

# Are Markups Too High?

## Competition, Strategic Innovation, and Industry Dynamics\*

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September 10, 2026

### Abstract

To study competition, innovation, and industry dynamics that arise as a result of their interaction, we develop a new oligopolistic general-equilibrium Schumpeterian growth model. This model ties together the endogenous growth, oligopolistic competition, and dynamic industrial organization literatures in a single unified framework. Within each industry, there are an endogenously determined number of large firms (“superstars”) that compete *à la* Cournot and a continuum of small firms which collectively constitute a competitive fringe. Firms dynamically choose their innovation strategies, cognizant of other firms’ choices, and their entry and exit are endogenous. The model is consistent with the macroeconomic trends observed in the United States since the 1970s, such as the domination of industries by a small number of superstar firms, the rise of markups, market concentration, profits, and R&D spending, and the decline in business dynamism, productivity growth, and the labor share. It replicates the empirical relationship between innovation and competition within and across industries. As an application, we estimate the model to disentangle the effects of separate mechanisms on the structural transition observed in the United States, which yields striking results: (1) While the increase in the average markup causes a significant static welfare loss, this loss is overshadowed by the dynamic welfare gains from increased innovation in response to higher profit opportunities. (2) The increasing costs of innovation are found to be the primary determinant of lackluster productivity growth, i.e., ideas are getting harder to find.

**Keywords:** innovation, markups, growth, strategic investment, industry dynamics, business dynamism.

**JEL Classification:** E20, L10, O30, O40.

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# 1 Introduction

Consumer welfare depends crucially on both competition and long-run productivity growth. Firms' forward-looking entry and innovation decisions determine the market structure in industries in terms of the number of competing firms and their productivities, and consequently, product market competition. In turn, product market competition determines which firms can reap the highest profits as the reward of their innovation efforts. Therefore, competition and growth are inseparably interlinked. Their joint study calls for a theoretical framework that can simultaneously capture the general-equilibrium effects of firms' strategic innovation decisions on economic growth and industrial structure, as well as the rich within-industry dynamics featuring heterogeneity in market shares, markups, and profitability, which in turn influence the (mis)allocation of resources.

Thus motivated, we develop a new unified framework that ties together the endogenous growth, oligopolistic competition, and dynamic industrial organization literatures, combining their most important features without giving up on tractability. It serves as a laboratory to answer a wide range of questions related to competition and growth, which is amenable to extensions in several directions. This framework is particularly well-suited for studying the underlying economic mechanisms behind the recent macroeconomic trends observed in the United States since the 1970s, such as the increase in market concentration and markups that were accompanied by lackluster productivity growth, and its application delivers some surprising new insights.

Our new framework possesses several desirable properties when it comes to questions related to market structure, competition, innovation, and growth, especially in light of the recent literature on rising concentration and markups. At the industry level, it is able to generate rich heterogeneity in market shares, consistent with the empirically-observed industry-level market share distributions. It offers realistic industry dynamics with firm heterogeneity within and across industries, and endogenous firm entry and exit that generate a distribution of industries populated by different numbers of large firms with different relative productivities. The model is also able to generate realistic firm life cycles with gradual changes in productivity and market shares.

At the firm level, the model captures static and dynamic strategic interactions between firms: (1) product market competition which determines relative prices, market shares, markups, profits, labor demand, and labor shares endogenously; (2) dynamic innovation decisions to improve firm productivity over time, optimally chosen in response to the innovation policies of competing firms. Finally, the framework is able to replicate the observed non-linear relationship between innovation and competition:<sup>1</sup> (1) a hump-shaped relationship between industry innovation and market concentration across industries,<sup>2</sup> and (2) a hump-shaped relationship between firm innovation and relative sales within industries.<sup>3</sup> Consistency in these last two dimensions is important, since welfare implications of a change in market concentration do not only depend on static inefficiencies caused by markups, but also on the dynamic inefficiencies in innovation and aggregate productivity growth.

This rich framework allows us to analyze recent trends in the US economy. Since the 1970s, there have been significant changes in firm dynamics within and across industries in the US, with quantitatively

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<sup>1</sup>The model can also generate other types of relationship between innovation and competition, depending on parameter values.

<sup>2</sup>See [Aghion, Bloom, Blundell, Griffith, and Howitt \(2005\)](#), and the stylized facts in Section 3.1.

<sup>3</sup>See Section 3.1.

important implications for the macroeconomy at large. Industries are increasingly dominated by a small number of large firms (“superstars”, “megafirms”) which compete against each other in the product market, as well as through dynamic strategic innovation decisions. At the aggregate level, average markup, market concentration, profits, and R&D spending are increasing, whereas business dynamism and the labor share are in decline.<sup>4</sup> Despite a rise in the late 90s and early 2000s, productivity growth has been slowing down. These sweeping changes have drawn considerable attention from academics, policymakers, and the public alike. Discovering and understanding the economic mechanisms underlying this transformation are key to assess the implications for efficiency, economic growth, and social welfare, which can then be used to formulate optimal policy responses. In this paper, we offer a unified framework to study these trends and uncover the underlying reasons.

Our new quantitative model with all its desirable properties remains highly tractable despite its rich dynamics and heterogeneity, and its quantification yields some striking insights. It can be described as a combination of a detailed oligopolistic competition model with endogenous entry and exit, and a new Schumpeterian growth model that features step-by-step innovation. Within each industry and at any given time, there is an endogenously determined number of large firms – the superstars – and a continuum of small firms which collectively constitute a competitive fringe. Relative to small firms, superstar firms in the model are characterized by higher productivity and larger market shares. Entrepreneurs choose the entry rate of new small businesses. Industry output is a CES aggregate of the production of superstar firms and the competitive fringe, and the superstars compete *à la* Cournot. This specification yields non-degenerate distributions of sales, employment, and markups in each industry, a contribution upon Schumpeterian growth models with Bertrand competition and homogeneous goods. The distributions depend on the number of superstar firms and the distribution of their productivities, as well as the relative productivity of the competitive fringe. These industry characteristics endogenously change over time according to the strategic innovation decisions of the superstars and the small firms. Motivated by higher profits, the superstars undertake costly R&D in order to improve their productivity relative to their competitors. Small firms also spend resources on R&D, and conditional on success, they join the ranks of the superstars. At the same time, a large firm that lags behind can lose its status as a superstar if its productivity relative to the leader falls to a sufficiently low level. Combined, these dynamics generate transitions between industry states, resulting in a stationary distribution along a balanced growth path equilibrium. Aggregate productivity growth in the economy is determined by the innovation decisions in each industry, weighted by this invariant distribution across industry states in a stationary economy. The model can generate the described hump-shaped relationship between innovation and competition within and across industries.

Our model provides a unified framework that simultaneously combines and extends three strands of literature. First, we generalize the Schumpeterian step-by-step innovation models in the endogenous growth literature to have an arbitrary number of large firms instead of a duopoly, and a competitive fringe of small firms to capture the existence of thousands of small firms observed in the real world, which delivers both realistic firm dynamics and market share distributions. Second, we augment static oligopolistic competition models such as [Atkeson and Burstein \(2008\)](#) and [Autor, Dorn, Katz, Patterson, and Van Reenen \(2020\)](#) with a completely endogenous industry structure featuring endogenous productivity growth, entry, and exit, while accounting for dynamic strategic interactions in a Markov Perfect equilibrium.

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<sup>4</sup>See [Akcigit and Ates \(2021\)](#) for an extensive summary and discussion of these trends.

Finally, our model constitutes a general equilibrium version of dynamic industrial organization models such as [Ericson and Pakes \(1995\)](#) with endogenous growth, where the ergodic distribution of the industry-states for a single industry simultaneously becomes the cross-sectional stationary distribution across a continuum of industries in the aggregate. This unified framework provides a laboratory for answering questions at the intersection of these three literatures.

We estimate our model via indirect inference using macro and micro level moments related to growth, R&D investment, markup distribution, profitability, productivity, and the relationship between market shares and innovation from three different samples. We split our data into three subsamples – an early subsample from 1976 to 1994, a late subsample from 1995 to 2005, and a later subsample after 2005 – and re-estimate. First, we use the estimated equilibrium to clarify the workings of the mechanisms in the model, with a special emphasis on the relationship between competition and innovation, and how it differs from other models in the literature that study similar questions. We then use the three estimates to disentangle the mechanisms underlying the structural transition in the US over these four decades. We achieve this by starting from the late and later period economies, and considering counterfactual economies where parameters governing individual mechanisms are reset back to their early period values. This helps us quantify what channels contribute the most to – or work against – the observed changes in the macroeconomic aggregates.

Perhaps one of the most important questions to ask is whether the observed increase in markups is detrimental to welfare and economic growth. While the static losses from increased markups are well-known and unambiguous, the dynamic effects can go in either direction, as evidenced by the hump-shaped relationship between innovation and competition. Increased competition can boost innovation as firms try to improve their relative productivity (“escape competition”), or lower it if they get discouraged by lower expected profits. Which channel dominates is a quantitative question. First, we show that most of the rise in markups is driven by a decrease in competition from small firms instead of a decrease in competition among large firms. Next, we conduct a counterfactual exercise in which we reset the competition from small firms from its late to its early period level, and compute the consumption-equivalent welfare change. The results are striking: the growth rate goes down by 19.9% of its value, and instead of a net gain, social welfare is reduced by 8.30%. Decomposing the change in welfare into its individual components reveals that although the static efficiency gains would improve welfare by 5.89%, the fall in profitability discourages innovation, and the dynamic losses from the decline in endogenous productivity growth more than offset the static gain. In other words, if markups had stayed the same across the period, economic growth would have been slower. Our results suggest that the dynamic effects of increasing market concentration on innovation and productivity growth should not be ignored when trying to understand the transformation in the US in the last four decades, and the significant increase in markups is not necessarily detrimental to welfare. These trends are maintained or even stronger when we consider the more recent period from 2006 to 2016.

Our model also has interesting predictions regarding the cost of innovation over time. While productivity growth increased between the early and late periods, our model suggests that the cost of innovation went up over the same period, both for large and small firms. These results point towards “the ideas are getting harder to find” hypothesis studied in [Gordon \(2012\)](#) and [Bloom, Jones, Van Reenen, and Webb \(2020\)](#). In other words, the rising cost of innovation has partially offset the positive effect of rising markups on

economic growth and welfare. If R&D efficiency had not decreased, productivity growth would have accelerated even faster between the early and late periods. We extend our analysis to the most recent period from 2006 to 2016, which has been characterized by a productivity slowdown. We show that our main results remain unchanged and that this period also features an increase in the cost of innovation, which more than offsets the positive effect of increased concentration on innovation and growth.

Our estimated model also delivers several predictions that can be tested, especially related to trends in productivity, market concentration, and the labor share. Although they are not targeted, we show that our estimation correctly predicts the increase in productivity dispersion documented by [Barth, Bryson, Davis, and Freeman \(2016\)](#) and the negative correlation between productivity dispersion and the labor share across industries highlighted in [Gouin-Bonenfant \(2022\)](#). In addition, our model is in line with several facts related to changes in the labor share documented in [Autor, Dorn, Katz, Patterson, and Van Reenen \(2020\)](#). These tests further confirm the external validity of the model.

Our quantitative results are found to be robust to introducing endogenous capital accumulation, as well as using different values for the elasticity of intertemporal substitution. Neither are they sensitive to using different targets to discipline markups. Our baseline estimation targets the sales-weighted markup moments from [De Loecker, Eeckhout, and Unger \(2020\)](#). Targeting cost-weighted markups from [Edmond, Midrigan, and Xu \(2023\)](#) does not lead to sizable differences. Motivated by the recent criticism in [Bond, Hashemi, Kaplan, and Zoch \(2021\)](#) regarding the consistency of the markup estimation methodology developed in [De Loecker and Warzynski \(2012\)](#), we also conduct an estimation which does not rely on any markup targets.

Solving for the non-stationary equilibria of our model is significantly more challenging than in standard macroeconomic models, given that it requires calculating the complete time paths of 86 continuous state variables given our choices.<sup>5</sup> Despite the complexity, the tractability of our framework and our choice to use a continuous-time setting render the computation of non-stationary equilibria feasible. We find that our welfare results remain robust to taking the transitional dynamics into account.

For further elucidation, we also solve the (unconstrained as well as constrained) social planner’s problem dynamically.<sup>6</sup> Consistent with our results regarding the welfare effect of increasing markups, the solution to the planner’s problem reveals that the dynamic inefficiencies due to under-investment in innovation are much more severe than the static inefficiencies due to market power, even though the latter are quite significant on their own. This result suggests that the optimal design of corporate taxation and R&D subsidies, studied in [Akcigit, Hanley, and Stantcheva \(2022\)](#), is first-order for social welfare and economic growth.

**Literature review:** This paper is related to the literature on the welfare cost of markups and a recent body of literature that investigates the increase in market concentration and the associated increase in markups and profit shares over the last few decades in the US as highlighted in [Barkai \(2020\)](#), [Gutiérrez and Philippon \(2017a\)](#), [Eggertsson, Robbins, and Wold \(2021\)](#), [Hall \(2018\)](#), [De Loecker, Eeckhout, and Unger \(2020\)](#), and [Grullon, Larkin, and Michaely \(2019\)](#).<sup>7</sup> [Gutiérrez and Philippon \(2017b\)](#) and [Gutiérrez,](#)

<sup>5</sup>For comparison, computing non-stationary equilibria in the canonical neoclassical growth model requires finding the complete time path of a single continuous state variable, the capital stock  $K_t$ .

<sup>6</sup>Even though we simplify the full dynamic problem significantly through our derivations, this still leaves 253 positive scalars to be simultaneously solved for through global optimization methods.

<sup>7</sup>[De Loecker and Eeckhout \(2018\)](#) also document similar trends for markups in other regions of the world.

Jones, and Philippon (2021) show that the increase in market concentration and the decline in competition can explain underinvestment by US firms. Covarrubias, Gutiérrez, and Philippon (2020) distinguish between so-called *good* and *bad* concentration. For instance, market concentration can be *good* if it is associated with technological change while increased concentration due to barriers to entry would be *bad*. They further suggest that market concentration in the US turned from being efficient in the 1990s to being inefficient after 2000. Rossi-Hansberg, Sarte, and Trachter (2021) find that the observed positive trend in market concentration at the national level in the US has been accompanied by a corresponding negative trend in average local market concentration. Baqaee and Farhi (2020) estimate that misallocation due to large and dispersed markups results in a TFP loss as large as 15%, while the reallocation of market shares towards high-markup firms improved static allocative efficiency and aggregate productivity. Our results further highlight the effect of rising market concentration on dynamic allocative efficiency. Recent work by Edmond, Midrigan, and Xu (2023) is closely related to our paper. Using a dynamic model with size-dependent markups, they find sizeable welfare losses from markups. Weiss (2020) studies the role played by intangible capital on markup trends and welfare in a model with oligopolistic competition and a one-time investment in intangible capital by firms. Compared to these papers, our model has continuous and strategic investment in productivity growth, and oligopolistic competition between an endogenous number of heterogeneous innovative firms. Our Schumpeterian structure delivers significant differences regarding the dynamics, growth, and welfare. De Loecker, Eeckhout, and Mongey (2022) also study the causes and consequences of market power in general equilibrium. Our model differs from their approach, as we endogenize productivity growth and model strategic interactions between firms in innovation. This difference is significant, since allowing for endogenous productivity growth can completely overturn the welfare implications of higher markups as we discussed earlier.

Our paper also adds to the endogenous growth literature studying the relationship between competition and innovation. In early Schumpeterian models of growth through innovation (e.g., Aghion and Howitt (1992)), more product market competition reduces rents and hence the incentives to invest in R&D and innovation. Aghion, Harris, Howitt, and Vickers (2001) propose a model of step-by-step innovation by superstar firms. By introducing an additional incentive to escape competition, this model can generate an inverted-U shape relationship between the degree of market competition (measured by the elasticity of substitution between products) and innovation. Using a similar model, Aghion, Bloom, Blundell, Griffith, and Howitt (2005) also generate an inverted-U shape relationship between competition and innovation.<sup>8</sup> They further provide empirical evidence for such an inverted-U shape relationship between innovation activity and industry competition using data from the UK. We also undertake an empirical analysis in which we look at the relationship between competition and innovation using data from the US. We verify that the findings in Aghion, Bloom, Blundell, Griffith, and Howitt (2005) also hold in the US using several measures of innovation. Furthermore, we also document a robust inverted-U relationship between the relative sales of a firm and its innovation. Our model is able to replicate the two hump-shaped relationships within and across industries without relying on exogenous heterogeneity,<sup>9</sup> and in the presence of endogenous firm entry.<sup>10</sup>

<sup>8</sup>See Gilbert (2006) for an extensive review of the literature on competition and innovation.

<sup>9</sup>For instance, in Aghion, Bloom, Blundell, Griffith, and Howitt (2005), exogenous heterogeneity in collusion across industries is assumed to generate the inverted-U result.

<sup>10</sup>Etro (2007) argues that the industry-level inverted-U relationship breaks down when endogenous entry is introduced to

Within the class of endogenous growth models, the closest papers to ours are [Peters and Walsh \(2019\)](#), [Akcigit and Ates \(2021, 2023\)](#), [Liu, Mian, and Sufi \(2022\)](#), [Olmstead-Rumsey \(2022\)](#), [Aghion, Bergeaud, Boppart, Klenow, and Li \(2023\)](#), and [De Ridder \(2024\)](#).<sup>11</sup> [Peters and Walsh \(2019\)](#) propose an extension of [Peters \(2020\)](#) to study the role of the decline in the growth rate of the labor force on the observed decline in business dynamism, increased market power, and slower productivity growth.<sup>12</sup> Building on [Acemoglu and Akcigit \(2012\)](#), [Akcigit and Ates \(2021, 2023\)](#) propose a model of endogenous growth and firm dynamics with heterogeneous markups and show that declining knowledge diffusion played a significant role in declining business dynamism. [Liu, Mian, and Sufi \(2022\)](#) show that a decline in the interest rate can lead to a rise in market concentration and a slowdown in productivity growth. [Olmstead-Rumsey \(2022\)](#) shows, using an endogenous growth model in which the quality of new ideas is heterogeneous, that the decline in small firms' innovativeness can be linked to recent trends in market concentration and productivity growth. [Aghion, Bergeaud, Boppart, Klenow, and Li \(2023\)](#) explain the rise in concentration and profits through falling firm-level costs of spanning multiple markets due to accelerating IT advances. [De Ridder \(2024\)](#) shows that the rise in intangible inputs can explain the recent trends in productivity growth and business dynamism as it causes a shift from variable to fixed costs. In both [Aghion, Bergeaud, Boppart, Klenow, and Li \(2023\)](#) and [De Ridder \(2024\)](#), the rise in concentration can be temporarily associated with an increase in productivity growth. In the long run, productivity growth decreases.

Most of the listed papers assume Bertrand competition with homogeneous goods in each industry.<sup>13</sup> Markups depend directly on the productivity gap between the leader and the follower. Unless firms are neck-and-neck, the leader takes over the whole industry. Our paper differs from the literature in its treatment of within-industry dynamics as discussed earlier. Our model features non-degenerate distributions of sales, employment, markups, and profits within each industry. It allows for an arbitrarily high and endogenous number of oligopolistically-competing firms in each industry.<sup>14</sup> These advances upon the previous literature allow us to hit the hump-shaped relationship between competition and innovation within and across industries, which helps discipline the estimated growth and welfare implications of higher market concentration and markups. The new competitive fringe feature of our model allows for realistic market share distributions and firm life cycles where entrants do not immediately become industry leaders, and we can distinguish new business entry from the emergence of new superstars.<sup>15</sup> Apart from the technical differences, our study also differs in its quantitative approach. Instead of searching for a single mechanism which can jointly explain all the changes in the macroeconomic aggregates to some

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[Aghion, Harris, Howitt, and Vickers \(2001\)](#). Our model provides a counterexample. Other counterexamples can be found in [Bento \(2014, 2020\)](#)

<sup>11</sup>In other related work, [Corhay, Kung, and Schmid \(2025\)](#) use a Romer-type endogenous growth model to study the asset pricing implications of increasing markups.

<sup>12</sup>In a model without endogenous growth, [Hopenhayn, Neira, and Singhania \(2022\)](#) also show that declining population growth can explain a large share of the observed decline in firm entry and productivity slowdown.

<sup>13</sup>Two exceptions are [Liu, Mian, and Sufi \(2022\)](#) and [Olmstead-Rumsey \(2022\)](#) which propose models of endogenous growth with Bertrand competition between two firms with differentiated products. However, they maintain the perpetual duopoly assumption that pervades the step-by-step innovation literature, as opposed to allowing an endogenous number of superstars in each industry as we do.

<sup>14</sup>[Peretto \(1996\)](#) features a model with an endogenous number of firms in the aggregate economy, but focuses on a symmetric equilibrium where all firms have the same productivity, innovation, and sales. [Impullitti and Licandro \(2018\)](#) also consider a model of endogenous growth with oligopolistic competition. In contrast to our framework, they focus on industries with a common (endogenous) number of homogeneous firms.

<sup>15</sup>[Ghazi \(2021\)](#) proposes a model with a competitive fringe and a single dominant firm but does not consider innovation by small firms.

degree, our estimation tightly hits all the changes, and we use the model to disentangle the contribution of each channel. This provides some guidance on which mechanisms should be further investigated to better understand the underlying sources of the structural transition, such as the widening productivity gap between the superstars and the rest, and the increasing costs of R&D.

Our paper is related to the broader literature on the decline in business dynamism. A large body of that literature shows that the entry rate of new firms has significantly decreased in the US since the early 1980s (see for instance, [Hathaway and Litan \(2014\)](#), [Decker, Haltiwanger, Jarmin, and Miranda \(2016\)](#), [Pugsley and Sahin \(2018\)](#)). The decline in firm entry can further affect productivity growth. For instance, [Lentz and Mortensen \(2008\)](#), [Garcia-Macia, Hsieh, and Klenow \(2019\)](#) and [Acemoglu, Akcigit, Alp, Bloom, and Kerr \(2018\)](#) find that a significant share of aggregate TFP growth and job creation is due to firm entry and young firms. Our quantitative exercise reveals that not only the share of output by small firms decreases but also that these firms are less likely to become superstar firms due to higher R&D costs.

Our results also add to the recent literature on the slowdown of TFP growth in the US. [Gordon \(2012, 2014\)](#) argues that the significant slowdown in the rate of productivity growth in the US since the 1970s is due to diminishing returns from R&D. [Bloom, Jones, Van Reenen, and Webb \(2020\)](#) show empirical evidence for a steady decline in R&D productivity over the course of the 20th century. As ideas are getting harder to find, sustaining a constant economic growth rate has required a simultaneous increase in research inputs. Our quantitative results suggest that the cost of R&D has been increasing since the late 1970s for both small and superstar firms.

Another important trend over the last decades in the US relates to the evolution of factor shares. In particular, the share of income paid to workers has steadily decreased over the last decades as highlighted in, among others, [Karabarbounis and Neiman \(2013\)](#) and [Elsby, Hobijn, and Şahin \(2013\)](#). At the same time, the profit share has followed an opposite trajectory ([Barkai \(2020\)](#)). A large literature has highlighted several potential sources for the decrease in the labor share such as technological change and automation (see, for instance, [Zeira \(1998\)](#), [Acemoglu and Restrepo \(2018\)](#), [Martinez \(2019\)](#)), globalization ([Elsby, Hobijn, and Şahin \(2013\)](#)), the decline in the relative price of capital ([Karabarbounis and Neiman \(2013\)](#)), increased cost of housing ([Rognlie \(2015\)](#)) or a rise in productivity dispersion ([Gouin-Bonenfant \(2022\)](#)). [Barkai \(2020\)](#) and [De Loecker, Eeckhout, and Unger \(2020\)](#) relate the decrease in the labor share to the rise in profitability and markups. [Autor, Dorn, Katz, Patterson, and Van Reenen \(2020\)](#) and [Kehrig and Vincent \(2021\)](#) attribute this trend to the rise of superstar firms which tend to display high markups and low labor shares. Our model is also able to generate a decline in the labor share over the same time period.

The paper is organized as follows: In Section 2, we introduce our new framework and derive equilibrium conditions. We also discuss non-stationary equilibria and the social planner’s problem. In Section 3, we discuss the empirical relationship between competition and innovation that is used to discipline our estimation. We also estimate the model. Section 4 describes some properties and new features of our model. Section 5 applies our new framework to the study of the sources and consequences of recent macroeconomic trends in the US, especially related to the rise in market concentration and markups. We further validate the model in Section 6 and check its robustness in Section 7. Section 8 concludes.

## 2 Model

### 2.1 Environment

**Preferences** Time is continuous and indexed by  $t \in \mathbb{R}_+$ . The economy is populated by an infinitely-lived representative consumer who discounts the future at rate  $\rho > 0$ . The representative consumer maximizes lifetime utility:

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

where  $C_t$  is consumption of the final good at time  $t$ , the price of which is normalized to one.

The household inelastically supplies one unit of labor in exchange for an endogenously determined wage rate  $w_t$ . Households own all the assets in the economy and face the following budget constraint:

$$\dot{A}_t = r_t A_t + w_t - C_t \quad (2)$$

where  $A_t$  is household wealth and  $r_t$  is the rate of return on assets.

**Final Good Production** The final good  $Y_t$  is produced competitively using inputs from a measure one of industries:

$$\ln(Y_t) = \int_0^1 \ln(y_{jt}) dj \quad (3)$$

where  $y_{jt}$  is production of industry  $j$  at time  $t$ .

**Industry Production** Each industry is populated by an endogenous number of superstar firms ( $N_{jt} \in \{1, \dots, \bar{N}\}$ ), each producing a differentiated variety, as well as by a competitive fringe composed of a mass  $m_{jt}$  of small firms producing a homogeneous good (small firm  $k$  in the fringe of industry  $j$  at time  $t$  produces  $y_{ckjt}$ ). Given that there is a continuum of small firms and their products are homogeneous, each small firm in the competitive fringe is a price taker.<sup>16</sup> Superstars compete in quantities. In particular, we allow for strategic interaction among superstars as variety production is the result of a static Cournot game. Total production of industry  $j$  at time  $t$  is given by:

$$y_{jt} = \left( \sum_{i=1}^{N_{jt}} y_{ijt}^{\frac{\eta-1}{\eta}} + \tilde{y}_{cjt}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}} \quad (4)$$

where  $y_{ijt}$  is the production of superstar firm  $i$  in industry  $j$  at time  $t$ ,  $\tilde{y}_{cjt} = \int_{F_{jt}} y_{ckjt} dk$  is the production of the competitive fringe in industry  $j$  at time  $t$ ,  $F_{jt}$  is the set of small firms in the fringe in industry  $j$  at time  $t$  and  $\eta > 1$  is the elasticity of substitution between varieties.

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<sup>16</sup>For a discussion of the importance and interpretation of the competitive fringe, see Section J in the Extra Appendix.

**Variety Production** Superstar firms in each industry produce their own variety using a linear production technology in labor:

$$y_{ijt} = q_{ijt}l_{ijt} \quad (5)$$

where  $q_{ijt}$  is the productivity of superstar firm  $i$  in industry  $j$  at time  $t$  and  $l_{ijt}$  is labor.

Similarly for every small firm  $k$  in the competitive fringe:

$$y_{ckjt} = q_{ckjt}l_{ckjt} \quad (6)$$

We assume that each small firm in the fringe in a given industry has the same productivity  $q_{ckjt}$ . Superstar firms within each industry differ according to their level of productivity which can be built over time through R&D and innovation.

**R&D and Innovation** Each superstar can perform R&D to improve the productivity of its variety. To generate a Poisson rate  $z_{ijt}$  of success in R&D, firm  $i$  must pay a cost in units of the final good equal to:

$$R_{ijt} = \chi z_{ijt}^\phi Y_t. \quad (7)$$

where  $\phi$  is the superstar R&D cost convexity parameter with  $\phi > 1$ , and  $\chi > 0$  is the scale parameter.

If a superstar successfully innovates at time  $t$ , its productivity is multiplied by  $(1 + \lambda)$ . We assume that the maximum number of productivity steps between any two superstar firms within an industry is  $\bar{n} \geq 1$ . For the competitive fringe, we assume that the relative productivity of small firms with respect to the leader is a constant, denoted by  $\zeta = \frac{q_{ckjt}}{q_{ijt}^{\text{leader}}}$ . Note that  $\zeta$  can be any positive real number, and it should be interpreted as the aggregate productivity of all firms in the fringe. In our model, the market share of each small firm is infinitesimally small compared to any superstar firm. However, the fringe as a whole has a positive market share, which is allowed to be larger in aggregate than the market share of some (or all) superstar firms producing a differentiated good. This implies that superstar firms in our model are characterized by higher productivity and larger market shares than every single small firm in equilibrium, but collectively, the small firms matter.

**Entry and Exit of Superstar Firms** At any time  $t$ , each small firm  $k$  in the competitive fringe can generate a Poisson arrival density  $X_{kjt}$  of entry into superstar firms when  $N_{jt} < \bar{N}$ . The associated R&D cost is given by

$$R_{kjt}^e = \nu X_{kjt}^\epsilon Y_t. \quad (8)$$

where  $\epsilon$  is the small firm R&D cost convexity parameter with  $\epsilon > 1$ , and  $\nu > 0$  is the scale parameter.

Because all small firms are homogeneous within an industry, they all perform the same level of innovation in equilibrium. We can rewrite the industry level Poisson rate of innovation  $X_{jt} = \int X_{kjt} dk = m_{jt} X_{kjt}$  and the industry level R&D expenditures of small firms  $R_{jt}^e = m_{jt} R_{kjt}^e$ .

When a small firm successfully innovates, it becomes a superstar, and the number of superstar firms in the industry is increased by one unless the number of firms in the industry is already equal to  $\bar{N}$ , in

which case entry is not allowed. The new entrant is assumed to enter as the smallest superstar firm in the industry, i.e., it is assumed to have a productivity level  $\bar{n}$  steps below the leader. In this sense, entry into superstars in our model should be interpreted as a small firm becoming more productive and large enough to strategically interact with other superstars.<sup>17</sup> In particular, our assumptions imply that firms more than  $\bar{n}$  steps below the leader in any industry are not large enough to be considered as having any meaningful strategic interaction with other firms.<sup>18</sup> Consistent with this interpretation of our model, a firm endogenously loses its superstar firm status when it is  $\bar{n}$  steps below the industry leader and the leader innovates. In that case, the number of superstar firms in the industry decreases by one.

**Entry and Exit of Small Firms** We also introduce entry into and exit from the competitive fringe, which allows for a realistic mapping between small firm entry in the model and new business creation in the data. This is different from the existing endogenous growth literature where entrants can immediately become the leader in their industry, or large enough to interact strategically with the current leader. In this sense, our model features a realistic firm life-cycle, where thousands of small firms enter, but only a select few become superstars, several years or even decades after entry. We assume an exogenous exit rate of small firms equal to  $\tau > 0$ . Regarding entry, there is a mass one of entrepreneurs who can pay a cost  $\psi e_t^2 Y_t$  to generate a Poisson rate  $e_t$  of starting a new small firm. The new firms are randomly allocated to the competitive fringe of an industry, which implies  $m_{jt} = m_t$  for all industries  $j$ . In order to keep the mass of entrepreneurs unchanged, we assume that they sell their firm on a competitive market at its full value and remain in the set of entrepreneurs.<sup>19</sup>

## 2.2 Equilibrium

**Consumer's problem** Household lifetime utility maximization delivers the standard Euler equation:

$$\frac{\dot{C}_t}{C_t} = r_t - \rho. \quad (9)$$

**Final Good Producers** The final good is produced competitively. The representative final good producer chooses the quantity of each variety in each industry which maximizes profit:

$$\max_{\{y_{ijt}\}_{i=1}^{N_{jt}}, \{\tilde{y}_{cjt}\}_{j=0}^1} \exp \left( \frac{\eta}{\eta-1} \int_0^1 \ln \left[ \sum_{i=1}^{N_{jt}} y_{ijt}^{\frac{\eta-1}{\eta}} + \tilde{y}_{cjt}^{\frac{\eta-1}{\eta}} \right] dj \right) - \int_0^1 \left( \sum_{i=1}^{N_{jt}} p_{ijt} y_{ijt} + p_{cjt} \tilde{y}_{cjt} \right) dj. \quad (10)$$

<sup>17</sup>A breakthrough innovation by small firms represents a jump in individual productivity. However, the resultant increase in productivity is different from  $\lambda$ , which naturally calls for different R&D cost functions for small firms and the superstars. See Section J in the Extra Appendix for a discussion of small firms' productivity.

<sup>18</sup>In the estimated model,  $\bar{n}$  is chosen large enough such that the largest superstars that we stop keeping track of are negligible compared to the leader in terms of revenue and profit in all industry-states.

<sup>19</sup>This is without loss of generality. Alternatively, we could have assumed that, upon new business creation, successful entrepreneurs are replaced by new entrepreneurs. This alternative assumption delivers exactly the same observed equilibrium, because all entrepreneurial profits accrue to the representative household, which would remain the same regardless of which assumption is chosen.

where  $p_{ijt}$  ( $p_{cjt}$ ) is the price of variety  $i$  (the competitive fringe variety) in industry  $j$  at time  $t$ . This leads to the following inverse demand function:

$$p_{ijt} = \frac{y_{ijt}^{-\frac{1}{\eta}} Y_t}{\sum_{k=1}^{N_{jt}} y_{kjt}^{\frac{\eta-1}{\eta}} + \tilde{y}_{cjt}^{\frac{\eta-1}{\eta}}} \quad (11)$$

and

$$\frac{y_{ijt}}{y_{kjt}} = \left( \frac{p_{kjt}}{p_{ijt}} \right)^\eta \quad (12)$$

where  $y_{ijt}$  should be replaced by  $\tilde{y}_{cjt}$  for the competitive fringe.

**Variety Producers** We assume that superstar firms within the same industry compete *à la* Cournot. Each firm maximizes profit:

$$\max_{y_{ijt}} p_{ijt} y_{ijt} - w_t l_{ijt} = \max_{y_{ijt}} \frac{y_{ijt}^{\frac{\eta-1}{\eta}} Y_t}{\sum_{k=1}^{N_{jt}} y_{kjt}^{\frac{\eta-1}{\eta}} + \tilde{y}_{cjt}^{\frac{\eta-1}{\eta}}} - \frac{w_t y_{ijt}}{q_{ijt}}. \quad (13)$$

This delivers the following best response functions for superstar firms:

$$y_{ijt} = \left[ \frac{\eta-1}{\eta} q_{ijt} \frac{\sum_{k \neq i} y_{kjt}^{\frac{\eta-1}{\eta}} + \tilde{y}_{cjt}^{\frac{\eta-1}{\eta}}}{\left[ \sum_{k=1}^{N_{jt}} y_{kjt}^{\frac{\eta-1}{\eta}} + \tilde{y}_{cjt}^{\frac{\eta-1}{\eta}} \right]^2} \frac{Y_t}{w_t} \right]^\eta \quad (14)$$

$$= \frac{\eta-1}{\eta} q_{ijt} \frac{\sum_{k \neq i} \left( \frac{y_{kjt}}{y_{ijt}} \right)^{\frac{\eta-1}{\eta}} + \left( \frac{\tilde{y}_{cjt}}{y_{ijt}} \right)^{\frac{\eta-1}{\eta}}}{\left[ \sum_{k=1}^{N_{jt}} \left( \frac{y_{kjt}}{y_{ijt}} \right)^{\frac{\eta-1}{\eta}} + \left( \frac{\tilde{y}_{cjt}}{y_{ijt}} \right)^{\frac{\eta-1}{\eta}} \right]^2} \frac{Y_t}{w_t} \quad (15)$$

The total production of the competitive fringe is given by:

$$\tilde{y}_{cjt} = q_{cjt} \frac{\frac{Y_t}{w_t}}{\sum_{k=1}^{N_{jt}} \frac{y_{kjt}^{\frac{\eta-1}{\eta}}}{\tilde{y}_{cjt}^{\frac{\eta-1}{\eta}}} + 1} \quad (16)$$

Relative production between each superstar variety and the competitive fringe within the industry can then be written as:

$$\left( \frac{y_{ijt}}{y_{kjt}} \right)^{\frac{1}{\eta}} = \frac{q_{ijt}}{q_{kjt}} \frac{\sum_{l \neq i} \left( \frac{y_{ljt}}{y_{ijt}} \right)^{\frac{\eta-1}{\eta}} + \left( \frac{\tilde{y}_{cjt}}{y_{ijt}} \right)^{\frac{\eta-1}{\eta}}}{\sum_{l \neq k} \left( \frac{y_{ljt}}{y_{ijt}} \right)^{\frac{\eta-1}{\eta}} + \left( \frac{\tilde{y}_{cjt}}{y_{ijt}} \right)^{\frac{\eta-1}{\eta}}} \quad (17)$$

$$\left(\frac{y_{ijt}}{\tilde{y}_{cjt}}\right)^{\frac{1}{\eta}} = \frac{\eta - 1}{\eta} \frac{q_{ijt}}{q_{cjt}} \frac{\sum_{l \neq i} \left(\frac{y_{ljt}}{y_{ijt}}\right)^{\frac{\eta-1}{\eta}} + \left(\frac{\tilde{y}_{cjt}}{y_{ijt}}\right)^{\frac{\eta-1}{\eta}}}{\sum_{l=1}^{N_{jt}} \left(\frac{y_{ljt}}{y_{ijt}}\right)^{\frac{\eta-1}{\eta}} + \left(\frac{\tilde{y}_{cjt}}{y_{ijt}}\right)^{\frac{\eta-1}{\eta}}}. \quad (18)$$

For each industry  $j$ , this is a system of  $N_{jt}$  equations and  $N_{jt}$  unknown production ratios which can be solved given relative productivities within the industry.

We can further derive variety prices ( $p_{ijt}$ ) and profits before R&D expenditures ( $\pi_{ijt}$ ) which only depend on relative productivities within the industry:

$$p_{ijt} = \frac{\eta}{\eta - 1} \frac{\sum_{k=1}^{N_{jt}} \left(\frac{y_{kjt}}{y_{ijt}}\right)^{\frac{\eta-1}{\eta}} + \left(\frac{\tilde{y}_{cjt}}{y_{ijt}}\right)^{\frac{\eta-1}{\eta}}}{\sum_{k \neq i} \left(\frac{y_{kjt}}{y_{ijt}}\right)^{\frac{\eta-1}{\eta}} + \left(\frac{\tilde{y}_{cjt}}{y_{ijt}}\right)^{\frac{\eta-1}{\eta}}} \frac{w_t}{q_{ijt}} \quad (19)$$

$$\pi_{ijt} = \frac{Y_t}{\left[\sum_{k=1}^{N_{jt}} \left(\frac{y_{kjt}}{y_{ijt}}\right)^{\frac{\eta-1}{\eta}} + \left(\frac{\tilde{y}_{cjt}}{y_{ijt}}\right)^{\frac{\eta-1}{\eta}}\right]^2} \frac{\eta + \sum_{k \neq i} \left(\frac{y_{kjt}}{y_{ijt}}\right)^{\frac{\eta-1}{\eta}} + \left(\frac{\tilde{y}_{cjt}}{y_{ijt}}\right)^{\frac{\eta-1}{\eta}}}{\eta} \quad (20)$$

Firms charge varying markups over marginal cost that depend on the number of competitors as well as their relative productivities:  $p_{ijt}q_{ijt}/w_t$ .

**Superstar Value Function and R&D Decision** Static production decision, markups, and profits within each industry only depend on the number of superstars, and the distribution of their relative productivities. In other words, the relevant state variables for a firm  $i$  in industry  $j$  at time  $t$  can be summarized by the vector of the number of productivity steps between superstar firm  $i$  and every other superstar firm  $k \in \{(1, 2, \dots, N_{jt}) \setminus \{i\}\}$  in the industry. Letting  $n_{ijt}^k \in \{-\bar{n}, -\bar{n} + 1, \dots, \bar{n} - 1, \bar{n}\}$  be the number of steps by which firm  $i$  in industry  $j$  leads firm  $k$  at time  $t$ , the relevant state variables for firm  $i$  in industry  $j$  at time  $t$  are given by the vector  $\mathbf{n}_{ijt} = \{n_{ijt}^k\}_{k \neq i}$  and  $N_{jt} = |\mathbf{n}_{ijt}| + 1$ .<sup>20</sup>

Henceforth, we drop the time subscripts unless otherwise needed. A superstar firm  $i$  chooses an innovation rate ( $z_i$ ) to maximize the value of the firm given by:

$$\begin{aligned} rV(\mathbf{n}_i, N) = & \max_{z_i} \pi(\mathbf{n}_i, N) - \chi z_i^\phi Y \\ & + z_i \left[ V(\mathbf{n}_i \setminus \{n_i^k = \bar{n}\} + \mathbf{1}, N - |\{n_i^k = \bar{n}\}|) - V(\mathbf{n}_i, N) \right] \\ & + \sum_{k: n_i^k = -\bar{n}} z_{kj} (0 - V(\mathbf{n}_i, N)) \\ & + \sum_{k: n_i^k \neq -\bar{n}} z_{kj} \left[ V(\mathbf{n}_i \setminus \{n_i^k\} \cup \{n_i^k - 1\} \setminus \{n_i^l = \bar{n} + n_i^k\}, N - |\{n_i^l = \bar{n} + n_i^k\}|) - V(\mathbf{n}_i, N) \right] \\ & + X_j [V(\mathbf{n}_i \cup \{\min\{\bar{n}, \bar{n} + \min(\mathbf{n}_i)\}\}, \min(N + 1, \bar{N})) - V(\mathbf{n}_i, N)] + \dot{V}(\mathbf{n}_i, N) \end{aligned} \quad (21)$$

The first line is the flow profit minus the cost of R&D. The second line is the change in firm value due to a successful innovation by firm  $i$  which happens with Poisson rate  $z_i$ . If firm  $i$  innovates, it increases its

<sup>20</sup>We can rewrite the relative productivity of firm  $i$  and  $k$  as  $\frac{q_{ijt}}{q_{kjt}} = (1 + \lambda)^{n_{ijt}^k}$ .

lead over any other firm by one. Any firm  $\bar{n}$  productivity steps below firm  $i$  exits the set of superstars. The third line corresponds to the change in value due to endogenous exit which arises if one of the industry leaders is  $\bar{n}$  steps ahead of firm  $i$  and innovates.

The fourth line comes from any other firm (not leading  $i$  by  $\bar{n}$ ) innovating. In that case, the lead of firm  $i$  with respect to the innovating firm decreases by one. In addition, if the innovating firm  $k$  is also leading any other firm  $l$  by  $\bar{n}$  (which happens if  $n_i^l - n_i^k = \bar{n}$ ), firm  $l$  exits. The first term in the fifth line is the effect of firm entry on the value of firm  $i$ . In that case, the entrant starts  $\bar{n}$  productivity steps below the industry leader. The second term on the same line is the growth in firm value.

We can guess and verify that, in a balanced growth path (BGP),  $V(\mathbf{n}_i, N) = v(\mathbf{n}_i, N)Y$ . In that case,  $\dot{V}(\mathbf{n}_i, N) = gv(\mathbf{n}_i, N)Y$  (where  $g$  is the growth rate of  $Y$ ). Using equation (9), we can write:

$$\begin{aligned} \rho v(\mathbf{n}_i, N) = & \max_{z_i} \frac{\pi(\mathbf{n}_i, N)}{Y} - \chi z_i^\phi \\ & + z_i \left[ v(\mathbf{n}_i \setminus \{n_i^k = \bar{n}\} + \mathbf{1}, N - |\{n_i^k = \bar{n}\}|) - v(\mathbf{n}_i, N) \right] \\ & + \sum_{k: n_i^k = -\bar{n}} z_{kj} (0 - v(\mathbf{n}_i, N)) \\ & + \sum_{k: n_i^k \neq -\bar{n}} z_{kj} \left[ v(\mathbf{n}_i \setminus \{n_i^k\} \cup \{n_i^k - 1\} \setminus \{n_i^l = \bar{n} + n_i^k\}, N - |\{n_i^l = \bar{n} + n_i^k\}|) - v(\mathbf{n}_i, N) \right] \\ & + X_j [v(\mathbf{n}_i \cup \{\min\{\bar{n}, \bar{n} + \min(\mathbf{n}_i)\}\}, \min(N + 1, \bar{N})) - v(\mathbf{n}_i, N)]. \end{aligned} \quad (22)$$

The optimal level of innovation is given by:

$$z_i = \left\{ \frac{[v(\mathbf{n}_i \setminus \{n_i^k = \bar{n}\} + \mathbf{1}, N - |\{n_i^k = \bar{n}\}|) - v(\mathbf{n}_i, N)]}{\chi \phi} \right\}^{\frac{1}{\phi-1}}. \quad (23)$$

Notice that the optimal innovation  $z_i$  depends on the innovation choices of all other firms in the same industry across all possible future histories. The innovation choices of other firms affect the value function determined by the Hamilton-Jacobi-Bellman equation (22). The value function, in turn, determines the innovation choice  $z_i$ . This introduces dynamic strategic interactions, where innovation policies of firms are functions of others' innovation policies. We focus on the Markov Perfect equilibrium at the intersection of all firms' best response functions, as is common in step-by-step innovation models such as [Aghion, Harris, Howitt, and Vickers \(2001\)](#).

**Small Firm Innovation and Entry into Superstar Firms** Since relative sales and innovation policies only depend on pairwise productivity differences and the number of firms in the industry, we can define  $\Theta = (N, \bar{n})$  as the state of the industry with  $N \in \{1, \dots, \bar{N}\}$  being the number of superstars in the industry and  $\bar{n} \in \{0, \dots, \bar{n}\}^{N-1}$  denoting the number of steps followers are behind the leader (in ascending order). We let  $f(\Theta) = \frac{1}{\eta-1} \ln \left( \sum_{i=1}^{N_j} \left( \frac{y_{ij}}{y_{cj}}(\Theta) \right)^{\frac{\eta-1}{\eta}} + 1 \right)$  and define  $p_{li}(\Theta)$  as the arrival rate of a leader innovation and  $p(\Theta, \Theta')$  as the instantaneous flows from state  $\Theta$  to  $\Theta'$ . In each industry  $j$  (with  $N_j < \bar{N}$ ), each small firm in the competitive fringe can perform R&D. All small firms within an industry are symmetric and

choose R&D investment to maximize:

$$\begin{aligned} rV^e(\Theta_j) &= \max_{X_{kj}} X_{kj} V(\{\tilde{\mathbf{n}}_j - \bar{n}\} \cup \{-\bar{n}\}, N_j + 1) - \tau V^e(\Theta_j) - \nu X_{kj}^\epsilon Y \\ &\quad + \sum_{\Theta'} p(\Theta_j, \Theta') (V^e(\Theta') - V^e(\Theta_j)) + \dot{V}^e(\Theta_j) \end{aligned} \quad (24)$$

where  $V^e(\Theta_j)$  is the value of a small firm in industry  $j$  and  $\tilde{\mathbf{n}}_j = \mathbf{n}_{kj}$  where  $k$  denotes a productivity leader in industry  $j$ .<sup>21</sup>

Guessing and verifying that, in a BGP,  $V^e(\Theta_j) = v^e(\Theta_j)Y$ , we can rewrite:

$$\begin{aligned} (\rho + \tau)v^e(\Theta_j) &= \max_{X_{kj}} X_{kj} v(\{\tilde{\mathbf{n}}_j - \bar{n}\} \cup \{-\bar{n}\}, N_j + 1) - \nu X_{kj}^\epsilon \\ &\quad + \sum_{\Theta'} p(\Theta_j, \Theta') (v^e(\Theta') - v^e(\Theta_j)) \end{aligned} \quad (25)$$

The optimal innovation intensity by a small firm in industry  $j$  is then:

$$X_{kj} = \left( \frac{v(\{\tilde{\mathbf{n}}_j - \bar{n}\} \cup \{-\bar{n}\}, N_j + 1)}{\nu \epsilon} \right)^{\frac{1}{\epsilon-1}} \quad (26)$$

Plugging in the optimal solution, the normalized value of a small firm is calculated as

$$v^e(\Theta_j) = \frac{1}{\rho + \tau} \left[ \left( 1 - \frac{1}{\epsilon} \right) \frac{v(\{\tilde{\mathbf{n}}_j - \bar{n}\} \cup \{-\bar{n}\}, N_j + 1)^{\frac{\epsilon}{\epsilon-1}}}{(\nu \epsilon)^{\frac{1}{\epsilon-1}}} + \sum_{\Theta'} p(\Theta_j, \Theta') (v^e(\Theta') - v^e(\Theta_j)) \right] \quad (27)$$

**Entrepreneurs and Entry into the Competitive Fringe** There is a mass one of entrepreneurs in the economy who can pay a cost  $\psi e^2 Y$  to create a Poisson rate  $e$  of becoming a small firm in a randomly selected industry. We assume that a successful entrepreneur immediately sells the small firm in a competitive market. The expected selling price of the new small firm of a successful entrepreneur is equal to:  $W = \sum_{\Theta} V^e(\Theta) \mu(\Theta)$ , where  $\mu(\Theta)$  is the mass of industries of type  $\Theta$ .<sup>22</sup> The value of being an entrepreneur ( $S$ ) can be written as:

$$rS = \max_e -\psi e^2 Y + eW + \dot{S} \quad (28)$$

Guessing and verifying that, in a BGP,  $S = sY$ , we obtain that:

$$e = \frac{W}{2\psi Y} = \frac{\sum_{\Theta} v^e(\Theta) \mu(\Theta)}{2\psi} \quad (29)$$

<sup>21</sup>Note that we use  $\int_{k=i} V_k^e(\Theta_j) dk = 0$  in the first term, i.e., the value of the small firm is insignificant compared to the value of the superstar firm it becomes, since it is of mass zero in the competitive fringe.

<sup>22</sup>We can show that the expected value of  $\sum_{\Theta'} p(\Theta, \Theta') (V^e(\Theta') - V^e(\Theta))$  in a stationary equilibrium is equal to zero (see Proposition 1 in Appendix A.2).  $W$  is thus equal to  $\frac{1-\frac{1}{\epsilon}}{\rho+\tau} \int_0^1 \frac{V(\{\tilde{\mathbf{n}}_j - \bar{n}\} \cup \{-\bar{n}\}, N_j + 1)^{\frac{\epsilon}{\epsilon-1}}}{(\nu \epsilon)^{\frac{1}{\epsilon-1}}} dj$ .

which implies:

$$s = \frac{[\sum_{\Theta} v^e(\Theta) \mu(\Theta)]^2}{4\psi\rho} \quad (30)$$

In a stationary equilibrium, entry into the competitive fringe equals exit from the competitive fringe which means:

$$e = \tau m \quad (31)$$

Combining equations (29) and (31), we get an equation that pins down the value of  $m$  as:

$$m = \frac{\sum_{\Theta} v^e(\Theta) \mu(\Theta)}{2\psi\tau} \quad (32)$$

**Equilibrium Definition** A Markov-Perfect Equilibrium is defined by a set of allocations  $\{C_t, Y_t, y_{ijt}, y_{ckjt}\}$ , policies  $\{l_{ijt}, l_{ckjt}, z_{ijt}, X_{kjt}, e_t\}$ , prices  $\{p_{ijt}, p_{cjt}, w_t, r_t\}$ , the number of superstars in each industry  $N_{jt}$ , a mass of small firms  $m_t$ , a set of vectors  $\{\mathbf{n}_{ijt}\}$  that denote the relative productivity distance between firm  $i$  and every other firm in the same industry  $j$  at time  $t$ , such that,  $\forall t \geq 0, j \in [0, 1], i \in \{1, \dots, N_{jt}\}$ :

- (i) Given prices, final good producers maximize profit.
- (ii) Given  $\mathbf{n}_{ij}$  and  $N_{jt}$ , superstars choose  $y_{ijt}$  to maximize profit.
- (iii) Given prices, small firms in the competitive fringe choose  $y_{ckjt}$  to maximize profit.
- (iv) Superstar firms choose innovation policy  $z_{ijt}$  to maximize firm value.
- (v) Small firms choose innovation policy  $X_{kjt}$  to maximize firm value.
- (vi) Entrepreneurs choose  $e_t$  to maximize profit.
- (vii) The real wage rate  $w_t$  clears the labor market.
- (viii) Aggregate consumption  $C_t$  grows at rate  $r_t - \rho$ .
- (ix) Resource constraint is satisfied:  $Y_t = C_t + \int_0^1 \sum_{i=1}^{N_{jt}} \chi z_{ijt}^{\phi} Y_t dj + \int_0^1 m_t v X_{kjt}^{\epsilon} Y_t dj + \psi e_t^2 Y_t$ .

**Growth Rate and Balanced Growth Path** We can derive the growth rate of the economy at time  $t$  ( $g_t$ ) as:<sup>23</sup>

$$g_t = -g_{\omega,t} + \sum [p_{lit}(\Theta) \ln(1 + \lambda)] \mu_t(\Theta) + \sum_{\Theta} \sum_{\Theta'} [f_t(\Theta') - f_t(\Theta)] p_t(\Theta, \Theta') \mu_t(\Theta) \quad (33)$$

where  $g_{\omega,t}$  is the growth rate of the relative wage,  $\omega_t = \frac{w_t}{Y_t}$ , the second term comes from the growth rate of the industry leaders, and the third term accounts for production reallocation as industries move between states. In a balanced growth path with time-invariant distribution over  $\Theta$ ,  $g_{\omega,t} = 0$ ,  $\mu_t(\Theta) = \mu(\Theta)$  and:

$$g = \sum_{\Theta} [p_{li}(\Theta) \ln(1 + \lambda)] \mu(\Theta) \quad (34)$$

<sup>23</sup>See Appendix A.1 for the full derivation.

which corresponds to the expected growth rate of industry leaders' log productivity. In other words, long-run growth is driven by industry leaders pushing the technological frontier in their industry. Other firms' (superstars and small firms) decisions influence the growth rate of the economy by affecting the incentives for industry leaders to invest in innovation,  $p_{li}(\Theta)$ , and the stationary distribution across industry states,  $\mu(\Theta)$ , which is a function of the innovation decisions by all firms in all industries through their contribution to the instantaneous flow matrix  $p(\Theta, \Theta')$ .<sup>24</sup>

### 2.3 Non-Stationary Equilibria and Transitional Dynamics

Most of the discussion above has focused on stationary (balanced growth path) equilibria. Despite the richness of our model in terms of heterogeneity and dynamics, it is possible to solve for non-stationary equilibria as well. Computing a non-stationary equilibrium is more complex than in standard macroeconomic models. The relevant state variables to keep track of are (1) the average log productivity level of industry leaders  $Q_t = \int \ln q_{jt}^{leader} dj$ , (2) the mass of small firms  $m_t$ , and (3) the industry-state distribution  $\mu_t(\Theta)$ , which is time-varying in a non-stationary equilibrium. Given our choices for  $\bar{n}$  and  $\bar{N}$  in our baseline estimation, this means solving for a non-stationary equilibrium starting from arbitrary initial conditions  $(Q_0, m_0, \mu_0(\Theta))$  requires finding the complete time paths of 86 continuous state variables under rational expectations, which might seem daunting at first.<sup>25</sup> Despite the complexity, the tractability of our framework and our choice to use a continuous-time setting render the computation of non-stationary equilibria feasible. This is accomplished without any deviation from the assumption of rational expectations. For brevity, the full details including the algorithm are relegated to Section A.9 of the Appendix.

We can distinguish two categories of decisions in the model. For a given industry state  $\Theta$ , within-industry relative labor demand, production, prices, markups, and profits are time-invariant due to the static nature of product market competition in a Markov Perfect equilibrium. So it suffices to solve for every possible industry equilibrium once. However, the innovation decisions of both superstars and small firms, as well as the new business creation decision of the entrepreneurs, depend on firm values, which in turn rely on the future predicted time paths of  $Q_t$ ,  $m_t$ , and  $\mu_t(\Theta)$ . These endogenous objects, in turn, depend on the optimal innovation and business creation decisions at every point in time. Their joint determination is what pins down the unique transition path towards the stationary equilibrium implied by the parameter values.

Of particular interest are the properties of non-stationary equilibria that initially start from a stationary equilibrium, and arise as a result of shocking the values of a subset of parameters. In such non-stationary equilibria, the speed at which important variables converge to their new stationary equilibrium values is important. In our quantitative experiments, we observe that firm value functions and innovation policies are quick to respond, in many cases jumping to the immediate vicinity of their long-run values. The state variables  $m_t$  and  $\mu_t(\Theta)$  are the slow-moving objects. As discussed earlier, the growth rate  $g_t$  of the economy given in equation (33) depends both on leader innovation rates  $p_{lit}(\Theta)$ , and the distribution of industries across industry states  $\mu_t(\Theta)$ . The former reacts immediately, but the latter adjusts more slowly,

<sup>24</sup>We provide an algorithm that can be used to solve for stationary equilibria in Section A.8 of the Appendix, which further elucidates the relationship between  $p(\Theta, \Theta')$  and  $\mu(\Theta)$  in a stationary equilibrium.

<sup>25</sup>For comparison, computing non-stationary equilibria in the canonical neoclassical growth model requires finding the complete time path of a single continuous state variable, the capital stock  $K_t$ .

since endogenous changes to the market structure take time. As a consequence, the growth rate of the economy can jump to a new level in response to shocks in parameter values, but it can take a while to reach its eventual stationary value.<sup>26</sup>

## 2.4 Computing Social Welfare

To calculate welfare, we need to compute the consumption stream of the representative household. In a non-stationary equilibrium, the time path of consumption needs to be directly calculated.<sup>27</sup> In a balanced growth path equilibrium, two components are sufficient: the growth rate of consumption  $g$ , and the initial consumption level  $C_0$ . This, in turn, requires us to compute initial output  $Y_0$  and aggregate spending on R&D and new business creation. The level of initial output  $Y_0$  is given by:

$$\ln(Y_0) = \int_0^1 \ln q_{j0}^{\text{leader}} dj + \ln \zeta - \ln \omega + \sum f(\Theta) \mu(\Theta) \quad (35)$$

All terms are time-invariant except for the average log productivity level of the industry leaders at time 0, given by  $Q_0 = \int_0^1 \ln q_{j0}^{\text{leader}} dj$ . When comparing welfare across economies, we can fix this term to be equal to zero in all economies without loss of generality.<sup>28</sup> Next, initial consumption  $C_0$  is given by

$$C_0 = Y_0 \frac{C_0}{Y_0} = Y_0 \left( 1 - \int_0^1 \sum_{i=1}^{N_{j0}} \chi z_{ij0}^\phi dj - \int_0^1 m_{0v} X_{kj0}^\epsilon dj - \psi e_0^2 \right) \quad (36)$$

where the second factor is the share of output left for consumption after R&D and entrepreneur entry costs are subtracted. Then, the welfare of the representative household in a BGP equilibrium can be calculated as:

$$W = \int_0^\infty e^{-\rho t} \ln(C_t) dt = \frac{\ln(C_0)}{\rho} + \frac{g}{\rho^2} \quad (37)$$

The model allows for a closed-form decomposition of changes in welfare across two economies as follows:

$$\Delta W = \frac{1}{\rho} \left[ \Delta \ln \zeta - \Delta \ln \omega + \Delta \sum f(\Theta) \mu(\Theta) + \Delta \ln \left( \frac{C}{Y} \right) \right] + \frac{1}{\rho^2} \Delta g \quad (38)$$

For two economies  $A$  and  $B$ , we can define a consumption equivalent welfare measure ( $\omega$ ) which corresponds to the percentage increase in lifetime consumption that an agent in economy  $A$  would need to be indifferent between being in economy  $A$  and  $B$ :

$$W_B = \frac{\ln(C_0^A(1 + \omega))}{\rho} + \frac{g^A}{\rho^2} \quad (39)$$

<sup>26</sup>The first and the third terms in equation (33) are also slow-moving, but their quantitative significance is dwarfed by that of the second term by several orders of magnitude.

<sup>27</sup>See Section A.9.1 in the Appendix for details.

<sup>28</sup>In other words, we keep the initial frontier technology level the same across counterfactual economies.

Solving for  $\omega$ , we get:

$$\omega = \exp \left( \left( W_B - \frac{g^A}{\rho^2} \right) \rho - \ln(C_0^A) \right) - 1 \quad (40)$$

## 2.5 Social Planner's Problem

Our model features several inefficiencies that interact, such as markup dispersion, R&D externalities, and business stealing. Consequently, decentralized equilibria are generically suboptimal. One important question is if the static inefficiencies due to oligopolistic competition and positive markups are quantitatively more or less important than the dynamic inefficiencies due to the positive knowledge spillovers and negative business stealing effects inherent in innovation decisions. This is a quantitative question that necessitates solving the dynamic social planner's problem, so that we can compare decentralized equilibria with allocations that shut down static and/or dynamic inefficiencies in the economy.

The social planner's problem can be solved in two parts. First, for a given distribution over industry states, the social planner chooses the optimal labor allocation that maximizes output: i.e., the allocation that would be obtained in the absence of heterogeneous markups in equilibrium. The second part of the planner's problem consists of optimally choosing dynamic innovation allocations for all small firms and superstars in every industry state, and the new business creation rate for entrepreneurs. In doing so, the planner also chooses the implied stationary distribution over industry states  $\mu(\Theta)$  and the stationary value of the mass of small firms  $m$ , while taking knowledge externalities into account. Since innovation and new business creation both use the final good in the economy, there is also a trade-off between how much resources to spend on improving productivity growth versus current consumption.

In Section A.5 of the Appendix, we provide a detailed description of the social planner's problem as well as its solution. We solve and discuss the planner's allocation for our estimated model in Section 4.4.

## 3 Data and Estimation

In this section, we start by discussing the relationship between competition and innovation in the data and our model. Next, we estimate our model using moments for the three subsamples. We describe our estimation procedure, and use the early-period estimated model to highlight its properties in Section 4. The three estimated stationary equilibria are used in the quantitative application of our model in Section 5 which attempts to disentangle the economic mechanisms underlying the various macroeconomic trends observed in the United States during this time period.

### 3.1 Relationship Between Competition and Innovation in the Data

Theoretically, the relationship between competition and innovation is ambiguous. Intense competition from peers can encourage a firm to innovate to escape competition, which would imply a positive relationship. At the same time, competition pushes down profitability, which discourages innovation – the so-called Schumpeterian effect.

Our theoretical framework allows the relationship between competition and innovation to be non-monotonic within and across industries. In particular, our model can generate a nonlinear relationship

between market concentration and industry innovation, as well as market share and firm innovation without any ex-ante heterogeneity.

Thanks to this new feature of our framework, we can require our model to replicate these empirically-observed relationships between industry concentration, market shares and innovation, which helps us discipline the counterfactual model implications for innovation, economic growth, and welfare. In other words, using our framework, we can replicate the nonlinear relationship between competition and innovation within and across industries, which creates a much tighter link between the model and the data compared to only matching the aggregate growth rate and R&D intensity.

We conduct an empirical analysis to investigate the aforementioned non-linear relationships within and across industries.<sup>29</sup> We use the USPTO Utility Patent Grant Data obtained from the NBER Patent Database Project, which covers the years 1976-2006 and UVA Darden Global Corporate Patent Dataset (Bena, Ferreira, Matos, and Pires (2017)) for the later subsample, and rely on Compustat North American Fundamentals Annual for financial statement information of US-listed firms for the same years. Following a dynamic assignment procedure, we link the two data sets. We relegate the details to Section A.3 in the Appendix. The stylized facts can be summarized as follows:

1. **Market concentration and industry innovation:** As previously documented in Aghion, Bloom, Blundell, Griffith, and Howitt (2005), the empirically-observed relationship between industry-level innovation and competition can exhibit an inverted-U shape. We confirm this finding using our data, where we document a robust inverted-U shape relationship between market concentration and several different innovation metrics.
2. **Relative sales and firm innovation:** We also investigate the within-industry relationship between competition and innovation. We document a robust inverted-U relationship between firm-level innovation and relative sales. This is consistent with other studies such as Hashmi and Biesebroeck (2016).

To establish the robustness of our results, we use several different metrics to capture innovation (patent count, patent quality, tail innovations, originality, generality, R&D expenses) as well as investments that are potentially correlated with innovation (physical capital investment, advertising), and direct measures of firm growth (sales growth, employment growth, asset growth). We confirm the robustness of our results with all the variables across numerous specifications outlined in the Appendix. We also conduct a hypothesis test developed by Lind and Mehlum (2010) to test for the existence of an inverted U, which is summarized in Section A.3.4.

### 3.2 Estimation

Ten parameter values must be determined:  $\rho, \lambda, \eta, \chi, \nu, \zeta, \phi, \epsilon, \psi, \tau$ . The consumer discount rate  $\rho$  is set to 0.04, which implies a real interest rate of 6% when the growth rate is 2%.<sup>30</sup> The rest are structurally

<sup>29</sup>We should stress that we do not claim that a causal relationship exists. This exercise documents correlation patterns that we would like our model to be able to reproduce. Market concentration and innovation are both endogenous variables in our model as well.

<sup>30</sup>We target a relatively high real interest rate to remain conservative. For instance, a lower real interest rate of 4% would halve the implied discount rate to  $\rho = 0.02$ . This would double the welfare contribution of the output growth rate relative to that from the initial consumption level, significantly amplify the dynamic welfare gains, and further strengthen our findings.

estimated following a simulated method of moments approach.<sup>31</sup> Aggregate moments in the model are mapped to aggregate moments in the data. Since the Compustat database consists of large US-listed firms, we map the moments obtained using the Compustat sample to moments obtained from superstar firms in our model. In this section, we discuss the data moments we use to discipline the parameter values, and provide the relevant data sources for each of these moments.<sup>32</sup>

The success of the SMM estimation depends on model identification, which requires that we choose moments that are sensitive to variations in the structural parameters. All these parameters are jointly estimated to match the following targeted data moments: the growth rate of productivity, aggregate R&D intensity, labor share, firm entry rate, (sales-weighted) average markup,<sup>33</sup> within-year standard deviation of markups, the linear term and the top point obtained from the intra-industry regression of a firm’s innovation on its relative sales,<sup>34</sup> average profitability, average relative quality of the leader, and its standard deviation across industries. We discuss them below:

1. **Growth rate:** To discipline output growth in our model, we obtain the annual growth rate of real output per hour from [Fernald \(2014\)](#), and calculate the averages for each subsample.
2. **Labor share:** We obtain the labor share estimates from [Karabarbounis and Neiman \(2013\)](#); in particular the time series for corporate labor share (OECD and UN). For capital share, we rely on the data from [Barkai \(2020\)](#).
3. **R&D intensity:** The data for aggregate R&D intensity is taken from the National Science Foundation, who report total R&D expenditures divided by GDP.
4. **Level and dispersion of markups:** To discipline markups, we target the sales-weighted average markup and the sales-weighted standard deviation of markups found in [De Loecker, Eeckhout, and Unger \(2020\)](#).
5. **Relationship between firm innovation and relative sales:** As discussed earlier, replicating the observed inverted-U relationship between market share and innovation helps us firmly discipline the counterfactual implications of the model regarding economic growth and social welfare. To achieve this, we target the relationship between firm innovation and relative sales. Innovation in the model is measured as the Poisson arrival event of quality improvement, whereas it is measured as average patent citations for each firm in the data. We normalize both by subtracting their means and dividing by their standard deviation.

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<sup>31</sup>See Section A.4.2 in the Appendix for the objective function (equation (46)) and the algorithm used for estimation.

<sup>32</sup>A more detailed description of the data moments and the estimation procedure is provided in Appendix A.4. In particular, we clarify the details regarding each moment, as well as the data sources the moments are obtained from, in Section A.4.1. In Section A.4.2, we discuss which moments help identify which parameters.

<sup>33</sup>In Section 7.4, we re-estimate the model using cost-weighted markups from [Edmond, Midrigan, and Xu \(2023\)](#), and the results are found to be similar. Motivated by [Bond, Hashemi, Kaplan, and Zoch \(2021\)](#), we also conduct another re-estimation that does not rely on any markup-based moments obtained through the [De Loecker and Warzynski \(2012\)](#) methodology. This strengthens our results.

<sup>34</sup>Matching the documented inverted U relationship is crucial. In the Extra Appendix, we illustrate that failing to capture this relationship (for instance, by producing a U-shaped curve instead of an inverted U) can reverse the growth and welfare results in the counterfactual experiments.

6. **Average profitability:** In the model, average profitability is calculated as static profit flow minus R&D expenses divided by sales. In the data, it is defined as operating income before depreciation divided by sales (OIBDP/SALE in Compustat.)
7. **Level and dispersion of leader quality:** We target the average relative quality of the leader in an industry, and its standard deviation across all industries. In the model, quality is known. In the data, we proxy quality by calculating the stock of past patent citations.
8. **Firm entry:** In our model, firm entry rate is defined as the entry rate of new small firms. We obtain the data counterpart – the entry rate of new businesses – from the Business Dynamics Statistics (BDS) database compiled by the US Census.

TABLE 1: BASELINE MODEL PARAMETERS AND TARGET MOMENTS

| <i>A. Parameter estimates</i> |                            |                          |  |                         |  |                          |
|-------------------------------|----------------------------|--------------------------|--|-------------------------|--|--------------------------|
| <i>Parameter</i>              | <i>Description</i>         | <i>Early (1976-1994)</i> |  | <i>Late (1995-2005)</i> |  | <i>Later (2006-2016)</i> |
| $\lambda$                     | innovation step size       | 0.1995                   |  | 0.4324                  |  | 0.2136                   |
| $\eta$                        | elasticity within industry | 22.9920                  |  | 5.1765                  |  | 7.1792                   |
| $\chi$                        | superstar cost scale       | 102.0927                 |  | 83.4984                 |  | 33.8836                  |
| $\nu$                         | small firm cost scale      | 1.3915                   |  | 1.8327                  |  | 1.8956                   |
| $\zeta$                       | competitive fringe ratio   | 0.6143                   |  | 0.5230                  |  | 0.5215                   |
| $\phi$                        | superstar cost convexity   | 3.8615                   |  | 3.6901                  |  | 2.9931                   |
| $\epsilon$                    | small firm cost convexity  | 2.7538                   |  | 2.3959                  |  | 1.9514                   |
| $\tau$                        | exit rate                  | 0.1144                   |  | 0.0964                  |  | 0.0833                   |
| $\psi$                        | entry cost scale           | 0.0144                   |  | 0.0210                  |  | 0.0298                   |

| <i>B. Moments</i>                    |                          |        |                         |        |                          |        |
|--------------------------------------|--------------------------|--------|-------------------------|--------|--------------------------|--------|
| Target moments                       | <i>Early (1976-1994)</i> |        | <i>Late (1995-2005)</i> |        | <i>Later (2006-2016)</i> |        |
|                                      | Data                     | Model  | Data                    | Model  | Data                     | Model  |
| growth rate                          | 1.61%                    | 1.63%  | 3.02%                   | 2.97%  | 1.31%                    | 1.31%  |
| R&D intensity                        | 2.40%                    | 2.26%  | 2.50%                   | 2.53%  | 2.70%                    | 2.65%  |
| average markup                       | 1.3014                   | 1.3058 | 1.4442                  | 1.4663 | 1.4856                   | 1.4861 |
| std. dev. markup                     | 0.306                    | 0.303  | 0.421                   | 0.496  | 0.508                    | 0.419  |
| labor share                          | 0.656                    | 0.622  | 0.644                   | 0.610  | 0.613                    | 0.603  |
| firm entry rate                      | 0.114                    | 0.114  | 0.096                   | 0.096  | 0.083                    | 0.083  |
| $\beta$ (innovation, relative sales) | 0.449                    | 0.586  | 0.631                   | 0.856  | 0.579                    | 0.616  |
| top point (intra-industry)           | 0.443                    | 0.431  | 0.515                   | 0.462  | 0.463                    | 0.395  |
| average profitability                | 0.136                    | 0.169  | 0.152                   | 0.211  | 0.163                    | 0.240  |
| average leader relative quality      | 0.751                    | 0.526  | 0.746                   | 0.711  | 0.765                    | 0.583  |
| std. dev. leader relative quality    | 0.224                    | 0.128  | 0.222                   | 0.161  | 0.213                    | 0.136  |

Notes: The estimation is done with the simulated method of moments. Panel A reports the estimated parameters. Panel B reports the simulated and actual moments.

Panel A of Table 1 reports the values of the parameters, whereas Panel B provides an overview of the values of the targeted moments in the data and the estimated model. The model tightly matches the eleven data moments. The Jacobian matrix of the model moments with respect to the model parameters in percentage terms is displayed in Table A3.

## 4 Model Properties

In this section, we use our estimated model for the early subsample to discuss its properties, and how it relates to the typical Schumpeterian framework in the literature. We discuss how our model can generate the empirically-observed inter-industry inverted-U relationship between industry innovation and market concentration (untargeted), and the within-industry inverted-U relationship between firm innovation and relative sales (targeted). We also discuss the new features of our model that deliver empirically-consistent firm and industry dynamics, firm life cycles, industry-level market share distributions, and market concentration.

### 4.1 Policy Functions

Figure 1 displays the optimal innovation policy functions followed by the firms in the estimated equilibrium obtained by targeting data moments for the early subsample. The left panel of Figure 1 depicts the innovation policy of a firm in an industry with two superstar firms. The relevant state variable is how many steps the current firm is ahead of its competitor, where negative numbers indicate that the current firm is lagging behind the competing firm. We see that the incentive to innovate is increasing from -5 to -1, and it is decreasing from -1 to 5. This means that a two-firm industry experiences the highest amount of superstar innovation when the two competing firms are close to each other in terms of productivity (neck-and-neck and one step difference.)

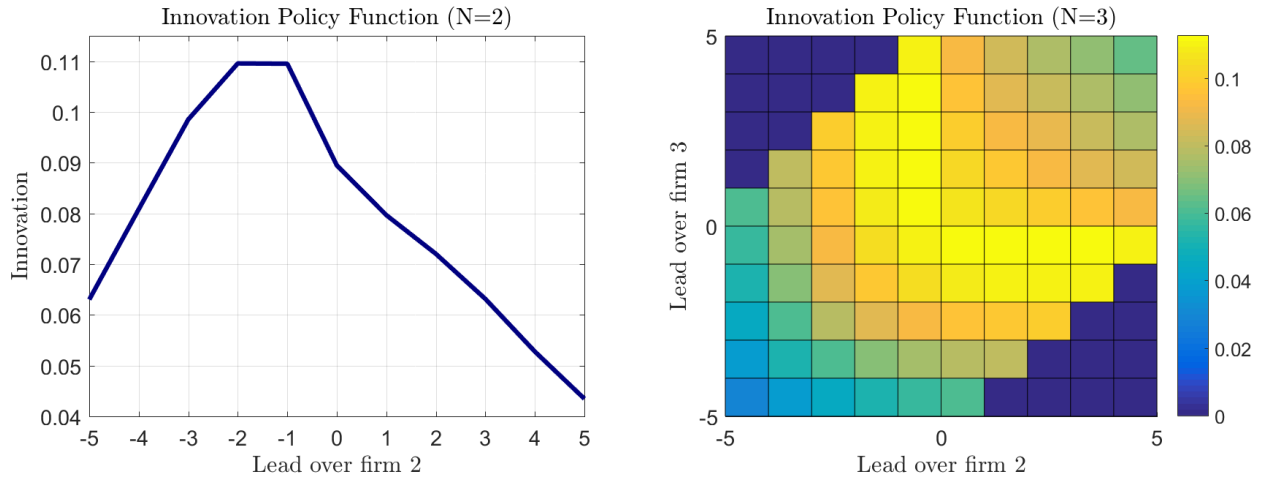


FIGURE 1: INNOVATION POLICY FUNCTION

Notes: This figure displays the optimal innovation policy functions followed by the firms in the estimated equilibrium obtained by targeting data moments for the early subsample. The left panel of this figure depicts the innovation policy of a firm in an industry with two superstar firms ( $N = 2$ ). The right panel of this figure does the same for a firm in an industry with three superstar firms ( $N = 3$ ). The lead is defined as the number of steps the current firm is ahead of its competitor, where negative numbers indicate that the current firm is lagging behind the competing firm.

The right panel of Figure 1 does the same for a firm in an industry with three superstar firms. This time the state variable is two-dimensional, and the innovation decision of the firm is a function of how many steps the current firm is ahead of both of its competitors. Since competitors that have the same relative distance in terms of quality are identical, the two-dimensional surface is symmetric along the antidiagonal.

There are also some illegal states which cannot happen as we assume the maximum number of steps between two firms cannot exceed  $\bar{n}$ . These correspond to the two blue triangles at the top left and bottom right corner, and should be ignored. Overall, the policy function shares some properties with the case for a two-firm industry. In particular, along the antidiagonal where the two competitors have the same quality, the innovation policy is once again increasing until the firms are close to being neck-and-neck, and then decreasing.

Figure B1 in the Appendix is the case for a firm in an industry with four superstars. In this case, the state variable is three-dimensional. Therefore, we split the innovation policy function into ten separate subfigures constructed similar to the right panel of Figure 1, where each subfigure corresponds to the fourth competitor being a certain number of steps behind the current firm. Note that there are more illegal cases that arise whenever  $n_4 \neq 0$  which are once again colored blue. Similar properties along the antidiagonal are observed.

## 4.2 Model-Implied Relationship Between Innovation and Competition

One key feature of our model compared to other models with endogenous markups is its ability to deliver a hump-shaped relationship between innovation and market shares at the industry level, which is shown in the left panel of Figure 2.<sup>35</sup> Each marker on the plot corresponds to the innovation choice of a firm given a firm state. The horizontal axis depicts the relative sales of the firm compared to the total sales of all superstars in the same industry. The legend for the figure clarifies the number of superstar firms in the industry the observation is coming from. The blue curve is the quadratic fit to the observations. We see the observations constitute an inverted-U shape both when they are all considered at the same time, and also separately conditioning on a certain number of superstar firms. The innovation choices are normalized by demeaning and dividing by the standard deviation. Each observation is assigned weights based on their occurrence dictated by the time-invariant distribution of industry types  $\mu(\Theta)$ . Likewise, the right panel of Figure 2 depicts the same for R&D spending on relative sales. The overall shape looks similar, but the differences are magnified as the innovation level increases, owing to the convexity of the superstar innovation cost function.

Figure 3 shows the model-implied relationship between market concentration and innovation across industries. We use the Herfindahl-Hirschman Index to measure market concentration.<sup>36</sup> The figure shows that there is an inverted-U relationship between an industry's market concentration and its total innovation. The vertical blue line corresponds to the top point of the quadratic polynomial fitted to the model-generated data, whereas the vertical red line corresponds to the average HHI of industries in the economy, weighted by their shares in the time-invariant industry state distribution  $\mu(\Theta)$ . Note that this average is lower than the top point. This reveals that the Schumpeterian creative destruction effect dominates the escape competition effect for most industries in the estimated economy. This foreshadows our finding that a change that increases market concentration would increase innovation overall. We would expect the opposite to be true if the red line was to the right of the blue line.

<sup>35</sup>It is worth noting that the model is flexible enough to generate the opposite relationship under alternative parameter values, i.e., a U-shape for the policy function, as well as a U-shape relationship between innovation and competition within and across industries. Therefore, the inverted-U relationship is an estimation result rather than a model implication.

<sup>36</sup>Note that the market share percentage of each individual small firm in the competitive fringe is zero.

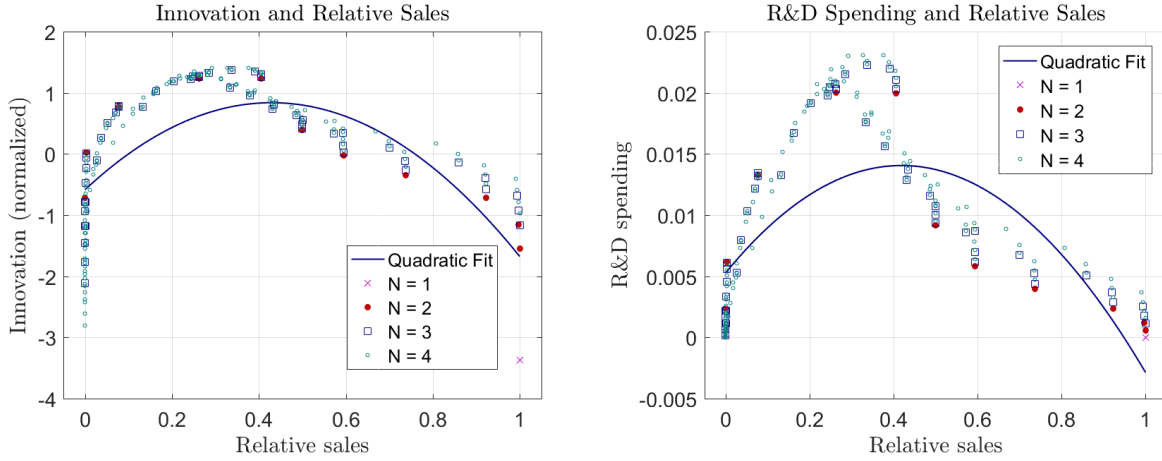


FIGURE 2: INNOVATION, R&D EXPENSES, AND FIRM RELATIVE SALES

Notes: The left panel of this figure illustrates the model-implied relationship between firms' innovation and relative sales, while the right panel shows the model-implied relationship between R&D spending and relative sales. The figure is based on the early subsample. The horizontal axis depicts the relative sales of the firm compared to the total sales of all superstars in the same industry. Each marker on the plot represents the innovation choice (left panel) or R&D spending choice (right panel) of a firm for a specific firm state. The innovation choices are normalized by demeaning and dividing by the standard deviation.  $N$  denotes the number of superstar firms in the industry the observation is coming from. The blue curve is the quadratic fit to the observations.

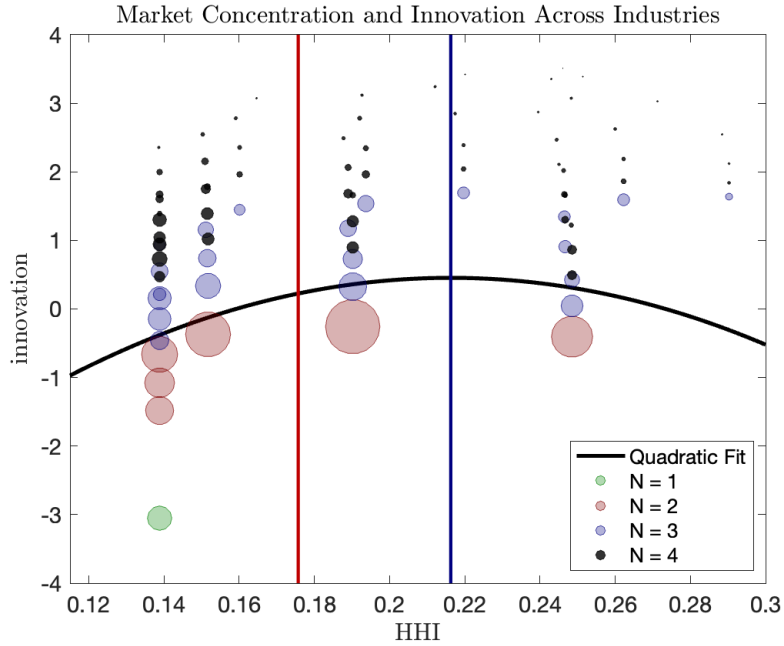


FIGURE 3: INNOVATION AND HHI

Notes: This figure illustrates the model-implied relationship between competition and innovation across industries. The figure is based on the early subsample. We measure market concentration using the Herfindahl-Hirschman Index. The figure reveals an inverted-U relationship between an industry's market concentration and its overall innovation. Each circle represents an industry state. The circle's color indicates the number of superstars in the industry, while its size signifies the share of that industry state in the baseline invariant distribution.  $N$  denotes the number of superstar firms in the industry the observation is coming from. The black curve provides a quadratic fit to the observations. The vertical blue line marks the top point of the quadratic polynomial fitted to the model-generated data. In contrast, the vertical red line corresponds to the average HHI of industries in the economy, weighted by their shares in the time-invariant industry state distribution.

It is worth mentioning that our model is able to generate this second relationship without explicitly targeting the quadratic relationship in the estimation. Furthermore, our model generates the inverted U without introducing any exogenous heterogeneity.<sup>37</sup> This is different from recent models that endogenize markups. In Schumpeterian models with a single active firm, all observations would be clustered at 1 for relative sales and HHI, implying no relationship. In step-by-step innovation models with perfect substitution and Bertrand competition, there would be two points at 0.5 and 1 for relative sales, and 0.5 and 1 for HHI, which would imply a linear relationship. In models with exogenous productivity evolution, we would get a flat line (no relationship). Finally, in models with innovation only at entry, there would be a monotone relationship between competition and innovation at entry, the shape of which depends on that of the cost function. After entry, there would be no relationship due to no incumbent innovation. Our model's ability to match this relationship aids in disciplining the counterfactual behavior of aggregate productivity growth in response to endogenous changes in market concentration, which helps discipline the estimated social welfare implications of increasing markups.

### 4.3 Model-Implied Market Share Distributions and Firm Dynamics

Though not targeted, our model generates realistic relative sales and concentration numbers unlike Schumpeterian models with Bertrand competition and homogeneous goods. Industries in the United States consist of thousands of firms on average. While superstar firms command a disproportionate share of the market, the remaining small firms still collectively account for a significant portion of the market. Existing Schumpeterian models feature at most two firms per industry and hence generate CR4 ratios of 100% in every industry. Our model avoids this issue through two of our contributions: (1) allowing an endogenous number of superstar firms and (2) introducing a competitive fringe that can collectively account for a large market share in each industry, even though each fringe firm is infinitesimally small. Even in industries with a single superstar firm, the competitive fringe ensures that the superstar captures only a fraction of the market. Our estimated model generates a realistic distribution of CR4 ratios across industries.<sup>38</sup>

In addition, the employment and sales growth profiles of individual firms in our model evolve slowly over time, which fits the data better than the instantaneous jumps between 0%, 50%, and 100% of the whole market observed in many models. Such abrupt changes in market shares are counterfactual. Our model delivers realistic firm life cycles in comparison. Entrepreneurs create thousands of new small businesses. Only a very small fraction of these small firms eventually succeed in becoming a superstar firm. Those that become a superstar firm start out  $\bar{n}$  steps behind the industry leader in terms of productivity, making them the smallest superstar in the industry. As time passes, if they succeed in their innovation efforts, they can rise up in the ranking slowly over time. Their market share tracks their productivity compared to their competitors, and it also changes only gradually as a result of their own innovation, or that of their competitors. Figure 2 gives an indication of the large degree of market share heterogeneity that our model can deliver. Finally, the introduction of entrepreneurs in the model also adds to the realistic life cycle of firms and allows our model to generate an entry rate of small firms that is directly comparable

<sup>37</sup>The original inverted-U paper by Aghion, Bloom, Blundell, Griffith, and Howitt (2005) achieves this through the introduction of exogenous collusion heterogeneity across industries.

<sup>38</sup>The distribution is similar to the empirical CR4 estimates we obtain by combining Compustat data with industry sales information from the Bureau of Economic Analysis. See Table L22 in the Extra Appendix.

to the way entry rate is usually measured using BDS data.

#### 4.4 Social Planner's Allocations

In Section 2.5, we had discussed the social planner's static and dynamic problems, and how they could be solved. In this section, we apply the developed solution methods to solve for the social planner's static and dynamic allocations using the parameter values obtained from the early sample estimation of our model.<sup>39</sup>

The static problem involves finding the allocation of labor that maximizes (log) output in the economy, given the productivity distribution  $[\{q_{ijt}\}_{i=1}^{N_{jt}}, q_{cjt}]_{j=0}^1$ . We take the initial productivities implied by the stationary industry-state distribution  $\mu(\Theta)$  in the decentralized equilibrium, and solve this problem. The social planner simply eliminates all markups observed in the decentralized equilibrium, which increases initial output by 27.5% of its value. This large number is comparable to those reported in Baqaee and Farhi (2020) and Edmond, Midrigan, and Xu (2023).

We then solve the (unconstrained) dynamic social planner's problem, again using the same parameter values. This time, the social planner not only eliminates all markups, but also chooses the small firm entry rate, as well as every innovation decision by every firm in every industry simultaneously, taking all the externalities into account, and cognizant of their effect on the stationary mass of small firms  $m$  and the industry state distribution  $\mu(\Theta)$ . The optimal allocation yields a growth rate of 3.56% per year, which is more than double what is observed in the decentralized equilibrium. The consumption-equivalent welfare gain obtained from switching to the first-best is found to be 71%, which is more than double the gains from eliminating static misallocation of labor due to markups. This means the dynamic inefficiency in the estimated economy is much more severe than the static efficiency due to oligopolistic competition.

Finally, we study a constrained optimal allocation, where the planner cannot choose positive R&D for large firms in single-superstar industries. In a decentralized equilibrium, single superstars do not perform R&D as they have no incentive to do so. As a result, implementing the first-best allocation with taxes and subsidies would require a 100% subsidy of R&D by large firms in single-superstar industries. Our constraint is motivated by the severe implementation problems this would entail. Our results show this constrained optimal allocation delivers a very large share of the welfare difference between the unconstrained first-best and the decentralized equilibrium allocations, at 62.3%.

### 5 Application: Understanding the Structural Transition and the Rise in Markups

As a quantitative application of our framework, we first rely on the early (1976-1994) and late (1995-2005) subsample estimations conducted in Section 3, and use the two estimated stationary equilibria to disentangle the economic mechanisms underlying the various macroeconomic trends observed in the United States during this time period. We then extend the analysis to 2006-2016. The estimated parameter values in the two subsamples are quite different, which captures the structural changes in the US economy throughout this time period. These estimates are reported in Table 1.

<sup>39</sup>A full description of the results can be found in Appendix A.5.4.

## 5.1 Changes in Structural Parameters

The elasticity of substitution within an industry,  $\eta$ , decreases from 22.99 to 5.18.<sup>40</sup> This parameter primarily governs the degree of static product market competition between superstar firms, and the significant decrease in its value indicates that superstar firms enjoy higher market power in the late subsample. At the same time, the ratio of the competitive fringe's productivity relative to the industry leader,  $\zeta$ , decreases from 0.614 to 0.523. This parameter captures the product market competition from non-superstar firms, and a decrease in its value indicates that superstar firms can charge higher markups thanks to reduced competitive pressure from (less productive) small firms. One potential factor behind this trend could be the slowdown in technology diffusion from market leaders to followers as discussed in [Akcigit and Ates \(2023\)](#).

If we turn to parameters that govern the innovation cost function of the superstars, we observe a decrease in the scale parameter  $\chi$  from 102.09 to 83.50, and the convexity  $\phi$  from 3.86 to 3.69. The first change reduces the cost of superstar innovation, whereas the second change allows innovation to be more concentrated across firms, as it reduces the diminishing returns to innovation within a firm. Given other parameter values, the decrease in  $\phi$  also increases innovation costs on average. These changes in  $\chi$  and  $\phi$  imply that the cost of a given level of innovation  $z$  is higher in the late period if  $z < 0.309$ , which is the case for all firms in the model. The innovation scale parameter for small firm innovation,  $\nu$ , increases from 1.39 to 1.83, and the convexity  $\epsilon$  decreases from 2.75 to 2.40. Both changes increase the cost of innovation for small firms, which reduces the entry rate of new superstar firms. Overall, these results are consistent with ideas getting harder to find over time as highlighted in [Bloom, Jones, Van Reenen, and Webb \(2020\)](#). Finally, the cost of new business entry rises as  $\psi$  increases from 1.44% to 2.10%. This rise in the entry cost of entrepreneurs and the associated decline in the entry rate of small firms are in line with the overall decline in business dynamism documented, for instance, in [Decker, Haltiwanger, Jarmin, and Miranda \(2016\)](#).

## 5.2 Disentangling the Structural Transition

In order to better understand and disentangle the effects of the transition implied by the estimated parameter values in the two subsamples, we conduct counterfactual exercises where we investigate the effects of each change separately. To do so, we compare the estimated late subsample economy against counterfactual economies in which we set the values of selected parameters to their early subsample estimates. These exercises illustrate how the economy would look like if there were no structural change in a particular mechanism. This, in turn, allows us to understand which mechanisms are the primary drivers of the time trends in important quantities such as the average markup, the labor share, output growth, as well as their implications for social welfare. In other words, we use our model as a tool to uncover how the structural parameters change over time, and establish which mechanisms induce the observed macroeconomic changes, in what magnitude, and in which direction.

The results are presented in Table 2, where the first column displays the benchmark values of chosen

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<sup>40</sup>In our model, the industry structure is endogenous, and therefore  $\eta$  is primarily identified by the dispersion of firm-level markups rather than the average, along with average profitability. In monopolistic competition models, the reported change in the value of  $\eta$  would imply an 18.6% increase in the average markup, whereas it slightly increases by 0.61% in our model, as shown in Section 5.2.1.

model moments in the late subsample. The last two columns of the bottom panel show the results of changing all the parameters to their early period values to provide context. All the remaining columns show how the moments change in each exercise. Below, we discuss these results in detail.

### 5.2.1 Competition from Superstars vs. Small Firms

We first look at what happens when we set the elasticity of substitution within an industry,  $\eta$ , to its early period value. The direct effect of the change is a decrease in the market power of the superstar firms, and average markup decreases slightly by 0.61% of its value, due to the general-equilibrium changes in the stationary distribution  $\mu(\Theta)$  towards lower markup industries. The reduction in market power relatively favors the industry leaders who have the highest productivity. Consequently, the average number of superstars per industry falls by 14.1%, and so does the initial output by 11.3%. There is a drop by 20.5% in superstar innovation, whereas small firm innovation drops significantly more by 45.6% of its value. The consequent decrease in the profitability of small firms reduces their mass by 33.6%. As a combined effect of the changes in innovation, there is a significant decrease in the growth rate by 16.2% of its value, which translates into a welfare loss of 21.1% in consumption-equivalent terms.<sup>41</sup>

This experiment reveals that the increase in the estimated market power of superstar firms (associated with the change in  $\eta$ ) results in increased economic growth due to better incentives to innovate and the resultant changes in the industrial structure. If the elasticity of substitution had not fallen, there would be less incentive to innovate to become superstar firms, which implies industries being dominated by an even smaller number of superstar firms. These superstar firms, in turn, would not innovate as much, since the “escape competition” effect is weaker – fewer superstar firms means less peer competition. Therefore, the average markup would stay virtually the same, and the static welfare gains would be limited. The dynamic losses from reduced growth overshadow slightly lower markups, resulting in lower welfare.

Next, we look at what happens when we set the competitive fringe’s productivity relative to the industry leader,  $\zeta$ , to its early period value. Unlike  $\eta$ , changes in this parameter capture the competition from small firms. This time, the average markup falls from 1.47 to 1.33. Given that the average markup in the early sample is 1.31, the change in  $\zeta$  can explain nearly all of the change in the average markup across time. While the reduction in markups improves static efficiency, increasing initial output by 5.26% and the labor share by 7.28%, average profitability falls by 22.0%. Consequently, firms have less incentive to innovate, reducing small firm innovation by 40.9% and superstar innovation by 22.5%. Combined together, this reduces the output growth rate from 2.97% to 2.38%. Despite the gains in static efficiency, social welfare drops by 8.30%.<sup>42</sup>

There are two main takeaways from this experiment. First, our model suggests that the overall increase and the polarization in markups which were observed after 1975 owe mostly to a reduction in competition from small firms ( $\zeta$ ), rather than a reduction in competition between superstar firms ( $\eta$ ), or

<sup>41</sup>Note that this welfare number should be interpreted with caution, since the change in  $\eta$  can be considered a change in consumer preferences rather than a change in production technology. Therefore, the drop in initial consumption might not indicate a welfare loss. However, the significant drop in the growth rate still means that a hypothetical consumer with unchanged preferences would be worse off.

<sup>42</sup>While welfare for the representative household drops by 8.30%, we show in Appendix A.6 that these losses are unevenly distributed between hypothetical pure workers and pure capitalists. Capital owners experience a much larger welfare loss from decreased markups than workers.

TABLE 2: DISENTANGLING THE STRUCTURAL TRANSITION

|                                       | Benchmark | Early $\eta$ | % change | Early $\zeta$ | % change | Early $\nu, \epsilon$ | % change |
|---------------------------------------|-----------|--------------|----------|---------------|----------|-----------------------|----------|
| growth rate                           | 2.97%     | 2.49%        | -16.19%  | 2.38%         | -19.93%  | 3.38%                 | 13.85%   |
| R&D intensity                         | 2.53%     | 2.23%        | -11.51%  | 1.57%         | -37.90%  | 3.11%                 | 23.14%   |
| average markup                        | 1.466     | 1.457        | -0.61%   | 1.329         | -9.33%   | 1.470                 | 0.24%    |
| std. dev. markup                      | 0.496     | 0.445        | -10.30%  | 0.409         | -17.42%  | 0.486                 | -1.99%   |
| labor share                           | 0.610     | 0.604        | -0.96%   | 0.654         | 7.28%    | 0.606                 | -0.60%   |
| entry rate                            | 0.096     | 0.096        | 0.00%    | 0.096         | 0.00%    | 0.096                 | 0.00%    |
| $\beta(\text{innov, relative sales})$ | 0.856     | 0.799        | -6.64%   | 0.858         | 0.30%    | 0.869                 | 1.56%    |
| top point (intra-industry)            | 0.462     | 0.451        | -2.44%   | 0.455         | -1.59%   | 0.476                 | 2.91%    |
| avg. profitability                    | 0.211     | 0.221        | 4.74%    | 0.164         | -21.96%  | 0.210                 | -0.54%   |
| avg. leader relative quality          | 0.711     | 0.768        | 8.04%    | 0.751         | 5.63%    | 0.640                 | -10.01%  |
| std. dev leader rel. quality          | 0.161     | 0.172        | 6.78%    | 0.172         | 6.41%    | 0.142                 | -11.94%  |
| superstar innovation                  | 0.170     | 0.135        | -20.54%  | 0.132         | -22.45%  | 0.213                 | 25.19%   |
| small firm innovation                 | 0.023     | 0.012        | -45.61%  | 0.013         | -40.86%  | 0.046                 | 102.00%  |
| output share of superstars            | 0.491     | 0.531        | 8.18%    | 0.405         | -17.44%  | 0.509                 | 3.78%    |
| avg. superstars per industry          | 2.145     | 1.842        | -14.10%  | 1.925         | -10.24%  | 2.653                 | 23.69%   |
| mass of small firms                   | 1.000     | 0.664        | -33.57%  | 0.672         | -32.77%  | 1.266                 | 26.58%   |
| initial output                        | 0.808     | 0.717        | -11.27%  | 0.851         | 5.26%    | 0.821                 | 1.57%    |
| CE Welfare change                     |           | -21.07%      |          | -8.30%        |          | 11.88%                |          |

|                                       | Benchmark | Early $\chi, \phi$ | % change | Early $\psi, \tau$ | % change | All     | % change |
|---------------------------------------|-----------|--------------------|----------|--------------------|----------|---------|----------|
| growth rate                           | 2.97%     | 3.20%              | 7.93%    | 3.00%              | 0.95%    | 1.63%   | -45.14%  |
| R&D intensity                         | 2.53%     | 2.62%              | 3.54%    | 2.56%              | 1.29%    | 2.26%   | -10.58%  |
| average markup                        | 1.466     | 1.466              | 0.01%    | 1.467              | 0.02%    | 1.306   | -10.95%  |
| std. dev. markup                      | 0.496     | 0.495              | -0.24%   | 0.495              | -0.11%   | 0.303   | -38.97%  |
| labor share                           | 0.610     | 0.609              | -0.06%   | 0.610              | -0.04%   | 0.622   | 1.92%    |
| entry rate                            | 0.096     | 0.096              | 0.00%    | 0.114              | 18.65%   | 0.114   | 18.65%   |
| $\beta(\text{innov, relative sales})$ | 0.856     | 0.833              | -2.71%   | 0.854              | -0.25%   | 0.586   | -31.57%  |
| top point (intra-industry)            | 0.462     | 0.462              | -0.06%   | 0.463              | 0.13%    | 0.431   | -6.74%   |
| avg. profitability                    | 0.211     | 0.210              | -0.18%   | 0.211              | -0.02%   | 0.169   | -19.77%  |
| avg. leader relative quality          | 0.711     | 0.702              | -1.18%   | 0.707              | -0.54%   | 0.526   | -25.98%  |
| std. dev leader rel. quality          | 0.161     | 0.161              | -0.33%   | 0.160              | -0.70%   | 0.128   | -20.56%  |
| superstar innovation                  | 0.170     | 0.187              | 9.58%    | 0.173              | 1.32%    | 0.207   | 21.16%   |
| small firm innovation                 | 0.023     | 0.026              | 15.88%   | 0.023              | 3.40%    | 0.031   | 38.71%   |
| output share of superstars            | 0.491     | 0.493              | 0.43%    | 0.492              | 0.22%    | 0.537   | 9.37%    |
| avg. superstars per industry          | 2.145     | 2.201              | 2.62%    | 2.166              | 1.01%    | 2.576   | 20.12%   |
| mass of small firms                   | 1.000     | 1.109              | 10.86%   | 1.051              | 5.12%    | 1.000   | 0.00%    |
| initial output                        | 0.808     | 0.809              | 0.17%    | 0.809              | 0.09%    | 0.789   | -2.40%   |
| CE Welfare change                     |           | 6.14%              |          | 0.76%              |          | -29.98% |          |

Notes: The table reports the changes in model moments when setting the parameters of interest back to their estimated levels in the early subsample while keeping other parameters fixed at their estimated values in the late subsample. The benchmark is the late-period stationary equilibrium.

the changing costs of innovation. This is consistent with the previous findings in the literature regarding the decline in business dynamism and “winner-takes-most” dynamics as in [Decker, Haltiwanger, Jarmin, and Miranda \(2016\)](#) and [Autor, Dorn, Katz, Patterson, and Van Reenen \(2020\)](#) among others. The output share of superstars increases because the relative productivity of small firms is lower. Second, our model’s implications regarding the social costs of increasing markups are quite different from other papers in the literature which focus on static efficiency gains alone. Our model suggests that the increase in markups can be welfare-improving when the dynamic effects on productivity growth are taken into account. Since this is a key difference of our model, we discuss the static vs. dynamic effects of increasing markups in richer detail in Section 5.2.4.

What could be the reason behind the estimated decline in the relative productivity of small firms? Several potential mechanisms exist, such as increasing globalization (access to international markets and inputs), advantages of the superstars in acquiring and exploiting data, changes in advertising and brand value, increasing costs of imitation (technological as well as legal), or a decline in knowledge spillovers. Our results highlight a direction for future research, suggesting that the key to understanding the increase in markups lies behind uncovering the factors that led to the decline in the relative productivity of small firms, and their relative contributions.

### 5.2.2 Costs of Superstar vs. Small Firm Innovation

In our third experiment, we set the parameters that govern the innovation cost function of small firms,  $\nu$  and  $\epsilon$ , to their early period values. Unsurprisingly, there is a very significant direct effect on small firm innovation which increases by 102.0% of its value. The average number of superstar firms per industry increases by 23.7%. Average profitability is virtually the same, so the Schumpeterian creative destruction effect does not change. On the other hand, the increased number of superstars boosts the “escape competition” effect, and superstar innovation increases by 25.2% of its value. Hence output growth increases from 2.97% to 3.38%. Coupled with a slight gain in initial output of 1.57%, social welfare improves by 11.88%.

Recall that in our model we define entry into superstars not as newly established firms. Through successful innovation, small firms become superstar firms. Whereas the decrease in the competitive fringe’s productivity  $\zeta$  captures the declining product market competition from small firms, the increase in the cost of small firm innovation reduces the frequency at which small firms can join the ranks of superstar firms. Therefore, our estimates suggest that the number of small firms with high growth potential (“gazelles”) has gone down, which allows industries to be dominated by fewer superstar firms. This finding is consistent with the recent evidence by [Sterk, Sedláček, and Pugsley \(2021\)](#), who find that both the share of such “gazelles” among all firms, and their average growth rates have fallen over time after 1975. As the experiment suggests, this leads to a weakening of the incentives to innovate by the remaining superstar firms, which hurts productivity growth.

Our fourth experiment reverts the parameters of the superstar innovation cost function,  $\chi$  and  $\phi$ , to their early period values. Superstar innovation increases by 9.58% in response. However, this increase is more than matched by a simultaneous increase in small firm innovation by 15.9%. Average profitability and the output share of superstars do not change by much, leading to virtually unchanged average markup and initial output. This means static efficiency remains comparable to the benchmark, and the 7.93%

increase in output growth translates to a 6.14% increase in welfare.

This experiment relates directly to the literature on the increasing costs of innovation (“ideas are getting harder to find”). As noted in [Bloom, Jones, Van Reenen, and Webb \(2020\)](#), the number of researchers employed in research and development of new ideas has been constantly increasing over the time period. Looking at the determinants of output growth in our model, the reduced competition from superstars and small firms push for higher growth, whereas increased innovation costs offset some of the competition channel, resulting in the observed increase in productivity growth. In this aspect, our findings differ from the popular hypotheses regarding how the decline in competition might have led to a productivity slowdown. There can be many reasons behind the decline in research productivity, ranging from the reduced arrival rate of general purpose technologies ([Gordon \(2012\)](#)) to stronger intellectual property protection ([Han \(2018\)](#)), increased patent litigation ([Galasso and Schankerman \(2014\)](#)), protective patenting ([Argente, Baslandze, Hanley, and Moreira \(2023\)](#)), or increasing misallocation of talent in innovation due to increasing wealth inequality ([Celik \(2023\)](#)). Our results suggest future research directed at identifying the reasons behind the decline in research productivity might hold the key to understanding the most recent decline in productivity growth. Comparing the results of the third and fourth experiments also highlights the larger role the decline in the R&D efficiency of small firms played in slowing down productivity growth. In comparison, the increasing costs of innovation for superstar firms have a significant, but smaller effect.

### 5.2.3 Entrepreneurship and Firm Entry

In our final experiment, we consider the effects of the decline in the firm entry rate, and the changes to the costs of founding new businesses. To this purpose, we set the scale parameter of the entrepreneur cost function,  $\psi$ , and the exit rate,  $\tau$ , to their early period values. From the early period to the late period, the exit rate  $\tau$  goes down, and the scale parameter  $\psi$  goes up. The prior increases the survival rate of small firms, therefore increasing the expected value obtained from founding a new business. The latter increases the cost of doing so. Therefore, the two changes push the equilibrium mass of small firms in opposite directions. The total effect is an increase by 5.12%. This increase raises small firm innovation by 3.40%, which also encourages more innovation by superstars at 1.32%. Initial output is virtually the same, and the growth rate increases by 0.95% of its value. The combined welfare effect is calculated as 0.76%.

The increasing cost of entrepreneurship and the decline in firm exit rate act to partially offset each other. If we consider their effects separately, reverting the value of  $\psi$  by itself leads to an increase in growth by 4.19% and welfare by 3.42%, whereas repeating the same exercise for  $\tau$  reduces growth and welfare by 3.78% and 2.97%, respectively. For average markups and market concentration, the relative productivity of small firms seems to matter much more than their total number. For productivity growth, the changes in costs of innovation dominate the changes in firm entry and the cost of founding new businesses.

### 5.2.4 Static vs. Dynamic Costs of Higher Markups

The second counterfactual experiment in Section 5.2.1 where the relative productivity of the competitive fringe  $\zeta$  was reverted to its early period value revealed that increased competition from small firms reduced the average markup to nearly its early period value, yet the dynamic change in welfare was a loss of 8.3%.

TABLE 3: STATIC VS. DYNAMIC COSTS OF HIGHER MARKUPS

|                                 | Static     |        | Static+New Distribution |        | Dynamic    |         |
|---------------------------------|------------|--------|-------------------------|--------|------------|---------|
|                                 | $\Delta W$ | CEWC   | $\Delta W$              | CEWC   | $\Delta W$ | CEWC    |
| competitive fringe productivity | 4.026      | 17.47% | 4.026                   | 17.47% | 4.026      | 17.47%  |
| relative wage                   | -1.693     | -6.55% | -1.756                  | -6.78% | -1.756     | -6.78%  |
| output of superstar firms       | -0.901     | -3.54% | -0.988                  | -3.87% | -0.988     | -3.87%  |
| consumption/output              | 0.000      | 0.00%  | 0.000                   | 0.00%  | 0.247      | 0.99%   |
| output growth                   | 0.000      | 0.00%  | 0.000                   | 0.00%  | -3.695     | -13.74% |
| total                           | 1.431      | 5.89%  | 1.281                   | 5.26%  | -2.167     | -8.30%  |

Notes: The table decomposes the change in welfare into its constituent parts using equation (38).

To better understand why this happens, it is useful to decompose the change in welfare into its constituent parts using equation (38). At the same time, our finding differs significantly from static analyses that focus on the efficiency gains from reduced markups without taking the implications for productivity growth and endogenous industry dynamics into account. This motivates us to also perform the decomposition where we only consider the static changes from reduced markups, and the static changes plus the endogenous change in the distribution of industries, while keeping the innovation policies and the output growth rate the same. The results are presented in Table 3.

The first column of Table 3 calculates and decomposes the change in welfare if we ignore the dynamics completely. The dynamics come into play through three model components: (1) the growth rate, (2) the change in consumption to output ratio due to R&D spending and the cost of new business entry, and (3) the changes in the relative wage rate  $\omega$  and the production by superstar firms  $\sum f(\Theta)\mu(\Theta)$  which both depend on the distribution of industries  $\mu(\Theta)$ . To calculate the static effects, we keep the growth rate, R&D spending, new business creation, and  $\mu(\Theta)$  at the late period levels. There is a large increase in output and welfare as a direct effect of increasing  $\zeta$ . Increased production increases labor demand, which pushes the relative wage  $\omega$  up, the effect of which is negative. Finally, increased production by small firms results in reduced supply from superstar firms, so the third component is negative as well. The direct effect dominates these endogenous (static) responses, and welfare is increased. Column 2 shows the change in consumption-equivalent welfare by each individual component. The combined effect is a significant 5.89% gain in welfare.

The third column repeats the same exercise as in column one with a single difference: we use the distribution of industries  $\mu(\Theta)$  implied by the dynamic long-run change in response to the increase in  $\zeta$  rather than retaining the late sample values. This changes the effects from the relative wage and the output of superstars slightly, and the gain in welfare remains close but lower at 5.26%. This means ignoring the long term effects on industrial structure – i.e., the number and relative qualities of superstars – would result in overestimating the welfare gains by 12%, which is not insignificant.

The fifth column displays the welfare decomposition for the full dynamic response. As alluded to in the second exercise, the difference in the initial output (and hence the static efficiency) is limited. There is a small welfare gain from the consumption to output ratio term due to reduced R&D spending and new business entry. However, there is a very significant decline due to reduced growth that wipes out both the static welfare gains from reduced markups and the gains from higher initial consumption. Therefore, the final tally is a loss of 8.30%, as the dynamic losses from reduced productivity growth valued at 13.74%

of consumption completely dominate the 5.26% gain from improved static efficiency. A static model that does not endogenize productivity growth would not be able to obtain this result, and highly overestimate the cost of increased markups in the US during this time period.

### 5.3 Extending the Analysis to the Later Subsample

So far, we have investigated the structural transition and its implication for business dynamism between the early and late subperiods. This section extends this analysis to the later subsample. In the data, the later subperiod experienced similar trends in terms of business dynamism (decrease in the labor share, increase in average markup, lower entry rate, higher R&D intensity) with one notable exception: productivity growth. While the late subsample experienced a surge in productivity growth, the later subperiod is characterized by a productivity slowdown (1.31% compared to 1.61% in the early subsample).

The calibration results for the later subsample are reported in Table 1. Compared to the early subsample, the later subsample features a lower elasticity of substitution within industry ( $\eta$ ), a decrease in the scale and convexity of superstar innovation cost ( $\chi$  and  $\phi$ ), an increase in the scale parameter of small firm innovation ( $\nu$ ) combined with a decrease in the convexity parameter ( $\epsilon$ ), a higher cost of entry ( $\psi$ ) and a lower relative productivity for the competitive fringe ( $\zeta$ ). These changes are qualitatively similar to those observed between the early and late subsamples.

Table B13 in the appendix reports the results of our counterfactual experiments aimed at disentangling the effects of the structural transition between the early and later subsample. Results are qualitatively similar to those obtained for the transition between the early and late subsamples. In particular, the decrease in the relative productivity of the competitive fringe ( $\zeta$ ) explains almost all of the increase in markups between the early and later subsamples. Reverting  $\zeta$  to its early value generates welfare losses evaluated at 5.28%. This welfare loss is due to 25.35% slower productivity growth, whose welfare effect more than offset the welfare gains from improvement in static allocative efficiency that delivers an increase in output by 1.67%.

The decrease in competition between superstar firms captured by  $\eta$  is also associated with significant welfare losses (8.64%) stemming from slower productivity growth combined with a lower level of initial output. The changes in parameters associated with innovation by both small and larger firms are consistent with ideas getting harder to find, as setting them to their early period values would generate significant growth and welfare gains. As in the transition from the early to the late period, the changes in entry and exit parameters mostly offset each other, with a very small welfare gain of 0.51% from resetting their values to the early subsample.

Overall, all the results obtained for the transition between the early and late subsamples apply to the transition to the later subperiod with minor quantitative differences. Almost all of the change in markups is explained by a decrease in competition from small firms and ideas are getting harder to find over time.

## 6 Model Validation

Beyond its ability to replicate the (untargeted) inverted-U shape relationship between market concentration and innovation (see Figure 3) and to generate realistic market shares, concentration ratios, and

firm life cycles, our estimated model also delivers several other predictions that can be tested, especially related to trends in productivity, market concentration, and the labor share. In particular, we show that our model correctly predicts the increase in productivity dispersion documented by [Barth, Bryson, Davis, and Freeman \(2016\)](#) and the negative correlation between productivity dispersion and the labor share across industries highlighted in [Gouin-Bonenfant \(2022\)](#). In addition, our model is in line with several facts related to changes in the labor share documented in [Autor, Dorn, Katz, Patterson, and Van Reenen \(2020\)](#).

## 6.1 Increase in Productivity Dispersion

Recent studies emphasize the role played by increased between-firm dispersion in explaining trends in income inequality. For instance, [Song, Price, Guvenen, Bloom, and Von Wachter \(2018\)](#) find that two-thirds of the rise in the variance of earnings is due to increased between-firm wage dispersion. In addition, [Barth, Bryson, Davis, and Freeman \(2016\)](#) document a significant rise in the variance of between-firm productivity (log revenue per worker) between 1977 and 2007.<sup>43</sup> In our model, productivity dispersion both within and across industries arises endogenously as the outcome of innovation. In particular, our quantitative exercise allows us to determine how productivity dispersion responds to the structural transition of the economy. Using the same measure as in [Barth, Bryson, Davis, and Freeman \(2016\)](#) (the variance of log revenue per worker), our estimation predicts a rise in productivity dispersion by 39.22% between the early and later subsamples which is close to the estimated 32.6% increase in [Barth, Bryson, Davis, and Freeman \(2016\)](#).

## 6.2 Productivity Dispersion, Value-Added, and the Labor Share

Building on the evidence from [Barth, Bryson, Davis, and Freeman \(2016\)](#), [Gouin-Bonenfant \(2022\)](#) further shows that an exogenous increase in productivity dispersion could explain the observed fall in the labor share in a model with labor market monopsony power. Testing one of the main predictions of his model, he shows, using Canadian data, that the industry-level labor share is negatively correlated with dispersion in productivity. In our model, both labor share and productivity dispersion are endogenously determined. Productivity dispersion within an industry depends on innovation activity whose returns, in turn, shape the productivity distribution. Given the rich structure of our model, we can also compute the correlation between the industry-level labor share and productivity dispersion. Thanks to our oligopolistic structure based on [Atkeson and Burstein \(2008\)](#), our model features a negative association between the industry-level labor share and the dispersion of productivity (TFPQ) in both subsamples, in line with the findings in [Gouin-Bonenfant \(2022\)](#).

Furthermore, as in [Autor, Dorn, Katz, Patterson, and Van Reenen \(2020\)](#) and [Kehrig and Vincent \(2021\)](#), [Gouin-Bonenfant \(2022\)](#) also documents a negative relationship between (log) firm-level labor share and (log) value-added. We repeat this regression in our model, and obtain a coefficient of -0.0982, which is very close to the value -0.112 that he documents for Canada.

<sup>43</sup>[Faggio, Salvanes, and Van Reenen \(2010\)](#) provide evidence for a similar increase in productivity dispersion in the UK since 1980. [Andrews, Criscuolo, and Gal \(2016\)](#) also highlight an increase in productivity difference between frontier and laggard firm in 24 OECD countries.

### 6.3 Market Concentration and the Labor Share

Using US firm-level data, [Autor, Dorn, Katz, Patterson, and Van Reenen \(2020\)](#) also highlight how the decrease in the labor share has been associated with several dimensions of the rise in market concentration and, in particular, the rise of superstar firms. First, they show that industry sales increasingly concentrate in a small number of superstar firms. In our model, the market share of superstar firms increases by 13.5% between the early and later subsamples. This result is comparable to those found in [Autor, Dorn, Katz, Patterson, and Van Reenen \(2020\)](#), if slightly lower, and is closest to the rise in manufacturing. This untargeted change in our model is directly related to the competition between superstars and small firms which we have shown to be decreasing over time and which is the main driver of the observed increase in markups.

Regressing the change in the 4-digit industry labor share on the change in market concentration (measured by the market share of top 4 and top 20 firms as well as the Herfindahl index), they further show that industries in which market concentration rose the most also experienced the sharpest decline in their labor share. Our model delivers the same prediction between our subsamples. In particular, focusing on the corresponding two relevant measures of concentration in our model (i.e., top 4 market share and the Herfindahl index), we also find a negative association between the change in market concentration and in the labor share.<sup>44</sup> This negative correlation can be obtained in our model thanks to our oligopolistic market structure based on [Atkeson and Burstein \(2008\)](#). From a quantitative perspective, the estimates from those regressions fall in the ballpark of those reported in [Autor, Dorn, Katz, Patterson, and Van Reenen \(2020\)](#). Our regression based on the top 4 share of sales delivers a coefficient of -0.211 (the estimates in [Autor, Dorn, Katz, Patterson, and Van Reenen \(2020\)](#) range between -0.146 and -0.339). For the Herfindahl index regression, our estimate is -0.391 (between -0.213 and -0.502 in [Autor, Dorn, Katz, Patterson, and Van Reenen \(2020\)](#)). These quantitative results in line with what is observed in the data can be seen as additional external validation of our model.

### 6.4 Decomposing the Decrease in the Labor Share

[Autor, Dorn, Katz, Patterson, and Van Reenen \(2020\)](#) show that the fall in the labor share is largely driven by a reallocation of market shares towards low labor share firms rather than from a change in the unweighted mean labor share across firms. In this section, we show that our estimated model delivers the same results. In particular, following [Autor, Dorn, Katz, Patterson, and Van Reenen \(2020\)](#), we can decompose the change in the labor share between two points in time as:

$$\Delta S = \Delta \bar{S}_S + \Delta \left[ \sum (\omega_i - \bar{\omega})(S_i - \bar{S}) \right]_S + \omega_{X,0}(S_{S,0} - S_{X,0}) + \omega_{E,1}(S_{E,1} - S_{S,1}) \quad (41)$$

The subscripts  $S$ ,  $E$ , and  $X$  denote surviving firms, entrants, and exiters, respectively.  $\omega_i$  is firm  $i$ 's share of value added,  $\bar{S}$  is the unweighted mean labor share,  $\bar{\omega}$  is the unweighted mean value-added share,  $\omega_{X,0}$  and  $\omega_{E,1}$  are the aggregate value added shares of exiters and entrants at the beginning ( $t = 0$ ) and the end ( $t = 1$ ), respectively, and  $S_{X,0}$  and  $S_{E,1}$  are the value added weighted mean labor share of exiters and entrants at the beginning and the end. The first term can be interpreted as the change in the aggregate

<sup>44</sup>In particular, we compute the change in market concentration and in the labor share for industries with the same number of firms and the same productivity step distribution in the early and late subsamples.

labor share due to within-firm changes among survivors, while the second term reflects the reallocation of market share among surviving firms with different labor shares. The final two terms represent the contributions of firm entry and exit to the change in the aggregate labor share.

Obtaining a comparable decomposition in our model requires simulation of firms over the transition as we need to follow the evolution of the market shares and labor shares of continuing firms, entrants and exiters. In order to do so, we perform simulations of firms starting from the early subsample. Specifically, we simulate 20 million firms, of which 200,000 have been superstars at least for some time interval within the associated time window.<sup>45</sup> The simulation starts from the BGP for the early subsample and simulates firms over the transition path from the early to the late calibration. That is, initial firms are drawn from the early period stationary equilibrium, the parameters are set to their late subsample values at time  $t = 0$ , and we simulate forward. New firms enter and exit over time.

The top panel of Figure B2 presents the results from our simulation exercise, alongside the corresponding findings from [Autor, Dorn, Katz, Patterson, and Van Reenen \(2020\)](#) (taken from their Figure VII, and reproduced in the bottom panel). In line with their results, our model predicts that most of the change in the labor share over time is due to the reallocation of market shares towards low labor share firms (second term,  $-5.3\%$  in our simulation vs.  $-4.9\%$ ), while the within-firm component plays a negligible role (first component,  $-0.5\%$  in our simulation vs.  $-0.4\%$ ). Additionally, as in [Autor, Dorn, Katz, Patterson, and Van Reenen \(2020\)](#) and [Kehrig and Vincent \(2021\)](#), the effects of entry and exit on the labor share largely offset each other (the sum of entry and exit components is  $-1.0\%$  in our simulation vs.  $-0.4\%$  in their paper), and the relative magnitudes and the directions are also consistent. These results demonstrate that our model is consistent with the (untargeted) decomposition of the source of the decrease in the labor share documented in the literature.

## 7 Robustness of Quantitative Results

It is important to test whether our model's sharp growth and welfare predictions are driven by the modeling assumptions or the data used for estimation. In this section, we present and discuss several robustness checks to show that this is not the case.

### 7.1 Non-Stationary Dynamics and the Welfare Costs of the Transition

The welfare results in Section 5.2 are obtained by comparing the actual and hypothetical stationary equilibria. One might be concerned that a comparison across stationary equilibria might be insufficient to capture the full differences in welfare across the separate scenarios, since some effects of the changes are instantaneous (e.g., the effects on static product market competition), whereas the rest take more time to manifest in full (e.g., the changes to the industry-state distribution  $\mu_t(\Theta)$ .) To capture the welfare differences from the point of view of an agent at  $t = 0$ , one needs to take the transitional dynamics in non-stationary equilibria into account.

Before we repeat our quantitative experiments, it is worth discussing how fast several economic variables of interest move during the transitions between the early and late period economies, as well as

<sup>45</sup>We properly weigh small firms in our simulation so that it is consistent with the value added share of small firms over the transition in the model.

between the late period and the most recent period of 2006-2016. Figures B3 and B4 display the time paths of selected variables for these two transitions, respectively.

As already discussed in Section 2.3, firms' value and innovation policy functions respond immediately by jumping to the immediate vicinity of their new stationary values, with little change over the transition. Likewise, given an industry state  $\Theta$ , the static industry equilibria respond immediately to the changes in parameters. However, the distribution over industry states  $\mu_t(\Theta)$ , the mass of small firms  $m_t$ , and aggregate moments adjust more slowly. Panel (f) of Figure B3 shows the evolution of the distribution of the number of firms per industry over time, which summarizes the change in  $\mu_t(\Theta)$ .<sup>46</sup> Average markups and the labor share converge to their new steady state very fast after an initial jump that very slightly overshoots their new long-run values (see Panels (c) and (e) of Figure B3). Firm entry is also relatively slower at converging to its balanced growth path level, experiencing an initial large drop followed by a gradual increase as can be seen in Panel (d) of Figure B3).

Economic growth initially rises significantly above its new long-term value, followed by a slow convergence to its new stationary value, producing a spike in productivity growth, followed by a progressive slowdown. R&D intensity follows a similar trajectory (see Panels (a) and (b) of Figure B3). In other words, our model delivers transitional dynamics that are characterized by a temporary surge in productivity growth – as has been observed in the data in the late 1990s and early 2000s – followed by a slowdown. The model is therefore able to replicate this pattern in the data even though we do not target the transition path between the two periods in our estimation.

In the transition between the late and later periods, productivity growth slows down considerably (see Panel (a) of Figure B4) which can be linked to the recent productivity slowdown discussed for instance in Gordon (2012, 2014). R&D intensity decreases at first and then slowly rises up towards its stationary value. Small firm entry rate increases initially and then falls towards its new lower stationary value. The average markup responds increases gradually towards its new higher long run value.

What about the counterfactual experiment results? In Section A.9.2 of the Appendix, we conduct the equivalents of the decomposition experiments, where we require all economies to start from the early period stationary equilibrium, and converge over time to the late stationary equilibrium. The welfare numbers are also recomputed taking the full transition into account, and are presented in Table A7. The welfare difference between the realized transition and the counterfactual of remaining in the early steady-state in perpetuum is now calculated to be -39.69%, as opposed to -29.98% in the baseline analysis. This shows that taking the non-stationary dynamics into account does not change the direction of the welfare impact of the structural transition in the US. The structural change that contributes the most to the loss in welfare is the change in the elasticity of substitution, the impact of which is calculated as 11.81%, which is lower than the 21.07% found in the baseline. Finally, we find that the dynamic gains in welfare associated with higher markups still dominate the static losses in efficiency, but the total welfare gain is smaller (2.21%). This is because the increase in aggregate productivity growth takes time to fully manifest due to the time it takes for the industry-state distribution  $\mu_t(\Theta)$  to converge to its stationary value, whereas the static losses from a less productive competitive fringe are instantaneous.

<sup>46</sup>We show this summary measure, since  $\mu_t(\Theta)$  is an 84-dimensional object under our choices for  $\bar{n}$  and  $\bar{N}$ .

## 7.2 Lower Elasticity of Intertemporal Substitution

The period utility function in the baseline model is the natural logarithm, which implies an elasticity of intertemporal substitution (EIS) of 1. This is done for tractability, as it allows an intuitive decomposition of welfare, and the computation of stationary and non-stationary equilibria is simpler since the discount term in the firm value functions,  $r - g$ , is equal to the discount factor of the representative household  $\rho$ . Conducting a survey of 1429 studies, [Havranek, Horvath, Irsova, and Rusnak \(2015\)](#) report that the average estimate of the EIS for the US is 0.594, with a standard error of 0.036. Since this number is quite low in comparison, one might worry that our choice regarding the preferences might exaggerate the dynamic welfare gains from increased growth. To establish the robustness of our results, we change the preferences given in equation (1) to

$$U = \int_0^\infty e^{-\rho t} \frac{C_t^{1-\theta}}{1-\theta} dt \quad (42)$$

where  $\theta$  is the constant relative risk aversion parameter. To remain conservative, we impose  $\theta = 2$ , which implies an EIS of 0.5; lower than the mean estimate for the US. We repeat the estimation with the new preferences, and the results are displayed in Table B14. To remain consistent with the baseline, we change the value of  $\rho$  to 0.02, so that the implied real interest rate under 2% growth is the same across estimations. Using the new estimation results, we repeat the counterfactual exercises in Section 5.2, and report the results in Table B15. In general, the results remain quite comparable. In particular, the dynamic losses from welfare still dominate the static gains in the experiment where markups are reduced to their early period level. The total welfare impact is still negative at -2.53%. We conclude that our choice of utility function does not drive our results.

## 7.3 Capital Accumulation

In the baseline model, production only uses labor as an input. This is done for tractability and ease of comparison to other work on endogenous markups discussed earlier. In this section, we show that extending our model to include endogenous physical capital accumulation does not change the results significantly. The details of this extended model can be found in Appendix A.7.

Unlike the previous two robustness checks, we do not re-estimate the model. This is because all targeted moments except R&D intensity remain exactly the same after the introduction of capital accumulation. However, consumption equivalent welfare changes are affected, since output is now also used for investment in physical capital. Table B16 presents the results of repeating the counterfactual exercises in Section 5.2. It is seen that the direction of welfare changes are maintained. In particular, reverting the value of  $\zeta$  to its early period value still results in a welfare loss of 7.06%. We conclude that abstracting away from capital accumulation does not drive our results.

## 7.4 Sensitivity to Markup Estimates

In our baseline estimation, we use the sales-weighted average markup estimates from [De Loecker, Eeckhout, and Unger \(2020\)](#) as an estimation target. Concerns have been raised regarding whether the cost- or sales-weighted average markup should be the focus of attention, given that it is the cost-weighted

average markup that summarizes the distortions in allocative efficiency in commonly-used theoretical frameworks.<sup>47</sup> Despite our choice to target the sales-weighted average markup, our model delivers lower values for the cost-weighted average markup in all three samples. This is consistent with what is observed in the data.

To further establish the robustness of our results, we re-estimate the model using cost-weighted average markup targets obtained from [Edmond, Midrigan, and Xu \(2023\)](#) to hit them precisely, and repeat our counterfactual experiments. Table B17 displays the results of re-estimation. The rise in markups is still welfare-enhancing at 9.34%.

More recently, [Bond, Hashemi, Kaplan, and Zoch \(2021\)](#) have raised concerns over the consistency of average markup estimates obtained using the [De Loecker and Warzynski \(2012\)](#) methodology, which both [De Loecker, Eeckhout, and Unger \(2020\)](#) and [Edmond, Midrigan, and Xu \(2023\)](#) follow. This raises the question of whether our results hinge on markup estimates that might potentially be biased. Fortunately, given the rich structure of our setting that ties several aggregate moments together, we can still estimate our model even if we do not explicitly target any markup-based moments. As seen in the decomposition exercise in Table 2, the relative productivity of small firms  $\zeta$  which governs the average markup, is also responsible for the majority of the change in the labor share. Therefore, even if we do not explicitly target the average markup, the labor share can be used to identify the value of  $\zeta$ , which in turn can identify the implied average markup through indirect inference. Following this line of reasoning, we re-estimate the model after dropping the average markup and the standard deviation of markups from the set of targeted moments.<sup>48</sup> Table B19 displays the results of re-estimation. The indirect inference suggests that the average markup has increased by 12.42% of its value between the early and late periods, which is similar to the 12.29% increase in the baseline. The average markup level in the early period is found to be at 1.296, very close to the 1.30 estimate in [De Loecker, Eeckhout, and Unger \(2020\)](#). The positive welfare effects associated with the increase in markups are still present: the welfare impact of keeping the relative productivity of small firms  $\zeta$  the same as in the early subsample would decrease welfare by 8.53%. Not relying on markup estimates obtained through the [De Loecker and Warzynski \(2012\)](#) methodology does not change our conclusions on the direction of the effect of rising markups on welfare.

## 7.5 An Alternative Baseline: Targeting Real GDP per Capita Growth

Our baseline calibration shows that the evolution over time of productivity growth has been non-monotone over the period that we study. In particular, the late period is characterized by significantly faster growth in real output per hour, while the later subsample experiences a decline (with a growth rate below the value in the early sample). While this overall pattern still holds when we measure the growth rate of GDP per capita, it features a less pronounced increase between the early and late subsample (from 2.19% in the early subsample up to 2.31% in the late subsample and down to 1.45% in the later subsample). One might therefore be concerned that relying on the growth rate of real output per hour could generate larger variations in productivity growth and that this might affect our quantitative results. In order to address this concern, we propose an alternative baseline economy in which we directly target the growth rate of

<sup>47</sup>See [Edmond, Midrigan, and Xu \(2023\)](#) among others.

<sup>48</sup>This is feasible since our model is already overidentified (9 parameters vs. 11 targets.)

GDP per capita from the US Bureau of Economic Analysis, and recalibrate.<sup>49</sup>

The estimation results are reported in Tables B21 and B22 for the early, late, and later subsamples, respectively. Results of the counterfactual experiments are presented in Tables B23 and B24, where the former disentangles the changes between the early and late periods, and the latter does the same for the early and later periods, mirroring our baseline analysis.

Despite these changes, from Tables B23 and B24, we can see that the main takeaways remain consistent with our baseline calibration. In particular, the rise in markups is again almost entirely explained by the decrease in the productivity of small firms ( $\zeta$ ), which leads to dynamic welfare gains that more than offset the static welfare loss from higher markups. The associated increase in markups between the early and late periods results in an 7.6% welfare gain (compared to 8.3% in the baseline calibration). The decline in competition between superstars (measured by the change in  $\eta$ ) generates lower welfare changes (12.76% welfare loss from reverting  $\eta$  to its early value, versus 21.07% in the baseline). This is largely due to the fact that, while the change in  $\eta$  does not increase average markups over time, it has a weaker effect on productivity growth in this alternative calibration (a 10.39% drop in growth versus 16.19% in the baseline). Similar trends can be seen from the late to the later subsample, where  $\zeta$  once again explains most of the change in markups over time. The welfare effects of declining competition over time – via both  $\eta$  and  $\zeta$  – remain significant. Our alternative baseline calibration still predicts that ideas are consistently getting harder to find for both small and larger firms across the three subsamples. Overall, the main conclusions are maintained: (1) ideas are getting harder to find in both the late and later subsamples, and (2) the decline in the productivity of small firms ( $\zeta$ ) would have generated large productivity gains if ideas were not getting harder to find over the same period of time.

## 7.6 Further Robustness Checks

We have built several other model extensions, and conducted more robustness checks, estimations, and counterfactual experiments beyond those reported thus far. For brevity, these are relegated to the Extra Appendix. These not only demonstrate the robustness of our quantitative results, but also showcase the flexibility of our new unified framework, which we hope will be of use to future researchers. We briefly list some of these below:

- **Allowing small firms to have positive profits either through decreasing returns to scale in production or through collusion.**

We extend the model and derive the static equilibrium conditions and the level of output for two alternative models: (i) decreasing returns to scale in production technology (for both small firms and superstars), and (ii) letting the small firms in the competitive fringe collude, and thereby act as if they were a superstar with the productivity of the fringe  $\zeta q_{jt}^{leader}$ . In both cases, we depart from the baseline model in which small firms were making zero profits. Letting small firms earn positive profits does not change our main results. More details about these extensions are relegated to the Extra Appendix Section C.

- **Extending the model to allow for multi-product firms.**

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<sup>49</sup>This was our original baseline in earlier working paper versions.

We extend the model to allow for multi-product firms as in [Klette and Kortum \(2004\)](#). In this extension, on top of all the dynamics present in the baseline framework, firms can also grow by entering new markets. Superstar firms are now collections of several “product lines” in different markets, which can be interpreted as products/industries/locations/industry-location pairs. Each product line of a superstar firm operates exactly as it did in the baseline model. However, the superstar firms can now conduct “expansion” R&D/radical innovation. Conditional on success, they enter a new product line, and their initial productivity is  $\bar{n}$  steps behind the product line leader, identical to that of a new superstar that could emerge in the same product line as a result of small firm innovation. Expansion R&D lets firms grow horizontally across product lines, and these product lines can be lost endogenously through the same mechanism that caused firms to lose their superstar status in the baseline model. The difference is that such an event only destroys the superstar’s presence in that particular product line, but a superstar with more than a single product line still survives. The extended model shows that embedding a [Klette and Kortum \(2004\)](#) superstructure in our model does not eliminate its tractability. See Section D of the Extra Appendix for more details.

- **Modeling competition à la Bertrand.**

We assume Cournot competition in our baseline analysis due to its ability to generate more variation in markups and more realistic market share distributions consistent with what is observed for large firms in the United States, but the fact remains that most of our results go through regardless of the specific assumption on whether firms compete in prices or quantities. We have re-estimated the model and performed a robustness check on our results with differentiated Bertrand competition instead. More details about this extension are relegated to the Extra Appendix Section E.

- **Using a broader intangible investment definition in the estimation.**

In the baseline estimation, we map firm-year-level innovation to firm-year-level average patent citations, and aggregate spending on innovation to aggregate spending on R&D in the data. We examine the robustness of our quantitative results by conducting an alternative estimation for the early and late subsamples in which we target (1) a measure of aggregate intangible investment to GDP rather than R&D to GDP alone, and (2) use a firm-year-level measure of total intangible investment to measure innovation, as opposed to relying on patent data, when obtaining the data moments that let us replicate the inverted-U relationship between innovation and relative sales. Our quantitative results remain robust. More details about this robustness check are relegated to the Extra Appendix Section F.

- **Increasing the maximum number of productivity steps between superstars ( $\bar{n}$ ) as well as the maximum number of superstars per industry ( $\bar{N}$ ).**

In setting up the model, we had to make a choice on the upper bound for the maximum number of productivity steps ( $\bar{n}$ ) and the maximum number of superstar firms within an industry ( $\bar{N}$ ) so that the equilibria are computable. While in theory these numbers could be arbitrarily large, increasing any of them rapidly increases the number of potential firm and industry states, which slows down the numerical solution of the model. We have chosen the baseline values as a good compromise between allowing the model to have rich enough heterogeneity within and across industries and

the time needed for estimation and computing counterfactual equilibria. In Section G of the Extra Appendix, we show that our quantitative results are virtually unchanged when we increase the value of  $\bar{N}$ . Increasing  $\bar{n}$  requires re-estimation, but the quantitative results likewise remain robust.

- **Imposing a quadratic R&D cost function to both small and large firms.**

While part of the existing literature uses quadratic R&D cost functions (see for instance [Akcigit and Kerr \(2018\)](#)), we have decided to estimate the convexity of the R&D cost functions for both small and superstar firms in our baseline analysis. As a robustness check, we have also re-estimated the model with quadratic R&D cost functions. It is worth noting that, when exogenously imposing quadratic costs, the model has a hard time matching the level of R&D intensity and the growth rate of the economy simultaneously. Despite the fact that the fit of the model is significantly worse than under our baseline calibration, setting R&D convexity to 2 does not significantly change the results of our counterfactual experiments. More details about this extension are relegated to the Extra Appendix Section H.

- **Examining the robustness of the results assuming a non-quadratic entrepreneur cost function.**

We choose a quadratic entrepreneur cost function in the baseline due to the lack of available data that could be used to separately identify the scale ( $\psi$ ) and convexity parameters. Unlike incumbent firms, for which we can empirically observe their innovation inputs (R&D expenditures) and outputs (patents, citations, sales growth, productivity growth, ...), we are not aware of any representative micro-data on business creation costs of entrepreneurs, which should ideally include not only the material costs of founding a new business, but also the opportunity cost of the entrepreneur(s). To mitigate the concerns that our quantitative results may be sensitive to the assumption about the entrepreneur cost function, we conduct two separate robustness checks. In the first one, we assume a higher convexity value of 3 instead of 2 for the entrepreneurs. In the second one, we assume a linear cost (i.e., free entry). No re-estimation is needed in either case, and the moment match is identical to that in the baseline. We repeat the counterfactual experiments. Our quantitative results remain robust in both settings. More details about these extensions are relegated to the Extra Appendix Section I.

- **Targeting the late sample moments over the transition.**

In Section 7.1, we addressed concerns that might be related to comparing welfare across steady states by deriving the transition dynamics between early and late steady states and measure welfare accordingly. One might be further concerned about the fact that the transition between steady states in our baseline analysis takes somewhat longer than the actual amount of time between the early and late subsamples. As a result, we conduct one additional robustness check in which we target the moments in the late sample along the transition to a new steady state. In particular, while the early stationary equilibrium remains the same as in our baseline analysis, we calibrate the late period stationary equilibrium by ensuring that the transition matches our targeted moments exactly 15 years along the transition.<sup>50</sup> The new transitional estimation results are reported in Table L25. The results

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<sup>50</sup> 15 years corresponds to the time period between the mid-points of the early and late subsamples.

of this new calibration of the associated counterfactual experiments can be found in Figure L4 and Table L26. Our conclusions remain unchanged compared to our baseline results.

- **Discretized Fringe.**

Our baseline model assumes the existence of mass of small firms in the competitive fringe producing a homogeneous good. This allows our model to deliver arbitrary and realistic measures of within-industry competition while keeping the model tractable. We nevertheless provide an extension of the model in which the competitive fringe is instead composed of a (large) discrete number of firms that are treated exactly in the same way as superstar firms, i.e., producing their own differentiated variety. As a result, small firms charge positive markups and obtain non-zero static profits. While the full discussion of this extension is relegated to the Extra Appendix J, our quantitative results remain similar to those obtained in our baseline calibration (see Tables L23 and L24).

## 8 Conclusion

We propose a new model of Schumpeterian growth in which firms strategically compete with other firms and dynamically choose their innovation strategies. Our model can account for an arbitrarily high number of firms in an industry, with endogenous entry and exit, and can generate non-degenerate sales, employment, markup, and innovation distributions within industries. This approach departs from much of the previous literature on endogenous growth studying markups, competition, and innovation, in which researchers use models featuring degenerate firm distributions with Bertrand competition in the product market. It also can generate endogenous industry dynamics in rich detail, and replicate the observed inverted-U relationship between innovation and competition both within and across industries.

We use the estimated model to gauge whether increasing markups boost or hinder aggregate innovation and economic growth. The findings reveal that while the increase in average markups causes a significant static welfare loss, this loss is overshadowed by the dynamic welfare gains from increased innovation in response to higher profit opportunities. Overall, our results suggest that the dynamic effects of increasing market concentration on innovation and productivity should not be ignored when trying to understand the transformation in the US in the last four decades; and the rise of superstar firms and markups is not necessarily detrimental to welfare.

Our results also highlight an increase in the costs of innovation over time. If the costs of innovation (for both small and superstar firms) were set back to their earlier levels, it would generate a further increase in productivity growth. These results point towards “the ideas are getting harder to find” hypothesis studied in [Gordon \(2012\)](#) and [Bloom, Jones, Van Reenen, and Webb \(2020\)](#).

We view our research as a starting point for understanding the aggregate implications of strategic interactions among heterogeneous firms. While our model shows the importance of using a model with non-degenerate firm distribution and realistic product market competition to gauge the welfare impact of rising markups, it can also be used in different settings where heterogeneous firms compete statically in the product market, and dynamically to improve their relative market shares. The model is highly tractable and could be easily extended to study the implications of various kinds of government policies, such as size-dependent R&D tax credits, subsidizing new business entry, and corporate taxation. We expect future

studies along these lines to be both promising and fruitful.

## **Data Availability Statement**

The data and code underlying this research are available on Zenodo at <https://dx.doi.org/10.5281/zenodo.21646423>.

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