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What Happened to U.S. Business Dynamism?

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Abstract

In the past several decades, the U.S. economy has witnessed a number of striking trends that indicate a rising market concentration and a slowdown in business dynamism. In this paper, we make an attempt to understand potential common forces behind these empirical regularities through the lens of a micro-founded general equilibrium model of endogenous firm dynamics. Importantly, the theoretical model captures the strategic behavior between competing firms, its effect on their innovation decisions, and the resulting "best versus the rest" dynamics. We focus on multiple potential mechanisms that can potentially drive the observed changes and use the calibrated model to assess the relative importance of these channels with particular attention to the implied transitional dynamics. Our results highlight the dominant role of a decline in the intensity of knowledge diffusion from the frontier firms to the laggard ones in explaining the observed shifts. We conclude by presenting new evidence that corroborates a declining knowledge diffusion in the economy. We document a higher concentration of patenting in the hands of firms with the largest stock and a changing nature of patents, especially in the post-2000 period, which suggests a heavy use of intellectual property protection by market leaders to limit the diffusion of knowledge. These findings present a potential avenue for future research on the drivers of declining knowledge diffusion.

Keywords: Business dynamism, market concentration, competition, knowledge diffusion, step-by-step innovations, transitional dynamics

JEL Classifications: E22, E25, L12, O31, O33, O34

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1 Introduction

Market economies are characterized by the so-called "creative destruction" where unproductive incumbents are pushed out of the market by new entrants or other more productive incumbents or both. A byproduct of this up-or-out process is the creation of higher-paying jobs and reallocation of workers from less to more productive firms. The U.S. economy has been losing this business dynamism since the 1980s and, even more strikingly, since the 2000s. This shift manifests itself in a number of empirical regularities: The entry rate of new businesses, the job reallocation rate, and the labor share have all been decreasing, yet the profit share, market concentration, and markups have all been rising. A growing literature has documented many dramatic empirical trends such as these and initiated a heated debate around the possible reasons behind the declining dynamism in the U.S. economy. We contribute to this important, and predominantly empirical, debate by offering a new micro-founded macro model, conducting a quantitative investigation of alternative mechanisms that could have led to these dynamics, and presenting some new facts on the rise of patenting concentration.

A central concern of our study is the identification of factors that could have driven these observed trends in U.S. business dynamism.[1] During the past 30 years, the U.S. economy has experienced many fundamental changes that might have contributed to these trends shifting the power balance among competing firms toward market leaders. Some of these changes in primitives, which we review in more detail in Appendix A, include reduced effective corporate taxes, increased research and development (R&D) subsidies, increased regulations, and heavier use of intellectual property, which limits the technologies that can be used by competing firms and lowers the effective knowledge diffusion. Incorporating these margins within a realistic theoretical framework, we explore two main quantitative questions based on various thought experiments in this study: First, how are the empirical trends observed since the 1980s linked together? Second, could these trends be driven by changes discussed in this paragraph that shifted the balance of market power?

Our research approach starts by summarizing the observed trends in the data and various changes in the economy that might have led to these trends. This initial discussion directs our attention to a certain class of models. Accordingly, we build a theoretical model that accounts for, in particular, endogenous market power and strategic competition among incumbents and entrants. Next, we calibrate this model to the U.S. economy as if it was in a steady state in 1980 and hit the economy with four alternative shocks to make it enter into alternative transition paths. We then compare the model-generated paths with the actual trends to identify the most powerful shock in explaining all of the observed facts simultaneously. Finally, we calibrate the

[1] We focus on 10 specific trends: (i) market concentration has risen, (ii) average markups have increased, (iii) the profit share of GDP has increased, (iv) he labor share of output has gone down, (v) the rise in market concentration and the fall in labor share are positively associated, (vi) productivity dispersion of firms has risen, (vii) firm entry rate has declined, (viii) the share of young firms in economic activity has declined, (ix) job reallocation has slowed down, and (x) the dispersion of firm growth has decreased. We review them in more detail in Section 2.

transition path of the model economy to reflect the changes that the U.S. economy has been experiencing in the past several decades. We then decompose the contribution of each channel of interest to the model-generated trends in order to quantify their potential importance in driving the empirical regularities that the U.S. economy has been witnessing.

A key advantage of studying 10 empirical trends jointly (as opposed to a smaller subset of them) with the help of a general equilibrium model is to exploit the power of "overidentification." A single empirical fact can potentially be explained by multiple alternative mechanisms; however, multiple empirical facts can (we hope) help us identify one single mechanism that might have led to the observed trends in the United States.

In a recent piece, Syverson (2019) emphasizes that the topic of "market power" has historically been studied mostly by micro industrial organization literature, which focused its attention on specific industries. While he welcomes the paradigm shift in macroeconomics toward this topic and its aggregate implications, he explains in detail why the macroeconomic discussion should rely more on microeconomic foundations. In this regard, our goal is to pull the macro and micro literatures closer by building a macro general equilibrium model that draws heavily on an early industrial organization literature that investigated the competition dynamics among incumbent firms in a winner-take-all race (e.g., Harris and Vickers, 1985, 1987; Budd et al., 1993). In the typical framework, two players race for a prize, and players exert different efforts depending on their own position relative to their competitors. A fruitful branch of endogenous growth literature has introduced these partial equilibrium models into a macro general equilibrium setting in order to study various aspects of product market competition with strategic interaction between competing firms (e.g., Aghion et al., 1997, 2001, 2005; Acemoglu and Akcigit, 2012; Akcigit et al., 2018). In a recent review of declining business dynamism, we consider a framework along these lines (Akcigit and Ates, 2019). The study presents a first-step discussion of the theoretical predictions of the standard model in comparison with the empirical evidence. In this paper, we extend the standard framework to have a richer setting suitable for quantitative analysis.

Similar to these studies, our theoretical framework centers on an economy that consists of many sectors. In each sector, two incumbent firms, which can also be interpreted as *the best* and *the rest*, compete à la Bertrand for market leadership. This competitive structure forces market leaders to post a limit price; hence, the mark-ups evolve endogenously as a function of the technology gap between firms. Market leaders try to innovate in order to open up the lead and increase their markups and profits. Follower firms try to innovate with the hope of eventually leapfrogging the market leader and gaining market power. Likewise, new firms attempt to enter the economy with the *hope* of becoming a market leader some day. A very important aspect of the model is the strategic innovation investment by the firms: Intense competition among firms, especially when the competitors are in a neck-and-neck position in terms of their productivity levels, induces more aggressive innovation investment and more business dynamism. Yet when the leaders open up their technological lead, followers lose their hope of leapfrogging the leader and lower their innovation effort. Likewise, entrants get discouraged when the markets are overwhelmingly dominated by the market leader, and the entry rate decreases.

Our structural model allows us to primarily analyze four important margins that shape the competition dynamics. First, corporate taxes affect profits and the return to being the market leader. Second, the government supports incumbents' productivity-enhancing investments through R&D subsidies. Third, the level of entry costs affect the incentives of potential new entrants. Finally, the amount of knowledge diffusion in the economy allows followers to copy the market leaders and remain close to them. Incidentally, the U.S. economy has observed significant changes along all of these margins in the past several decades. Changes in these four margins have different implications as to how competition and business dynamism evolve over time in our model. Thus, our model allows us to run a horse race between these important channels and ascertain which one(s) among them has greater power in explaining the observed empirical trends in the U.S. economy.

We calibrate the model to pre-1980 moments in the data as if the U.S. economy was in a steady state. We then conduct two sets of experiments. The first set of experiments focuses on each of the four channels *individually*, illustrating the potential of each channel in generating observed empirical trends. For instance, we implement a large drop in the effective corporate tax rates between 1980 and 2010 and compare the model-simulated transition paths with all post-1980 empirical trends. We repeat this analysis with all four channels described previously. The second set of experiments matches the transition path of the model to the transitional dynamics of the U.S. economy, allowing all four channels to move *jointly*, and then quantifies their individual contributions. Both sets of exercises indicate that, even though each channel can have some effect at different levels, *reduction in knowledge diffusion* between 1980 and 2010 is the most powerful force in driving all of the observed trends simultaneously. For instance, while each of the remaining channels can rarely account for more than 10 percent of the observed trends, the knowledge diffusion channel accounts for more than 70 percent of most symptoms of declining business dynamism and at least 50 percent of all considered trends.

Reduction in knowledge diffusion is able to account for these trends as follows. When knowledge diffusion slows down over time, as a direct effect, market leaders are shielded from being copied, which helps them establish stronger market power. When market leaders have a bigger lead over their rivals, the followers get discouraged; hence, they slow down. The productivity gap between leaders and followers opens up. The first implication of this widening is that market composition shifts to more concentrated sectors. Second, limit pricing allows stronger leaders (leaders further ahead) to charge higher markups, which also increases the profit share and decreases the labor share of gross domestic product (GDP). Since entrants are forward looking, they observe the strengthening of incumbents and get discouraged; therefore, entry goes down. Discouraged followers and entrants lower the competitive pressure on the market leader: When they face less threat, market leaders relax and they experiment less. Hence, overall dynamism and experimentation decrease in the economy.

Although the main goal of this paper is positive rather than normative, we also discuss briefly the welfare implications of market concentration within the framework of our model. An interesting observation is that lower market concentration is not always welfare enhancing. In cases when the knowledge diffusion is high and competition is too fierce, weighing on leader firms' innovation incentives, a lower level of knowledge diffusion can improve aggregate innovation and welfare. However, our quantitative results indicate that in the calibrated baseline economy, a higher rate of knowledge diffusion is unequivocally welfare improving, implying that the baseline diffusion rate is inadequate from a welfare perspective.

We conclude our quantitative analysis with various robustness exercises and discuss some model extensions. We also elaborate on three additional channels—a decline in the interest rate, a fall in research productivity, and a decrease in workers' market power relative to employers/firms—whose potential links to some of the observed trends considered here have recently drawn the attention of the literature. We assess the potential of these channels in jointly accounting for the empirical trends under consideration and show that each one of them leads to some counterfactual response in a number of margins.

As a cautious remark, our results do not mean, and are far from implying, that the decline in knowledge diffusion is the only driver of the observed trends. Indeed, each empirical trend might have its own leading factors, and those factors may be different than the ones studied here. However, our analysis instead shows that among the mechanisms we consider—changes in corporate taxation, government support for incumbents, increased regulatory burden, and reduced knowledge diffusion (potentially due to anticompetitive use of intellectual property)—the last one stands out as a powerful force when 10 empirical facts are considered together. Therefore, our results stress the importance of future research to understand the underlying reasons for slower knowledge diffusion. To this end, we conclude our study by presenting some brand-new, striking trends on the increased concentration of patents through both their production and purchase by market leaders, as well as on the strategic use of patents, especially since the early 2000s. We hope that these findings ignite a broader conversation in the literature.

The rest of the paper is organized as follows. Section 2 reviews the literature; it also revisits the empirical trends that the literature has interpreted as the signs of declining business dynamism. After presenting the empirical evidence that motivates the theory, Section 3 introduces the theoretical model, and Section 4 describes its calibration. Sections 5 and 6 present the experiments that identify and quantify the importance of each margin using the calibrated model. Section 7 discusses the welfare implications. Section 8 presents robustness exercises, discusses model extensions, and investigates the implications of additional channels with regard to observed empirical trends. Section 9 provides some new empirical facts on the distribution of the use of intellectual property in the U.S. economy, which could shed some light on the reason why knowledge diffusion has slowed down over time. Section 10 concludes.

2 Empirical Regularities and Literature Review

While the contribution of our work is mainly quantitative, it draws heavily on empirical work in the literature. Therefore, in this section, we first review the findings of this literature. To summarize, we focus on the following empirical regularities:

1. Market concentration has risen.
2. Average markups have increased.
3. The profit share of GDP has increased.
4. The labor share of output has gone down.
5. The rise in market concentration and the fall in labor share are positively associated.
6. Productivity dispersion of firms has risen. Similarly, the labor productivity gap between frontier and laggard firms has widened.
7. Firm entry rate has declined.
8. The share of young firms in economic activity has declined.
9. Job reallocation has slowed down.
10. The dispersion of firm growth has decreased.

Next, we will briefly discuss the mechanisms the literature has proposed to explain these regularities. We refer the interested reader to Akcigit and Ates (2019) for a more extensive review.

To start, a set of recent papers document an increasing market concentration in the United States (Fact 1; see Furman and Giuliano, 2016; Autor et al., 2017a,b; Barkai, 2017; Grullon et al., 2017; and Gutiérrez and Philippon, 2016, 2017, among others).[2] Second, several recent studies show an increase in average markups (Fact 2; see Nekarda and Ramey, 2013; De Loecker and Eeckhout, 2017; Gutiérrez and Philippon, 2017; Eggertsson et al., 2018; and Hall, 2018, among others).[3] Relatedly, a subset of these studies also highlight an increase in the aggregate profit share (Fact 3). These findings drew considerable attention from both academic and policy circles, as they likely indicate an increase in firms' market power and a decline in industry competition. For instance, Gutiérrez and Philippon (2016) argue that increased industry concentration drives the weak investment performance of U.S. firms via a decline in competition. Eggertsson et al. (2018) and Farhi and Gourio (2018) argue that increased market power can help explain several macro-finance regularities, with Eggertsson et al. (2018) also emphasizing persistently low interest rates. Liu et al. (2019) also focus on the role of low interest rates as a culprit of rising market concentration and declining business dynamism.[4] Barkai (2017) claims that higher concentration

[2] Bajgar et al. (2019) and Kalemli-Ozcan et al. (2019) document similar patterns for European countries as well, focusing on consolidated firm accounts.

[3] Calligaris et al. (2018) and De Loecker and Eeckhout (2018) document similar patterns for various other countries as well.

[4] We discuss the effects of declining interest rates further in Section 8.1.

is associated with lower competition and results in a declining factor income of labor. However, it is worth noting that higher market concentration may not necessarily imply higher market power of firms (Syverson, 2004a,b). In fact, Autor et al. (2017b) and Bessen (2017) contend that higher market concentration is a result of higher market competition and the rise of more productive firms.[5] Bessen (2017) documents that sales concentration is strongly correlated with the use of information and communication technologies at the industry level. In a similar vein, Crouzet and Eberly (2018) observe that at the industry level, the firms with the largest size and highest growth rate are the ones whose investment in intangible capital grows the fastest.[6]

The fourth regularity that we include in our analysis is the secular decline in the aggregate labor share of GDP in the United States (Fact 4; see Karabarbounis and Neiman, 2013; Elsby et al., 2013; and Lawrence, 2015). The literature has proposed a variety of explanations for this decline, including increased offshoring or foreign sourcing of inputs (Elsby et al., 2013, and Boehm et al., 2017); a fall in corporate tax rates (Kaymak and Schott, 2018); a slowdown in population growth (Hopenhayn et al., 2018); a slowdown in productivity growth (Grossman et al., 2017); higher prevalence of robots in production and replacement of production workers by automated machinery (Acemoglu and Restrepo, 2017); and declining competition due to increased market concentration (Barkai, 2017). Autor et al. (2017b) also consider higher market concentration as a driver of declining labor share but relate it to the emergence of winner-take-all dynamics in many industries with a rise of "superstar" firms.[7] They highlight the positive industry–level relationship between the rise in concentration and the fall of labor share, another regularity we consider in this paper (Fact 5). In a recent study, Aghion et al. (2019) also focus on this relationship in an endogenous growth model à la Klette and Kortum (2004), extending the model to zero in on the relocation of activity between incumbent firms (abstracting from firm entry) across balanced growth paths.[8]

We also consider some facts that suggest a decline in business dynamism. First, the productivity dispersion has increased in the United States, as shown by Decker et al. (2018). Similarly, Andrews et al. (2015, 2016) establish that, across the OECD economies, the gap between the average productivity levels of frontier firms (top 5 percent of firms with the highest productivity) and the laggard ones has been widening, suggesting the rise of "best versus the rest" dynamics, a relationship captured by the market structure of our theoretical model (Fact 6). Second, there

[5]While most of these papers analyze industries at the national level, Rossi-Hansberg et al. (2018) find that, for several industries, the increase in market concentration at the national level coincides with a decline in concentration at the local level, raising the question of the "relevant" market. Some policymakers bring forward similar critiques based on the definition of relevant markets (see OECD, 2018b, by the U.S. delegation and OECD, 2018a).

[6]Gutiérrez and Philippon (2019) also note that the two explanations—rising market power and decreasing competition versus the rise of more efficient "superstar" firms—do not necessarily describe mutually exclusive stories in that leaders can become more efficient while using this advantage to also become "more entrenched."

[7] Diez et al. (2018) also find support for the superstar-firm argument in an international comparison using multi-country firm-level data. However, recent work by Gutiérrez and Philippon (2019) argues that the superstar firms have been losing their share in economic activity in the United States, especially in the post-2000 period.

[8]Using a similar setting, De Ridder (2019) shows that the effect of an increase in firms' efficiency of technology adoption can depress aggregate innovation in a balanced growth path while increasing market power of firms.

has been a secular decline in firm (and establishment) entry rates in the United States in the past several decades (Fact 7; see Decker et al., 2016b; Gourio et al., 2014; and Karahan et al., 2016). Likewise, the employment share of young firms has also been declining steadily (Fact 8; see Decker et al., 2016b, and Furman and Orszag, 2018), which is particularly worrying given the disproportionate contribution of high-growth young firms to job creation (Bravo-Biosca et al., 2013, and Haltiwanger et al., 2013). Decker et al. (2016a) also provide two additional regularities—namely, the decline in the gross job reallocation rate (Fact 9) and the fall in the dispersion of firm growth rates (Fact 10). The authors claim that these observations are driven by the shrinking contribution of high-growth young firms to economic activity, which in turn they attribute to the declining responsiveness of firms to idiosyncratic productivity shocks. Pugsley et al. (2018) argue that the fall in rapid-growth young firms (gazelles) is due to a structural shift in the ex-ante heterogeneity of firms in the United States, with a decline in the prevalence of high-potential firms. Emphasizing the effects of the Great Recession, Davis and Haltiwanger (2019) highlight the role of housing market cycles and credit conditions in the decline of young firm activity.

Our investigation finds that a decline in knowledge diffusion explains the large set of trends in the data. The widening productivity gap between frontier and laggard firms, as illustrated by Andrews et al. (2016), may be indicative of a distortion in the flow of knowledge between these firms. The authors stress that digitalization and the increasing reliance of production processes on tacit knowledge may disproportionately benefit frontier firms in ways that cannot be easily incorporated by laggard firms. Thus, the changing nature of technologies and the increasing importance of tacit knowledge in the form of big and proprietary data could limit spillovers from frontier to laggard firms. For instance, data-dependent production processes could generate data-network effects—more data helps an incumbent firm serve customers better, thus attracting more customers, which in turn generates more data that improve services, which in turn entices more customers—that put large and established firms that produce large databases in an advantageous position (The Economist, 2017). Indeed, Calligaris et al. (2018) find that markup differences between frontier and laggard firms are the highest in digitally-intensive sectors. These dynamics resonate also with the findings of Grullon et al. (2017) that U.S. firms in the most concentrated industries hold the largest and relatively more valuable patent portfolios.

Regulations are another factor that could hamper technology diffusion between frontier and laggard firms. In this regard, anticompetitive effects of weak antitrust laws and enforcement have been raised as a concern (Grullon et al., 2017). Indeed, a strand in the law literature emphasizes the paradigm shift in the application of antitrust laws in a direction that underlines product market efficiency rather than size-based concentration in the interpretation of laws (Baker, 2012; Khan, 2016; Lynn, 2010). Lower antitrust enforcement and increased consolidation could harm the competitive dynamics of the market. For instance, Cunningham et al. (2018) underscore the "killer acquisitions" in the pharmaceutical industry, preemptive mergers to buy out a potential future competitor. Such consolidation may cause large firms to focus on defending their stakes rather than investing in productive activity, limiting the potential flow of knowledge to follower firms and its productive use by them. Bessen (2016) observes that rent-seeking and lobbying activity have gained traction in the United States in the post-2000 period. These arguments resonate with the findings of Andrews et al. (2016), who claim that the lack of pro-competitive product market reforms has contributed to the widening productivity gap between frontier and laggard firms across the OECD countries.

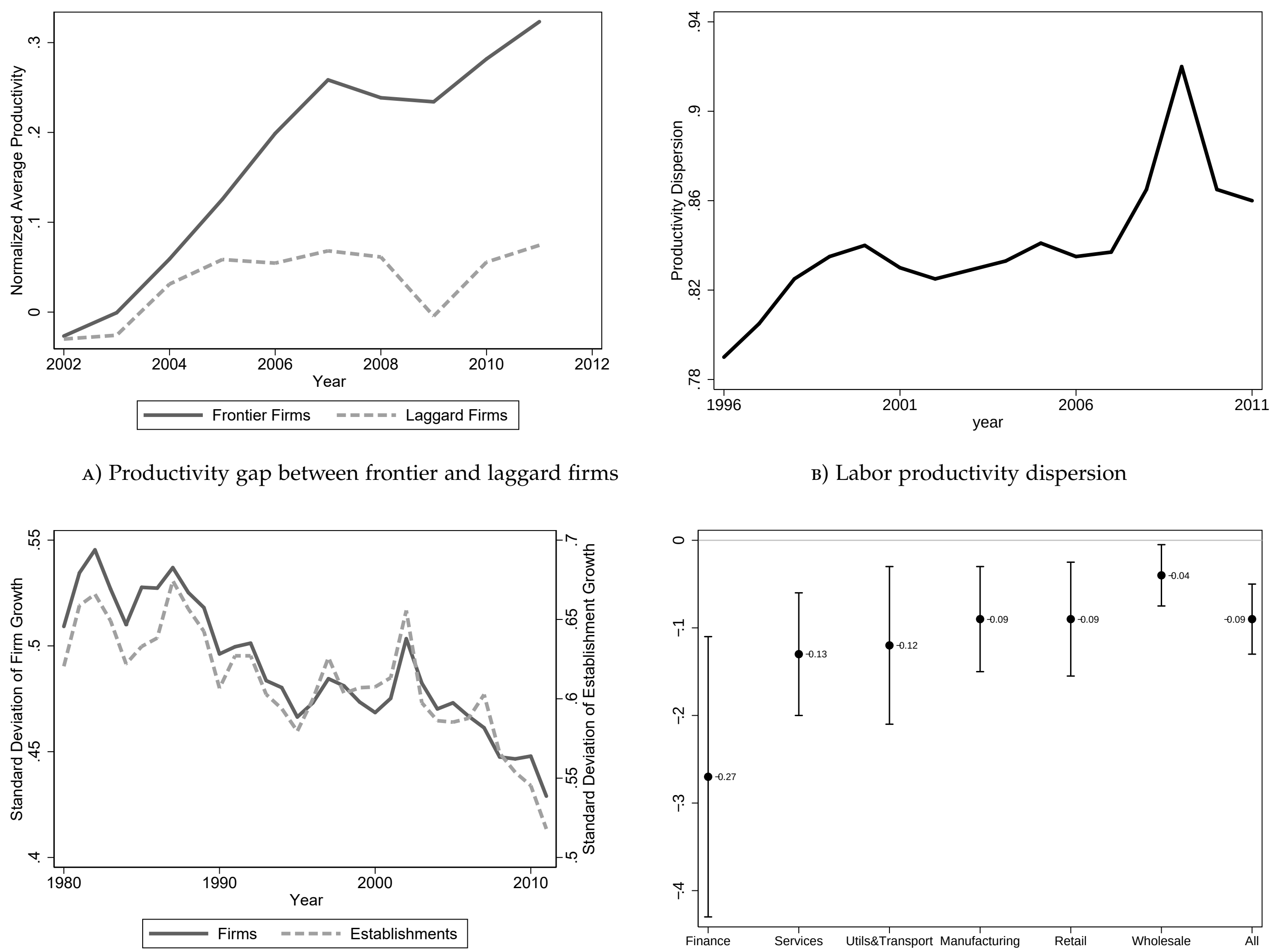
To sum up briefly, our study takes a holistic approach to account for all of the empirical trends mentioned in this section. We analyze shifts in market power and business dynamics jointly as endogenous market outcomes through the lens of a structural model instead of taking them as "market primitives" as criticized by Syverson (2019). Moreover, our quantitative analysis, carefully accounting for transitional dynamics, evaluates the strength of potential channels that could have contributed to the observed changes and underscores the dominant role played by the knowledge diffusion margin. Finally, we advance the debate on market concentration and business dynamism by presenting new evidence from patent data that highlights changing concentration patterns.

3 Model

This section presents a closed-economy endogenous growth model of strategic interaction and innovation in which firms compete over the ownership of intermediate-good production. The economy is composed of a continuum of intermediate goods that are inputs in the production of the final good, which is in turn consumed by the representative households. In each intermediate product line, two active incumbent firms engage in Bertrand price competition to obtain a monopoly of production. Intermediate firms produce using labor and are heterogeneous in their productivity and thus in the marginal cost of production. Firms invest in cost-saving innovative activity to improve their productivity in the spirit of step-by-step models, which allows for heterogeneous technological gaps between competitors. An appealing feature of the model is that, combined with optimal limit pricing that stems from Bertrand competition, different relative productivity levels generate a distribution over heterogeneous markup levels. In addition, there is an outside pool of entrants that engage in research activity to enter the market by replacing the technological follower in a particular line.

Among several channels that affect firm incentives in our model, we include a probability of exogenous technology spillovers that, once realized, allow a technological laggard firm to close the gap with the frontier. This channel governs the knowledge diffusion between the technological frontier and the follower, one of the main channels that we consider in our quantitative investigation as potential drivers of the declining business dynamism in the United States. In the model, the implications of these potential factors hinge on their effect on the distribution of firms across relative technology levels and the resulting transitional dynamics, whose law of motions we describe in this section.

Before the details of the model are provided, a discussion of the empirical evidence that guides our modeling choice is in order. The top panels of Figure 1 show that the dispersion of productivity levels is rising, with Panel 1a illustrating the widening of productivity between frontier and laggard firms across OECD countries, while Panel 1b makes a similar case for the U.S. manufacturing industry. Perhaps puzzlingly, however, the dispersion of firm growth rates has been declining simultaneously, as shown in Panel 1c. The theoretical model we build here reflects this relationship through the endogenous strategic behavior of firms in response to their technological position relative to their competitors. A widening of the gap (higher productivity dispersion) results in lower innovation incentives (and a declining growth dispersion) through two channels: (i) a discouragement effect on the follower that falls further behind and (ii) a diminishing escape competition effect on the leader as it opens the technology gap. Moreover,



a) Productivity gap between frontier and laggard firms

b) Labor productivity dispersion

c) Dispersion of firm growth

d) Correlation between changes in concentration and labor share

Figure 1: Empirical Trends That Inform the Theory

Notes: Panel 1a is taken from Andrews et al. (2016), Panel 1b from Decker et al. (2018), Panel 1c from Decker et al. (2016b), and Panel 1d from Autor et al. (2017b).

Panel 1d suggests a negative correlation between concentration and labor share at the industry level. Our theoretical model reflects this relationship through the shift of production to more productive frontier firms as the technology gap between them and the laggards opens up. In sum, the endogenous competition structure of our framework helps us speak to salient features of changing business dynamism in the United States. Now we present the model details.

3.1 Preferences

We consider the following continuous-time economy. In this environment, there is a representative consumer that derives logarithmic utility from consumption:

$$U_t = \int_t^\infty \exp\left(-\rho\left(s-t\right)\right)\ln C_s \, ds,$$

where C_t represents consumption at time t and $\rho > 0$ is the discount rate. The budget constraint of the representative consumer reads as

$$C_t + \dot{A}_t = w_t L_t + r_t A_t + G_t,$$

where L_t denotes labor (supplied inelastically), A_t denotes total assets, and G_t denotes lump-sum taxes levied or transfers distributed by the government. We normalize labor supply such that $L_t = 1$. The relevant prices are the interest rate r_t, the wage rate w_t, and the price of the consumption good P_t, which we take to be the numeraire. Because households own the firms in the economy, the asset market clearing condition implies that the total assets A_t equal the sum of firm values, i.e., $A_t = \int_{\mathcal{F}} V_{ft} \, df$ with $\mathcal{F}$ denoting the measure of firms.

3.2 Technology and Market Structure

3.2.1 Final Good

The final good, which is used for consumption, is produced in perfectly competitive markets according to the following production technology:

$$\ln Y_t = \int_0^1 \ln y_{jt} \, dj, \tag{1}$$

where y_{jt} denotes the amount of intermediate variety $j \in [0,1]$ used at time t. Each variety is produced by a monopolist, which we describe next.

3.2.2 Intermediate Goods and Innovation

Incumbents. In each product line j, two incumbent firms $i = \{1,2\}$ produce two perfectly substitutable varieties of intermediate good j according to a linear production technology:

$$y_{ijt} = q_{ijt} l_{ijt},$$

where l_{ijt} denotes the labor employed and q_{ijt} is the associated labor productivity of firm i. The total industry output is given by $y_{jt} = y_{ijt} + y_{-ijt}$, where $-i$ denotes the competitor of firm i with $-i = \{1,2\}$ and $-i \neq i$. The intermediate-good firms compete for market leadership à la Bertrand. As a result, the firm that has a higher labor productivity obtains a cost advantage and therefore captures the whole market to supply the intermediate good j. We call a firm i the market leader (follower) in j if $q_{ij} > q_{-ij}$ ($q_{ij} < q_{-ij}$). Firms are neck-and-neck if $q_{ij} = q_{-ij}$. We normalize initial productivity levels to unity such that $q_{ij0} = 1$.

Firms' productivity evolves through successive innovations. When a leader innovates between t and $t + \Delta t$, its productivity level improves proportionally by a factor $\lambda > 1$ such that $q_{ij(t+\Delta t)} = \lambda q_{ijt}$. By contrast, an innovation by a follower may be an incremental or drastic one. With probability $(1-\phi)$, the follower's innovation improves its productivity proportionally by λ, as in the case of leader innovation—a process called *slow catch-up* (see Acemoglu and Akcigit, 2012). With probability ϕ, a follower can incidentally come up with an innovation that brings about a drastic improvement in productivity, allowing the follower to close the gap with the leader—a process called *quick catch-up*.

Another source of quick catch-up is the flow of knowledge between competitors. In particular, we assume that quick catch-up can also occur at an exogenous Poisson flow rate δ. In this case, the follower can replicate the frontier technology and catch up with the leader. In a sense, this exogenous catch-up probability reflects the degree to which followers can learn from the technology frontier, capturing, in essence, spillovers from the "best" to "rest" of the firms. Therefore, we label δ as the "knowledge diffusion" parameter.

In each product line, the leader and the follower are separated by a certain number of technology gaps, which reflect the difference between the total number of technology rungs these firms' productivities build on. Specifically, suppose that, in line j, firm i's productivity level reflects n_{ijt} past improvements. Then the relative productivity level is given by

$$\frac{q_{ijt}}{q_{-ijt}} = \frac{\lambda^{n_{ijt}}}{\lambda^{n_{-ijt}}} = \lambda^{n_{ijt} - n_{-ijt}} \equiv \lambda^{m_{ijt}},$$

where $m_{ijt} \in \mathbb{N}$ defines the technology gap between firm i and the competitor $-i$. We assume that there is a large but exogenously given upper limit in the technology gap, denoted by $\bar{m}$.[9] As will

[9] This innocuous assumption renders the state space finite and enables the computation of the equilibrium.

be clear, m_{ijt} is a sufficient statistic to describe firm-specific payoffs independent of the product line j. Therefore, we will drop industry subscript j whenever $m_{it} \in \{-\bar{m}, ..., 0, ..., \bar{m}\}$ refers to a firm-specific value. Accordingly, when we say the leader is m-steps ahead or, reciprocally, the follower is m-steps behind, we mean that the follower needs to improve its productivity m steps more than the leader to become neck-and-neck. Lastly, we will use the notation $m_{jt} \in \{0, ..., \bar{m}\}$ to denote the technology gap between competitors in sector j. We call sectors with positive gaps ($m_{jt} > 0$) "unleveled" and sectors with no gap ($m_{jt} = 0$) neck-and-neck or "leveled."

Firms invest in R&D to obtain or retain market leadership by improving their productivity. To conduct R&D, firms hire labor. When a firm employs h_{ijt} R&D workers, it generates an innovation with the arrival rate of x_{ijt}. Let R_{ijt} denote the R&D expenditures of firm i in product line j at time t. We consider a convex cost of generating the arrival rate x_{ijt} in the form of

$$R_{ijt} = \alpha \frac{x_{ijt}^{\gamma}}{\gamma} w_t,$$

where γ is the (inverse) elasticity of R&D with respect to R&D workers and w_t denotes the wage rate that prevails in the economy. As a result, the R&D production function is given by $x_{ijt} = \left(\gamma \frac{h_{ijt}}{\alpha}\right)^{\frac{1}{\gamma}}$.

Entrants. Every period, a new entrepreneur in each product line invests in R&D to enter the business. If the entrepreneur generates a successful innovation, it replaces the follower in the product line (or one of the two incumbents with the same probability if it enters a neck-and-neck line).[10] If the innovation attempt fails, the entrant disappears.

Similar to the follower innovation, an entrant innovation may be drastic, with probability $\tilde{\phi}$, allowing it to catch up with the frontier technology.[11] With probability $(1 - \tilde{\phi})$, the innovation is incremental, improving on the productivity level of the existing follower proportionally with step size λ. If the entrant hires $\tilde{h}_{ijt}$ R&D workers, it generates an innovation arrival rate $\tilde{x}_{ijt}$, and the expenditures on R&D investment are given by

$$\tilde{R}_{ijt} = \tilde{\alpha} \frac{\tilde{x}_{ijt}^{\tilde{\gamma}}}{\tilde{\gamma}} w_t.$$

We assume that firms benefit from knowledge diffusion only after they enter the market and engage in perpetual innovative activity. This distinction between entrant and follower firms will highlight the role of distortions to the knowledge flow between frontier and laggard firms in driving business dynamism and, in particular, firm entry, even when no direct negative effect on

[10]The process of entrants replacing the follower or neck-and-neck firms reflects the data where entrants enter the market small and never as large conglomerates.

[11] In the remainder of the discussion, a " ˜ " sign will refer to values that pertain to an entrant.

firm entry is assumed. As we shall see, this margin proves crucial in understanding empirical trends.

In Figure 2, we demonstrate how leadership positions in intermediate product lines evolve as a result of incumbent and entrant innovations.

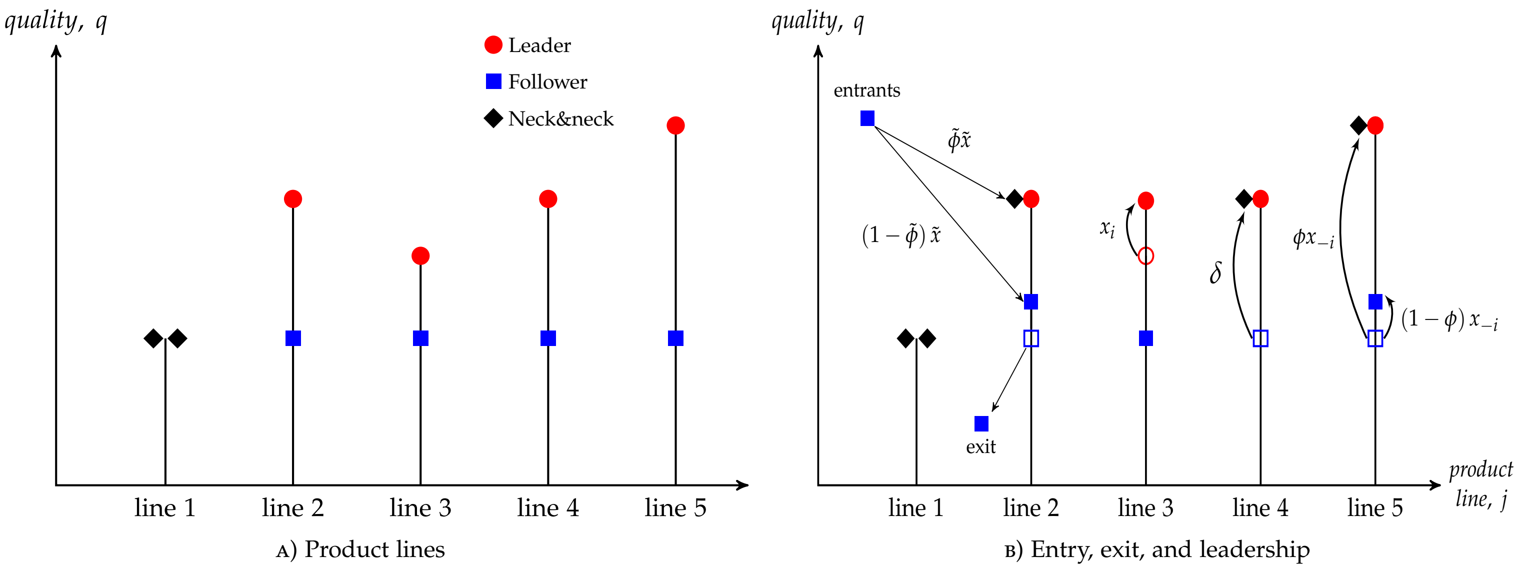


Figure 2: Evolution of product lines

Notes: Panel A exhibits the positions of competing incumbent firms with heterogeneous quality gaps in a set of product lines. Panel B illustrates the effects of innovation by incumbents and entrants as well as knowledge diffusion and the resulting dynamics of entry, exit, and technological leadership. Empty squares or circles denote the previous position of firms that innovate or exit.

The left panel has five product lines with heterogeneous technology gaps. Notice that in line 1, firms are in a neck-and-neck position. The right panel shows the changes in leadership. Line 5 illustrates the two cases associated with a follower innovation: an incremental productivity increase and a drastic one that takes the follower to the neck-and-neck level. Similarly, an entrant can have an incremental or drastic innovation, as shown in line 2, and the entrant drives the previous follower (or one of the neck-and-neck firms if entry is to a leveled sector) out of business. Line 4 illustrates the effect of knowledge diffusion, which enables the follower to close the technology gap. Finally, as shown in line 3, leaders can also innovate and improve their technology lead.

3.3 Equilibrium

In this section, we focus on the Markov Perfect Equilibrium of the model, where the equilibrium strategies depend only on payoff-relevant state variable m_{it}. We start with the description of the static equilibrium and then introduce the details of firm value functions, innovation decisions, and the resulting aggregate dynamics.

Households. Optimal household decisions determine the equilibrium interest rate of the economy. The Euler equation implies

$$r_t = g_t + \rho, \tag{2}$$

where g_t is the growth rate of output.

Final- and Intermediate- Good Production. The optimization of the representative final-good producer generates the following demand schedule for the intermediate good $j \in [0, 1]$:

$$y_{ijt} = \frac{Y_t}{p_{ijt}}, \tag{3}$$

where p_{ijt} is the price of intermediate good j that the monopolist producer i charges. The unit-elastic demand schedule implies that the final-good producer spends an equal amount Y_t on each intermediate good j.

Given the linear production function, an intermediate producer's marginal cost becomes

$$mc_{it} = \frac{w_t}{q_{it}}, \tag{4}$$

which increases in the wage rate and decreases in the firm's labor productivity.[12] Moreover, Bertrand competition leads to limit pricing such that the intermediate producer sets its price to the marginal cost of its competitor:

$$p_{it} = \frac{w_t}{q_{-it}}. \tag{5}$$

Then the optimal equilibrium quantities of the intermediate varieties produced are given as

$$y_{it} = \begin{cases} \frac{q_{-it}}{\omega_t} & \text{if} \quad q_{it} > q_{-it} \\ 0 & \text{if} \quad q_{it} < q_{-it} \end{cases}, \tag{6}$$

where $\omega_t \equiv w_t / Y_t$ denotes the normalized wage level. We assume that in neck-and-neck sectors, i.e., when $q_{it} = q_{-it}$, the production is assigned randomly to both firms. The optimal production employment of the intermediate producer follows as

$$l_{it} = \frac{y_{it}}{q_{it}} = \frac{1}{\omega_t \lambda^{m_{it}}} \quad \text{for} \quad m_{it} \geq 0. \tag{7}$$

The operating profits of the intermediate producer exclusive of R&D expenditures becomes

$$\pi(m_{it}) = (p_{it} - mc_{it})\, y_{it} = \left(1 - \frac{1}{\lambda^{m_{it}}}\right) Y_t \quad \text{for} \quad m_{it} \geq 0, \tag{8}$$

[12] We dropped the subscript j for brevity and will do so in the remainder fo the discussion unless it would cause confusion.

and $\pi(m_{it}) = 0$ otherwise. Similarly, the price–cost markup reads as

$$mk(m_{it}) = \frac{p_{it}}{mc_{it}} - 1 = \lambda^{m_{it}} - 1 \;\text{ for }\; m_{it} \geq 0, \tag{9}$$

and $mk(m_{it}) = 0$ otherwise. Notice that markups, and thus profits, are positive only for market leaders and depend on the technological difference between the leader and the follower. As such, this structure provides a useful ground to analyze the markup dynamics in the economy, which are determined by the distribution of industries across heterogeneous gap differences, which in turn evolve based on firms' endogenous innovation decisions.

3.3.1 Firm Values and Innovation

Incumbents. We denote the stock market value of an incumbent firm in the payoff-relevant state m_{it} at time t by V_{mt} (dropping the subscripts on m for simplicity). Then the value function of a leader that is m-steps ahead is given by

$$\begin{aligned} r_t V_{mt} - \dot{V}_{mt} = \max_{x_{mt}} \Big\{ & (1-\tau_t)\left(1 - \frac{1}{\lambda^m}\right) Y_t - (1-s_t)\,\alpha \frac{x_{mt}^{\gamma}}{\gamma} w_t + x_{mt}\left[V_{m+1t} - V_{mt}\right] \\ & + \left(\phi x_{-mt} + \tilde{\phi}\tilde{x}_{-mt} + \delta\right)\left[V_{0t} - V_{mt}\right] \\ & + \left((1-\phi)\,x_{-mt} + (1-\tilde{\phi})\,\tilde{x}_{-mt}\right)\left[V_{m-1t} - V_{mt}\right]\Big\}. \end{aligned} \tag{10}$$

The first line on the right-hand side of the expression captures the profits net of R&D expenditures, taxed at the corporate income tax rate τ_t. The second term in the first line is the expenditures on R&D, which is subsidized by the government at rate s_t. The last term captures the improvement in a leader's position as a result of successful innovation.[13] As reflected in the second line, if there is a drastic innovation by the follower or by an entrant, or if knowledge diffuses at rate δ, the leader finds itself in a neck-and-neck position. Finally, the last line of the expression captures the case of nondrastic innovation by competitors, in which the position of the leader deteriorates by one step.

Similarly, the value of an m-step follower is defined as

$$\begin{aligned} r_t V_{-mt} - \dot{V}_{-mt} = \max_{x_{-mt}} \Big\{ & -(1-s_t)\,\alpha \frac{x_{-mt}^{\gamma}}{\gamma} w_t + (1-\phi)\,x_{-mt}\left[V_{-m+1t} - V_{-mt}\right] \\ & + \left(\phi x_{-mt} + \delta\right)\left[V_{0t} - V_{-mt}\right] \\ & + x_{mt}\left[V_{-m-1t} - V_{-mt}\right] + \tilde{x}_{-mt}\left[0 - V_{-mt}\right]\Big\}. \end{aligned} \tag{11}$$

Notice that the follower does not produce and, therefore, does not generate any profits. Nevertheless, forward-looking followers invest in R&D with the prospect of taking over the leader

[13] When the $\bar{m}$-step leader innovates, the gap does not increase because of the imposition of an upper limit on the potential size of gaps. As a result, an $\bar{m}$-step leader optimally chooses not to invest in R&D.

through successive innovations and reaping potential profits. Moreover, a drastic innovation and the exogenous catch-up shock can bring them directly to the frontier. When there is successful entry to the product line, the follower exits the market, receiving a continuation value of zero. Finally, the value of a neck-and-neck incumbent is given by[14]

$$r_t V_{0t} - \dot{V}_{0t} = \max_{x_{0t}} \left\{ -\left(1-s_t\right)\alpha \frac{x_{0t}^{\gamma}}{\gamma} w_t + x_{0t}\left[V_{1t} - V_{0t}\right] + x_{0t}\left[V_{-1t} - V_{0t}\right] + \frac{1}{2}\tilde{x}_{0t}\left[0 - V_{0t}\right] \right\}. \quad (12)$$

Before we compute optimal innovation efforts, the next lemma defines the normalized firm values, which render the problem stationary.

Lemma 1 *Define the normalized value v_{mt} such that $V_{mt} = v_{mt} Y_t$. Then, for $m > 0$, v_{mt} is given by*

$$\begin{aligned} \rho v_{mt} - \dot{v}_{mt} = \max_{x_{mt}} \Big\{ & \left(1-\tau_t\right)\left(1 - \frac{1}{\lambda^m}\right) Y_t - \left(1-s_t\right)\alpha \frac{x_{mt}^{\gamma}}{\gamma} w_t + x_{mt}\left[v_{m+1t} - v_{mt}\right] \\ & + \left(\phi x_{-mt} + \tilde{\phi}\tilde{x}_{-mt} + \delta\right)\left[v_{0t} - v_{mt}\right] \\ & + \left(\left(1-\phi\right)x_{-mt} + \left(1-\tilde{\phi}\right)\tilde{x}_{-mt}\right)\left[v_{m-1t} - v_{mt}\right] \Big\}. \end{aligned}$$

Normalized values for $m \leq 0$ are defined reciprocally.

Proof. These normalized values follow directly from using the definition $V_{mt} = v_{mt} Y_t$ and substituting households' Euler condition given in equation (2). ■

The first order conditions of the problems defined earlier yield the following optimal innovation decisions:

$$x_{mt} = \begin{cases} \left[\frac{1}{\alpha(1-s_t)}\left(v_{m+1t} - v_{mt}\right)\right]^{\frac{1}{\gamma-1}} & \text{if } m \geq 0 \\ \left[\frac{1}{\alpha(1-s_t)}\left\{\left(1-\phi\right)v_{m+1t} + \phi v_{0t} - v_{mt}\right\}\right]^{\frac{1}{\gamma-1}} & \text{if } m < 0 \end{cases}. \quad (13)$$

Entrants. Recall that entry is directed at particular product lines, and a successful entrant replaces the follower (or one of the incumbents with an equal probability if entry is to a line in a neck-and-neck state). The problem of an entrant that aims for a product line with an m-step gap is given as

$$\max_{\tilde{x}_{-mt}} \left\{ -\tilde{\alpha}\frac{\tilde{x}_{-mt}^{\tilde{\gamma}}}{\tilde{\gamma}} w_t + \tilde{x}_{-mt}\left[\left(1-\tilde{\phi}\right)V_{-m+1t} + \tilde{\phi}V_{0t} - 0\right] \right\}, \quad (14)$$

[14] Notice that, when there is successful entry, the neck-and-neck incumbent exits with a 1/2 probability because, by assumption, the entrant randomly replaces one of the two incumbents with the same technology.

where $m > 0$.[15] The resulting optimal innovation decisions of entrants are specified as

$$\tilde{x}_{mt} = \begin{cases} \left[\tilde{\alpha}^{-1}\left\{\left(1-\tilde{\phi}\right)v_{m+1t} + \tilde{\phi}v_{0t}\right\}\right]^{\frac{1}{\tilde{\gamma}-1}} & \text{if } m < 0 \\ \left[\tilde{\alpha}^{-1}v_{1t}\right]^{\frac{1}{\tilde{\gamma}-1}} & \text{if } m = 0 \end{cases}. \tag{15}$$

We close the model by specifying aggregate wage and output. To this end, we first define $Q_t \equiv \exp\left(\int_0^1 \ln q_{jt} dj\right)$ as the aggregate productivity index of the economy and $\mu_{mt} \equiv \int_0^1 \mathbb{I}\left\{\left|\log\left(q_{ijt}/q_{-ijt}\right)\right| = m\right\} dj$ as the measure of product lines, where the technological gap between the leader and follower is m steps ($\mathbb{I}\{\cdot\}$ denotes the identity function). Then the final-good production function in equation (1) yields the wage rate as a function of Q_t and μ_{mt}:

$$w_t = Q_t \lambda^{-\sum_{k=0}^{\bar{m}} k\mu_{kt}}. \tag{16}$$

Notice that higher markups suppress the aggregate wage level.

The labor market clearing condition holds at all times, i.e.,

$$1 = \int_0^1 \left[l_{ijt} + l_{-ijt} + h_{ijt} + h_{-ijt} + \tilde{h}_{jt}\right] dj, \tag{17}$$

and implies the following normalized wage ω_t:

$$\omega_t = \left(\sum_{k=0}^{\bar{m}} \mu_{kt}\lambda^{-k}\right)\left[1 - \sum_{k=0}^{\bar{m}} \mu_{kt}\left(\frac{\alpha}{\gamma}\left(x_{kt}^{\gamma} + x_{-kt}^{\gamma}\right) + \frac{\tilde{\alpha}}{\tilde{\gamma}}\tilde{x}_{-kt}^{\tilde{\gamma}}\right)\right]^{-1}. \tag{18}$$

The last expression uses the optimal R&D labor demand schedules

$$h_{ijt} = \frac{\alpha}{\gamma}x_{ijt}^{\gamma} \quad \text{and} \quad \tilde{h}_{jt} = \frac{\tilde{\alpha}}{\tilde{\gamma}}\tilde{x}_{jt}^{\tilde{\gamma}}. \tag{19}$$

Combining equations (16) and (18) gives the level of final output:

$$Y_t = Q_t \lambda^{-\sum_{k=0}^{\bar{m}} k\mu_{kt}} \omega^{-1}. \tag{20}$$

Notice that the final output depends positively on the productivity index and negatively on average markups. It is also inversely related to the labor share, which, in a static sense, depends

[15] The problem of an entrant aiming for a line in a neck-and-neck state is defined similarly, except that any innovation by the entrant improves on the follower only by one step:

$$\max_{\tilde{x}_{0t}} \left\{-\tilde{\alpha}\frac{\tilde{x}_{-mt}^{\tilde{\gamma}}}{\tilde{\gamma}}w_t + \tilde{x}_{0t}\left[V_{1t} - 0\right]\right\}.$$

Because there is no notion of a technology leader in a neck-and-neck state, there is no drastic entrant innovation that allows it to catch up with the technology frontier.

negatively on the average technology gaps—i.e., a shift in the technology gap distribution to larger gaps decreases the labor share statically (see equation 18). In addition, the difference between the government's corporate tax income and subsidy expenditure is given by

$$G_t = \sum_{k=0}^{\bar{m}} \mu_{kt} \left[\tau_t \left(1 - \lambda^{-k}\right) Y_t - s_t \left(\frac{\alpha}{\gamma} x_{kt}^{\gamma} + \frac{\alpha}{\gamma} x_{-kt}^{\gamma} \right) w_t \right], \tag{21}$$

which is distributed back to (collected from) the households in a lump sum when $G_t > 0$ ($G_t < 0$). The aggregate R&D expenditure is specified as

$$R_t = w_t \int_0^1 \left[h_{ijt} + h_{-ijt} + \tilde{h}_{jt} \right] \, dj. \tag{22}$$

Finally, we define the evolution of aggregate productivity and the gap size distribution, which jointly determine the dynamics of the model. The transition path of Q_t is determined by innovations of incumbent firms and entrants that enter neck-and-neck industries, which improve the productivity of workers employed in intermediate-good production:

$$\ln Q_{t+\Delta t} - \ln Q_t = \ln \lambda \left[\mu_{0t} \left(2x_{0t} + \tilde{x}_{0t} \right) + \sum_{k=1}^{\bar{m}} \mu_{kt} x_{kt} \right] \Delta t + o\left(\Delta t\right), \tag{23}$$

which also defines the aggregate growth rate in the balanced growth path (BGP). Here, $o\left(\Delta t\right)$ represents second-order terms, which captures the probability of two or more innovations within the interval Δt.[16] The transition of μ_{mt} for $\bar{m} > m > 1$ is as follows:

$$\begin{aligned} \frac{\mu_{mt+\Delta t} - \mu_{mt}}{\Delta t} = \;& x_{m-1t}\mu_{m-1t} + \left(\left(1-\phi\right) x_{-m-1t} + \left(1-\tilde{\phi}\right) \tilde{x}_{-m-1t} \right) \mu_{m+1t} \\ & - \left(x_{mt} + x_{-mt} + \tilde{x}_{-mt} + \delta \right) \mu_{mt} + o\left(\Delta t\right) / \Delta t. \end{aligned} \tag{24}$$

Briefly, the first term on the right-hand side represents the additions to the measure due to innovations of leaders at $m-1$. The second term sums the additions of incumbents that were previously at $m+1$ and deteriorated because of incremental innovations by the follower or a new entrant. Finally, the measure of industries at position m shrinks when there is an innovation by incumbents or entrants in those industries or when an exogenous catch-up shock hits, as captured in the second line. For brevity, we leave the expressions for special cases of μ_{mt} with $m = 0$, $m = 1$, and $m = \bar{m}$ to Appendix B.1.

Definition 1 (Equilibrium) *A Markov Perfect Equilibrium in this economy is an allocation*

$$\left\{ r_t, w_t, p_{jt}, y_{jt}, x_{jt}, \tilde{x}_{jt}, h_{jt}, \tilde{h}_{jt}, l_{jt}, R_t, L_t, Y_t, C_t, G_t, Q_t, \left\{ \mu_{mt} \right\}_{m \in \{-\bar{m}, \ldots, \bar{m}\}} \right\}_{j \in [0,1]}^{t \in [0,\infty)}$$

such that (i) the sequence of prices and quantities $\{p_{jt}, y_{jt}\}$ satisfies equations (3)–(5) and maximize the

[16] The term satisfies $\lim_{\Delta t \to 0} o\left(\Delta t\right) / \Delta t = 0$.

operating profits of the incumbent firm in the intermediate-good product line j; (ii) the R&D decisions $\{x_{jt}, \tilde{x}_{jt}\}$ *are defined in equations (13) and (15), and the aggregate R&D expenditure* R_t *is specified in equation* (22); *(iii) the supply of labor* $L = 1$ *is equal to the sum of intermediate-good producers' profit-maximizing production worker demand (given in equation 7) and optimal R&D worker demand (given in equation 19), as in equation* (17); *(iv)* Y_t *is as given in equation (20), and* $C_t = Y_t$; *(v) aggregate wage* w_t *clears the labor markets at every t; (vi) interest rate* r_t *satisfies the households' Euler equation; (vii) the government's tax collection and subsidy expenditure balance obtains* G_t *in equation* (21), *and the government holds a balanced budget at all times once the lump-sum transfers to or taxes from households are accounted for; and (viii)* Q_t *and* $\{\mu_{mt}\}_{m\in\{-\bar{m},\ldots,\bar{m}\}}$ *evolve as specified in equations* (23) *and* (24) *consistent with optimal R&D decisions.*

In our quantitative exploration, we will analyze the implications of four main channels: a decline in corporate tax rates (τ), an increase in R&D subsidy rates (s), an increase in entry costs ($\tilde{\alpha}$), and a decline in knowledge diffusion (δ). In the past several decades, the U.S. business environment has witnessed significant shifts in all of these margins. There has been a decline in the effective corporate tax rate, especially after 2000; federal R&D tax credits were introduced for the first time in 1981; and a web of regulations that are potentially more cumbersome for business entry has rapidly expanded, which we describe in more detail in Appendix A. Moreover, a heavy use of intellectual property protection and a concentration of patenting in the hands of top firms, patterns that we discuss in light of novel empirical evidence in Section 9, likely distorted the flow of knowledge between frontier and follower firms. What is common to these mechanisms is that they can affect firm incentives and the nature of competition in asymmetric ways that favor frontier firms, leading to higher concentration and declining business dynamism eventually. In the following quantitative analysis, we use our structural model to identify and quantify the effects of these likely culprits behind declining business dynamism.

4 Calibration of the Initial Balanced Growth Path

Our ultimate aim in this paper is to quantify the relative importance of some key potential drivers of declining U.S. business dynamism. In particular, as noted previously, we focus on four channels: a decline in corporate income tax rates, an increase in R&D subsidies, an increase in entry costs, and a decline in knowledge diffusion. In our main exercise, we will assume that the model starts from a BGP in 1980 and then replicate the transitional dynamics of the U.S. economy in the post-1980 period to back up the relative variation in each of these margins. Therefore, we will first describe how we determine the initial BGP of the economy, which reflects the average long-term conditions of the U.S. economy in the pre-1980s period. Before doing so, we first introduce the analytical expressions for the model counterparts of the empirical variables on which we focus in our quantitative analysis.

4.1 Model Counterparts of Empirical Variables of Interest

Entry Rate. The firm entry rate is determined by the distribution of sectors across technology gaps and the intensity of entrant innovation aimed at those sectors:

$$entry\ rate_t = \frac{1}{2}\sum_{k=0}^{\bar{m}} \mu_{kt}\tilde{x}_{kt}, \tag{25}$$

where the division by 2 reflects the fact that there are two firms operating in each line.

Labor Share. Labor share of GDP is given by

$$labor\ share_t = \frac{w_t L}{Y_t} = \omega_t.$$

Markups. Average markup level is defined by

$$markup_t = \sum_{k=0}^{\bar{m}} \mu_{kt}\left(\lambda^k - 1\right). \tag{26}$$

Profit Share. Profit share of GDP is given by

$$profit\ share_t = 1 - \omega_t. \tag{27}$$

Concentration. Average sales concentration measured by the Herfindahl-Hirschman Index (HHI) is determined by the share of leveled sectors, where sales are equalized because of Bertrand competition, and the share of unleveled sectors, where the leaders are the sole supplier, i.e.,

$$\begin{aligned} hhi_t &= (1-\mu_{0t}) \times [(100\%)^2 + (0\%)^2] + \mu_{0t} \times [(50\%)^2 + (50\%)^2] \\ &= 0.5 + 0.5\mu_{0t}. \end{aligned} \tag{28}$$

Productivity Gap. The productivity gap between frontier and laggard firms is defined as the difference between the average (log) productivity across leaders and followers. Precisely, define the average productivity across leader firms with an m-step advantage as $\ln Q_{mt} = \int_{\mu_{mt}} \sum_{i=1}^{2} (\ln q_{ijt}) \mathbb{I}\{q_{ijt} > q_{-ijt}\} dj$ and the corresponding measure for the followers as $\ln Q_{-mt} = \int_{\mu_{mt}} \sum_{i=1}^{2} (\ln q_{ijt}) \mathbb{I}\{q_{ijt} < q_{-ijt}\} dj$. Then the economy-wide productivity gap becomes

$$\begin{aligned} productivity\ gap_t &= \sum_{k=1}^{\bar{m}} \left(\ln Q_{mt} - \ln Q_{-mt}\right) \\ &= \sum_{k=1}^{\bar{m}} \mu_{kt} \ln \lambda^k. \end{aligned} \tag{29}$$

Other Variables. The other three variables—employment share of young firms, gross job reallocation, and cross-sectional dispersion of firm growth—cannot be summarized in analytic expressions. We calculate the employment share of young firms by simulation. We compute the gross job reallocation rate including entrant and exiting firms and accounting for both production and R&D workers. We follow Decker et al. (2014) in defining job creation and destruction rates, which in turn are based on the firm-level employment-growth measure proposed by Davis et al. (1996), a metric that takes a value between $[-2, 2]$. We compute the standard deviation of firm growth based on the same formula.

4.2 Data and Identification

The calibrated balanced growth path of our model reflects the state of the U.S. economy before the early 1980s. Eleven structural parameters define this balanced growth path: $\theta \equiv \{\rho, \tau, s, \lambda, \alpha, \tilde{\alpha}, \gamma, \tilde{\gamma}, \phi, \tilde{\phi}, \delta\}$. We set five of these externally. On the household side, we take the time discount parameter $\rho = 5\%$. In combination with the calibrated growth rate of our economy, this rate results in a long-run interest rate of about 6.5%, a reasonable value for the United States (see Cooley and Prescott, 1995). On the firm side, we set the curvature parameter of the R&D production function for incumbents to $\gamma = 1/0.35$, in line with previous work in the literature (Kortum, 1993; Acemoglu and Akcigit, 2012; Acemoglu et al., 2016). We also assume that the entrants' R&D production function has the same curvature value, i.e., $\tilde{\gamma} = \gamma$. Finally, we set the corporate income tax to $\tau = 30\%$, mimicking the effective rate in the United States before the 1980s, and the R&D subsidy rate to $s = 5\%$, using the pre-1981 estimate in Akcigit et al. (2018). The policy parameters are constant along the BGP.

We calibrate the rest of the parameters $\{\lambda, \alpha, \tilde{\alpha}, \phi, \tilde{\phi}, \delta\}$ to a set of six data targets that are informative about the key features of the model. The first target we include is the average annual (utilization-adjusted) total factor productivity (TFP) growth rate obtained from the Federal Reserve Bank of San Francisco's (FRBSF) database (see Fernald, 2012), which helps us discipline the step size λ. To capture the long-run trend, we compute the average over two decades, a period that runs from the early years of the available National Science Foundation data for R&D spending until 1980, which yields our second target. We include the average annual ratio of aggregate R&D spending to GDP to obtain information on the R&D cost scale parameter α. To put discipline on the scale parameter of entrants' R&D cost function $\tilde{\alpha}$, we use the average firm entry rate in the United States, for which the data are available from the U.S. Census Bureau's Business Dynamics Statistics starting only from 1978. The fourth target we include is the average markup, calculated based on De Loecker and Eeckhout (2017) and Eggertsson et al. (2018), which informs the calibration about the exogenous probability of catch-up δ.[17] Notice that in our model economy, average markup depends on the basic step size λ and the distribution of firms

[17] Because these two recent and prominent studies obtain markedly different estimates for average markup in the United States, we take the simple average of their estimates as our markup target in our exercises.

across gaps. Therefore, given λ, the average markup is informative about the shape of the gap distribution, which in turn is closely related to δ because it determines the rate with which product lines switch to the neck-and-neck state. Similarly, we also target the aggregate profit share in the economy, the increase in which will be of interest when we calibrate the transition path of the model. The measure we use for this target is the ratio of before-tax profits (adjusted for inventory valuation and capital consumption) of domestic U.S. corporations to the gross value added, obtained from the NIPA (national income and product accounts) tables maintained by the Bureau of Economic Analysis. Finally, we target the employment share of young firms in the economy, available from Decker et al. (2016b) starting from 1981. This target is informative about the probability of an innovation being drastic, which we take to be the same for both followers and entrants (i.e., $\tilde{\phi} = \phi$). The idea is that drastic innovations allow firms to catch up with the frontier quickly, increasing the chances of capturing the production of an intermediate good and starting to employ production workers. As most entrants start as followers (except the ones that enter a leveled industry), these parameters influence how quickly young firms start producing and thus the employment share of young firms in the economy. In the model, we obtain this moment simulating an economy with 10^4 firms for a long period.

4.3 Parameter Values, the Model Fit and Sensitivity Analysis

Table 1 summarizes the calibrated parameters, and Table 2 presents the fit of the model to data. Despite its parsimonious structure, the model is fairly successful in matching key moments in the data, except for some overestimation in aggregate profit share and markups. The results suggest that the initial condition of the model economy replicates well the state of the U.S. economy before the early 1980s.

Table 1: List of parameter values

Panel A: Externally calibrated			**Panel B: Internally calibrated**		
Parameter	Value	Description	Parameter	Value	Description
ρ	5%	Rate of time preference	λ	1.044	Innovation step size
$\gamma, \tilde{\gamma}$	1/0.35	R&D cost curvature	α	7.179	R&D scale, incumbents
τ	30%	Corporate income tax	$\tilde{\alpha}$	0.075	R&D scale, entrants
s	5%	R&D subsidy	δ	2.78%	Exogenous catch-up
			$\phi = \tilde{\phi}$	4.23%	Drastic innovation prob.

Table D.1 in Appendix D summarizes the percentage change in each calibration moment used in Section 4 in response to a 1 percent change in each calibrated parameter. A few quick takeaways stand out. First, the employment share of young firms is quite sensitive to almost every parameter except the R&D cost scale of incumbent firms. Second, the most sensitive variable to (α) is the aggregate share of R&D in GDP. Third, the aggregate growth rate is exclusively sensitive

Table 2: Model fit

	Moment	Model	Data	Source
M1	TFP growth	1.32%	1.37%	FRBSF
M2	R&D to GDP	2.40%	2.40%	NSF
M3	Firm entry	13.57%	13.55%	BDS
M4	Markup	1.18	1.08	DLE (2017), ERW (2018)
M5	Profit share	10.9%	6%	NIPA
M6	Employment (age<5)	20.11%	18.00%	Decker et al. (2015)

Notes: The moments are averages across to decades prior to 1981 if data are available (M1,M2,M4,M5); if not, they reflect the average over the most recent available years before 1981. As our model does not feature capital in production, the profit share is scaled proportionally such that the aggregate labor and profit shares of GDP add to 1 while their ratio is kept at the actual value in the data. This adjustment reflects the fact that the model lacks physical capital as a productive input. See Section 4.2 for further details regarding the moments.

to the step size (λ). Fourth, while the employment share of young firms is strongly sensitive to the drastic innovation probability (ϕ), the effect of ϕ on other variables is very muted. Lastly, the aggregate profit share is most sensitive to the knowledge diffusion parameter (δ), while markups are also most sensitive to δ, second only to λ. In contrast to the case of ϕ, the effect of δ on other variables relative to its effect on young firms' employment share is also much stronger.

In the next two sections, we use our model to investigate potential mechanisms that may have contributed to the empirical trends discussed in Section 2. We proceed in two steps. In Section 5, we illustrate the implications of variations in the channels of interest by introducing shocks one at a time to the respective parameters governing those channels. This exercise helps us understand the relative ability of different margins to account for the observed empirical trends and the underlying dynamics. In Section 6, we turn to the analysis of the transition path and focus on the joint moves in these margins. In particular, we first replicate the transition path of the U.S. economy in the post-1980 period allowing joint variations in all four channels. Then we quantify the contribution of each individual channel to the model-generated trends (which replicate their data counterparts) by shutting them down one at a time. This exercise provides the main result of our quantitative analysis regarding the culprit behind declining business dynamism.

5 Understanding the Mechanisms in Isolation

In this section, we shock the initial BGP of the model through one parameter at a time and present the responses of model-based variables in order to illustrate the dynamics generated by each channel. Again, these channels are (i) a decline in corporate taxes, (ii) an increase in R&D tax subsidies, (iii) a rise in entry costs, and (iv) a decrease in the rate of knowledge diffusion. A crucial feature of this analysis is that, because our calibration strategy matches the initial BGP to pre-1980 statistics in the data, the BGP does not reflect any precondition with regards to the empirical trends that we analyze later. Therefore, our model-based responses will almost exclusively rely on information that predates the shifts in the U.S. business environment, which we aim at explaining here, with the minimal exceptions clarified later. In other words, the exercise will reflect only minimal information from the observed dynamics of declining business dynamism. Nevertheless, as we shall see next, the response of the model to a decline in the intensity of knowledge diffusion tracks the empirical trends quite closely.

Our approach is to introduce a path of shocks to $\{\tilde{\alpha}_t, \delta_t, \tau_t, s_t\}$ one at a time. We assume that each change takes place over a period of 30 years, accounting for the three decades between 1980 and 2010. We specify the paths of shocks as follows. In the data, the corporate income tax rate decreases from 30% to 20%, and R&D subsidies increase from 5% to 20% (see Section 6.1 for further details). To demonstrate the strengths and weaknesses of these channels, we consider larger moves: a drop to 0 percent for corporate tax rates and a an increase to 50 percent in R&D subsidies in linear fashion.

Because it is difficult to obtain reliable estimates of firm entry costs and the intensity of knowledge diffusion, we determine the size and shape of the changes in these margins by forcing the model-generated response to match the decreasing profile of establishment entry in the data.[18] This exercise implies a 300 percent rise in the entry cost and a 65 percent decline in knowledge diffusion intensity. Figure 3 illustrates the implied time paths of the entry rate in

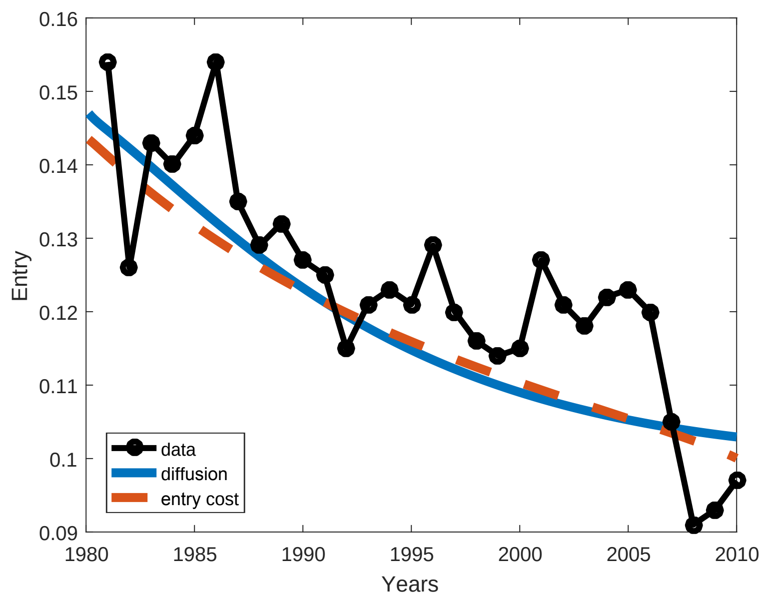


Figure 3: Path of entry rate, model vs. data

Notes: The figure superimposes the observed decline in the entry rate with the model-generated entry paths in the two experiments regarding the entry cost and the knowledge diffusion. In both experiments, the change in the respective channel is disciplined to capture the path of the empirical entry rate.

[18]In the experiments presented in this section, the observed path of entry constitutes the only piece of information that pertains to the transitional dynamics in the data and yet informs our exercise. For the specifics of the computation of the transition path, please see Section 6.1. See Appendix C for the details of the solution algorithm.

these two experiments, superimposed with their counterpart in the data. The figure demonstrates the success of the individual channels in generating the decline in entry observed in the data.

Table 3 summarizes the key qualitative results. It shows the direction of the observed change in each variable (column 1) and compares them with their model counterparts in each experiment. A few observations stand out. First, changes in corporate tax rates (column 2) and R&D subsidies (column 3) fail to generate most trends observed in the data. Second, despite a considerably better performance, the decline in entry cost (column 4) fails to replicate changes in key aspects of the data such as increasing markups. Finally, the intriguing result is that the fall in the knowledge diffusion intensity (column 5) has remarkable success in accounting for most empirical trends. Next, we discuss our findings regarding each channel in more detail.

Table 3: Qualitative experiment results

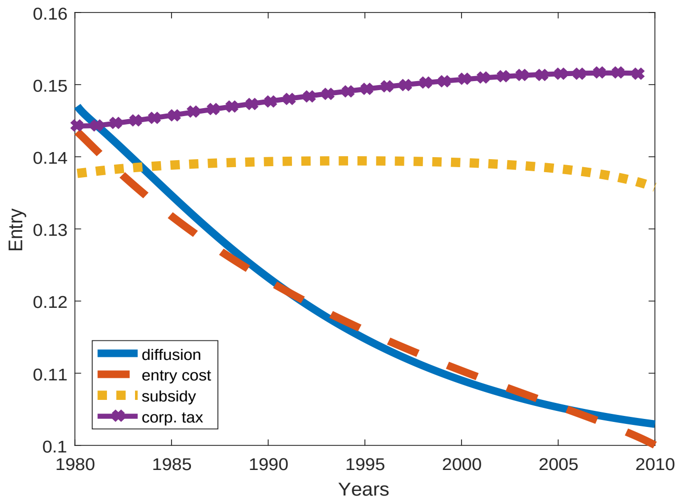
	Data (1)	**Lower corporate tax** (2)	**Higher R&D subsidies** (3)	**Higher entry cost** (4)	**Lower knowledge diffusion** (5)
Concentration	$\uparrow$	$\longleftrightarrow$	$\longleftrightarrow$	$\longleftrightarrow$	$\uparrow$
Markups	$\uparrow$	$\longleftrightarrow$	$\longleftrightarrow$	$\longleftrightarrow$	$\uparrow$
Profit share	$\uparrow$	$\longleftrightarrow$	$\downarrow$	$\longleftrightarrow$	$\uparrow$
Labor share	$\downarrow$	$\longleftrightarrow$	$\uparrow$	$\longleftrightarrow$	$\downarrow$
Entry*	$\downarrow$	$\longleftrightarrow$	$\longleftrightarrow$	$\downarrow$	$\downarrow$
Young firms' empl. share	$\downarrow$	$\longleftrightarrow$	$\downarrow$	$\downarrow$	$\downarrow$
Frontier vs. laggard gap	$\uparrow$	$\longleftrightarrow$	$\longleftrightarrow$	$\longleftrightarrow$	$\uparrow$
Gross job reallocation	$\downarrow$	$\longleftrightarrow$	$\downarrow$	$\longleftrightarrow$	$\downarrow$
Dispersion of firm growth	$\downarrow$	$\downarrow$	$\downarrow$	$\uparrow$	$\downarrow$

Notes: Upward arrows indicate an increase in the variable of interest, downward arrows indicate a decline, and flat arrows indicate no or negligible change. If the absolute magnitude of the response of a variable is less than 20 percent of the actual change in the data, we denote it by a flat arrow.
* In columns 4 and 5, the experiments match the decline in entry by construction (see Figure 3).

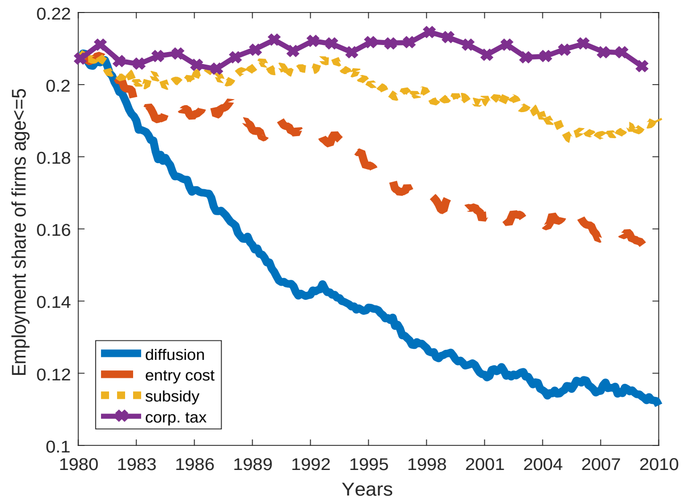
5.1 Decline in Corporate Tax Rates

Figure 4 presents the model-based counterparts of four empirical trends of interest, which we will use to spotlight the differences between patterns that emerge in each experiment. As indicated by crossed purple lines, the effect of the decline in corporate tax rates on most margins is close to nil.[19] Importantly, the response of firm entry is negligible (and positive, if anything), a stark

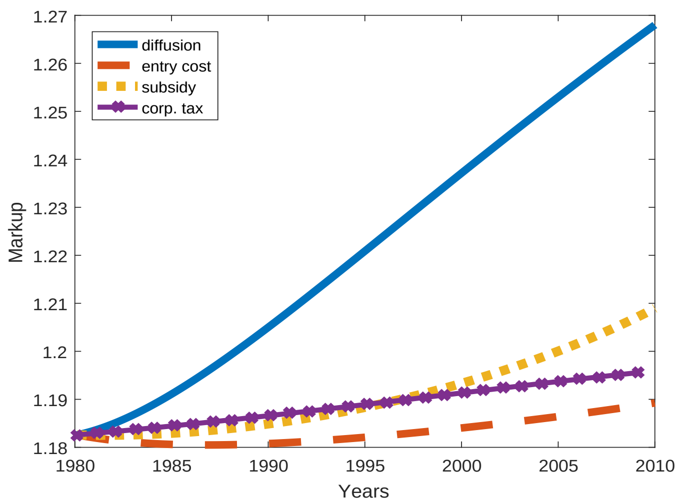
[19] The negligible response of the aggregate profit share to a decrease in corporate profit taxes may seem odd at first glance. However, notice that the figure shows before-tax profit share, which in turn depends on the distribution



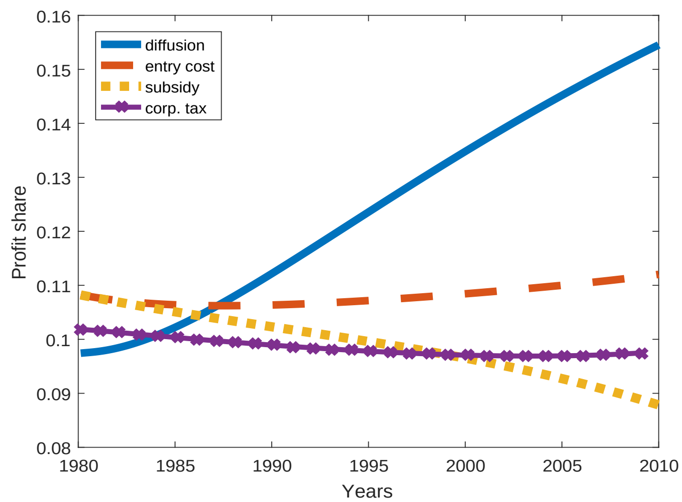
A) Entry



B) Employment share of young firms



C) Markup



D) Profit share

Figure 4: Implied responses to changes in individual channels

contrast to the trend in the data. The reason is that higher operating profits have only an indirect, and positive, effect on the entry decision. The value of the followers, in turn, is indirectly affected by higher profits only through the followers' forward-looking behavior and the chances of taking over the industry, which die off quickly for followers lagging further behind the frontier because of the intensifying discouragement effect. Therefore, lower corporate taxes create only a muted and positive effect on firm entry. This negligible effect also implies a subdued influence on the firm distribution across gaps and thus on concentration and markups, among other variables (recall that a leader's markup level depends on the size of its lead). The limited effect on firm entry and the gap distribution is also responsible for the muted response of the employment

of firms across gaps. As expected, the share of after-tax profits rises mechanically with the drop in corporate taxes (not shown here).

share of young firms and other variables listed in column 2 of Table 3.

5.2 Increase in R&D Subsidies

In Figure 4, the dotted yellow lines denote the responses to the increase in R&D subsidies. Although the responses to the increase in R&D subsidies are slightly stronger, they are still very far away from the empirical patterns, most crucially in the case of firm entry. The increase in innovative activity affects firms' distribution across gaps, moving some variables such as markups and the employment share of young firms (and gross job reallocation, to some extent) in the right direction, although the magnitude of the changes is very limited. Moreover, the profit share of GDP declines counterfactually. This result may appear at odds with the pickup in markups, but the rationale is as follows. The profit share of GDP is slightly different than the average (operational) profitability of firms, which would reflect only the distributional changes and move, therefore, in parallel to markups. However, the profit share of GDP is related to the aggregate labor share, which reflects the wage level in the economy. With higher R&D subsidies, the demand of leading firms for R&D employment increases, pushing up the wage level in the economy. Reciprocally, the profit share of GDP decreases. Higher wages also imply a higher cost of entry, which drives the slight decline in the entry rate.

5.3 Increase in Entry Costs

As described earlier, the increase in entry costs analyzed here is such that the response of firm entry matches the empirical pattern. Therefore, it is no surprise that in Figure 4a the model-generated entry rate (dashed red line) closely follows its empirical counterpart, with entry being discouraged by higher costs of entry innovation. In contrast to the tax and subsidy experiments, the decline in entry costs is able to generate a modest fall in the employment share of young firms, as lower firm entry implies lower supply of new and young firms.

Despite some success in capturing entry and young firm dynamics, the rise in entry cost fails to generate any significant move in markups and the profit share. The main reason for these results is that a fall in entry itself does not alter incumbent incentives to a degree that can cause a large enough shift in the distribution of firms toward larger gaps. On the contrary, the share of leveled sectors increases mildly, as reflected by the counterfactual decline in market concentration (column 4 in Table 3). The mechanics behind this result is as follows. Lower entry implies a lower churning for the follower firms, damping the negative business stealing effect exerted by entry on the innovation incentives of followers. This lower churning rate, in turn, boosts innovation by the followers, increasing the share of leveled sectors and thus pushing down concentration. But this shift loses steam over time, allowing the sectoral distribution to move slightly toward larger gaps, which causes some pickup in markups and the profit share, albeit a very small one. The weak distributional response is also responsible for the experiment's failure to replicate other patterns such as gross job reallocation.

5.4 Decline in Knowledge Diffusion

Similar to the previous experiment, the pattern that we introduce for the decline in knowledge diffusion is such that the model response in firm entry matches the empirical pattern, with the lower catch-up probability decreasing the value of being a follower and thus the benefit for entry. In stark contrast to the previous experiments, however, the decline in knowledge diffusion succeeds in generating reasonable variations in all margins in correct directions (indicated by solid blue lines). Average markup and the profit share of GDP rise dramatically, while the decline in the employment share of young firms is the strongest. Moreover, as shown in the last column of Table 3, aggregate labor share decreases as well, a feature that all previous experiments miss. In addition, both gross job reallocation and the standard deviation of firm growth decline in line with the empirical regularities.

The crux of this experiment lies in the shift of the gap distribution to larger gaps induced by the decline in knowledge diffusion. The decline in δ decreases the intensity with which leaders of any lead find themselves in a neck-and-neck position, thus resulting in larger masses of product lines across relatively larger gap differences. This shift induces higher concentration, average markups, and profit share. Less catch-up also leads to less job reallocation and a fall in firm growth dispersion. Moreover, with lower knowledge diffusion, the process of new (and therefore young) firms, which start the business replacing followers, taking over production slows down, resulting in a lower employment share of young firms in the economy. Notice that the decline in this margin is larger than in the experiment of higher entry costs, even though the magnitude of the drop in the entry rate is almost the same in both experiments. A stronger response occurs in this exercise because of the additional negative effect of lower knowledge diffusion, decreasing the intensity with which young followers catch up with the leaders and eventually take over the production.

Overall, these model responses imply that a decline in knowledge diffusion stands out as a likely suspect behind the decline in U.S. business dynamism. In order to assess quantitatively whether this was actually the case, we next turn to the analysis where we let these four forces be jointly at play and quantify their relative importance.

6 Investigation of Joint Forces

The channels we consider here have been moving simultaneously over the years. For example, changes in corporate tax policies and the introduction of R&D subsidies were major policy changes that happened during the 1980s (see Appendix A). Although our previous analysis indicates that some channels may fail to account for several empirical trends, individual forces may have reinforced each other. Moreover, even though certain margins may have the potential to explain the shifts in the economy, the data may suggest only little changes in those margins, with limited effect on the economy. In this section, we present a decomposition exercise that carefully addresses these considerations.

In order to correctly gauge the contribution of each margin to the observed trends, we need to discipline their relative strength by the data. Therefore, we study the joint moves implied by the calibrated transition path of the model. We will first calibrate shock paths for each channel that will jointly allow the model to replicate salient empirical trends in the data. Then, by shutting down each channel one at a time, we will quantify the contribution of each specific force to the observed changes in U.S. business dynamism. In our analysis, we will also discuss the performance of the calibrated transition path with respect to changes that are not targeted by the calibration and now serve as out-of-sample validation tests.

6.1 Disciplining the Transition Path of the Model

The transitional dynamics of our model, which capture the evolution of U.S. business dynamism from the early 1980s until the late 2000s, is shaped by changes in the four channels of interest. Eight additional parameters govern these changes: $\theta^{tr} \equiv \{\tau_T, s_T, \tilde{\alpha}_T, \delta_T, \nu_\tau, \nu_s, \nu_{\tilde{\alpha}}, \nu_\delta\}$. The first four denote the terminal values of parameters that govern the entry cost, knowledge diffusion intensity, corporate taxes, and R&D subsidies, respectively. The other four parameters denoted by ν determine the path of the changes in the first four parameters from their BGP levels to their terminal values. Precisely, we assume that the path of the change in a parameter value follows a simple functional form that ensures a smooth transition pattern. The key term of the parametric structure is $\exp(-\frac{t}{T}\nu)$, where t is the specific period during the transition and T is the terminal period, after which the parameters settle at their terminal values.[20] Thus, the curvature parameters ν measure the speed of adjustment in the parameter values and are to be determined by the data. We consider a transition over three decades, setting $T = 30$.[21]

[20] The exact functional form is such that, for any parameter ϵ that changes during the transition, its value in period t is given by

$$\begin{aligned}\epsilon_t &= \epsilon_0 + \frac{\exp(-\frac{t}{T}\nu_\epsilon) - 1}{\exp(\nu_\epsilon) - 1}\left(\epsilon_T - \epsilon_0\right)\\ &\equiv \epsilon_0 + f\left(t;\nu\right)\left(\epsilon_T - \epsilon_0\right),\end{aligned}$$

with $f\left(t;\nu\right) \in [0,1]$ for all $t \in [0,T]$. Here, ϵ_0 denotes the value of the parameter in the calibrated initial BGP, and ϵ_T is the terminal value. Notice that a value of ν_ϵ close to zero implies an almost linear change in ϵ. Higher values of ν_ϵ imply an abrupt shift (increase or decline) in ϵ initially, which then quickly reaches its terminal value, resembling a one-time shock in the limit. See Figure 5 in this section and Figure D.4 (in Appendix D) for the calibrated paths of parameters over the transition period.

[21] Notice that the transition does not necessarily mean that the model economy reaches its new BGP in T periods. The economy continues its convergence to the new BGP even after changing parameters reach their terminal values.

Two of the terminal values, τ_T and s_T, are set externally to the corresponding levels in the data. Corporate profit taxes in the United States decline to an average of about 20% in the 2000s. Akcigit et al. (2018) calculate that R&D subsidy rates in the United States rose to an average of about 20% in the post-1981 period. We also set ν_τ and ν_s to unity, implying that they change almost linearly over the transition. We calibrate the remaining four parameters that pertain to the entry cost and knowledge diffusion, matching six data points. Four of these targets are the terminal values of the establishment entry rate, the average markup, the aggregate profit share, and the employment share of young firms, capturing the aggregate variations in U.S. business dynamism. These targets are particularly informative about the terminal parameter values α_T and δ_T. Moreover, we include two additional targets that help the calibrated model replicate the empirical trend in the establishment entry rate. These targets are the relative decline in entry after the first 10 and 20 years. Therefore, our calibration strategy forces the model to reflect not only the decline in entry, but also its time path. This feature, in turn, disciplines the transition path of the model economy, informing the calibration about ν_α and ν_δ.

We solve the transition path of the model using an iterative backward solution method. For brevity, we defer the details of the procedure to Appendix C.

6.2 Parameter Values and the Model Fit

Table 4 summarizes the calibrated parameters. Importantly, the comparison of the BGP and terminal values of δ and $\tilde{\alpha}$ indicates a 60 percent increase in the entry cost and a 60 percent decline in the intensity of knowledge diffusion. Moreover, the calibrated curvature parameters $\nu_{\tilde{\alpha}}$ and ν_δ imply that $\tilde{\alpha}$ changes almost linearly, while δ drops quickly and then slowly converges to its terminal value (Figure 5).[22]

Table 4: List of parameter values

Panel A: Externally calibrated			Panel B: Internally calibrated		
Parameter	Value	Description	Parameter	Value	Description
τ_T	20%	Corporate income tax	$\tilde{\alpha}_T$	0.120	R&D scale, entrants
s_T	20%	R&D subsidy	δ_T	1.09%	Exogenous catch-up
ν_τ	1	Corporate income tax	$\nu_{\tilde{\alpha}}$	0.829	R&D scale, entrants
ν_s	1	R&D subsidy	ν_δ	5.012	Exogenous catch-up

[22]See Figure D.4 in Appendix D for the paths of s and τ.

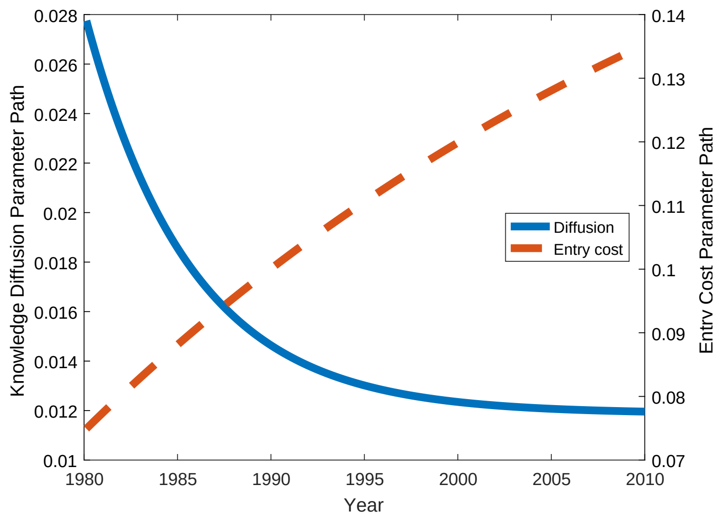


Figure 5: Transition paths of $\tilde{\alpha}$ and δ

The transition path mirrors very closely the dynamics of U.S. business dynamism, as depicted in Figure 6 (overleaf). The figure superimposes the calibrated paths of variables used in the calibration with the actual data points. Notice that the calibration uses multiple data points only from the path of the entry rate; the other target variables provide information only on the terminal changes. The model's ability to match the empirical pattern of the entry rate is reassuring about the path of the parameter changes in the model. In addition, the transition paths of other variables are replicated quite successfully as well.

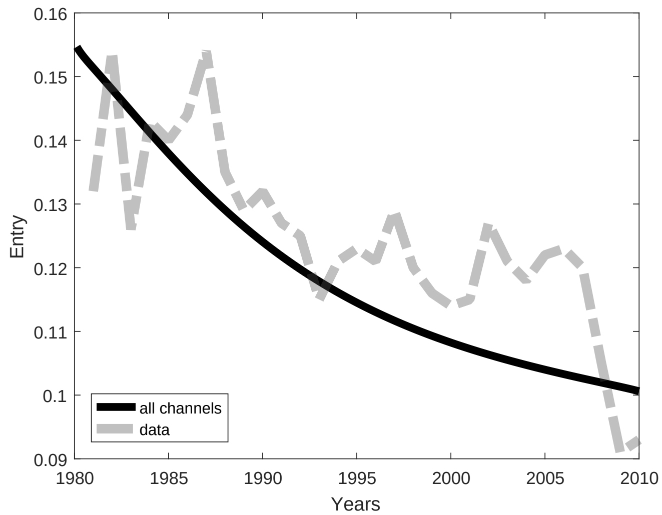
It is also worth noting that our calibration strategy does not condition on several other empirical regularities discussed in Section 2, which we now consider as out-of-sample tests for the calibrated economy. Table 5 compares empirical changes in these margins with the model-generated responses. The model also replicates these moments quite successfully, except for the change in sales concentration and the widening of the productivity gap. The reason for the former is that, in this model, within-industry concentration can take only two levels: $1/2$ in the

Table 5: Changes (Δ) in untargeted moments during the transition

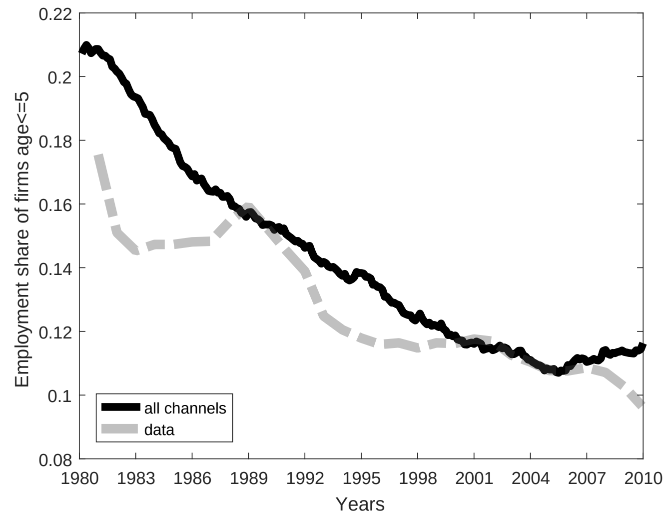
	Moment	Data	Model
D1	Δ Labor Share	-8%	-5%
D2	Δ Concentration	5%	1%
D3	Δ Job Reallocation	-7%	-9%
D4	Δ Firm Growth Dispersion	-8%	-11%
D5	Δ Productivity Gap	25%	8%

Notes: The changes reflect the total deviation between 1980 and 2010. The empirical magnitudes are taken from Karabarbounis and Neiman (2013) (D1), Autor et al. (2017b) (D2), Decker et al. (2015) (D3,D4), and Andrews et al. (2016) (D5). D1-D4 reflect changes in the United States, whereas D5 refers to the OECD average in manufacturing sector. D2 reflects the change in the concentration share of top four firms in the U.S. manufacturing sector.

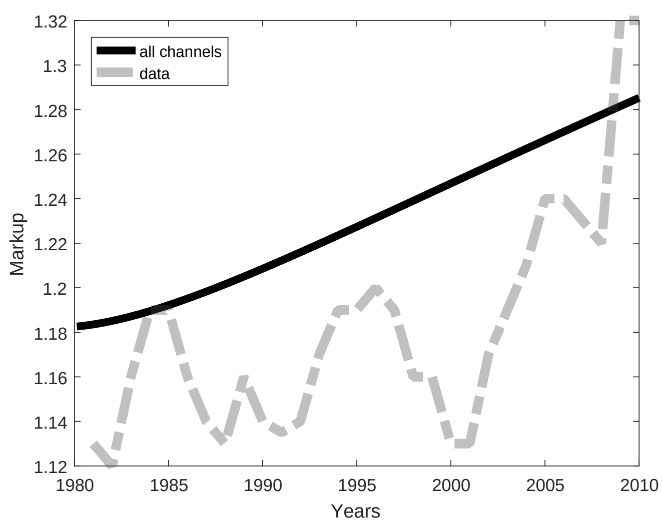
leveled sector and 1 in all of the the unleveled sectors (see Section 4.1).[23] In this regard, the model generates richer heterogeneity in terms of markups and profit shares compared with sales concentration.



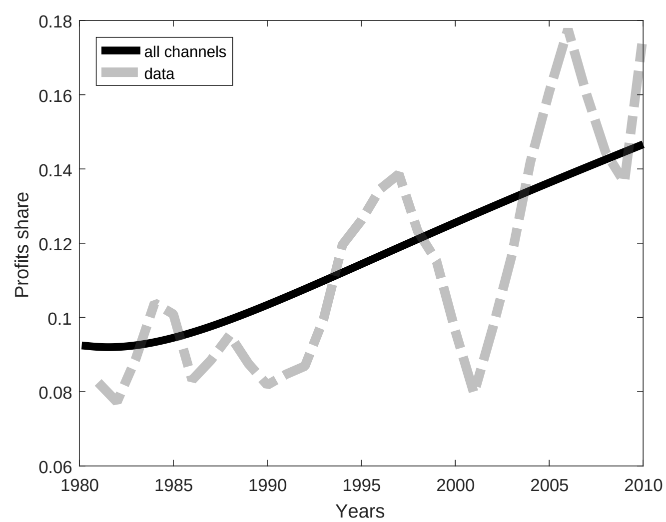
A) Entry



B) Employment share of young firms



C) Markup



D) Profit Share

Figure 6: Calibration Targets

Notes: The calibration procedure targets the terminal points in Panels 6b, 6c, 6d and the decennial declines in entry in Panel 6a. Solid black lines show the model–generated paths when all four channels are moving.

Regarding the widening of the productivity gap between frontier and laggard firms, notice that the empirical magnitude is computed across the OECD countries, while we calibrate our model to the U.S. data. Our conclusion is that, to the extent that a similar widening happens in

[23] A constant-elasticity-of-substitution aggregator in the final-good production can generate a richer heterogeneity in sales concentration but would also add complication to the computational analysis without further insight. Therefore, we decided to work with the current version of the model.

the United States, which appears to be the case in light of the declining productivity dispersion shown in Figure 1b, this model captures such dynamics reasonably well.

6.3 Decomposition Results

Finally, we turn to the counterfactual experiments, where we shut down each channel one at a time. Shutting down a specific channel means that the parameter governing the particular margin remains constant at the initial BGP level over the transition period. Therefore, each experiment obtains the hypothetical transition path that would have arisen had the specific channel remained unchanged over time. Then the resulting difference between the hypothetical path and the calibrated transition path provides a measure of the relative magnitude of the role played by the specific channel in driving the model responses. Figure 7 illustrates the thought experiment decomposing the entry rate, with the solid black line denoting the calibrated path while other lines denote the hypothetical paths generated by the experiments. A quick glance at this figure reveals that the contributions of declining corporate income tax rates (purple crossed line) and increasing R&D subsidy rates (yellow line with short-long dashes) are quite limited. This result holds for most of the other trends, as summarized in Table 6, and is consistent with our findings in the previous section.

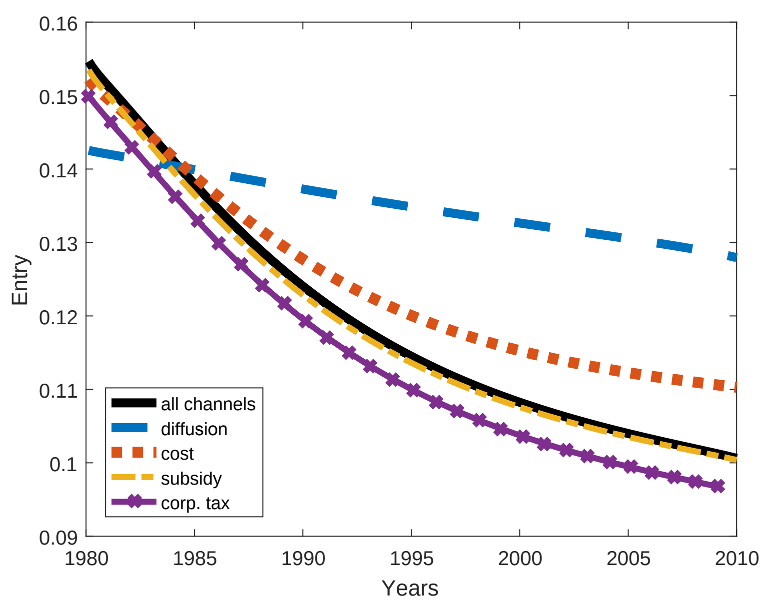


Figure 7: Decomposition of the entry decline

Notes: The solid black line denotes the calibrated path. Each of the rest of the lines represent an experiment with one channel shut down.

Denoting a variable of interest by X, its value at time t when all four channels move by X_t^4, and its hypothetical value when channel i is shut down by $X_t^{4\backslash i}$, we can express the contribution of the channel i to the total deviation over the three decades as follows:

$$contribution_i = \frac{X^4_{2010} - X^{4\backslash i}_{2010}}{X^4_{2010} - X^4_{1980}}. \tag{30}$$

Accordingly, Table 6 presents the magnitudes of the decomposed contributions. In line with the findings of Section 5, the results decisively highlight that the largest contributions to the variations in model-generated variables stem from the slowdown in knowledge diffusion. Other channels account for a meaningful part of transitional dynamics only in a limited number of variables. For instance, the higher entry cost accounts for 18 percent of the decline in entry rate, corroborating the findings in the recent work by Gutiérrez et al. (2019). Its negative effect on entry generates 22 percent of the decline in job reallocation. However, given that the rest of the contributions rarely exceed 10 percent, we will focus our attention on the discussion of the knowledge diffusion channel to avoid repetition.

Table 6: Quantitative experiment results (contributions as in equation 30)

Channel i	**Lower corporate tax**	**Higher R&D subsidies**	**Higher entry cost**	**Lower knowledge diffusion**
Entry	-8.2%	-0.4%	17.9%	50.6%
Labor	-9.0%	-7.7%	3.6%	78.7%
Markup	7.6%	10.8%	3.6%	84.2%
Profit	-9.0%	-7.7%	3.6%	78.7%
Concentration	4.3%	7.1%	-7.2%	96.2%
Young firms	-13.2%	-7.7%	-1.3%	71.2%
Prod. gap	7.2%	10.5%	3.5%	83.8%
Reallocation	-6.9%	0.2%	13.6%	48.5%
Dispersion	32.7%	29.2%	-44.6%	136%

Notes: Percentage values measure the share of the contribution from the specific channel to the total model-generated deviation between 1980 and 2010. Negative values mean that adding the specific channel moves the model-generated variable in the opposite of the empirical counterpart. A value larger than 100% means that the difference between the hypothetical and empirical paths is larger than the observed variation.

6.3.1 Decline in Knowledge Diffusion

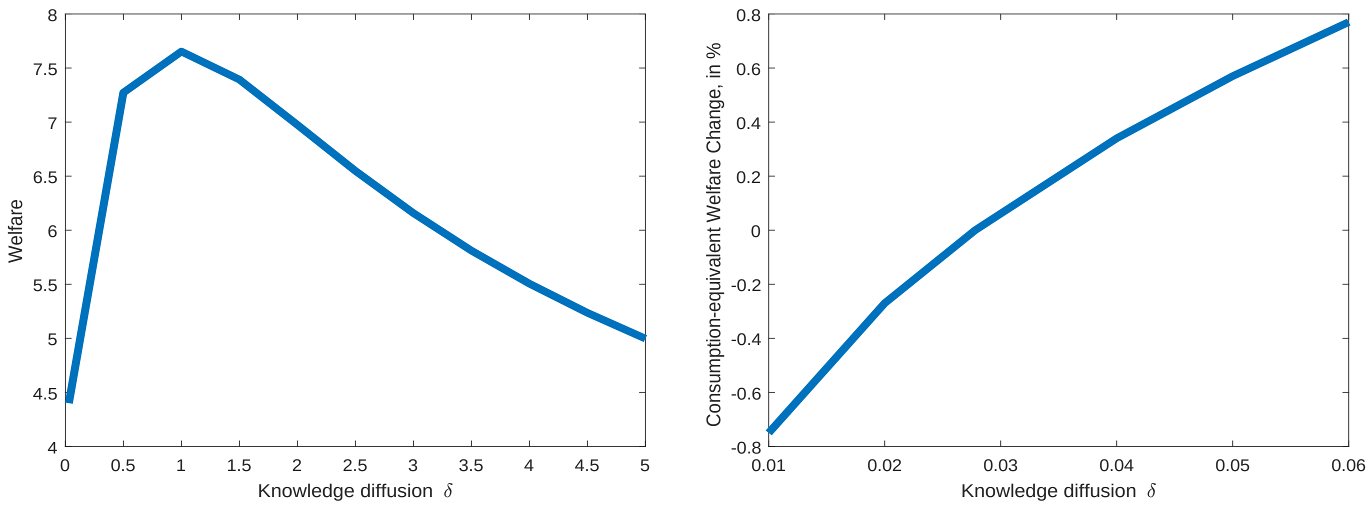
The calibrated 60 percent decline in knowledge diffusion accounts for more than 70 percent of the variation in all but two variables, in which case the contribution is half of the total change. The results clearly demonstrate the major role a weaker knowledge diffusion plays in generating the trends in the aggregate variables. To summarize the mechanics briefly again, the effect operates through a direct and indirect channel. With knowledge diffusion slowing down, the direct effect is that market leaders are protected from being imitated. As a result, the technology gaps start widening, presenting market leaders a stronger market power. Market concentration and markups rise on average. Profit share of GDP increases, and labor share decreases. Larger gaps also discourage the followers, causing the productivity gap between them and the leaders to open up. The strengthening of leaders also discourages forward-looking entrants; hence, firm entry and the employment share of young firms go down. Discouraged followers and entrants exert smaller competitive pressure on market leaders; as a result, market leaders relax, and they experiment less. Hence, overall dynamism and experimentation decrease in the economy.

To sum up, our quantitative investigation in this section underscores the importance of potential distortions in knowledge diffusion in explaining the declining U.S. business dynamism. Section 9 zeros in on this interesting theoretical mechanism and presents novel empirical evidence on the symptoms of a decline in the intensity of knowledge diffusion in the United States. Before delving into the empirical findings, we next discuss the welfare implications of our model and then conclude our quantitative exploration with the discussion of additional mechanisms, robustness exercises, and model extensions.

7 Market Power and Welfare

Our main goal in this paper is not normative but positive, and the model is designed accordingly. Yet our framework can potentially speak to the intriguing observation by Syverson (2019) on the ambiguous relationship between aggregate welfare and market power (when measured by market concentration). He points out that higher concentration can be associated with an increase or decrease in aggregate welfare, depending on the specific market structure or the source of higher concentration (pure market power or efficiency gains). In this section, we briefly elaborate on this relationship, analyzing the normative implications of our model.

The relationship between market power (manifested in higher average markup or concentration) and aggregate welfare is also ambiguous in our model. Consider a change in the intensity of knowledge diffusion. In one extreme, in which knowledge diffusion occurs almost with certainty, incumbents lose their market power immediately and thus have no incentive to innovate. This negative effect on innovation incentives essentially destroys the engine of aggregate growth in the economy. In the other extreme, in which knowledge diffusion almost never occurs, incumbents would open up their technological edge, leading to higher concentration and markups on average. Yet too many sectors may shift away from close competition—which, through an escape-competition effect, provides a strong incentive to innovate—again damping innovation incentives and thus aggregate growth. Clearly, the two cases imply opposite shifts in market power and the nature of competition. However, in both cases, innovation incentives are reduced (because of too much or too little competition), generating a loss in aggregate growth, which in turn translates into lower welfare. Figure 8a indeed confirms this conjecture. The figure depicts aggregate welfare as a function of the knowledge diffusion parameter δ along the BGP (with other parameters kept fixed).[24] The graph presents an inverse-U shape, implying that a higher or lower intensity of diffusion may be welfare enhancing, depending on the initial diffusion intensity.



A) Welfare

B) Consumption-equivalent welfare

Figure 8: Implied responses to changes in individual channels

Notes: The left panel compares the welfare across BGPs that are differentiated by the level of δ. The right panel shows the percentage deviation in consumption-equivalent welfare from the baseline over three decades in response to a shift in δ from the calibrated value. The values of δ on the horizontal axis can become larger than 1, as δ denotes a flow rate, with the implied probability of the diffusion event in a unit interval of time given by $\delta\Delta t$.

In light of the preceding deliberation, we ask next whether, in the calibrated economy, a higher or lower knowledge diffusion is welfare improving in the transition. Figure 8b depicts the change in consumption-equivalent welfare as a function of the knowledge diffusion parameter δ. To generate this graph, we basically repeat the exercise in Section 5 by introducing a change in δ over the period of three decades. We then compute the change in consumption-equivalent welfare by comparing the resulting consumption path with the baseline one, i.e., the path that arises when there is no change in δ from the calibrated value and the economy evolves along the calibrated BGP. In Figure 8b, we focus on a range of values around the calibrated level, and the horizontal axis refers to the terminal value of δ. The value zero on the vertical axis pinpoints the baseline economy at the calibrated δ value on the horizontal axis. The results imply that in the baseline case, higher knowledge diffusion increases the consumption-equivalent welfare, as the function is strictly increasing. Indeed, doubling δ would create a 0.7 percent higher welfare in consumption-equivalent terms over a 30-year period. Hence, while the model can generate a decrease or increase in welfare with higher market power—in the same vein as in Syverson (2019)—the calibrated economy happens to benefit from a higher degree of knowledge diffusion, which translates into a higher degree of competition and a lower level of average markup.

[24] For brevity, we present the derivation of welfare in Appendix B.2.

8 Alternative Mechanisms, Robustness, and Extensions

In this section, we discuss the model implications of three additional channels—a decline in the interest rate, in research productivity, and in the market power of workers relative to firms—in light of empirical trends. We then repeat the decomposition exercise from Section 6, which constitutes our main quantitative finding, under alternative specifications to gauge the robustness of our results. We end the section with a discussion of some model extensions.

8.1 Alternative Mechanisms

In our quantitative analysis, we focused on four prominent channels from the literature. Yet it is worth noting a few others that have been debated more recently with regard to their partial or direct link to some of the trends we consider here. These mechanisms are a secular decline in the interest rate (Eggertsson et al., 2018; Liu et al., 2019), a decline in research productivity (implying that ideas are getting harder to find; Gordon, 2016, and Bloom et al., 2017), and a decline in workers' market power relative to employers/firms (Bivens et al., 2014; Naidu et al., 2018). In this section, we shed some light on the potential of these alternative mechanisms to play a dominant role in jointly driving the empirical trends in consideration, repeating the exercise in Section 5. We introduce shock paths to the variables that govern the alternative mechanisms one at a time, and Table 7 summarizes the results comparing them with our baseline findings. To preview, we find that while some of the alternative mechanisms considered here could have contributed to some empirical trends, each one of them generates counterfactual responses in other trends, which we review more in detail now.

Table 7: Qualitative experiment results for alternative mechanisms

	Data (1)	Lower corporate tax (2)	Higher R&D subsidies (3)	Higher entry cost (4)	Lower knowledge diffusion (5)	Declining interest rate (6)	Ideas getting harder (7)	Weaker power of workers (8)
Concentration	↑	⟷	⟷	⟷	↑	⟷	↓	⟷
Markups	↑	⟷	⟷	⟷	↑	⟷	↓	↑
Profit share	↑	⟷	↓	⟷	↑	↓	↓	↑
Labor share	↓	⟷	↑	⟷	↓	↑	↑	↓
Frontier vs. laggard gap	↑	⟷	⟷	⟷	↑	⟷	⟷	↑
Entry	↓	↑	⟷	↓	↓	↑	↓	↑
Young firms' empl. share	↓	⟷	↓	↓	↓	⟷	↓	⟷
Gross job reallocation	↓	↑	↑	⟷	↓	↑	↓	↑
Dispersion of firm growth	↓	↓	↓	↑	↓	↓	↑	↓

Notes: Upward arrows indicate an increase in the variable of interest, downward arrows indicate a decline, and flat arrows indicate no or negligible change. If the absolute magnitude of the response of a variable is less than 20 percent of the actual change in the data, we denote it by a flat arrow.

8.1.1 Declining Interest Rates

A stark trend observed in the U.S. economy since the 1980s has been a secular decline in interest rates, with short-term nominal interest rates even hitting a zero lower bound in the aftermath of the Great Recession (Summers, 2014b). This drastic shift has, of course, drawn the attention of many researchers, who have built a large body of work looking at the causes and implications of a low interest rate environment. Closer to our work, Liu et al. (2019) argued more recently that a decline in interest rates could be the reason behind the increase in measured market power and a decline in productivity growth, which the authors hypothesize in a basic Schumpeterian step-by-step innovation model. As the argument goes, lower interest rates increase the return on investment, but more strongly for market leaders, because those firms are the ones that generate positive profits. In this exercise, we assess the potential of this channel for driving the observed trends we consider here.

To generate an exogenous fall in the interest rate, we proceed along the lines proposed by Liu et al. (2019). In particular, we introduce a steady decline to the discount rate (ρ) over the transition, as we did with other parameters in Section 5. Recall that the household's optimization obtains

$$r_t = g_t + \rho.$$

The magnitude of the decline in ρ is about 4 percent, which generates an analogous fall in the interest rate over three decades, in line with the fall in the natural rate of interest since the 1980s (Williams, 2015).[25] Column 6 in Table 7 shows that while this channel could have contributed (albeit by a narrow margin) to an increase in market power measured by average markups, its implication for firm entry appears to be at odds with the observed decline in the data. Indeed, similar to the implications of a drop in corporate tax rates, the decline in interest rates increases incumbent firm value and pushes up firm entry, in contrast to the data. Moreover, the quantitative effect of this channel on several other margins is quite muted. Therefore, we conclude that while the decline in interest rates might have contributed to some observed trends in the data, it is unlikely through the lens of our model that it has played a dominant role in jointly driving the trends in U.S. business dynamism.

8.1.2 Ideas Getting Harder

In an extensive work, Gordon (2016) argues that the U.S. economy has run out of low-hanging fruit ideas that are easier to obtain and yet have broad economic applications, implying a lower aggregate growth rate in the foreseeable future. In a similar vein, the intriguing work of Bloom et

[25] Williams (2015) applies the methodology established by the seminal work of Laubach and Williams (2003) to estimate the natural rate of interest to more recent data to extend the series. His findings indicate a fall in the natural rate of interest from around 4 percent in 1980 to about 2 percent right before the Great Recession and a further 2 percent drop over the next few years, with an outsized decline during the recession.

al. (2017) contends that novel and productivity-enhancing ideas have become harder to generate, which manifests itself in a declining research productivity. The authors document, using both macro and firm-level data, that the idea output (measured by variables such as TFP growth) per researchers employed has been steadily falling over most of the past century. To reflect on the potential effects of this shift, we consider an increase in the cost of R&D for both entrant and incumbent firms via higher scale parameters (α and $\tilde{\alpha}$) in a similar exercise to the "higher entry cost" experiment in Section 5.

Recall that the R&D cost functions read as

$$R_{ijt} = \alpha \frac{x_{ijt}^{\gamma}}{\gamma} w_t \quad \text{and} \quad \tilde{R}_{ijt} = \tilde{\alpha} \frac{\tilde{x}_{ijt}^{\gamma}}{\gamma} w_t.$$

Effectively, higher scale parameters means that, in order to generate the same innovation rate, firms need to devote more resources, which translates into a decline in research productivity. Measurements by Bloom et al. (2017) imply an average decrease in research productivity over three decades by a factor of about 15 for Compustat firms and by a factor of about 6 for aggregate series. Accordingly, we consider an extreme 10-fold increase in the scale parameter of R&D cost in our exercise. The results indicate that such a drastic shift would be able to pull down firm entry and the employment share of young firms, as shown in column 7 of Table 7. However, a distortion on firms' innovative activity via this margin would counterfactually damp concentration or other measures of market power through the lens of the model. Therefore, this channel would not be able to jointly account for all of the trends we consider here, missing chiefly the changes in market power.

8.1.3 Weaker Market Power of Labor

The third alternative mechanism concerns a decline in workers' relative market power. Recent work (Bivens et al., 2014; Naidu et al., 2018) suggests that this decline could have depressed wage growth despite sizeable productivity gains, which would translate into a lower aggregate labor share.[26] We capture the potential effect of this change via an exogenous rise in the step size (λ). Recall that operating profits $\pi(m_{it}) = (1 - \lambda^{-m_{it}}) Y_t$ depend negatively on λ and the wage level is given as

$$w_t = Q_t \lambda^{-\sum_{k=0}^{\bar{m}} k \mu_{kt}}.$$

Therefore, a higher step size translates into higher operational profits of firms and to a (statically) lower labor share. The increase we introduce to λ is so as to match the decline in the aggregate labor share observed in the data. The last column of Table 7 indicates again that this channel also fails to jointly generate the observed empirical trends. While it could have contributed to an

[26] The findings of recent work by Bivens et al. (2017) and Farber et al. (2018) indicate that a decline in unionization could have suppressed a broad-based wage growth. Azar et al. (2017) document an increase in monopsony power in labor markets.

intensification in market power and a decline in aggregate labor share, this time, the counterfactual implication is that it cannot generate a decline in the entry rate and the employment share of young firms (if anything, it increases entry).

In sum, when the moves we have observed in the U.S. business environment are considered jointly, our analysis suggests a limited effect from the alternative mechanisms analyzed in this section. However, it is essential to note that these mechanisms have most likely been crucial factors behind several other prominent trends in the economy, which are beyond the scope of the analysis in this paper.[27]

8.2 Robustness

This section assesses the robustness of our main quantitative results under five alternative specifications.

8.2.1 Untargeting Markup

In the empirical literature, there is a lively debate about the magnitude of the change in markup levels. While De Loecker and Eeckhout (2017) find a drastic increase in markups, a number of other papers observe a less dramatic rise (Nekarda and Ramey, 2013; Eggertsson et al., 2018; Hall, 2018). Considering this empirical disagreement, we opted for a middle ground, including an average markup target when matching our model's transition path to the evolution of the U.S. economy. Now we go one step further and recalibrate the transition path, dropping the change in markups from the set of targets altogether. Dropping the change in markups from our target list makes barely any difference in our transition calibration. Therefore, the decomposition results are almost identical to the baseline results as well. Hence, we conclude that our quantitative results do not crucially depend on the magnitude of the increase in markups.

8.2.2 Revisiting Effective Corporate Tax Rates

As discussed in Appendix A, corporations take advantage of several regulatory loopholes to decrease their effective tax burden. Therefore, to the extent these practices became more common in recent decades, there might be a concern as to whether the decline in average effective corporate tax rates has been more dramatic than what we have penciled into our calibration based on national accounts data. In that case, we would artificially restrict the potential role the changes in corporate tax rates could actually play in driving model-based responses. To alleviate this concern, we consider an extreme case where we assume that corporate tax rates decline to 0 percent

[27] For instance, lower real interest rates raise concerns for financial stability (Summers, 2014a). Farber et al. (2018) highlight the negative effect of declining unionization on income inequality.

over the transition period. Setting $\tau_T = 0$ and keeping the rest of the parameters determined by the initial BGP fixed, we reran our transition calibration. Then, as in Section 6.3, we recalculated the contribution of the knowledge diffusion channel to the model-generated responses. Table 8 summarizes these decomposition results along with the findings from other robustness exercises that we discuss later. For brevity, we show only the effect for the knowledge diffusion channel, as in the last column of Table 6. The first column of Table 8 shows the baseline results, and the second one shows the findings in this exercise. As revealed by the comparison of the first two columns, the effect under this specification is quantitatively very similar to the baseline, corroborating our original findings that exhibit the significant contribution of a decline in knowledge diffusion to the model-based dynamics.

Table 8: Robustness analysis for decomposition results: knowledge diffusion channel

	Baseline	**Zero tax**	**Low ϕ**	**High ϕ**	**Quadratic R&D cost**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Entry	50.6%	50.0%	44.3%	1.0%	-0.4%
Labor	78.7%	78.8%	74.1%	76.5%	69.5%
Markup	84.2%	77.3%	89.9%	50.4%	79.2%
Profit	78.7%	48.2%	78.1%	31.6%	65.9%
Concentration	71.2%	85.0%	86.9%	150%	125%
Young firms	96.2%	73.9%	98.8%	-0.6%	35.7%
Prod. gap	83.8%	76.8%	89.5%	50.6%	78.4%
Reallocation	48.5%	43.6%	37.6%	35.0%	-58.6%
Dispersion	136%	117%	114%	7.7%	423%

Notes: Percentage values measure the share of the contribution from the knowledge diffusion channel to the total model-generated deviation between 1980 and 2010. Negative values mean that adding the knowledge diffusion channel moves the model-generated variable in the opposite of the empirical counterpart. A value larger than 100% means that the difference between the hypothetical and empirical paths is larger than the observed variation.

8.2.3 Alternative Values for Drastic Innovation

In the model, drastic innovation and knowledge diffusion both lead to a quick catch-up of follower firms. By decoupling the two channels, we allow firms the chance to endogenously generate drastic innovations even when there are distortions to the knowledge diffusion channel. In this way, we avoid assigning an artificially large importance to knowledge diffusion and grant a fair treatment to other potential channels of interest. However, having two similar sources of quick catch-up may raise questions about their identification. Reassuringly, the sensitivity analysis in Section 4.3 demonstrates that exogenous knowledge diffusion has a much stronger effect on margins such as markups and profits than the endogenous drastic innovation channel does. Yet we still find worth discussing the robustness of our quantitative results to alternative values of ϕ. To this end, we recalibrate the transition of the model under the assumption of a low and a high value of ϕ (keeping other parameters fixed) and regenerate our decomposition results in these alternative environments.

We start with the discussion of low-ϕ case. Setting ϕ to one-tenth of the original value while keeping other parameters listed in Table 1 fixed, we recalibrate the parameters that define the transition path of the model. Next, we recompute the quantitative effect of the recalibrated decline in knowledge diffusion intensity. The results, shown in the third column of Table 8, demonstrate that the original findings still go through: The knowledge diffusion channel has a very high power in explaining the transition path of the model variables.

Next, we repeat the same exercise with a high value of ϕ, which we set to about 42 percent, 10 times the baseline value. This extreme value implies that almost half of the innovations generated by followers are of a drastic nature and leaves very little scope for the exogenous knowledge diffusion in the model. The fourth column of Table 8 presents the results based on the recalibrated transition path in this specification. The significant finding is that in this case, the knowledge diffusion channel contributes very little to variations in entry-related margins (in particular, the entry rate and the employment share of young firms). These margins are now almost fully explained by a calibrated increase in the entry cost (not shown). This finding is perhaps expected given the extremely limited scope for the diffusion channel in this specification. But a more striking observation is that even in this constrained specification, the knowledge diffusion channel has the most significant power in driving the increase in market concentration, markups, and aggregate profit share and the reciprocal decline in aggregate labor share. The common denominator of these margins is that they crucially depend on the shifts in the distribution of sectors across technology gaps. Therefore, this exercise shows that even in this case, the changes in knowledge diffusion are the main driver of such distributional shifts in the economy.

8.2.4 R&D Elasticity

In quantitative Schumpeterian growth literature, a commonly used value for the labor elasticity of R&D expenditure is 0.5, implying a quadratic R&D cost function (see Acemoglu et al., 2018, for a discussion). Therefore, we next repeat our decomposition exercise under the assumption of quadratic R&D cost functions. To this end, we recalibrate the transition path, setting $\gamma = \tilde{\gamma} = 2$ while keeping other calibrated parameters listed in Table 1 fixed. The last column in Table 8 presents the results. Similar to the exercise with a higher drastic innovation probability, we observe that while the explanatory power of a decline in knowledge diffusion becomes negligible (most of the entry decline is driven by higher entry cost), the channel retains its significance in accounting for changes in variables such as aggregate profit share and average markup.

A seemingly confusing finding is that a decline in knowledge diffusion plays a considerable role in driving the decline in young firms' employment share despite its negligible effect on firm entry. The reason is that, in fact, the decline in knowledge diffusion does not fail to generate meaningful action in firm entry (as opposed to the exercise with a high ϕ). While lower δ provides an additional force that drives down firm entry, it also causes an initial jump in this variable, implying a steeper decline over the transition.[28] Therefore, shutting down the diffusion channel implies a smaller magnitude for the decline in firm entry; but because the initial jump is also removed, the terminal value of firm entry barely changes. Therefore, we obtain a seemingly negligible contribution from the knowledge diffusion channel, as shown in Table 8 (see also equation 30). Nevertheless, the ability of this channel to generate meaningful dynamics still manifests itself in other variables such as the employment share of young firms.

8.3 Model Extensions

In this study, we focus on 10 empirical regularities and aim at analyzing them in a comprehensive but parsimonious setting. Yet the model is flexible enough to incorporate other features that can prove useful in future research. One such extension could be the generalization of the market structure in intermediate-good production. Currently, perfect competition among intermediate-good producers implies that only one firm produces the particular good. As a result, the concentration measure (HHI) takes two values (1/2 or 1). A straightforward generalization would be to use a constant-elasticity-of-substitution production function at the industry level à la Aghion et al. (2001), which would make both firms produce in each product line. Accordingly, one would obtain more heterogeneity in terms of concentration. However, this extension would complicate the computation of the model, especially over the transition (a key contribution of the study), without adding much further insight, as the key mechanism of the model would remain intact. Therefore, we stuck to the current version of the model.

Another possible extension relates to the labor share distribution of firms. Autor et al. (2017b) and Kehrig and Vincent (2018) argue that most of the labor share decline at the industry level stems from the relocation of activity to low-labor-share, highly productive firms (rather than a widespread decline in firms' labor share). Accordingly, they find that the labor share distribution of firms has barely changed.[29] On the one hand, our model is consistent with the empirical observation that low-labor-share firms capture a higher share of economic activity as market concentration increases. On the other hand, the model does not generate a stable labor share distribution.[30] To reflect on these empirical findings, the model can be extended by assigning heterogeneous research productivity types to firms.[31] In this study, we did not take that route, because it would come at a significant loss in tractability—an essential feature for our structural

[28] This initial response stems from the increase in leader's value, incentivizing firm entry, especially to leveled sectors. As the elasticity of R&D cost function is lower in this exercise, the initial response of firm entry to the change in incumbent firms' value is also more pronounced.

[29] The evidence is more decisive for the manufacturing sector.

[30] Indeed, the distribution shifts toward lower-labor-share firms in lockstep with increasing concentration and average markups in the model.

[31] Aghion et al. (2019) consider such type heterogeneity to analyze labor share dynamics of incumbent firms.

analysis of transitional dynamics. While the aforementioned regularities are a few from many other empirical trends that could be added to the extensive set analyzed here, notice that they are not crucial for our main quantitative results (the pecking order among potential drivers in terms of their power in explaining observed trends in the economy). This corollary holds because the inconsistency is not specific to the dynamics created by a particular channel, but it is rather a model feature. Therefore, we proceed with the current parsimonious framework and leave these additional considerations to future research.

9 New Evidence for Future Research: U.S. Patent Trends

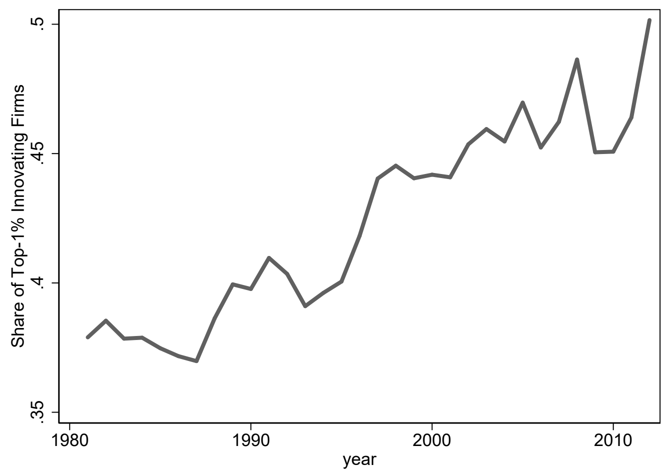
In Section 6, we established that a decline in knowledge diffusion is the dominant culprit behind the observed market power and business dynamism trends in the United States. A natural follow-up question is, what caused a decline in knowledge diffusion? Providing a decisive answer to this question is beyond the scope of the analysis presented here. Nevertheless, we think it is worth reflecting briefly on this question in light of some new empirical evidence, which may prove useful in guiding future research in this direction.

In Akcigit and Ates (2019), we elaborate on several candidates that could justify a decline in knowledge diffusion—use of tacit knowledge and data in production, outsourcing of production processes, and regulations, to name a few. We extend the discussion here by providing new evidence on the use (or abuse) of patents in the United States. Patent and reassignment data from the U.S. Patent and Trademark Office (USPTO) provide a fertile ground for investigating patterns of knowledge diffusion, as firms rely heavily on patent protection to shield themselves from imitators. A decline in imitators' ability to copy and learn from market leaders' technology due to heavier, and especially strategic, use of patents by the leaders would limit the flow of knowledge between firms and lead to a reduction in the intensity of knowledge diffusion. Therefore, we now turn our attention to the changes in the use of patents in the U.S. economy across time.

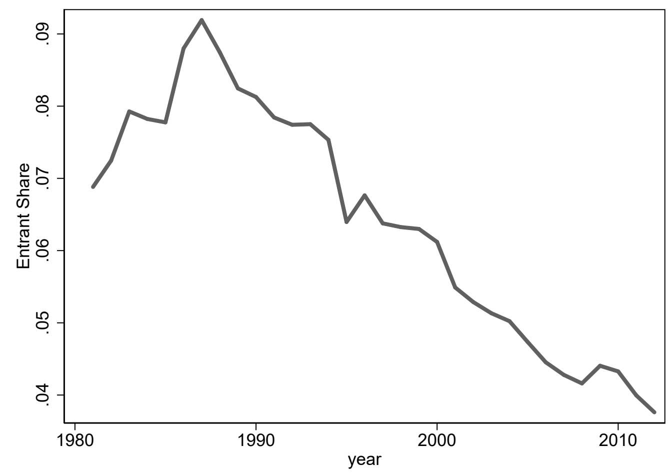
Patent Concentration and Post-1980 Trends

As we reviewed in Section 2, many indicators of business dynamism suggest a declining trend since the 1980s along with rising market concentration. We first investigate if there has been a concomitant change in patenting concentration. To answer this question, Figure 9a looks at the share of patents registered by the top 1 percent of innovating firms with the largest patent stocks. The ratio exhibits a dramatic increase. While in the early 1980s about 35 percent of patents were registered by the top 1 percent of firms sitting on the largest patent stocks, this ratio reached almost 50 percent in three decades.[32] In addition, the share of patents registered by new entrants (firms that patent for the first time) exhibits the opposite trend: Notwithstanding the

[32]Notice that the increase in this ratio has been larger than the rise in market concentration (see Autor et al., 2017b).



A) Share of Patents of the Top 1% Patenting Firms



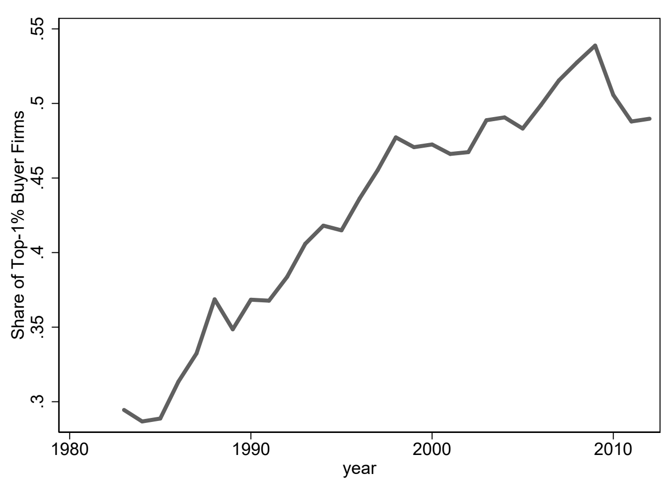
B) Entrants' Patent Share over Time

Figure 9: Registry of Patents

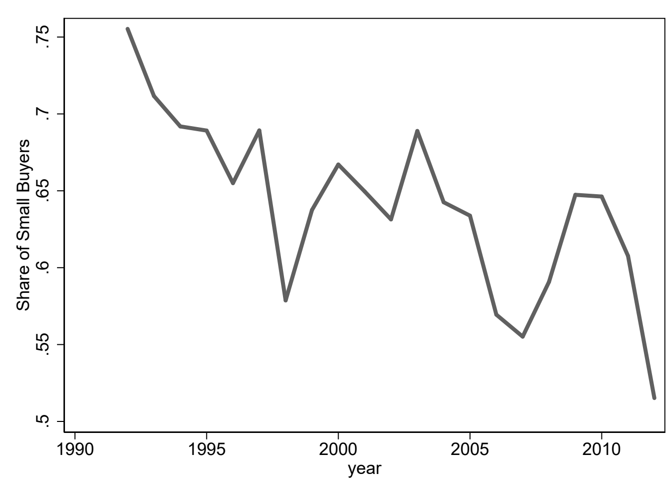
Source: Authors' own calculation using U.S. Patent and Trademark Office data

small pickup in the early 1980s, there has been a dramatic secular decline in the entrants' share since then, with the ratio falling more than 50 percent in 25 years (Figure 9b).

A common practice that market leaders follow is to buy patents in the market to strengthen their intellectual property arsenals. This way, leaders can create a dense web of patents or "patent thickets" (Shapiro, 2001), which makes it difficult for competitors to get close to the market leader's technology domain and potentially leapfrog. To investigate related patterns, we make use of patent reassignment data, which keep detailed records of all transactions of patents be-



A) Share of Top-1% Buyers over Time



B) Share of Small Buyers over Time

Figure 10: Reassignment of Patents

Source: Authors' own calculation using U.S. Patent and Trademark Office data tween entities. As in patent registries, we observe stark trends in patent reassignments since the 1980s. Figure 10a focuses on the purchasing trends of the top 1 percent of firms with the largest patent portfolios. The figure reveals that while 30 percent of the transacted patents were reassigned to the firms with the largest patent stocks in the 1980s, the share went up to 55 percent by 2010. This drastic increase has crowded out small players in the market, as illustrated in Figure 10b. The figure shows the likelihood of a patent to be assigned to a small firm, conditional on that patent being transacted from another small firm and recorded.[33] In the past two decades, the fraction of transacted patents that are reassigned to small firms has dropped dramatically from 75 percent to almost 50 percent, implying a shift of ownership from the hands of small firms to large ones.

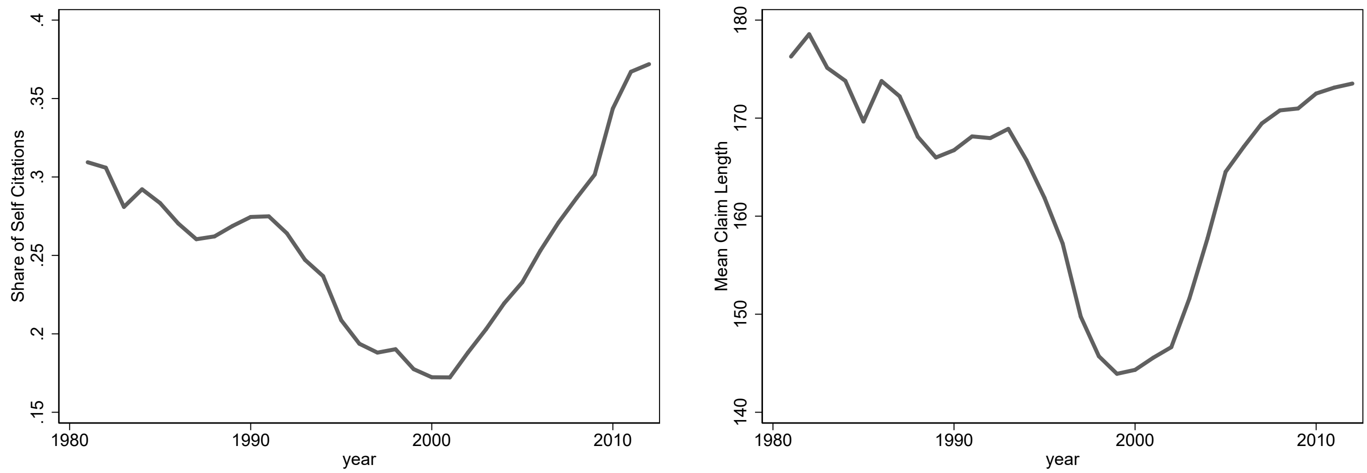
These figures reveal that concentration in patent production and reassignment has surged, and firms with the largest patent (knowledge) stock have further expanded their intellectual property arsenals. Given that patents are exclusively used to prevent competitors from using the patent holders' technology, these trends can imply that the heavy use of patents by market leaders might have caused the decline in knowledge diffusion from the best to the rest. Furthermore, empirical evidence shows that the decline in business dynamism has accelerated after 2000, especially in some high-tech sectors (Decker et al., 2016b). A closer look at the patent data reveals corroborating evidence on the potential strategic use of patents, which we elaborate next.

Strategic Use of Patents and Post-2000 Trends

In this part, we investigate whether firms produce strategic patents, which help the firm build thickets around its core business to ensure that technologies are not easily copied and challenged by others. To this end, we make use of patent records, which contain a lot of information about the potential use of specific patent files. Two pieces of information are especially useful for our purposes: citations and text of claims. We start with the analysis of the former.

Either firms can explore new areas of research to expand into new fields, or they can focus on their existing technologies and try to build a protective wall around them. Akcigit and Kerr (2018) dub the former exploratory patents as "external" and the more exploitative ones as "internal" patents. If a firm's aim is mostly protecting its core technology, the new internal patent will cite many patents from the firm's existing portfolio. In contrast, if a firm's aim is expanding into new fields, more citations will be made in that case to patents that are not in the firm's portfolio. In this regard, the fraction of self-citations is informative about how internal a patent is and how likely it is that a patent serves to build a thicket. Figure 11a explores the self-citation dynamics over time. The striking observation is that while until 2000 patents were becoming more explorative in nature based on our earlier interpretation, this trend reverses completely around 2000, and patents become more exploitative and internal since then.

[33] The designation as a "small business concern" derives from the USPTO's U.S. Patent Grant Maintenance Fee



A) Share of Self Citations over Time

B) Average Claim Length over Time

Figure 11: Self-citation and Claim Length Patterns

Source: Authors' own calculation using U.S. Patent and Trademark Office data

Another interesting piece of information on a patent file is the length of its claims. If a firm is introducing a novel technology that makes a broad contribution to the field, the relevant patent would be expected to have a relatively short claim, reflecting the broader scope. However, if a patent is making a marginal contribution to an already crowded area, then the claims are likely to be much longer and also much narrower in scope. Therefore, the length of the claim could show us how broad or narrow the contributions are. Figure 11b shows the evolution of average patent claim length over time. Intriguingly, patent claims were getting shorter until 2000, suggesting that patents were becoming broader in scope, which completely reversed again around 2000. Since then, claim length has been increasing steadily, indicating that patents are getting narrower in scope and also less original.

These post-2000 observations likely imply that patents have recently been used to crowd existing technology fields with incremental additional information, limiting the scope for spillovers to competitors. Intriguingly, the timing of these dramatic changes coincides with the period when business dynamism has slowed down even more. While several measures of business dynamism have indicated a slowdown in most sectors of the U.S. economy since the 1980s, the decline in the high-tech sector has become most visible in the 2000s (Decker et al., 2016b). As shown in Figure 12, the dispersion of firm growth in high-tech sectors started to decline steadily around 2000. Decker et al. (2016b) document that other measures of business dynamism, such as gross job reallocation, reverberate with this post-2000 pattern, again especially in high-tech sectors. In this regard, our post-2000 findings tell a coherent story with these empirical regularities, suggesting a concurrent slowdown in knowledge diffusion and business dynamism.

Events database, which records information on patent renewals.

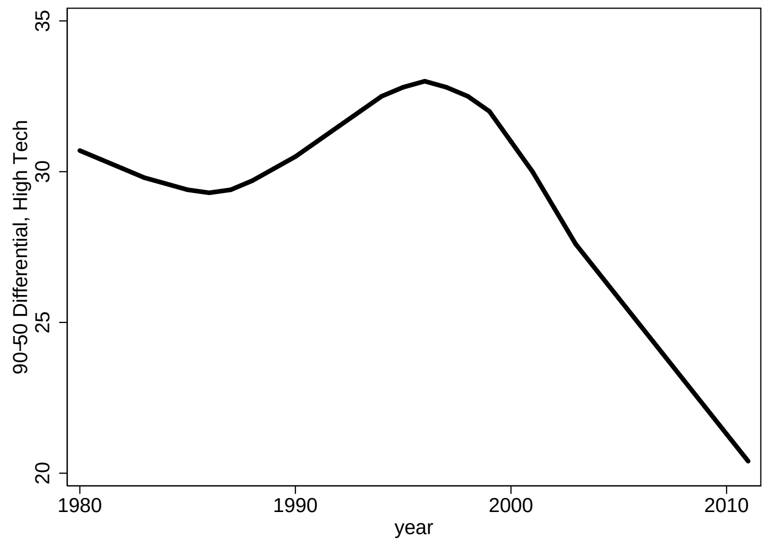


Figure 12: 90-50 Differential in High Tech Sector

Notes: Taken from Decker et al. (2016b). Similar patterns are documented for the 50-10 differential, for the balanced sample of continuers, and gross job reallocation in the Information sector.

To sum up, these results constitute strong suggestive evidence that the concentration and use of patents, or intellectual property more broadly, have dramatically changed over time. Patent concentration has been trending up since the 1980s, and the nature of patents produced started to shift around 2000 toward more internal and narrower in scope, indicating a more strategic use of patents. These observations are broadly consistent with declining knowledge diffusion from the technology frontier to followers and have likely contributed to declining business dynamism through the lens of our model.

10 Conclusion

In this paper, we shed light on the heated debate about rising market concentration and declining business dynamism using a micro-founded structural model of endogenous firm dynamics. The key mechanism of the framework is the strategic innovation decisions of firms in response to the degree of competition they face, which reflects their technological position relative to their competitors. The resulting best–versus–the–rest dynamics help the model jointly account for several prominent empirical trends that the U.S. economy has observed over the past several decades. This structural framework allows us to assess the importance of four relevant channels that could have contributed to the observed regularities. We accomplish this analysis in two quantitative exercises in which we carefully account for the responses of aggregate variables of interest over the transitional period. Both exercises highlight the dominant role of a slowdown in knowledge diffusion from the frontier firms to the follower ones in explaining empirical trends.

This result hinges on the trickle-down effect of slower knowledge diffusion on firm entry as well as the compositional dynamics arising from the less frequent catching–up of followers with the market leaders, distorting competition dynamics.

In their extensive study, Andrews et al. (2016) show a widening productivity gap between frontier and laggard firms, which the authors interpret to indicate declining knowledge diffusion. In parallel, our complementary empirical investigation presents new evidence on the potential symptoms of slower knowledge diffusion from the U.S. patent data. In particular, we document a higher concentration of patent ownership through both production and acquisition of new patents, echoing the broader patterns of market concentration. Moreover, we observe an increasingly more strategic use of patents in the post-2000 era, as indicated by their increasingly internal nature. These changes have likely contributed to the decline in business dynamism, with the flow of knowledge or spillovers to competitors becoming more constrained over time.

The findings of this paper also present a direction for both future research and policy design. As discussed previously, several channels could have distorted the diffusion of knowledge. A short list of candidates include globalization, regulations, the changing nature of production and the increasing use of data. In addition, our empirical investigation points to an intensified use of patents to deter knowledge spillovers and potential competition. Opening the black box of the nature of knowledge diffusion and determining the drivers of its slowdown are vital topics for future research in this direction. In terms of policy, the results suggest that the appropriate response to revive business dynamism should focus on post-entry distortions that impede competition between leader and follower firms. Such competition policy would not only affect incumbent firms, but also incentivize business entry through positive trickle-down effects.

Finally, our work emphasizes the importance of a comprehensive approach that links micro-level changes in market primitives to macro outcomes in analyzing the drivers of prominent empirical trends in the U.S. economy. The distinction between market primitives and the observed outcomes is essential in that it helps us avoid enforcing a certain relationship between macro outcomes that might be related in various ways—a criticism by Syverson (2019)—and get to the root of those outcomes. While each one of candidate mechanisms can potentially speak to some specific trends, a comparative study of all these channels in light of all empirical regularities allows us to determine the relative quantitative bite of these channels and to identify the potential common cause. We believe that such quantitative comparison is vital for academic work to guide policy decisions.

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Appendices

A Some Notable Changes in the U.S. Economy

In the past several decades, there have been some notable (regulatory) changes in the United States that have shaped the channels that we consider as potential drivers of declining business dynamism and rising market concentration. In this section, we briefly discuss these changes with a focus on the corporate tax rates, R&D subsidies, and entry costs (see Section 9 in the main text for the changes in the knowledge diffusion margin).

The U.S. tax system experienced two major overhauls in the 1980s with the passage of the Economic Recovery Act of 1981 and the Tax Reform Act of 1986. Although the United States has notoriously sustained the highest statutory corporate income tax rates among the developed countries until recently, the Tax Reform Act actually decreased this rate substantially in 1986, as shown by the solid black line in Figure A.1. Moreover, despite high statutory rates, the effective tax rates that determine the actual corporate tax bill paid by the firms are known to be much lower due to various tax benefits. According to the estimates of the CBO, the effective rate was about 19 percent in 2012, almost 20 percent below the statutory rate (Congressional Budget Office, 2017).[34] Indeed, the average effective rates were lower in the period after 1980

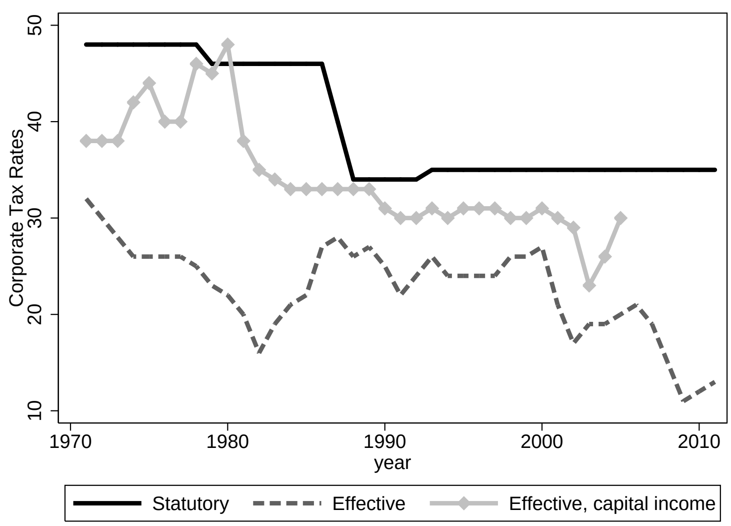

Figure A.1: Effective Corporate Tax Rate in the U.S.

Notes: Statutory tax rates are obtained from Internal Revenue Service Statistics of Income Historical Table 24 and show the value for the top bracket. Statutory tax rates have been at least the level shown in the graph for corporate income brackets above USD75,000. Effective corporate tax rate is calculated as Tax Receipts on Corporate Income/(Corporate Profits After Tax (without IVA and CCAdj)+Federal Government's Tax Receipts on Corporate Income) using Federal Reserve Economic Data (U.S. Bureau of Economic Analysis, 2019). Effective corporate tax rates on capital income is taken from Congressional Research Service report RS21706 (Gravelle, 2004).

[34] For instance, while trucking companies paid 30 percent, biotech companies paid less than 5 percent of their income as tax in 2009 (Appelbaum, 2011). Even more, some companies such as General Electric not only did not pay

than the previous two decades and have fallen further strongly after 2000 (dashed line). Finally, the effective corporate tax rate on capital income has declined as well, as depicted by the marked solid line.

Probably a less-known change has occurred in the R&D support provided by the U.S. government. In 1981, the government introduced a federal R&D tax credit for the first time. Starting in 1982 with Minnesota, several states followed suit by introducing their own state-level R&D tax credits. Figure A.2 summarizes these changes. The gray bar denotes the introduction of the federal tax credit, and the subsequent bars show the total number of U.S. states with a provision of R&D tax credits, along with their names. This substantial support for R&D boosted firms' investment in innovative activity (Akcigit et al., 2018), which is especially true for large established incumbents—the recipients of the bulk of R&D tax credit claims (Tyson and Linden, 2012)—given that firms need to generate taxable profits to claim the credit.[35] Figure A.2 also shows that there were significant changes in both R&D expenditure of firms and domestic innovative activity following these aggressive policy changes. Average R&D intensity of publicly traded U.S. firms showed a dramatic increase (solid line). Moreover, after an expected delay, the annual share of patents registered by U.S. residents in total patent applications increased as well (dashed line).

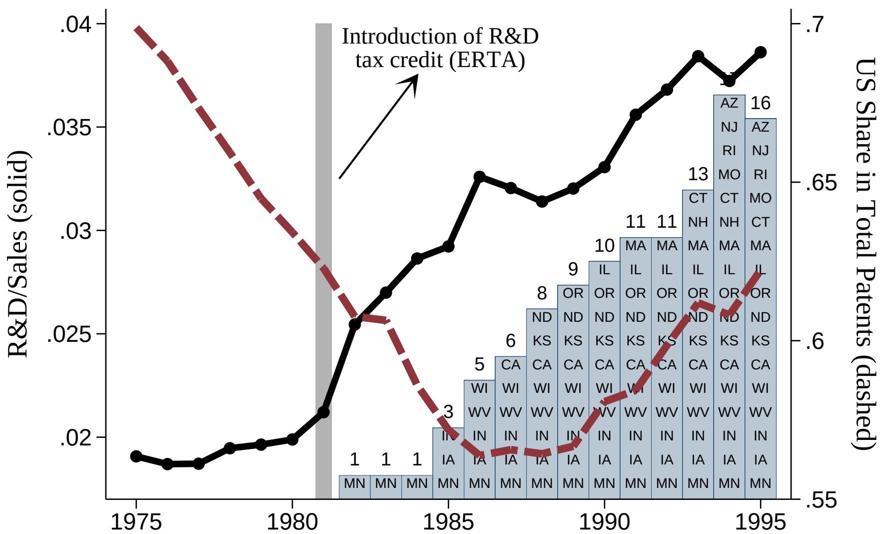

Figure A.2: Federal and State-level R&D Tax Credit in the U.S.

Source: Akcigit et al. (2018).

Market economies are regulated to level the playing field for competing firms and encourage a more dynamic business environment. Yet too much regulation could slow the economy by simply distorting the incentives to invest and grow. "Overregulation" has become a growing concern among policy circles, especially with its potentially larger burden on small businesses (Crain and

any taxes, they even claimed positive tax benefits (Kocieniewski, 2011).

[35] In fact, the nonrefundability feature of the U.S. R&D tax credits is subject to major criticism, along with the lack of preferential rates for small firms, which contrasts with schemes in other major economies such as France and the United Kingdom (Congressional Budget Office, 2007; Tyson and Linden, 2012). These features are especially important for the efficiency of tax credits in supporting the innovative activity of highly dynamic small and young firms, which are usually the firms that are constrained by the high cost of R&D capital.

Crain, 2010; U.S. Chamber of Commerce Foundation, 2017), and the current U.S. administration is working hard to scale back the regulatory framework.[36] The detrimental effect of higher entry barriers, and regulations in particular, on business entry has also been documented by the academic literature (Klapper et al., 2006; Klapper and Love, 2010). In more recent work, Gutiérrez et al. (2019) stress the importance of higher entry costs in terms of the regulatory framework in driving the decline in business entry and competition.

The level of regulatory burden in the economy is hard to measure. However, the length of the Federal Register, where all new rules, executive orders, and other legal notices are published, gives a clue about how the regulatory burden has evolved in the United States. Figure A.3 plots the number of pages in the Federal Register over time. The increase in the amount of flow of new regulations lends some support to the argument that regulatory burden on U.S. businesses has grown, which could reasonably be expected to have weighed on entrants and small businesses. In this sense, this regulatory shift could have had some detrimental impact on the business dynamism. In light of this debate, we also investigate changes in the cost of entry in our quantitative analysis.

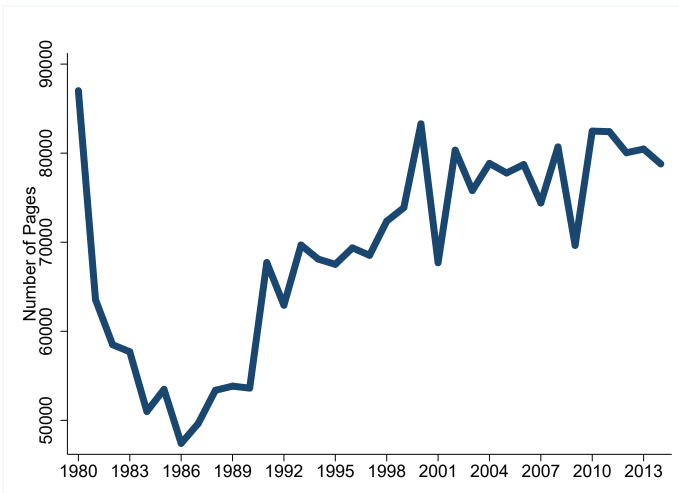

Figure A.3: The Number of Pages in the Federal Register of the U.S.

Notes: Data is obtained from Regulatory Studies Center.

[36] See the *Wall Street Journal* article "The Trump Regulatory Game Plan."

B Additional Analytical Derivations

B.1 Evolution of μ_{mt}

$$\frac{\mu_{\bar{m}t+\Delta t}-\mu_{\bar{m}t}}{\Delta t}=x_{\bar{m}-1t}\mu_{\bar{m}-1t}-\left(x_{-\bar{m}t}+\tilde{x}_{-\bar{m}t}+\delta\right)\mu_{\bar{m}t} \tag{B.1}$$

$$\frac{\mu_{1t+\Delta t}-\mu_{1t}}{\Delta t}=\left(2x_{0t}+\tilde{x}_{0t}\right)\mu_{0t}+\left(\left(1-\phi\right)x_{-2t}+\left(1-\tilde{\phi}\right)\tilde{x}_{-2t}\right)\mu_{2t}-\left(x_{1t}+x_{-1t}+\tilde{x}_{-1t}+\delta\right)\mu_{1t} \tag{B.2}$$

$$\frac{\mu_{0t+\Delta t}-\mu_{0t}}{\Delta t}=\sum_{k=1}^{\bar{m}}\left(\phi_f x_{-kt}+\phi_e\tilde{x}_{-kt}+\delta\right)\mu_{kt}+\left(\left(1-\phi\right)x_{-1t}+\left(1-\tilde{\phi}\right)\tilde{x}_{-1t}\right)\mu_{1t}-\left(2x_{0t}+\tilde{x}_{0t}\right)\mu_{0t} \tag{B.3}$$

B.2 Welfare

In the model economy, aggregate welfare over horizon T calculated at time t_0 is given by

$$\mathbb{W}_{t_0}^{c}=\int_{t_0}^{t_0+T}\exp(-\rho\left(s-t\right))\log C_{cs}\,ds.$$

In Section 7, we report the difference in consumption-equivalent welfare between a counterfactual and the baseline economy using the following relationship:

$$\int_{t_0}^{t_0+T}\exp(-\rho\left(s-t_0\right))\log C_{cs}^{new}\,ds=\int_{t_0}^{t_0+T}\exp(-\rho\left(s-t_0\right))\log\left(\left(1+\varsigma\right)C_{cs}^{base}\right)\,ds. \tag{B.4}$$

If a parameter change generates a new income sequence C_{ct}^{new} between t_0 and t_0+T satisfying the above relationship, we say that the representative household in the counterfactual economy has a ς% higher (lower) consumption-equivalent welfare over horizon T, with $\varsigma>0$ ($\varsigma<0$). In other words, when $\varsigma>0$ ($\varsigma<0$), the representative consumer in the baseline economy would need to receive ς% higher (lower) income at each point in time between t_0 and t_0+T in order to obtain the same level of welfare it would have in the counterfactual scenario.

C Solution Algorithm

Before the discussion of the calibration results, a brief description of our solution algorithm is in order. The algorithm builds on the one developed by Akcigit et al. (2018), who construct an open-economy version of the model considered here. Our aim to find the transition path that emerges as the result of endogenous responses of firms to changes in parameters. We solve a discretized version of the system. The solution algorithm assumes that the economy is initially in the BGP and that the shocked parameter values converge to their new BGP value in T periods, where each period is divided into eight sub-periods. Notice that, due to the endogenous firm decisions and the resulting endogenous adjustments in aggregate variables, the convergence of the economy the new BGP takes longer, which we assume to happen $T_{bgp} > T$ periods. The algorithm is an iterative backward solution method (see Acemoglu et al., 2016). The progression of the algorithm starts with solving for the terminal balanced growth path and then derives firm values and aggregate variables over the transition going backward from the terminal state. A summary of steps is as follows.

1. Start with a guess of parameter values.
2. Compute the initial balanced growth path, where time derivatives are zero by definition. Compute the innovation rates, the implied growth rates, and finally the interest rate compatible with balanced growth.
3. Compute the terminal balanced growth path in T_{bgp} defined by the terminal parameter values similarly.
4. Next calculate the equilibrium over the transition. Guess a time path for the interest rate with the terminal value set to its new BGP level. Solve for firm values and innovation rates backward in time starting from the terminal BGP.
5. Using the resulting sequences and starting from the initial gap distribution implied by the initial BGP, simulate forward the income path and its growth rate. Use the Euler equation to derive the implied interest rate sequence and compare it to the series fed initially.
6. Update the guess for the interest rate series with the implied one and restart from step 2 until the two converge. Once they do, use the final interest rate series and firm decisions to compute the moments of interest.
7. Compare model-based moments to data targets. Search over the parameter space until the following objective function (see Acemoglu et al., 2018) is minimized:

$$\sum_{k=1}^{N} \frac{|\text{model}(k) - \text{data}(k)|}{\frac{1}{2}|\text{model}(k)| + \frac{1}{2}|\text{data}(k)|},$$

   where k denotes each moments and N is the number of targets.

D Additional Quantitative Results

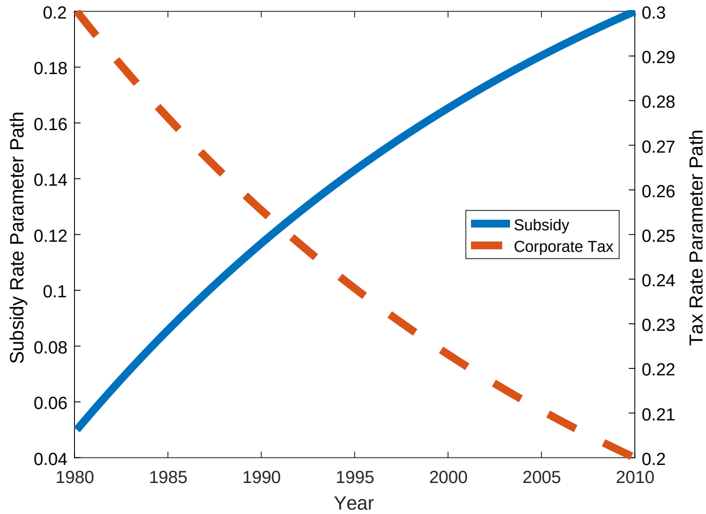

Figure D.4: Transition paths of s and τ

Table D.1: Sensitivity analysis: responses to 1% change in parameters

	R&D scale incumbent α	**R&D scale entrant** $\tilde{\alpha}$	**Step size** λ	**Knowledge diffusion** δ	**Drastic innovation** $\phi = \tilde{\phi}$
Growth	-0.32%	-0.07%	1.35%	0.10%	0.02%
Entry	-0.09%	-0.21%	0.32%	0.30%	0.09%
R&D	-0.46%	0.03%	1.22%	-0.44%	-0.10%
Profit	-0.34%	0.09%	1.05%	-0.78%	-0.19%
Markup	-0.07%	0.01%	0.21%	-0.13%	-0.03%
Young	0.26%	2.82%	2.99%	2.24%	1.17%

Notes: Table entries show the elasticity of moments to each parameter. Precisely, they show the percentage change in each target in response to a 1 percent increase in each parameter, keeping the other parameters constant at their calibrated value.