Faster Markets, Slower Growth:

Consumers' Attention, Market Shares and Competition in R&D*

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Abstract

Using data from U.S. public companies over recent decades, we document a paradox: while prospective market leaders have gained market share at an increasing speed, overall turnover in leadership has slowed. Although the dynamism of market shares suggests more contestable markets, the persistence of leadership indicates the opposite. We address this puzzle with a model of endogenous growth, where improved consumer access to market data accelerates market share dynamics and increases firms' incentives to innovate. Greater competition enhances R&D productivity but also amplifies the misallocation of knowledge production. Consequently, innovation occurs through larger but less frequent spikes. Our model aligns with the data, predicting higher market concentration, increased markups, reduced turnover, and slower growth, even alongside more dynamic market shares and higher R&D spending. Ultimately, the paper shifts attention from insufficient competition in the goods market to inefficient competition in the R&D sector as a potential driver of secular fall in aggregate productivity.

Keywords: data economy, information frictions, rational inattention, quality-ladder, Shumpeterian creative destruction, market power.

JEL codes: E23, E31, L14, L15, O30, O41.

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1 Introduction

An upsurge in market concentration is a well-established fact observed over the last few decades across various countries.[1] One manifestation of this phenomenon is the decline in the turnover of market share leadership among public companies in the US.[2] This observation has raised concerns that a lack of competitiveness in the market for consumer goods is one of the main drivers of the contemporaneous global decline in productivity.[3] In particular, mechanisms such as predatory pricing (Motta, 2004), strategic acquisitions (Cunningham et al., 2021), or lobbying (Akcigit et al., 2023; Gutiérrez and Philippon, 2019) may prevent laggard firms from increasing their market share to a level where they could challenge market leaders. Consequently, laggard firms may have weaker incentives to invest in R&D, potentially explaining lower aggregate productivity and slower economic growth.

Our first contribution is the documentation of a new stylized fact, which contrasts with the idea of lower competition in final markets for consumer goods. We analyze data from public U.S. companies over the last five decades. Our findings reveal that the mean and median growth in market share before a company becomes a market leader for the first time increased by approximately 50% in the last two decades across sectors. Furthermore, various average measures of speed and volatility in market share across sectors support the view that markets have become more liquid and contestable in recent years. Overall, while more recent market leaders have secured larger market shares for longer periods, they achieved leadership status much faster. Thus, although increased market concentration might suggest reduced competition, the dynamism of market shares indicates the opposite.

We propose a model resolving this paradox, showing that faster market share dynamics can lead to lower turnover in market leadership and a steady rise in R&D spending as observed in the data. The model incorporates two key factors: first, an increase in consumers' attention to product quality; second, a negative externality arising from R&D competition that slows the overall rate of innovation. Overall, our paper shifts the focus from insufficient competition in the goods market to inefficient competition in the R&D sector as a potential explanation for secular stagnation.

[1] For example, see evidence in Autor et al. (2017, 2020) and De Loecker et al. (2020).

[2] See Olmstead-Rumsey (2019) and our own analysis in Section 2.

[3] See Gutiérrez and Philippon (2017); Gordon (2012); Syverson (2017); Byrne et al. (2016); Baqaee and Farhi (2020); Akcigit and Ates (2021), among others.

As in Grossman and Helpman (1991), economic growth depends on the rate of innovation in quality products. Our first innovative contribution is to incorporate consumers' rational inattention to product quality. Consumers choose how frequently to incur a utility cost to acquire information about new products in the market. Consequently, for a given attention cost, higher expected innovation leads to greater consumer attention. This mechanism implies that the market share of an innovative firm takes time to converge to its steady state, depending on the distribution of quality across varieties and the attention costs.

On the other hand, firms active in the market compete in price à la Bertrand, maximizing rents derived from differences in quality and customer base. Firms enter the market as innovators, succeeding through a process of innovation. This innovation process occurs at the level of research labs, akin to start-ups, which decide to enter and invest in the R&D sector to gain a chance at innovation—and thereby become active firms.

Our second innovative contribution lies in modeling R&D competition. In our framework, labs incur a fixed cost to generate knowledge across n research fields. The productivity of each lab in a given field is drawn from an exogenous distribution, as in Jones (2023). We make two key assumptions. First, the most productive lab in a field secures a patent, preventing others from using its knowledge in that field. Second, to enter the market with an innovative product, a lab must improve knowledge across all n fields. These assumptions reflect the idea that the development of a new product requires expertise in multiple fields and that leaderships in R&D allows finding ways to hinder competitors' progress, as documented by Argente et al. (2020a).

This leads to a misallocation of knowledge production when different labs excel in different fields, deterring each other from entering the goods market with an innovative product. In particular, as the number of labs increases, competition increases the expected scale of innovation in the market, but reduces its frequency. This dynamic arises because, while the expected maximum productivity in any given field increases with the number of labs, so too does the probability of misallocation, preventing the emergence of innovative products. Specifically, we demonstrate that as long as the re-allocation of produced knowledge – that we model parsimoniously as stochastic mergers between patent holders – is not perfectly efficient, the likelihood of successful innovation decreases with the number of active labs. Consequently, the relationship between the number of active labs and expected innovation shows up as an inverted U-shape: initial gains in R&D

productivity across fields are eventually outweighed by the declining probability that all needed advancements are implemented together within a single innovation product.

We show that the inefficiency in the allocation of knowledge is a sufficient force to let a decline in attention cost to explain a slow down in productivity. We think about the spectacular improvement in data technologies in the last two decades, as a secular decrease in information cost, allowing consumers to search, compare and buy product across different firms on cheap information platforms. In our model, an initial increase in consumers' attention, magnifies the present value of being a market leader, stimulating entry in R&D. A greater number of labs spurs knowledge production, but jeopardizes the probability that a new market leader emerges, as the probability of an innovation goes down. At the same time, when innovation occurs, it is larger in scale, granting the innovator greater market power, allowing it to sustain a higher markup, and enabling its market share to converge more quickly to a larger value. In turn, the larger scale of innovation and the lower frequency of innovation both increase the present value of being an innovator,which stimulates additional entry into R&D and increases R&D spending, creating a general equilibrium feedback loop.

A decline in information costs can explain the sustained upward trend in R&D expenditures and output, coupled with the inverted U-shaped trajectory of economic growth observed in the data. Initially, rising incentives to invest in R&D lead to an increase in the number of research labs, driving productivity and growth upward. However, as more research labs become active in R&D, the misallocation effect dominates, reversing the relationship between R&D spending and economic growth.

Finally, we show that misallocation in R&D knowledge leads to excessive private spending on R&D as information costs decline. This mechanism overturns the typical result of insufficient private R&D spending derived from viewing R&D through the lens of a public goods analogy. In our model, absent misallocation, a constrained social planner would find it socially optimal to subsidize entry, even considering the cost of information. However, when information costs are sufficiently low, excessive funding of research labs emerges, invalidating the public good policy prescription.

Literature review. Since Smith (1776), competition has been seen as a key driver of social efficiency. However, Schumpeter (1942), as formalized by Aghion and Howitt (1992), argued that intense competition, while efficient in allocating resources given existing technology, may discourage innovation by reducing the short-term profits needed to incentivize laggard firms to catch up with the leader (see also Scherer (1967) and Kamien and Schwartz (1975)).

Aghion et al. (2005) shows that the relationship between competition and innovation is an inverse-U shape. Initially, more competition can push laggard firms to engage in R&D by diminishing their pre-innovation rents. Eventually, stronger competition will deter such investments drying-up post-innovation incentives of followers. Griffith and Van Reenen (2021) study the optimal level of competition i.e. the one generating the highest levels of innovation.

In contrast to these works, in our model, post-innovation rents can increase although innovation output can decrease, which is essential to replicate increasing spending in R&D with decreasing productivity as observed in the data. This divergence occurs because as the number of active labs goes up the misallocation of produced knowledge gets larger. We think such misallocation being the result of patent deterrence in the spirit of Argente et al. (2020b). They show that market leaders often patent without commercialization, with 62% of patents unused, reducing creative destruction by 2.5%.

While several approaches diverge on the specific driver of slowdown in business dynamism, they share the implication that decreasing productivity growth results from diminished private incentives to innovate. Recent trends in US point toward a [4] Explanations for this slowdown have focused on various secular trends, including knowledge diffusion (Akcigit and Ates, 2023; Olmstead-Rumsey, 2019), IT technology (Aghion et al., 2023; Lashkari et al., 2024), and declining fertility rates (Peters and Walsh, 2022). The trends we document suggest that these incentives have increased over the last half century, not decreased.[5] Hence, we consider a secular trend consistent with increased private incentives to innovate: consumers' improved access to data technology. As we show, this trend is directly reflected in the increased speed of market share dynamics. In turn, these higher incentives to innovate exacerbates a pre-existing negative externality in the innovation process, stemming from excessive competition in R&D.

Finally, recent work emphasizes advertising and, more generally, consumer acquisition

[4] Akcigit and Ates (2021) provide a throughout review of evidence focusing on the U.S. Among the most notable features of this decline, they emphasize an increased market concentration, higher markups, a lower firm entry rate, a decrease in the labor share, and a fall in productivity growth. We review some of these trends more specifically in Section 2.3.

[5] We find that a larger proportion of firms issue patents, the market value of patents has steadily increased, and the ratio of R&D to sales has also risen among public firms.

as an important driver of productivity growth. Cavenaile and Roldan-Blanco (2021) find that advertising substitutes for investment in R&D. Ignaszak and Sedlácek (2022) document that expansions of firms' customer bases boost their incentives to innovate. Like these papers, we place consumer acquisition as a key driver of investment in R&D. We document an increasing rate at which this acquisition realizes, and attribute this feature to increased consumers' attention to market innovation. We see this as the secular trend that, in turn, drives the productivity slowdown.[6]

2 Trends in innovation and business dynamics

This section examines aggregate trends in the dynamics of innovation and businesses in the US. Our analysis reveals two contrasting pictures. On the one hand, markets have become more concentrated and sluggish, with existing leaders capturing higher market shares and facing a reduced turnover in leadership. On the other hand, firm dynamics exhibit unprecedented vitality, as the speed at which emerging leaders acquire market share and declining businesses loose them has increased over time. This renewed vitality is also reflected in private effort in R&D.

2.1 Increased market concentration

Our analysis relies on yearly Compustat data for companies listed in the US from 1960 to 2022.[7] Market concentration has increased steadily over the past decades in the US (Autor et al., 2017, 2020; Grullon et al., 2019; Olmstead-Rumsey, 2019). Despite the inevitable sample selection bias toward large firms in Compustat, evidence of this increased concentration within industries is clearly visible. Figure 1a shows the evolution of the average market share of the largest firm (by sales) in narrowly defined industries (4-digit SIC).[8] We henceforth refer to the largest firm in an industry as the market leader. As the figure demonstrates, the average market leader's share increased from approximately 40% in the 1970s to nearly 55% in recent years. A similar pattern of rising concentration is observed when calculating the sum of squared market shares within each industry

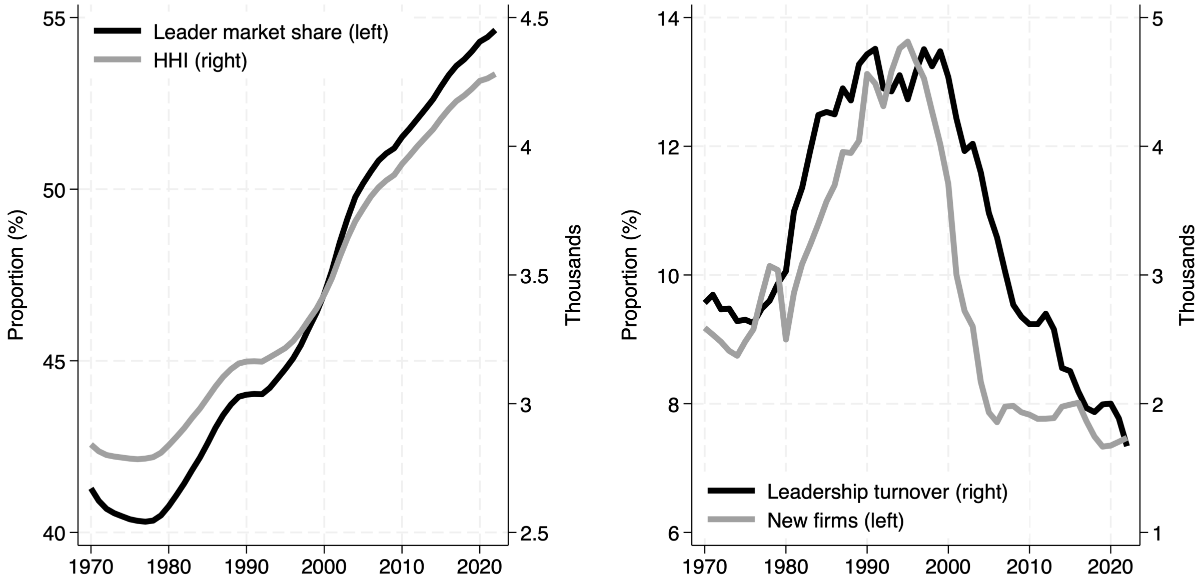
[6] Instead, Bornstein (2018) argues that population aging is likely to generate more inertia in market share dynamism. Our evidence suggest otherwise.

[7] We restrict the sample to firms with an industry identifier (SIC), excluding the following sectors: Agriculture, forestry, and fishing; Mining and construction; Transportation and public utilities; Finance, insurance, and real estate; Public administration. All the patterns reported in this section continue to hold when including these sectors.

[8] All the patterns reported in this section continue to hold when considering 3-digit SIC industries.

(Herfindahl-Hirschman Index). These trends support the view that markets have become more concentrated over the last half-century, with market leaders steadily capturing an increasing proportion of total sales within industries.

Figure 1: Trends in market concentration



(a) Concentration

(b) Turnover

Notes: Both panels display 10-year moving averages. Market shares are defined as the ratio of a firm's sales to total industry sales within a 4-digit SIC industry. Panel 1a: A leader's market share is defined as the highest market share within an industry, while the Herfindahl-Hirschman Index (HHI) is calculated as the sum of squared market shares (in percentage terms) within an industry. Averages are weighted by industry sales for each year. Panel 1b: Leadership turnover is the proportion of market leaders that were not leaders in the previous year. New firms refer to the flow of firms (identified by unique Compustat identifiers) entering the Compustat sample for the first time since 1960.

Moreover, this increased concentration has been accompanied by a decrease in leadership turnover, suggesting that market leaders are not only larger but also more likely to maintain their leadership in their respective markets. Figure 1b shows the evolution of the leadership turnover rate—the proportion of market leaders that were not leaders in the previous year. As the figure illustrates, turnover has halved since the early 2000s.

A similar dynamic is observed in the entry rate of firms into the Compustat sample. This decline in firm entry is not specific to listed companies in the US, as previously documented by Decker et al. (2016), Gourio et al. (2016), and Karahan et al. (2024), among others.

Overall, the trends reported in Figure 1 suggest that market leaders have gained greater dominance in their respective markets, making it increasingly difficult to challenge their leadership since the early 2000s. This evidence complements a large and growing body of research documenting a slowdown in US business dynamism across many dimensions, as thoroughly reviewed in Akcigit and Ates (2021, 2023). Among these other dimensions of the slowdown, we emphasize two which are central to the present paper: a steady increase in average markups (e.g., Hall, 2018; Autor et al., 2020; De Loecker et al., 2020; Eggertsson et al., 2021), and a decline in productivity growth since the 2000s (e.g., Baqaee and Farhi, 2020; Akcigit and Ates, 2021; Olmstead-Rumsey, 2019).

2.2 Market share dynamism

We document novel trends indicative of an increased dynamism of firms within their industries. In contrast to the insights derived from turnover rates and market concentration, market shares within industries have become more dynamic: the rate at which firms gain and lose market share has increased over time. This suggests that overtaking current market leaders might have become easier—not more difficult—albeit conditionally on innovating and entering a market.

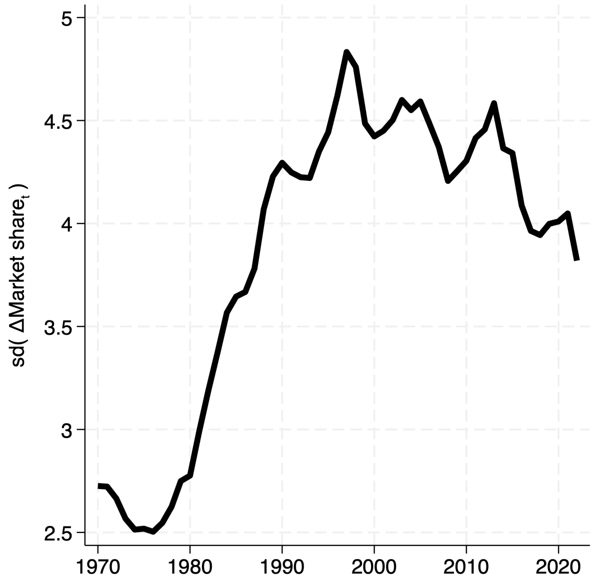
Figure 2 illustrates these trends. Panel 2a shows the evolution of the standard deviation of year-on-year changes in market share. As observed, firms' market shares were relatively stable in the 1970s but have become significantly more volatile since the 1990s.

This increased volatility in firms' market shares can be attributed to the faster pace at which growing firms acquire new market share. We measure this pace using the ratio of a firm's market share increase, $\Delta\text{Market share}_t$, to its potential maximum increase, $1-\text{Market share}_{t-1}$. Panel 2b depicts the evolution of this market speed metric, averaged across growing firms and weighted by sales. Notably, the speed at which firms acquire new market shares has nearly doubled since the 1970s.

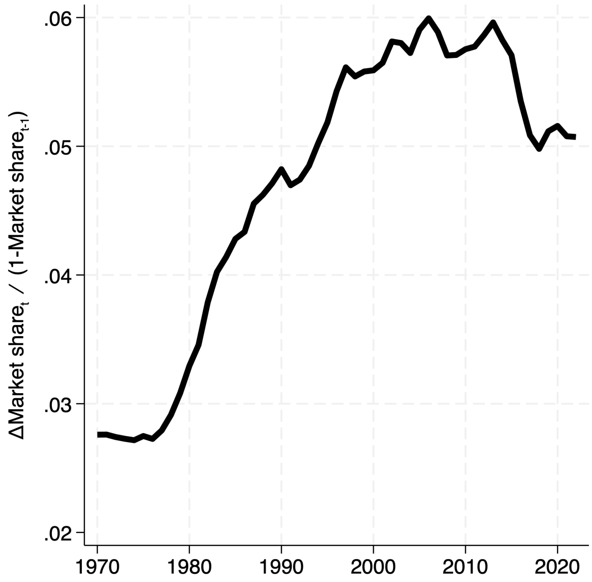
A similar pattern is observed in the speed at which firms lose market share when in decline. We refer to this measure as the speed of separation, which is defined as the negative market share growth of firms experiencing a drop in market share ($-\Delta$ $\text{Market share}_t/$ $\text{Market share}_{t-1}$). Panel 2c reports a pattern similar to that observed for acquisitions: market speed has nearly doubled since the 1970s. Finally, Panel 2d shows that these trends are also evident at the industry level, focusing on the fastest-declining and fastest-growing firms within each industry.

These higher speeds of market share acquisition and separation suggest that markets can adapt more swiftly to innovations, potentially making it easier for future leaders to establish a leadership position in their industries. Panel 3a provides suggestive evidence supporting this idea, examining the change in market share during the year before a firm

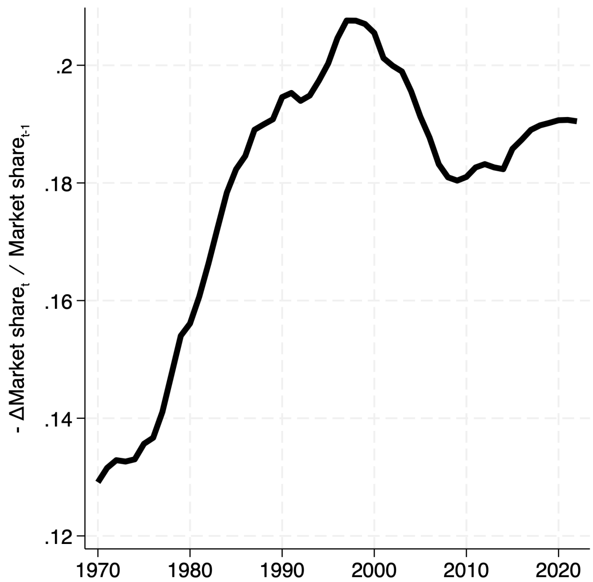
Figure 2: Trends in market speed



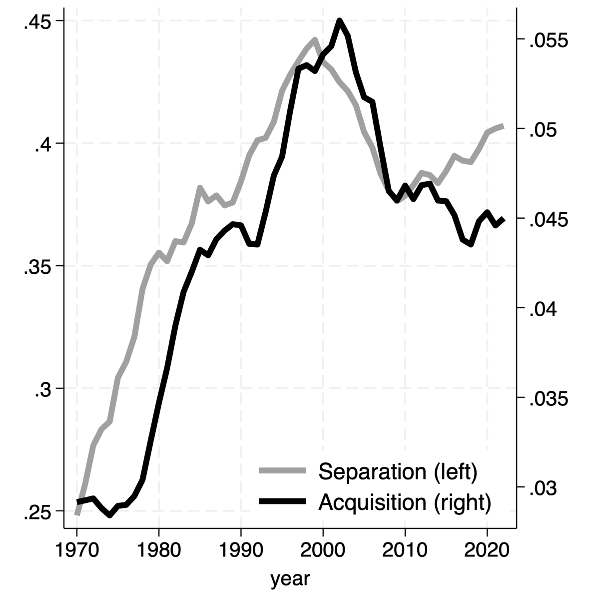
(a) Market share volatility



(b) Market share acquisition



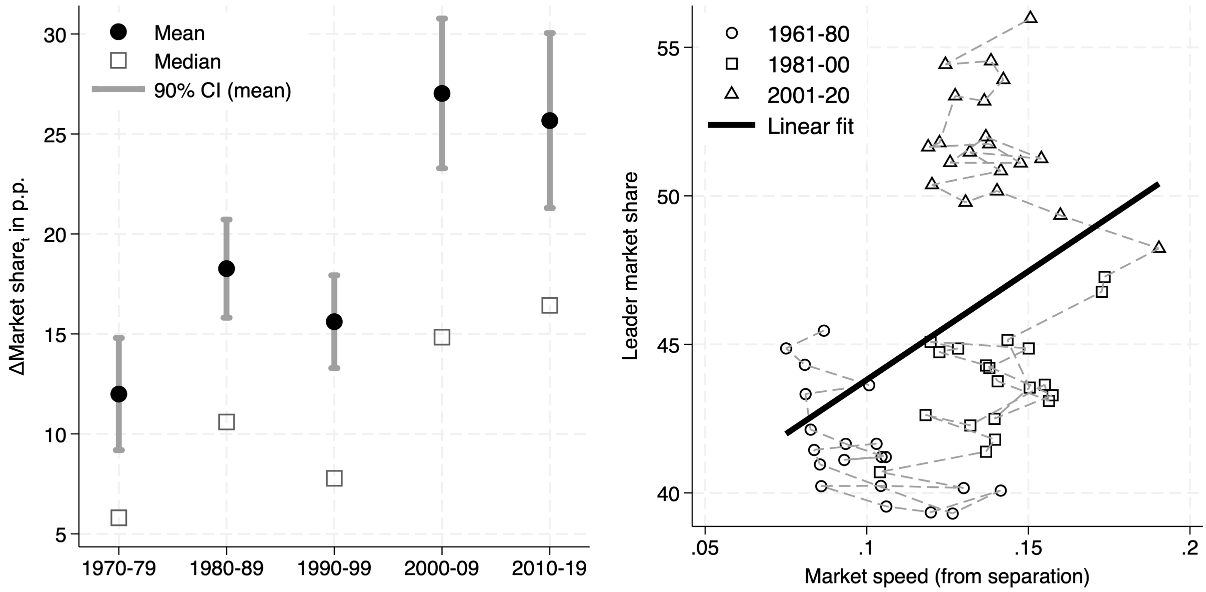
(c) Market share separation



(d) Fastest in industry

Notes: All panels display 10-year moving averages. Market shares are defined as the ratio of a firm's sales to total industry sales within a 4-digit SIC industry. Panel 2a: Standard deviation of firm's year-on-year change in market share. Includes all firms, with yearly averages weighted by firm sales. Panel 2b: Ratio of change in market share to the potential increase in market share (i.e., the sum of market shares of other firms in the same industry). Focuses on firms experiencing an increase in market share, with yearly averages weighted by firm sales. Panel 2c: Firm's market share growth (absolute value). Focuses on firms experiencing a decrease in market share, with unweighted yearly averages. Panel 2d: Measure of market share separation (acquisition) as computed in Panel 2c (Panel 2b) for the firm with the highest separation (acquisition) rate in industry. Fastest (either growing or declining) firm in industry, yearly averages weighted by industry sales.

Figure 3: Trends in market speed and leadership



(a) First time leader

(b) Speed and concentration

Notes: Market shares are defined as the ratio of a firm's sales to total industry sales within a 4-digit SIC industry, and a leader is the firm with the highest market share in its industry. Panel 3a: Average and median change in market share in the year when a firm becomes a leader for the first time. Unweighted statistics by decade. Panel 3b: Leader market share from Panel 1a (w/o moving averages). The measure of market speed from separation in each industry is the average speed of declining firms in that industry. Averages across industries are weighted by industry sales.

first becomes a leader in its industry. Whether considering the average or median change, these new leaders have increasingly captured a larger proportion of their market in the year they established their leadership positions.

Finally, Panel 3b examines the relationship between trends in market speed and concentration. It shows that markets have exhibited different combinations of speed and concentration over the past 60 years. In the 1960s and 1970s, both speed and concentration were low. During the 1980s and 1990s, market speed increased while concentration remained relatively low. It was only in the 2000s that concentration rose drastically, resulting in markets characterized by both high speed and high concentration.

What drives variations in firms' market shares and, consequently, the increased market speed? Recent empirical work indicates that variations in market shares are largely attributable to changes in customer bases. Afrouzi et al. (2023) decompose market share growth into the acquisition of new customers (extensive margin) and the average sales per customer (intensive margin). Using merged Compustat-Nielsen data, they find that the extensive margin accounts for approximately three-quarters of the variation in firms' market shares. Similar findings are reported in Einav et al. (2021) for a broader set of firms. Additionally, Argente et al. (2021) document that customer acquisition plays a particularly significant role in explaining the growth of successful entrants in the food sector. Together, these studies and the trends presented in this section suggest that the pace at which customers accrue to and separate from firms has increased over time.

2.3 Increased private effort in R&D activities

The last set of trends we present relates to the R&D process. It depicts an unambiguous picture: private innovation efforts have increased over the last half-century, as evidenced by trends in both research inputs (investment in R&D) and outputs (patents).

Panel 4a reports the evolution of the R&D expenditure-to-sales ratio. Whether examining the average ratio across firms (weighted by sales) or total expenditure across firms, US public companies have been allocating an increasing proportion of their revenue to R&D activities. This trend is not specific to the large firms included in Compustat. Instead, as noted by Jones (2016), it reflects broader US macroeconomic dynamics, characterized by increasing investment and employment in the R&D sector.

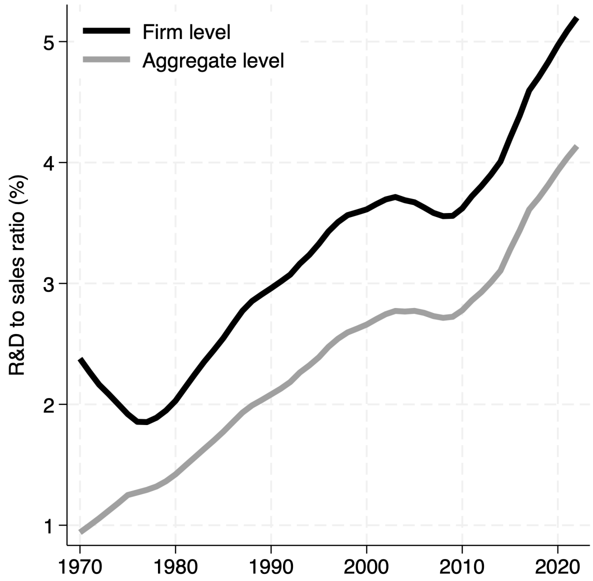
Firms' increasing efforts to innovate are also evident from the quantity and market value of patents, both of which serve as measures of private R&D outputs. To illustrate these trends, we use the measure of patent values developed by Kogan et al. (2017) (henceforth KPSS (2017)). This measure estimates the market value of patents issued in the US and assigned to public firms by analyzing variation in firms' excess stock returns during a short window around patent approval dates.[9]

Panel 4b shows the proportion of firms in our Compustat sample that reported at least one new patent in the current year. This proportion reflects the extensive margin of firm patenting activities. As shown, it has increased steadily over time. Furthermore, the increasing trend in patenting activities is more pronounced among larger firms, as evidenced by the evolution of the sales-weighted proportion relative to the unweighted proportion. The increase in patenting activities is also evident in the rising number of patents issued each year (Panel 4c). This trend is not limited to public companies but reflects a broader pattern observed across US firms.[10] Finally, the average market value of patents has also increased over the same period (Panel 4d), suggesting that markets expect higher rents from patents.

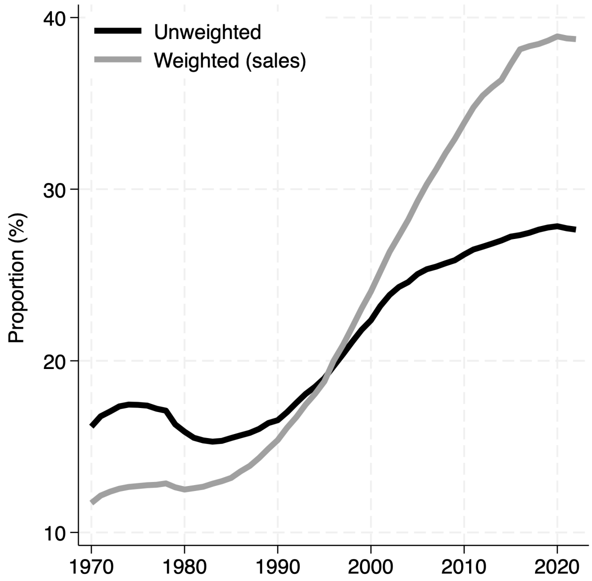
[9] We use the 2023 vintage of their dataset, which is available online on the authors' webpage.

[10] Statistics from the United States Patent and Trademark Office show that 47,072 patents were granted in 1970 and 164,575 in 2020 to holders of US origin.

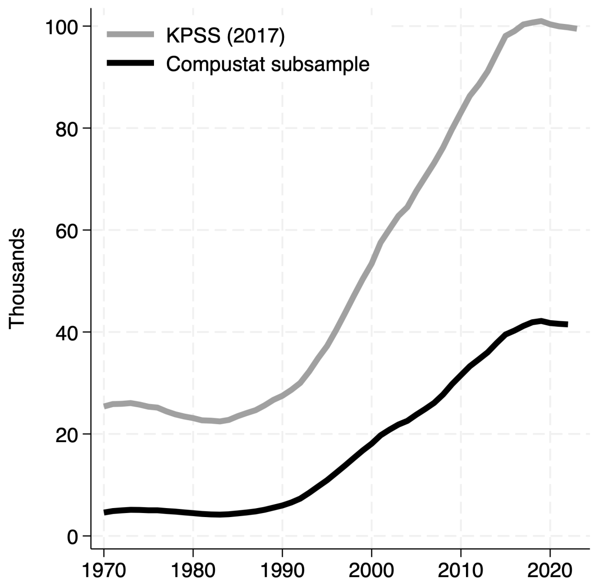
Figure 4: Trends in R&D expenditure and patents



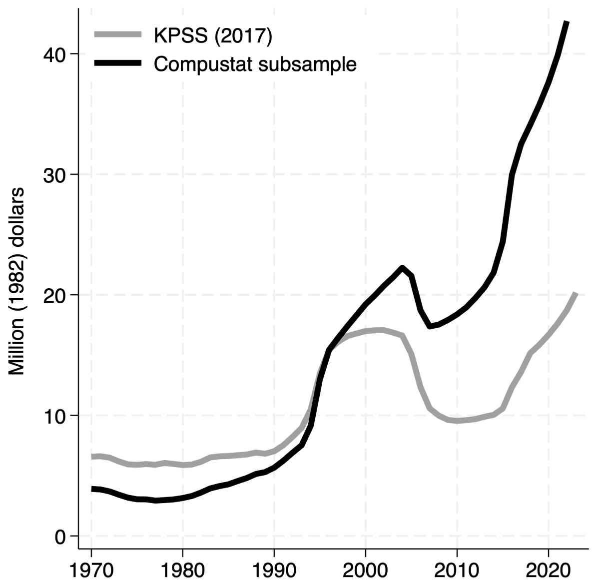
(a) R&D expenditure



(b) Patenting firms



(c) New patents



(d) Av. patent value

Notes: All panels display 10-year moving averages. Panel 4a: Ratio of firm R&D expenses (xrd variable in Compustat) to sales for each firm in the Compustat dataset (black line), yearly averages weighted by firm sales. The grey line is the ratio of the sum of R&D expenses to the sum of sales for each year. Panel 4b: Proportion of firms issuing at least one new patent in the year. Yearly averages weighted by firm sales (grey) and unweighted (black). Panel 9b: number of patents in KPSS2017 and in our subsample of Compustat data. Panel 9b: ratio of total patent value to number of patent, unweighted. Patent data from KPSS2017.

Together, these trends suggest that investment in R&D and its expected private returns, as measured by market value, have been increasing over time. Potentially, these trends may be driven by R&D activities of market leaders, which can differ from those of other firms (Olmstead-Rumsey, 2019; Argente et al., 2020a; Akcigit and Ates, 2023). Figure 9 in the Online Appendix shows that similar trends hold when excluding market leaders. Relatedly, the total value and number of patents at the time when firms become leaders for the first time has also increased on average (Figure 8, Online Appendix).

3 Model

We propose a model in which consumers are endogenously attentive to market innovations. As we show, attention drives the dynamism of market shares in industries. When the cost of attention decreases, consumers promptly identify market innovations and reallocate their demand to the best-seller. This mechanism provides an explanation to the increased dynamism of market shares that we have documented.

3.1 Attention to market innovation

Households. The economy is populated by a continuum of infinitely-lived households with unit mass, indexed by $h \in (0,1)$. Households are *ex ante* homogeneous but differ *ex post* due to information frictions, which we describe below. Each household is endowed with a single unit of labor, which it supplies inelastically. Following Grossman and Helpman (1991), households choose a consumption path to maximize the following intertemporal utility function:

$$U = \int_0^\infty e^{-\rho t} \ln u_h(t) dt \tag{1}$$

where $u_h(t)$ is the instantaneous utility of household h at time t, and ρ is the discount factor. Utility is derived from the consumption of a household-specific consumption basket, aggregated using a Cobb-Douglas technology:

$$\ln u_h(t) = \int_0^1 \ln \left[\sum_{i \in \mathbf{i}_{h,v}(t)} q_{i,v}(t) x_{i,v}(t) \right] dv, \tag{2}$$

In equation (2), $x_{i,v}(t) \in \mathbb{R}^+$ denotes the quantity consumed of a product sold by producer i in industry v, with associated quality $q_{i,v}(t)$. The summation indicates that goods within the same industry v are perfect substitutes, while goods are imperfect substitutes across industries. Finally, $\mathbf{i}_{h,v}(t)$ refers to the set of producers in industry v from which the household may buy. In fact, each variety v is produced by a countable set of producers, each denoted by (i, v), where $i \in \mathcal{N}(v, t) \equiv \{1, .., N(v, t)\}$, differing in the quality of their production $q_{i,v}(t)$ at time t.

Thus, $\mathbf{i}_{h,v}(t) = \mathcal{N}(v, t)$ corresponds to the unrestricted case, where a household can buy from any producer in industry v. However, in general, a household might not be fully aware of the set of available sellers. Consequently, buying decisions may be restricted due to information frictions. In such case, we have $\mathbf{i}_{h,v}(t) \subset \mathcal{N}(v, t)$. In the following, we refer to industries and varieties, producers and sellers, or households and customers interchangeably.

Inattention. Information about existing sellers in an industry arrives stochastically. More specifically, a household can devote some time to search the different sellers in industry v. When a search occurs at time k, the household observes all active sellers in industry v, implying $\mathbf{i}_{h,v}(k) = \mathcal{N}(v, k)$, and each seller offers a contract. We model a contract offered at time k as a fixed per-unit price $p_{i,v}(t)$ from k onward, at which the household can purchase any quantity $x_{h,v}(t)$ of quality $q_{i,v}(t)$ at $t > k$. This search arises at an endogenous Poisson rate $\eta_{h,v}(t)$, which may vary across households and industries. In between two searches ($t > k$), the household is restricted to buy among the set of sellers it already knows, $\mathbf{i}_{h,v}(k) \subseteq \mathcal{N}(v, t)$, which does not include sellers that have entered the market since the last search.

Attention is endogenous insofar as each household decides its search rate (or attention) in each industry $\eta_{h,v}(t)$. We assume that each time a search is performed, the household incurs a fixed utility cost κ. Without lack of generality, search rates are re-optimized at search dates, implying that search rates are chosen in expectation and are constant in between two searches. Perfect attention is the limiting case when $\eta_{h,v}(t) \mapsto \infty$.

Household optimization. Each household maximizes expected discounted utility (1) subject to a no-Ponzi game condition, the information structure, and the intertemporal budget constraint $\dot{a}_h(t) = r(t)a_h(t) + w(t) - c_h(t)$ where $a_h(t)$ denotes financial assets, $w(t)$ the wage rate, $r(t)$ the instantaneous rate of return, and $c_h(t)$ consumption expenditure. Thanks to the time separable feature of (1) and the homothetic aggregator (2), the household problem breaks into two stages.

In the first stage, the household allocates expenditure to maximize $u_h(t)$ given information $(\mathbf{i}_{h,v})_{v\in[0,1]}$ and sellers' prices and qualities. Because goods are perfect substitutes within industries, a household buys from the seller with the highest quality-price ratio in $\mathbf{i}_{h,v}$. To break ties, we assume that when two quality-price ratios are the same, the demand goes to the highest quality. Moreover, solving the static optimization yields a unit elastic demand $c_h(t) = x_{h,j,v}(t)p_{j,v}(t)$ where $j = \arg\sup_{i\in\mathbf{i}_{h,v}(t)} q_{i,v}(t)/p_{i,v}(t)$.

In the second stage, the household allocates intertemporal expenditures and search rates to maximize U given the static allocation from the first step. The later implies

$$\ln u_h(t) = \ln c_h(t) + \int_0^1 \ln\left(\sup_{i\in\mathbf{i}_{h,v}(t)} \frac{q_{i,v}(t)}{p_{i,v}(t)}\right) dv. \tag{3}$$

Because of this additive structure, the intertemporal allocation of expenditures is unaffected by information frictions and the Euler equation takes the usual form $\frac{\dot{c}_h(t)}{c_h(t)} = r(t)-\rho$. Consequently, the utility lost from not searching in all industries at time t is

$$\int_0^1 \ln\left(\sup_{i\in\mathcal{N}(v,t)} \frac{q_{i,v}(t)}{p_{i,v}(t)}\Big/ \sup_{i\in\mathbf{i}_{h,v}(t)} \frac{q_{i,v}(t)}{p_{i,v}(t)}\right) dv, \tag{4}$$

which depends on the quality-price ratio of the best seller versus that of the perceived best seller given the household information. Thus, when the household is searching in market v at time t, the optimal search rate in industry v is the solution to

$$\begin{aligned} I_h(v,t) = \min_{\eta_v}\Bigg\{ \int_0^\infty e^{-(\eta_v+\rho)s}\mathbb{E}\Bigg[\ln\left(\sup_{i\in\mathcal{N}(v,t+s)} \frac{q_{i,v}(t+s)}{p_{i,v}(t+s)}\Big/ \sup_{i\in\mathbf{i}_{h,v}(t)} \frac{q_{i,v}(t+s)}{p_{i,v}(t+s)}\right)\Bigg|\mathbf{i}_{h,v}(t)\Bigg] ds \\ + \int_0^\infty \eta_v e^{-(\eta_v+\rho)s} I_h(v,t+s)ds\Bigg\} + \kappa \end{aligned} \tag{5}$$

The expectation is taken with respect to the (endogenous) process of innovation in qualities, which we discuss next. The first term in equation (5) represents the expected discounted utility loss from not searching and keeping $\mathbf{i}_{h,v}(t)$ constant. The second term gives the discounted expected continuation value for searching again in the future. Finally, the last term, κ, is the search cost. Consequently, the optimal search intensity solves $\partial I_h(v,t)/\partial\eta_v = 0$ for all households and industries. The following Lemma characterizes this optimal search intensity when the innovation process in market v is stationary.

Lemma 1. *Let* $\lambda_v = \left[\sup_{i\in\mathcal{N}(v,t+\Delta t)} q_{i,v}(t+\Delta t)/p_{i,v}(t+\Delta t)\right]/\left[\sup_{i\in\mathcal{N}(v,t)} q_{i,v}(t)/p_{i,v}(t)\right]$ *be* *the proportional increase in the price-quality ratio when there is an innovation between time t and $t + \Delta t$ in market v. Moreover, let z_v be the rate of such innovation. Then, optimal attention,*

$$\eta(z_v \ln \lambda_v) = \sup \left(\sqrt{\frac{z_v \ln \lambda_v}{\kappa}} - \rho, 0 \right), \tag{6}$$

is decreasing in the search cost, κ, and discount rate, ρ, and increasing in expected market innovation, $z_v \ln \lambda_v$.

That is, consumers tend to be more attentive in markets where innovations are frequent and large. We next characterize how attention drives the dynamism of market shares.

3.2 Market share dynamics

Pricing Let us adopt the convention that given two intermediate producers $(i, j) \in N(v, t)$, then $i > j$ if and only if $q_{i,v} > q_{j,v}$. The production of one unit of intermediate good requires one unit of labor. Producers in a same industry compete à la Bertrand in prices when proposing a contract to searching households. Consequently, the best-quality seller $N(v, t)$ sets the limit price

$$p_{N(v,t)}(t) = w(t)\lambda_{N(v,t)}, \tag{7}$$

where $\lambda_{N(v,t)} \equiv q_{N(v,t),v}/q_{N(v,t)-1,v}$ is the quality improvement relative to the second-best intermediate producer. In fact, the pricing of the best-quality seller matches the price-quality contract of the second-best quality seller, when the latter prices at marginal cost, $q_{N(v,t)}(t)/p_{N(v,t)}(t) = q_{N(v,t)-1}(t)/w(t)$.

From Bertrand competition, overtaken producers, $i < N(v, t)$, set their price for new customers at the lowest possible price, i.e., the marginal cost. Since marginal costs are uniform, constant, and independent of produced quantity, it follows from (7) that producers $i < N(v, t)$ do not acquire new customers. However, the new leadership has no effect on the price/contract proposed to remaining customers. Therefore, overtaken leaders continue to make profits from remaining contracts with non searching customers.

This simple structure of price competition has the advantage of not introducing intertemporal arbitrage into the price setting problem. Moreover, it parallels the standard price competition in Schumpeterian growth models where a leader sets a limit price proportional to its innovation size. The only difference here is that overtaken leaders have a passive profit renting behavior, where they keep on making profits on remaining customers.

The price-quality contract ensures that once a buyer is matched to a producer, the producer cannot fully extract customer surplus. In the absence of such contract, a producer would have an incentive to behave as a monopolist on its (non-searching) customers. The contracts offered dependent only on whether the producer is a leader, or has been overtaken. Nevertheless, since overtaken producers do not attract new customers, there is no price discrimination. Indeed, each producer has a unique price, similar to (7), which depends only on the quality improvement when entering the market, $\lambda_{i,v}$. Hence, in the following we denote $p_{i,v}(t)$ the price of producer i at time t which is independent of the time when the contract was signed with a customer.

Market shares We have seen that individual demand from customer h to producer i is $x_{h,i,v}(t) = c_h(t)/p_{i,v}(t)$ if $i = \arg\sup_{j \in \mathbf{i}_{h,v}(t)} q_{j,v}(t)/p_{j,v}(t)$ and zero otherwise. Aggregating across customers, the total demand for intermediate producer i in sector v is

$$x_{i,v}(t) \equiv \int_0^1 x_{h,i,v}(t)dh = s_{i,v}(t)\frac{c(t)}{w(t)\lambda_{i,v}}, \tag{8}$$

where $s_{i,v}(t)$ is the market share of customers buying from producer (i,v). The following lemma shows that market shares evolves endogenously, growing whilst producer (i,v) is the best-seller and shrinking otherwise.

Lemma 2. *Market shares are governed by the differential equation*

$$\dot{s}_{i,v}(t) = \begin{cases} \eta_v(t)[1 - s_{i,v}(t)] & \text{if } i = N(v,t) \\ -\eta_v(t)s_{i,v}(t) & \text{otherwise} \end{cases} \tag{9}$$

which depends only on consumers' search rate.

As a result, the model directly links the growth rate of market shares in an industry to consumers' attention: the higher the search intensity, the faster new leaders grow and overtaken producers lose market share. In particular, the model encompasses the standard dynamics of market shares in Schumpeterian growth model as the limiting case with $\kappa \mapsto 0$. As this limit, consumers are perfectly attentive to market innovations,

$\eta_v(t) \mapsto \infty$, and the best industry seller serves all the market while the market shares of other sellers is nil.

Consistent with intuition, improvements in data technology—such as easier access to inexpensive information platforms to search, compare, and purchase products across firms—should stimulate market dynamism. Our model indicates that these advancements in data technology, as measured by a decrease in the information cost κ, are reflected in the dynamism of market shares within industries. More specifically, it predicts that a decreased cost of information spurs an increase in market share volatility, driven by higher rates of market share acquisition and separation. These predictions are consistent with the trends in market shares documented in Section 2.2.

4 Competition in R&D and innovation

We present the research and development (R&D) sector. In the model, competition between research labs generates a negative spillover: the larger the number of labs active in R&D, the better the quality of innovations, but the lower the probability of an innovation emerging. This externality arises from competition between labs, which makes their patenting strategies more likely to block innovations. Ultimately, this externality enables us to relate the observed increase in private effort in R&D activities to the dynamics of entry, markups, and TFP growth.

4.1 Value of innovation

Profit Conditionally on serving a share $s_{i,v}(t)$ and having an innovation size $\lambda_{i,v}$, profit is

$$\pi_{i,v}\left(\lambda_{i,v}, s_{i,v}(t), t\right) \quad = \quad s_{i,v}(t)\,\Pi\left(\lambda_{i,v}, t\right), \tag{10}$$

where $\Pi\left(\lambda_{i,v}, t\right) \equiv c(t)(1-\lambda_{i,v}^{-1})$ are the profits with perfect attention.

From this representation of profits, we observe that a producer's life cycle essentially has two regimes: an expansive phase, during which the producer is the best seller in its market and attracts new customers; and a declining phase, during which customers turn to the current best seller. In the absence of information frictions, as $\eta_v(t) \to \infty$, we recover the standard prediction that a new best seller instantaneously captures all customers in its market, while overtaken sellers exit the market.

Value function Leadership is overtaken at the (endogenous) rate $z_v(t)$, and we assume that there is no internal innovation. The value function of a leader, $V_N(\lambda, s, t)$, depends on the size of the producer's innovation, λ, the market share, s, and time, t. As long as the leader is not overtaken, it accumulates new customers. However, with rate $z_v(t)$, the producer is overtaken by a new leader. When a firm is overtaken, it does not exit the market, but keep on making profits on remaining customers. Let the value function of an overtaken leader write $V_{-N}(\lambda, s, t)$. Dotted variable refer to *total* time derivative. The following Lemma characterizes these value functions.

Lemma 3. *The value function of a leader, $V_N(\lambda, s(t), t)$, must solve the HJB equation*

$$r(t)V_N(\lambda, s(t), t) = \pi_N(\lambda, s(t), t) + z_v(t)\left[V_{-N}(\lambda, s(t), t) - V_N(\lambda, s(t), t)\right] + \dot{V}_N(\lambda, s(t), t) \quad (11)$$

where

$$V_{-N}(\lambda, s(t), t) = s(t)\int_t^{\infty} \exp\left(-\int_t^u [r(s') + \eta_v(s')]ds'\right)\Pi(\lambda, u)\, du \quad (12)$$

is the value of being overtaken at time t.

Consequently, the value function of an innovator entering the market at time t with innovation size λ is given by $V_N(\lambda, 0, t)$, as it enters with no initial market share.

4.2 Competition in R&D

Setup The R&D sector consists of L research labs competing to become innovators. Each lab is active in R research fields, reflecting the multidimensional nature of innovation. R&D production is independent across research fields and labs. For each research field $r \in \{1, ..., R\}$, each lab $\ell \in \{1, ..., L\}$ draws an idea with productivity $x_r > 0$ from a distribution with cumulative probability $F(x)$ and density $f(x)$. A lab obtains a patent if its productivity draw surpasses those of its competitors. These assumptions capture the notion that developing a new product requires expertise across multiple fields, and that the most productive labs can hinder the progress of competitors through patenting.

Research field The probability that a lab $\ell \in L$ gets a patent in field r is given by

$$P(L) \equiv \frac{1}{L} \int_0^\infty L\, F(x)^{L-1}\, f(x)\, dx \; = \frac{1}{L} \tag{13}$$

where $h(x, L) \equiv L\, F(x)^{L-1}\, f(x)$ is the probability density that x is the highest among L productivity draws, with its cumulative being $F(x)^L$. We immediately note that $\partial F(x)^L / \partial L = F(x)^L \ln F(x) < 0$ for any finite x. Hence, as L increases, a relatively larger mass is put on larger realizations. The same is true for, $f(x)F(x)^{L-1}$, i.e., the probability that among the L active labs, a given lab $\ell \in L$ extracts productivity x and that the other $L-1$ labs extract productivity lower than x.

Moreover, the expected productivity in a given research field r, expressed in terms of the contribution to the final innovation size λ (hence the normalization by $1/R$), is given by

$$\lambda(r, L) \equiv \int_0^\infty x^{\frac{1}{R}}\, h(x, L)\, dx. \tag{14}$$

Lemma 4. *A larger number of labs L, decreases the probability that a lab holds a patent, but increases the expected productivity of a patent, that is*

$$\frac{\partial P(L)}{\partial L} < 0 \; and \; \frac{\partial \lambda(R, L)}{\partial L} > 0 \tag{15}$$

for any field.

The total innovation size of an innovator, denoted by λ, is equal to one plus the geometric mean of productivity across all fields. Only patented discoveries can lead to an innovation, implying that the productivity of non-patented discoveries is zero. Consequently, research fields are perfect complements in the innovation process and labs can prevent other labs from innovating by exploiting their domination in some research fields.

4.3 Innovation size and rate

All-fields champion. We present first the starkest version of our mechanism by assuming that a lab becomes an innovator of productivity only if it gets a patent for every research fields, i.e., it is an all-fields champion. Since labs are ex-ante identical, their individual probability of getting a patent is $1/L$. As L increases, the probability that lab ℓ wins all the R research contests is $P(L)^R$. Consequently, the expected probability that the society has an innovator $Z(L)$ decreases. Instead, as L increases, the expected innovation of an innovator, $\lambda = 1 + \lambda(r, L)^R$, increases.

Imperfect patent allocation While illustrative, the assumption that innovators must be champions across all fields is restrictive. Instead, we show that the mechanisms derived under this assumption continue to hold even when there are small rigidities in patent allocations. To this end, consider that two patent holders can agree to merge into a single patent holder with probability $q \in [0, 1]$.

As the number of patent holders increases, the likelihood that they all merge into a single innovator decreases. Specifically, the probability that there are k patent holders, denoted $P_k(R, L)$, follows recursively from

$$P_k(R, L) \;=\; P_k(R-1, L)\,\frac{k}{L} \;+\; P_{k-1}(R-1, L)\,\frac{L-(k-1)}{L}, \tag{16}$$

where the probability that one patent holder emerges when there is only one field is $P_1(1, L) = 1$, which also implies $P_0(1, L) = 0$, and there cannot be more patent holders than fields, $P_{k>R-1}(R-1, L) = 0$. The recursive formula states that for k patent holders to emerge with R fields, it should be that: i) either k emerged already when considering $R-1$ fields, and the champion of the Rth field is one of them; ii) or $k-1$ emerged already with $R-1$ fields, and the champion of the R field is not one of them.

Therefore, the probability that the society has an innovator is

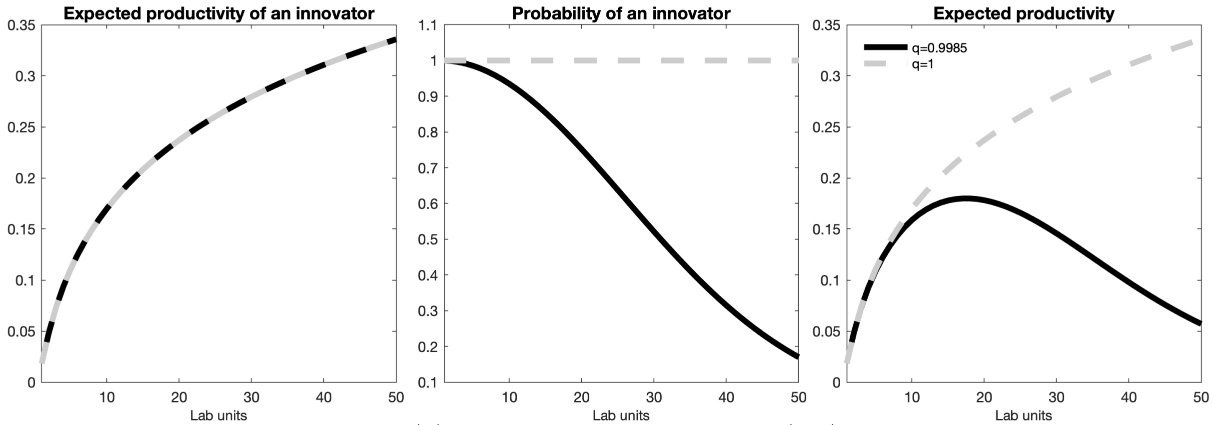
$$Z(R, L, q) \equiv \sum_{k=1} q^{k-1}\, P_k(R, L), \tag{17}$$

where we assume a sequential merging process. When $q = 1$, there is no patent allocation rigidity and an innovator always emerges, $Z(R, L, 1) = 1$. At the other extreme, when $q = 0$, we are back to the all-fields champion assumption with $Z(R, L, 0) = L^{-R}$. In general, we have that $Z(R, L, q)$ decreases with L as long as $q < 1$.

Finally, the expected productivity of an innovator, $\lambda = 1 + \lambda(r, L)^R$, is unaffected as it is independent of the patent merging process.

Illustration Figure 5 illustrates this innovation process. We set $F(x)$ to follow a Weibull distribution with a scale of 0.04 and a shape of 0.7, define the number of fields as $R = 200$,

Figure 5: Patent allocation and innovation.



Notes: The figure assumes that $F(x)$ is a Weibull distribution $W(a, b)$ with scale $a = 0.04$ and shape $b = 0.7$ and the number of research fields is $R = 200$. The grey tilded line corresponds corresponds to no rigidity in patent allocation, while the black lines assumes that two labs merge with probability $q = 0.9985$. The left panel reports the expected size of an innovation, $\lambda(r, L)^R$, the middle panel the probability of such innovation, $Z(R, L, q)$, and the right panel a measure of expected market innovation, $Z(R, L, q) \times \lambda(r, L)^R$.

and allow the number of labs L to vary.

In the left panel, we observe that a larger number of active labs L increases the expected productivity at occurrence, given by $\lambda(r, L)^R$. This occurs because greater competition increases the likelihood of identifying the most productive ideas. In the middle panel, however, we see that as the number of labs increases, the probability of achieving an innovation decreases when $q < 1$. This happens because imperfections in the reallocation of patents reduce the likelihood that any single lab possesses all the technological advances (patents) required to innovate.

Finally, we observe that the expected productivity, which combines productivity size and probability of occurrence, can either increase or decrease depending on which effect dominates. With imperfect reallocation, expected productivity may initially increase with the number of labs but eventually decrease as the lower probability of achieving innovation outweighs the productivity gains.

4.4 Participation in the R&D competition

To participate in the R&D race previously described, a lab ℓ must employ a fixed quantity of labor, denoted by Φ. There is free entry into the R&D race. Without loss of generality, we assume that an innovator enters market v with productivity $\lambda_v(t) = 1 + \lambda(R, L_v(t))^R$, where $L_v(t)$ is the number of labs entering the race in market v at time t. That is, we treat innovation as deterministic and ignore the stochastic nature of productivity within fields. Naturally, this approach is equivalent to assuming that the number of research fields, R, is large.

Each R&D race occurs over a fixed duration of time, $\Delta > 0$. Once a race stops, another starts immediately. Once a race ends, the next one begins immediately. To incorporate these races, which occur in discrete time intervals, into a continuous-time model, we assume that each race can be approximated by a constant rate of innovation, $z_v(L_v(t)) = Z(R, L_v, q)/\Delta$. This normalization ensures that the probability of an innovation occurring within the interval Δ is indeed $Z(R, L_v, q)$. That is, while the overall interval of a race is fixed, field productivity draws occur uniformly over this interval.

Finally, when an innovation occurs and an innovator enters into the market, labs are retributed (or owe shares of the innovator) in proportion to their contribution, i.e., the number of patents that they own initially. Consequently, the expected gains of a lab are

$$\underbrace{\frac{V_N(1+\lambda(R,L)^R,0,t)\ z(R,L,q)}{R}}_{\text{expected value patent}} \underbrace{\sum_{p=1}^{R} p \binom{R}{p} L^{-p}(1-1/L)^{R-p}}_{\text{expected patents}} \tag{18}$$

Free entry into R&D implies that this expected gain equals $\phi = \Phi/\Delta$, when $L_v(t) > 0$.

5 Productivity slowdown

This section characterizes the general equilibrium in this economy, illustrating how consumers' inattention and imperfect patent allocation relate in equilibrium.

5.1 Decreasing attention cost

Equilibrium definition A dynamic general equilibrium in this economy is given by a time-path of choices $\{c_h(t), a_h(t), \eta_{h,v}(t), x_{i,v}(t), L_v(t)\}_{v,h\in[0,1],i\in N(v,t)}^{t\in(0,\infty)}$, prices $\{w(t), r(t), p_{i,v}(t)\}_{v\in[0,1],i\in N(v,t)}^{t\in(0,\infty)}$, qualities $\{q_{i,v}(t)\}_{v\in[0,1],i\in N(v,t)}^{t\in(0,\infty)}$, sellers $\{i : i \in N(v,t)\}_{v\in[0,1]}^{t\in(0,\infty)}$, and households' information $\{\mathbf{i}_{h,v}(t)\}_{v,h\in[0,1]}^{t\in(0,\infty)}$ such that for all t

1. Households choose $c_h(t)$, $a_h(t)$, and $\eta_{h,v}(t)$, as described in section 3.1.

2. Firms set prices to serve their demand, $x_{i,v}(t)$, which depends on households' information and qualities, as described in section 3.2.

3. The asset market clears, and the aggregate Euler equation pins down the interest rate $r(t)$.

4. The labor market clears, pinning down the wage rate $w(t)$.

5. The free entry condition in R&D holds, pinning down the number of labs $L_v(t)$ in each market.

6. The dynamics of qualities and entries is consistent with the innovation process described in section 4.

7. The dynamics of information is consistent with households' attention choices $\eta_{h,v}(t)$.

We define the growth rate in this economy, denoted $g(t)$, to be the rate of increase of the average consumption basket, $u(t)$, such that $\ln u(t) \equiv \int_0^1 \ln u_h(t) dh$.

Balanced growth The following proposition characterizes the balanced growth path of the economy when the interest rate is constant.

Proposition 5. *Along a balanced growth path such that the interest rate, $r(t)$, is constant, we have*

$$g = \frac{\dot{Q}(t)}{Q(t)} = z(R, L, q) \ln \left(1 + \lambda(R, L)^R\right), \tag{19}$$

where

$$\ln Q(t) \equiv \int \sum_{i \in \mathcal{N}(v,t)} s_{i,v}(t) \ln q_{i,v}(t) \; dv \tag{20}$$

the quality index. The rate g is also the growth rate of the best-quality index $\ln Q_N(t) \equiv \int \ln q_{N(v,t),v}(t) dv$. Moreover, the number of labs is constant over time and across sectors. It solves the free entry condition

$$z(R, L, q) \frac{\sum_{p=1}^{R} \binom{R}{p} L^{-p} (1 - 1/L)^{R-p} \; p}{R} V_N(1 + \lambda(R, L)^R, 0) = \phi, \tag{21}$$

where $V_N(1 + \lambda(R, L)^R, 0)$ is the value function of an innovator entering the market with an initial market share $s(t) = 0$, given by

$$V_N(1 + \lambda(R, L)^R, 0) = \frac{\lambda(R, L)^R}{1 + L\phi(1 + \lambda(R, L)^R)} \frac{\eta}{(z(R, L, q) + \rho)(\eta + \rho)} \tag{22}$$

where $\eta \equiv \eta(z \ln(1 + \lambda(R, L)^R))$ *from Lemma 1 is also constant across sectors and time.*

Illustration We discuss the effect of a decrease in the attention cost, κ, on the balanced growth path (BGP). This exercise is meant to provide a qualitative illustration only. To simplify the exposition, we first consider a scenario with perfect patent allocation, $q = 1$. Figure 6 provides an illustration (grey line). This figure obtains from calibrating model parameters to match 2% growth, a 3% annual interest rate, a 15% markup rate, and a market speed of 0.02. This calibration is meant to capture features of business dynamism during the 1970s in the US. This BGP is our starting point, from which we asses how a decreasing attention cost κ affects the BGP. Our calibration leaves one free parameter, q, which we set to a value close to one. We choose this value as it allows us to illustrate an inverted U-shape for growth.

A decrease in attention cost induces households to search more frequently for the best-quality seller. This results in increased market share dynamism and improved allocation of buyers toward best-quality sellers. Consequently, the ratio of the best-to-actual quality indexes,

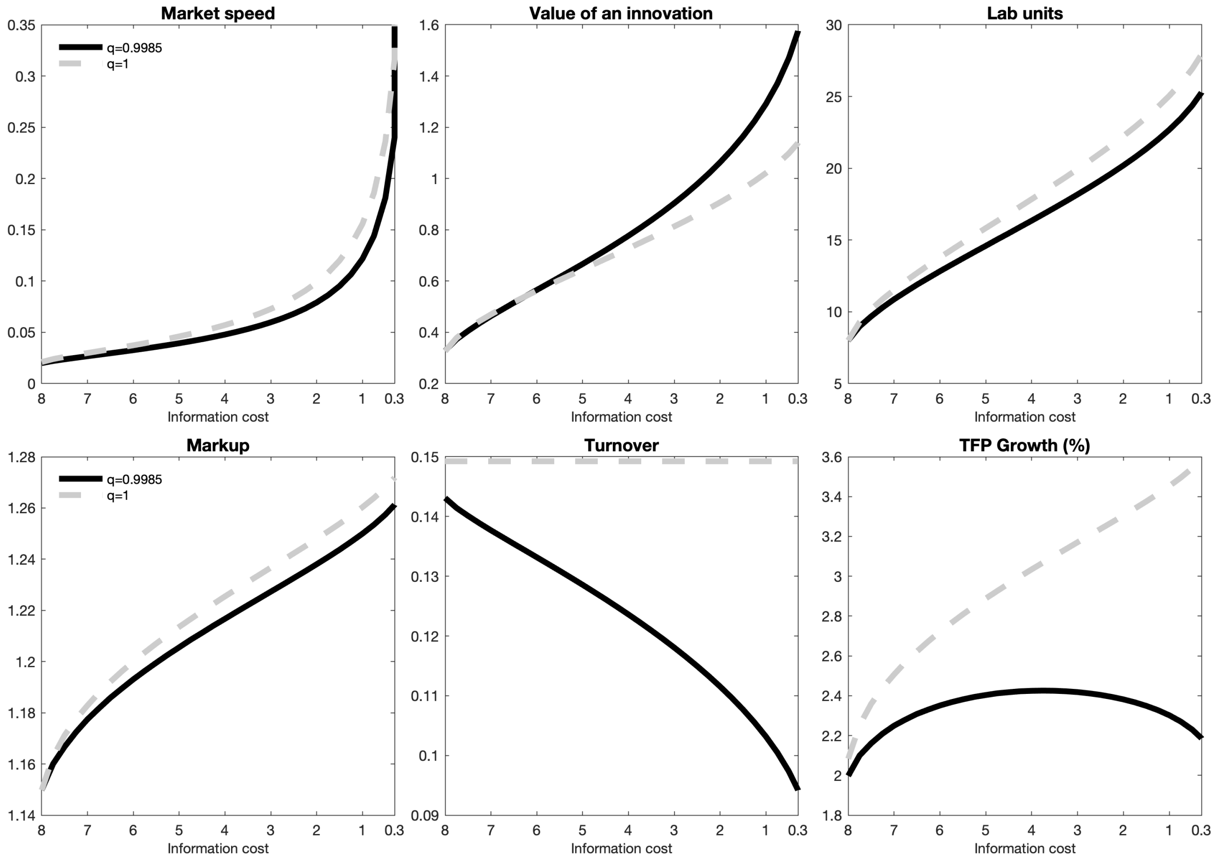
$$\ln\left(Q_N(t)/Q(t)\right) = g/\eta, \tag{23}$$

which serves as a measure of consumption good misallocation in this economy, decreases along the BGP.

This increased market dynamism raises the value function of becoming an innovator. As a result, free entry into R&D activities leads to the establishment of more research labs. With a higher number of labs engaging in R&D, the expected productivity in each research field, $\lambda(r, L)$, increases, as does the expected productivity of an innovator, $\lambda(r, L)^R$. When labs can merge without friction, the rate at which these innovations are realized remains unaffected. This process ultimately leads to higher growth in the economy. The resulting feedback loop further enhances households' attention, the value of an innovator, the number of labs, the size of innovations, and growth.

Notably, as $\kappa \to 0$, the model reassembles otherwise standard Schumpeterian growth models (e.g., Grossman and Helpman (1991)). The only deviation is our treatment of the innovation process: in our model, R&D generates improvements in the size of innovations while keeping the rate of innovation constant, whereas in most models, R&D increases the rate of innovation while keeping the size of innovations constant.

Figure 6: Decreasing attention cost and balanced growth path



The main effect of imperfect patent allocation, $q < 1$, is to induce negative spillovers in the innovation process. As is visible from Figure 6, the increase in the number of labs induced by a lower attention cost results in a decrease innovation rate (turnover) when $q < 1$. Thus, attention has an ambiguous effect on growth depending on the extent of this spillover—an ambiguity we illustrate with a calibration where the effect is first increasing and then decreasing.

Overall, this exercise shows that a decrease in attention cost and a negative spillover in knowledge production can reproduce the dynamics of businesses observed in the US and, in particular, an increase dynamism in market shares and private investment in R&D, simultaneously with more concentrated markets, higher markups and less entry. Interestingly, the model has the potential to reproduce the inverted U-shape observed in TFP growth.

5.2 Welfare

In order to discuss normative implications of our theory, we compute aggregate (utilitarian) welfare in this economy.

Lemma 6. *Along the balanced growth path, (utilitarian) aggregate welfare is*

$$\rho W = \underbrace{\ln c(0) + \ln Q_N(0) + \ln \tilde{a}(0)}_{\textit{initial cdt.}} - \underbrace{\ln \lambda}_{\textit{markup}} - \underbrace{\frac{z}{\eta} \ln \lambda}_{\textit{inattention}} + \underbrace{\frac{z}{\rho} \ln \lambda}_{\textit{innovation}} \tag{24}$$

where $\ln \tilde{a}(0) \equiv \int_0^1 \ln \left(\frac{c_h(0)}{c(0)} \right) dh$ *captures the welfare effect of endowment inequality.*

This expression for welfare emphasizes three mechanisms in this economy. First, markets are imperfect, and the welfare effect of monopoly power is captured by the size of markups. Second, innovations in the quality of goods drive growth, and welfare increases with the rate and size of these innovations. These two effects are standard in Schumpeterian growth models and, for example, are present in Grossman and Helpman (1991, eq. 15). Finally, inattention results in the misallocation of buyers, generating a welfare cost proportional to the ratio of the rate of innovation to the rate of attention. This inattention effect is novel.

Optimal growth follows from maximizing (24) with respect to the number of labs such that the labor market clears and the technology constraints on z, λ, and η hold.[11] Consequently, we are looking at a second-best allocation that does no correct for imperfect market competition and misallocation of buyers due to their (endogenous) attention.

Figure 7: Planner and free entry in R&D

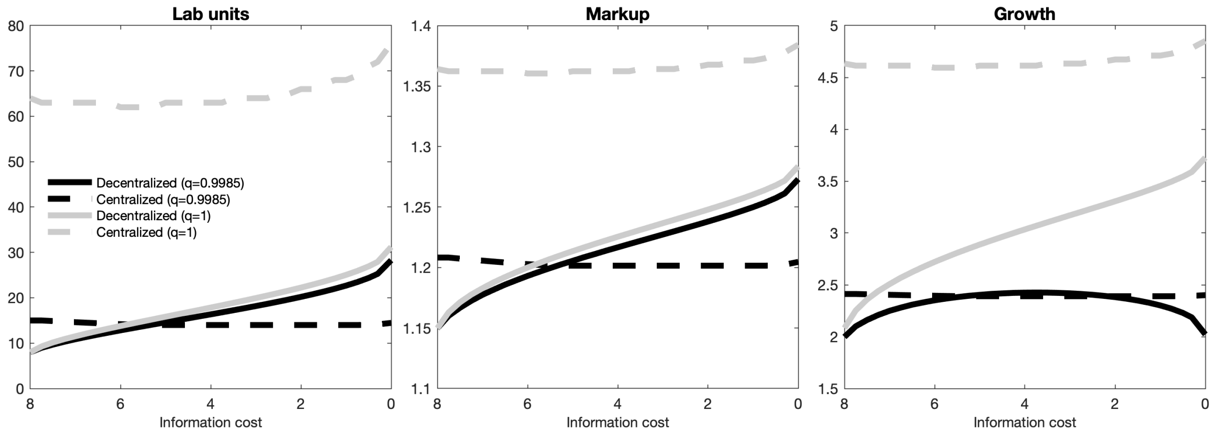


Figure 7 illustrates the evolution of the number of labs in the decentralized and centralized (social planner) balanced growth path as information costs decline. As shown in the left panel, when there is no negative externality in the innovation process ($q = 1$), the

[11] Specifically, these constraints write respectively: $c(t) = \left(\lambda^{-1} + L\phi\right)^{-1}$, $z = P_s(R, L, q)/\Delta$ where $P_s(R, L, q)$ is defined in equation (17), $\lambda = 1 + \lambda(R, L)$ from equation (14), and $\eta = \eta(z \ln \lambda)$ from equation (6).

social planner assigns greater value to innovation than the private sector. Consequently, the decentralized number of labs (solid gray line) consistently falls below the social optimum when $q = 1$. Furthermore, the social value of innovation increases with consumers' attention, as reduced buyer misallocation enhances efficiency, leading to a higher optimal number of labs.

However, excessive R&D effort can occur when there is a negative externality in the innovation process. Specifically, the socially optimal number of labs is significantly lower once this externality is taken into account. Consequently, private incentives to innovate can exceed the social value of innovation. This excessive competition in R&D becomes more likely as information costs rise.

The middle and right panels further indicate that this excessive number of labs results in excessively high markups and an excessively low rate of innovation. Interestingly, they also highlight that a decrease in information costs can initially be socially beneficial, as it increases the number of labs and helps close the initial gap with the centralized equilibrium. However, greater attention ultimately leads to excessive private investment in R&D, excessively high markups, infrequent innovation, highly concentrated markets, and insufficient growth.

References

Afrouzi, H., Drenik, A., and Kim, R. (2023). Concentration, market power, and misallocation: The role of endogenous customer acquisition. Technical report, National Bureau of Economic Research.

Aghion, P., Bergeaud, A., Boppart, T., Klenow, P. J., and Li, H. (2023). A theory of falling growth and rising rents. *Review of Economic Studies*, 90(6):2675–2702.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., and Howitt, P. (2005). Competition and Innovation: an Inverted-U Relationship. *The Quarterly Journal of Economics*, 120(2):701–728.

Aghion, P. and Howitt, P. (1992). A Model of Growth through Creative Destruction. *Econometrica*, 60(2):323–351.

Akcigit, U. and Ates, S. T. (2021). Ten facts on declining business dynamism and lessons from endogenous growth theory. *American Economic Journal: Macroeconomics*, 13(1):257–298.

Akcigit, U. and Ates, S. T. (2023). What happened to us business dynamism? *Journal of Political Economy*, 131(8):2059–2124.

Akcigit, U., Baslandze, S., and Lotti, F. (2023). Connecting to Power: Political Connections, Innovation, and Firm Dynamics. *Econometrica*, 91(2):529–564.

Argente, D., Baslandze, S., Hanley, D., and Moreira, S. (2020a). Patents to products: Product innovation and firm dynamics. Technical report, CEPR Discussion Paper No. DP14692.

Argente, D., Baslandze, S., Hanley, D., and Moreira, S. (2020b). Patents to Products: Product Innovation and Firm Dynamics. FRB Atlanta Working Paper 2020-4, Federal Reserve Bank of Atlanta.

Argente, D., Fitzgerald, D., Moreira, S., and Priolo, A. (2021). How do firms build market share? *Available at SSRN 3831706*.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., and Reenen, J. V. (2017). Concentrating on the fall of the labor share. *American Economic Review*, 107(5):180–185.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., and Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, 135(2):645–709.

Baqaee, D. R. and Farhi, E. (2020). Productivity and misallocation in general equilibrium. *The Quarterly Journal of Economics*, 135(1):105–163.

Bornstein, G. (2018). Entry and profits in an aging economy: The role of consumer inertia. *Manuscript*.

Byrne, D. M., Fernald, J. G., and Reinsdorf, M. B. (2016). Does the United States Have a Productivity Slowdown or a Measurement Problem? *Brookings Papers on Economic Activity*, 47(1 (Spring):109–182.

Cavenaile, L. and Roldan-Blanco, P. (2021). Advertising, innovation, and economic growth. *American Economic Journal: Macroeconomics*, 13(3):251–303.

Cunningham, C., Ederer, F., and Ma, S. (2021). Killer Acquisitions. *Journal of Political Economy*, 129(3):649–702.

De Loecker, J., Eeckhout, J., and Unger, G. (2020). The rise of market power and the macroeconomic implications. *The Quarterly Journal of Economics*, 135(2):561–644.

Decker, R. A., Haltiwanger, J., Jarmin, R. S., and Miranda, J. (2016). Where has all the skewness gone? the decline in high-growth (young) firms in the us. *European Economic Review*, 86:4–23.

Eggertsson, G. B., Robbins, J. A., and Wold, E. G. (2021). Kaldor and piketty's facts: The rise of monopoly power in the united states. *Journal of Monetary Economics*, 124:S19–S38.

Einav, L., Klenow, P. J., Levin, J. D., and Murciano-Goroff, R. (2021). Customers and retail growth. Technical report, National Bureau of Economic Research.

Gordon, R. J. (2012). Is U.S. Economic Growth Over? Faltering Innovation Confronts the Six Headwinds. NBER Working Papers 18315, National Bureau of Economic Research, Inc.

Gourio, F., Messer, T., and Siemer, M. (2016). Firm entry and macroeconomic dynamics: a state-level analysis. *American Economic Review*, 106(5):214–218.

Griffith, R. and Van Reenen, J. (2021). Product market competition, creative destruction and innovation. CEP Discussion Papers dp1818, Centre for Economic Performance, LSE.

Grossman, G. M. and Helpman, E. (1991). Quality ladders in the theory of growth. *The review of economic studies*, 58(1):43–61.

Grullon, G., Larkin, Y., and Michaely, R. (2019). Are us industries becoming more concentrated? *Review of Finance*, 23(4):697–743.

Gutiérrez, G. and Philippon, T. (2017). Declining Competition and Investment in the U.S. NBER Working Papers 23583, National Bureau of Economic Research, Inc.

Gutiérrez, G. and Philippon, T. (2019). The Failure of Free Entry. NBER Working Papers 26001, National Bureau of Economic Research, Inc.

Hall, R. E. (2018). New evidence on the markup of prices over marginal costs and the role of mega-firms in the us economy. Technical report, National Bureau of Economic Research.

Ignaszak, M. and Sedlácek, P. (2022). Customer acquisition, business dynamism and aggregate growth. Technical report, Working Paper.

Jones, C. I. (2016). The facts of economic growth. In *Handbook of macroeconomics*, volume 2, pages 3–69. Elsevier.

Jones, C. I. (2023). Recipes and Economic Growth: A Combinatorial March Down an Exponential Tail. *Journal of Political Economy*, 131(8):1994–2031.

Kamien, M. I. and Schwartz, N. L. (1975). Market Structure and Innovation: A Survey. *Journal of Economic Literature*, 13(1):1–37.

Karahan, F., Pugsley, B., and Şahin, A. (2024). Demographic origins of the start-up deficit. *American Economic Review*, 114(7):1986–2023.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The quarterly journal of economics*, 132(2):665–712.

Lashkari, D., Bauer, A., and Boussard, J. (2024). Information technology and returns to scale. *American Economic Review*, 114(6):1769–1815.

Motta, M. (2004). *Competition Policy: Theory and Practice*. Cambridge University Press.

Olmstead-Rumsey, J. (2019). Market concentration and the productivity slowdown. *MPRA Paper*, 93260.

Peters, M. and Walsh, C. (2022). Population growth and firm-product dynamics. *NBER Working Paper*, 29424.

Scherer, F. M. (1967). Research and Development Resource Allocation Under Rivalry. *The Quarterly Journal of Economics*, 81(3):359–394.

Schumpeter, J. (1942). *Capitalism, Socialism and Democracy*. Routledge, London, UK.

Smith, A. (1776). *An Inquiry into the Nature and Causes of the Wealth of Nations*. Number smith1776 in History of Economic Thought Books. McMaster University Archive for the History of Economic Thought.

Syverson, C. (2017). Challenges to Mismeasurement Explanations for the US Productivity Slowdown. *Journal of Economic Perspectives*, 31(2):165–186.

A Mathematical appendix

A.1 Proof of Lemma 1

The expected utility loss from not searching again until time $t+d$ for a consumer searching at time t in market v write

$$E\left[\ln\left(\sup_{i\in\mathcal{N}(v,t+d)}\frac{q_{i,v}(t+d)}{p_{i,v}(t+d)}\Big/\sup_{i\in\mathcal{N}(v,t)}\frac{q_{i,v}(t)}{p_{i,v}(t)}\right)\middle|\mathbf{i}_{h,v}(t)\right]=z_v d\ln\lambda_v \tag{25}$$

where $z_v d$ is the expected number of innovation in a time interval of length d. The innovation process, characterized by (z_v,λ_v), being stationary, so is $I_h(v,t)$. Hence, equation (5) write

$$\begin{aligned} I_h(v) &= \ln\lambda_v\int_0^{\infty}e^{-(\eta_v+\rho)t}z_v t dt+\frac{\eta_v}{\eta_v+\rho}I_h(v)+\kappa \\ &= \frac{z}{\rho(\eta_v+\rho)}\ln\lambda_v+\frac{\eta_v+\rho}{\rho}\kappa\ , \end{aligned} \tag{26}$$

Where the second equality is obtained from integrating by parts and using l'Hopital's rule.

A.2 Proof of Lemma 3

Discretize the time space is small steps of size Δt. The value function of a leader serving a share $s(t)$ of its market is

$$\begin{aligned} V_N(\lambda,s(t),t) &= \pi(\lambda,s(t),t)\Delta t \\ &\quad + e^{-r(t+\Delta t)\Delta t}\left[z_v(t+\Delta t)\Delta t+o(\Delta t)\right]V_{-N}(\lambda,s(t+\Delta t),t+\Delta t) \\ &\quad + e^{-r(t+\Delta t)\Delta t}\left[1-z_v(t+\Delta t)\Delta t-o(\Delta t)\right]V_N(\lambda,s(t+\Delta t),t+\Delta t) \end{aligned} \tag{27}$$

where $z_v(t+\Delta t)\Delta t+o(\Delta t)$ is the probability of being overtaken in a time interval Δt.

Using a first order approximation of $V_N(\lambda,s(t+\Delta t),t+\Delta t)$ and $V_{-N}(\lambda,s(t+\Delta t),t+$

$\Delta t)$, we get

$$\begin{aligned} V_N(\lambda, s(t), t) &= \pi(\lambda, s(t), t)\Delta t \\ &\quad + e^{-r(t+\Delta t)\Delta t}\left[z_v(t+\Delta t)\Delta t + o(\Delta t)\right]\left(V_{-N}(\lambda, s(t), t) + \dot{V}_{-N}(\lambda, s(t), t)\Delta t\right) \\ &\quad + e^{-r(t+\Delta t)\Delta t}\left[1 - z_v(t+\Delta t)\Delta t - o(\Delta t)\right]\left(V_N(\lambda, s(t), t) + \dot{V}_N(\lambda, s(t), t)\Delta t\right), \end{aligned}$$

where dot denotes the total derivative with respect to time. The expression reported in (11) then follows from subtracting $e^{-r(t+\Delta t)\Delta t}V_N(\lambda, s(t), t)$ from both sides, dividing by Δt, and taking the limit as $\Delta t \mapsto 0$.

A.3 Proof of Proposition 5

From the Euler equation, the growth rate of expenditure, $c_h(t)$, is constant across consumers and, thereby, equals the growth rate of aggregate consumption expenditures, $\dot{c}(t)/c(t) = r - \rho$. Labor is used in the production of intermediate goods and lab activities. Hence, market clearing on the labor market implies $\int x_v(t)dv + \int L_v(t)\phi dv = 1$, where

$$x_v(t) \equiv \sum_{i \in \mathcal{N}(v,t)} x_{i,v}(t) = \frac{c(t)}{w(t)} \sum_{i \in \mathcal{N}(v,t)} \frac{s_{i,v}(t)}{\lambda_{i,v}} \tag{28}$$

Thus, we get

$$\begin{aligned} \int x(v,t)dv &= \frac{c(t)}{w(t)} \int \sum_{i \in \mathcal{N}(v,t)} \frac{s_{i,v}(t)}{\lambda_{i,v}} dv \\ \iff \quad w(t)\left[1 - \int L_v(t)\phi dv\right] &= c(t) \int \sum_{i \in \mathcal{N}(v,t)} \frac{s_{i,v}(t)}{\lambda_{i,v}} dv \end{aligned} \tag{29}$$

We choose wage as the numéraire, $w(t) = 1$ for all t. Given our assumption that each lab has the same innovation size, λ, the market clearing condition (29) implies that aggregate consumption expenditures are constant when the number of labs in each sector is constant, an assumption that we maintain for now (and confirm later).

Moreover, equations (3) and (7) imply

$$\ln u(t) = \int \ln c_h(t) dF(h) - \ln \lambda + \ln Q(t) \tag{30}$$

Consequently, growth, $g \equiv \dot{u}(t)/u(t)$, is given by the growth rate of the quality index

$Q(t)$ such that

$$\ln Q(t) \equiv \int \sum_{i \in \mathcal{N}(v,t)} s_{i,v}(t) \ln q_{i,v}(t) \; dv. \tag{31}$$

We turn to the computation of the growth rate of this quality index. Guess that the innovation rate, z, is constant over time and across sectors. Then, from Lemma 1, so is the rate of search, η. Now, consider a market v in which there is no innovation during an interval Δt. Therefore, the average quality in this market evolves as

$$\begin{aligned}
\ln \bar{q}_v^{\not i}(t+\Delta t) &= \sum_{i \in \mathcal{N}(v,t)} s_{i,v}(t+\Delta t) \ln q_{i,v}(t) \\
&= \left(s_{N(v,t),v}(t) + \eta \Delta t (1 - s_{N(v,t),v}(t))\right) \ln q_{N(v,t),v}(t) + \sum_{j=1}^{N(v,t)-1} (1-\eta\Delta t) s_{j,v}(t) \ln q_{j,v}(t) \\
&= \ln \bar{q}(t) + \eta \Delta t \sum_{j=1}^{N(v,t)-1} s(j,t) \left[\ln q_{N(v,t),v}(t) - \ln q_{j,v}(t)\right] \\
&= \ln \bar{q}(t) + \eta \Delta t [\ln q_{N(v,t),v}(t) - \ln \bar{q}(t)]
\end{aligned} \tag{32}$$

Instead, when there is an innovation during an interval Δt, we have

$$\begin{aligned}
\ln \bar{q}^{i}(t+\Delta t) &= \sum_{i \in \mathcal{N}(v,t)} s_{i,v}(t+\Delta t) \ln q_{i,v}(t) + \eta\Delta t[\ln q_{N(v,t),v}(t) + \ln \lambda] \\
&= \sum_{i \in \mathcal{N}(v,t)} (1-\eta\Delta t) s_{i,v}(t) \ln q_{i,v}(t) + \eta\Delta t[\ln q_{N(v,t),v}(t) + \ln \lambda] \\
&= \ln \bar{q}(t) + \eta\Delta t[\ln q_{N(v,t),v}(t) + \ln \lambda - \ln \bar{q}(t)] \\
&= \ln \bar{q}^{\not i}(t+\Delta t) + \eta \Delta t \ln \lambda
\end{aligned} \tag{33}$$

We can use these expressions to compute the evolution of the economy wide quality index during an interval Δt

$$\begin{aligned}
\ln Q(t+\Delta t) &= \int_0^1 z\Delta t \ln \bar{q}^{i}(t+\Delta, v) + (1-z\Delta t) \ln \bar{q}^{\not i}(t+\Delta t, v) dv \\
&= \ln Q(t) + \eta \Delta t (\ln Q_N(t) - \ln Q(t)) + z\eta(\Delta t)^2 \ln \lambda \\
\frac{\dot{Q}(t)}{Q(t)} &= \eta \left[\ln Q_N(t) - \ln Q(t)\right]
\end{aligned} \tag{34}$$

where we have defined a best-quality index

$$\ln Q_N(t) \equiv \int \ln q(N,v,t)dv. \tag{35}$$

Along a BGP, $Q(t)$ must grow at a constant rate. From the above expression, we see that it requires a constant ratio $Q_N(t)/Q(t)$. The growth rate of $Q_N(t)$ follows from realizing that $\ln Q_N(t+\Delta t) = \ln Q_N(t) + z\Delta t \ln\lambda$. It follows that

$$\frac{\dot{Q}_N(t)}{Q_N(t)} = z\ln\lambda = \frac{\dot{Q}(t)}{Q(t)} \tag{36}$$

Using (34) and the above equality, we obtain $\ln\left(Q_N(t)/Q(t)\right) = g/\eta$.

We are left to show that the innovation rate, z, is constant over time and sectors. To this end, realize that the value function of being overtaken along the BGP write

$$\begin{aligned} V_{-N}(\lambda, s(t), t) &= s(t)\int_t^{\infty} e^{-(\rho+\eta)(u-t)}\Pi\left(\lambda, u\right)du \\ &= c(t)s(t)\frac{1-\lambda^{-1}}{\eta_v+\rho} \end{aligned} \tag{37}$$

Consequently, using the method of undetermined coefficients, we get

$$V_N(\lambda, s(t), t) = (1-\lambda^{-1})c(t)\left[\frac{1}{z+\rho}\frac{\eta}{\eta+\rho} + \frac{s(t)}{\eta+\rho}\right] \tag{38}$$

where, from the labor market clearing condition, $c(t) = \left(\lambda^{-1} + \int L_v\phi dv\right)^{-1}$, is constant over time.

The R&D race takes place in an interval of length Δ such that $z(R, L_v, q) \equiv P_s(R, L_v, q)/\Delta$. As stated in the text, we assume that when two or more labs merge, they split the gains from innovating in proportion of the patents they hold. Consequently, free entry in the R&D sector implies

$$z(R,L,q)\frac{\sum_{p=1}^{R}\binom{R}{p}L^{-p}(1-1/L)^{R-p}p}{R}V_N(1+\lambda(R,L)^R,0) - \phi = 0 \tag{39}$$

Where $\binom{R}{p}L^{-p}(1-1/L)^{R-p}$ is the Binomial probability that a lab holds p patents out of R when an innovation realizes, in which case the gain is $(P/R)\times V_N(1+\lambda(R,L)^R,0)$. The first term in the free entry condition is the expected gain from innovating, and the second is the fixed cost of running a lab.

To the extent that all the terms in the free entry condition are independent of time and sector, so must be $L_v(t) = L$. This confirms our guess that $z = z(R, L_v(t), q)$ is constant along the BGP.

A.4 Proof of Lemma 6

Let $W \equiv \int_0^1 U_h dh$ be social welfare. From (3), along the BGP,

$$\begin{aligned} \int_0^1 \ln u_h(t)dh &= \int_0^1 \ln c_h(t)dh - \ln\lambda + \ln Q(t) \\ &= \int_0^1 \ln c_h(0) - \frac{\eta+z}{\eta}\ln\lambda + \ln Q_N(t) \\ &= \ln\tilde{a}(0) + \ln c(0) - \frac{\eta+z}{\eta}\ln\lambda + \ln Q_N(0) + tz\ln\lambda \end{aligned} \tag{40}$$

where $\ln\tilde{a}(0) \equiv \int_0^1 \ln\left(\frac{c_h(0)}{c(0)}\right) dh$ is a measure of consumption dispersion which directly relates to inequalities in initial asset holdings. Therefore, it follows from integrating

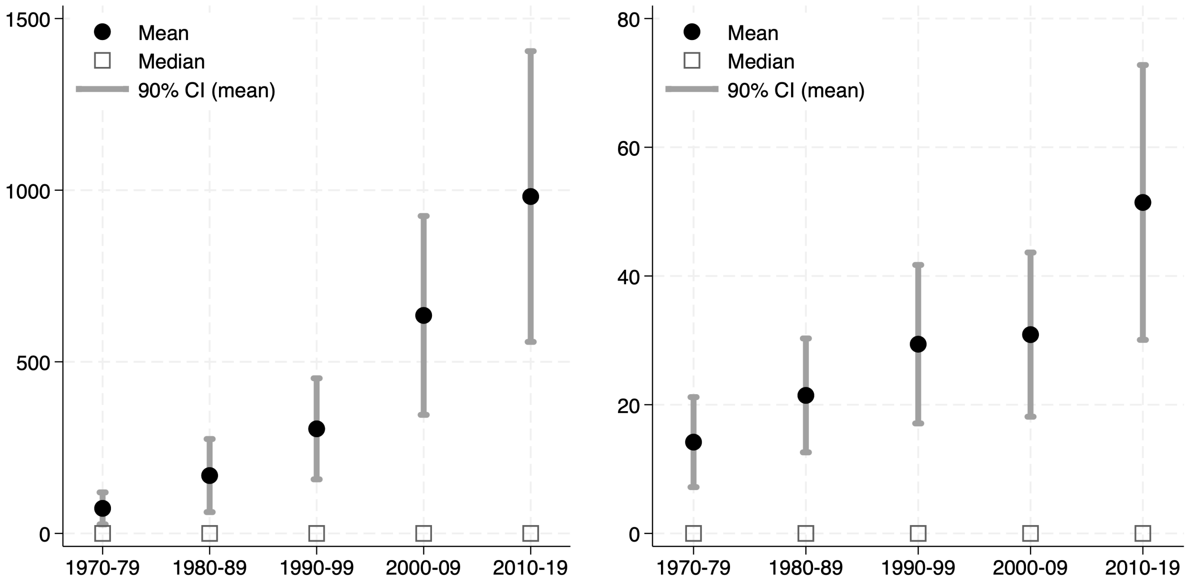
$$\rho W = \ln\tilde{a}(0) + \ln c(0) - \frac{\eta+z}{\eta}\ln\lambda + \ln Q_N(0) + \frac{z}{\rho}\ln\lambda \tag{41}$$

Online Appendix

(Not for publication)

B Complementary Trends

Figure 8: Patents at first time leadership

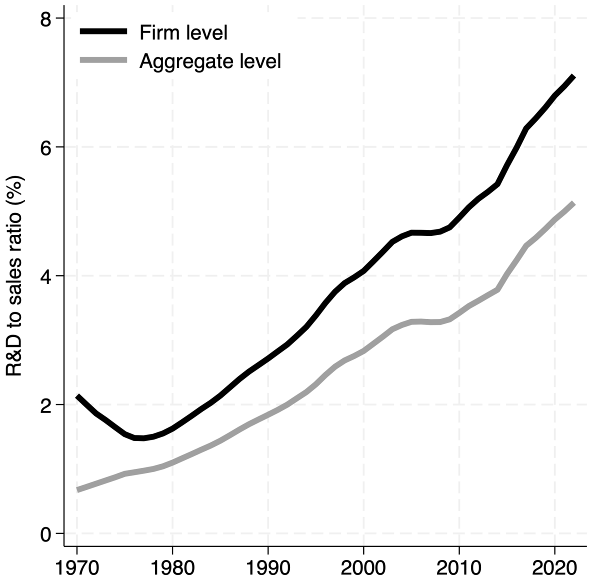


(a) Total patent value at first leadership (Million 1982 dollars)

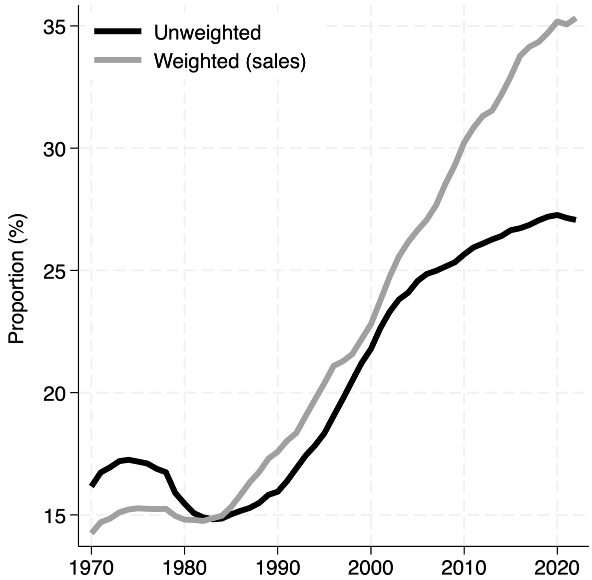
(b) Number of patents at first leadership

Notes: Average and median total value (panel 8a) and number (panel 8b) of patents in the year when a firm becomes a leader for the first time. Patent data from KPSS (2017). Unweighted statistics, winsorized at the top 1%.

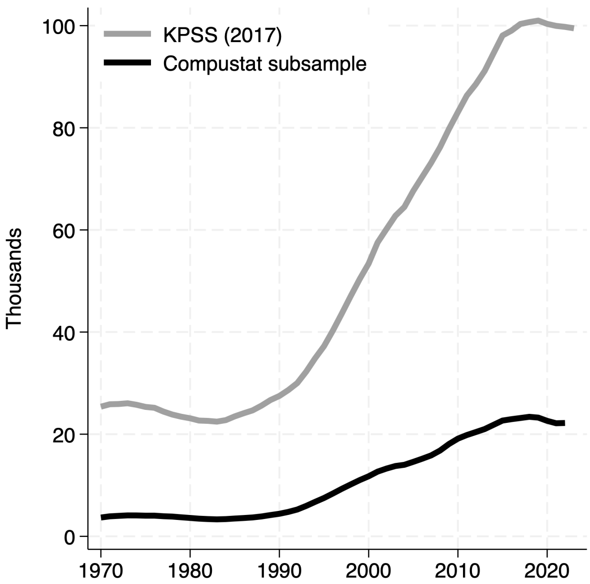
Figure 9: Trends in R&D expenditure and patents (excluding leaders)



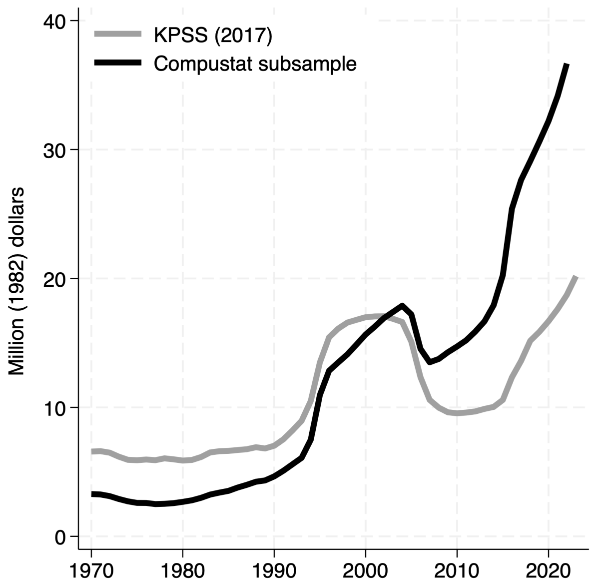
(a) R&D expenditure



(b) Patenting firms



(c) New patents



(d) Av. patent value

Notes: All panels display 10-year moving averages and exclude market leaders (excepted for KPSS2017). Panel 4a: Ratio of firm R&D expenses (xrd variable in Compustat) to sales for each firm in the Compustat dataset (black line), yearly averages weighted by firm sales. The grey line is the ratio of the sum of R&D expenses to the sum of sales for each year. Panel 4b: Proportion of firms issuing at least one new patent in the year. Yearly averages weighted by firm sales (grey) and unweighted (black). Panel 9b: number of patents in KPSS (2017) and in our subsample of Compustat data. Panel 9b: ratio of total patent value to number of patent, unweighted. Patent data from KPSS (2017).