\alpha}}} \right)^{1-\alpha} P_{-1} < P_{-1} \tag{14}$$

(See Appendix X for detailed derivations). Intuitively, prices decline more sharply as the breakthrough magnitude increases; in other words when $z_h/\underline{z}$ is large. Prices also decrease immediately at the time of the breakthrough, $P_0 = P_1$, as shown by equating entry values in Periods 0 and 1. Equations 14 and 8 imply that the number of firms rises proportionally to the drop in the price level, as formalized in Proposition 1 below.

Proposition 1. *The number of firms rises at the time of the breakthrough,* $N_0 > N_{-1}$

$$\frac{N_0}{N_{-1}} = \left(\frac{P_{-1}}{P_0} \right)^{\sigma + \frac{\alpha}{1-\alpha}} = \left(\frac{\gamma + \lambda \left(\frac{z_h}{\underline{z}} \right)^{\frac{1}{1-\alpha}}}{\gamma + \lambda} \right)^{\sigma(1-\alpha)+\alpha} > 1$$

Next, I show that the number of firms decline after the breakthrough, $N_1 < N_0$. The mechanism driving the decline is that the average productivity $\tilde{z}$ only rises in the long run, because breakthrough entrants are young in the short run, so that $\tilde{z}_{-1} = \tilde{z}_0$ but $\tilde{z}_1 > \tilde{z}_0$. Using equations 8 and 6 and noting that $N_1/N_{y1} = 1 + \lambda$,[12] we find that the shakeout size is

[12]The equality comes from leveraging Period $t = -1, 1$ steady state properties: $N_t = N_{y,t} + N_{o,t} =$

proportional to the increase in average productivity, as formalized in Proposition 2 below.

Proposition 2. *The number of firms decline after the breakthrough,* $N_1 < N_0$

$$\frac{N_1}{N_0} = \left(\frac{\tilde{z}_0}{\tilde{z}_1}\right)^{\frac{1}{1-\alpha}} = \left(\frac{1+\lambda}{1+\lambda\frac{z_h}{\underline{z}}}\right)^{\frac{1}{1-\alpha}} < 1 \tag{15}$$

Therefore, the number of firms rises at the breakthrough ($N_0 > N_{-1}$) and then falls in a shakeout ($N_1 < N_0$).

5.4.2 Size of the Shakeout Depends on Returns to Scale and Productivity Gap

Crucially, the size of the shakeout depends on the size of the learning curve ($z_h/\underline{z}$) and the industry-specific returns to scale (α). To interpret the Shakeout Index within the framework of this model, we can express it through equation 15, linking it back to the empirical findings in the earlier sections:

$$\begin{aligned} \text{Shakeout Index} &= 1 - \frac{N_1}{N_0} \\ &= 1 - \left(\frac{1+\lambda}{1+\lambda\frac{z_h}{\underline{z}}}\right)^{\frac{1}{1-\alpha}} \end{aligned} \tag{16}$$

As the returns to scale (α) gets big, the size of the shakeout increases:

$$\begin{aligned} \lim_{\alpha \to 1} \text{Shakeout Index} &= 1 \\ \lim_{\alpha \to 0} \text{Shakeout Index} &= 1 - \frac{1+\lambda}{1+\lambda\frac{z_h}{\underline{z}}} < 1 \end{aligned}$$

Figure 16 illustrates the path of the normalized number of firms, consistent with the definition in Section III, Figure 7. The left panel compares varying levels of returns to scale (α), demonstrating that, as indicated by the equation, the magnitude of the shakeout increases with higher returns to scale.

$N_{y,t} + \lambda N_{y,t} = (1+\lambda) N_{y,t}$. Thus for $t = -1, 1$, $N_{y,1}, N_{o,1}$ can be replaced as $N_{y,t} = \frac{1}{1+\lambda} N_t$, $N_{o,t} = \frac{\lambda}{1+\lambda} N_t$

Moreover, we can see in (16) that as $z_h/\underline{z}$ gets large, the size of the shakeout increases. In other words, since the learning curve was large in computer manufacturing (computer manufacturing was much more productive in 2000 compared to 1980), then the shakeout was relatively large. In fact,

$$\begin{aligned} \lim_{z_h/\underline{z}\to\infty} \text{Shakeout Index} &= 1 \\ \lim_{z_h/\underline{z}\to 1} \text{Shakeout Index} &= 0 \end{aligned}$$

The right panel of Figure 16 contrasts different magnitudes of the learning curve ($z_h/\underline{z}$), showing that, as in the equation above, the shakeout becomes more pronounced as the learning curve steepens.

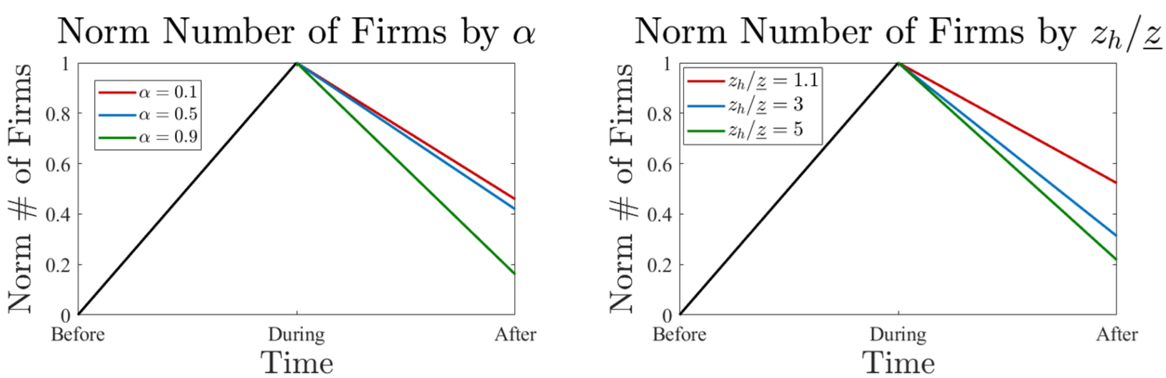

Figure 16. The figure shows the normalized number of firms, consistent with Section III Figure 7. The raw number of firms derived from the model is normalized using the same procedure applied in earlier sections. The plot presents the normalized firm numbers across the three static equilibria: before, during, and after the breakthrough.

5.4.3 Breakthrough Firms Drive the Shakeout

Consistent with Fact 5, in the model the shakeout is driven by the exit of new entrants that entered during the breakthrough, not by the exit of incumbents that had entered before. To quantify the contribution of breakthrough entrants to the shakeout, I consider what percent of the entrants that were young firms at the breakthrough in Period 0 exited before becoming old firms in Period 1:

$$\text{Relative Decline} = 1 - \frac{N_{o,1}}{N_{y,0}}$$

We can find $N_{y,0}$ using $N_{o,0} = N_{o,-1}$, $N_{o,-1} = \frac{\lambda}{1+\lambda}N_{-1}$, and equation 14; and $N_{o,1} = \frac{\lambda}{1+\lambda}N_1$. Solving for these variables yields the following proposition.

Proposition 3. *The shakeout is driven by the exit of breakthrough firms, according to the expression:*

$$\textit{Relative Decline} = 1 - \left(\frac{1+\lambda}{\lambda} - \left(\frac{\gamma+\lambda}{\gamma+\lambda\left(\frac{z_h}{\underline{z}}\right)^{\frac{1}{1-\alpha}}} \right)^{\sigma(1-\alpha)+\alpha} \right)^{-1} \left(\frac{1+\lambda}{1+\lambda\frac{z_h}{\underline{z}}} \right)^{\frac{1}{1-\alpha}} \tag{17}$$

The intuition comes from a similar analysis as the previous section. Taking the limit as $\alpha \to 1$, the Relative Decline $\to 1$.

Moreover, as $z_h/\underline{z} \to \infty$, Relative Decline $\to 1$. As $z_h/\underline{z} \to 1$, Relative Decline $\to 1-\lambda$.

5.4.4 An Equilibrium where No Shakeout Occurs

The industry will not see a shakeout if the learning curve is small, that is the young firms operate with relatively high productivity compared to the old firms. The previous example assumed the breakthrough technology had the property that young firms operate with low productivity:

$$h_y(z) = \begin{cases} \underline{z} \text{ w.p. } \gamma \\ 0 \text{ w.p. } 1-\gamma \end{cases}$$

Consider a different breakthrough technology that will generate an equilibrium where no shakeout occurs: young firms operate with the same productivity as old firms:

$$h_y(z) = \begin{cases} z_h >> \underline{z} \text{ w.p. } \gamma \\ 0 \text{ w.p. } 1-\gamma \end{cases}, \quad h_o(z) = \begin{cases} z_h >> \underline{z} \text{ w.p. } \lambda \\ 0 \text{ w.p. } 1-\lambda \end{cases}$$

The equations above remain the same, except the Period 0 equilibrium is identical to the Period 1 equilibrium: $P_0 = P_1$, $\tilde{z}_0 = \tilde{z}_1$, which implies $N_0 = N_1$.

Next I show that $N_1 > N_{-1}$, that is the number of firms rise monotonically. The result that $\tilde{z}_1 > \tilde{z}_{-1}$ follows immediately. We show that $P_1 < P_{-1}$ by equating the Period -1 and 1 entry conditions to obtain:

$$P_1 < \frac{\underline{z}}{z_h} P_{-1} \tag{18}$$

We can compare N_1 and N_{-1} to see that the number of firms rise monotonically, using equations 8, 18, 13, 12:

$$\frac{N_1}{N_{-1}} = \left(\frac{z_h}{\underline{z}}\right)^{\sigma-1}$$

Thus, as long as the inter-industry elasticity of substitution (σ) is greater than 1, then the number of firms will rise monotonically, and there will be no shakeout. Figure 17 illustrates the trajectory of the normalized number of firms, as in the equations presented above.

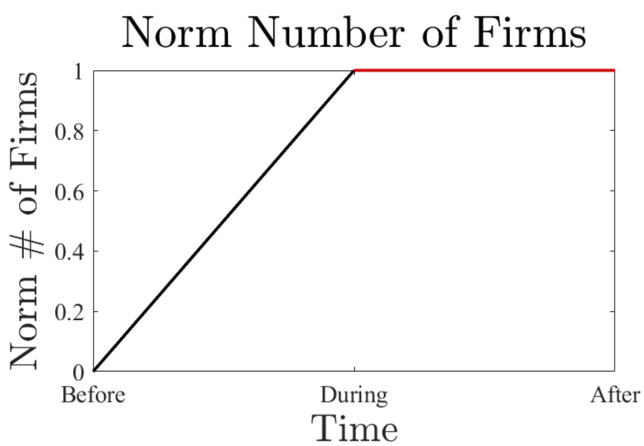

Figure 17. The figure presents the normalized number of firms, using the same definition and normalization procedure as in Section III Fact 3.2.

To summarize, the model captures several key empirical findings. It aligns with Facts 1 and 2 by allowing for industry responses to breakthroughs that can be either non-monotonic, with an initial surge in firm numbers followed by a shakeout, or monotonic, with firm numbers rising consistently. The model also aligns with Fact 5, as shakeouts are driven by the exit of new entrants following the breakthrough. Mechanically, it supports Fact 4 due to the assumption that firms operate for only two periods, ensuring that entrants absorb the labor in the industry. Lastly, consistency with Fact 3 will be demonstrated in the subsequent section.

5.5 Labor re-allocates towards breakthrough industries

This section will address Fact 3. TBD.

5.6 A Discussion on the Transition Path

TBD. A fully developed transition path would endogenously address Fact 4. Currently, the outcome relies on the two-period lifespan assumption for firms. Here, I outline the essential components and potential challenges in modeling the transition path, providing guidance for future researchers who may have the capacity to fully solve for it.

6 Conclusion

This paper challenges the conventional wisdom that technological breakthroughs inevitably lead to industry shakeouts. By examining a wide range of industries across the U.S. economy, I show that most breakthrough industries do not experience a sharp decline in the number of firms. Additionally, my analysis reveals that the frequency of breakthroughs has been steadily decreasing over time. The variation in industry shakeouts is driven largely by differences in returns to scale and the productivity gap between older and younger firms.

These findings raise important questions for future research. First, while this paper focuses on the extensive margin of firm numbers, further study is needed to understand how breakthroughs impact industry concentration on the intensive margin: in terms of market share, sales, or employment. Second, the decline in entry-driven breakthrough frequency warrants investigation – whether due to changes in the nature of innovation, barriers to entry, or broader economic factors. Finally, understanding the aggregate welfare implications of breakthroughs, both in the short and long run, remains crucial, especially when considering how industrial policies or subsidies might shape these dynamics. These questions are key to understanding how innovation will continue to reshape industries and economies in the future.

Data Availability

This paper uses the confidential microdata of the US economic censuses and LBD. Code to replicate the tables and figures in this paper can be found in TBD.

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