What Happened to US Business Dynamism?

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We attempt to understand potential common forces behind rising market concentration and a slowdown in business dynamism in the US economy, through a micro-founded general equilibrium model of endogenous firm dynamics. The model captures the strategic behavior between competing firms, its effect on their innovation decisions, and the resulting "best-versus-the-rest" dynamics. We consider multiple potential mechanisms that can drive the observed changes and use the calibrated model to assess their relative importance, with particular attention to the implied transitional dynamics. Our results highlight the dominant role of a decline in the intensity of knowledge diffusion from frontier firms to laggard ones. We present new evidence that corroborates a declining knowledge diffusion in the economy.

I. Introduction

Market economies are characterized by "creative destruction," where unproductive incumbents are pushed out of the market by new entrants, other more productive incumbents, or both. A by-product of this up-or-out process is the creation of higher-paying jobs and reallocation of

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workers from less to more productive firms. The US 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 has initiated a heated debate around the possible reasons behind the declining dynamism in the US 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 and inventor concentration.

A central concern of our study is the identification of factors that could have driven these observed trends in US business dynamism.[1] During the past several decades, the US 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 include reduced effective corporate taxes; increased research and development (R&D) subsidies; increased regulatory burden, potentially with a heavier toll on new and small firms; and heavier use of intellectual property, in a way that limits the technologies that can be used by competing firms and lowers the effective knowledge diffusion.[2] Incorporating these margins within a realistic theoretical framework, we explore two main quantitative questions based on various thought

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[1] We focus on 10 specific trends: (i) market concentration has risen, (ii) average markups have increased, (iii) the profit share of GDP (gross domestic product) has increased, (iv) the labor share of output has gone down, (v) the rise in market concentration and the fall in the 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, and (x) the dispersion of firm growth has decreased. We review them in more detail in sec. II.

[2] We review these specific changes in more detail in app. A (apps. A–G are available online). Of note, they are not meant to be exhaustive; rather, they serve as exemplary

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 US economy as if it were 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 transition path of the model economy to reflect the changes that the US economy has experienced 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 US economy has witnessed.

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 the 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, Harris, and Vickers 1993). In the typical framework, two players race for a prize, and the players exert different efforts,

motivations for the choice of channels on which we focus. They are also not necessarily exclusive. For instance, while we mention regulatory burden in the context of firm entry, there may certainly be other specific regulations (or the lack thereof) that could limit the diffusion of knowledge, as we discuss in sec. II and, in more detail, in Akcigit and Ates (2021).

depending on their position relative to their competitor's. 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, Harris, and Vickers 1997; Aghion et al. 2001, 2005; Acemoglu and Akcigit 2012; Akcigit, Ates, and Impullitti 2018). In a recent review of declining business dynamism, we consider a framework along these lines (Akcigit and Ates 2021). 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 obtain a richer setting suitable for quantitative analysis, including transitional paths.

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," produce imperfect substitutes of the same good with different productivity levels and compete à la Bertrand for market leadership. This competitive structure gives the market leader—the technologically more advanced firm—a pricing advantage in proportion to its technology lead over its rival; hence, the markups 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 someday. 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 affects 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 US 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 among them have greater power in explaining the observed empirical trends in the US economy.

We calibrate the model to pre-1980 moments in the data as if the US economy were 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 2015 and compare the model-simulated transition paths with all post-1980 empirical trends. We repeat this analysis with all four channels described above. The second set of experiments matches the transition path of the model to the transitional dynamics of the US 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 2015 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% of the observed trends—a notable exception is the dominant role of the entry cost channel in driving firm entry—the knowledge-diffusion channel accounts for more than 80% of most symptoms of declining business dynamism and at least 60% of almost all considered trends.

Reduction in knowledge diffusion is able to account for these trends as follows. When knowledge diffusion slows 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. 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 farther ahead) to charge higher markups, which also increases the profit share and decreases the labor share of 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 experiment less. Hence, overall dynamism and experimentation in the economy decrease.

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 where 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 a discussion of alternative hypotheses, whose potential links to some of the observed trends considered here have recently drawn the attention of the literature. Using numerical examples, we first 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'. 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. We end this section discussing our model's implications as to demographic shifts and declining firm-level responsiveness.

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 from the ones studied here. However, our analysis instead shows that among the mechanisms we consider—changes in corporate taxation, government support for incumbents, increased cost of entry, 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 also show that a similar trend of concentration has been taking place in the realm of inventors. We hope that these findings ignite a broader conversation in the literature.

The rest of the paper is organized as follows. Section II reviews the literature; it also revisits the empirical trends that the literature has interpreted as the signs of declining business dynamism. Section III introduces the theoretical model and the empirical evidence motivating it, and section IV describes its calibration. Sections V and VI present the experiments that identify and quantify the importance of each margin, using the calibrated model. Section VII discusses the welfare implications. Section VIII investigates the implications of additional channels with regard to observed empirical trends and provides a summary of robustness exercises. Section IX presents new empirical facts on the use of intellectual property and the concentration of inventors in mature firms in the US economy, which could shed some light on the reasons knowledge diffusion has slowed over time. Section X concludes.

II. 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 the labor share are positively associated.
6. The productivity dispersion of firms has risen; similarly, the labor productivity gap between frontier and laggard firms has widened.
7. The firm entry rate has declined.
8. The share of young firms in economic activity has declined.
9. Job reallocation has slowed.
10. The dispersion of firm growth has decreased.

Next, we briefly discuss the mechanisms the literature has proposed to explain these regularities. We refer the interested reader to Akcigit and Ates (2021) for a more extensive review.

To start, a set of recent papers documents an increasing market concentration in the United States (fact 1; see Furman and Giuliano 2016; Gutiérrez and Philippon 2016, 2017; Autor et al. 2017a, 2017b; Grullon, Larkin, and Michaely 2019; and Barkai 2020, among others).[3] Second, several recent studies show an increase in average markups (fact 2; see Nekarda and Ramey 2013; De Loecker, Eeckhout, and Unger 2017; Gutiérrez and Philippon 2017; Eggertsson, Robbins, and Wold 2018; and Hall 2018, among others).[4] Relatedly, a subset of these studies also highlights 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 (Akcigit et al. 2021). For instance, Gutiérrez and

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

[4] Calligaris, Criscuolo, and Marcolin (2018) and De Loecker and Eeckhout (2018) document similar patterns for various other countries as well.

Philippon (2016) argue that increased industry concentration drives the weak investment performance of US firms via a decline in competition. Eggertsson, Robbins, and Wold (2018) and Farhi and Gourio (2018) argue that increased market power can help explain several macrofinance regularities, with Eggertsson, Robbins, and Wold (2018) also emphasizing persistently low interest rates. Liu, Mian, and Sufi (2022) also focus on the role of low interest rates as a culprit of rising market concentration and declining business dynamism.[5] Barkai (2020) claims that higher concentration 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, 2004b). 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.[6] 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 (2019) 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.[7]

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 Elsby, Hobijn, and Şahın 2013; Karabarbounis and Neiman 2014; and Lawrence 2015). The literature has proposed a variety of explanations for this decline, including increased offshoring or foreign sourcing of inputs (Elsby, Hobijn, and Şahın 2013; Boehm, Flaaen, and Pandalai-Nayar 2017); a fall in corporate tax rates (Kaymak and Schott 2018); a slowdown in population growth (Hopenhayn, Neira, and Singhania 2018);[8] a slowdown in productivity growth (Grossman et al. 2017); higher

[5] We discuss the effects of declining interest rates further in sec. VIII.A.

[6] While most of these papers analyze industries at the national level, Rossi-Hansberg, Sarte, and Trachter (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 policy makers bring forward similar critiques based on the definition of relevant markets (see OECD 2018a, 2018b, the latter by the US delegation).

[7] By contrast, De Ridder (2019) argues that an increase in firms' efficiency of adopting intangible inputs can depress aggregate innovation in a balanced-growth path, increasing the market power of firms. Gutiérrez and Philippon (2019) note that the two explanations—rising market power and decreasing competition vs. 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." Deviating from these arguments, Olmstead-Rumsey (2020) emphasizes worsening quality of innovation by laggard firms to account for similar trends.

[8] Hopenhayn, Neira, and Singhania (2018), as well as Peters and Walsh (2021), argue that a decline in population growth is responsible for a broader range of changes in firm dynamics. We elaborate on this topic in sec. VIII.A.4.

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 2020).[9] 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.[10] They highlight the positive industry-level relationship between the rise in concentration and the fall of the labor share, another regularity we consider in this paper (fact 5). In a recent study, Aghion et al. (2023) 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 across balanced-growth paths.

We also consider a number of facts that suggest a decline in business dynamism. First, the productivity dispersion has increased in the United States, as shown by Decker et al. (2020). Similarly, Andrews, Criscuolo, and Gal (2015, 2016) establish that, across the OECD economies, the gap between the average productivity levels of frontier firms (the top 5% of firms with the highest productivity) and 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 has been a secular decline in firm (and establishment) entry rates in the United States in the past several decades (fact 7; see Gourio, Messer, and Siemer 2014; Decker et al. 2016; and Karahan, Pugsley, and Şahın 2021). Likewise, the employment share of young firms has also been declining steadily (fact 8; see Decker et al. 2016 and Furman and Orszag 2018), which is particularly worrying, given the disproportionate contribution of high-growth young firms to job creation (Bravo-Biosca, Criscuolo, and Menon 2013; Haltiwanger, Jarmin, and Miranda 2013). Decker et al. (2016) 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 (Decker et al. 2020).[11] Sterk ⓡ Sedláček ⓡ Pugsley (2021) argue that the

[9] Berger, Herkenhoff, and Mongey (2019) and Lipsius (2018) dismiss the argument that labor market concentration has contributed to the fall in the aggregate labor share.

[10] Diez, Leigh, and Tambunlertchai (2018) also find support for the superstar-firm argument in an international comparison using multicountry 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.

[11] We discuss how our analysis relates to lower responsiveness of firms in sec. VIII.A.4.

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 declining 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, Criscuolo, and Gal (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 help 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 (*Economist* 2017). Indeed, Calligaris, Criscuolo, and Marcolin (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, Larkin, and Michaely (2019) that US 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, Larkin, and Michaely 2019). 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 (Lynn 2010; Baker 2012; Khan 2016). Lower antitrust enforcement and increased consolidation could harm the competitive dynamics of the market. For instance, Cunningham, Ederer, and Ma (2021) underscore the "killer acquisitions" in the pharmaceutical industry, which are 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, Criscuolo, and Gal (2016), who claim that the lack of procompetitive product market reforms has contributed to the widening productivity gap between frontier and laggard firms across the OECD countries.

To sum up, 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). Such analysis is possible because of the distinct nature of the theoretical framework, which succinctly and realistically captures the endogenous relationship between market competition and firm dynamics. Moreover, our quantitative analysis, carefully accounting for transitional dynamics, evaluates the relevance of a number of potential channels that could have contributed to the observed changes and underscores the dominant role played by the knowledge-diffusion margin. This quantitative investigation also advances the analysis of this class of models in ways and detail not examined before. Finally, we further the debate on market concentration and business dynamism by presenting new evidence from the patent and inventor data that highlights changing patterns of concentration and strongly points to a decline in knowledge diffusion.

III. 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 produce imperfectly substitutable varieties and engage in Bertrand price competition to expand their market shares. These 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 Bertrand competition, different relative productivity levels generate a distribution over heterogeneous markup levels. In addition, there is an outside pool of entrants that engages 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 technologically 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 laws of motion 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 *A* illustrating the widening of productivity between frontier and laggard firms across OECD countries while *B* makes a similar case for the US manufacturing industry. Perhaps puzzlingly, however, the dispersion of firm growth rates has been declining simultaneously, as shown in figure 1*C*. 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

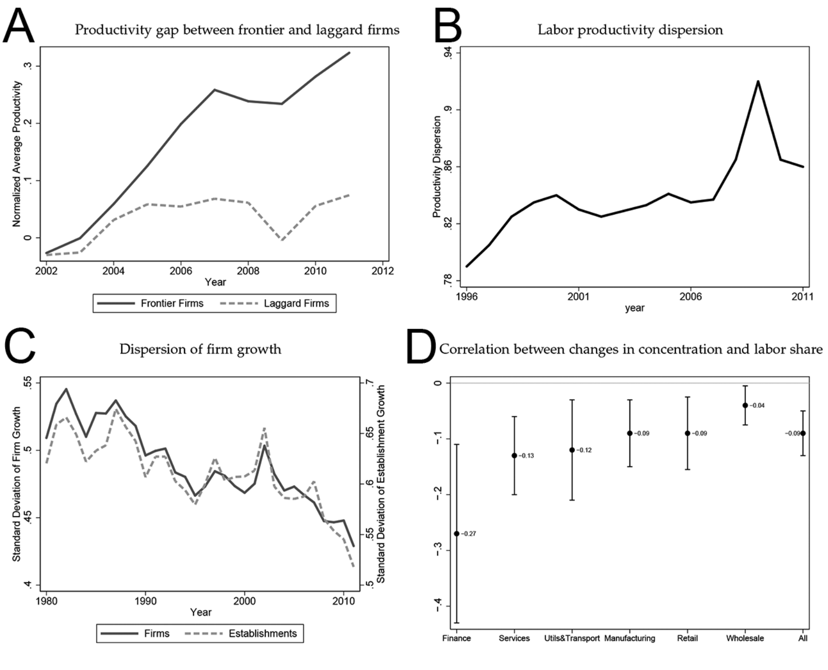

FIG. 1.—Empirical trends that inform the theory. *A* is taken from Andrews, Criscuolo, and Gal (2016), *B* from Decker et al. (2020), *C* from Decker et al. (2016), and *D* from Autor et al. (2017b).

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 farther behind and (ii) a diminishing escape-competition effect on the leader as it opens the technology gap. Moreover, figure 1*D* suggests a negative correlation between concentration and the 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.

A. *Preferences*

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

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

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

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

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 (denoted by V_{ft}); that is, $A_t = \int_{\mathcal{F}} V_{ft} \, df$, with $\mathcal{F}$ denoting the set of firms.

B. *Technology and Market Structure*

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 monopolistically competitive intermediate firms, which we describe next.

2. Intermediate Goods and Innovation

Incumbents.—In each product line j, two incumbent firms $i = \{1, 2\}$ produce imperfectly 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

$$y_{jt} = \left(y_{ijt}^{\beta} + y_{-ijt}^{\beta}\right)^{1/\beta},$$

where $-i$ denotes the competitor of firm i, with $-i = \{1, 2\}$ and $-i \neq i$. The CES (constant elasticity of substitution) parameter $\beta \in (0, 1)$ governs the degree of substitutability between varieties, with higher values implying that the varieties are closer substitutes. The intermediate-good firms compete in prices. As a result, the firm that has a higher labor productivity obtains a cost advantage and therefore captures a larger share of the market for good j in the Bertrand equilibrium. We call 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 $\lambda^{n_t} > 1$ such that $q_{ij(t+\Delta t)} = \lambda^{n_t} q_{ijt}$, where λ denotes the basic step size and $n_t \in \mathbb{R}$ denotes the size of the improvement. As we specify below, the innovation size will be a function of the size of the technology lead the leader commands. By contrast, an innovation by a follower may be an incremental or a drastic one. With probability $1 - \phi$, the follower's innovation improves its productivity proportionally by one step, 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. As such, 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 the rest of the firms. Therefore, we label δ as the "knowledge-diffusion" parameter.[12]

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. We define $m_{ijt} \equiv N_{ijt} - N_{-ijt} \in \mathbb{N}$ as the technology gap between firm i and competitor $-i$. Then, the relative productivity level is given as a function of m_{ijt}:

$$\frac{q_{ijt}}{q_{-ijt}} = \lambda^{\mathbb{F}(N_{ijt}-N_{-ijt})} \equiv \lambda^{\mathbb{F}(m_{ijt})},$$

where $\mathbb{F}(\cdot)$ arises from the heterogeneity of innovation sizes and is clarified below. We assume that there is a large but exogenously given upper limit in the technology gap, denoted by $\bar{m}$.[13] As will be clear, m_{ijt} is a sufficient statistic to describe firm-specific payoffs independent of the product line j. Therefore, we drop industry subscript j whenever $m_{it} \in \{-\bar{m}, \ldots, 0, \ldots, \bar{m}\}$ refers to a firm-specific value. Accordingly, when we say that the leader is m steps ahead or, reciprocally, the follower is m steps behind, we mean that the follower needs to improve its productivity by m steps more than the leader to become neck and neck. Finally, we use the notation $m_{jt} \in \{0, \ldots, \bar{m}\}$ 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."

The function $\mathbb{F}(\cdot)$ governs (partially) the additional payoff from opening up the technology gap with the competitor and follows from the specification of innovation sizes. Let us define the innovation sizes by $n_{ijt} \equiv f(m_{ijt})$. Note that $f(m_{ijt}) = 1$ brings the model back to the standard structure of step-by-step innovation models (Akcigit and Ates 2019). It also follows that $\mathbb{F}(m_{ijt}) = \Sigma_0^{m_{ijt}} f(m_{ijt})$ for $0 < m_{ijt} < \bar{m}$ and $\mathbb{F}(0) = 0$.[14] We

[12] This interpretation follows a long literature on technology diffusion (Aghion et al. 2001, 2005; Acemoglu and Akcigit 2012; Perla and Tonetti 2014; Buera and Oberfield 2020; Benhabib, Perla, and Tonetti 2021; and Perla, Tonetti, and Waugh 2021, to name a few) and refers to a broader dynamic in the economy that is not confined to R&D activity. Alternative interpretations of this channel could possibly be entertained. However, these considerations are subject to two important caveats. First, it is worth assessing whether δ is the most appropriate way to model the specific mechanism within the model. Second, in light of our quantitative findings, the alternative channel would have to be consistent with a decline in δ. Only a few options could meet these criteria, and our quantitative and empirical analyses suggest that the knowledge diffusion stands out as a highly relevant mechanism that could appropriately be used to define δ. For further remarks on the interpretation of this channel, please refer to sec. VIII.A.4.

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

[14] This structure implies that $\mathbb{F}(-m_{ijt}) = -\mathbb{F}(m_{ijt})$.

specify and calibrate the exact form of $f(\cdot)$ in section IV, and we keep the general notation for now. In the spirit of Akcigit and Kerr (2018), this generalization of the innovation structure introduces heterogeneity in the size of innovations, depending on firm size. It not only brings the model closer to the data but also provides additional flexibility regarding its aggregate implications. Still, as established in the quantitative analysis, the main mechanism and the key results are robust to this generalization.

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 $x_{ijt} = [\gamma(h_{ijt}/\alpha)]^{1/\gamma}$.

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, that entrepreneur 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).[15] If the innovation attempt fails, the entrant disappears.

Like a follower innovation, an entrant innovation may be drastic, with probability $\tilde{\phi}$, allowing it to catch up with the frontier technology.[16] 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

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

In figure 2, we demonstrate how leadership positions in intermediate-product lines evolve as a result of incumbent and entrant innovations. Figure 2*A* has five product lines with heterogeneous technology gaps. Note that in line 1, firms are in a neck-and-neck position. Figure 2*B* shows the changes in leadership. Line 5 illustrates the two cases associated with a

[15] 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.

[16] In the remainder of the discussion, a tilde signifies values that pertain to an entrant.

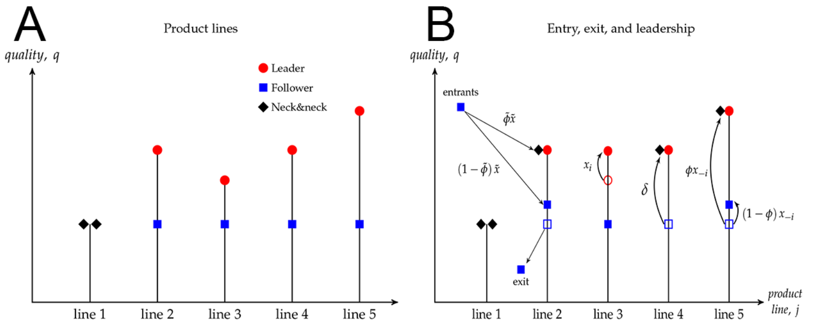

FIG. 2.—Evolution of product lines. *A* exhibits the positions of competing incumbent firms with heterogeneous quality gaps in a set of product lines. *B* illustrates the effects of innovation by incumbents and entrants as well as knowledge diffusion and the resulting dynamics of entry, exit, and technological leadership. Open squares or circles denote the previous position of firms that innovate or exit.

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 a 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.

C. Equilibrium

In this section, we characterize the dynamic general equilibrium of the model, where a key element of equilibrium strategies is the 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.

1. Static Equilibrium

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 $j \in [0, 1]$:

$$y_{ijt} = \frac{p_{ijt}^{1/(\beta-1)}}{p_{ijt}^{\beta/(\beta-1)} + p_{-ijt}^{\beta/(\beta-1)}} Y_t, \tag{3}$$

where p_{ijt} is the price of the variety of good j firm i produces. The functional form in equation (1) implies that the representative final-good producer spends an equal amount Y_t on each intermediate good j—that is, $\Sigma_{i=1,2} p_{ijt} y_{ijt} = P_t Y_t = Y_t$ holds in equilibrium for all j. Defining $z_{ijt} \equiv p_{ijt} y_{ijt} / Y_t$ as the market share of firm i in line j, we have[17]

$$z_{ijt} = p_{ijt}^{\beta/(\beta-1)} \left(p_{ijt}^{\beta/(\beta-1)} + p_{-ijt}^{\beta/(\beta-1)} \right)^{-1}. \tag{4}$$

Then, the equilibrium price of firm i follows as

$$p_{ijt} = \frac{1 - \beta z_{ijt}}{\beta \left(1 - z_{ijt}\right)} \mathrm{mc}_{ijt}, \tag{5}$$

where $\mathrm{mc}_{ijt} = w_t / q_{ijt}$ denotes the marginal production cost of intermediate producer i.

Equations (3)–(5) define uniquely the equilibrium quantities of intermediate varieties, the market shares of intermediate firms, and the prices they charge. Importantly, the market shares, and thus the revenue of the firm, depend only on the relative productivity levels of competitors. To see this, rewrite equation (4) such that $z_{ijt} = [1 + (p_{-ijt}/p_{ijt})^{\beta/(\beta-1)}]^{-1}$. The price ratio follows from equation (5) as

$$\frac{p_{-ijt}}{p_{ijt}} = \frac{1 - \beta\left(1 - z_{ijt}\right)}{1 - \beta z_{ijt}} \frac{1 - z_{ijt}}{z_{ijt}} \frac{q_{ijt}}{q_{-ijt}} \equiv \Xi(z_{ijt}) \lambda^{\mathbb{F}(m_{ijt})},$$

using the identity $z_{-ijt} = 1 - z_{ijt}$. Consequently, equation (4) implicitly defines the market shares as an increasing function of the relative productivity levels. As we shall see next, what matters then for the payoff-relevant variables is the productivity gap between rivals, and therefore the identity of the specific industry becomes irrelevant for a firm's payoff.

The optimal production employment of the intermediate producers follows as[18]

$$l(m_{it}) = \frac{y_{it}}{q_{it}} = q_{it}^{-1} \frac{z_{it}}{p_{it}} Y_t = \omega_t^{-1} \frac{\beta z_{it}(1 - z_{it})}{1 - \beta z_{it}}, \tag{6}$$

[17] Then, $z_{ijt} + z_{-ijt} = 1 \ \forall j$ holds in equilibrium at all times. In equilibrium, the technologically more advanced firm has a higher market share—i.e., $z_{ijt} > 1/2$ if $q_{ijt} > q_{-ijt}$.

[18] In the remainder of the discussion, we drop the subscript j unless doing so leads to confusion.

where $\omega_t \equiv w_t/Y_t$ denotes the normalized wage level. The operating profits of the intermediate-good producer exclusive of R&D expenditures becomes

$$\pi(m_{it}) = (p_{it} - \mathrm{mc}_{it})y_{it} = \frac{(1-\beta)z_{it}}{1-\beta z_{it}}Y_t. \tag{7}$$

Similarly, the price-cost markup reads as

$$\mathrm{mk}(m_{it}) = \frac{p_{it}}{\mathrm{mc}_{it}} - 1 = \frac{1-\beta}{\beta(1-z_{it})}. \tag{8}$$

Note that because firms' market shares depend on the technological difference between the leader and the follower, markups and profits do so as well. Consequently, 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 according to firms' endogenous innovation decisions.

2. 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

$$\begin{aligned} r_t V_{mt} - \dot{V}_{mt} = \max_{x_{mt}} \Big\{ & (1-\tau_t)\pi(m) - (1-s_t)\alpha\frac{x_{mt}^{\gamma}}{\gamma}w_t + x_{mt}(V_{m+1t} - V_{mt}) \\ & + \left(\phi x_{-mt} + \tilde{\phi}\tilde{x}_{-mt} + \delta\right)(V_{0t} - V_{mt}) \\ & + \left[(1-\phi)x_{-mt} + \left(1-\tilde{\phi}\right)\tilde{x}_{-mt}\right](V_{m-1t} - V_{mt})\Big\}. \end{aligned} \tag{9}$$

The first term on the right-hand side of the expression captures the operating profits, taxed at the corporate income tax rate τ_t. The second term in the first line is for 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.[19] As reflected in the second line, if there is a drastic innovation by the follower (with probability ϕ) or by an entrant (with probability $\tilde{\phi}$), 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

[19] 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.

by competitors (with $1-\phi$ or $1-\tilde{\phi}$), in which the position of the leader deteriorates by one step.

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

$$\begin{aligned} r_t V_{-mt} - \dot{V}_{-mt} = \max_{x_{-mt}} \Bigg\{ & (1-\tau_t)\pi(-m) - (1-s_t)\alpha \frac{x_{-mt}^{\gamma}}{\gamma} w_t \\ & + (1-\phi)x_{-mt}(V_{-m+1t} - V_{-mt}) \\ & + (\phi x_{-mt} + \delta)(V_{0t} - V_{-mt}) \\ & + x_{mt}(V_{-m-1t} - V_{-mt}) + \tilde{x}_{-mt}(0 - V_{-mt}) \Bigg\}. \end{aligned} \tag{10}$$

The followers also generate positive profits, subject to the tax rate τ_t. These forward-looking firms invest in R&D with the prospect of taking over the leader 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[20]

$$\begin{aligned} r_t V_{0t} - \dot{V}_{0t} = \max_{x_{0t}} \Bigg\{ & (1-\tau_t)\pi(0) - (1-s_t)\alpha \frac{x_{0t}^{\gamma}}{\gamma} w_t + x_{0t}(V_{1t} - V_{0t}) \\ & + x_{-0t}(V_{-1t} - V_{0t}) + \frac{1}{2}\tilde{x}_{0t}(0 - V_{0t}) \Bigg\}, \end{aligned} \tag{11}$$

where x_{-0t} denotes the innovation rate of the competitor. In equilibrium, both neck-and-neck firms innovate at the same rate; that is, $x_{0t} = x_{-0t}$.

Before we derive optimal innovation efforts, the following lemma defines the normalized firm values.

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

$$\begin{aligned} \rho v_{mt} - \dot{v}_{mt} = \max_{x_{mt}} \Bigg\{ & (1-\tau_t)\hat{\pi}(m) - (1-s_t)\alpha \frac{x_{mt}^{\gamma}}{\gamma} \omega_t + x_{mt}(v_{m+1t} - v_{mt}) \\ & + \left(\phi x_{-mt} + \tilde{\phi}\tilde{x}_{-mt} + \delta\right)(v_{0t} - v_{mt}) \\ & + \left[(1-\phi)x_{-mt} + \left(1-\tilde{\phi}\right)\tilde{x}_{-mt}\right](v_{m-1t} - v_{mt}) \Bigg\}, \end{aligned}$$

with $\hat{\pi}(m) = \pi(m)/Y_t = (1-\beta)z_{it}(1-\beta z_{it})^{-1}$. Normalized values for $m \leq 0$ are defined reciprocally.

[20] Note that, when there is successful entry, the neck-and-neck incumbent exits with a one-half probability because, by assumption, the entrant randomly replaces one of the two incumbents with the same technology.

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). QED

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

$$x_{mt} = \begin{cases} \left[\dfrac{1}{\alpha\omega_t(1 - s_t)}(v_{m+1t} - v_{mt})\right]^{1/(\gamma-1)} & \text{if } m \geq 0, \\ \left\{\dfrac{1}{\alpha\omega_t(1 - s_t)}[(1 - \phi)v_{m+1t} + \phi v_{0t} - v_{mt}]\right\}^{1/(\gamma-1)} & \text{if } m < 0. \end{cases} \tag{12}$$

Entrants.—Recall that entry is directed at particular product lines and that 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

$$\max_{\tilde{x}_{-mt}}\left\{-\tilde{\alpha}\frac{\tilde{x}_{-mt}^{\tilde{\gamma}}}{\tilde{\gamma}}w_t + \tilde{x}_{-mt}\left[\left(1 - \tilde{\phi}\right)V_{-m+1t} + \tilde{\phi}V_{0t} - 0\right]\right\}, \tag{13}$$

where $m > 0$.[21] The resulting optimal innovation decisions of entrants are specified as follows:

$$\tilde{x}_{-mt} = \begin{cases} \left\{(\tilde{\alpha}\omega_t)^{-1}\left[\left(1 - \tilde{\phi}\right)v_{m+1t} + \tilde{\phi}v_{0t}\right]\right\}^{1/(\tilde{\gamma}-1)} & \text{if } m > 0, \\ \left[(\tilde{\alpha}\omega_t)^{-1}v_{1t}\right]^{1/(\tilde{\gamma}-1)} & \text{if } m = 0. \end{cases} \tag{14}$$

We close the model by specifying aggregate wage and output. To this end, we first define $Q_t \equiv \exp(\int_0^1 \ln q_{jt}^{\max}\, dj)$ as the productivity frontier of the economy, where $q_{jt}^{\max} = \max\{q_{ijt}, q_{-ijt}\}$ denotes the highest productivity level that prevails among the two competitors in line j. We also define $\mu_{mt} \equiv \int_0^1 \mathbb{I}\{|\log(q_{ijt}/q_{-ijt})| = \mathbb{F}(m)\}\, dj$ 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 substituting equations (3) and (5) in the final-good production function yields the wage rate as a function of Q_t and μ_{mt}:

[21] 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 by only one step:

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

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.

$$w_t = Q_t \exp\left\{\frac{1-\beta}{\beta}\sum_{k=0}^{\bar{m}}\mu_{kt}\ln\left(\left[\frac{\beta(1-z_{kt})}{1-\beta z_{kt}}\right]^{\beta/(1-\beta)} + \left[\frac{\beta z_{kt}}{1-\beta(1-z_{kt})}\lambda^{-\mathbb{F}(k)}\right]^{\beta/(1-\beta)}\right)\right\}. \quad (15)$$

Here, z_k denotes the market share of a firm that is k steps ahead of its competitor. An inspection of the term in logs shows that it is a decreasing function of the step size; therefore, a shift in the sectoral distribution toward more concentrated sectors (without changing the productivity frontier) suppresses the aggregate wage level.

The labor market–clearing condition holds at all times, that is,

$$1 = \int_0^1 \left(l_{ijt} + l_{-ijt} + h_{ijt} + h_{-ijt} + \tilde{h}_{jt}\right) dj, \quad (16)$$

and implies the following normalized wage ω_t:

$$\omega_t = \left\{\sum_{k=0}^{\bar{m}}\mu_{kt}\left[\frac{\beta z_{kt}(1-z_{kt})}{1-\beta z_{kt}} + \frac{\beta z_{kt}(1-z_{kt})}{1-\beta(1-z_{kt})}\right]\right\}\left\{1 - \sum_{k=0}^{\bar{m}}\mu_{kt}\left[\frac{\alpha}{\gamma}(x_{kt}^{\gamma} + x_{-kt}^{\gamma}) + \frac{\tilde{\alpha}}{\tilde{\gamma}}\tilde{x}_{-kt}^{\tilde{\gamma}}\right]\right\}^{-1}. \quad (17)$$

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

$$h_{ijt} = \frac{\alpha}{\gamma}x_{ijt}^{\gamma} \quad \text{and} \quad \tilde{h}_{jt} = \frac{\tilde{\alpha}}{\tilde{\gamma}}\tilde{x}_{jt}^{\tilde{\gamma}}. \quad (18)$$

The normalized wage rate, which corresponds to the labor share, decreases statically in response to a shift in the sectoral distribution toward larger productivity gaps.[22]

Combining equations (1) and (6) gives the level of final output:

$$Y_t = Q_t\lambda^{-\sum_{k=0}^{\bar{m}}\mathbb{F}(k)\mu_{kt}}\omega^{-1} \times \exp\left(\sum_{k=0}^{\bar{m}}\mu_{kt}\ln\left(\left[\lambda^{\mathbb{F}(k)}\frac{\beta z_{kt}(1-z_{kt})}{1-\beta z_{kt}}\right]^{\beta} + \left[\frac{\beta z_{kt}(1-z_{kt})}{1-\beta(1-z_{kt})}\right]^{\beta}\right)^{1/\beta}\right). \quad (19)$$

Note that the final output depends positively on the productivity index. In addition, the difference between the government's corporate tax income and subsidy expenditure is given by

$$G_t = \sum_{k=0}^{\bar{m}}\mu_{kt}\left[\tau_t(\pi(k) + \pi(-k)) - s_t\left(\frac{\alpha}{\gamma}x_{kt}^{\gamma} + \frac{\alpha}{\gamma}x_{-kt}^{\gamma}\right)w_t\right], \quad (20)$$

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

[22] The first bracketed term decreases in the productivity gap, while the difference inside the second term in braces increases, as the overall incentive to innovate is lower in sectors with larger technology gaps between the follower and the leader, freeing up labor to be used for production.

$$R_t = w_t \int_0^1 \left(h_{ijt} + h_{-ijt} + \tilde{h}_{jt}\right) dj. \tag{21}$$

Finally, we define the evolution of the productivity frontier 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:

$$\ln Q_{t+\Delta t} - \ln Q_t = \ln\lambda \left[\mu_{0t}(2x_{0t} + \tilde{x}_{0t}) + \sum_{k=1}^{\bar{m}} \mu_{kt} x_{kt} f(k)\right] \Delta t + o(\Delta t), \tag{22}$$

which also defines the aggregate growth rate in the balanced-growth path (BGP).[23] The transition of μ_{mt} for $\bar{m} > m > 1$ is as follows:

$$\begin{aligned}\frac{\mu_{mt+\Delta t} - \mu_{mt}}{\Delta t} = {} & x_{m-1t}\mu_{m-1t} + \left[(1-\phi)x_{-m-1t} + \left(1-\tilde{\phi}\right)\tilde{x}_{-m-1t}\right]\mu_{m+1t} \\ & - \left(x_{mt} + x_{-mt} + \tilde{x}_{-mt} + \delta\right)\mu_{mt} + o(\Delta t)/\Delta t.\end{aligned} \tag{23}$$

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 dynamic general equilibrium in this economy is an allocation

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

such that (i) the sequence of prices and quantities $\{p_{jt}, y_{jt}\}$ satisfies equations (3)–(5) and maximizes the 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 (12) and (14), and the aggregate R&D expenditure R_t is specified in equation (21); (iii) the supply of labor $L = 1$ is

[23] Here, $o(\Delta t)$ represents second-order terms, which capture the probability of two or more innovations within the interval Δt and satisfies $\lim_{\Delta t\to 0} o(\Delta t)/\Delta t = 0$. Note that the term includes $f(k)$ and corresponds to the standard model when $f(k) = 1$. Note also that the growth of aggregate output differs from this expression during the transition, because the distribution of technology gaps—and, hence, the market shares and markups—also shifts.

equal to the sum of intermediate-good producers' profit-maximizing production worker demand (given in eq. [6]) and optimal R&D worker demand (given in eq. [18]), as in equation (16); (iv) Y_t is as given in equation (19), 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 (20), 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 (22) and (23), consistent with optimal R&D decisions.

In our quantitative exploration, we 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 US 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 IX, 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, eventually leading to higher concentration and declining business dynamism. In the following quantitative analysis, we use our structural model to identify and quantify the effects of these likely culprits behind declining business dynamism.

IV. Calibration of the Initial BGP

Our ultimate aim in this paper is to quantify the relative importance of some key potential drivers of declining US business dynamism. In particular, as noted above, 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 assume that the model starts from a BGP in 1980 and then replicate the transitional dynamics of the US economy in the post-1980 period to back up the relative variation in each of these margins. Therefore, we first describe how we determine the initial BGP of the economy, which reflects the average long-term conditions of the US 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.

A. *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:

$$\text{entry rate}_t = \frac{1}{2}\sum_{k=0}^{\bar{m}} \mu_{kt}\tilde{x}_{-kt}, \tag{24}$$

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

Labor share.—The labor share of GDP is given by

$$\text{labor share}_t = \frac{w_t L}{Y_t} = \omega_t.$$

Markups.—Average markup level is defined by

$$\text{markup}_t = \sum_{k=0}^{\bar{m}} \mu_{kt}\,\text{mk}(k). \tag{25}$$

Profit share.—The profit share of GDP is given by

$$\text{profit share}_t = 1 - \omega_t. \tag{26}$$

Concentration.—Market concentration within a sector increases with the productivity gap and has a nondegenerate distribution across sectors. Accordingly, the average sales concentration measured by the Herfindahl-Hirschman Index (HHI) is given by

$$\text{hhi}_t = \sum_{k=0}^{\bar{m}} \mu_{kt}\left[z_k^2 + (1 - z_k)^2\right]. \tag{27}$$

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 $\ln Q_{mt} = \int_{\mu_{mt}} \Sigma_{i=1}^{2} (\ln q_{ijt}) \mathbb{I}\{q_{ijt} > q_{-ijt}\} dj$ and the corresponding measure for the followers as $\ln Q_{-mt} = \int_{\mu_{mt}} \Sigma_{i=1}^{2} (\ln q_{ijt}) \mathbb{I}\{q_{ijt} < q_{-ijt}\} dj$. Then, the economy-wide productivity gap becomes

$$\text{productivity gap}_t = \sum_{k=1}^{\bar{m}} (\ln Q_{mt} - \ln Q_{-mt}) = \sum_{k=1}^{\bar{m}} \mu_{kt} \ln \lambda^{\mathbb{F}(k)}. \tag{28}$$

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, Haltiwanger, and Schuh (1996), a metric that takes a value in $[-2, 2]$. We compute the standard deviation of firm growth with the same formula.

B. *Data and Identification*

The calibrated BGP of our model reflects the state of the US economy before the early 1980s. Thirteen structural parameters define this BGP: $\Theta \equiv \{\rho, \tau, s, \beta, \lambda, \psi, \alpha, \tilde{\alpha}, \gamma, \tilde{\gamma}, \phi, \tilde{\phi}, \delta\}$. Among these, ψ governs $\mathbb{F}(m)$. Specifically, we consider the general functional form $\mathbb{F}(m) = m^{\psi}$ and, thus, $f(m) = (m + 1)^{\psi} - m^{\psi}$. The latter is constant if $\psi = 1$—which, again, corresponds to the standard structure—and decreasing in m if $\psi < 1$. We set five parameters 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, that is, $\tilde{\gamma} = \gamma$. 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, Ates, and Impullitti (2018). The policy parameters are constant along the BGP.

We calibrate the rest of the parameters $\{\beta, \lambda, \psi, \alpha, \tilde{\alpha}, \phi, \tilde{\phi}, \delta\}$ to a set of seven data targets that are informative about the key features of the model. While all these parameters are calibrated jointly, with each influencing all targeted moments to some degree, specific targets are more informative about certain parameters. To discuss these relationships briefly, the first target we consider is the average annual (utilization-adjusted) total factor productivity (TFP) growth rate obtained from the Federal Reserve Bank of San Francisco's database (see Fernald 2012), which helps us discipline the step size λ. To capture the long-run trend, we compute the average over 2 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 US Census Bureau's Business Dynamics Statistics starting only from 1978. The calibration also targets the contribution of entrants to changes in the aggregate productivity in the early 1980s, as estimated by the seminal contribution of Foster, Haltiwanger, and Krizan (2000). 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., $\tilde{\phi} = \phi$). Note that the magnitude of an entrant's contribution to productivity growth in the model depends not only on the entry rate but also on whether the new firm enters with a drastic or an incremental innovation and, in the latter case, whether it can quickly catch up with the leader during the first year following entry. Therefore, the probability of drastic innovation is closely tied to the target of entrants' contribution to productivity fluctuations.

The next two targets we include are the average markup (calculated following De Loecker, Eeckhout, and Unger 2017 and Eggertsson, Robbins, and Wold 2018) and the aggregate profit share in the economy, calculated as the ratio of before-tax profits of domestic US corporations to the gross value added (obtained from the National Income and Product Accounts [NIPA] of the Bureau of Economic Analysis [BEA]). These two targets discipline $\{\beta, \psi\}$. Recall that in the model, firm-level markups and profits are direct functions of these two parameters.[24] Finally, we include the dispersion of firm growth rates (Decker et al. 2016) in order to pin down the level of δ. The parameter δ defines a key source of quick catch-up in the model and hence has a direct effect on the firm growth rates as well as on their dispersion, as it is an important factor influencing the distribution of sectors over technology gaps.

C. *Parameter Values and the Model Fit*

Table 1 summarizes the calibrated parameters, and table 2 presents the fit of the model to data. One highlight is that the calibration suggests that ψ is less than 1, implying a slightly decreasing return to innovation as the technology gap widens, consistent with the negative relationship between firm size and the returns to innovation in Akcigit and Kerr (2018). Overall, the model is quite successful in matching key moments in the data, despite its parsimonious structure. The results suggest that

[24] For instance, eq. (8) shows that the markup level is a function of β and the market share $z(m)$, which in turn is a function of the relative productivity levels (see the discussion in sec. III.C) and, thus, $\mathbb{F}(\cdot)$. The same applies to the firm-level profitability, although the exact calibration target is the aggregate profit share of GDP. The latter is a broader concept in the model, because at the aggregate level, it reflects not only static operational profits of firms but also R&D expenditure. As such, it conveys a distinct piece of information, as compared with measures that stem from firms' static optimization.

TABLE 1
List of Parameter Values

A. Externally Calibrated			B. Internally Calibrated		
Parameter	Value	Description	Parameter	Value	Description
ρ (%)	5	Rate of time preference	β	.978	CES parameter
γ, $\tilde{\gamma}$	1/.35	R&D cost curvature	λ	1.009	Innovation step size
τ (%)	30	Corporate income tax	ψ	.865	Step size curvature
s (%)	5	R&D subsidy	α	.007	R&D scale, incumbents
			$\tilde{\alpha}$	.565	R&D scale, entrants
			δ	8.38	Exogenous catch-up
			$\phi = \tilde{\phi}$ (%)	.92	Drastic-innovation probability

the initial condition of the model economy replicates well the state of the US economy before the early 1980s.

Table D.1 summarizes the percentage change in each calibration moment used in section IV in response to a 1% change in each calibrated parameter. A few quick takeaways are worth noting. First, the aggregate growth rate is exclusively sensitive to the step size (λ) as well as its curvature (ψ). Second, one of the variables most sensitive to α is the aggregate share of R&D in GDP. Third, the drastic-innovation probability (ϕ) has a notable effect on the contribution of net entry to productivity, whereas its effect on other variables is very muted. By contrast, all variables except the aggregate growth rate are fairly sensitive to the knowledge-diffusion parameter (δ), including the entry rate.

TABLE 2
Model Fit

Moment	Model (%)	Data (%)	Source
M1, TFP growth	1.40	1.37	Federal Reserve Bank of San Francisco
M2, R&D to GDP	2.41	2.40	National Science Foundation
M3, firm entry	11.9	12.0	Business Dynamics Statistics, Census Bureau
M4, markup	10.1	10.0	De Loecker, Eeckhout, and Unger 2017; Eggertsson, Robbins, and Wold 2018
M5, profit share	5.96	6.00	BEA (NIPA)
M6, net entry contribution	29.5	30.0	Foster, Haltiwanger, and Krizan 2000
M7, firm growth dispersion	54.7	54.0	Decker et al. 2016

Note.—The moments are averages across 2 decades before 1981 if data are available (M1, M2, M4, and M5); if not, they reflect the average over the most recently available years before 1981. M6 refers to the net entry component of productivity fluctuations between 1977 and 1982, as in Foster, Haltiwanger, and Krizan (2000). The markup reflects an average value based on De Loecker, Eeckhout, and Unger (2017) and Eggertsson, Robbins, and Wold (2018). See sec. IV.B for further details regarding the moments.

In the next two sections, we use our model to investigate potential mechanisms that may have contributed to the empirical trends discussed in section II. We proceed in two steps. In section V, we present illustrative exercises to highlight the implications of variations in the channels of interest. In each exercise, we introduce 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 VI, 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 US 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.

V. 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 regard to the empirical trends transpiring in the post-1980 period that we analyze later. Therefore, our model-based responses almost exclusively rely on information that predates the shifts in the US business environment, which we aim at explaining here, with the minimal exceptions clarified below. In other words, the exercise will reflect only minimal information from the various trends that define the 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 35 years, accounting for more than 3 decades between 1980 and 2015. 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 sec. VI.A for further details). To demonstrate the strengths and weaknesses of these channels, we consider larger moves: a drop to 0%

for corporate tax rates and an increase to 50% in R&D subsidies in linear fashion.[25]

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 firm entry in the data.[26] This exercise implies a 200% rise in the entry cost and a 90% decline in knowledge-diffusion intensity. Figure 3 illustrates the implied time paths of the entry rate in these two experiments, superimposed with their counterparts in the data. It demonstrates the capacity of these individual channels to generate 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 (col. 1) and compares it with its model counterparts in each experiment. A few observations stand out. First, changes in corporate tax rates (col. 2) and R&D subsidies (col. 3) fail to generate most trends observed in the data. Second, despite a considerably better performance, the increase in entry cost (col. 4) fails to replicate changes in key aspects of the data, such as increasing markups. Finally, the intriguing result is that a fall in the knowledge-diffusion intensity (col. 5) has remarkable success in accounting for most empirical trends. Next, we discuss our findings regarding each channel in more detail.

A. *Decline in Corporate Tax Rates*

Figure 4 presents the model-based counterparts of four empirical trends of interest, which we use to spotlight the differences between patterns that emerge in each experiment. As indicated by the purple lines with crosses, the effect of the decline in corporate tax rates on many margins is close to nil.[27] Moreover, when the effect is noticeable, its direction contradicts the data in most cases, as listed in column 2 of table 3. Consider the entry rate, for instance. Lower corporate taxes and thus higher operating profits raise the value of becoming an incumbent firm. The

[25] We consider these magnitudes, which are considerably larger than their empirical counterparts, for the sake of visibility and clarity in the demonstration of the effects of the specific channels. As highlighted by our quantitative results in sec. VI, the effects of the changes in these margins that are analogous to the data are in the same direction as the results shown here but are much more muted.

[26] 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 sec. VI.A. See app. C for the details of the solution algorithm.

[27] The negligible response of the aggregate profit share to a decrease in corporate profit taxes may seem odd at first glance. However, note that the figure shows the before-tax profit share, which in turn depends on the distribution of firms across gaps. As expected, the share of after-tax profits rises mechanically with the drop in corporate taxes (not shown here).

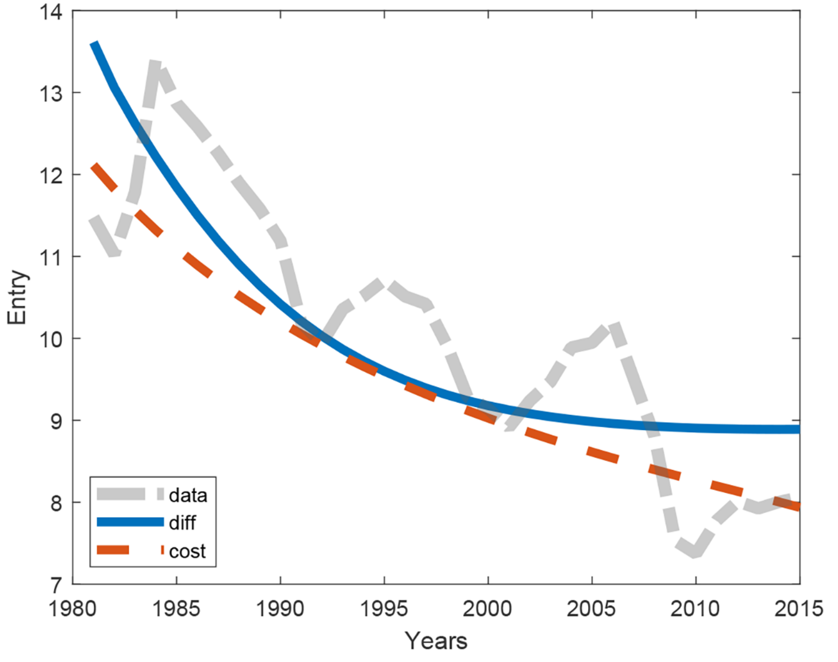

Fig. 3.—Path of entry rate, model versus data. The figure superimposes the observed decline in the entry rate with the model-generated entry paths in the two experiments regarding entry cost and knowledge diffusion (diff). In both experiments, the change in the respective channel is disciplined to capture the path of the empirical entry rate.

increased gain, in turn, motivates entrants and pushes up the entry rate. In addition, the limited effect of lower tax rates on markups and the profit share implies a subdued influence on the firm distribution across gaps. The counterfactual rise in the entry rate, together with a rather limited effect on the gap distribution, is also responsible for the muted response of the employment share of young firms.

B. Increase in R&D Subsidies

In figure 4, the dotted yellow lines denote the responses to the increase in R&D subsidies. As is the case with corporate taxes, only a few variables respond to the increase in R&D subsidies in a noticeable way, and the responses are still very far away from the empirical patterns, most crucially in the case of firm entry. The increase in innovative activity increases the demand for R&D labor, pushing up wages and the labor share and depressing the profit share counterfactually. This increase in wages adds to the cost of entry, decreasing entry slightly. Together with some variation

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	↑	↑	↑	⟷	↑
Markups	↑	⟷	⟷	⟷	↑
Profit share	↑	⟷	↓	⟷	↑
Labor share	↓	⟷	↑	⟷	↓
Entry[a]	↓	↑	⟷	↓	↓
Young firms' employment share	↓	⟷	↓	↓	↓
Frontier-laggard gap	↑	⟷	⟷	⟷	↑
Gross job reallocation	↓	↑	⟷	↓	↓
Dispersion of firm growth	↓	↑	⟷	↓	↓

Note.—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% of the actual change in the data, we denote it with a flat arrow.

[a] In cols. 4 and 5, the experiments match the decline in entry by construction (see fig. 3).

that higher R&D subsidies generate in the sectoral distribution across technology gaps, the decline in the entry rate helps the employment share of young firms decrease. This distributional shift also generates some increase in the average concentration. However, these shifts are not enough to generate sizeable variation in other variables, including the average markup, as shown in column 3 of table 3.

C. *Increase in Entry Costs*

As described above, 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 4*A* 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 increase 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. The mechanics behind this result are as follows. Lower entry implies a lower

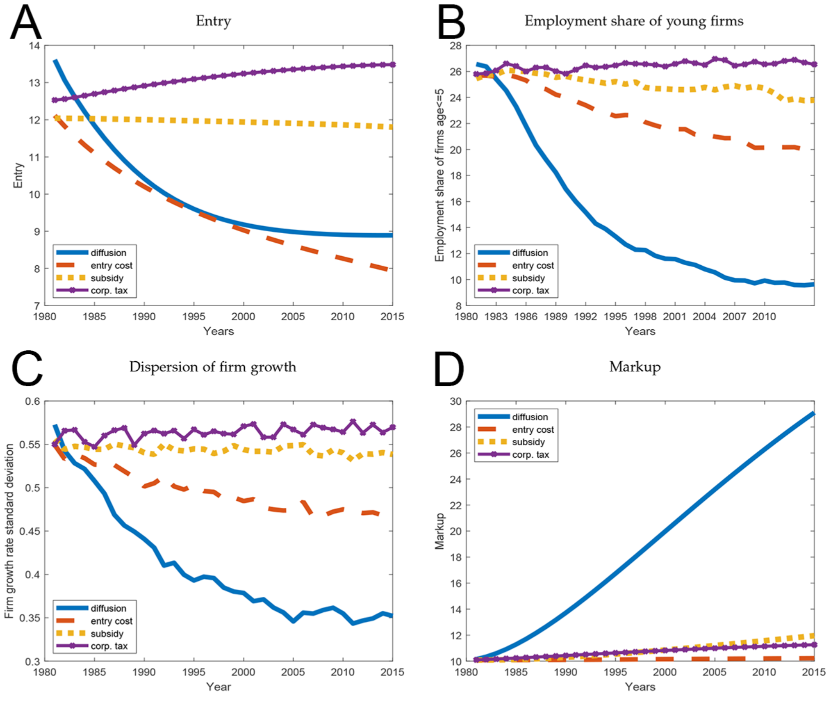

FIG. 4.—Implied responses to changes in individual channels. The series in *B* and *C* are based on simulated data.

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, counteracting a shift in sectoral distribution toward larger gaps. The weak distributional response is also responsible for the experiment's failure to replicate some other patterns, although the commensurate decline in the entry rate with the data helps higher entry costs exert notable influence on a few other variables.

D. 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 the correct directions (indicated by solid blue lines in fig. 4).

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, the 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 gap 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. These changes do not stem only from the direct effect of a lower catch-up rate. Indirectly, the ensuing shift in the technology gap distribution toward larger gaps implies a lower degree of competition in more sectors, discouraging followers (who fall farther behind) and leaders (who feel less competitive threat) from innovating.[28] Moreover, with lower knowledge diffusion, the process of new (and therefore young) firms—which start the business replacing followers—taking over production slows, resulting in a lower employment share of young firms in the economy. Note that the decline in this margin is larger than that 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 US 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.

VI. 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 app. 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

[28] An additional consequence is that the within-firm productivity growth falls, consistent with Decker et al. (2017).

margins may have the potential to explain the shifts in the economy, the data may suggest only minor 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 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 quantify the contribution of each specific force to the observed changes in US business dynamism. In our analysis, we 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.

A. *Disciplining the Transition Path of the Model*

The transitional dynamics of our model, which capture the evolution of US business dynamism from the early 1980s until the mid-2010s, are 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 $\exp(-(t/T)\nu)$, where t is the specific period during the transition and T is the terminal period, after which the parameters settle at their terminal values.[29] Thus, the curvature parameters ν measure the speed of

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

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

with $f(t;\nu) \in [0, 1]$ 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. Note 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 fig. 5, in this section, and fig. D.4 for the calibrated paths of parameters over the transition period.

adjustment in the parameter values and are to be determined by the data. We consider a transition over 3 decades, setting $T = 35$.[30]

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, Ates, and Impullitti (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 five data points. Three of these targets are the terminal values of the firm entry rate, the average markup, and the dispersion of firm growth, capturing the aggregate variations in US business dynamism.[31] 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 firm entry rate. These targets are the relative declines in entry after the first 10 and 20 years. They provide information about the time path of the economy via the path of the entry rate, which, in turn, disciplines the transition path of the model economy, informing the calibration about ν_α and ν_δ. Note also that we pick our targets parsimoniously in order to leave most trends of interest untargeted. This strategy sets a high standard for assessing the validity of the model, examining its various dimensions in light of a diverse set of empirical trends without imposing specific structure that is directly informative about these margins.

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

B. 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 144% increase in the entry cost and a 65% decline in the intensity of knowledge diffusion. Moreover, the calibrated curvature parameters $\nu_{\tilde{\alpha}}$ and ν_δ imply that

[30] Note 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.

[31] The path of the average markup reflects estimates by Nekarda and Ramey (2013) and Eggertsson, Robbins, and Wold (2018), who find more modest increases in this variable, in line with most work in the literature. In this way, we avoid attributing an artificially high weight to the knowledge-diffusion channel—note its significant effect on this margin—which would be the case if we used more extreme estimates for the rise in markups.

TABLE 4
List of Parameter Values

A. Externally Calibrated			B. Internally Calibrated		
Parameter	Value	Description	Parameter	Value	Description
τ_T (%)	20	Corporate income tax	$\tilde{\alpha}_T$	1.381	R&D scale, entrants
s_T (%)	20	R&D subsidy	δ_T	2.99	Exogenous catch-up
ν_τ	1	Corporate income tax	$\nu_{\tilde{\alpha}}$	.019	R&D scale, entrants
ν_s	1	R&D subsidy	ν_δ	7.360	Exogenous catch-up

$\tilde{\alpha}$ changes almost linearly, while δ drops quickly and then slowly converges to its terminal value (fig. 5).[32]

The transition path mirrors very closely the dynamics of US business dynamism, as depicted in figure 6. The figure superimposes the calibrated paths of variables used in the calibration with the actual data points. Note 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 match to the empirical pattern of the entry rate lends credibility about the path of the parameter changes in the model. In addition, the transition paths of other variables are replicated quite successfully.

It is also worth noting that our calibration strategy does not condition on several other empirical regularities discussed in section II, which we now consider as validity checks for the calibrated economy. Table 5 compares empirical changes in these margins with the model-generated responses. The model tracks these changes successfully as well, generating meaningful variations in each variable.[33] Moreover, the model dynamics are consistent with additional salient features of the data, such as a decline in the rate of churn of top firms out of their positions (Bessen et al. 2020) and a decline in firm responsiveness to shocks (Decker et al. 2020; see sec. VIII.A.4 for a detailed account). Though not part of the main focus of the analysis, age-related dynamics in the calibrated transition also exhibit patterns that mimic their empirical counterparts exceptionally closely—a striking finding, given that the model construction and the analysis do not specifically target these dynamics (please see app. E for the details). In particular, the model-based age distribution and both the level and the changes in the exit rates of firms within age bins are very much in line with the data—additional plausible out-of-sample predictions boosting the reliability of the model-based dynamics. These dynamics follow mostly from the decline in knowledge diffusion, as established by the decomposition exercises, which we discuss next.

[32] See fig. D.4 for the paths of s and τ.

[33] Complementing the widening productivity gap, we also report the increase in the standard deviation of log TFPR (revenue-based TFP) in the US manufacturing sector as computed by Decker et al. (2018), whose magnitude is also on par with the data.

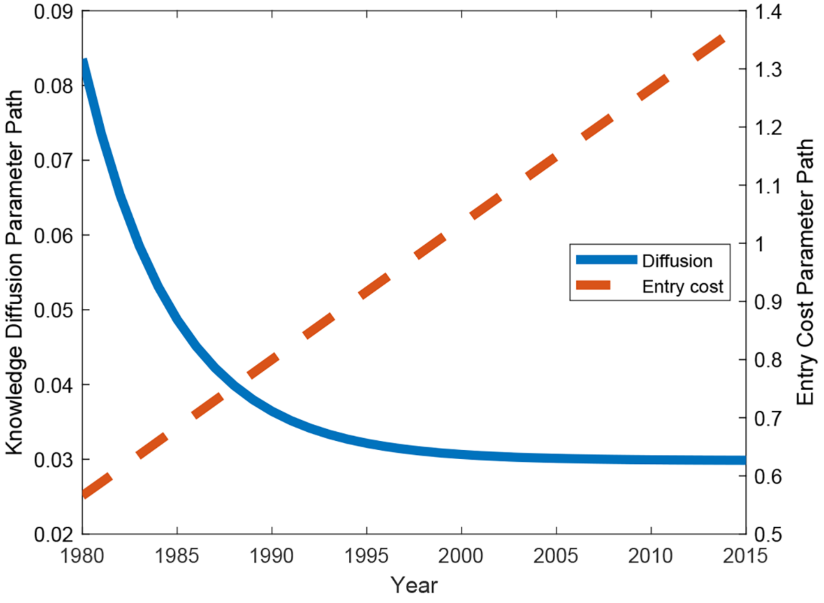

FIG. 5.—Transition paths of $\tilde{\alpha}$ (entry cost) and δ (knowledge diffusion).

C. *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.

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

$$\text{contribution}_i = \frac{X_{2015}^4 - X_{2015}^{4\backslash i}}{X_{2015}^4 - X_{1980}^4}. \tag{29}$$

Table 6 presents the magnitudes of the decomposed contributions. Echoing the findings of section V, the results decisively highlight that the largest contributions to the variations in model-generated variables stem

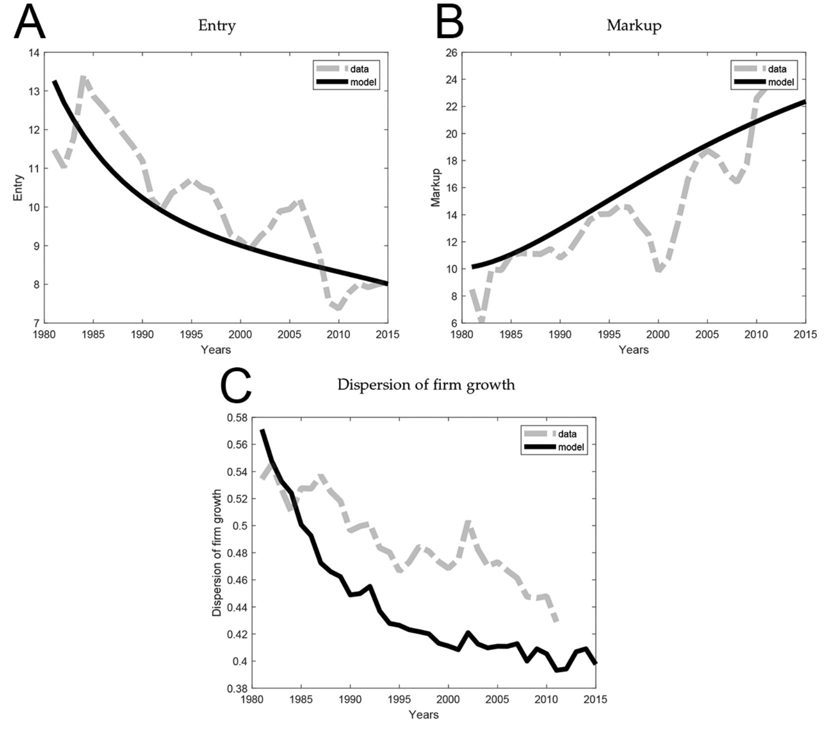

FIG. 6.—Calibration targets. The calibration procedure targets the terminal points of these series and the decennial declines in entry in *A*. Solid lines show the model-generated paths when all four channels are moving. The dispersion of firm growth is available until 2011; we fit a linear trend line to determine the target of the terminal point in 2015.

from the slowdown in knowledge diffusion. Other channels account for a meaningful part of transitional dynamics only in a limited number of variables. Notably, the higher entry cost accounts for 78% of the decline in entry rate, corroborating the findings in recent work by Gutiérrez, Jones, and Philippon (2019). That said, its negative effect on entry generates only 18% of the decline in job reallocation and 23% of the variation in the employment share of young firms. Given that the rest of the contributions rarely exceed 10%, we focus our attention on the discussion of the knowledge-diffusion channel to avoid repetition.

Decline in knowledge diffusion.—The calibrated 65% decline in knowledge diffusion accounts for more than 60% of the variation in almost all variables, except for the entry rate, which is—perhaps unsurprisingly—accounted for chiefly by the substantial rise in the entry cost. The results clearly demonstrate the major role a weaker knowledge diffusion plays in generating the trends in the aggregate variables. To summarize the

TABLE 5
Level Changes (Δ) in Untargeted Moments during Transition

Moment	Data (%)	Model (%)
D1, Δ concentration	+6	13.5
D2, Δ profit share	+8	5.7
D3, Δ labor share	−8	−5.7
D4, Δ young-firm employment share	−6	−13.5
D5, Δ job reallocation	−7	−8.4
D6, Δ productivity gap	+25	12.8
D7, Δ TFPR SD	+8	7.7

Note.—The changes reflect the total deviation between 1980 and 2015. The empirical magnitudes are taken from Autor et al. (2017b; D1), Karabarbounis and Neiman (2014; D3), Decker et al. (2015; D4, D5), and Andrews, Criscuolo, and Gal (2016; D6), who report changes over the post-2000 period. D2 reflects the authors' calculation using BEA data. D1–D5 reflect changes in the United States, whereas D6 refers to the OECD average in the manufacturing sector. We also report the increase in the standard deviation of log TFPR (revenue-based TFP) in the US manufacturing sector, as computed by Decker et al. (2018; D7). D1 reflects the change in the concentration share of the top four firms in the US manufacturing sector.

mechanics briefly again, the effect operates through direct and indirect channels. With knowledge diffusion slowing, 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. The profit share of GDP increases, and the labor share decreases. Larger gaps also discourage the followers, causing the productivity gap between them and the

TABLE 6
Quantitative Experiment Results (Contributions as in Eq. [29])

Channel i	Lower Corporate Tax (%)	Higher R&D Subsidies (%)	Higher Entry Cost (%)	Lower Knowledge Diffusion (%)
Entry	−10.7	−1.0	78.1	24.5
Labor	−7.1	−9.9	2.4	109.8
Markup	6.1	6.3	1.6	91.4
Profit	−7.1	−9.9	2.4	109.8
Concentration	3.8	4.2	1.1	87.4
Young firms	−2.5	1.0	23.4	60.7
Productivity gap	5.3	5.6	1.5	90.1
Reallocation	−14.0	−2.5	17.7	66.3
Dispersion	−13.4	−.7	27.7	60.7

Note.—Percentage values measure the share of the contribution from the specific channel to the total model-generated deviation between 1980 and 2015. Negative values mean that adding the specific channel moves the model-generated variable in the opposite direction 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.

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.[34] Discouraged followers and entrants exert smaller competitive pressure on market leaders; as a result, market leaders relax and 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 declining US business dynamism. Section IX zeroes 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.

VII. 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 a 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

[34] The reason the effect on the young-firm employment share is considerably higher than that on the entry rate is that a decline in knowledge diffusion also affects the post-entry dynamics of the young firms. This channel influences the entry rate through the value of becoming an incumbent (and the subsequent compositional dynamics), which also contributes to the effect on the young employment share. But the latter is also affected directly by the degree of knowledge diffusion, as it is a determinant of the rate of the quick catch-up.

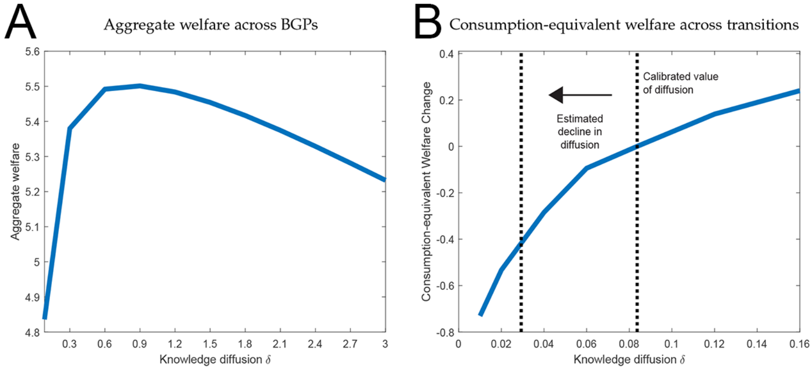

FIG. 7.—Implied responses to changes in individual channels. *A* compares the welfare across BGPs that are differentiated by the level of δ. *B* shows the percentage deviation in consumption-equivalent welfare from the baseline over three and a half decades in response to a shift in δ from the calibrated value based on model simulations. 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 $\delta\Delta t$.

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 7*A* 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).[35] 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.

In light of the preceding deliberation, we ask next whether, in the calibrated economy, higher or lower knowledge diffusion is welfare improving in the transition. Figure 7*B* 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 V by introducing a change in δ over the period of 35 years. We then compute the change in consumption-equivalent welfare by comparing the resulting consumption path with the baseline one, that is, the path that arises when there is no

[35] For brevity, we present the derivation of welfare in app. B.2.

change in δ from the calibrated value and the economy evolves along the calibrated BGP. In figure 7*B*, 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. For instance, doubling the level of δ would create about a quarter-percent higher welfare in consumption-equivalent terms over a 35-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.

VIII. Alternative Mechanisms and Robustness

Next, we discuss the model implications of three additional channels—declines in the interest rate, in research productivity, and in the market power of workers relative to firms—in light of empirical trends. We also discuss how our analysis relates to some other notable shifts in the US economy put forth in the literature. These include a decline in the population growth rate and the responsiveness of firms to shocks. Finally, we repeat the decomposition exercise from section VI, which constitutes our main quantitative finding, under alternative specifications to gauge the robustness of our results. We briefly summarize the highlights and present the detailed discussion in appendix G.

A. 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, Robbins, and Wold 2018; Liu, Mian, and Sufi 2022), a decline in research productivity (implying that ideas are getting harder to find; Gordon 2016; Bloom et al. 2017), and a decline in workers' market power relative to employers' (Bivens et al. 2014; Naidu, Posner, and Weyl 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 V. 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

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	↓	⟷	↑	⟷	↓	⟷	↑	↓
Entry	↓	↑	⟷	↓	↓	↑	↓	↑
Young firms' employment share	↓	⟷	↓	↓	↓	⟷	↓	↓
Frontier-laggard gap	↑	⟷	⟷	⟷	↑	⟷	↓	↑
Gross job reallocation	↓	↑	↑	⟷	↓	↑	↓	↑
Dispersion of firm growth	↓	↓	↓	↑	↓	↑	↓	↑

Note.—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% of the actual change in the data, we denote it with a flat arrow.

one of them generates counterfactual responses in other trends, which we review more in detail now.[36]

1. Declining Interest Rates

A stark trend observed in the US 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, Mian, and Sufi (2022) 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.[37] 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, Mian, and Sufi (2022). In particular, we introduce a steady decline to the discount rate (ρ) over the transition, as we did with other parameters in section V. Recall that the household's optimization obtains

$$r_t = g_t + \rho.$$

The magnitude of the decline in ρ is about 4%, which generates an analogous fall in the interest rate over 3 decades, in line with the fall in the natural rate of interest since the 1980s (Williams 2015).[38] Column 6 in table 7 shows that while this channel could have contributed (albeit by

[36] An additional theoretical mechanism we could incorporate in the model is type heterogeneity, which could help the model generate a stable labor-share distribution, as observed in the data (Autor et al. 2017b; Kehrig and Vincent 2018). While this could be an interesting extension—albeit at the expense of theoretical and computational tractability—it would not be crucial for our main quantitative results, as this added mechanism does not differentiate between the alternative channels we explore in the main analysis. Please see Akcigit and Ates (2019) for a more detailed discussion.

[37] An important feature of the model used by Liu, Mian, and Sufi (2022) is that it allows only for slow catch-up between the leaders and followers. By contrast, López-Salido, Goldberg, and Chikis (2021) show that if the model admits any drastic innovation by laggards, which the authors argue is to be the case in the data, lower interest rates boost productivity growth.

[38] 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% in 1980 to about 2% right before the Great Recession and a further 2 percentage point drop over the next few years, with an outsized decline during the recession.

a narrow margin) to an increase in market power measured by concentration, 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 US business dynamism.

2. Ideas Getting Harder to Find

In an extensive work, Gordon (2016) argues that the US 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 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 researcher 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 an exercise similar to the "higher-entry-cost" experiment in section V.

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 mean 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 3 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.

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, Posner, and Weyl 2018) suggests that this decline could have depressed wage growth despite sizeable productivity gains, which would translate into a lower aggregate labor share.[39] We capture the potential effect of this change via an exogenous rise in the step size (λ). Recall that operating profits in equation (7) are an increasing function of the market share. Recall that the market share, in turn, increases with the relative productivity level, which is a positive function of λ. Therefore, a higher step size translates into higher operational profits of firms and 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 intensification in market power and a decline in the aggregate labor share, this time, the counterfactual implication is that it cannot generate a decline in the entry rate (if anything, it increases entry). It also pushes up job reallocation and growth dispersion. In fact, this change reinvigorates dynamism in the economy.

In sum, when the moves we have observed in the US 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 other prominent trends in the economy, which are beyond the scope of the analysis in this paper.[40]

4. Additional Mechanisms

A widely discussed phenomenon in many advanced economies is demographic shifts, and a number of recent studies examine the link between declining population growth and several trends in firm dynamics (Hopenhayn, Neira, and Singhania 2018; Peters and Walsh 2021). Our model could potentially reflect on this margin. Indeed, a version of the model with population growth reveals interesting implications.[41] The analytical derivations show that the main implication of growth in the size of population and, thus, the workforce is that it introduces an additional

[39] 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, Marinescu, and Steinbaum (2017) document an increase in monopsony power in labor markets.

[40] 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.

[41] We present the details of the extended model in app. F.

source of firm growth. Importantly, the rate of change due to this source is common to all firms, without any differentiation between leaders and followers. This observation underlies the key finding: population growth does not affect the key dynamics of the model, notably, the dynamics of competition. As such, fluctuations in population growth do not bear any relevance to the model counterparts of the empirical trends of interest or the relative strength of the channels of interest that can potentially explain these trends—within the confines of this framework, at least. But while this specific channel within the extended framework provides useful insights, one could also interpret demographic shifts from a broader perspective through the lens of the baseline model. Indeed, the aforementioned work conceptualizes the main mechanism through the link between population growth and the size of the pool of the entrant firms. Our baseline analysis can shed light on this link—even without adding population growth—once the rise in entry costs is interpreted as a reflection of falling population growth. Our exercises in sections V and VI show the implications of this margin. Clearly, the changes along this margin generate notable effects on some variables, most importantly on the entry rate. However, the analysis also highlights that for many other trends that we strive to understand, most notably the dynamics of competition between incumbent firms, the crucial driver is the decline in knowledge diffusion.

Another observation worth deliberating is the decline in firm responsiveness to shocks. Decker et al. (2020) argue that the decline in job reallocation stems from lower responsiveness by firms to idiosyncratic shocks, which the authors motivate with higher adjustment costs within the Hopenhayn and Rogerson (1993) framework. Interestingly, our model also generates dynamics consistent with lower responsiveness as the main mechanism unfolds. Consider the frontier firms. As the gap between competitors opens and the leaders capture a larger share of the market, the marginal return to leader innovations declines even if the step size remains the same, because the additional market share that can be captured diminishes with higher technology gaps. Consequently, the response of a leader to the same innovation—for example, in terms of production—is smaller if she has a more comfortable lead over her rival. Similarly, the followers that fall farther behind benefit relatively less from incremental innovations—which play a predominant role in their dynamics—and also respond less to the same incremental innovation. Thus, our analysis adds another perspective to the lower responsiveness in the economy documented by Decker et al. (2020). Ultimately, the responsiveness of firms to shocks depends on both the cost of responding to these shocks and the return to responding to them. While Decker et al. (2020) emphasize the former aspect, our mechanism highlights the decreasing returns to innovation as the technology gap between the leader and the follower widens.

Finally, one caveat is that part of the main mechanism could, in theory, reflect issues with the implementability of ideas. It may be the case that followers learn from the frontier but may find it harder to implement their ideas for various reasons—for example, increased threat of litigation.[42] That said, we contend that the bulk of the existing empirical evidence, which we discuss in detail in section IX, strongly points to a lower degree of knowledge diffusion in the US economy. Therefore, we center our analysis on this margin.

B. Robustness

We also assess the robustness of our main quantitative results under five alternative specifications. Specifically, we consider (i) a full drop in corporate tax rates over the transition; (ii, iii) an artificially low (high) level for the drastic-innovation rate ϕ; (iv) a higher value for ψ, the curvature of the innovation step sizes; and (v) a quadratic R&D cost function ($\gamma = \tilde{\gamma} = 2$). In all experiments, we recompute the contribution of the knowledge diffusion decline to the model-generated trends. The results emphasize that our main conclusion goes through in all these alternative specifications, reassuring us about their robustness. For brevity, we do not delve deeper into the exercises here and refer the interested reader to appendix G for a detailed discussion of the results.

IX. New Evidence regarding Knowledge Diffusion

In section VI, 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 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 (2021), 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 three main pillars that define the creation and diffusion of knowledge throughout the economy: patents, inventors, and worker mobility. To briefly summarize our findings, we observe that patents—the stock of knowledge—are increasingly accumulated in the hands of firms

[42] To the extent that technologies to compete with the frontier become increasingly complex and their deployment becomes disproportionately more costly for the laggard firms, this margin could also reflect heterogeneous adjustment costs in the economy.

that already own the largest stock of patents, both via production of new patents and via purchases of existing ones. As a mirror image of this patent concentration, we also observe a concentration of inventors. Inventors are increasingly employed by large and established firms instead of small and young ones, which indicates that knowledge is persistently and exclusively accumulating in the hands of frontier firms—also considering the evidence on the declining rate of inventor entrepreneurship and lower worker mobility. Finally, we review the evidence on declining worker mobility in the US economy. Because workers carry their knowledge and experience when they switch jobs, this decline is consistent with a decline in the diffusion of knowledge. Bolstering these findings, we also discuss the relevant work from the literature and highlight the corroborating evidence proposed by other researchers.

A. *Evidence from the Patent Data*

Patent and reassignment data from the US 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. To appraise these possibilities, we explore the changes in the use of patents in the US economy across time.

1. Patent Concentration and Post-1980 Trends

As we reviewed in section II, many indicators of business dynamism suggest a declining trend since the 1980s, along with rising market concentration. We first investigate whether there has been a concomitant change in patenting concentration. To answer this question, figure 8*A* looks at the share of patents registered by the 1% of innovating firms with the largest patent stocks. The ratio exhibits a dramatic increase. While in the early 1980s about 35% of patents were registered by the top 1% of firms sitting on the largest patent stocks, this ratio reached almost 50% in 3 decades.[43] In addition, the share of patents registered by new entrants (firms that patent for the first time) exhibits the opposite trend: notwithstanding the 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% in 25 years (fig. 8*B*).

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

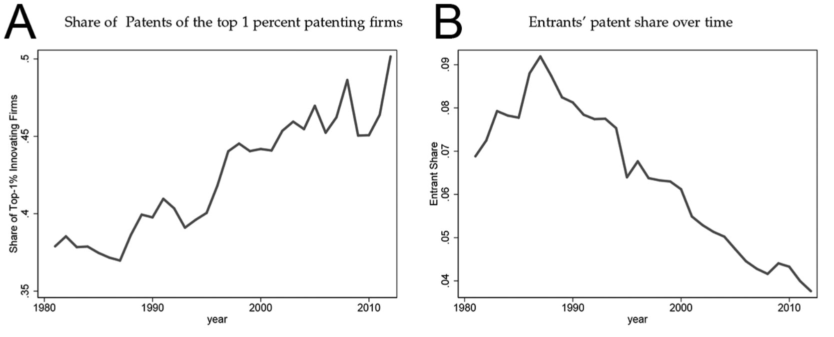

FIG. 8.—Registry of patents. Source: Authors' own calculation using USPTO data.

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.[44] For instance, Argente et al. (2020) show that while market leaders introduce new products less frequently, they are more likely to patent these inventions, with their patenting being associated with a declining rate of product innovation by their competitors.[45] To investigate related patterns, we use patent-reassignment data, which keep detailed records of all patent transactions between entities. As in patent registries, we observe stark trends in patent reassignments since the 1980s. Figure 9*A* focuses on the purchasing trends of the 1% of firms with the largest patent portfolios. It reveals that while 30% of the transacted patents were reassigned to the firms with the largest patent stocks in the 1980s, the share went up to 55% over 3 decades. This drastic increase has crowded out small players in the market, as illustrated in figure 9*B*. 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.[46] In the past 2 decades, the fraction of transacted patents that are reassigned to small firms has dropped dramatically, from 75% to just above 50%, implying a shift of ownership from small firms to large ones.

[44] For empirical work on patent thickets, see Hall and Ziedonis (2001), Ziedonis (2004), Clarkson and DeKorte (2006), Cockburn and MacGarvie (2009), Galasso and Schankerman (2010), Bessen and Meurer (2013), von Graevenitz, Wagner, and Harhoff (2013), and Hall, von Graevenitz, and Helmers (2021).

[45] Using a theoretical model, the authors show that as firm size increases, firms are more likely to use their patents to deter competition, and the protective value of their patents rises relative to their productive value, consistent with their findings in the data.

[46] The designation as a "small business concern" derives from the USPTO's US Patent Grant Maintenance Fee Events database, which records information on patent renewals.

FIG. 9.—Reassignment of patents. Source: Authors' own calculation using USPTO data.

These figures reveal that concentration in patent production and reassignment has surged and that firms with the largest patent (knowledge) stock have further expanded their intellectual property arsenals.[47] Given that patents are exclusively used to prevent competitors from using the patent holder's technology, these trends can imply that the heavy use (or abuse) 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 since 2000, especially in some high-tech sectors (Decker et al. 2016). A closer look at the patent data reveals corroborating evidence on the potential strategic use of patents, on which we elaborate next.

2. 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 to protect its core technology, the new

[47] Echoing our findings, Chattergoon and Kerr (2021) document that the spatial concentration of patents has substantially risen since the 1980s, especially for software patents, with the share of software patents held by companies in the top six tech clusters having more than tripled.

internal patent will cite many patents from the firm's existing portfolio. By contrast, if a firm's aim is to expand into new fields, more citations will be made 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 10*A* explores the self-citation dynamics over time. The striking observation is that while until 2000, patents were becoming more explorative in nature, according to our earlier interpretation, this trend reversed completely around 2000, with patents becoming more exploitative and internal since then.

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, 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 10*B* 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, a trend that completely reversed 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 even more. While several measures of business dynamism have indicated a slowdown in most sectors of the US economy since the 1980s, the decline in the high-tech sector has become most visible in the 2000s (Decker et al. 2016). As shown in figure 11, the dispersion of

Fig. 10.—Self-citation and claim-length patterns. Source: Authors' own calculation using USPTO data.

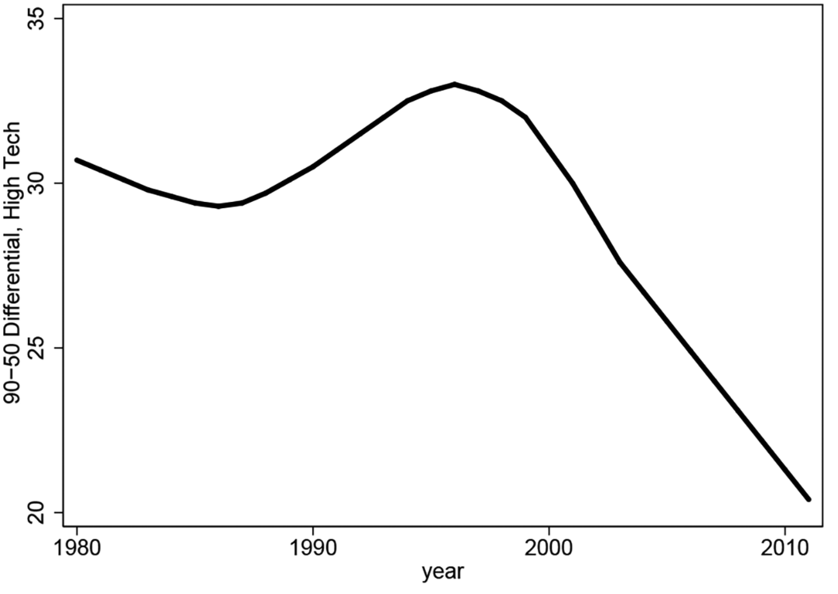

Fig. 11.—The 90-50 differential in the high-tech sector. Taken from Decker et al. (2016). Similar patterns are documented for the 50-10 differential, for the balanced sample of continuers, and for gross job reallocation in the information sector.

firm growth in high-tech sectors started to decline steadily around 2000. Decker et al. (2016) document that other measures of business dynamism, such as gross job reallocation, reverberate with this post-2000 pattern, again especially in high-tech sectors.

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 the 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.

B. *Evidence from Micro Data on Inventors*

In the previous section, we documented trends in the generation and flow of ideas, using data on patents in order to understand changes in the knowledge diffusion in the US economy. In this section, we explore the reflection of these patterns on the employment dynamics of inventors—the central agents for the generation and flow of ideas through the economy. In particular, we discuss some of the findings on inventor dynamics documented in the complementary work by Akcigit and Goldschlag (2020), who build a novel data set that compiles detailed information on the population of inventors, linking patents to individuals, businesses, and employee-employer relationships.[48] The results show a concentration of inventors in more mature firms, with their innovative output and its quality decreasing in relative terms.[49] The analysis highlights that the inventive productivity of inventors who are similar a priori diverge upon job switches, with the inventor hired by a mature firm producing fewer patents with fewer forward citations received, on average, relative to the one moving to a young firm.

To start, Akcigit and Goldschlag (2020) demonstrate a steady decline in the share of inventors working in young firms (firms that are 5 years old or younger) since the early 2000s, paralleled by a concentration of inventors in mature incumbent firms (fig. 12). This trend echoes other observations, such as the decline in the employment share of young firms and the decline in the patent share of entrants. By itself, though, this observation is not worrying if inventors become more productive at more mature firms. However, an event-study analysis shows that this is not the case. The authors study the events of inventor hires to measure the impact of being hired by a mature firm on the innovativeness and earnings of an inventor relative to being hired by a young firm. The results show that the number of patent applications by inventors drops after they join more established incumbents (relative to inventors with comparable characteristics who join young firms).[50] In addition, the citations to the patents for which inventors apply after being hired by a mature incumbent are also lower than those to the patents registered by inventors hired by young firms, suggesting a deterioration in the quality of innovative output among inventors at incumbent firms. In addition, unreported results suggest that the share of self-citations of inventors hired by mature incumbents increases relative to that of inventors hired by young firms. As discussed above, higher self-citation of patents implies a more internal and exploitative content, consistent with the intuition that the patent plays a more protective role. A striking note is that, while the output of inventors deteriorates after they switch to more mature incumbents, they earn relatively more in their new roles. This result suggests that the private return to inventors' activity increases when they are hired by mature firms, whereas the public return decreases. Clearly, this finding, together with the increasing share

[48] Because of data availability, the period of analysis is after the year 2000.

[49] "Mature firms" refers to firms that employ more than 1,000 workers and are older than 20 years.

[50] This observation is consistent with the findings of Akcigit and Kerr (2018) that young firms are more R&D and innovation intensive than older firms.

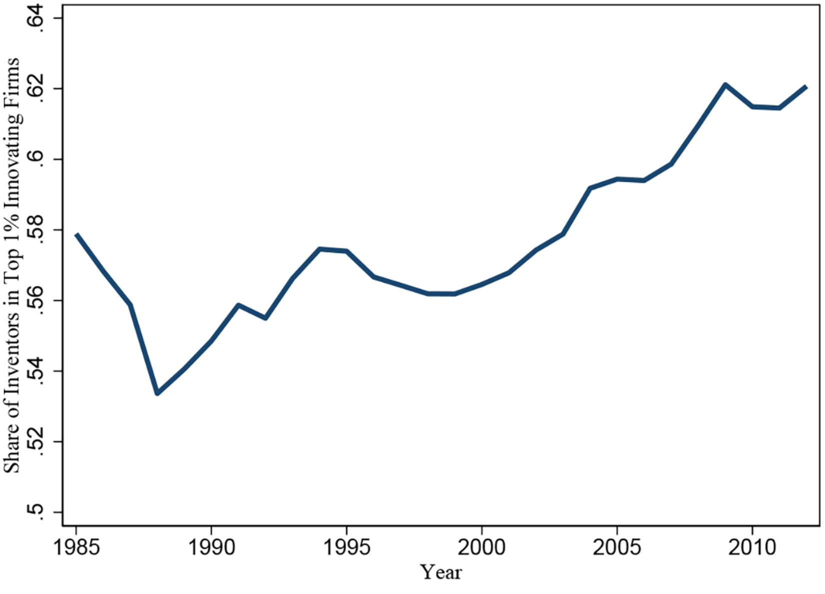

FIG. 12.—Share of inventors in top 1% of firms. Source: Authors' own calculation from the USPTO data.

of inventors in more established incumbents, is concerning from the perspective of aggregate welfare.[51]

The falling share of inventors in young firms may be an artifact of the falling share of activity by young firms in the economy, which is one of the 10 facts we highlight in the paper. However, Akcigit and Goldschlag (2020) also reveal that inventors themselves have also become less entrepreneurial over time, with the probability of an inventor being an entrepreneur herself in a given year declining over time. This observation is particularly worrying, given that start-ups founded by inventors exhibit faster employment growth over the first decade of their lives than start-ups founded by noninventor entrepreneurs. Thus, the lower frequency of inventor entrepreneurs in the post-2000 era likely contributed to the declining prevalence of high-growth young firms and the concurrent decline in job reallocation rates (Decker et al. 2016).

To summarize, the results imply that inventors are hired by larger, mature firms more intensively; that their innovation output and its quality decrease relative to those of similar inventors hired by young firms; and

[51] One possibility could be that successful inventors are hired by mature firms in a managerial capacity to oversee R&D activity, potentially improving the innovative efficiency of other inventors and the firm, though perhaps at the expense of their own productivity. A careful analysis of occupation-level data by Akcigit and Goldschlag (2020) shows that this is not prevalent.

that despite this, their earnings increase, suggesting a conflict between public and private returns from their innovative activity. In addition, inventors' entrepreneurial activity has slowed. These observations suggest that young firms' access to new ideas is becoming increasingly limited—through both production and dissemination of ideas—consistent with a decline in knowledge diffusion and business dynamism, especially considering the decline in the mobility of workers across firms, which we discuss next.

C. Worker Mobility

A fluid labor market and the mobility of workers across jobs have long been heralded as important, efficiency-enhancing features of the US economy. Worker mobility is also a significant facilitator of dissemination of knowledge across firms, as workers bring their knowledge and experience to the new firm when they switch jobs (Stoyanov and Zubanov 2012; Poole 2013; Fons-Rosen et al. 2017). However, these characteristics of the US economy have been steadily weakening over the past several decades, as documented by numerous papers (Davis and Haltiwanger 2014; Hyatt 2015; Bosler and Petrosky-Nadeau 2016) and in line with some facts we highlight in this paper. In this part, we extend our review of these facts by focusing on worker mobility and argue that these shifts are consistent with lower knowledge diffusion in the economy.

While there has been a persistent decline in the job-to-job flow rate in the United States since the mid-1990s (Hyatt 2015), this observation by itself does not suggest a worrisome situation. It could be the case that the lower worker mobility reflects better employee-job matches initially—for example, owing to improved job search technology—which would boost overall productivity. In his analysis, Hyatt (2015) finds this channel less plausible and argues that part of the reason could be increased complexity of production technology. Increased complexity and job specialization would make it harder to train and replace workers. This argument also resonates with the findings of Bessen et al. (2020), who illustrate that in recent decades, top firms—which are also large firms that, on average, exhibit lower job turnover rates—invest more intensively in proprietary technologies.[52] Such technologies are harder for other firms to learn from and adopt, and part of the difficulty could stem from the associated decline in worker mobility. This reasoning would be consistent with notable work on the effect of worker mobility on knowledge spillovers, which we briefly summarize next.

Using data on Danish workers and firms, Stoyanov and Zubanov (2012) document that workers' job switches lead to productivity spillovers. Hiring

[52] The authors also document an attendant decline in the rate of churn of top firms.

workers from more productive firms generates sizeable productivity gains in the receiving firm with lower productivity. The impact in the reverse direction is negligible, which the authors argue to support a knowledge-diffusion channel associated with worker mobility. Interestingly, and consistent with the theoretical mechanism in our analysis, they also show that a higher rate of worker mobility, and thus knowledge spillover, is associated with lower productivity dispersion in an industry. The authors also note that spillovers are larger when hiring highly educated, high-skill workers but are not exclusively associated with those. They document productivity gains with medium-skilled workers, suggesting that spillovers happen above and beyond information that can possibly be patented. These findings echo earlier work on worker mobility and R&D spillovers (Rao and Drazin 2002). Kaiser, Kongsted, and Rønde (2015) document a positive association between the two and show that the mobility of R&D workers shapes even the citation patterns between the old firm and the hiring firm, pointing to additional knowledge transfer. Maliranta, Mohnen, and Rouvinen (2009) document that transferring R&D workers to non-R&D positions can also enhance a firm's productivity, pointing to broader channels defining knowledge diffusion via worker mobility. Last but not least, Song, Almeida, and Wu (2003) analyze the transition of engineers from US firms to non-US ones, together with their patenting and citation patterns, and find corroborating evidence on learning by hiring. In light of this literature, the persistent decline in worker mobility in the US economy is consistent with a decline in knowledge diffusion.

X. 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 US 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, Criscuolo, and Gal (2016) show a widening productivity gap between frontier and laggard firms, which they 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 US 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. In parallel, inventors become more concentrated at the top and mature firms, and the broader workflow in the economy is falling. 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 above, several channels could have distorted the diffusion of knowledge. A short list of candidates includes 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. Comprehending the nature of knowledge diffusion and determining the most prominent 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 postentry distortions that impede competition between leader and follower firms. Such a competition policy would not only affect incumbent firms but also incentivize business entry through positive trickle-down effects. Motivated by these deliberations, in an ongoing work (Akcigit, Ates, and Kalemli-Özcan 2022), we study the link between foreign competition and knowledge diffusion in the OECD countries. Our current findings show that, while foreign presence in a sector has a direct negative effect on firm-level revenue productivity growth (Fons-Rosen et al. 2017), this effect is mitigated in more concentrated sectors, suggesting that foreign competition alleviates the negative effect of concentration on domestic firms.

Finally, our work emphasizes the importance of a comprehensive approach that links micro-level changes in market primitives to macroeconomic outcomes in analyzing the drivers of prominent empirical trends in the US economy. The distinction between market primitives and the observed outcomes is essential, in that it helps us avoid enforcing a certain relationship between macroeconomic outcomes that might be related in various ways—a criticism by Syverson (2019)—and get to the root of those outcomes. While each candidate mechanism 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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