Increase in Turbulence and Market Power*

Agnieszka Markiewicz[†] Riccardo Silvestrini[‡]

November 8, 2022

Abstract

During the last four decades, the U.S. industries have experienced heterogeneous increases in market power. This paper argues that this heterogeneity can be explained by the different dynamics of turbulence across sectors. To show it, we build a model of a sector where firms differ by their productivity level, and they compete under oligopolistic competition. Business dynamics are captured in the model by sequential idiosyncratic entry, exit, and productivity shocks. A sector-specific increase in turbulence accelerates the turnover of leaders and the mobility of firms over the productivity distribution. This leads to reallocation of market shares towards the most productive firms that charge the lowest price. Their cost leadership allows them to charge the highest markups and gain the steepest profits, driving the increase in sectoral market power. The model can explain between 35% and 57% of the cumulative increase in the observed markups, and its predictions are supported by the U.S. and European data.

Keywords: Markups, Market power, Oligopolistic competition, Turbulence
JEL: D21, D50, L13

*__Disclaimer__: this paper has previously circulated under the title *Heterogeneous Increase in Sectoral Market Power: the Role of ICT*. We thank Ariel Burstein, Yao Chen, Andrea Colciago, Diego Comin, Maarten de Ridder, Robert Dur, Ana Figueiredo, Simon Gilchrist, Basile Grassi, John Haltiwanger, Albert Jan Hummel, Jurjen Kamphorst, Virgiliu Midrigan, Alessandra Peter, Andreas Pick, Lorenzo Pozzi, John Van Reenen, Peter Sedláček, Bauke Visser, Casper De Vries, Felix Ward, our discussants Eric Bartelsman, Sergio Feijoo, Byoungchan Lee, Francesco Manaresi, Rutger Schilpzand and Ali Sen, and the conference participants to the Society for Economic Dynamics 2022 Annual Meeting, CompNet 2022 Annual Conference, 4^{th} International Conference on European Studies, 25^{th} Conference on Theories and Methods in Macroeconomics, WEAI 2021 Virtual International Conference, Nederlandse Economenweek 2020, KVS New Paper Sessions 2022 and 2020, Tinbergen Institute Macro Day, University of Oxford NuCamp Virtual PhD Workshop, 1^{st} Ventotene Workshop in Macroeconomics, 17^{th} Conference on the Comparative Analysis of Enterprise Data, University of Kent Firm Dynamics, Market Structures and Productivity in the Macroeconomy, 46^{th} Simposio de la Asociación Española de Economía, 9^{th} Summer Workshop of the Polish Central Bank, and the seminar participants at the Erasmus School of Economics, Banque de France and New York University for their helpful comments and suggestions.

[†]Erasmus University Rotterdam and Tinbergen Institute, markiewicz@ese.eur.nl
[‡]Erasmus University Rotterdam and Tinbergen Institute, silvestrini@ese.eur.nl

1 Introduction

The market power of U.S. firms has risen over the last four decades. Price markups, market concentration and profit margins have all increased, but the magnitude of these trends strongly differs across industries. The recent trends in market power have been accompanied by growing barriers-to-entry and rising turbulence (Comin and Philippon (2005), Comin and Mulani (2006)). In this paper, we investigate to what extent these two trends can explain the heterogeneity in market power dynamics across sectors.

First, we build a measure of sectoral turbulence that captures the time-varying persistence of firms' productivity in a sector. Similar to Comin and Philippon (2005) and Dong, Liu, and Wang (2022), we define turbulence as the inverse of the 5-year Spearman rank correlation of firms' productivity. An increase in turbulence captures a higher turnover of firms over the productivity distribution and therefore it implies a more dynamic environment. In Compustat data, in as much as 49% of sectors, the turbulence has, in fact, increased since the 1960s. In sectors with the highest increases in turbulence, i.e. above the median, the markups have grown the fastest. We call them high-turbulence sectors. In sectors where the turbulence has declined (below the median) the markups have grown the least. We refer to those sectors low-turbulence sectors.

To understand how increasing barriers-to-entry and turbulence affect market power dynamics, we build a model of a sector that reflects the market structure of a typical U.S. industry. In this economy, firms differ by their productivity level, and they compete under oligopolistic competition. Their price markups, profits and market shares are all endogenously determined by market conditions. Intuitively, a firm endowed with the highest productivity, and thus with the lowest marginal cost, is able to charge the lowest price and to expand its market share. Its cost leadership allows it to charge the highest markup. Business dynamics are captured in the model by sequential idiosyncratic exit, entry, and productivity shocks.

Initially, the model is calibrated to reproduce key features of the U.S. industries between 1960 and 1980, a period with relatively low and stable market power of firms and turbulence. Then, we carry out two main experiments. In the first one, we permanently increase turbulence and entry costs to mimic a high-turbulence sector. The second experiment introduces only higher entry costs to proxy a low-turbulence sector. We compare the transition paths to the new steady states in these two experiments (sectors).

Both sectors display an increase in market power: price markups, profit rates and market concentration go up. However, the magnitudes and the mechanisms underlying the observed trends are very different across sectors. In the high-turbulence sector, the median revenue-weighted markup and market concentration grow, 35% more than in the low-turbulence markets. These trends are driven by the most productive, high markup firms. Intuitively, a higher turbulence boosts the likelihood of changing the productivity ranks for all firms. However, since the firms endowed with the most productive type cannot further increase their productivity, by definition, a higher turbulence only raises their chances of moving downwards in the productivity ranks. If this happens, the large available market share is captured by the remaining highly productive firms. Given their growing market shares, those firms charge even higher markups.

In contrast, in the low-turbulence sector, in the absence of a turbulence shock there is little reallocation, and the modest increase in markups is mainly driven by growing markups of the incumbents.

We evaluate the relevance of the model's mechanism in the data and asses the importance of reallocation and within components in markups' growth. To do it, we apply Haltiwanger (1997)'s decomposition to the markups in high and low-turbulence sectors in Compustat. Because of the concern that publicly traded firms, covered by Compustat, are not representative of the distribution of the entire universe of firms, we also rely on a second dataset, CompNet, which covers a more representative sample of firms across Europe.

We show that the reallocation of market shares is a distinctive feature of high-turbulence sectors, both in the model and in the data. In both the U.S. Compustat and the European CompNet, the reallocation of market shares towards the most productive firms primarily drives the growth in markups and market concentration. In low-turbulence sectors, instead, the (lower) growth in sectoral markups is driven by the growing markups of the incumbents.

We also assess how well the model tracks the paths of market power variables in the U.S. data over the last three decades and their heterogeneity across sectors. In Compustat, the cumulative increase in the median markup in high-turbulence sectors is between 6.13% and 10.08% and our model can explain between 35% and 57% of this increase, depending on the empirical markup's measure. Because the market power measures crucially depend on the patterns of the costs of firms, in addition to markups, we analyze revenue-weighted profit rates. The observed increase in profit rates is substantially higher than in markups and reaches 24% in high-turbulence sector and 16.19% in low-turbulence sector in Compustat and 21% and 17% in the model.

We explore an alternative mechanism that relies solely on the heterogeneous entry costs across sectors. An uneven increase in entry costs fails to mimic the data patterns in two dimensions: (i) reallocation of market shares and (ii) divergence across sectors. Intuitively, an increase in entry costs on its own drives the markups up through the crowding out of small firms. The lack of reallocation of market shares towards high-markup firms translates into a sluggish increase in market power so that both types of sectors display similar transition paths, in contrast to the data and the benchmark model dynamics.

Related literature

Our paper is closely related to the growing literature on the macroeconomic implications of micro-level uncertainty, e.g. Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018). Specifically, we exploit the fact that firm-level volatility and turbulence have increased since the 1980s. This trend has been documented by Comin (2000), Comin and Philippon (2005), Campbell, Lettau, Malkiel, and Xu (2001), Chaney, Gabaix, and Philippon (2002) and Davis et al. (2006)), among others. Comin and Philippon (2005) and Comin and Mulani (2009) additionally show that the increase in turbulence has been uneven across sectors. Our turbulence measure is very similar to the one proposed by Dong et al. (2022), but they study its impact on business cycle fluctuations, while our focus is on the long-run trends.

Our work is also related to the literature exploring the rise in market concentration and markups in recent decades, e.g. Grullon, Larkin, and Michaely (2019) and De Loecker, Eeckhout, and Unger (2020). Autor, Dorn, Katz, Patterson, and Van Reenen (2020) attribute these developments to the rise of superstar firms, whose advantage in productivity allows them to increase their market shares, without compromising consumers' welfare and firms' investments. De Loecker et al. (2020) and Gutiérrez and Philippon (2019) argue, instead, that the observed increase in the market concentration and markups reflects an increase in the market power of large firms as well as a reduction in the competition within U.S. industries. In a way, our paper reconciles both hypotheses: although the increase in market power is largely driven by the reallocation of market shares towards the most productive firms, rising entry costs amplify this trend. This finding is similar to the one in De Loecker, Eeckhout, and Mongey (2019), who uncover the importance of changes in both market structure and technology to shape the observed trends in market power. Yet, we focus on differences in sectoral dynamics instead of aggregate trends.

In our model, the most productive firms determine market concentration and markups' dynamics. The proposed mechanism conceptually builds on Gabaix (2011) since, in an environment with a finite number of firms, idiosyncratic shocks propagate to the aggregate economy. The most recent contributions to the literature studying the role of large firms for the aggregate dynamics include Carvalho and Grassi (2019) and Burstein, Carvalho, and Grassi (2019). In contrast to these papers, which study business cycle fluctuations, we focus on long-run (sectoral) trends.

Our propagation mechanism relies on firms' stochastic entry and exit dynamics in the spirit of Jovanovic (1982) and Hopenhayn (1992). Importantly, to capture more realistically the current market structure of U.S. sectors, our framework departures from the competitive environment of a continuum of firms in Hopenhayn (1992). We propose an environment characterized by a finite number of heterogeneous firms competing under oligopolistic competition, which is inspired by Atkeson and Burstein (2008). Because we are interested in the evolution of market power over time, our model differs from the one by Atkeson and Burstein (2008) in one crucial dimension. Instead of the static competition game, we introduce the sequential and forward-looking entry in the spirit of Bilbiie, Ghironi, and Melitz (2012). Together with idiosyncratic productivity shocks, these model features allow us to capture realistic business dynamics where the number of entrants, price markups and profits are determined endogenously, similarly to Edmond, Midrigan, and Xu (2018).

The remainder of the paper is organized as follows. Section 2 describes the sectoral heterogeneity in the degree of the increase in market power, as well as in firms' turbulence, linking the two facts. In section 3, we describe a tractable, oligopolistic competition model with a finite number of firms, which populate a single sector. In section 4, we explain the calibration strategy. Section 5 carries out the main quantitative exercise where we compare the transition dynamics of a high and a low-turbulence sector. In section 6, we confront our model directly with the data. Section 7 presents an alternative experiment that relies on heterogeneous increase in entry costs, while Section 8 concludes.

2 Facts

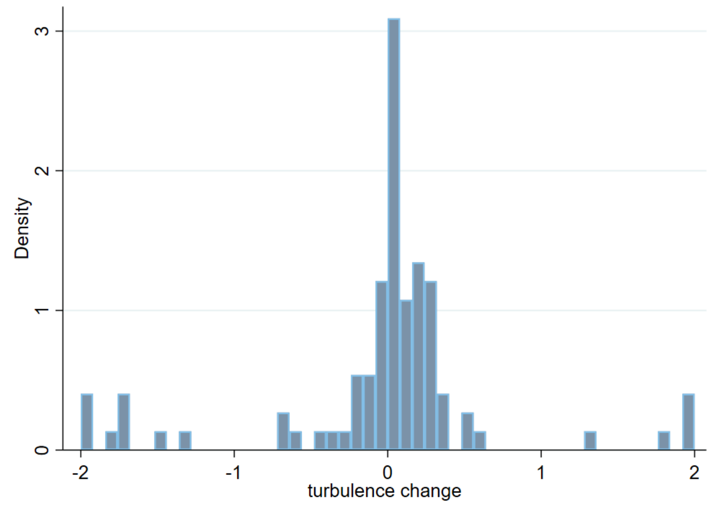
We first construct an empirical measure of turbulence and document the divergence of its long-run trends across U.S. industries. We then present the evidence of sectoral heterogeneity in the market power shifts and demonstrate that they correlate with the turbulence trends. We conclude with the discussion of the empirical evidence regarding the aggregate increase in entry costs.

2.1 Turbulence across U.S. industries

Based on Comin and Philippon (2005), we compute a time-varying turbulence proxy at the sectoral level. To do so, using Compustat data, we first construct a measure of firm-level labor productivity and we rank all Compustat firms according to their productivity within each NAICS 3-digit sector and each year.[1] We then compute the Spearman's rank correlation of productivity, ι_{it}, within each sector i over a five-year horizon, between year

[1]Our measure of labor productivity is output (revenues) per worker.

Figure 1: Distribution of changes in turbulence $\Delta\tau_i$ across NAICS 3-digit sectors between 1965 and 2012.



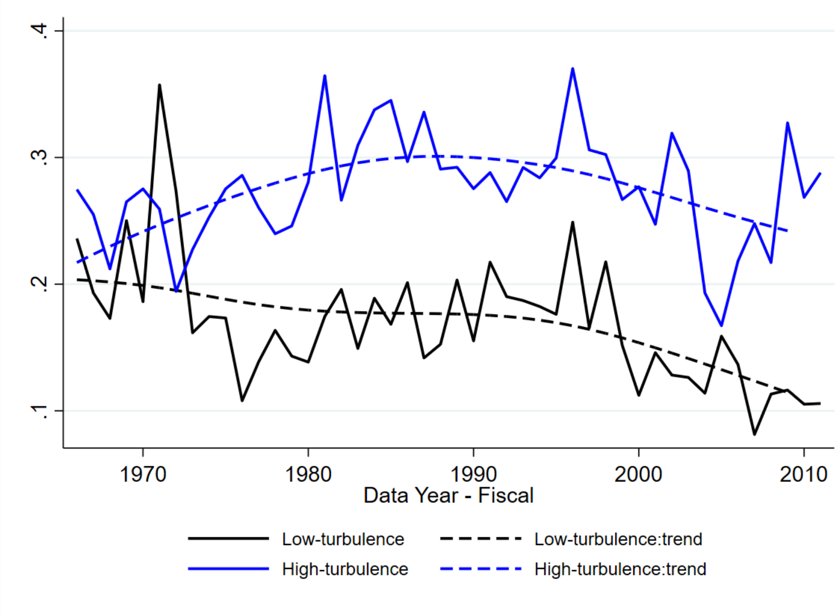
Notes: The graph plots the distribution of changes in turbulence measure $\Delta\tau_i$ across NAICS-3 sectors between 1965 and 2012. The positive numbers indicate an increase in turbulence $\Delta\tau_i$.

t and $t+5$, and repeat the computation for each year on a rolling window. Finally, we define turbulence in sector i and year t as $\tau_{it} \equiv 1 - \iota_{it}$. A high turbulence τ_{it} indicates more churning of firm ranks in the productivity distribution.

While the recent literature documents an aggregate slowdown in the turnover of firms, in many sectors the turbulence τ_{it} has, instead, increased since the 1960s. We compute the change in the turbulence $\Delta\tau_i$ in each NAICS-3 sector between 1965 and 2012 and plot its distribution in Figure 1. As much as 49% of U.S. sectors have experienced an increase in turbulence. We split the sectors into two groups: high-turbulence (superscript ^{ht}) and low-turbulence (superscript ^{lt}), which are defined relatively to the median change in the turbulence proxy $M(\Delta\tau)$ across all sectors.

Table 5 in Appendix F shows the outcome of the split with 15 largest high and low-turbulence sectors, in terms of their revenue-based market shares. There is no typical high and low-turbulence sector, however, some patterns emerge. Services are more frequently classified as high-turbulence sectors while manufacturing industries are more likely to fall into the low-turbulence category. Additionally, the heavy manufacturing industries as Primary Metal (331) or Transportation equipment (336) and traditional services including Rail transportation (481) tend to be classified as low-turbulence. In contrast, high-turbulence sectors include younger industries that rely more heavily on new technologies: Manufacturing of Electrical Equipment and Components (335), Motion Pictures and Sound Recording (513) or Telecommunications (517).

Figure 2: Evolution of turbulence τ_{it} in high and low-turbulence sectors between 1960 and 2012.



Notes: The graph plots high-turbulence measure τ_t^{ht} and low-turbulence measure τ_t^{ht} between 1960 and 2012.

After classifying the sectors, we construct high-turbulence cost-weighted average τ_t^{ht} and low-turbulence cost-weighted τ_t^{lt} as follows:

$$\tau_t^{ht} = \sum_{i=1}^{N} \tau_{it}\omega_{it} \quad \text{if} \quad \Delta\tau_i > M(\Delta\tau)$$

$$\tau_t^{lt} = \sum_{i=1}^{N} \tau_{it}\omega_{it} \quad \text{if} \quad \Delta\tau_i \leq M(\Delta\tau) \tag{1}$$

where ω_{it} are the cost-based shares and $M(\Delta\tau)$ denotes the median across sectors. Figure 2 displays these two series. The black solid line plots the dynamics of τ_t^{lt} between 1965 and 2012 and the dashed black line shows the underlying HP trend. Similarly, the blue solid line plots τ_t^{ht} and the dashed blue line plots its trend.

Initially, both series display very similar levels of turbulence. However, around year 1980, the high-turbulence series τ_t^{ht} exhibits an upwards shift and since then remains permanently above the low-turbulence one, indicating a more frequent reshuffling of firms within the sectors. Towards the end of the sample period, both series τ_t^{ht} and τ_t^{lt} display a declining trend. There are two reasons why this movement is unlikely to explain the uneven growth in market power across sectors. First, the decline in turbulence occurs at the end of the sample while the increase in markups has been the strongest in the 1980s

(Figure 4). Second, the downward trend seems to be common to all types of sectors (the trends move in parallel), and therefore is unlikely to rationalize the heterogeneous trends.

The heterogeneity in turbulence dynamics is not unique to Compustat data. In Figure 10 of Appendix B, we use CompNet dataset to document large differences in turbulence across sectors in Europe.

2.2 Heterogeneous increase in market power and turbulence

There is a large body of empirical evidence showing the growing market power of U.S. firms over the last four decades. A wide range of U.S. industries has experienced an increase in concentration of sales and employment, and an increase in markups and profit margins. This has been well documented by Autor et al. (2020), De Loecker et al. (2020), Grullon et al. (2019), and Gutiérrez and Philippon (2017), among others. A less known fact is that there are large differences in the degree to which sectors have experienced the recent increase in market power.[2]

Figure 3 plots the distribution of the cumulative growth rates in cost-weighted sectoral markups between 1965 and 2016, constructed in four different ways. To compute firm level markups, we follow the definition proposed by De Loecker et al. (2020):

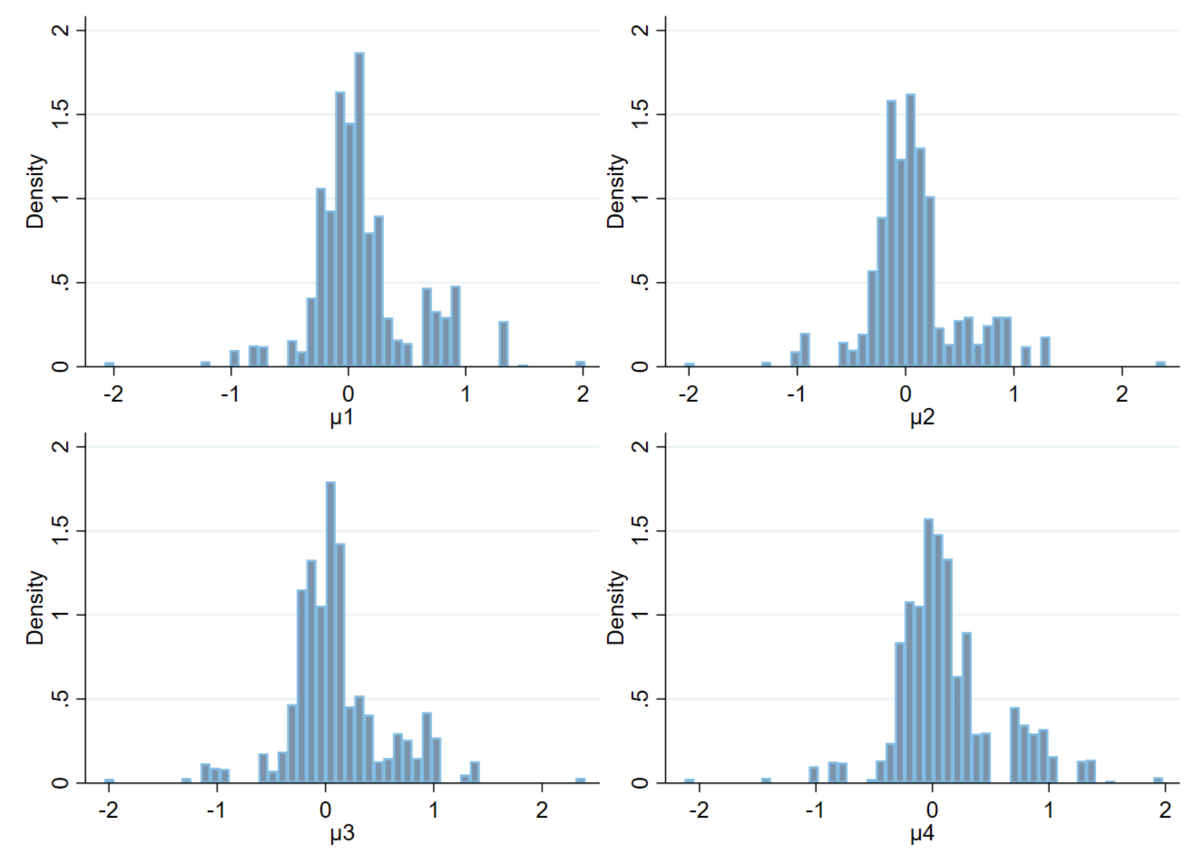
$$\mu_{it}^{k} = \theta_{it}^{k} \frac{P_{it} Q_{it}}{P_{it}^{v} V_{it}}, \tag{2}$$

with $k \in [1, 4]$ indicating the different identification used to estimate the (firm i specific) output elasticity of the variable input in year t, θ_{it}^{k}. $P_{it}Q_{it}$ represents the value of total sales of firm i in year t and $P_{it}^{v}V_{it}$ are the costs of the firm's variable input of production. Variable input value is defined as the "cost of goods sold" (COGS in Compustat) and it covers all expenses attributable to the production including materials, intermediate inputs, labor cost, and overhead.

We start by assuming a constant and equal across sectors output elasticity: $\theta_{it}^{1} = \theta^{1} = 0.85$. θ_{it}^{2} is time-varying and firm-specific and is constructed from the cost shares as follows: $\theta_{it}^{2} = \frac{P_{it}^{v} V_{it}^{v}}{\Sigma_{j}^{J} P_{it}^{j} V_{it}^{j}}$ where $\frac{P_{it}^{v} V_{it}^{v}}{\Sigma_{j}^{J} P_{it}^{j} V_{it}^{j}}$ represents the share of the variable input of production: labor, material and overhead relative to the sum of all inputs $\Sigma_{j}^{J} P_{it}^{j} V_{it}^{j}$ being (i) labor, material and overhead (COGS), and (ii) capital expenses. θ_{it}^{3} is constructed in a similar way, but instead of the firm-level output elasticity, we take the median across all the firms in each NAICS 3-digit sector and in each year t. Finally, θ_{it}^{4} is sector specific but constant over the

[2] A handful of studies documenting heterogeneous trends in markups include Bessen (2017), Calligaris, Criscuolo, and Marcolin (2018), Diez, Fan, and Villegas-Sánchez (2019), and Bajgar, Criscuolo, and Timmis (2021).

Figure 3: Distribution of markups growth rates between 1965 and 2016, across sectors.



Notes: The graph plots the distribution of markups growth rates across NAICS-3 sectors between 1965 and 2016. Sectoral markups are constructed from firm-level markups using cost-shares of firms in the sector. The details on how markups are computed can be found in Appendix A.

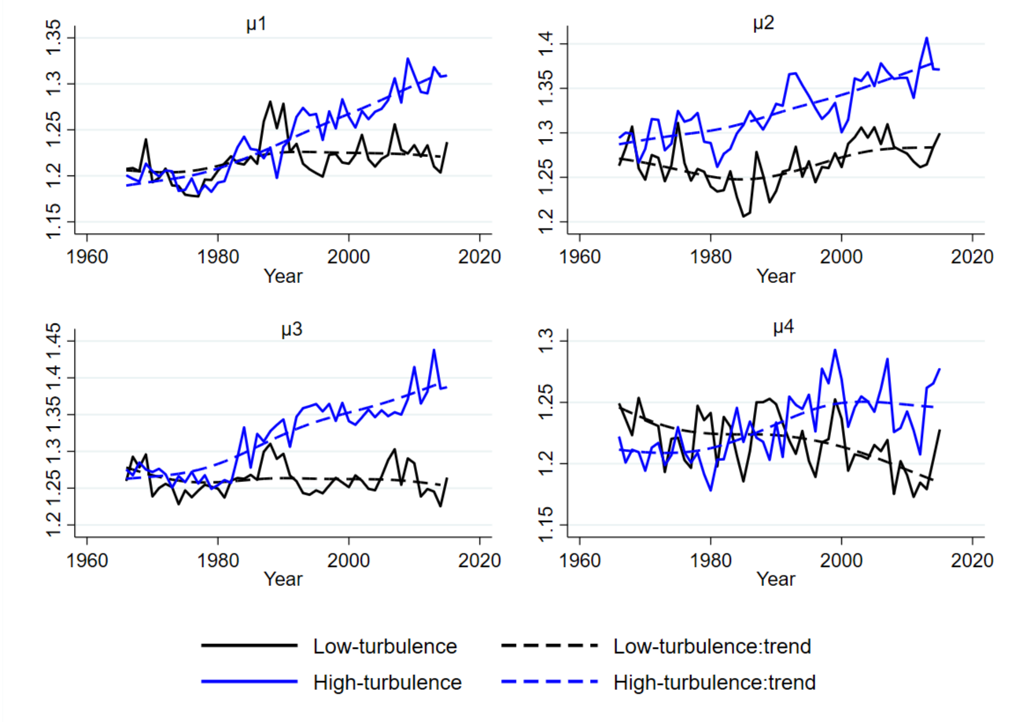
sample period version of θ^2_{it}. All four firm-level markups μ^k_{it} are aggregated to the NAICS 3-digit level using production cost shares.

Figure 3 shows that, in some sectors, the markups have declined over the sample period while in others they more than doubled. The differences between sectors are huge.

To verify if the heterogeneity in markup trends is related to the turbulence measure, we split the NAICS 3-digit sectors in Compustat into high-turbulence sectors and low-turbulence sectors, according to the definition in equation (1), and compute the median markup in each type of sector.

Figure 4 plots the evolution of those markups in high-turbulence sectors (blue solid line) and the underlying HP-filtered trend (blue dashed line), and for low-turbulence sectors (black solid and dashed lines). No matter the measure, the increase in markups is always higher in high-turbulence sectors than in the low-turbulence sectors. The median high-turbulence markup's growth is between 6% and 10% over the sample period, depending on

Figure 4: Evolution of markups in high and low-turbulence sectors in the U.S.



Notes: The graph presents the median of the cost-weighted average markups for high-turbulence sectors in Compustat (blue solid line), and the underlying HP-filtered trend (blue dashed line), and for low-turbulence sectors (black solid line), and the underlying HP trend (black dashed line). Each panel relies on a different methodology for the estimation of firm-level markups described in Appendix A.

the markup's measure. We therefore find a much more modest increase in markups than De Loecker et al. (2020) but comparable to the findings by Gutiérrez and Philippon (2017), Barkai (2020), Nekarda and Ramey (2020), and Edmond, Midrigan, and Xu (2021).

Similar to the turbulence series in Figure 2, both markups in Figure 4 comove in the beginning of the sample and start to diverge around the year 1980; the high-turbulence markups remain above the low-turbulence markups until the end of the sample. In contrast, the low-turbulence median markups in Figure 4 display flat or declining patterns.

Although publicly traded firms, covered by Compustat, account for 29% of the private U.S. employment (Davis et al., 2006), there is a concern that they are not representative of the distribution of the entire universe of firms. We therefore rely on a second dataset, CompNet, that provides statistics computed for a more representative sample of firms across Europe. In Appendix B, we show that also in CompNet (i) markups are systematically higher in sectors with higher turbulence and (ii) markups increase by more in sectors where turbulence goes up.

2.3 Entry Costs

A sharp decline in aggregate entry rates of both firms and establishments and in the absolute number of entrants has been observed in the U.S. since the 1980s. The BDS suggest that the decline is in the order of $25 - 30\%$ and $20 - 15\%$, respectively.

An increase in entry costs has been proposed as one of the main reasons for the observed decline in the U.S. business dynamism, e.g. Gutiérrez, Callum, and Philippon (2019) and Gutiérrez and Philippon (2019). However, in contrast to the heterogeneous patterns of turbulence, U.S. industries have experienced similar increases in entry barriers, making them an unlikely explanation for the divergent trends in market power. In fact, the main driver of the recent increase in barriers-to-entry seems to be the growing complexity of regulation, as argued by Davis (2017) and Gutiérrez et al. (2019). Since most of the recent regulations have been issued by the Environmental Protection Agency, which primarily focuses on aggregate outcomes, this increase in regulation burden is an economy-wide phenomenon, Goldschlag and Tabarrok (2018).

Importantly, although some sectoral variation in the degree of complexity exists between industries, Goldschlag and Tabarrok (2018) show that they are not predictive of the sectoral heterogeneity in business dynamism. Yet, we do not entirely rule out the possibility that an uneven increase in entry costs produced different market power dynamics between sectors, and we test this hypothesis in our model in Section 7.

3 Model

To analyse the recent market power dynamics we build on the framework by Atkeson and Burstein (2008). Because we are interested in the evolution of market power over time, our model differs from the one by Atkeson and Burstein (2008) in one crucial dimension. Instead of the static competition game, we introduce the sequential and forward-looking entry in the spirit of Bilbiie et al. (2012). Together with idiosyncratic productivity shocks, these model features allow us to capture realistic business dynamics where the number of entrants, price markups and profits are determined period-by-period by changes in market conditions, similarly to Edmond et al. (2018).

In our environment firms differ by their productivity level and they compete under oligopoly. The economy is populated by a finite number of firms. This is important because it implies that every incumbent possesses a non-atomistic mass, which translates into a strictly positive market share that depends on firms' relative productivity level. This allows for an intuitive link between the relevant quantities in the model, e.g. concentration or markup indexes, with their empirical counterparts. Individual markups grow monotonically in individual market shares. Since the core dynamics take place on the firms' side, a simple representative household is modelled on the demand side, in the spirit of Bilbiie et al. (2012).

3.1 Firms and Competition

3.1.1 Production

The economy features a single sector in which firms compete under oligopolistic competition á la Cournot, producing differentiated varieties y_{jt}, where the subscript $_j$ represents a firm with productivity j.[3] After the production takes place, the individual goods are aggregated into the bundle Y_t through a standard C.E.S. function. The aggregate output Y_t is used solely for consumption purposes. We assume that the economy is populated by a *finite* number of firms N_t. Their non-atomistic market share depends on the idiosyncratic productivity level and on the number and type of active competitors. When allowing for oligopolistic competition, the distribution of the market shares has a clear impact on the markup distribution.

Firms draw their productivity level $x(i)$ from a known discrete distribution function $f(x)$. Idiosyncratic productivity is assumed to be time-varying and its dynamics can be summarized by a stationary and non-degenerating Markov process: in each period t, q_{ij} represents the probability of moving from productivity level $x(i)$ to $x(j)$ between period t and period $t+1$ and $\sum_j q_{ij} = 1$, $\forall i$. The number of distinct and active productivity levels, i.e. the number of firm types, is represented by S.[4]

Within each productivity type firms are identical and, thus, they are entirely identified by their productivity level. In the following, the variables related to a firm with a productivity, $x(i)$, are identified by the index (i). Each firm type i produces an imperfectly substitutable good $y_t(i)$, which is aggregated into the bundle Y_t. The aggregator function is a standard C.E.S. function for discrete aggregation:

$$Y_t \equiv \left[\sum_{j=1}^{N_t} y_{jt}^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} = \left[\sum_{i=1}^{S} N_t(i) y_t(i)^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} \tag{3}$$

where θ is the elasticity of substitution between varieties, with $\theta > 1$, $N_t(i)$ is the number of firms endowed with productivity level i, and N_t represents the total number of incumbents.

[3]The case of Bertrand competition is described in Online Appendix 2.

[4]It is important to specify *active*. We model $S+1$ types: the type 0, i.e. the firm with productivity $x(0)$, mimics a productivity level that is not enough to guarantee firm survival and it is a proxy for fixed costs of production, which are not modelled explicitly. Thus, if a firm draws this productivity it is forced to leave the market immediately and this allows us to focus on the dynamics of S types only.

Production is linear in labor $l_t(i)$ and depends on the idiosyncratic productivity $x(i)$, which acts as a labor-augmenting technology:

$$y_t(i) = x(i) l_t(i) \tag{4}$$

Firms compete under oligopolistic competition a la Cournot.[5] Firms maximize their per-period nominal profits by choosing the optimal quantity $y_t(i)$:

$$\max_{y_t(i)} p_t(i) y_t(i) - W_t l_t(i) \tag{5}$$

Subject to (4) and to the aggregate demand constraint:

$$y_t(i) = \left(\frac{p_t(i)}{P_t}\right)^{-\theta} Y_t$$

where W_t is the nominal wage, while P_t is the aggregate price index, defined as a function of the individual prices $p_t(i)$ as: $P_t \equiv \left[\sum_{j=1}^{N_t} p_{jt}^{1-\theta}\right]^{\frac{1}{1-\theta}} = \left[\sum_{i=1}^{S} N_t(i) p_t(i)^{1-\theta}\right]^{\frac{1}{1-\theta}}$.

In Online Appendix 2, we show that under this form of competition the optimal real price $\rho_t(i) = p_t(i)/P_t$ satisfies:

$$\rho_t(i) = \mu_t(i) \frac{w_t}{x(i)} \tag{6}$$

where $w_t = W_t/P_t$ is the real wage. As in Edmond, Midrigan, and Xu (2015), the markup $\mu_t(i)$ can be defined as a function of the market share $\omega_t(i)$, where $\omega_t(i) = \rho_t(i)^{1-\theta}$ given our structural assumptions about the sector(s). The markup $\mu_t(i)$ is:

$$\mu_t(i) = \left(\frac{\theta}{\theta - 1}\right) \left(\frac{1}{1 - \omega_t(i)}\right) \tag{7}$$

The markup's definition in equation (7) nests the monopolistic competition case: when $\omega_t(i) \to 0$, the resulting markup is the standard $\theta/(\theta - 1)$, independent from the number and type of competitors and from the idiosyncratic productivity level.

Our markup generalizes that result, and can be summarized as an extra idiosyncratic markup over the monopolistic benchmark, which increases in the relative productivity level and, thus, in the market share $\omega_t(i)$. Using equation (6) and the aggregate demand constraint, we can write the real profits for the firm with productivity $x(i)$ as:

$$d_t(i) = \left(1 - \frac{1}{\mu_t(i)}\right) \rho_t(i)^{1-\theta} Y_t \tag{8}$$

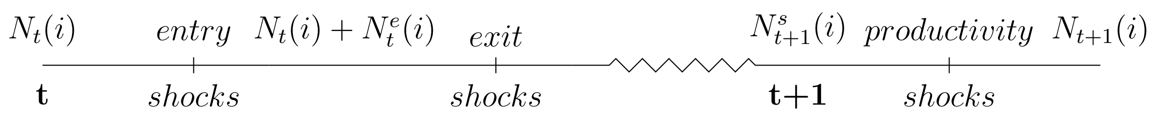
Profits $d_t(i)$ are increasing in the markup $\mu_t(i)$, with a lower bound on zero whenever $\mu_t(i) = 1$, as under perfect competition. Given that the markup is increasing in the

[5] Under the chosen specification, incumbents internalize that the quantity they select affects the sectoral output Y_t, but not the total expenditure $P_t Y_t$ allocated to consumption, as well as the wage of the economy.

market share, profits are increasing in the market share as well. The intuition is straightforward: a firm endowed with technology $x(S)$ and associated lowest marginal cost is able to charge the lowest relative price, with respect to the other incumbents. Because of its cost leadership, it gains largest market share and can charge, in turn, higher markups that generate higher profits.

3.1.2 Idiosyncratic Exit, Entry and Productivity Shocks

Firms are subject to idiosyncratic entry, productivity and exit shocks. At the beginning of period t, surviving incumbents from period $t-1$, $N_t^s(i)$, are hit by productivity shocks, whose ex ante type-specific probabilities are known and determined by a Markov process. Then, entry occurs and potential entrants also draw a productivity level, $x(i)$, which determines whether the firms can successfully enter the market. At the very end of period t, each firm can be hit by an idiosyncratic exit shock. The timing of the shocks' occurrence is summarized in the timeline and explained in detail below.



Before entering the market, each potential entrant draws a productivity level $x(i)$ from a discrete distribution function $f(x)$, the same as the incumbents'. With probability Ω_0, the potential entrant is successful, i.e. with probability $1-\Omega_0$ the firm draws the null productivity and cannot join the market. Given the number of potential entrants M_t, the number of successful entrants N_t^e follows a binomial distribution with success probability Ω_0 and M_t trials. Conditional on successful entry, there is a probability Ω_i of drawing the productivity level $x(i)$. Again, given N_t^e, the number of successful entrants of type i, $N_t^e(i)$, follows a multinomial distribution with N_t^e trials.

After the successful draw, and before knowing the exact productivity level assigned for period t, entry cost must be paid by each entrant in order to join the market. Real entry costs are measured in terms of units of labor and they are equal to $f_{e,t}w_t$.[6] The entry fee $f_{e,t}w_t$ is payed conditional on successful entry only. Firms enter the market up to the point where their expected value is at least equal to the cost of entry. The free entry condition is:

$$(1-\Omega_0)\,0 + \Omega_0 \left[\sum_{i=1}^{S} \Omega_i e_{i,t}(i) - f_{e,t}w_t \right] \geq 0 \tag{9}$$

where $e_{i,t}(i)$ is the value of the potential entrant when the productivity $x(i)$ is drawn. When considering entry, the marginal entrant internalizes that its action affects the (expected)

[6] Alternatively, we could have specified entry cost in terms of consumption. However, under this second specification, profits are increasing in entry, if entry is low enough.

number of operating firms in the following periods. As a result, the value of a potential entrant is different from the value of an incumbent of the same type. We differentiate the variables related to the entrants by subscript $_i$.

Importantly, entry triggers the *business stealing effect* as it has an impact on the expected sectoral price and, hence, on the expected profits and firm value and, it is a direct consequence of the assumption of the finite number of firms.

The number of potential entrants M_t is pinned down, in each period, by a sequential selection mechanism. Each potential entrant has the perfect knowledge of the market and its active competitors but does not know its own type or the types of other potential entrants. Given the number of incumbents and their type, the first potential entrant evaluates the entry condition in Equation 9. If the condition is positive, a second potential entrant decides if entry is still profitable, internalizing the entry decision of the first entrant. This selection continues until the condition turns negative for the potential entrants number M_{t+1}, and this pins down M_t.

At the very end of period t, each firm i can be hit by an idiosyncratic exit shock with a time invariant exogenous probability $\delta(i)$.[7] The exit shocks realize after the entry of new firms has occurred, and they can hit potentially every firm. As in Bilbiie et al. (2012), the entrants start producing only in the period that follows their entry so that new firms may be forced to leave the market even before being active.

After exit has occurred at the end of period t, the economy enters period $t+1$ with a given number of surviving firms of type (i) $N^s_{t+1}(i)$. Conditional on the number of survivors, the number of incumbents of each type in period $t+1$ is determined by the realization of idiosyncratic productivity shocks.[8] In particular, the number of firms endowed with the productivity $x(i)$ in period t which survives in period $t+1$, $N^s_{t+1}(i)$, follows a binomial distribution with success probability $1-\delta(i)$ and $N^e_t(i) + N_t(i)$ trials. Finally, given the number of survivors of each type, the realization of multinomial distributions determines the fraction of survivors endowed with productivity $x(i)$ that keeps their own productivity level, $N^i_{t+1}(i)$, against the number of survivors that switch to any of the remaining types j, $N^i_{t+1}(j)$.

[7]Exit is modelled as an exogenous shock due to our assumptions regarding types. Indeed, if we assumed fixed costs of production, the resulting threshold for break even would either wipe out all the firms in low-productive types or no firm at all. An alternative would be to let firms draw a fixed cost from a known distribution each period. However, if we allow the distribution to be type specific, this is isomorphic to our assumption about exogeneity.

[8]The law of large numbers cannot be used in our framework due to the finite number of firms. As a result, it is not possible to reduce the idiosyncratic stochastic processes to their expected values, making the aggregate exit, entry and productivity dynamics deterministic laws. Due to this feature, the law of motion of firms evolves according to (the realization of) binomial or multinomial distributions. This is the reason why we continue to talk about exit, entry and productivity dynamics as shocks.

3.2 Households

The household side of the economy is kept as simple as possible. The economy is populated by a continuum of identical households of unitary mass. The representative household consumes an aggregate consumption bundle c_t and supplies labor L_t. The quantity of labor supplied has two purposes: a fraction of the aggregate labor supply is employed in the production process and the remaining part is used to invest in new firms.[9]

The household can invest in a portfolio that represents the ownership of the firms, by purchasing shares x_{t+1}. Finally, the households receive the rents F_t from the investment fund which pays the entry costs for every successful entrant. The rents equal, thus, the difference between the total value of the entrants and the total entry costs paid.

The household maximizes her lifetime utility in real terms, U:

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \left(\ln c_t - \chi \frac{L_t^{1+\frac{1}{\phi}}}{1+\frac{1}{\phi}} \right) \tag{10}$$

where c_t and L_t are aggregate consumption and labor supply, as defined above, $0 \leq \beta \leq 1$ is the discount factor, $\chi \geq 0$ is a scale parameter for the disutility of labor, useful for calibration, and $\phi > 1$ represents the elasticity of labor supply. The maximization is subject to the budget constraint:

$$c_t + x_{t+1} V_{t+1,t} = L_t w_t + x_t V_t + F_t \tag{11}$$

For the sake of clarity, the period t value of the entire portfolio, gross of dividends, is represented here by V_t, while $V_{t+1,t}$ describes the period t value of the new portfolio purchased in period t to be carried to period $t+1$. Given the definition above, $w_t L_t$ describes the total labor income.

The value of the portfolio is the sum of the net-of-dividend value of the portfolio in period t, A_t, and dividends payments, D_t:

$$V_t = A_t + D_t = \sum_{i=1}^{S} \left[e_t(i) + d_t(i) \right] N_t(i) \tag{12}$$

[9] In the standard model with monopolistic competition, the marginal entrant has atomistic mass. Hence, in equilibrium: $\sum_{i=1}^{S} e_t(i) N_t^e(i) = \sum_{i=1}^{S} e_{i,t}(i) N_t^e(i) = N_t^e w_t f_{e,t} = w_t L_t^e$, where L_t^e is the fraction of labor supplied used to repay entry costs. However, in this setting, $e_t(i) \neq e_{i,t}(i)$ and profits possibilities are not exploited completely due to the integer nature of the number of competitors and entrants. Due to these issues, we must assume the existence of an investment fund. The fund creates new firms at their costs and sell them at their higher value to the households. Given that profit possibilities are not exhausted, the fund makes profits, and these rents are distributed as lump sum transfers to the households, closing the budget constraint. With the introduction of the fund, in equilibrium we still have that the labor supply that is used to invest in new firms, i.e. L_t^e, is equal to $N_t^e f_{e,t}$.

Entry occurs in the beginning of period t, when the representative household purchases the portfolio to be brought to period $t+1$. Because this happens before the exit shock occurs (end of period t), the household does not know the number of surviving firms and finances them all. The value of the purchased portfolio is:

$$V_{t+1,t} = \sum_{i=1}^{S} e_t(i) \left[N_t(i) + N_t^e(i) \right] \tag{13}$$

Finally, for completeness, the rents received by the intermediary are equal to the following (note that they do not affect the maximization of the household being a lump sum transfer):

$$F_t = \sum_{i=1}^{S} e_t(i) N_t^e(i) - N_t^e w_t f_{e,t}$$

Given that $c_t = 1/\lambda_t$, the F.O.C. with respect to L_t is:

$$\chi L_t^{\frac{1}{\phi}} c_t = w_t \tag{14}$$

By combining the F.O.C.s with respect to c_t and x_{t+1}, the following equation can be written:

$$V_{t+1,t} = \beta E_t \left[\left(\frac{c_t}{c_{t+1}} \right) V_{t+1} \right] \tag{15}$$

This condition is equivalent, in expectation, to the following Euler equations for assets value that derive from the definition of $e_t(i)$, similar to the one for $e_{i,t}(i)$, and of the stochastic discount factor $\Lambda_{t+1,t}$ as $\beta \frac{c_t}{c_{t+1}}$:[10]

$$e_t(i) = \beta \left(1 - \delta(i)\right) E_t \frac{c_t}{c_{t+1}} \left[\sum_{j=1}^{S} q_{ij} \left(d_{t+1}(j) + e_{t+1}(j) \right) \right] \tag{16}$$

for $i = 1, 2, ..., S$.

3.3 Aggregation

In equilibrium, the representative household holds the entire portfolio of firms, i.e. $x_{t+1} = x_t = 1$. Using the definition of F_t the following resource constraint can be obtained:

$$c_t + N_t^e w_t f_{e,t} = L_t w_t + \sum_{i=1}^{S} d_t(i) N_t(i) \tag{17}$$

[10]This is true provided that $E_t \beta \frac{c_t}{c_{t+1}} (e_{t+1}(i) + d_{t+1}(i)) E_t N_{t+1}(i) = E_t \beta \frac{c_t}{c_{t+1}} (e_{t+1}(i) + d_{t+1}(i)) N_{t+1}(i)$

From the definition of the aggregate output, we obtain aggregate labor supply:

$$L_t = L_t^p + L_t^e = N_t^e f_{e,t} + \sum_{i=1}^{S} l_t(i) N_t(i)$$

where L_t^p represents the labor employed for production, L_t^e the one used to finance entry. Finally, from the definition of the aggregate price:

$$1 = \sum_{i=1}^{S} N_t(i) \rho_t(i)^{1-\theta} \tag{18}$$

and

$$Y_t = c_t \tag{19}$$

3.4 Risky steady state

Due to the assumption regarding the finite number of firms, paired with stochastic entry, exit and productivity dynamics, the standard definition of the deterministic steady state, where entry perfectly balances exit, cannot be applied. Building on Coeurdacier, Rey, and Winant (2011) and Juillard (2011), we derive instead a version of the *Risky Steady State*. The proposed equilibrium with risk-neutral agents describes a state in which no shocks occur but economic agents take into consideration the possibility that the shocks might happen in the future. In the steady state, households invest in entry up to the point where it compensates the *expected* exit, thus keeping the number of incumbents and entrants constant over time in expectation.[11] As in the calibration below, we consider a particular case in which the number of active types S is equal to 3.

The definition of the *Risky Steady State* follows. Given the steady state value for the exogenous entry costs f_e, and given the calibration of the exogenous parameters, the steady state is the set $\{\rho(i), w, d(i), Y, N(i), N^e(i), N^e, M, e(i), L, c\}$ with $i = 1, 2, 3$ that solves the system of equations described in Appendix C. Note that this deterministic equilibrium holds in expectation, since we consider the expected realizations of the stochastic processes. Because of that, no restriction is put on the integer nature of the variables relative to the number of firms (incumbents and entrants). This means that a marginal entrant can be of infinitesimal size, as the free entry condition closes: the effect of its entry on the mass of competitor is negligible. Given that, marginally, entry does not affect the sectoral price and the profits here, the value of an incumbent or of a potential entrant of the same type is equivalent.

[11] The steady state we present here is the one that would also emerge under the assumption of oligopolistic competition within sectors and continuum of sectors in aggregate, in the spirit of Atkeson and Burstein (2008).

4 Calibration

Our key quantitative exercise compares the transition paths between two steady states in two types of sectors. The initial and common steady state of the economy is calibrated to reproduce key features of the U.S. industries between 1960 and 1980, the period with relatively low and stable market power of firms and turbulence. The values of the internally and externally calibrated parameters are presented in Table 1. Since the two permanent shocks are the key drivers of the model dynamics, we pay particular attention to their calibration and present their values before and after the shocks in a separate table (Table 2).

To keep the analysis tractable, the discrete distribution function of productivities consists of four mass points: $x(0)$, $x(1)$, $x(2)$ and $x(3)$, with $x(3) > x(2) > x(1) > x(0)$. Thus, we keep track of four types of firms and three active types: $S = 3$. The choice of $S = 3$ is based on the fact that the firms differ little from each other within different percentiles of the size distribution and the main differences can be found between the very top firms and the rest, Crouzet, Mehrotra, et al. (2017). The null productivity mimics the presence of fixed costs of production, which are not introduced explicitly in the model.

Each period t represents a quarter and the discount factor β is fixed at the value of 0.99, implying an annual interest rate of approximately 4%. The parameter that governs the elasticity of substitution between goods, θ, is set to 10, in line with the estimates from Edmond et al. (2015).

The elasticity of labor supply ϕ is equal to 0.5, as in Boar and Midrigan (2019). We normalize the multiplier for the disutility of labor, χ, to a value such that the labor supply in the final steady state for the high-turbulence sector is equal to 1. Under this specific calibration, in the baseline experiment $\chi \approx 0.88$. The remaining internally calibrated parameters are set to match the key U.S. economy quantities.

4.1 Productivity levels, entry and exit probabilities

In the data, firm-level productivities are distributed under a power law. To accommodate this fact, we assume that the function $f(x)$ is the discrete counterpart of a continuous Pareto distribution with a minimum at 1 and a tail parameter $\kappa = 1.05$.[12] This results in three productivity levels $x(1) = 1.315$, $x(2) = 4.631$ and $x(3) = 80.309$, which reflect the underlying assumption about firms' productivity: they represent, respectively, the 25^{th} percentile, the 80^{th} percentile and 99^{th} percentile of the Pareto distribution. Similarly, the ex-ante probability of being a successful entrant, Ω_0, is equal to 0.75, reflecting the

[12] Axtell (2001) estimates a tail parameter of 1.059.

assumption that an entrant is successful whenever a productivity higher than $x(1)$ is drawn from the continuous Pareto distribution. This implies that $\Omega_0 = Pr[x \geq x(1)]$, which gives $\Omega_0 = 0.75$. Given that Ω_2 and Ω_3 represent, respectively, the conditional probability of drawing productivity level $x(2)$ and $x(3)$ for a successful entrant, they are set to 0.2533 and 0.0133.[13] Given this calibration, $x(3)$ describes large and highly productive firms, $x(2)$ medium-large incumbents and $x(1)$ unproductive small to medium firms.

The parameter that determines the likelihood of an exit shock for type 3 firms, $\delta(3)$, is calibrated to 0.005, the quarterly exit rate of top 1% firms in terms of size from the BDS dataset, see Tian (2018).

In order to identify all the entries of Markov transition matrix, that governs the degree of turbulence in a sector, we need to impose a set of restrictions. Our identification strategy relies on the assumption that the most productive firms are a subset of highly-productive type-2 firms and, therefore, both types share some characteristics. Accordingly, we assume that exit probabilities are the same, i.e. $\delta(2) = \delta(3) = 0.005$, and that the probabilities of receiving a detrimental productivity shock that lowers the productivity level to $x(1)$ are equal for both types as well, $q_{31} = q_{21}$.[14] Following Tian (2018), we set $\delta(1)$ to 0.03. Note that, although not targeted, this calibration, together with the Markov transition described below, delivers a yearly business destruction rate of approximately 10%, as in Colciago (2016).

4.2 Increase in turbulence and entry costs

We model two major changes that started to take place in the U.S. economy in the 1980s. The first one is the sector-specific increase in turbulence, and the second is the common increase in entry costs.

Sectoral Turbulence

In Compustat data, we split the sectors into 2 types according to Equation (1). Both types of sectors exhibit a stable turbulence of 0.21 (5-year Spearman rank correlation of 0.79) before the 1980s. Accordingly, in both sectors' initial steady states, the Markov transition matrix, once iterated, displays a 5-year Spearman rank correlation of 0.79. In contrast, after the 1980s, we see a strong heterogeneity between the two types: in high-turbulence sectors, there is a structural break in the mean of turbulence, and the 5-year

[13] Since $\Omega_2 = Pr[x \geq x(2) \wedge x \leq x(3) | x \geq x(1)] = \frac{0.19}{\Omega_0} = 0.2533$ and $\Omega_3 = Pr[x \geq x(3) | x \geq x(1)] = \frac{0.01}{\Omega_0} = 0.0133$.

[14] A different approach would be to set $q_{31} = 0$, as we do later for q_{13}, and to iterate the Markov process to pin down q_{21}, given $\delta(2)$ and $\delta(3)$.

Table 1: **Calibration of fixed exogenous parameters**

Parameter	Calibration	Target
S	3	Four types of firms, three active
β	0.99	$\approx 4\%$ yearly interest rate
θ	10	Edmond et al. (2015)
ϕ	0.5	Elasticity of labor supply in Boar and Midrigan (2019)
χ	0.88	Aggregate labor supply = 1 in high-turbulence
$x(1)$	1.315	25^{th} percentile in a Pareto with $\kappa = 1.05$
$x(2)$	4.631	80^{th} percentile in a Pareto with $\kappa = 1.05$
$x(3)$	80.309	99^{th} percentile in a Pareto with $\kappa = 1.05$
Ω_0	0.75	$Pr[x > x(1)]$ under Pareto with $\kappa = 1.05$
Ω_2	0.2533	$Pr[x \geq x(2) \wedge x \leq x(3) \vert x \geq x(1)]$ under Pareto with $\kappa = 1.05$
Ω_3	0.0133	$Pr[x \geq x(3) \vert x \geq x(1)]$ under Pareto with $\kappa = 1.05$
$\delta(1)$	0.03	$\approx$ Exit rate for small firms in BDS, Tian (2018)
$\delta(2)$	0.005	$= \delta(3)$ for identification strategy
$\delta(3)$	0.005	$\approx$ Exit rate for top 1% firms in BDS, Tian (2018)

Notes: The table presents the calibration of the exogenous parameters. The second column describes the value assigned to the parameters. The third column describes the targets of the calibration. These parameters are kept fixed along the entire transition in every simulation.

Spearman rank correlation drops from 0.79 to 0.62. There is only a small reduction in the 5-year Spearman rank correlation in the low-turbulence sectors, and this reduction is not significantly different from zero. Therefore, in the low-turbulence sector, the degree of turbulence remains the same for the entire transition. In the high-turbulence sector, the productivity process parameters are recalibrated to match the change in the target, namely, the decline in 5-year Spearman rank correlation from 0.79 to 0.62. This implies turbulence of 0.38 in the second steady state of high-turbulence sector.

The calibration of the elements of the Markov matrices is the following. First, we pin down the ex-ante probability that a top-20% firm never leaves its leadership position for 5 years: $[(1-\delta(2))(1-q_{21})]^{20}$. We calibrate it to match the turnover probability from Comin and Philippon (2005), a 5-year top firms turnover of 0.1 in 1980 and 0.27 in 2005. This delivers $q_{21} = q_{31} = 2.5545e^{-04}$ for the common initial steady state and $q_{21} = q_{31} = 0.0107$ for the high-turbulence final steady state. Using the values for q_{21} and q_{31}, we calibrate the remaining elements of the Markov matrix by matching the 5-year productivity rank Spearman correlation, for high (0.62) and low-turbulence sectors (0.79). The values of all the Markov entries are reported in Table 2. Additional details are presented in Appendix D.

Increase in entry costs

Measuring entry cost is inherently difficult. In our calibration, we proceed as follows. First, we set the initial entry costs to match the number of incumbents in a typical U.S. 4-digit or 6-digit NAICS sector. Second, we target the existing proxies for the increase in entry costs in the data. Specifically, in the initial steady state, entry costs are normalized to 0.05. In the benchmark exercise, we set the increase in entry costs to 100% so that after the shock entry cost equals 0.1.[15]

We choose a 100% hike in entry costs, as it represents the magnitude implied by (i) the increasing required investment in R&D and (ii) the observed growth in the complexity of regulation.

Table 2: **Calibration of the key exogenous parameters pre and post-shift**

Parameter	Pre-shock	Post-shock	Target
f_e	0.05	0.1	Bloom et al. (2020) and Gutiérrez et al. (2019)
q_{11}	0.9883	0.9734	5-year correlation = 0.79 pre-shock and = 0.62 post
q_{12}	0.0117	0.0266	$1 - q_{11}$
q_{13}	0	0	Assumption for computational purposes
q_{21}	$2.5545e^{-04}$	0.0107	5-year leaders turnover = 0.1 pre-shock and = 0.27 post
q_{22}	0.9866	0.9704	5-year correlation = 0.79 pre-shock and = 0.62 post
q_{23}	0.0131	0.0189	$1 - q_{21} - q_{22}$
q_{31}	$2.5545e^{-04}$	0.0107	$= q_{21}$ for identification strategy
q_{32}	0.0131	0.0162	$1 - q_{31} - q_{33}$
q_{33}	0.9866	0.9731	5-year correlation = 0.79 pre-shock and = 0.62 post

Notes: The table presents the calibration of the remaining exogenous parameters. The numerical targets for the turnover are taken from 1980 (pre-shock) and 2005 (post-shock) estimates in Comin and Philippon (2005), as well as our empirical estimates from 1960 to 2015.

One way of interpreting the entry costs in our model is as the foregone labor force required to introduce a new variety in the economy. Bloom, Jones, Van Reenen, and Webb (2020) estimate a sharp increase in the number of effective workers employed in R&D in the U.S., required to sustain a stable technological growth when the research productivity is decreasing. They show that the number of researchers more than doubled between 1980 and 2000. Assuming that R&D is (also) used to create new varieties/products, this implies a 100% increase in entry costs in our framework.

Davis (2017) and Gutiérrez et al. (2019) show that the main driver of the recent increase in barriers-to-entry is the growing complexity of regulation. The median number of regulatory clauses, a proxy for the complexity of regulation and, thus, entry costs, more

[15] We additionally calibrate the model with a smaller increase in entry costs of 0.06, which is used to match the decline in the number of entrants in BDS between 1980 and 2016. As in the data, this calibration delivers a 15% reduction in entrants. Our qualitative results are robust to this more conservative calibration.

than doubled during our sample period, suggesting more than 100% increase in entry costs. These are the targets for our calibration.

5 Model simulations

In our main quantitative exercise, we study the transition dynamics between two steady states of two different sectors. In both sectors, the initial steady state is the same and corresponds to the period pre-80s, when the markups and other measures of U.S. market concentration were low. We then assume that in both types of sectors entry costs go up. In the high-turbulence sector, we additionally increase the turnover of firms over the productivity distribution by imposing a sector-specific turbulence shock.

To highlight the key mechanism, we compute the stationary distributions of productivity types implied by the Markov process only, before and after the change in turbulence, and report them in Table 3.[16] $x(1) - x(3)$ are the frequencies of each firm type. Before the shift, both type-2 and type-3 are equally likely and only a small probability of being type-1 firms exists ($x(1) = 0.021$). After the increase in turbulence that rises the likelihood of movements in productivity ranks, type-1 is more frequent ($x(1) = 0.286$) and the volatility of type is almost twice as high as before the shift ($\sigma = 0.291$ versus $\sigma = 0.581$). The stationary distribution after the shift in turbulence implies therefore a more dynamic environment.

Table 3: **Stationary distribution of firm types pre and post increase in turbulence**

Parameter	Pre-shock	Post-shock
$x(1)$	0.021	0.286
$x(2)$	0.494	0.419
$x(3)$	0.485	0.295
EV	2.464	2.009
σ^2	0.291	0.581

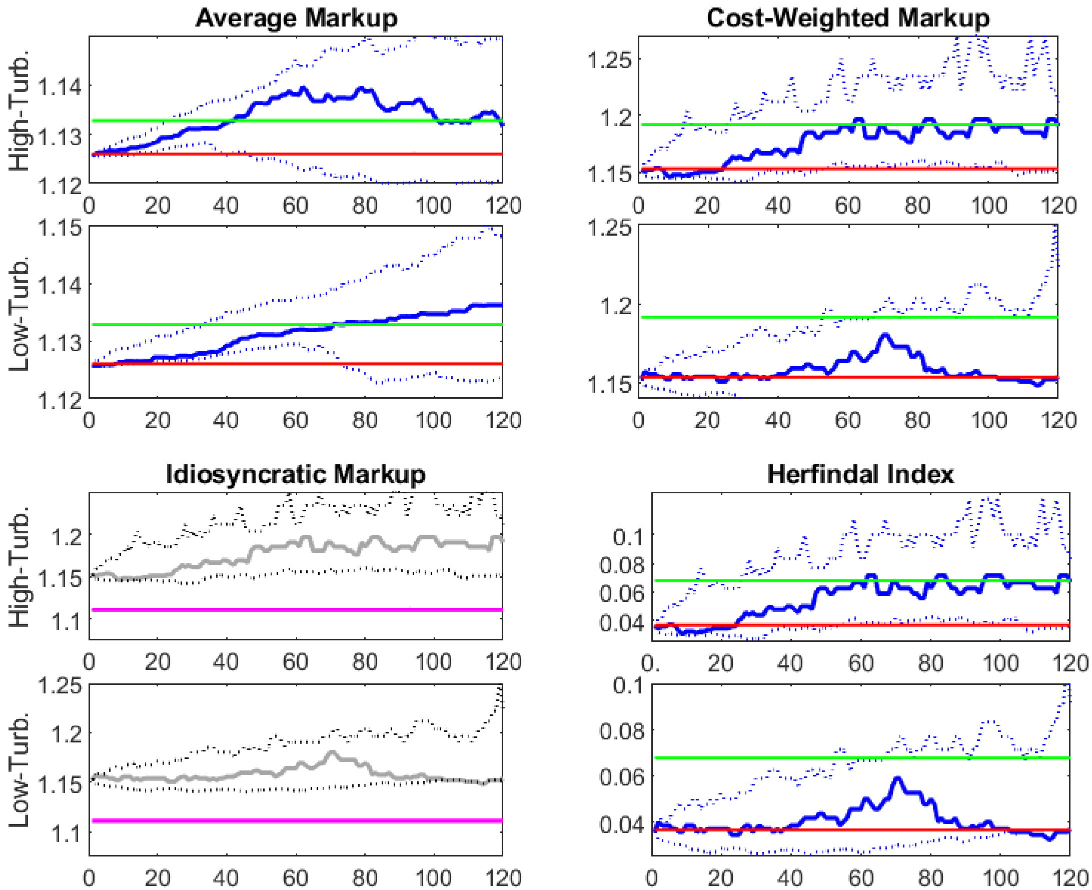
Notes: The table describes the stationary distributions of firm productivity types implied by the Markov before and after the increase in turbulence. $x(1) - x(3)$ are the frequencies of each firm type, EV is the expected value of type, and σ^2 is type's variance.

5.1 Transition dynamics in a high versus low-turbulence sector

We solve the model using the original algorithm described in detail in Online Appendix 4. We simulate the model economy over 120 periods (30 years) and repeat the experiment 100 times to build confidence intervals. We present the results of one simulation instead

[16]The *true* stationary distribution of the model entails somewhat different firms' shares, as it also internalizes the presence of heterogeneous entry and exit shocks.

Figure 5: Evolution of concentration and markups, high vs low-turbulence sector.



Notes: The graph presents the response of the sectors to a common increase in entry costs and a sector-specific increase in turbulence, in the high-turbulence sector only. The blue solid lines describe the dynamics of the variables over time, and the dotted blue lines their confidence intervals. The red and green lines represent, respectively, the initial and the final steady state for the high-turbulence sector. In the left-bottom panels, the grey lines represent the individual markups charged by the firms endowed with the highest productivity type, while the purple line describes the median markup.

of averaging over 100 to preserve the properties deriving from our assumption about the finite number of firms. Each one of 100 simulations can be interpreted as one sector in an economy.[17]

Figure 5 presents the paths of the key variables of interest: market concentration and price markups. The first two rows of the figure plot the evolution of sectoral markups in high (first row) and low-turbulence sectors (second row) computed in two different ways: (i) arithmetic average markup and (ii) cost-weighted markup. The average markup increases in both types of sectors. This trend is mainly driven by higher entry cost that

[17]We also implement an alternative simulation where, instead of a one-time shift, the growth in entry cost and turbulence follows progressive, empirical paths. The results of this exercise are qualitatively similar to the ones presented here and they are described in Appendix E.

results in a change in the composition of firms in the sector. In particular, increasing entry costs prohibit type-1 firms from joining the market and their relative number declines in favor of high-markup, type-3 firms.

The cost-weighted markup, presented in the 2 top-right panels of Figure 5 behaves differently, conditional on the sector type. In high-turbulence sector, it increases by 4.5% but only by 1.5% in the low-turbulence sector.[18] The intuition is as follows. Higher turbulence increases the likelihood of changing type for all firms. However, since the type-3 firms cannot become more productive, by definition, higher turbulence only raises their chances of moving downwards in the productivity ranks or exiting the market. If this happens, a large available market share is captured by other type-3 firms.

The increase in cost-weighted markup in high-turbulence sector is therefore driven by the high-markup firms via two mechanisms. First, the available market shares are reallocated to the most productive high-markup firms. Second, given their growing market shares, those firms charge even higher markups. In the next section, we evaluate the importance of each of these channels.

The lower panels of Figure 5 corroborate the intuition that the dynamics of the cost-weighted markups are mainly driven by high-markup firms. Two lower-left panels plot individual markups in high and low-turbulence sectors. The grey solid line shows the evolution of the markup of type-3 firms, whose increase is closely mirrored by the sectoral cost-weighted markup (top-right panel of Figure 5). In contrast, the median firm (purple solid lines) always charges the monopolistic competition markup of 1.11, because of its atomistic market shares. The impact on the dynamics of aggregate markup is therefore negligible. This is similar to the data, where the median markup has been constant over the last several decades, while the increase in the average markup has been driven by growing markups of the top firms, see De Loecker et al. (2020).

Both higher entry costs and turbulence contribute to the reduction of the number of firms operating in the market. The declining number of firms translates into a growing Herfindahl index (HHI) over the transition to the second steady state, in both sectors (bottom-right panels in Figure 5). The increase in high-turbulence sector is however twice as large as in the low-turbulence sector.

6 Model versus data

We study how well the model captures the market power dynamics across industries in two following ways. First, we evaluate the importance of reallocation and within components

[18] These numbers are somewhat different when comparing the changes between 2 steady states and they are presented in Table 4.

in the markups growth. To do it, we apply Haltiwanger (1997)'s decomposition to the model's markups in high and low-turbulence sectors and contrast it with the markup's decomposition in Compustat NAICS-3 digid sectors. Second, we compute a set of untargeted unconditional moments in our simulated sectors and compare them with their empirical counterparts.

6.1 Reallocation of market shares

The growth of the revenue-weighted markup between period t and $t-1$, $\Delta\bar{\mu}_t^R$, can be written as:[19]

$$\begin{aligned}
\Delta\bar{\mu}_t^R &= \sum_{i=1}^{3} N_t(i)\omega_{t-1}(i)\frac{\theta}{\theta-1}\left(\frac{1}{1-\omega_t(i)}-\frac{1}{1-\omega_{t-1}(i)}\right)+ \\
&+ \sum_{i=1}^{3} N_t(i)\left(\frac{\theta}{\theta-1}\frac{1}{1-\omega_{t-1}(i)}-\bar{\mu}_{t-1}^R\right)(\omega_t(i)-\omega_{t-1}(i))+ \\
&+ \sum_{i=1}^{3} N_t(i)\frac{\theta}{\theta-1}\left(\frac{1}{1-\omega_t(i)}-\frac{1}{1-\omega_{t-1}(i)}\right)(\omega_t(i)-\omega_{t-1}(i))+ \\
&+ \sum_{i=1}^{3} N_t^e(i)\omega_t(i)\left(\frac{\theta}{\theta-1}\frac{1}{1-\omega_t(i)}-\bar{\mu}_{t-1}^R\right)-\sum_{i=i}^{3} N_{t-1}^{ex}(i)\omega_{t-1}(i)\left(\frac{\theta}{\theta-1}\frac{1}{1-\omega_{t-1}(i)}-\bar{\mu}_{t-1}^R\right)
\end{aligned} \tag{20}$$

where N_t^{ex} is the number of exiting firms in period t.

The within changes (first line of Equation 20) represent variations in the average markup driven by changes in the firm-level markups, keeping the market shares constant at the previous period level.[20]

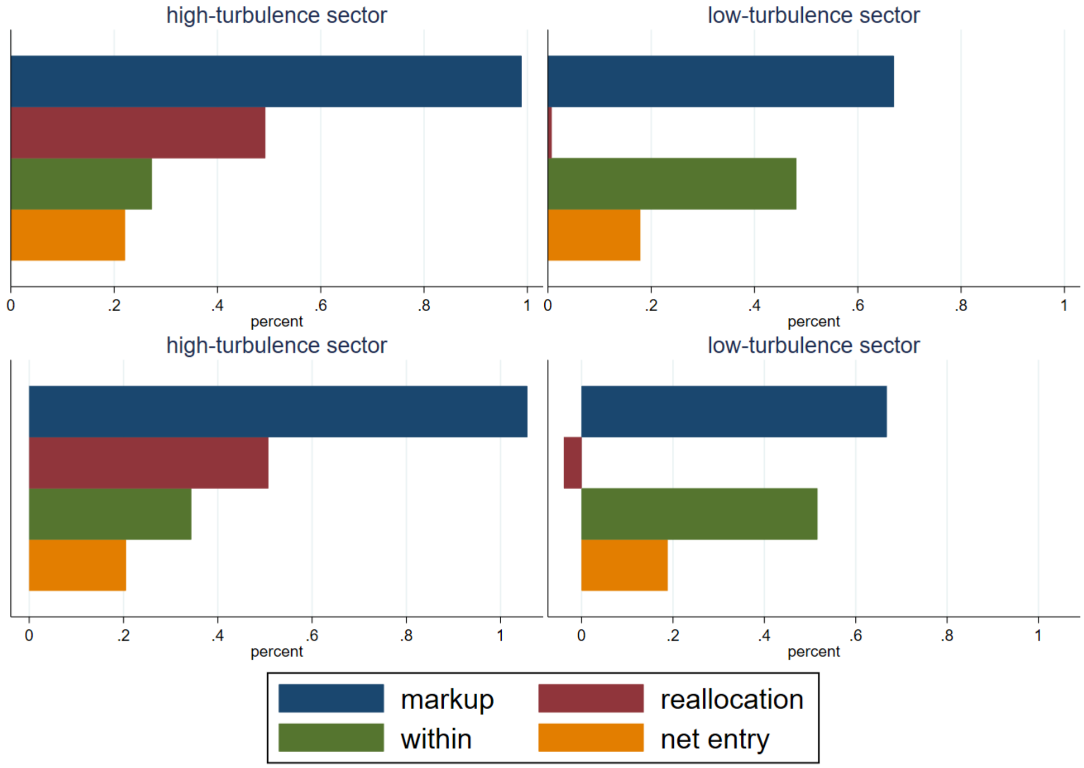
The reallocation of market power (between changes) are captured by the second and third lines of Equation 20, which represent: (i) changes in average markup induced by pure changes in market shares, keeping markups constant, and (ii) cross-terms changes. The last line of 20 describes changes driven by net entry.

We apply a similar decomposition to the average markups' changes in high and low-turbulence sectors in Compustat data, between 1980 and 2016, keeping in minds that the

[19]We follow De Loecker et al. (2020) and decompose the revenue-weighted average. Note that, in our framework, quantitative results are virtually unchanged when using the cost-weighted average.

[20]There is a drawback of this decomposition in the context of our model. Individual markups are a function of market shares only. As a result, changes in market shares directly translate into the changes in markups and hence appear as the *within* component. Consequently, the importance of the within channel is likely to be overestimated by construction. We keep it in minds when interpreting the results of the decomposition.

Figure 6: Decomposition of the average change in markups in high versus low-turbulence sectors between 1980 and 2016 in Compustat.



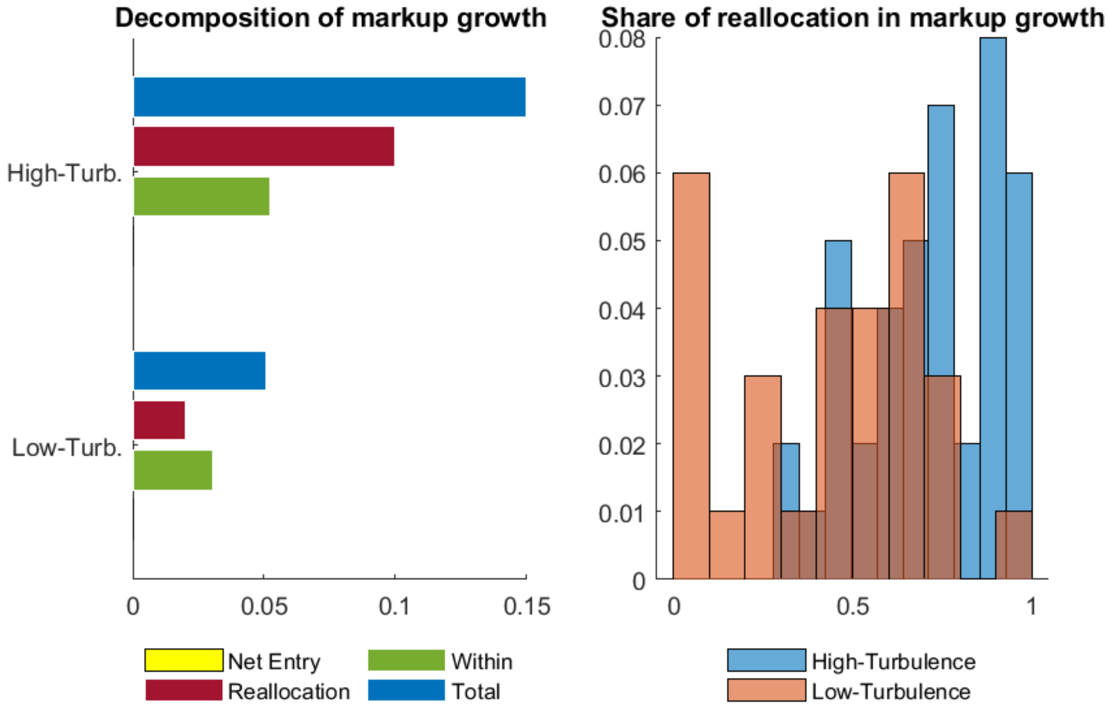
Notes: The figure presents the decomposition of the average change in the revenue-weighted markups μ_2 and μ_4 in high-turbulence (top panel) and low-turbulence sectors (bottom panel). To decompose the markup's increase, we follow Haltiwanger (1997). The construction of μ_2 and μ_4 is described in Appendix A.

net entry component is not meaningful.

Figure 6 shows the decomposition of two different markups in Compustat (μ_2 and μ_4 from section 2.2) and the left panel of Figure 7 displays a similar decomposition of the markup in the model. There is a striking difference between sectors in the way their markups' growth is generated. In the data, in high-turbulence sectors, half of the increase comes from the reallocation of market shares towards high-markup firms. In the model, an even larger share of markups' average growth is derived from the reallocation of market shares. In contrast, both in the data and in the model, markups in the low-turbulence sectors are primarily driven by the growth of the markups of the incumbents (within component).

Since the results presented in the left panel of Figure 7 are based on one simulated sector, the right panel of Figure 7 also shows the importance of reallocation component in markups growth in each of 100 simulations. The figure plots the distribution of the

Figure 7: Decomposition of the average change in markups in high versus low-turbulence sectors in the model.



Notes: (Left panel) the graph presents the decomposition of the average change in sectoral markup in high-turbulence sectors (top) and low-turbulence sectors (bottom). The decomposition is based on one representative simulation from our baseline model. (Right panel) the graph shows the frequency of the shares of the reallocation component in markups' growth in high and low-turbulence sectors, over 100 simulations.

shares of the reallocation component in the markup's growth in simulated high-turbulence sectors (blue) and low-turbulence sectors (red). While reallocation of market shares occurs in both types of sector, only in the one with higher turbulence it is frequently the largest driver of markups growth.

We provide additional empirical support for the main mechanism driving increase in markups using CompNet. In Appendix B, we show that in 7 European countries (i) stronger reallocation of the market shares is associated with higher turbulence and (ii) in sectors with higher reallocation of market shares the markups grew the fastest.

6.2 Untargeted moments

To assess the model's ability to replicate data behavior over time and across sectors, Table 4 reports the moments along two dimensions. The top panel of Table 4 presents statistics based on time-series and the lower panel in cross-section. The top panel summarizes to what extent the model can capture growth in the market power proxies. In the data, the variables indicated as Δx_T correspond to cumulative changes in the median variable x between 1980 and 2016. In the model, the changes Δx_T are computed as cumulative changes in the variables of interest between the two steady states. The last two columns of Table 4 report the ratios between high and low-turbulence sectors. The lower panel of Table 4 reports the dispersion in the market power variables with $\sigma_{\Delta x_T}$ being a standard deviation of the cumulative changes of the variable x. To calculate the dispersion of a variable of interest in the model, we simulate it 100 times for each type of sector and compute the standard deviation across all the realisations.

The top panel of Table 4 reports the increase in two measures of market power: cost-weighted markups and revenue-weighted profit rates. We compute markups in four different ways, described in Appendix A. For all those measures, the cumulative growth rates are higher in high-turbulence than low-turbulence sectors. The median increase in markup in high-turbulence sectors is between 6.13% and 10.08% and in the model equals 3.5% implying that our model can explain between 35% and 57% of the observed increase, depending on the markup's measure. In the low-turbulence sector, the increase is between 3.83% and 6.84% and the model explains between 38% and 68% of it.

Any conclusions regarding whether market power increased depend on the patterns of the costs of firms. Therefore, in addition to the evolution of markups, we analyze relative profit rates. At the firm level, they are computed as sales minus total costs of production (production including overhead and capital expenses) and they are weighted by relative sales in a NAICS 3-digit sector.

The last row of the top panel of Table 4 reports the cumulative change in the profit rates. The observed increase in profit rates are substantially higher than in markups and reach 24% in high-turbulence sector and 16.19% in low-turbulence sector in Compustat and 21% and 17% in the model. Intuitively, in a high-turbulence sector, the increasing market shares allow the most productive firms to charge the highest markups and profits. In a low-turbulence sector, the growth of the most productive firms in terms of size is lower and so are their profits.

The last two columns of the table indicate that the model delivers even better predictions for the relative growth in market power proxies across sector types.

The bottom panel of Table 4 shows how well the model matches the data in cross-section. Specifically, we compute the standard deviation of the cumulative changes in markups $\sigma_{\Delta\mu_T}$ and profit rates $\sigma_{\Delta d_T}$. Markup's cumulative growth dispersion in the model somewhat underestimates the one in the data. However, the model captures well the relative dispersion between the sectors which is between 1.5 and 2 times as high in the

Table 4: **Model versus data: high-turbulence versus low-turbulence**

	Over-time					
	High-turbulence		Low-turbulence		Ratio	
	Data	Model	Data	Model	Data	Model
$\Delta\mu_T^1$	6.13	3.50	5.56	2.60	1.10	1.35
$\Delta\mu_T^2$	8.02	3.50	5.54	2.60	1.48	1.35
$\Delta\mu_T^3$	9.47	3.50	6.84	2.60	1.38	1.35
$\Delta\mu_T^4$	10.08	3.50	3.83	2.60	2.63	1.35
Δd_T	23.98	21.06	16.19	17.03	1.48	1.24
	Cross-section					
	High-turbulence		Low-turbulence		Ratio	
	Data	Model	Data	Model	Data	Model
$\sigma_{\Delta\mu_T^1}$	0.554	0.016	0.246	0.007	2.252	2.178
$\sigma_{\Delta\mu_T^2}$	0.404	0.016	0.283	0.007	1.425	2.178
$\sigma_{\Delta\mu_T^3}$	0.554	0.016	0.246	0.007	2.252	2.178
$\sigma_{\Delta\mu_T^4}$	0.501	0.016	0.281	0.007	1.785	2.178
$\sigma_{\Delta d_T}$	2.094	0.298	1.461	0.248	1.431	1.200

Notes: This table reports untargeted moments in high-turbulence relative to low-turbulence sectors, in Compustat NAICS 3-digit sectors between 1980 and 2016. Δx_T denotes the cumulative changes in variable x. μ is cost-weighed markup. d is the revenue-weighted profit rate and $\sigma_{\Delta x_T}$ reports cross-sectional dispersion of cumulative changes in variable x across sectors. The last two columns report the ratios between high and low-turbulence sector for the variable of interest.

high turbulence sector as in the low-turbulence one. The dispersion of cumulative profit rates is about 40% higher in high-turbulence sectors in the data and 20% higher in the model (last row of Table 4).

While the model underestimates the dispersion of the market power variables across sectors, it matches rather well the observed cumulative changes in those quantities and their heterogeneity across sectors.

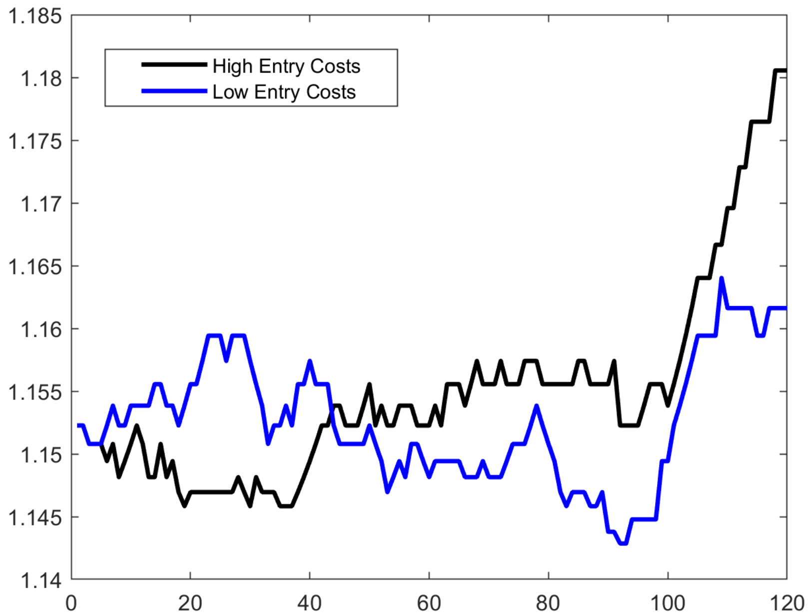
7 Heterogeneous entry costs

An increase in entry costs is known to deteriorate competition. So far, we have assumed that both sectors experience an increase in entry cost of the same magnitude. However, if high-turbulence sectors are characterized by a higher increase in entry costs, this could drive a stronger increase in market power, without resorting to the turbulence shock.

We investigate this competing hypothesis in an exercise where one sector experiences the increase in entry cost of the same magnitude as in the baseline simulation, while in the second sector the increase is half as large. None of the sectors experiences the turbulence shock. All the other parameters of the model are set to the same values as in the baseline exercise.

Figure 8 plots the paths of the markups in the two sectors generated by this alternative

Figure 8: Comparison of markups, heterogeneous increase in entry costs.



Notes: The graph plots the markups in a sector with high entry cost (black line) and low entry cost (blue line).

simulation. The blue line is the markup of the sector that experiences a lower increase in entry costs.

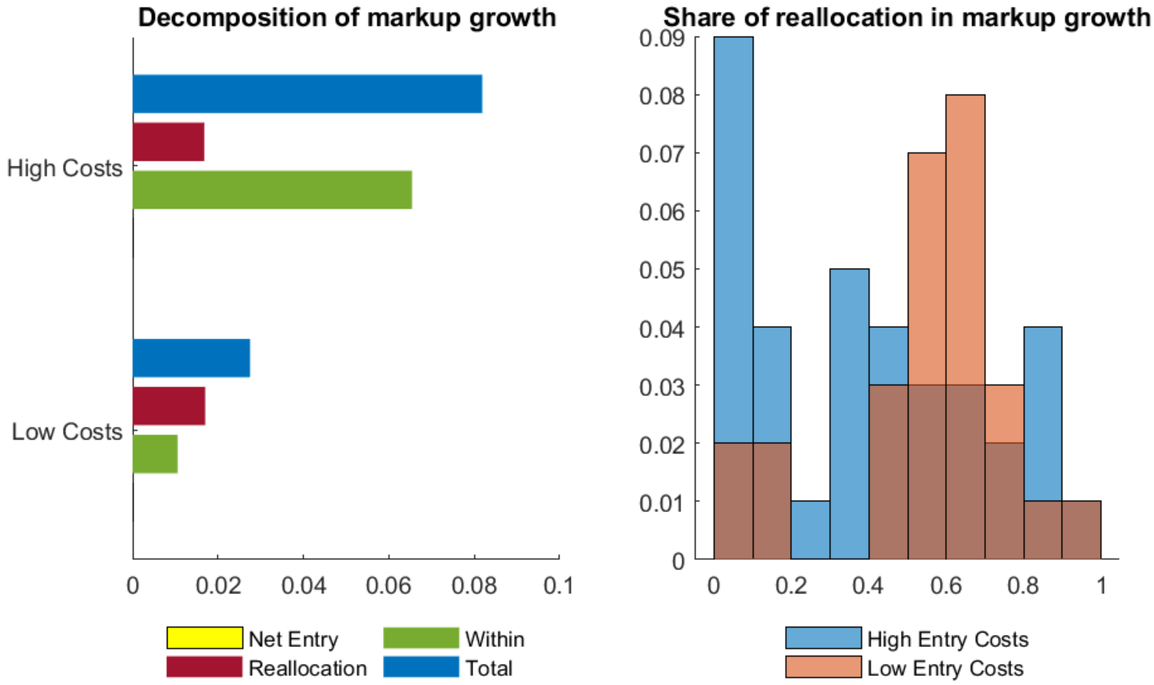
An uneven increase in entry costs fails to mimic the data patterns in two dimensions: (i) reallocation of market shares and (ii) divergence across sectors. Intuitively, an increase in entry costs on its own drives the markups up through the crowding out of small firms and through growing markups of the most productive incumbents. This is visualised in the left panel of Figure 9 where, instead of reallocation, the observed increase in markups comes from the within component (green bars) and the reallocation component is rarely important in markups' growth (right panel of Figure 9).

The lack of reallocation of market shares towards high-markup firms translates into a sluggish increase in markups documented in Figure 8. Even after 60 periods both markups move together in contrast to the data and the benchmark model.

8 Conclusion

In this paper, we argue that the heterogeneity in market power dynamics across sectors can be explained by the divergent trends in turbulence observed since the 1980s. We show this in an oligopolistic model economy, populated by a finite number of firms. Firms differ by

Figure 9: Decomposition of the increase in markup with higher entry costs.



Notes: The graph presents the decomposition of the average yearly percentage change in sectoral markup in high-entry cost sector (top bars in the left panel) and low-cost entry sectors (bottom bars in the left panel), in the model. The left panel shows the decomposition for one representative simulation. The right panel shows the distribution of the shares of the reallocation component in markups' growth in sectors with high increase in entry cost (blue bars) and low entry cost (red bars).

their productivity level and their markups increase in the market share and productivity level. Business dynamics are captured by sequential entry, exit and productivity shocks.

The initial steady state is calibrated to reproduce key features of the U.S. industries pre-1980. We then simulate an economy that approximates a high-turbulence sector which is exposed to an increase in turbulence and to a sharp increase in entry costs. We contrast the resulting dynamics with the simulation of a low-turbulence sector which only experiences an increase in entry costs.

Although both sectors display an increase in market power, the magnitudes of these trends are very different. A higher turbulence triggers reallocation of market shares towards more productive, larger firms that charge higher markups. As a result, markups, market concentration and profits increase in the high-turbulence sector. In contrast, in the low-turbulence sector, the increase in markup is modest and mainly driven by the change in the composition of firms populating the sector.

In a high-turbulence sector, the declining total number of firms translates into a growing

Herfindahl index (HHI) over the transition to the second steady state. In the absence of a reallocation channel in the low-turbulence sector, the HHI displays hardly any growth over the transition path.

The results demonstrate the importance of reallocation mechanism for market power dynamics because it amplifies the trends generated by the change in the composition of firms populating the sector. The intuition of the model is strongly supported by the U.S. (Compustat) and European (CompNet) data. The differences in the market power dynamics across sectors are associated with heterogeneous turbulence trends.

References

Atkeson, A., & Burstein, A. (2008). Pricing-to-market, trade costs, and international relative prices. *American Economic Review*, *98*(5), 1998–2031.

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

Axtell, R. L. (2001). Zipf distribution of US firm sizes. *Science*, *293*(5536), 1818–1820.

Bajgar, M., Criscuolo, C., & Timmis, J. (2021). Intangibles and industry concentration: Supersize me.

Barkai, S. (2020). Declining labor and capital shares. *Journal of Finance*.

Bessen, J. (2017). Information technology and industry concentration.

Bilbiie, F. O., Ghironi, F., & Melitz, M. J. (2012). Endogenous entry, product variety, and business cycles. *Journal of Political Economy*, *120*(2), 304–345.

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., & Terry, S. J. (2018). Really uncertain business cycles. *Econometrica*, *86*(3), 1031–1065.

Bloom, N., Jones, C. I., Van Reenen, J., & Webb, M. (2020). Are ideas getting harder to find? *American Economic Review*, *110*(4), 1104–44.

Boar, C., & Midrigan, V. (2019). *Markups and inequality* (Tech. Rep.). National Bureau of Economic Research.

Burstein, A., Carvalho, V., & Grassi, B. (2019). Bottom-up markup fluctuations. In *2019 meeting papers* (Vol. 505).

Calligaris, S., Criscuolo, C., & Marcolin, L. (2018). *Mark-ups in the digital era* (Tech. Rep.). OECD Science, Technology and Industry Working Papers 2018/10.

Campbell, J. Y., Lettau, M., Malkiel, B. G., & Xu, Y. (2001). Have individual stocks become more volatile? an empirical exploration of idiosyncratic risk. *The Journal of Finance*, *56*(1), 1–43.

Carvalho, V. M., & Grassi, B. (2019). Large firm dynamics and the business cycle. *American Economic Review*, *109*(4), 1375–1425.

Chaney, T., Gabaix, X., & Philippon, T. (2002). Firm volatility. *unpublished paper, Massachusetts Institute of Technology*.

Coeurdacier, N., Rey, H., & Winant, P. (2011). The risky steady state. *American Economic Review*, *101*(3), 398–401.

Colciago, A. (2016). Endogenous market structures and optimal taxation. *Economic Journal*, *126*(594), 1441–1483.

Comin, D. (2000). *An uncertainty-driven theory of the productivity slowdown: Manufacturing* (Tech. Rep.).

Comin, D., & Mulani, S. (2006). Diverging trends in aggregate and firm volatility. *The Review of Economics and Statistics*, *88*(2), 374–383.

Comin, D., & Mulani, S. (2009). A theory of growth and volatility at the aggregate and firm level. *Journal of Monetary Economics*, *56*(8), 1023–1042.

Comin, D., & Philippon, T. (2005). The rise in firm-level volatility: Causes and consequences. *NBER macroeconomics annual*, *20*, 167–201.

Crouzet, N., Mehrotra, N., et al. (2017). Small and large firms over the business cycle. *Unpublished working paper*, *101*.

Davis, S. J. (2017). Regulatory complexity and policy uncertainty: headwinds of our own making. *Becker Friedman Institute for Research in economics working paper*(2723980).

Davis, S. J., Haltiwanger, J., Jarmin, R., Miranda, J., Foote, C., & Nagypal, E. (2006). Volatility and dispersion in business growth rates: Publicly traded versus privately held firms [with comments and discussion]. *NBER macroeconomics annual*, *21*, 107–179.

De Loecker, J., Eeckhout, J., & Mongey, S. (2019). *Quantifying market power* (Tech. Rep.). Working Paper.

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

De Loecker, J., & Warzynski, F. (2012). Markups and firm-level export status. *American economic review*, *102*(6), 2437–71.

Diez, M. F. J., Fan, J., & Villegas-Sánchez, C. (2019). *Global declining competition.* International Monetary Fund.

Dong, D., Liu, Z., & Wang, P. (2022). Turbulent business cycles. *Available at SSRN 4082333*.

Edmond, C., Midrigan, V., & Xu, D. Y. (2015). Competition, markups, and the gains from international trade. *American Economic Review*, *105*(10), 3183–3221.

Edmond, C., Midrigan, V., & Xu, D. Y. (2018). *How costly are markups?* (Tech. Rep.). National Bureau of Economic Research.

Edmond, C., Midrigan, V., & Xu, D. Y. (2021). How costly are markups?

Etro, F., & Colciago, A. (2010). Endogenous market structures and the business cycle. *Economic Journal*, *120*(549), 1201–1233.

Gabaix, X. (2011). The granular origins of aggregate fluctuations. *Econometrica*, *79*(3), 733–772.

Goldschlag, N., & Tabarrok, A. (2018). Is regulation to blame for the decline in american entrepreneurship? *Economic Policy*, *33*(93), 5–44.

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

Gutiérrez, G., Callum, J., & Philippon, T. (2019). Entry costs and the macroeconomy. *IMF Working Paper*.

Gutiérrez, G., & Philippon, T. (2017). Declining competition and investment in the US. *NBER Working Paper*.

Gutiérrez, G., & Philippon, T. (2019). *The failure of free entry* (Tech. Rep.). National Bureau of Economic Research.

Haltiwanger, J. C. (1997). Measuring and analyzing aggregate fluctuations: the importance of building from microeconomic evidence. *Federal Reserve Bank of St. Louis Review*, *79*(3), 55.

Hopenhayn, H. A. (1992). Entry, exit, and firm dynamics in long run equilibrium. *Econometrica*, *60*(5), 1127–1150.

Jovanovic, B. (1982). Selection and the evolution of industry. *Econometrica*, *50*(3), 649–670.

Juillard, M. (2011). Local approximation of dsge models around the risky steady state. *Working Paper*, *87*.

Krusell, P., & Smith, A. A., Jr. (1998). Income and wealth heterogeneity in the macroeconomy. *Journal of Political Economy*, *106*(5), 867–896.

Nekarda, C. J., & Ramey, V. A. (2020). The cyclical behavior of the price-cost markup. *Journal of Money, Credit, and Banking: 50th Anniversary Issue*.

Tian, C. (2018). Firm-level entry and exit dynamics over the business cycles. *European Economic Review*, *102*, 298–326.

Appendix A: Compustat

We use the entire universe of firms included in Compustat between 1955 and 2016. We trim the data on the cost shares. The top 1% and the bottom 1% of the firms in terms of their cost shares are dropped. Since we compute the Spearman rank correlations of productivity levels in each sector of each year, we only keep the sectors that have at least 5 firms in each year.

Markups

We follow De Loecker et al. (2020) to compute firm level markups resulting from the cost-minimisation problem: To compute firm level markups, we follow the definition proposed by De Loecker et al. (2020):

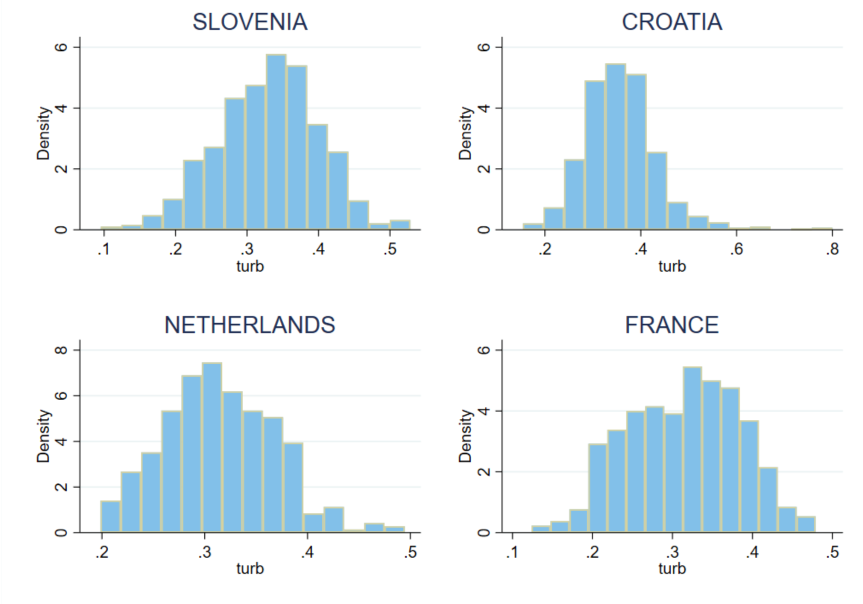
$$\mu_{it}^k = \theta_{it}^k \frac{P_{it}Q_{it}}{P_{it}^v V_{it}}, \tag{21}$$

with $k \in [1, 4]$ indicates the definition of θ_{it}^k, the (firm i specific) output elasticity in year t. $P_{it}Q_{it}$ represent the value of total sales of firm i and $P_{it}^v V_{it}$ are the costs of its variable input of production. Variable input value is defined as the "cost of goods sold" (COGs) and it covers all expenses attributable to the production of the goods sold by the firm including materials, intermediate inputs, labor cost, and overhead. $\theta_{it}^1 = \theta^v = 0.85$. θ_{it}^2 is time-verying and firm-specific and is constructed from the cost shares as follows: $\theta_{it}^2 = \frac{P_{it}^v V_{it}^j}{\Sigma_j^J P_{it}^v V_{it}^j}$ where $\frac{P_{it}^v V_{it}^j}{\Sigma_j^J P_{it}^v V_{it}^j}$ represents the share of the cost of production: labor, material and overhead relative to the sum of all inputs $\Sigma_j^J P_{it}^v V_{it}^j$ being (i) labor, material and overhead (COGS), and (ii) capital expenses. θ_t^3 is constructed similar to θ_{it}^2, but instead of the firm-level one, we take the median of the NAICS 3-digit sector in each year t. Finally, θ^4 is sector specific but constant over the sample period version of θ_{it}^2. All four firm-level markups μ_{it}^k are aggregated to the NAICS 3-digit level using production cost shares.

Profit rates

Profits are computed as (i) real sales minus real cost of production minus capital expenses and (ii) real sales minus real cost of production minus deflated capital stock. The profit rates are computed as profits relative to the real sales and they are aggregated to the NAICS 3-digid sector level using the sales weights.

Figure 10: Dispersion of turbulence across sectors in 4 European countries



Notes: The graph plots the distribution of average turbulence across sectors in Slovenia, Croatia, Netherlands and France.

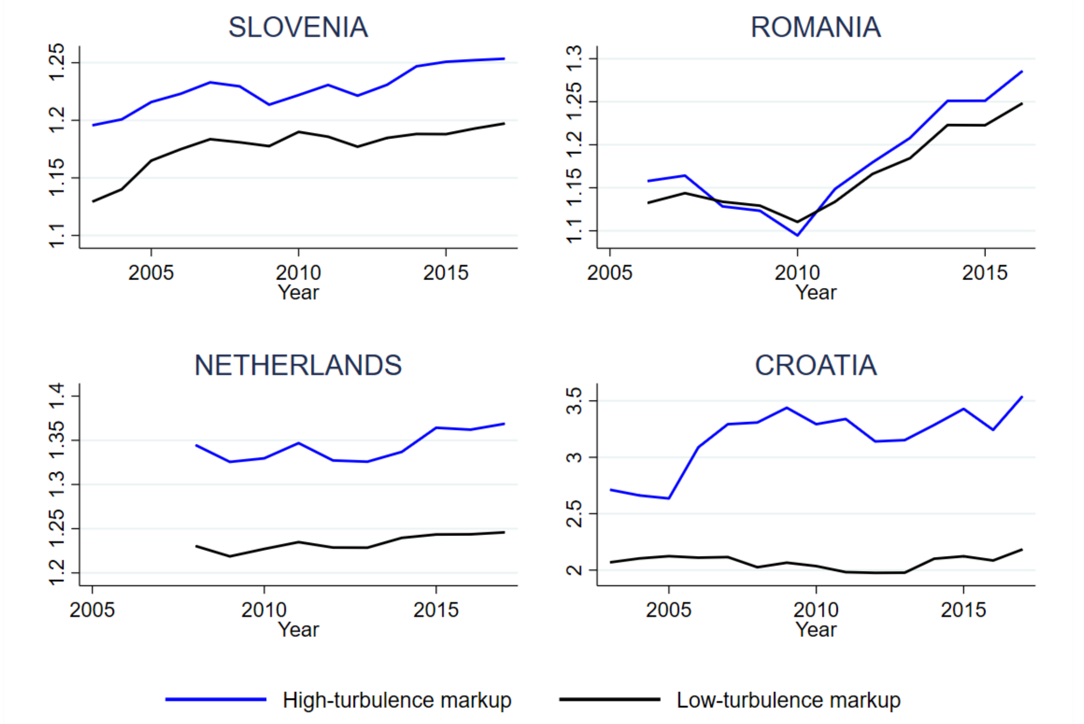
Appendix B: CompNet

To ensure that the results are not driven by the specific sample of publicly listed firms, we also test the main mechanisms of the model on the European dataset, CompNet, that gathers information from the entire universe of firms. Since CompNet consists of the information provided by national statistical offices that differ in a way of gathering and processing the data, we test the hypotheses of our model for each country individually.

CompNet contains transition matrices for firms' quintiles over size distribution, within sectors and over a three-year window. We use these probabilities to compute the (inverse of) 5-year Spearman correlation of the size distribution for each sector and use it as a proxy for the turbulence.[21] Not all the countries in CompNet sample contain the necessary information on markups and transition probabilities and in several cases the time span is too short so we need to eliminate several of them. That leaves us with 7 countries: the Netherlands, Croatia, Finland, Italy, Slovenia, France and Romania. Additionally, the sample for each country is short, ranging between 1999 and 2010. Instead of using the changes in the turbulence, we therefore classify sectors according to their average degree of turbulence. Figure 10 plots the dispersion of the turbulence across sectors in 4 countries. In each of them, there are large differences in turbulence across sectors.

[21]In the model, productivity levels directly translate into firms' size.

Figure 11: Evolution of average markups in high-turbulence and low-turbulence sectors in Europe



Notes: The graph presents the average markups for high-turbulence sectors in CompNet (blue line) and low-turbulence sector (black line). The four panels plot De Loecker and Warzynski (2012) markups derived from the OLS estimation of revenue-based translog production function at the sector level. The dots indicate point estimates for individual countries and the bars 95% confidence intervals.

For each country, we compute the median turbulence across sectors and qualify sectors above the median as high-turbulence and below the median as low-turbulence.

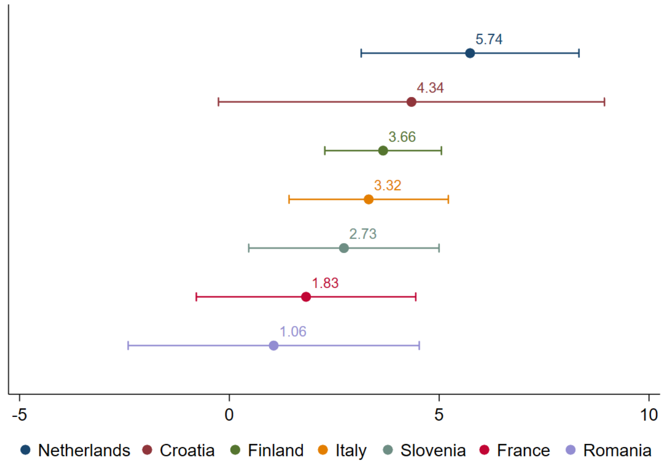
Markups in high versus low-turbulence sectors

Figure 11 plots markups in high (blue lines) and low-turbulence (black lines) sectors in four countries: Slovenia, Romania, the Netherlands and Croatia. Similar to the U.S. data, markups in Europe are always higher in sectors with higher turbulence.

We test formally the relationship between markups and turbulence by estimating the following panel regression for each country individually: $\mu_{it} = \alpha_i + \beta\tau_{it} + \gamma_t + \epsilon_{it}$, where μ_{it} is the markup in sector i and year t, τ_{it} stands for turbulence, γ_t for time dummies and α_i for sector fixed effects. The markups series, μ_{it}, are standardised.

Figure 12 plots β's from the panel regressions for each of the 7 countries, over the respective sample periods. All of the coefficients are positive and 4 of them are statistically

Figure 12: Markups and turbulence in European countries



Notes: The graph shows β's from the regression: $\mu_{it} = \alpha_i + \beta\tau_{it} + \gamma_t + \epsilon_{it}$. Markups are computed according to De Loecker and Warzynski (2012) who estimate the revenue-based translog production function at the sector level. The dots indicate point estimates for individual countries and the bars 95% confidence intervals.

significant at 5% level implying that higher turbulence is associated with higher markups.

Turbulence, markups and reallocation of market shares in European countries.

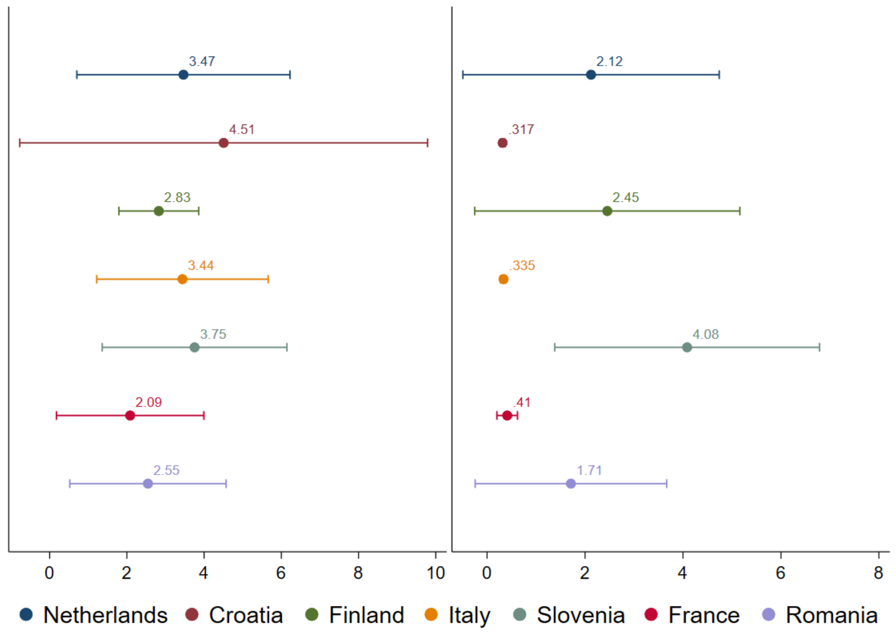
The finding that markups are higher in more turbulent sectors, presented in Figure 12, does not necessarily imply that the increase in markups has been the result of a stronger reallocation of market shares towards high-markup firms.

We test this hypothesis in 2 steps by investigating the following relationships (i) the share of reallocation in markups change and turbulence and (ii) the share of reallocation in markups change and the markups growth. Reallocation is measured by the between component in the decomposition in Equation 20. Markups are directly available in CompNet and they are computed according to De Loecker and Warzynski (2012) from the revenue-based translog production function at the sector level.

Figure 13 displays β's from the panel regressions: $y_{it} = \alpha_i + \beta x_{it} + \gamma_t + \epsilon_{it}$. In the left panel y_{it} is the reallocation component of markups growth and x_{it} is the turbulence measure. In the right panel, y_{it} is the reallocation component of markups growth and x_{it} is the markup.

In all 7 countries, stronger reallocation of the market shares is associated with higher turbulence (left panel of Figure 13). In all countries but Croatia, this relationship is statistically significant. Similarly, in all 7 countries, in sectors with higher reallocation of market shares the markups grew the fastest (right panel). This relationship is significant

Figure 13: Turbulence, markups and reallocation of market shares



Notes: The graph shows standardised β's from the regression: $y_{it} = \alpha_i + \beta x_{it} + \gamma_t + \epsilon_{it}$. In the left panel y_{it} is the between component in the decomposition in equation 20 and x_{it} is the turbulence measure. In the right panel y_{it} is the between component and x_{it} is the markup computed according to De Loecker and Warzynski (2012) and based on the revenue-based translog production function at the sector level. The dots indicate point estimates for individual countries and the bars 95% confidence intervals.

at 5% level for 4 countries. These findings jointly corroborate the model's hypothesis that higher turbulence leads to stronger reallocation of market shares towards the high-markup firms and drives the sectoral markups upwards.

Appendix C: Risky Steady State

The equilibrium conditions for the *Risky Steady State* presented in the main text are:

Production

$$\rho(i) = \left[\left(\frac{\theta-1}{\theta}\right)\left(1-\rho(i)^{1-\theta}\right)\right]^{-1}\frac{w}{x(i)} \quad for \quad i=\{1,2,3\}$$

$$d(i) = \left(\frac{1}{\theta}+\left(\frac{\theta-1}{\theta}\right)\rho(i)^{1-\theta}\right)\rho(i)^{1-\theta}Y \quad for \quad i=\{1,2,3\}$$

Entry and Exit

$$N(i) = \sum_{j=1}^{3} q_{ji}\left[1-\delta(j)\right]\left[N(j)+N^e(j)\right] \quad for \quad i=\{1,2,3\}$$

$$N^e = \Omega_0 M$$

$$N^e(i) = \Omega_i N^e \quad for \quad i=\{2,3\}$$

$$N^e = N^e(1)+N^e(2)+N^e(3)$$

$$f_e w = \left(1-\Omega_2-\Omega_3\right)e(1)+\Omega_2 e(2)+\Omega_3 e(3)$$

Households

$$\chi L^{\frac{1}{\phi}} c = w$$

$$e(i) = \beta\left[1-\delta(i)\right]\sum_{j=1}^{3}\left[q_{ij}\left(d(j)+e(j)\right)\right] \quad for \quad i=\{1,2,3\}$$

Aggregation

$$Y = c$$

$$c + N^e f_e w = wL + N(1)d(1)+N(2)d(2)+N(3)d(3)$$

$$1 = N(1)\rho(1)^{1-\theta}+N(2)\rho(2)^{1-\theta}+N(3)\rho(3)^{1-\theta}$$

Appendix D: Calibration of Markov process

Given that we will obtain a system of three equations, we start by restricting the probability to switch from productivity $x(1)$ to $x(3)$ to be equal to zero, i.e. $q_{13} = 0$. The Markov process is then iterated for 20 periods while keeping the three unknown values:

$$\begin{bmatrix} x & 1-x & 0 \\ q_{21} & y & 1-y-q_{21} \\ q_{31} & 1-z-q_{31} & z \end{bmatrix}$$

This means that, abstracting from exit shocks, the probability $p(1|1)_5$ that a type 1 firm keeps its own productivity level after a 5-year period (i.e. 20 periods in our model) is given by the first element of the row vector resulting from:

$$\begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x & 1-x & 0 \\ q_{21} & y & 1-y-q_{21} \\ q_{31} & 1-z-q_{31} & z \end{bmatrix}^{20} = \begin{bmatrix} p(1|1)_5 & p(2|1)_5 & p(3|1)_5 \end{bmatrix}$$

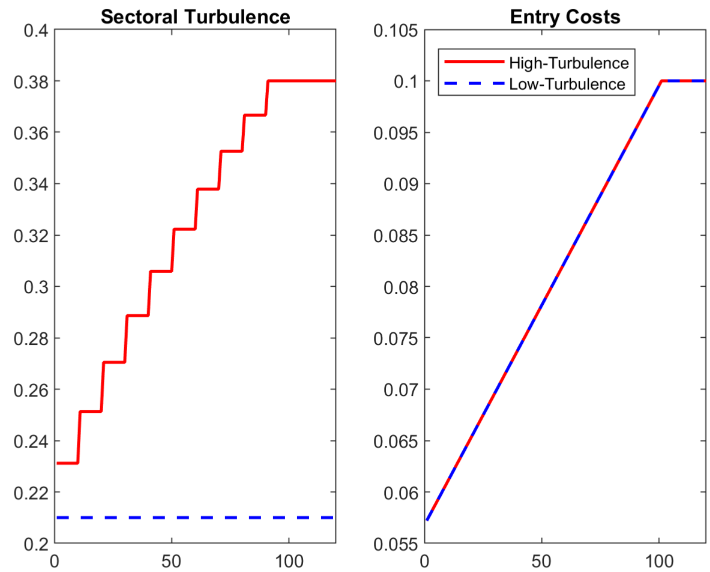
The same can be computed for the probabilities of keeping productivity $x(2)$ or $x(3)$ after 5 years conditional on starting on that given productivity level. Given those highly non-linear equations in terms of x, y and z, we restrict the solution for the three unknowns to be in the interval $[0, 1]$. Our goal is to have $p(1|1)_5 = p(2|2)_5 = p(3|3)_5 = 0.79$ in the common initial steady state and $p(1|1)_5 = p(2|2)_5 = p(3|3)_5 = 0.62$ for the final high-turbulence steady state. In this way, no matter the initial condition, the ex-ante correlation between the productivity of a firm at time t and at time $t + 20$ equals 0.79 before and 0.62 after the permanent turbulence shock.

Appendix E: Alternative Calibration: Step Increase in Entry Cost and Turbulence

In the following, we present an alternative benchmark. In this experiment, the magnitude of the shocks in the same. However, we change their timing to better proxy the empirical increase in entry costs and in turbulence: instead of imposing period-0 permanent shocks, we directly feed their stylized series to the model.

Figure (14) presents the paths of two shocks. The left panel shows that firms' turbulence is constant in low-turbulence sectors at the calibrated pre-eighties value, exactly as in the benchmark scenario. However, instead of a one-period jump, turbulence steadily increase in the high-turbulence sector, as shown by the green line in the left panel of Figure (14). The same is true for the common increase in entry costs, displayed in the right panel. Comin and Philippon (2005) estimate aggregate turbulence and how it rose from

Figure 14: Paths of Shocks



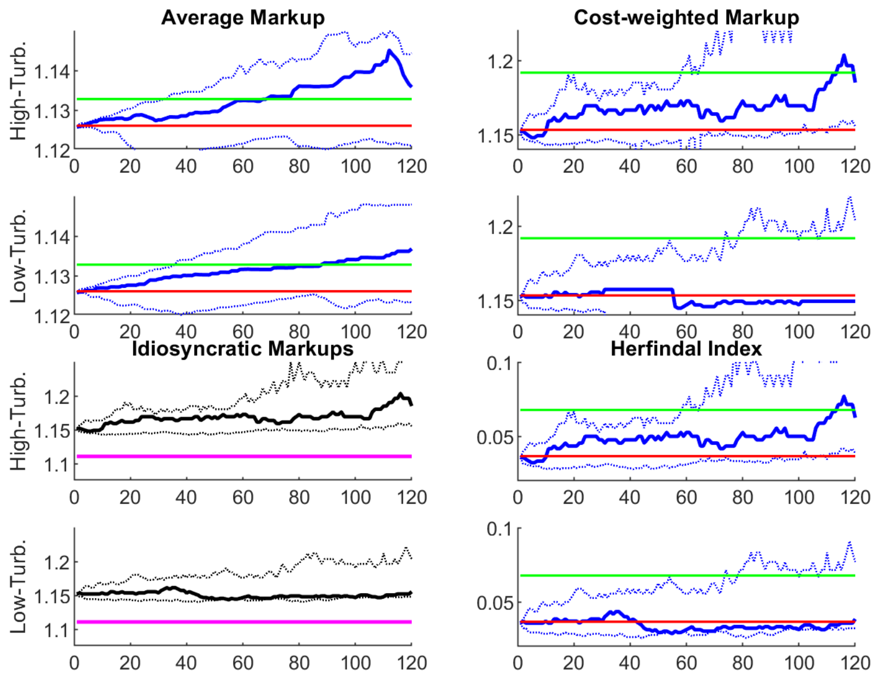
Notes: The Figure presents the exogenous series for the shocks. The left panel display the flat pattern of firms' turbulence in low-turbulence sectors (red line) and the increase in turbulence for high-turbulence sectors (green line). The right panel presents the common increase in entry costs.

0.2 in 1980 to almost 0.3 in 2000. Our series is slightly higher but because it is estimated on high-turbulence sectors only.

Figure (15) represents the transition dynamics under the alternative simulation. Qualitatively, the two models deliver the same results. Yet, in this alternative simulation, it takes much longer to reach the steady states. As a result, the sectoral heterogeneity is weaker, and arises only at the end of the sample.

Appendix F: Sectors' Classification

Figure 15: Evolution of Concentration and Markups, high vs low-turbulence sector. Alternative model



Notes: The graph presents the response of a sector to an increase in entry costs and a decline in the persistence of the firms' productivity distribution. The black solid lines describe the dynamics of the variables over time, and the dotted black lines the confidence intervals. The red and green lines represent, respectively, the initial and the final steady state in high-turbulence sector. Shocks occur in steps.

Online Appendix 1: Derivation of the aggregate demand constraint

In this appendix, the aggregate demand constraint is derived. There are two ways in which the constraint can be derived: the first assumes a continuum of final good producers competing under perfect competition, which purchase the individual firms' production. The final good producers use the individual outputs as inputs to produce the aggregate bundle Y_t, which is sold to the households at a price P_t. The second method, which exploits the fact that the aggregate production is entirely consumed by the households, is based on the minimization of the total aggregate expenditure. In the following, we present both methods, primarily because they complement each other and, together, they provide a consistent definition of the aggregate price P_t as a function of the individual prices $p_t(i)$. Note that the time index t is dropped in the following since firms maximize their per-period profits (no frictions regarding re-optimization are present).

Table 5: **Classification NAICS-3 Sectors, Low vs. High Turbulence, top-15 sectors per market share**

	Low-Turbulence		High-Turbulence
ID	Name	ID	Name
312	Beverages and tobacco	211	Oil and gas
322	Paper	311	Food and kindred products
324	Petroleum and coal products	325	Chemicals
326	Plastics and rubber products	332	Fabricated metal products
327	Nonmetallic mineral products	333	Machinery, except electrical
331	Primary Metal	335	Electrical equipment and components
334	Computer electronic products	423	Merchant wholesalers, durables
336	Transportation equipment	445	Food and beverage stores
422	Miscellaneous manufacturing	486	Pipeline transportation
424	Merchant wholesalers, nondurables	511	Newspaper and books
452	General merchandise stores	513	Motion picture and sound recording
481	Air transportation	517	Telecommunications
482	Rail transportation	523	Other information services
515	Broadcasting (except Internet)	524	Insurance carriers and related activities
519	Other information services	541	Professional, scientific, and technical services

Notes: The table presents the largest NAICS-3 sectors, in terms of market shares, within low and high-turbulence sectors. ID represents the 3-digit NAICS code for the sector, according to which sectors are ordered in the table.

The first method implies aggregate/sectoral producers. Each individual good $y(i)$ is aggregated into a final output Y, purchased by the households at a price P. The maximization of the final good producers is:

$$\max_{y(i)} PY - \sum_{i=1}^{N} p(i)y(i)$$

subject to:

$$Y = \left[\sum_{i=1}^{N} y(i)^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}$$

The aggregator function through which the individual goods and the final good can be linked follows a standard C.E.S. function, as presented in the constraint of the maximization (note that N is the number of firms in the economy). Note that $\theta > 1$ represents the elasticity of substitution between intermediate goods. The F.O.C. with respect to $y(i)$ is:

$$P\left(\frac{\theta}{\theta-1}\right)\left[\sum_{i=1}^{N} y(i)^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}-1}\left(\frac{\theta-1}{\theta}\right)y(i)^{\frac{\theta-1}{\theta}-1} = p(i)$$

This can be rewritten as:

$$PY^{\frac{1}{\theta}}y(i)^{-\frac{1}{\theta}} = p(i)$$

From this F.O.C., we obtain the demand for the individual output as:

$$y(i) = \left(\frac{p(i)}{P}\right)^{-\theta} Y$$

Alternatively, given that the entire production is consumed by the households, i.e. $c(i) = y(i)$ and $C = Y$, we can obtain the same condition, and a definition for the aggregate price P, from the minimization of the households' consumption expenditure. Households choose the optimal mixture of varieties $c(i)$ to minimize the aggregate expenditure, given an aggregate level of consumption C, by purchasing each good directly from the firms. Formally:

$$\min_{c(i)} \sum_{i=1}^{N} p(i)c(i)$$

subject to:

$$C = \left[\sum_{i=1}^{N} c(i)^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}$$

The Lagrangian is:

$$\mathcal{L} = \sum_{i=1}^{N} p(i)c(i) + \lambda \left[C - \left[\sum_{i=1}^{N} c(i)^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}\right]$$

The F.O.C. with respect to $c(i)$ is:

$$p(i) = \lambda \left(\frac{\theta}{\theta-1}\right) \left[\sum_{i=1}^{N} c(i)^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}-1} \left(\frac{\theta-1}{\theta}\right) c(i)^{\frac{\theta-1}{\theta}-1}$$

which is equal to:

$$\lambda C^{\frac{1}{\theta}} c(i)^{-\frac{1}{\theta}} = p(i)$$

By raising each side to the power of $1-\theta$ and summing from 1 to N, we can write:

$$\lambda^{1-\theta} C^{\frac{1-\theta}{\theta}} \sum_{i=1}^{N} c(i)^{\frac{\theta-1}{\theta}} = \sum_{i=1}^{N} p(i)^{1-\theta}$$

Using the definition of aggregate consumption C provided above:

$$\lambda = \left[\sum_{i=1}^{N} p(i)^{1-\theta}\right]^{\frac{1}{1-\theta}} \equiv P$$

Finally, we can plug back the expression for the Lagrange multiplier λ in the F.O.C. and write:

$$c(i) = \left(\frac{p(i)}{P}\right)^{-\theta} C$$

which is consistent with the aggregate demand constraint presented above.

Online Appendix 2: Maximization of the intermediate goods' producers under Cournot and Bertrand

Cournot In this appendix we present the maximization for the intermediate goods producers. The notation follows the one introduced in the Online Appendix 1 and the time index is dropped for convenience. Each variety $y(i)$ is produced by employing one factor of production only. In particular, production is linear in labor $l(i)$ and depends on the idiosyncratic productivity level $x(i)$:

$$y(i) = x(i)l(i)$$

Inside the economy/industry, firms compete oligopolistically á la Cournot. In the next appendix, we present an alternative market structure (Bertrand competition). The incumbents internalize that their optimal quantity affects the sectoral output Y. However, firms cannot alter the total consumption expenditure $EXP = PY$ that is allocated to the production side of the economy. Firms maximize their per-period nominal profits by choosing the optimal quantity $y(i)$:

$$\max_{y(i)} p(i)y(i) - Wl(i) = y(i)\left(p(i) - \frac{W}{x(i)}\right)$$

subject to the following aggregate demand constraint:

$$y(i) = \left(\frac{p(i)}{P}\right)^{-\theta} Y$$

where W is the nominal wage. Substituting the idiosyncratic price $p(i)$ using the demand constraint, we can write the Lagrangian as:

$$\mathcal{L} = y(i)^{-\frac{1}{\theta}+1} PY^{\frac{1}{\theta}} - W\frac{y(i)}{x(i)} = EXPy(i)^{-\frac{1}{\theta}+1} Y^{\frac{1}{\theta}-1} - W\frac{y(i)}{x(i)}$$

where the second equality comes from the definition of aggregate expenditure EXP provided above. The F.O.C. with respect to $y(i)$ is:

$$EXP\left(\frac{\theta-1}{\theta}\right) y(i)^{-\frac{1}{\theta}} Y^{\frac{1}{\theta}-1} - EXP\left(\frac{\theta-1}{\theta}\right) y(i)^{-\frac{1}{\theta}+1} Y^{\frac{1}{\theta}-2} \left(\frac{y(i)}{Y}\right)^{-\frac{1}{\theta}} - \frac{W}{x(i)} = 0$$

Plugging back the definition of total expenditure EXP, this can be written as:

$$\left[\left(\frac{\theta-1}{\theta}\right) - \left(\frac{\theta-1}{\theta}\right)\left(\frac{y(i)}{Y}\right)^{1-\frac{1}{\theta}}\right] PY^{\frac{1}{\theta}} y(i)^{-\frac{1}{\theta}} = \frac{W}{x(i)}$$

Note that the market share $\omega(i)$ can be defined as the ratio between the individual revenues and the total revenues, i.e. $\frac{p(i)y(i)}{PY}$. Hence, using the aggregate demand constraint for $y(i)$:

$$\omega(i) = \frac{p(i)y(i)}{PY} = \left(\frac{y(i)}{Y}\right)^{1-\frac{1}{\theta}} = \left(\frac{p(i)}{P}\right)^{1-\theta}$$

It is worth to mention that the market share reasonably reduces to $1/N$ if we assume homogeneity across firms. This would provide the same markup function as the one presented in Etro and Colciago (2010). Using the aggregate demand constraint again, we can simplify the LHS of the F.O.C. and write:

$$\left[\left(\frac{\theta-1}{\theta}\right)(1-\omega(i))\right] p(i) = \frac{W}{x(i)}$$

In the main text, we directly present the implicit formula for the relative price $\rho(i) = p(i)/P$, which can be easily computed from the previous equation:

$$\rho(i) = \left[\left(\frac{\theta-1}{\theta}\right)\left(1-\rho(i)^{1-\theta}\right)\right]^{-1} \frac{w}{x(i)} = \mu(i)\frac{w}{x(i)}$$

where $w = W/P$ is the real wage.

Bertrand Assume that intermediate goods producers compete oligopolistically on prices under Bertrand competition. Production still is linear in labor $l(i)$ and depends on the idiosyncratic productivity level $x(i)$:

$$y(i) = x(i)l(i)$$

Inside the economy/industry, firms compete oligopolistically á la Bertrand. Thus, the incumbents internalize that their optimally chosen price affects the sectoral price P, defined in Online Appendix 1. However, firms cannot alter the total consumption expenditure $EXP = PY$ that is allocated to the production side of the economy. Firms maximize their per-period nominal profits by choosing the optimal nominal price $p(i)$:

$$\max_{p(i)} p(i)y(i) - Wl(i) = y(i)\left(p(i) - \frac{W}{x(i)}\right)$$

subject to the aggregate demand constraint:

$$y(i) = \left(\frac{p(i)}{P}\right)^{-\theta} Y$$

where W is the nominal wage. Substituting the individual quantity $y(i)$ using the demand constraint, we can write the Lagrangian as:

$$\mathcal{L} = p(i)^{1-\theta}P^{\theta}Y - \frac{W}{x(i)}p(i)^{-\theta}P^{\theta}Y = p(i)^{1-\theta}P^{\theta-1}EXP - \frac{W}{x(i)}p(i)^{-\theta}P^{\theta-1}EXP$$

where the second equality comes from the definition of aggregate expenditure EXP, provided above.

The F.O.C. with respect to $p(i)$ is:

$$(1-\theta)\,p(i)^{-\theta}P^{\theta-1}EXP+(\theta-1)\,p(i)^{1-\theta}P^{\theta-2}EXP\left(\frac{p(i)}{P}\right)^{-\theta}+$$

$$+\theta\frac{W}{x(i)}p(i)^{-\theta-1}P^{\theta-1}EXP-\frac{W}{x(i)}\,(\theta-1)\,p(i)^{-\theta}P^{\theta-2}EXP\left(\frac{p(i)}{P}\right)^{-\theta}=0$$

Multiplying by $\frac{p(i)^{1+\theta}}{-\theta P^{\theta-1}EXP}$, this can be written as:

$$p(i)\left(\frac{\theta-1}{\theta}\right)\left[1-\left(\frac{p(i)}{P}\right)^{1-\theta}\right]=\frac{W}{x(i)}\left[1-\left(\frac{\theta-1}{\theta}\right)\left(\frac{p(i)}{P}\right)^{1-\theta}\right]$$

As previously, the market share $\omega(i)$ can be defined as the ratio between the individual revenues and the total revenues, i.e. $\frac{p(i)y(i)}{PY}$. Hence, using the aggregate demand constraint for $y(i)$:

$$\omega(i)=\frac{p(i)y(i)}{PY}=\left(\frac{p(i)}{P}\right)^{1-\theta}$$

The implicit formula for the relative price $\rho(i)=p(i)/P$, can be easily computed from the previous equation:

$$\rho(i)=\frac{1-\left(\frac{\theta-1}{\theta}\right)\rho(i)^{1-\theta}}{\left(\frac{\theta-1}{\theta}\right)\left(1-\rho(i)^{1-\theta}\right)}\frac{w}{x(i)}=\mu(i)\frac{w}{x(i)}$$

where $w=W/P$ is the real wage.

It is possible to compare the markup under both market structures. The markup under Bertrand competition $\mu(i)^B$ is:

$$\mu(i)^B=\frac{1-\left(\frac{\theta-1}{\theta}\right)\rho(i)^{1-\theta}}{\left(\frac{\theta-1}{\theta}\right)\left(1-\rho(i)^{1-\theta}\right)}=\frac{1}{\left(\frac{\theta-1}{\theta}\right)\left(1-\rho(i)^{1-\theta}\right)}-\frac{\left(\frac{\theta-1}{\theta}\right)\rho(i)^{1-\theta}}{\left(\frac{\theta-1}{\theta}\right)\left(1-\rho(i)^{1-\theta}\right)}=\mu(i)^C-\frac{\omega(i)}{1-\omega(i)}$$

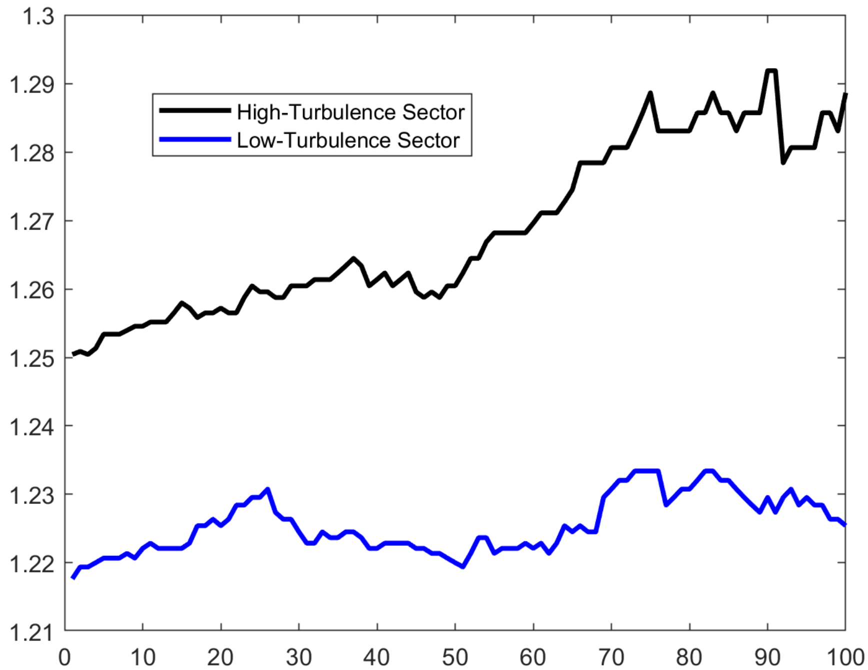
where $\mu(i)^C$ is the markup under Cournot competition.

Whenever the market share goes to zero, the markups are the same as they both converge to the monopolistic competition markup $\frac{\theta}{\theta-1}$. If the market share is non-zero, the markup is always lower under Bertrand competition. In particular as:

$$\frac{\partial(\mu(i)^C-\mu(i)^B)}{\partial\omega(i)}=\frac{1}{(1-\omega(i))^2}$$

the difference in the markups is increasing in the market share. Given that high market share firms charge higher markups, under Bertrand competition the markup dispersion is lower.

Figure 16: Comparison of markups, high vs. low-turbulence sectors.



Notes: The graph presents the comparison in markups between the low-turbulence sector and the high-turbulence sectors, in which we allow the elasticity of substitution between goods to be sector-specific. In particular, $\theta = 10$ in low-turbulence sectors, as in the benchmark, while $\theta = 6$ in high-turbulence sectors. Both primitives are kept constant over the transition.

Online Appendix 3: Heterogeneous substitutability

Substituability between goods might differ across sectors. For instance, new high-tech products cannot be readily substituted. Therefore, a lower substitutability in high-turbulence sectors, which group several high-tech industries, could allow their producers to expand their market shares more, and can justify the level differences in markups between high and low-turbulence sectors. To test this hypothesis, we allow the elasticity of substitution between goods, θ, to differ across sectors.

Figure (16) shows the trends in markups. Regarding the calibration, we set $\theta = 10$ in low-turbulence sectors, as in the benchmark model, while here $\theta = 6$ in high-turbulence sectors. Both primitives are kept constant over the transition. Under this alternative model, results are qualitatively similar. However, by allowing θ to be sector-specific, we can match the initial level difference in markups, as well as the larger increase in markup in high-turbulence sector, relative to the benchmark exercise in the main text (black line in Figure 16). There two drawbacks of this alternative calibration. First, we would need to quantify the heterogeneity in substitutability between sector types.

Second, heterogeneous elasticity of substitution could obscure the impact of turbulence on the market power dynamics across sectors. We therefore opt for the benchmark calibration with equal elasticities in the main text.

Online Appendix 4: Algorithm and Theoretical Challenges.

In this appendix, we present the original algorithm developed to simulate the dynamic behavior of the economy. For tractability reasons, some further assumptions have been added with respect to the baseline theoretical model: the discussion about their impact on the equilibrium outcomes is presented below.[22]

In order to introduce the algorithm and its main mechanisms, we describe here the dynamics of the economy for a given period t. When the entry decisions are formed during period t, the current number of incumbents and their types, i.e. $N_t(1)$, $N_t(2)$ and $N_t(3)$, is known. Indeed, note that they come from the realization of the stochastic processes that regulate exit and productivity shocks, which have already occurred between period $t-1$ and period t and at the very beginning of period t. Given those three quantities, the first step in our solution technique is to pin down the number of potential entrants, M_t, by using a sequential approach.

Starting from a given stock of zero entrants, namely from $M_t = 0$, we evaluate the free entry condition for the first entrant, in formula:

$$(1 - \Omega_2 - \Omega_3)\, e_{1,t}(1) + \Omega_2 e_{2,t}(2) + \Omega_3 e_{3,t}(3) - f_{e,t} w_t$$

Whenever the condition is positive, i.e. when the expected value for the new firm is higher than the entry costs, the marginal entrant joins the market. If this happens, the algorithm continues by re-evaluating the free entry condition. This time, however, the condition is computed conditional on the number of potential entrants being one. The idea behind the procedure is that the sector may present some unexploited profit possibilities. Whenever those expected revenues are higher than the entry costs, the entrant joins the market. However, its entry increases future competition and, thus, it lowers firms' value, making harder for new competitors to enter. The algorithm continues with this mechanism until the free entry condition turns negative because entry is not profitable anymore.

[22] The assumptions are imposed on how firms form their expectations. The constraints simplify the computation of the stream of expected future profits, which is required to pin down the value of the firms. This type of restriction is not new to the literature and it is often assumed in order to solve similar dynamic problems. See, for instance, Krusell and Smith (1998).

Note that, in the computation of the competitive equilibrium, the number of successful entrants N_t^e, and, hence, $N_t^e(1)$, $N_t^e(2)$ and $N_t^e(3)$ as well, is not known with certainty since it depends on the realization of stochastic processes, given the equilibrium M_t. The same uncertainty holds for period $t+1$ competitors $N_{t+1}(1)$, $N_{t+1}(2)$ and $N_{t+1}(3)$, since they depend on the realization of idiosyncratic exit and productivity shocks. The households solve this uncertainty by considering the expected values of these quantities in their maximization process.[23] In formulas:

$$N_{t+1}(i) = \sum_{j=1}^{3} \left[q_{ji} \left(1 - \delta(j)\right) \left(N_t^e(j) + N_t(j)\right) \right]$$

where

$$N_t^e = \Omega_0 M_t$$
$$N_t^e(3) = \Omega_3 N_t^e$$
$$N_t^e(2) = \Omega_2 N_t^e$$
$$N_t^e = N_t^e(1) + N_t^e(2) + N_t^e(3)$$

Furthermore, note that the equations above hold for the incumbents: from the perspective of a potential entrant, the expected number of competitor is different since the latter internalizes that, by entering the market with a productivity level $x(i)$, the number of type-i firms is $N_t(i) + N_t^e(i) + 1$. As explained in the modelling section, this means that the entrants internalize the effects of their entry on the future price index, hence creating the wedge between their value and the value of the incumbents. These dynamics are taken into account in the algorithm.

In order to be able to compute the first part of the algorithm, i.e. to pin down M_t, some simplifying assumptions have been included. The constraints regard how firms form their expectations. First of all, potential entrants are imposed to expect that period $t+1$ output Y_{t+1}, and, hence, consumption c_{t+1}, does not change between period t and period $t+1$. The assumption affects the computation of the expected profits for period $t+1$, which are necessary to pin down the value of the incumbents and of the (potential) entrants. In other words, potential entrants do not consider the effect of their entry on the sectoral production of the following periods and they assume that the economy is on a stable path. This assumption is quite restrictive: in the per-period profits maximization, we assume

[23] One alternative solution is to consider separately every possible state of the world for $N_t^e(i)$ and $N_{t+1}(i)$ given $N_t(i)$ and a specific M_t. In every state of the world it is possible to pin down the value for the marginal entrant and, only after this, obtain $e_{i,t}(i)$ as the average of the values computed, weighted by the probability that a given state occurs. In this way, every state of the world conserves a finite number of firms. However, this solution method gets computationally unsolvable quite easily.

Cournot competition, which entails that the producers internalize that their optimally chosen quantity has an impact on the contemporaneous aggregate output.

Nevertheless, the assumption may still be justified. When the number of active incumbents in the sector grows, the marginal effect of entry on output growth is negligible, since the competition is already tight. This is true in our case, given that the steady state present hundreds of incumbents, and the effect of entry on output is particularly irrelevant if the entrant does not realizes as a superstar firm with productivity $x(3)$. Furthermore, the effect of entry on future competition and prices, i.e. the increase in the expected number of competitors, is clear from the firm's perspective (this is why we assumed that the entrant can internalize these dynamics). On the other hand, the aggregate effects on consumption and output are significantly harder to be predicted *ex ante*, given that they rely also on households' response. Thus, it is not unreasonable to assume that firms are partially myopic and that their period t expectation of Y_{t+1} is simply Y_t.[24] Finally, note that this assumption affects also the stochastic discount factor, which reduces to β.

A second assumption regards the computation of the firms' value itself, and it is in line with the previous constraint. When firms evaluate their stream of conditional expected profits, which pins down their own value, they anticipate correctly the number of competitors in period $t+1$, required to estimate period $t+1$ profits. However, it is imposed that those profits are assumed to stay constant from period $t+2$ onward, conditional of being active in the market. Again, firms are myopic, since they consider that similar entry and exit dynamics occur every period. Given these assumptions, the value of incumbents and entrants can be easily defined as, respectively:

$$e_t(i) = \frac{\beta\,(1-\delta(i))}{1-\beta\,(1-\delta(i))} d_{t+1}(i)$$

and

$$e_{i,t}(i) = \frac{\beta\,(1-\delta(i))}{1-\beta\,(1-\delta(i))} d_{i,t+1}(i)$$

Note that an alternative approach to the above restrictions is to directly assume that firms are myopic and render the entry choice static.[25] Results do not vary significantly since the value function takes a similar form. However, we think that it is worth to keep the entry choice dynamic, even at the costs of some restrictive assumptions.

Once M_t is pinned down, the algorithm proceeds with the simulation of the stochastic realization of N_t^e from the given M_t and of $N_t^e(1)$, $N_t^e(2)$ and $N_t^e(3)$ from the realized

[24] Alternatively, one could say that firms are myopic simply because they perceive the economy as if it was in the steady state. Hence, incumbents and entrants expect no variations in the aggregate quantities over time, although they internalize idiosyncratic exit and entry dynamics.

[25] Similar to the approach in De Loecker et al. (2019).

N_t^e. Conditional on those variables, and recalling that $N_t(1)$, $N_t(2)$ and $N_t(3)$ are pre-determined, we can compute the competitive equilibrium of the economy by solving the household's maximization problem, constrained by the previous assumptions. It is worth to mention that, when clearing the market, $N_t^e(1)$, $N_t^e(2)$ and $N_t^e(3)$ are now known by the households, differently from the information set through which M_t is determined. Finally, having solved for the market equilibrium, the stochastic realizations of the idiosyncratic exit and productivity processes are computed. In this way, we can obtain the realized $N_{t+1}(1)$, $N_{t+1}(2)$ and $N_{t+1}(3)$ from the previous quantities, which serve as a basis for the algorithm in the following period.