Mergers, Firm Size, and Volatility in a Granular Economy*

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Abstract

This paper studies the impact of mergers and acquisitions (M&A) at the micro and macro levels. A negative size-volatility relationship implies that merger-induced growth lowers firm-level volatility. We demonstrate this relationship is characterized by the linear combination of log-log and log-linear functions, where the latter arises from variable markups and suggests that volatility declines disproportionately with firm size. At the aggregate level, mergers increase market concentration and amplify granular fluctuations. Thus, aggregate volatility rises despite the fall in post-merger firm-level volatility. Counterfactual analysis using a quantitative model of mergers indicates that domestic mergers increase aggregate volatility by 3.7 to 9.3%.

JEL classification codes: E30, E32, F12, G34, L22

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1 Introduction

What are the effects of mergers and acquisitions (M&A) at the micro and macro levels? Mergers affect individual firms involved in the deals, their industries, and the aggregate economy. Firm-level productivity gains through mergers have a direct impact on aggregate productivity, and the reallocation of resources from less to more productive firms also raises productivity and growth at the economy-wide level (e.g., Xu, 2017; Dimopoulos and Sacchetto, 2017; David, 2020). At the same time, mergers may affect the volatility of firms and generate firm dynamics that influence aggregate fluctuations.[1] In this paper, we investigate the impact of mergers on this second moment of firm-level and aggregate growth.

Mergers create larger firms, and an inverse size-volatility relationship (e.g., Sutton, 2002; Koren and Tenreyro, 2013; Yeh, 2021) implies that at the micro-level, the volatility of sales growth declines for the individual acquirer firm after the merger event. However, at the aggregate level, the share of large firms rises as a result of mergers and the firm-size distribution becomes more fat tailed. As demonstrated by Gabaix (2011), in a granular economy, the idiosyncratic shocks of large firms contribute significantly to the macroeconomic fluctuations observed. Therefore, even though mergers lower *firm-level* volatility, they also amplify granular fluctuations and in fact increase *aggregate* volatility.

To derive this result, we focus on the role of individual firm size and changes to the aggregate firm-size distribution. We develop a quantitative multi-sector model of horizontal mergers in a granular economy.[2] The model employs the nested constant-elasticity-of-substitution (CES) demand structure, where within each sector, there is a discrete number of heterogeneous firms producing differentiated varieties (Atkeson and Burstein, 2008). Entrants pay a sunk entry cost to make productivity draws from an initial distribution, and production requires the payment of variable and fixed costs. In the merger market, firms conduct costly search as acquirers and targets within their industry (David, 2020). For each pair of acquirer and target firms, a merger technology function determines the productivity of the merged entity (i.e., post-merger acquirer). Firms face idiosyncratic productivity shocks after the merger market closes, which generate fluctuations in aggregate output growth.

We first show theoretically that there is a negative size-volatility relationship at the firm level, which implies that merger-induced firm growth reduces the volatility of the post-merger acquirer. Our model features oligopolistic competition, where firms command strategic market power and internalize the effects of their pricing decisions on the sectoral price index (e.g., Bernard et al., 2018; Parenti, 2018). Hence, they charge variable markups and this results in the incomplete pass-through of shocks to prices (Atkeson and Burstein, 2008; Burstein et al., 2020). The inverse relationship between firm size and volatility is generated as larger firms have

[1] Firm dynamics from entry and exit have been shown to amplify productivity shocks and play an important role in shaping the business cycle. For example, see Clementi and Palazzo (2016), Lee and Mukoyama (2018), and Carvalho and Grassi (2019).

[2] Throughout this paper, we focus on horizontal mergers in the domestic economy. We rely on the Danish register data for our empirical and quantitative analysis, and in Denmark, domestic horizontal mergers account for the majority of deals (see Appendix Figure A.2 and Section 3).

lower pass-through and their sales are less sensitive to shocks. We find that the relation between this strategic market power effect on volatility and firm size is well-approximated by a log-linear function. This novel result contrasts with the log-log relationship that has been utilized in the prior literature (e.g., Stanley et al., 1996; Sutton, 2002). While the log-log relationship implies that volatility falls proportionally with firm size, the log-linear relationship gives an alternative prediction that volatility decreases disproportionately more for large firms. We introduce the former into the model by assuming that the variance of shocks declines with size, whereas the latter arises from firms' strategic market power and variable markups. Thus, the firm size-volatility relationship is characterized by the linear combination of log-log and log-linear functions. Importantly, we show that the log-linear component dominates when market shares are high and volatility decays more rapidly than the rate suggested by the log-log function. This finding has implications for aggregate volatility in general. Here, it is especially critical for quantifying the impact of mergers, given that large firms are often involved.

Mergers also affect the aggregate economy through changes in market conditions. Using our theoretical framework, we decompose the impact of mergers on volatility into an extensive and intensive margin. Aggregate volatility, measured by the standard deviation of total output growth, is increasing in market concentration. At the extensive margin, the larger, more productive firms created by mergers intensify market competition. For a given productivity distribution, selection effects drive less productive firms out of the market and the cutoff productivity level increases. In a discrete setting, the market shares of firms that are forced to exit are distributed among the surviving firms. This in turn raises market concentration and aggregate volatility. At the intensive margin, for a given productivity threshold, the firm-size distribution shifts to become more fat tailed. Compared to the initial (i.e., pre-merger) productivity distribution, the post-merger distribution has more mass in its right tail. Because the shocks of large firms have greater influence on total output, mergers amplify granular fluctuations and this intensive margin also contributes to a more concentrated and volatile economy. However, this is mitigated by the decline in firm-level volatility of post-merger acquirers. Both channels at the micro level (i.e., the variance of shocks and variable markups) serve to dampen the effects of mergers at the macro level.

Using detailed register data for the country of Denmark, we provide empirical evidence for our model and quantify the effects of mergers. Large firms dominate economic activity around the world, and Denmark is no exception. The top 50 and 100 firms account for roughly one-quarter and one-third of total domestic sales, respectively (see Appendix Figure A.1), which is very similar to a large country like the US (Gabaix, 2011). The rise in large firms may in part be attributed to M&A deals. Globally, the number of M&A transactions has risen steadily, reaching record levels in 2015 with so-called "mega-deals" between some of the world's biggest companies.[3] From the Danish data, we find that 70% of the top 100 firms in the year 2015 completed at least one M&A deal as an acquirer in the last twenty years.

Empirically, we employ the universe of firms in Denmark from the register data to examine

[3]For example, see `https://archive.annual-report.thomsonreuters.com/2015/articles/2015-year-of-the-mega-deal.html`. Appendix Figure A.2 also shows the rise in M&A deals in Denmark.

the firm size-volatility relationship. First, we estimate the traditional log-log relationship between volatility and firm size (e.g., Koren and Tenreyro, 2013; Yeh, 2021). Both cross-sectional and panel regressions confirm that there is a negative relationship, where the latter specification includes firm fixed effects. Based on our theory, (log) volatility is characterized by the linear combination of log-log and log-linear functions. Thus, we also estimate a specification with firm size in both logs and levels. Both coefficients are negative, though the log term is more precisely estimated. While this might seem to imply a lack of importance for the role of variable markups, the fact that there are few large firms and many small firms means that the fit of the regression will favor the log-log relationship. As an alternative approach, we bin firms into deciles by size and run a set of log-log regressions where we progressively drop the smallest decile. A striking pattern emerges. As larger and larger firms remain in the sample, the magnitude of the estimated coefficient in the log-log regression monotonically increases. This is precisely what strategic market power and the implied log-linear component predict.

We calibrate the model's parameters by targeting key moments in the Danish data with regards to the firm-size distribution and domestic M&A activity. The data includes not only firm identifiers, but also unique establishment identifiers that can be tracked over time. Hence, the change in an establishment's firm identifier to that of an existing firm indicates the sale of ownership and a merger deal (Smeets et al., 2016). We employ a sample of 3,575 horizontal mergers from 1993 to 2015. In the model, a stationary condition is imposed that links the pre-merger and post-merger productivity distributions. By assuming that the post-merger distribution is Pareto, this allows us to back out the counterfactual pre-merger distribution.

Comparing the benchmark economy with mergers to a counterfactual economy without mergers, we find that domestic M&A increase the granularity of the economy and thus, aggregate volatility. With constant markups, aggregate volatility rises by 4.4% under the assumption of independently and identically distributed (i.i.d.) shocks, and 3.7% under the assumption that the variance of shocks declines with firm size. A decomposition reveals that the intensive margin, i.e., due to the shift in productivity distribution, accounts for the majority of the total effect. Alternatively, in a multi-sector economy with variable markups, mergers increase volatility by 9.3 to 12.4%. To quantify the contribution of variable markups and incomplete pass-through, we consider a hypothetical scenario of the multi-sector economy where firms charge constant markups and shocks have complete pass-through to prices. Shutting down the channel of variable markups overestimates aggregate volatility by almost 50%. Therefore, even though the regression analysis cannot inform us of the importance of variable markups, our counterfactual exercises demonstrate that their quantitative effects are indeed economically significant. The contribution of variable markups in mitigating the impact of large firms created through mergers is larger compared to the dampening effect of heterogeneous shocks. Moreover, they also explain the heterogeneity of outcomes observed across sectors. Our results under the settings of constant and variable markups may be interpreted as lower and upper bounds for the impact of mergers on aggregate volatility, depending on the degree of firms' market power.

1.1 Literature review

The results of this paper extend several lines of research in the prior literature. Most broadly, our work relates to a large literature that studies business cycles and macroeconomic fluctuations. Business cycles may arise from aggregate shocks to supply or demand, or sectoral shocks which propagate through the economy.[4] A growing strand of literature examines the contribution of shocks at the even more disaggregate firm level. In seminal work, Gabaix (2011) establishes the key result that in a granular economy with a fat-tailed firm-size distribution which follows Zipf's law, the law of large numbers does not apply and firm-level shocks do not cancel out. Studies show that these micro-level shocks contribute substantially to macro-level fluctuations (e.g., Gabaix, 2011; di Giovanni et al., 2014; Magerman et al., 2016).[5]

Our paper examines an important channel for the creation of large firms and the rise in granular fluctuations, namely, mergers and acquisitions. By investigating the origins of large firms, our research contributes to a further understanding of the fundamental driving forces behind business cycles. Related work by di Giovanni and Levchenko (2012) examines international trade as an alternative channel for generating a more fat-tailed firm-size distribution and increasing aggregate volatility. While we focus on the domestic market, an extension of our model with trade would amplify the effects of mergers. The results of Carvalho and Grassi (2019) indicate that large firm dynamics at the extensive margin are influential in shaping business cycles. Furthermore, the largest firms in the world are typically multinationals, and di Giovanni et al. (2018) demonstrate that their shocks propagate at an international scale and drive the comovement of business cycles globally. This suggests that cross-border M&A may have similar effects to the ones studied in our paper.

Our paper also adds to the literature that studies the economic implications of M&A. At the micro-level, mergers may be viewed as a capital reallocation process that increases productive efficiency (e.g., Jovanovic and Rousseau, 2008; Maksimovic et al., 2011), and case studies of various industries show that mergers may generate pro-competitive outcomes as a result of these efficiency gains (e.g., Ashenfelter et al. (2015), Sheen (2014), Braguinsky et al. (2015), see also Eckbo (2014) for a survey). Such gains arising from horizontal mergers often come at the expense of lower competition and a rise in market concentration (e.g., Williamson, 1968). Antitrust authorities that screen M&A deals often rely on changes in the Herfindahl-Hirschman index (HHI) as an indicator for their effects on competition (e.g., Whinston, 2007; Asker and Nocke, 2021). However, aggregate volatility is also a function of market concentration. Besides potential welfare loss from anti-competitive effects, mergers generate additional costs as the result of a more volatile economy.

Our work is closely related to recent studies that examine the macroeconomic implications of

[4]For instance, economies face aggregate shocks to technology, total factor productivity, as well as fiscal shocks from changes in government policy (e.g., Kydland and Prescott, 1982; Long and Plosser, 1983; Greenwood et al., 1988; Rotemberg and Woodford, 1992). Sector linkages imply that sector-specific shocks can play an important role in generating aggregate fluctuations (e.g., Stockman, 1988; Horvath, 1998, 2000; Acemoglu et al., 2012).

[5]The role of granular forces has also been studied in relation to comparative advantage in international trade (Gaubert and Itskhoki, 2021) and the banking sector (Bremus et al., 2018). Furthermore, Gaubert et al. (2021) examine welfare and antitrust policy implications from a merger between two firms in oligopoly.

M&A. For example, David (2020) demonstrates that output and consumption rise not only due to productivity gains achieved by the consolidation of acquirer and target firms, but also from the reallocation of resources across firms.[6] Similar to our model, Cavenaile et al. (2021) present a framework of oligopoly in a discrete setting, where firms are either price-setters or price-takers. They study the role of antitrust policies for firm innovation. In contrast to this prior literature, we focus on the dynamic implications of mergers in terms of macroeconomic volatility in the business cycle. Our multi-sector model also takes into account the strategic interactions of firms to allow for variable (i.e., endogenous) markups. De Loecker and Eeckhout (2021) document a very strong correlation over time between global M&A activity and aggregate markups, which suggests that incorporating the channel of variable markups is important in understanding the impact of mergers.[7] While not our main focus, we also find that mergers increase output and welfare. Hence, countries face a trade-off between efficiency gains that increase (static) welfare but also greater volatility in their business cycles. This has important implications for policy-makers when evaluating mergers and antitrust policy. In particular, merger waves imply that economies have become more susceptible to shocks that hit large firms.[8]

Lastly, we contribute by providing a micro-foundation for the negative firm size-volatility relationship, departing from Gibrat's law for variance. Early work by Stanley et al. (1996) and Sutton (2002) hypothesize a log-log relationship, and a microfoundation is provided by Klette and Kortum (2004).[9] Koren and Tenreyro (2013) and Yeh (2021) have also assumed and estimated the log-log functional form, finding varying degrees of departure from Gibrat's law. In contrast to this previous work, we demonstrate that the firm size-volatility relationship is better characterized not by the log-log function itself, but rather, by its linear combination with the log-linear function. This result is generated from firms' market power and variable markups, especially for large firms, and implies that volatility decreases disproportionately with firm size. We provide empirical evidence consistent with this hypothesis, and also show quantitatively the significance of this channel in the context of M&A.[10]

The paper is organized as follows. In Section 2, we present our general equilibrium model of mergers and discuss implications for firm-level and aggregate volatility. Section 3 describes the data and investigates the firm size-volatility relationship empirically. In Section 4, we outline our estimation strategy and present our estimates, as well as results from counterfactuals. Lastly, Section 5 concludes.

[6]See also Xu (2017), Dimopoulos and Sacchetto (2017), and Levine (2017) for recent contributions in this line of research. Similar models of heterogeneous firms with mergers are examined in the context of cross-border M&A (e.g., Nocke and Yeaple, 2007; Blonigen et al., 2014; Brakman et al., 2018).

[7]Using data from the Worldscope database, De Loecker and Eeckhout (2021) find that between 1985 and 2016, global M&A increased more than tenfold and the aggregate markup rose by around 30 percentage points.

[8]For example, merger waves are well-documented in the finance literature, see among others, Harford (2005), Maksimovic et al. (2013), and Eckbo (2014).

[9]Gibrat's law for variance states that the variance of the growth rate is independent of size (Gabaix, 2009). Klette and Kortum (2004) generate the log-log relationship by modeling innovation and firm growth as a Poisson process that depends on the firm's stock of knowledge. Related empirical work by Davis et al. (2006) compares the volatility of privately held firms to publicly traded companies and finds the former to be considerably larger. In more recent work, Herskovic et al. (2020) explain the lower variance of large firms with network effects.

[10]Interestingly, the non-parametric estimation of the firm size-volatility relationship by Yeh (2021) using US data also shows that volatility falls faster at larger firm sizes. We discuss this further in Section 3.2.

2 Model

In this section, we present a multi-sector model of heterogeneous firms with horizontal mergers. We then characterize the equilibrium and discuss the implications of mergers for firm-level and aggregate volatility. The economy is set in continuous time and has an infinite horizon.

2.1 Preferences

A representative household is assumed to have log utility of consumption and linear disutility of work.[11] The rate of time discount is denoted by ρ, equal to the real interest rate. The household maximizes utility given labor income and dividends from firms' profits:

$$U(Y, \mathcal{L}) = \log Y - \psi \mathcal{L} \ \ s.t. \ \ w\mathcal{L} + \Pi = PY, \tag{1}$$

where Y is the final good, $\mathcal{L}$ is labor supply, w is the wage, Π is aggregate firm profits, and P is the aggregate price index. Y aggregates output from N sectors using a CES aggregator:

$$Y = \left[\sum_{k=1}^{N} D_k^{\frac{1}{\phi}} Y_k^{\frac{\phi-1}{\phi}} \right]^{\frac{\phi}{\phi-1}}, \tag{2}$$

where Y_k is output in sector k and D_k is the demand shifter. The sectoral price index is P_k, and the aggregate price index is defined by

$$P = \left[\sum_{k=1}^{N} D_k P_k^{1-\phi} \right]^{\frac{1}{1-\phi}}. \tag{3}$$

The elasticity of substitution across sectors is $\phi \geqslant 1$. Within each sector, there is a discrete number of heterogeneous firms producing differentiated varieties. Goods are assumed to be imperfect substitutes, and more substitutable within than across sectors, i.e., $\varepsilon > \phi$ (Atkeson and Burstein, 2008). Denote M_k as the number of varieties, or equivalently, firms, in sector k, and the output and price of firm i as y_{ki} and p_{ki}, respectively. Sectoral output in k combines individual firms' output also using a CES aggregator:

$$Y_k = \left[\sum_{i=1}^{M_k} y_{ki}^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}}, \tag{4}$$

and the associated sectoral price index is

$$P_k = \left[\sum_{i=1}^{M_k} p_{ki}^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}}. \tag{5}$$

[11] This assumes that the Frisch elasticity of labor supply is infinity. Burstein et al. (2020) show their main results under the same assumption, and further generalize their model and specifically, the expression for aggregate volatility (i.e., Eq. (27)) for any arbitrary value of the Frisch elasticity. Their results also apply in our extension that features horizontal mergers. As shown in Eq. (17), the assumption of linear disutility implies that market size PY is exogenous. Given that there is a discrete number of firms and the model must be simulated with a large number of samples when analyzing the variable markup model, this approach is practically more feasible than one which requires endogenous PY to be solved in combination with the merger market.

Solving the consumer's maximization problem yields the demand function:

$$y_{ki} = \left(\frac{p_{ki}}{P_k}\right)^{-\varepsilon} Y_k = \left(\frac{p_{ki}}{P_k}\right)^{-\varepsilon} \left(\frac{P_k}{P}\right)^{-\phi} D_k Y. \tag{6}$$

2.2 Markups and profits

New entrant firms pay a sunk entry cost wc_k^e to obtain a random productivity draw z_{ki} from the initial productivity distribution $F_k(z_{ki})$ with range $\mathbf{z}_k = \{z_{k1}, z_{k2}, ...\}$, where $z_{k1} < z_{k2} < ....$ The probability mass function is defined accordingly as $f_k(z_{k1}) \equiv F_k(z_{k1})$ and $f_k(z_{kj}) \equiv F_k(z_{kj}) - F_k(z_{k,j-1}) \; \forall \; j \geqslant 2$. All costs are measured in labor units. If firms choose to stay in the market, they must pay the fixed cost of production wc_k^d. For entrants, this happens after their productivity is revealed. Variable costs consist of wage payments to labor ℓ_{ki}, which, for simplicity, is assumed to be the only factor of production.

After the merger market clears (discussed below), all firms (i.e., entrants, incumbents with and without a merger deal) receive an independent shock to their productivity ϵ_{ki}. Following di Giovanni and Levchenko (2012), this shock is assumed to be transitory, and the mean of the shocks is normalized such that $\mathbb{E}_\epsilon[(z_{ki}\epsilon_{ki})^{\varepsilon-1}] = z_{ki}^{\varepsilon-1}$. The marginal cost of a firm with productivity z_{ki} is equal to w/z_{ki}, and its markup is

$$m_{ki} = \frac{p_{ki}}{w/z_{ki}} = \frac{p_{ki}y_{ki}}{w\ell_{ki}}. \tag{7}$$

For notational convenience, $m_{ki} \equiv m_{ki}(z_{ki})$. We use the two notations interchangeably for variables that depend on the firm's productivity. Hence, by Eq. (6), expected profits are:

$$\pi_{ki}^E(z_{ki}) = \mathbb{E}_\epsilon\left[\left(p_{ki} - \frac{w}{z_{ki}}\right) y_{ki}\right] - wc_k^d = \mathbb{E}_\epsilon\left[\left(\frac{m_{ki}w}{z_{ki}}\right)^{1-\varepsilon}\left(1 - \frac{1}{m_{ki}}\right) P_k^\varepsilon Y_k\right] - wc_k^d. \tag{8}$$

Under constant markups, the multi-sector model collapses to a single sector, which implies a unique elasticity of substitution across firm varieties, $\phi = \varepsilon = \widetilde{\varepsilon}$, and a constant markup of $\frac{\widetilde{\varepsilon}}{\widetilde{\varepsilon}-1}$.

2.3 Mergers

The merger market is modeled following David (2020). Incumbent firms participate and search on both sides, i.e., for targets as acquirers and vice versa. Due to search and matching frictions, firms incur a cost of effort (e.g., time) which is increasing in their search intensity. In this paper, we consider only horizontal mergers of firms in the same sector k, which constitute the vast majority of M&A deals in Denmark (see Smeets et al. (2016) and Section 3 below).

A merger involves a one-to-one match between an acquirer and target firm.[12] For an acquirer

[12]For tractability, we follow previous literature (e.g., di Giovanni and Levchenko, 2012; Burstein et al., 2020) and assume that firms produce and sell one good. After the deal is completed, the merged entity (i.e., post-merger acquirer) continues to produce the same variety as the pre-merger acquirer. Meanwhile, the target exits and its variety is no longer sold on the market. A model of multi-product firms and mergers under oligopolistic competition is presented in (Chan et al., 2022). They show, both theoretically and empirically with the same Danish data, that the combined product range of the acquirer and target falls after the merger.

with productivity z_{ki}^a purchasing a target with productivity z_{ki}^t, we define the productivity of the merged entity by the merger technology function:

$$s[z_{ki}^a, z_{ki}^t] = A(z_{ki}^a)^\gamma (z_{ki}^t)^\nu. \tag{9}$$

The acquirer obtains a share of merger gains equal to $\Sigma_{ki}^a(z_{ki}^a, z_{ki}^t) = \beta\Sigma_{ki}(z_{ki}^a, z_{ki}^t)$, where β is the acquirer's bargaining power under Nash bargaining. Likewise, for the target, $\Sigma_{ki}^t(z_{ki}^a, z_{ki}^t) = (1-\beta)\Sigma_{ki}(z_{ki}^a, z_{ki}^t)$. Merger gains are defined as the difference between the value of the merged entity and the values of the pre-merger acquirer and target firms:

$$\Sigma_{ki}(z_{ki}^a, z_{ki}^t) = V_{ki}\left(s[z_{ki}^a, z_{ki}^t]\right) - V_{ki}(z_{ki}^a) - V_{ki}(z_{ki}^t). \tag{10}$$

To complete the deal, the acquirer must offer the target an acquisition price equal to the target's value plus its share of the merger gains: $V_{ki}(z_{ki}^t) + (1-\beta)\Sigma_{ki}(z_{ki}^a, z_{ki}^t)$.[13]

As an acquirer, firms search with intensity $\lambda_{ki}(z_{ki})$ for meeting a potential target, and this requires search costs (in labor units) of

$$C\big(\lambda_{ki}(z_{ki})\big) = \frac{B}{\eta}\big(\lambda_{ki}(z_{ki})\big)^\eta. \tag{11}$$

Meanwhile, targets search with intensity $\mu_{ki}(z_{ki})$ to find a potential acquirer, and face the same convex search cost function. The meeting rate in the merger market of sector k depends on the minimum of the total search intensities of acquirers and targets, given by $\sum_{z_{ki}=\bar{z}_k}^{z_k^m} \lambda_{ki}(z_{ki})g_k(z_{ki})$ and $\sum_{z_{ki}=\bar{z}_k}^{z_k^m} \mu_{ki}(z_{ki})g_k(z_{ki})$, respectively.[14] For example, when the total search intensity of targets is greater than that of acquirers, the meeting rate depends on the latter, and targets are on the long side of the market. While firms draw from the *pre-merger* (i.e., initial) productivity distribution $F_k(z_{ki})$, the distribution evolves as a result of mergers. Total search intensities depend on the productivity distribution in the *post-merger* equilibrium $G_k(z_{ki})$, with its probability mass function $g_k(z_{ki})$ defined analogously to $f_k(z_{ki})$.

The rate at which an acquirer with type z_{ki}^a meets a target with type z_{ki}^t is equal to

$$\lambda_{ki}(z_{ki}^a) \underbrace{\min\left\{\frac{\sum_{z_{ki'}=\bar{z}_k}^{z_k^m} \mu_{ki}(z_{ki'})g_k(z_{ki'})}{\sum_{z_{ki'}=\bar{z}_k}^{z_k^m} \lambda_{ki}(z_{ki'})g_k(z_{ki'})}, 1\right\}}_{\theta_k^a} \underbrace{\frac{\mu_{ki}(z_{ki}^t)g_k(z_{ki}^t)}{\sum_{z_{ki'}=\bar{z}_k}^{z_k^m} \mu_{ki}(z_{ki'})g_k(z_{ki'})}}_{\Gamma_k(z_{ki}^t)}.$$

Market tightness on the acquirer side is given by θ_k^a, and the relative search intensity of targets with productivity z_{ki}^t by $\Gamma_k(z_{ki}^t)$. We have analogous expressions on the target side with θ_k^t as market tightness and $\Lambda_k(z_{ki}^a)$ as the relative search intensity of acquirers.[15]

[13] An acquirer makes a purchase if merger gains are positive: $\Sigma_{ki}(z_{ki}^a, z_{ki}^t) - (1-\beta)\Sigma_{ki}(z_{ki}^a, z_{ki}^t) = \Sigma_{ki}^a(z_{ki}^a, z_{ki}^t) \geqslant 0$.

[14] Note that we switch between indexing firms by $i \in \{1, ..., M_k\}$ and by their productivity $z_{ki} \in \{\bar{z}_k, ..., z_k^m\}$.

[15] Specifically, $\theta_k^t \equiv \min\left\{\frac{\sum_{z_{ki'}=\bar{z}_k}^{z_k^m} \lambda_{ki}(z_{ki'})g_k(z_{ki'})}{\sum_{z_{ki'}=\bar{z}_k}^{z_k^m} \mu_{ki}(z_{ki'})g_k(z_{ki'})}, 1\right\}$ and $\Lambda_k(z_{ki}^a) \equiv \frac{\lambda_{ki}(z_{ki}^a)g_k(z_{ki}^a)}{\sum_{z_{ki'}=\bar{z}_k}^{z_k^m} \lambda_{ki}(z_{ki'})g_k(z_{ki'})}$. The first-order condition for optimal search of targets is $C'\big(\mu_{ki}(z_{ki})\big) = B \cdot \big(\mu_{ki}(z_{ki})\big)^{\eta-1} = \theta_k^t \mathbb{E}_{z_{ki}^a}\left[\Sigma_{ki}^t(z_{ki}^a, z_{ki})\right]$.

Using these expressions, we compute the expected merger gains of acquirers and targets. The value of a firm is equal to the present discounted value of its expected profits plus expected merger gains net of search costs:

$$rV_{ki}(z_{ki}) = \max_{\lambda_{ki}(z_{ki}),\mu_{ki}(z_{ki})} \pi^E_{ki}(z_{ki}) - wC\big(\lambda_{ki}(z_{ki})\big) - wC\big(\mu_{ki}(z_{ki})\big) + \lambda_{ki}(z_{ki})\theta^a_k \mathbb{E}_{z^t_{ki}}\left[\Sigma^a_{ki}(z_{ki}, z^t_{ki})\right] + \mu_{ki}(z_{ki})\theta^t_k \mathbb{E}_{z^a_{ki}}\left[\Sigma^t_{ki}(z^a_{ki}, z_{ki})\right], \tag{12}$$

where r is the discount rate. Moreover, the first-order condition for the optimal search intensity of acquirers (and analogously for targets) is:

$$C'\big(\lambda_{ki}(z_{ki})\big) = B \cdot \big(\lambda_{ki}(z_{ki})\big)^{\eta-1} = \theta^a_k \mathbb{E}_{z^t_{ki}}\left[\Sigma^a_{ki}(z_{ki}, z^t_{ki})\right]. \tag{13}$$

2.4 Firm-size distributions and general equilibrium

For entrants that draw productivity below the threshold $\bar{z}_k$, the fixed cost of production is too large and they choose to exit the market. The cutoff firm must have a value of zero (cf. zero profit condition in Melitz (2003)):

$$V_{ki}(\bar{z}_k) = 0. \tag{14}$$

The cutoff $\bar{z}_k$ also defines the lower bound of the productivity distribution $G_k(z_{ki})$ for active firms in the market. Denote M^e_k as the number of potential entrants in sector k. In a stationary equilibrium, the number of firms that enter and exit the market must be equal at any point of the productivity distribution. The stationary condition for each type $z_{ki} \geqslant \bar{z}_k$ is:

$$\begin{aligned}
&\underbrace{M^e_k f_k(z_{ki})}_{\text{Entrants}} + \underbrace{M_k \sum_{z^a_{ki}=\bar{z}_k}^{z^m_k} \lambda_{ki}(z^a_{ki})\theta^a_k \mathbf{1}\left[\Sigma_{ki}(z^a_{ki}, s^{-1}[z_{ki}, z^a_{ki}] \geqslant 0)\right] \Gamma_k(s^{-1}[z_{ki}, z^a_{ki}]) g_k(z^a_{ki})}_{\text{Merged firms}} \\
&= \underbrace{\delta_k M_k g_k(z_{ki})}_{\substack{\text{Exiting firms}\\ \text{from shock}}} + \underbrace{M_k \lambda_{ki}(z_{ki})\theta^a_k g_k(z_{ki}) \sum_{z^t_{ki}=\bar{z}_k}^{z^m_k} \mathbf{1}\left[\Sigma_{ki}(z_{ki}, z^t_{ki}) \geqslant 0\right] \Gamma_k(z^t_{ki})}_{\text{Exiting acquirers in mergers}} \\
&+ \underbrace{M_k \mu_{ki}(z_{ki})\theta^t_k g_k(z_{ki}) \sum_{z^a_{ki}=\bar{z}_k}^{z^m_k} \mathbf{1}\left[\Sigma_{ki}(z^a_{ki}, z_{ki}) \geqslant 0\right] \Lambda_k(z^a_{ki})}_{\text{Exiting targets in mergers}},
\end{aligned} \tag{15}$$

where $s^{-1}[z_{ki}, z^a_{ki}] = \{z^t_{ki} : s[z^a_{ki}, z^t_{ki}] = z_{ki}\}$ is a function that determines the productivity of the target merging with an acquirer with productivity z^a_{ki} to create a new firm with productivity z_{ki}, and $\mathbf{1}[\cdot]$ is the indicator function. Incumbent firms face an exogenous probability of exit δ_k. To close the model, the number of entrants is determined by the free entry condition:

$$\sum_{z_{ki}=z_{k1}}^{z^m_k} V_{ki}(z_{ki}) f_k(z_{ki}) = wc^e_k. \tag{16}$$

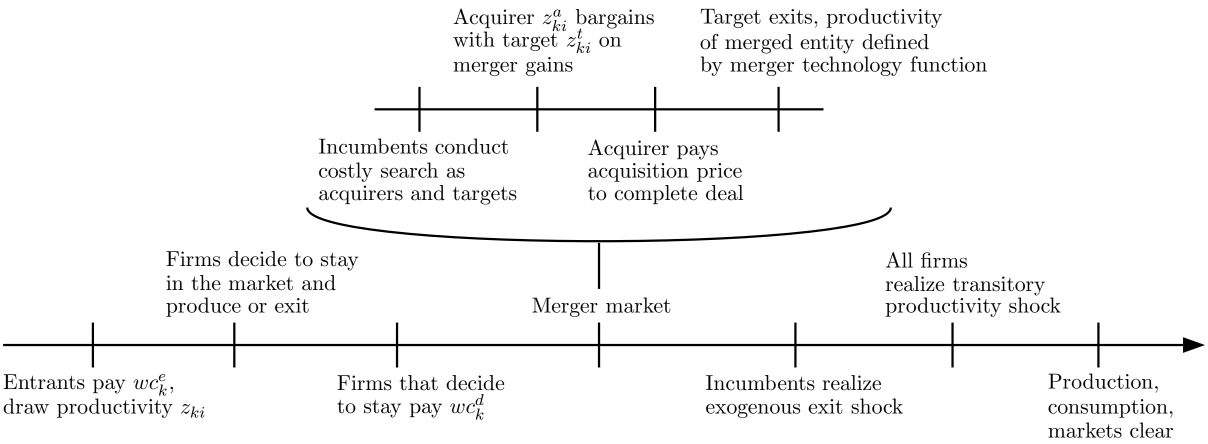


Figure 1: The timing of the economy.

That is, the expected value of entry is equal to the sunk cost of entry.

Following di Giovanni and Levchenko (2012), transitory shocks are realized after firms' decision to produce and do not affect the number of firms M_k. Denote the merger rate in sector k as Υ_k, then the number of mergers is $\Upsilon_k M_k$.[16] Aggregate variables must satisfy the goods and labor market clearing conditions in equilibrium. Thus, total output is equal to total consumption and the household's budget constraint holds.[17] From the household's maximization problem:

$$PY = \frac{w}{\psi}. \tag{17}$$

Lastly, aggregating across all sectors, labor supply must be equal to the sum of production labor, fixed costs of production, sunk costs of entry, and search costs.[18]

The timing of the economy is summarized in Figure 1. Conditional on $\{\psi, c^d_k, c^e_k, \delta_k, \gamma, \nu, A, B, \eta\}$ and the initial productivity distribution $F_k(z_{ki})$, a *stationary equilibrium* consists of expected firm profits $\pi^E_{ki}(z_{ki})$, value function $V_{ki}(z_{ki})$, entry threshold $\bar{z}_k$, wage rate w, sectoral prices P_k, sectoral output Y_k, the mass of active firms M_k, the mass of entrants M^e_k, and the post-merger productivity distribution $G_k(z_{ki})$ such that: (i) the household maximizes its utility, (ii) firms maximize their value, (iii) the goods and labor markets clear, and (iv) the evolution of firm types follows the stationary condition in Eq. (15).

[16]The merger rate is $\Upsilon_k \equiv \sum_{z^t_{ki}=\bar{z}_k}^{z^m_k} \sum_{z^a_{ki}=\bar{z}_k}^{z^m_k} \mu_{ki}(z^t_{ki})\theta^t_k \mathbf{1}\left[\Sigma_{ki}(z^a_{ki}, z^t_{ki}) \geqslant 0\right] \Lambda_k(z^a_{ki}) g_k(z^t_{ki})$, or equivalently, $\sum_{z^a_{ki}=\bar{z}_k}^{z^m_k} \sum_{z^t_{ki}=\bar{z}_k}^{z^m_k} \lambda_{ki}(z^a_{ki})\theta^a_k \mathbf{1}\left[\Sigma_{ki}(z^a_{ki}, z^t_{ki}) \geqslant 0\right] \Gamma_k(z^t_{ki}) g_k(z^a_{ki})$. Note that aggregating the stationary condition gives $M^e_k\left(1 - F_k(\bar{z}_k)\right) = M_k(\delta_k + \Upsilon_k)$.

[17]All costs (i.e., variable costs, fixed costs of production, sunk costs of entry, and search costs in the merger market) are subtracted to obtain realized aggregate profits Π (i.e., after the transitory shocks are revealed). Because merger gains are realized in the same period as profits (see Eq. (12)), aggregate profits are zero in this model except for the difference between expected and realized profits. This derivation is shown in Appendix B.

[18]Denote L_k as production labor. Labor market clearing implies $\mathcal{L} = \sum_{k=1}^{N}\Big(L_k + M_k c^d_k + M^e_k c^e_k + M_k \sum_{z_{ki}=\bar{z}_k}^{z^m_k} \Big[C\big(\lambda_{ki}(z_{ki})\big) + C\big(\mu_{ki}(z_{ki})\big)\Big] g_k(z_{ki})\Big)$.

2.5 Mergers and firm-level volatility

Using this framework, we examine the impact of mergers on firm-level volatility. Denote firm-level sales as $r_{ki} \equiv p_{ki}y_{ki}$. The growth rate of sales is approximated by the log change, i.e., $\widehat{r}_{ki} \equiv \frac{\Delta r_{ki}}{r_{ki}} \approx \Delta \log r_{ki}$, and volatility is measured by the standard deviation of sales growth, i.e., $\sigma[\widehat{r}_{ki}] \equiv \sqrt{\mathbb{V}ar[\widehat{r}_{ki}]}$.

One channel through which firm size affects volatility is in the variance of shocks. Suppose that the productivity shocks are not i.i.d., but their variance declines with firm size. This may capture, for instance, the diversification of firms as they grow larger. In particular, we follow Sutton (2002) and di Giovanni and Levchenko (2012) to assume a power law relationship between the standard deviation of shocks and firm size:

$$v_z(\mathcal{s}_{ki}) = \bar{v}_z \mathcal{s}_{ki}^{-\chi}. \tag{18}$$

Because we are interested in comparing the volatilities of economies (or sectors) with a fixed size, firm size can equivalently be measured by r_i or $\mathcal{s}_i$. Doing so affects volatility proportionally, but leaves ratios unchanged. However, if one were to compare $\chi = 0$ to a non-zero value, Eq. (18) would have to be adjusted by $(PY)^{\chi}$ computed at the non-zero value. Under this assumption of the power law alone, size and volatility would follow a log-log relationship. If shocks are i.i.d., we have $v_z(\mathcal{s}_{ki}) = \bar{v}_z \ \forall \ i$ and this channel is simply shut off.

Now, we analyze the markup adjustments of firms under Cournot competition following Burstein et al. (2020). By Eq. (7), the market share of firm i in sector k is:

$$\mathcal{s}_{ki} = \frac{p_{ki}y_{ki}}{P_k Y_k} = \frac{z_{ki}^{\varepsilon-1} \mathcal{m}_{ki}^{1-\varepsilon}}{\sum_{i'=1}^{M_k} z_{ki'}^{\varepsilon-1} \mathcal{m}_{ki'}^{1-\varepsilon}}. \tag{19}$$

With Cournot competition, the firm's markup is an increasing function of its market share:

$$\mathcal{m}_{ki} = \frac{\varepsilon}{\varepsilon - 1} \left[1 - \left(\frac{\varepsilon/\phi - 1}{\varepsilon - 1} \right) \mathcal{s}_{ki} \right]^{-1}. \tag{20}$$

Furthermore, define the pass-through rate as:

$$\alpha_{ki} \equiv \frac{1}{1 + (\varepsilon - 1)\frac{\partial \log \mathcal{m}_{ki}}{\partial \log \mathcal{s}_{ki}}} = \frac{\varepsilon - 1 - \left(\frac{\varepsilon}{\phi} - 1\right) \mathcal{s}_{ki}}{\varepsilon - 1 + (\varepsilon - 2)\left(\frac{\varepsilon}{\phi} - 1\right) \mathcal{s}_{ki}} \leqslant 1 \text{ if } \varepsilon \geqslant 1, \tag{21}$$

where the markup elasticity is $\frac{\partial \log \mathcal{m}_{ki}}{\partial \log \mathcal{s}_{ki}} = \left(\frac{\varepsilon}{\phi} - 1\right) \mathcal{s}_{ki} \left[\varepsilon - 1 - \left(\frac{\varepsilon}{\phi} - 1\right) \mathcal{s}_{ki}\right]^{-1}$. In the case of constant markups, $\mathcal{m}_i = \frac{\tilde{\varepsilon}}{\tilde{\varepsilon} - 1}$ for all firms, the markup elasticity is zero, and pass-through is complete. By contrast, pass-through is incomplete under variable markups, i.e., $\alpha_{ki} < 1$. Given that the log change in price can be expressed as:[19]

$$\widehat{p}_{ki} = -\alpha_{ki}\widehat{z}_{ki} + (1-\alpha_{ki})\widehat{P}_k, \tag{22}$$

the variance of firm-level sales growth is:

$$\mathbb{V}ar[\widehat{r}_{ki}] = \mathbb{V}ar\left[(1-\varepsilon)\widehat{p}_{ki} + (\varepsilon-1)\widehat{P}_k + \sum_{k'\neq k}(\phi-1)\mathcal{S}_{k'}\widehat{P}_{k'}\right]$$

where $\mathcal{S}_k \equiv \frac{P_k Y_k}{PY}$ is the share of sector k's sales. Next, we examine how this expression differs between the cases of constant and variable markups. Consider first the economy under constant markups with a single sector. From Eq. (22), we have $\widehat{p}_i = -\widehat{z}_i$, and by Eq. (5):

$$\mathbb{V}ar[\widehat{r}_i] = (\widetilde{\varepsilon}-1)^2\mathbb{V}ar\left[\widehat{z}_i + \sum_{i'=1}^{M} s_{i'}\widehat{z}_{i'}\right] = (\widetilde{\varepsilon}-1)^2\big(1+\textstyle\sum_{i'=1}^{M} s_{i'}^2 - 2s_i\big)[v_z(s_i)]^2. \tag{23}$$

Taking the logarithm of this equation, we can approximate the middle term by $-2s_i$ if market shares are small. Therefore, we can characterize the firm size-volatility relationship by the linear combination of log-log and log-linear functions. However, note that the log-linear term appears only if firms take into account the effects of their pricing decisions on the price index, in particular through the term $\sum_{i'=1}^{M} s_{i'}\widehat{z}_{i'}$.

Under variable markups, Eq. (23) is generalized to

$$\mathbb{V}ar[\widehat{r}_{ki}] = (\varepsilon-1)^2 \underbrace{\alpha_{ki}^2\left(1+\frac{\sum_{i'=1}^{M_k}(s_{ki'}\alpha_{ki'})^2}{\big(\sum_{i'=1}^{M_k} s_{ki'}\alpha_{ki'}\big)^2} - \frac{2s_{ki}\alpha_{ki}}{\sum_{i'=1}^{M_k} s_{ki'}\alpha_{ki'}}\right)}_{\text{Strategic market power effect on volatility}}[v_z(s_{ki})]^2 + \text{Constant}_1, \tag{24}$$

where the constant is a function of variables in other sectors k'. We refer to the term before $[v_z(s_{ki})]^2$ as the "strategic market power" (SMP) effect on volatility, to distinguish this channel from the size-variance relationship associated with shocks. Analogous to the case of constant markups, this term appears when firms internalize the impact of their prices on the sectoral price index (e.g., Neary, 2003; Bernard et al., 2018; Parenti, 2018). If firms are small in the aggregate economy, this effect disappears under constant markups where there is only one sector. Conversely, firms are large within sectors in the multi-sector model, which gives rise to strategic market power and variable markups.

We first demonstrate that the log SMP effect falls with firm size, then show the rate is linear. To derive analytical results, assume for simplicity that all aggregate sums (i.e., $\sum_{i'=1}^{M_k}(s_{ki'}\alpha_{ki'})^2$ and $\sum_{i'=1}^{M_k} s_{ki'}\alpha_{ki'}$) are constant. The derivative of the log SMP effect with respect to s_{ki} is:

$$-2\left[-\left(1-\frac{s_{ki}\alpha_{ki}}{\sum_{i'} s_{ki'}\alpha_{ki'}}\right)\frac{\partial \log\alpha_{ki}}{\partial s_{ki}} + \frac{s_{ki}\alpha_{ki}}{\sum_{i'} s_{ki'}\alpha_{ki'}}\frac{1}{s_{ki}}\right], \tag{25}$$

[19] The derivation relies on Eqs. (7), (19), (20), and a first-order Taylor approximation.

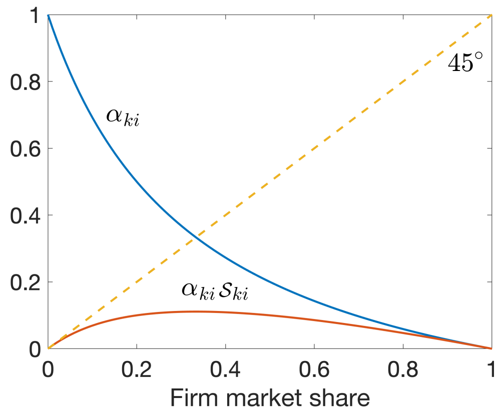


Figure 2: This figure plots the pass-through rate α_{ki} and the pass-through rate multiplied by the market share $\alpha_{ki}s_{ki}$ against the market share, assuming $\phi = 1$ and $\varepsilon = 5$.

This is a weighted average and the semi-elasticity is negative. Figure 2 plots the inverse relationship between pass-through rates and market shares. When market shares are large, productivity shocks are absorbed by changes in the markup such that fluctuations in the growth rate of sales are suppressed. Thus, we can conclude that merger-induced firm growth is associated with a decline in post-merger firm-level volatility, even if the variance of shocks were held fixed.

Moreover, it can be shown that the derivative w.r.t. s_{ki} in Eq. (25) is roughly constant. By contrast, the derivative w.r.t. $\log s_{ki}$ becomes more negative as s_{ki} increases. Figures 3(a) and (b) plot the logarithm of the SMP effect on volatility against s_{ki} and $\log s_{ki}$, respectively, using the parametrization in Section 4 below with $\phi = 1$ and $\varepsilon = 5$. While Figure 3(a) is not exactly linear, the slope is close to constant, especially in comparison to Figure 3(b).[20] Hence, we rely on the log-linear functional form as an approximation for the effect of variable markups on volatility. Assuming $\phi = 1$, which implies Cobb-Douglas preferences over sectors, the constant in Eq. (24) drops out. The volatility of firm-level sales growth in Eq. (24) can be rewritten in the form:

$$\log \sigma[\hat{r}_{ki}] = -c_1 \log s_{ki} - c_2 s_{ki} + \text{Constant}_2. \tag{26}$$

How important is each channel? In Figure 4(a), we first plot the log-log and log-linear

[20] The derivative of the log SMP effect w.r.t. $\log s_{ki}$ is: $-2\left[-\left(1 - \frac{s_{ki}\alpha_{ki}}{\sum_{i'} s_{ki'}\alpha_{ki'}}\right)\frac{\partial \log \alpha_{ki}}{\partial \log s_{ki}} + \frac{s_{ki}\alpha_{ki}}{\sum_{i'} s_{ki'}\alpha_{ki'}}\right]$. By more closely examining the semi-elasticity and elasticity:

$$\frac{\partial \log \alpha_{ki}}{\partial s_{ki}} = \frac{-(\varepsilon-1)^2(\frac{\varepsilon}{\phi}-1)}{\left(\varepsilon - 1 + (\varepsilon-2)(\frac{\varepsilon}{\phi}-1)s_{ki}\right)\left(\varepsilon - 1 - (\frac{\varepsilon}{\phi}-1)s_{ki}\right)}, \text{ and}$$

$$\frac{\partial \log \alpha_{ki}}{\partial \log s_{ki}} = \frac{-(\varepsilon-1)^2(\frac{\varepsilon}{\phi}-1)s_{ki}}{\left(\varepsilon - 1 + (\varepsilon-2)(\frac{\varepsilon}{\phi}-1)s_{ki}\right)\left(\varepsilon - 1 - (\frac{\varepsilon}{\phi}-1)s_{ki}\right)},$$

we notice that the derivative of the log SMP effect on volatility w.r.t. s_{ki} puts less weight on the term $1/s_{ki}$ exactly when s_{ki} is small, so two roughly balance out. The semi-elasticity is very flat, which means that the derivative of the SMP effect is roughly constant. By contrast, the elasticity becomes more negative as s_{ki} rises. The derivative w.r.t. $\log s_{ki}$ is a weighted average between this elasticity and a constant, so it must become more negative as s_{ki} increases. As an example, Appendix Figures A.3 plots these functions for $\phi = 1$ and $\varepsilon = 5$.

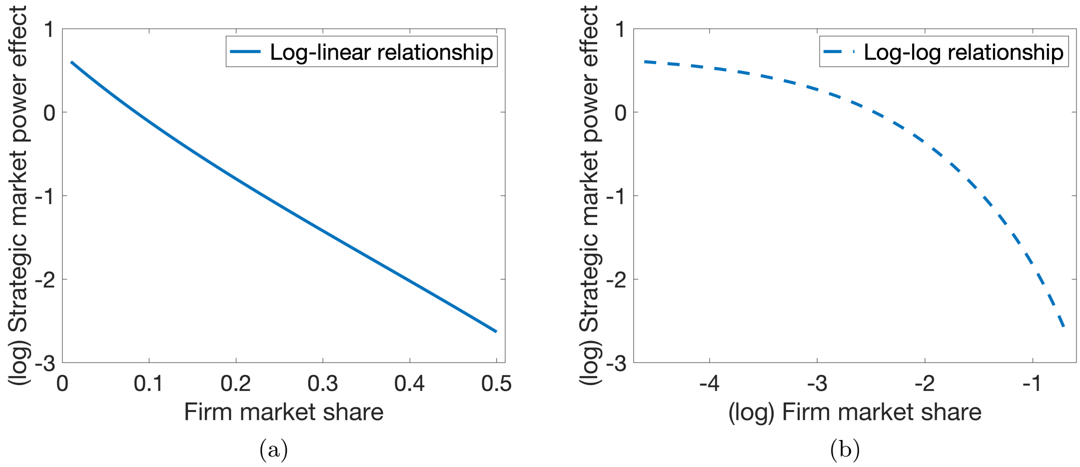


Figure 3: This figure plots the (log) strategic market power effect on volatility in Eq. (24) against firm market share in (a) levels, and (b) logarithms. For purposes of illustration, we assume $\phi = 1$ and $\varepsilon = 5$, $\sum_{i'=1}^{M_k} (s_{ki'} \alpha_{ki'})^2 = 1$, and $\sum_{i'=1}^{M_k} s_{ki'} \alpha_{ki'} = 1$.

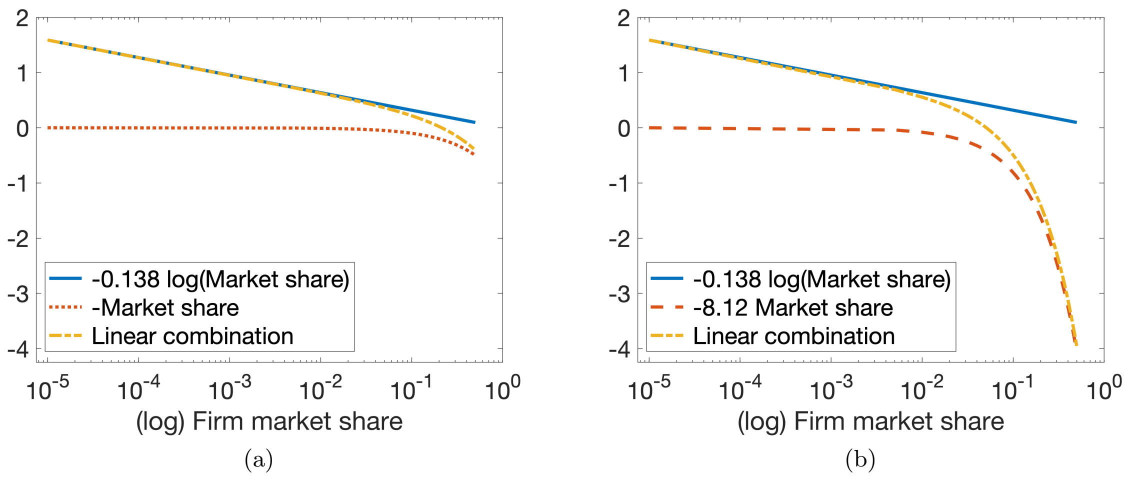


Figure 4: Each figure plots three equations with $\log \sigma[\hat{r}_{ki}]$ on the vertical axis: (i) $-0.138 \log(s_{ki})$, (ii) $-s_{ki}$ for the constant markup case in (a) and $-8.12 s_{ki}$ for the variable markup case in (b), and (iii) their linear combination. Market shares range from 10^{-5} to 0.5.

components separately for the constant markup case, as well as their linear combination on a logarithmic x-axis. We set $c_1 = 0.138$ (see Section 3 below) and $c_2 = 1$. When market shares are small, $\log s_i$ is much larger than the linear term s_i, and the log-linear function dominates. Even at higher market shares, deviations from the log-log function are not large. Under constant markups, even if firms have strategic market power, its effects on volatility are somewhat negligible.

We make the same plots under variable markups in Figure 4(b), where from Section 3 below, the linear component in Eq. (26) has a coefficient of -8.12. While it is still true that the log-log function describes the firm size-volatility relationship well for small firms, the result is quite different for large firms. At large market shares, the log-linear function dominates. In contrast to Figure 4(a), the steep slope indicates that volatility decays much more rapidly under variable markups compared to constant markups, and also compared to the log-log function. Acquirer firms tend to be large, even before the merger events, which implies that variable markups may play an important role in contributing to lower firm-level volatility.

2.6 Mergers and aggregate volatility

We have shown that mergers reduce *firm-level* volatility by increasing firm size. Volatility of sales growth falls either due to variable markups or lower variance in shocks. How do mergers affect the aggregate economy? We now derive expressions for *aggregate* volatility to understand the impact of mergers at the macro level. By Eq. (17), PY is a constant. Therefore, variance of output Y depends on fluctuations in the aggregate price index P, and in turn, the sectoral price indices, P_k. Allowing for the variance of shocks to decline with firm size, then:

$$\mathbb{V}ar\left[\widehat{P}_k\right] = \bar{v}_z^2 \sum_{i=1}^{M_k} \left(\frac{\alpha_{ki} \mathcal{S}_{ki}^{1-\chi}}{\sum_{i'=1}^{M_k} \alpha_{ki'} \mathcal{S}_{ki'}} \right)^2 ,$$

and by the definition of the aggregate price index in Eq. (3), the variance of output growth is:

$$\mathbb{V}ar\left[\widehat{Y}\right] = \bar{v}_z^2 \sum_{k=1}^{N} \mathcal{S}_k^2 \sum_{i=1}^{M_k} \left(\frac{\alpha_{ki} \mathcal{S}_{ki}^{1-\chi}}{\sum_{i'=1}^{M_k} \alpha_{ki'} \mathcal{S}_{ki'}} \right)^2 . \tag{27}$$

Aggregate volatility in this economy defined by the standard deviation $\sigma\left[\widehat{Y}\right]$.

Under the assumption of constant markups, the power law for firm size follows immediately from the assumptions of CES preferences and the Pareto distribution of firm productivity (di Giovanni and Levchenko, 2012). The economy is granular if the firm-size distribution follows a power law in which the absolute value of the power law exponent is sufficiently close to one, i.e., $\xi/(\widetilde{\varepsilon}-1) \approx 1$, where ξ is the Pareto shape parameter and $\widetilde{\varepsilon}$ is the elasticity of substitution. Under such conditions where Zipf's law holds, Gabaix (2011) shows that the law of large numbers does not apply, and aggregate volatility decays at the slower of rate $\log M$ instead of $\sqrt{M}$. First, consider $\chi = 0$. Under constant markups, we have complete pass-through with $\alpha_{ki} = 1$ and Eq. (27) reduces to

$$\mathbb{V}ar\left[\widehat{Y}\right] = \bar{v}_z^2 HHI,$$

where HHI is the Herfindahl-Hirschman index. In other words, aggregate volatility is an increasing function of market concentration.

Intuitively, mergers create larger, more productive firms which drives up market concentration. Thus, in an economy with constant markups and i.i.d. shocks, mergers increase aggregate volatility. We can decompose the net effect of mergers into an extensive and intensive margin. The extensive margin is driven by selection effects. Because the market becomes more competitive, less productive entrants must exit. In other words, holding fixed the (initial) productivity distribution, the threshold for market entry increases. Denote $\bar{z}$ ($\bar{z}^F$) as the cutoff productivity in the economy with (without) mergers. In a discrete setting, the market shares of firms with productivity $\bar{z}^F \leqslant z_i < \bar{z}$ that were active in an economy without mergers must be distributed among the surviving firms with productivity $z_i > \bar{z}$. Under constant markups, market shares are simply

$$\mathcal{S}_i = \frac{z_i^{\varepsilon-1}}{\sum_{z_{i'}=\bar{z}}^{z^m} z_i^{\varepsilon-1} f(z_i)}.$$

Comparing the economy with mergers to the one without, market size effectively rises for the surviving firms. Therefore, their market shares grow proportionally by the factor $\frac{\sum_{z_{i'}=\bar{z}^F}^{z^m} z_i^{\varepsilon-1} f(z_i)}{\sum_{z_{i'}=\bar{z}}^{z^m} z_i^{\varepsilon-1} f(z_i)} > 1$, where the summation in the numerator (denominator) has the lower bound $\bar{z}^F$ ($\bar{z}$). The Herfindahl index must increase by the same factor, and by Eq. (27), the economy is more volatile.[21]

Next, by holding fixed the cutoff productivity level at $\bar{z}$, we isolate the intensive margin accounted for by the shift in the productivity distribution. As smaller target firms are consolidated by larger acquirers, the initial (i.e., pre-merger) productivity distribution $F(z_i)$ changes into the post-merger distribution $G(z_i)$. The creation of larger merged entities generates a more fat-tailed firm-size distribution. Again, the market becomes more concentrated and volatile. Thus, mergers amplify granular fluctuations of the macroeconomy. Note that this driving force is further strengthened by any productivity gains that the merged entity experiences, which depend on the merger technology function. While we cannot derive further analytical results, a comparison of the pre and post-merger firm-size distributions is illustrated in Figure 8 of Section 4.3 below where the model is quantified.

Even under variable markups, the two driving forces have similar effects within individual sectors. Analysis of the extensive margin differs slightly, as the market shares of firms that exit due to selection effects are no longer proportionally distributed. Instead, we know that in equilibrium, firms with the largest market shares charge the highest markups. Analogously, when the effective market size increases for the surviving firms, the largest firms benefit the most, and their markups and market shares rise disproportionately more than the smaller firms.

Importantly, we now incorporate our previous analysis of firm-level volatility to understand the overall impact of mergers on aggregate volatility. In the setting with variable markups, Eq. (27) shows that volatility is not exactly a function of the Herfindahl index. Rather, market shares are weighted by pass-through rates α_{ki}. From Eq. (21), α_{ki} is decreasing $\mathcal{S}_{ki}$, which means that the weight of large firms in the sectoral (and aggregate) price index is smaller *vis-*

[21] The extensive margin described here encompasses both the entry and selection effects in David (2020), where the former accounts for the change in the number of firms (or mass in a continuous setting) and the latter the change in the cutoff productivity. While a change in the cutoff productivity holding the number of firms fixed affects average productivity in David (2020), we are interested in volatility, which depends on the Herfindahl index and the allocation of market shares. If we hold the number of firms and the productivity distribution fixed and increase the cutoff productivity from $\bar{z}^F$ to $\bar{z}$, then the price index and sales of all firms would adjust proportionally by $\frac{1-F(\bar{z}^F)}{1-F(\bar{z})}$. Average productivity increases, but the distribution of market shares and the Herfindahl index remain unaffected. The number of firms must change to release market shares that are distributed among the surviving firms.

à-vis the setting with constant markups. As shown by Burstein et al. (2020), the impact of large firms on volatility is mitigated by incomplete pass-through. Because mergers are a driving force behind a more granular economy, the response of aggregate volatility depends on the relationship between α_{ki} and s_{ki}. Figure 2 indicates that their product $\alpha_{ki}s_{ki}$ is increasing (at a decreasing rate) for market shares below 0.33. Hence, unless there are extremely dominant players in industries, mergers are expected to generate greater variance in total output growth.

Finally, Eq. (27) reveals that the inverse relationship between firm size and the variance of shocks also affects aggregate volatility through the exponent χ. The variance of large firms is lower, which serves to dampen aggregate fluctuations and the impact of mergers. However, there is an opposite effect on small firms. di Giovanni and Levchenko (2012) refer to this as a "double-edged sword". *A priori*, there is no clear-cut prediction on how aggregate volatility changes. Estimates of χ in the literature vary, but are generally close to 0.16 (e.g., Sutton, 2002; Gabaix, 2011; di Giovanni and Levchenko, 2012). We obtain an estimate of similar magnitude below. To summarize, higher market concentration as a result of mergers drives up aggregate volatility, which is potentially mitigated by the decrease in firm-level volatility from merger-induced firm growth. Data used for the empirical analysis and quantification of the model are described next.

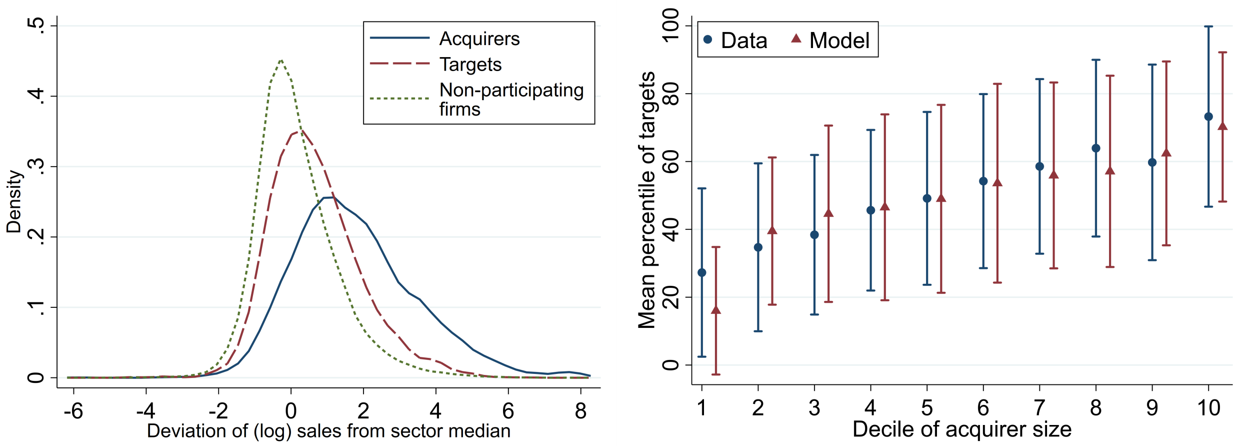
3 Data

3.1 Mergers and patterns in the data

We employ detailed register data from Statistics Denmark for our empirical analysis and quantification of the model. The dataset contains the universe of firms, including both the participants and non-participants of the merger market. Instead of relying on external transaction-level M&A data (e.g., Thomson Reuters SDC Platinum, Zephyr), we identify merger deals from the dataset itself and the acquirer and target firms involved. Specifically, we follow the methodology in Smeets et al. (2016). The establishment register *IDAS* provides a unique establishment identifier that can be followed over time, along with a firm identifier in both the current and following year. This allows for changes in the firm identifier to be tracked. For establishments that share a firm identifier, a change of this identifier to that of an existing firm indicates a change of ownership, which we classify as a merger deal. The pre-merger firm identifier of the establishments before the switch determines the target firm, while the post-merger firm identifier gives the acquirer firm.[22]

From the data registers *FIRM*, *UHDI*, *IDAN*, and *BEF*, we obtain information on firms'

[22] Following Smeets et al. (2016), spurious changes to non-existing firm identifiers, for instance, when headquarters move to a different location, are excluded. Moreover, we also remove all partial mergers from our sample. This eliminates scenarios where: (i) the acquirer receives a fraction of the target's establishments, and the target remains in the market as an independent firm (i.e., with its original firm identifier) after the merger, or (ii) the target's establishments are purchased and controlled by multiple acquirers. Hence, we study the M&A deals in which the acquirer gains full ownership of the target. Lastly, as in Smeets et al. (2016), we exclude joint mergers where two or more firms merge to create a firm with a new (i.e., non-existing) identifier. In this case, the acquirer and target firms cannot be differentiated.



(a) (b)

Figure 5: This figures plots: (a) the kernel densities of the firm size for acquirers, targets, and non-participating firms, and (b) the mean percentile rank of targets across deciles of acquirer size in the data and from model simulation. In both panels, firm size is measured by the log deviation of domestic sales from the sector median.

annual revenues, exports, number of employees, and their 4-digit Danish industry codes. These industry codes correspond to the NACE Rev. 2 classification in the year 2007. We restrict the sample to firms in private industries (i.e., excluding utilities, public administration and defense, education, health services, culture and entertainment) with at least 5 full-time employees between the ages of 18 and 65. We also exclude firms from agriculture, mining, and finance and insurance due to a lack of information. To ensure that sectors have a sufficiently large number of firms, we employ a broad classification to group firms into 17 related sectors, listed in Appendix Table A.3. For example, the manufacture of food, beverages, and tobacco products, which have different 2-digit industry codes, are combined into one category. In line with our model, we focus on horizontal mergers of firms within the same sector. Using our broad sector definitions, 80% of merger deals are classified as horizontal. Even at the 2-digit level, 70% of deals are completed within the same sector.

Our sample contains 3,575 horizontal merger events for the period from 1993 to 2015. In Figure 5(a), we first compare the size of acquirers, targets, and non-participating firms. Firm size is measured by domestic sales, which are computed by subtracting annual exports from total sales. For each group, we plot kernel densities of the firms' (log) domestic sales normalized by the sector median. Overall, acquirers tend to be the biggest firms. Interestingly, we find in the Danish data that on average, targets are also larger than the firms not engaged in M&A activity. Similar patterns can be obtained with other measures such as employment.

Second, we demonstrate in Figure 5(b) that there is a positive sorting pattern between acquirers and targets based on firm size. Earlier literature (e.g., Xu, 2017; David, 2020) documents positive assortative matching in the merger market using M&A transaction-level data. This has been shown for firm profits and productivity, where the latter is measured by the ratio of sales to assets. Here, we split the sample of acquirers into deciles by their domestic sales (again, measured by deviations from the sector median). Next, for each target firm, we compute their percentile rank within the sample of targets. For each decile of acquirer size, we then compute the mean percentile of targets purchased by acquirers in that bin. Figure 5(b) displays strong positive assortative matching on domestic sales between acquirers and targets. Together with Figure 5(a), these graphs suggest that merger-induced firm growth may be substantial, as targets are generally bigger than the average firm. Moreover, the largest acquirers are most likely to be affected.

Due to limitations of the register data, we focus on domestic M&A. Using external data from Zephyr (Bureau van Dijk), Appendix Figure A.2 plots the number of domestic and cross-border merger deals with a Danish target company from 1997 to 2015. The former comprises two-thirds of the total number of deals, and has also experienced significantly higher growth.[23]

3.2 Firm size-volatility relationship

As demonstrated in Section 2.5, the relation between firm size and volatility can be approximated by the linear combination of log-log and log-linear relationships. We now examine the fit of these functional forms using the firm-level data.

As a first step, we replicate the regressions of Koren and Tenreyro (2013) and Yeh (2021) for Denmark. The dependent variable is the (log) volatility of domestic sales growth over a 5-year period (i.e., 1995-9, 2000-4, 2005-9, and 2010-4), and the regressor of interest is the average size of the firm, measured by its (log) market share within the sector. Sales are deflated using the GDP deflator. This log-log functional form follows directly by assuming a power law relationship between volatility and size (i.e., Eq. (18)), which implies $c_1 = \chi$ and $c_2 = 0$ in Eq. (26). Table 1 Panels A and B present estimates from the cross-sectional and panel regressions, respectively. The former employs sector-year fixed effects, while the latter also includes firm fixed effects. Because sector-year fixed effects control for market size, we would obtain numerically identical coefficients if the regressor were the value of sales instead of market share. We restrict the sample to firm-period observations where all five years within the period are observed, but note that results are similar with the entire sample.

Consistent with the prior literature, we find a negative size-volatility relationship at the firm level in Table 1 Panel A column 1. The coefficient estimate in the cross-section is only -0.0387. This is significantly smaller in magnitude than previous cross-sectional estimates. For example, Stanley et al. (1996) and Sutton (2002) find values between -0.15 and -0.21. However, recall that our sample consists of all firms with 5 or more employees, whereas Stanley et al. (1996) and Sutton (2002) consider much larger, publicly traded companies in the Compustat database. We return this point below. The panel regression coefficient in Panel B column 1 is -0.1422,

[23]From Zephyr, we collect data on both "completed-confirmed" and "completed-assumed" horizontal deals, where the same sector classifications as described above are employed. For comparability, we also restrict the set of deals to those in which the acquirer obtains 100% of the final ownership stake. Note that while we can identify changes in foreign ownership from the Danish register data for a subset of the sample, we do not observe the foreign acquirers nor their characteristics, which is necessary for estimating the model.

Table 1: Firm size-volatility Relationship

Panel A: Cross-sectional regression results					
Dep. var.	(log) Volatility	(log) Strategic market power effect		(log) Volatility	(log) Adjusted volatility
	(1)	(2)	(3)	(4)	(5)
(log) Market share	-0.0387***		-0.0139***	-0.0378***	-0.0319***
	(0.0034)		(0.0001)	(0.0037)	(0.0035)
Market share		-8.2725***		-0.6126	
		(0.0047)		(0.8769)	
Sector-year FE	Y	Y	Y	Y	Y
N	49,064	49,064	49,064	49,064	49,064
R^2	0.133	0.985	0.220	0.133	0.133

Panel B: Panel regression results					
Dep. var.	(log) Volatility	(log) Strategic market power effect		(log) Volatility	(log) Adjusted volatility
	(1)	(2)	(3)	(4)	(5)
(log) Market share	-0.1422***		-0.0106***	-0.1384***	-0.1377***
	(0.0126)		(0.0002)	(0.0128)	(0.0126)
Market share		-8.1172***		-3.3036*	
		(0.0076)		(1.9116)	
Sector-year FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
N	49,064	49,064	49,064	49,064	49,064
R^2	0.628	0.998	0.922	0.628	0.629

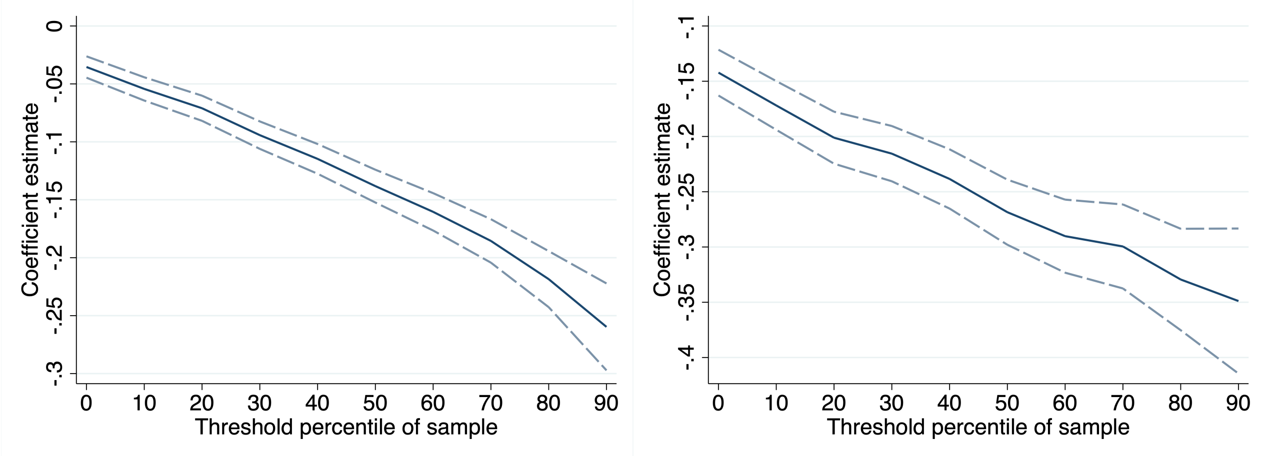
Notes: Volatility is measured by the standard deviation of domestic sales growth over a 5-year period (i.e., 1995-9, 2000-4, 2005-9, and 2010-4). Strategic market power effect in columns 2 and 3 refers to Eq. (24), assuming $\phi = 1$ and $\varepsilon = 5$. "Adjusted volatility" in column 5 is volatility minus the strategic market power effect on volatility. Robust standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.

which is much closer in magnitude to previous estimates in the literature. Koren and Tenreyro (2013), again for US firms in Compustat, obtain an estimate of -0.16 using panel regressions with firm fixed effects and the volume of sales as the measure of size. Even with the universe of US firms, Yeh (2021) obtains a value of -0.149, which is very close to our estimate.[24]

Next, we investigate the hypothesized log-linear component in the firm size-volatility relationship. In columns 2 and 3, the dependent variable is the (log) strategic market power effect on volatility in Eq. (24), which we compute using the register data assuming $\phi = 1$ and $\varepsilon = 5$. In Panel A, we see that the fit is much better with market share in levels ($R^2 = 0.985$) as opposed logs (0.220). This is consistent with our analysis in Section 2.5, especially Figure 3.

In column 4, we estimate the coefficients c_1 and c_2 in Eq. (26) without any constraints on ϕ and ε. In either Panel A or B, we find that the coefficients of market share in logs and levels are both negative. Although the linear term is less precisely estimated, this does not necessarily mean that strategic market power has no quantitative significance. From Figure 4(b), we know that the log-log relationship dominates for small firms and the contribution of variable markups to volatility becomes relevant only when market shares are large. In the data, the firm-size distribution roughly follows Zipf's law (e.g., Gabaix, 2011), with many small firms and few

[24]If employment is used instead as the measure of firm size, Koren and Tenreyro (2013) and Yeh (2021) find estimates of -0.134 and -0.215, respectively.



(a) (b)

Figure 6: This figure plots coefficient estimates from regressions of (log) volatility on (log) firm size for different samples using: (a) the cross-section for the period 2010-4 with sector fixed effects; and (b) the panel for the periods from 1995 to 2014 with firm and sector-year fixed effects. The threshold percentile indicates the lower bound of firm size in the sample.

large firms. Therefore, it is not surprising that the ordinary least squares (OLS) regression fits the log-log function well, while the log-linear function is not precisely estimated.

Finally, in column 5, we obtain a model-based estimate of χ in the log-log relationship, taking into account the variable markup channel. Again, we impose $\phi = 1$ and $\varepsilon = 5$ to compute the strategic market power effect and subtract it from volatility to obtain what we call "adjusted volatility" as the dependent variable (in logs). In Panel B, the coefficient is -0.1377, which is slightly smaller in magnitude compared to the baseline estimate in column 1.

The log-linear component predicts that volatility falls disproportionately and much faster for large firms. We provide further evidence consistent with this idea in Figure 6. In Figure 6(a), we estimate the log-log relationship at the cross-section for the period 2010-4. This corresponds to the specification in Table 1 Panel A column 1 (with sector in place of sector-year fixed effects). Results are qualitatively similar for the other periods (see Appendix Table A.1). The horizontal axis indicates the size threshold above which firms remain in the sample. For example, a value of 0 means that all firms are included, a value of 10 means that only firms above the 10th percentile are included, and so on.

A striking pattern is observed. As the threshold percentile rises and the sample is restricted to larger and larger firms, the coefficient estimate clearly declines and increases in magnitude. Moreover, the coefficient magnitudes vary substantially, ranging from 0.035 in the entire sample to 0.26 for the top 10 percent of firms. We obtaining a similar finding for the panel regression, as shown in Figure 6(b). This evidence is consistent with Figure 4(b), and strongly supports our hypothesis that the firm size-volatility relationship is characterized by the linear combination of the log-log *and* log-linear functions. Furthermore, it is interesting to note that in the non-parametric estimation of Figure 1 in Yeh (2021), deviations from the log-log specification are not large, as we had also concluded. Yet, the shape of the non-parametric relationship follows a similar pattern to ours, with the slope becoming steeper for large firms.

3.3 Mergers and firm-level volatility

Based on the results above, we expect the volatility of acquirer firms to decrease after a merger. Comparing the pre and post-merger period, the domestic sales of acquirers grow on average by over 30%.[25] As before, volatility is measured by the standard deviation of domestic sales growth over a five-year interval. Denote the merger year by $\tau = 0$. As an example, two years before the merger year, we compute the standard deviation of sales growth between $-4 \leqslant \tau \leqslant 0$. Because consolidation of the target firm inflates the growth rate of the acquirer in the year after the merger, we exclude it from the calculation of volatility in $\tau \in \{-1, 0, +1, +2, +3\}$. In other words, for these years, volatility is computed over four years instead of five.

In Figure 7, we plot the acquirer's change in volatility five years before and after a merger. Specifically, we employ a simple event-study design and estimate the following regression:

$$\log(\text{Volatility})_{kit} = c_i + c_t + \sum_{\tau=-5,\, \neq 0}^{+5} \beta_\tau \mathbf{1}\left[t - \text{MergerYear}_i = \tau\right] + e_{kit}. \tag{28}$$

To keep the sample clean, we drop firms that have multiple years with acquisition deals. The specification in Eq. (28) is a two-way fixed effects (TWFE) estimator that includes both firm (c_i) and time (c_t) fixed effects to control for unobserved heterogeneity. Thus, we estimate changes over time within a firm. The coefficients of interest are β_τ, which can interpreted as (approximate) percentage changes in volatility in year τ relative to the merger year. The event window considered is 11 years, and we bin distant relative years (i.e., $\tau{<}{-5}$ and $\tau{>}{+5}$) with two indicator variables. These coefficients are not shown in Figure 7, but are reported in Appendix Table A.2. Figure 7 shows no obvious pre-trends before the merger. Importantly, we find that volatility clearly falls after the merger. The acquirer's volatility declines around 8% in the two years following a merger, and an even larger 11-18% in the three years after that.

Appendix Table A.2 further demonstrates that the results are quantitatively similar when we include non-participating firms in the sample as a control group, and also when we use the imputation estimator from Borusyak et al. (2021) to address the issues of staggered treatment and heterogeneous treatment effects. Moreover, including the year after the merger in the computation for $\tau \in \{-1, 0, +1, +2, +3\}$, not surprisingly, raises volatility in these specific years. However, we continue to find a significant decline for $\tau{>}{+3}$, corroborating our main results.

[25]This is the coefficient estimate from a regression of (log) domestic sales on an indicator variable for the post-merger period, along with firm and year fixed effects. Here, the post-merger indicator variable is equal to 1 in the five years after the merger, and 0 in the merger year and the five years before.

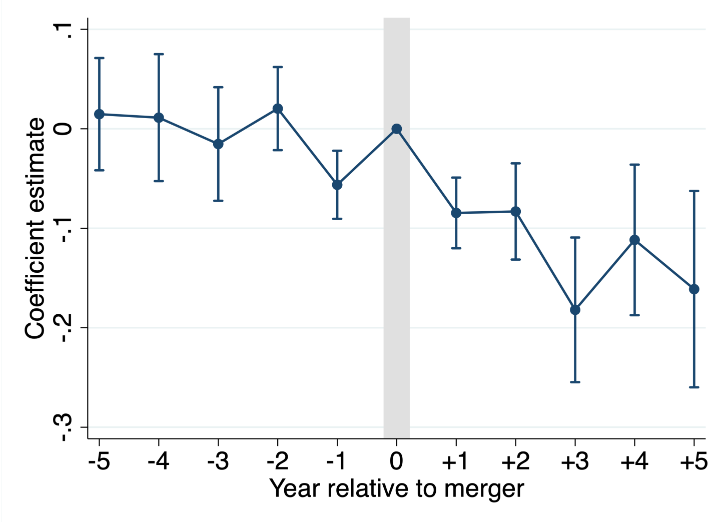


Figure 7: This figure plots coefficient estimates over the event window from estimating Eq. (28), along with 90% confidence intervals, to show the impact of mergers on (log) volatility. Volatility is measured by the standard deviation of domestic sales growth over 5 years in for $\tau \in \{-5, -4, -3, -2, +4, +5\}$, and over 4 years for $\tau \in \{-1, 0, +1, +2, +3\}$.

4 Quantitative assessment

4.1 Estimation

To estimate the model parameters, we match key moments in our model to the Danish data. Details of the estimation process are provided in Appendix C. Because we do not explore the heterogeneity of the merger market across sectors, we estimate the merger market parameters under constant markups. However, to make the results more comparable between the constant and variable markup models, where applicable, we aggregate across sectors to obtain the equivalent economy-wide moments or parameters.

In the multi-sector model under variable markups, we set the elasticity of substitution across sectors $\phi = 1$, which implies Cobb-Douglas preferences over sectors (e.g., Atkeson and Burstein, 2008). Thus, D_k is exactly equal to the sales share of each sector k. Moreover, we follow Gaubert and Itskhoki (2021) and choose a value of $\varepsilon = 5$ for the elasticity of substitution within a sector. We take the post-merger productivity distribution to be the observed distribution in the data, and assume that it follows a Pareto distribution with shape parameter ξ_k, i.e., $G_k(z_{ki}) = 1 - \underline{z}_k^{\xi_k} z_{ki}^{-\xi_k}$. In a first step, we estimate ξ_k, from which we derive the elasticity of substitution $\tilde{\varepsilon}$ for the constant markup model.

Following Burstein et al. (2020), ξ_k is set to match the model-implied market concentration as measured by the Herfindahl index to its observed values in the data. To do so, we need to solve the equilibrium in the economy under variable markups. We normalize wage $w = 1$ as the numéraire, and set the number of firms $M = 100{,}000$, which is roughly the average number of firms with 5 or more full-time employees in any given year. The share of firms in each sector M_k is presented in Appendix Table A.3 column 1. Now, for a guess of the shape parameter ξ_k, we randomly draw M_k productivity levels from the Pareto distribution with scale parameter 1. This allows us to solve firm market shares $\mathcal{s}_{ki}$ as a fixed point problem using Eqs. (19) and (20) and calculate the Herfindahl index. We repeat this process for 1,001 random samples and take the median value. The guess of ξ_k is updated until the market concentration in each sector matches the data (see Appendix Table A.4 column 1). Estimates of ξ_k and the ratios $\frac{\xi_k}{\varepsilon-1}$ are shown in Appendix Table A.4 columns 2 and 3, respectively. The latter ranges from 1.08 to 1.45, which suggests that the firm-size distributions are indeed fat tailed.

Next, we compute firm-level markups $\mathcal{m}_{ki}$ using Eq. (20) and aggregate up to the sector level ($\mathcal{M}_k$). Using the sectoral market shares $\mathcal{S}_k$ from Appendix Table A.3 column 2, we determine the economy-wide markup $\mathcal{M}$. Hence, moving from oligopoly to monopolistic competition, we set $\widetilde{\varepsilon} = \frac{\mathcal{M}}{\mathcal{M}-1} = 4.85$ in the constant-markup economy. Furthermore, the market size PY is normalized to 100 (i.e., marginal disutility of labor $\psi = 0.01$). By employing the same methodology as above, we obtain the Pareto shape parameter of the productivity distribution in the constant-markup economy $\xi = 4.48$. From the sectoral exit rates δ_k (see Appendix Table A.3 column 3), we compute the aggregate exogenous exit rate, i.e., $\delta = \sum_k M_k \delta_k = 0.113$. Firms are considered to leave the market when they have no production for three years straight. Because this includes the scenario where the firm is acquired as a target, we subtract raw exit rates by the merger rates of each sector.

4.2 Merger market parameters

We follow the approach in David (2020) and use simulated method of moments (SMM) to estimate the merger market parameters, $\Theta = \{\gamma, \nu, A, B, \eta\}$. Because we do not have data on transaction values, we cannot estimate the merger premium as in David (2020). Instead, we rely on his estimate of the acquirer's bargaining power $\beta = 0.51$. The discount rate is $\rho = r = 0.05$.

Given candidate values of γ, ν, and A, the merger matrix is defined by computing the productivity of the merged firm $s[z_i^a, z_i^t]$ for every pair of acquirer and target (see Eq. (9)). We perform value function iteration, where, for candidate values of B and η in the search cost function (i.e., Eq. (11)), the value of the firm is updated according to Eq. (12). The cutoff firm has a normalized productivity level of $\bar{z} = 1$. Thus, by Eq. (14), we solve for c^d such that the cutoff firm has zero value, i.e., $V_i(\bar{z}) = 0$.[26] We then simulate the economy to obtain the model-implied moments. Following David (2020), the five moments chosen are: (i) the median acquirer size, (ii) median target size, (iii) share of targets in the bottom decile of the firm-size distribution, (iv) aggregate merger rate, and (v) coefficient of variation of target size. Here, firm size is again measured by domestic sales, and the first two moments are measured as deviations from the median firm in logarithms. Because our register data contains the universe of firms, the merger rate is one order of magnitude smaller than David (2020), who uses a sample of

[26] We normalize the cutoff productivity $\bar{z}$ (or $\bar{z}_k$ $\forall k$ in the variable-markup economy) to 1, instead of the sunk cost of entry c^e (or c_k^e). Hence, in the variable-markup economy, we allow sunk entry costs to vary across sectors. In other words, rather than fixing c_k^e and guessing M_k (or equivalently, the price index P_k), we fix M_k and solve for c_k^e. This is equivalent to finding a sunk cost of entry that satisfies the free entry condition and generates a model-implied survival rate that matches the data.

Table 2: Merger Market Moments and Parameter Estimates

Parameter	Estimate	Target moment	Data	Model
γ	0.90 (0.01)	Median of $\log(r^A_{ki})$	1.72	1.71
ν	0.42 (0.01)	Median of $\log(r^T_{ki})$	0.67	0.67
A	1.01 (0.001)	Share of targets in bottom decile	0.05	0.05
B	1.00×10^{11} (0.28×10^{11})	Aggregate merger rate	0.005	0.005
η	13.00 (0.14)	Coefficient of variation of r^T_{ki}	2.47	2.47

Notes: Log sales, $\log(r_{ki})$, are measured by deviations from the median firm. Annual averages of the data moments are computed over the sample period. Per data confidentiality requirements, the median is approximated by the mean of the five observations centered around it. Bootstrapped standard errors in parentheses account for sampling error and simulation error following the method in Eaton et al. (2011).

Compustat firms. This procedure is iterated to minimize the difference between the moments constructed with the simulated economy and the data.[27]

The parameter estimates are presented in Table 2. Their magnitudes are similar to those from David (2020). In particular, with regards to the merger technology function, we obtain $\gamma = 0.90$ and $\nu = 0.42$. Their sum is greater than 1, which suggests that there are strong complementarities in the mergers. Next, the value of A estimated is 1.01. This parameter estimate is slightly greater than 1, which implies additional productivity gains for all acquirer-target pairs. Merger-induced firm growth contributes to a more fat-tailed firm-size distribution, which we discuss below in Section 4.3. We obtain $B = 1.00\times10^{11}$ and $\eta = 13.0$, which suggests a very convex search cost function.

To gauge the model fit, we find that all of the targeted moments in Table 2 can be matched by the model. This includes the average sizes of the merger partners, the dispersion of targets, and the merger rate. Moreover, Figure 5(b) shows that the model can replicate the positive assortative matching pattern from the data fairly well. Using the sample of acquirers and targets generated by the model, we repeat the same set of calculations. Consistent with the data, the average size of targets is monotonically increasing in the size of acquirers. Furthermore, we find that the model also performs well in matching the average size of targets for any decile in the distribution of acquirers.

[27] We iterate on our procedure to minimize the loss function $\left(m-\widehat{m}(\Theta)\right)' W \left(m-\widehat{m}(\Theta)\right)$, where m is the vector of the five target moments from the data, $\widehat{m}(\Theta)$ is the vector of corresponding moments constructed using the simulated economy with parameters $\Theta = \{\gamma, \nu, A, B, \eta\}$, and W is a matrix of weights. We use the generalized inverse of the estimated variance-covariance matrix of the moments computed from the data. As in David (2020), the parameters are jointly estimated, which implies that the individual parameters and moments do not have a one-to-one mapping. Appendix Figure A.5 demonstrates that the moments display sensitivity to the parameters. For example, an increase in γ, all else equal, raises merger gains and therefore lowers the median size of acquirers. A rise in B discourages mergers and the merger rate declines, while an increase in η raises the search costs especially of larger firms. Thus, smaller firms search more, and the dispersion of targets increases.

4.3 Counterfactuals under constant markups

4.3.1 Solving the equilibrium

We begin by conducting counterfactuals in the economy under constant markups to understand how mergers affect aggregate volatility. This is a simpler setup with complete pass-through of productivity shocks to firm-level prices. Thus, we turn off the channel of markup adjustments by the firm and study the remaining forces (e.g., shift in the firm-size distribution), which are present in both the constant and variable-markup economies.

With the merger market parameters estimated, we use the stationary condition in Eq. (15) to construct the pre-merger productivity distribution $F(z_i)$. The aggregate survival rate is $\frac{M}{M^e} = \left[\sum_{k=1}^{N} \frac{M_k^e}{M_k} \frac{M_k}{M}\right]^{-1} = 0.54$, where the sectoral survival rates are taken from Appendix Table A.3 column 4. These rates are defined as successful entry after five years, and are similar to those found in, for example, the US (e.g., Bartelsman et al., 2013). Hence, we derive the probability mass function $f(z_i)$ for all $z_i \geqslant \bar{z}$. This also allows us to compute the sunk cost of entry c^e using the free entry condition in Eq. (16). By definition, firms with productivity below $\bar{z}$ exit the market after discovering their productivity draws.

Figure 8 plots the firm-size distributions in the benchmark economy with $G(z_i)$ and the counterfactual economy with $F(z_i)$ for $z_i \geqslant \bar{z}$. We zoom into the section with lower values of (log) sales to demonstrate how the two distributions differ. Note that in the benchmark economy with mergers, $G(z_i)$ follows the Pareto distribution. Thus, the firm-size distribution follows a power law and has the constant slope of $\xi/(\widetilde{\varepsilon} - 1)$. The figure shows that at the lowest levels of productivity and sales, the (log) fraction of firms with sales greater than c, $P\{Sales_i > c\}$, is higher in the counterfactual economy without mergers compared to the benchmark economy with mergers. However, at the right tail where firms and their sales are large, the reverse is true. Hence, mergers generate a more fat-tailed firm-size distribution. As the economy becomes more granular, firm-level idiosyncratic shocks result in greater aggregate fluctuations.

The counterfactual economy without mergers is less competitive, as there are fewer large firms and smaller firms can more easily survive (e.g., David, 2020). Denote the counterfactual cutoff productivity level as $\bar{z}^F < \bar{z}$. The stationary condition does not directly provide information on the shape of the pre-merger productivity distribution for $\bar{z}^F \leqslant z_i < \bar{z}$. Following David (2020), we extrapolate the function $f(z_i)$ for $z_i < \bar{z}$ to generate a reasonable estimate of the productivity distribution. Details are provided in Appendix D.[28] Without mergers, the economy collapses to the Melitz (2003) model without trade, with $F(z_i)$ as the productivity

[28] To extrapolate $f(z_i)$, we run a regression of $\log[f(z_i)]$ on $\log(z_i)$ $\forall$ $z_i \geqslant \bar{z}$. Then, we extend the productivity grid space for $z_i < \bar{z}$ (also log-spaced), and compute $\log[f(z_i)]$ for these additional grid points given the value of $\log[f(\bar{z})]$ and the slope coefficient obtained from the regression. For comparison, Appendix Figure A.4 also shows the productivity distribution from simply performing a linear extrapolation. The distributions do not deviate much for values of z_i close to $\bar{z}$, and the result for $\sigma[\widehat{Y}^G]/\sigma[\widehat{Y}^F]$ is 1.040, which is very close to the estimate of 1.044 obtained using the alternative method proposed in the main text. The reason for not using linear extrapolation is that in the economy under variable markups, the number of firms in each sector is constrained to M_k, which is much smaller. The randomness of the productivity draws implies that there is no guarantee for $f_k(\bar{z}_k)$ to be greater than the next point in the probability mass function. If $f_k(\bar{z}_k)$ were less than the next point in the probability mass function, simple linear extrapolation would predict a probability mass function that is *increasing* for $z_{ki} < \bar{z}_k$.

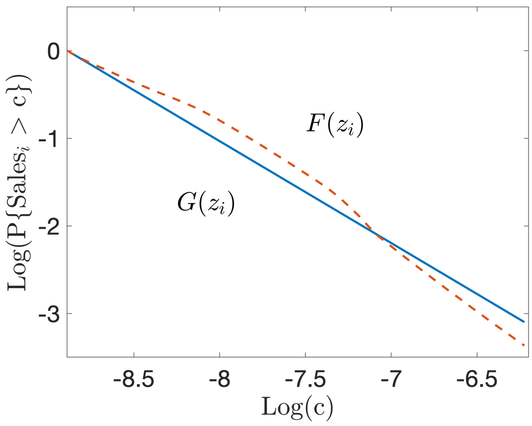


Figure 8: This figure plots the firm-size distributions of the benchmark economy under $G(z_i)$ and the counterfactual economy under $F(z_i)$ for $1 \leqslant z_i \leqslant 10^{0.3}$. The sum of the probability mass functions (i.e., $\sum_{z_i=\bar{z}}^{z^m} g(z_i)$ and $\sum_{z_i=\bar{z}}^{z^m} f(z_i)\left[\sum_{z_i=\bar{z}}^{z^m} f(z_i)\right]^{-1}$) is equal to 1. Firm size is measured by domestic sales.

distribution. Therefore, we can directly determine $\bar{z}^F$ by solving for the point that satisfies the free entry condition. It is straightforward to then compute the number of firms in the counterfactual equilibrium M^F.

4.3.2 Results

We now compare aggregate volatility in the benchmark economy under $G(z_i)$ against the counterfactual economy under $F(z_i)$. First, we consider the case of i.i.d. productivity shocks with constant variance (i.e., $\chi = 0$ in Eq. (18)). The median volatility of each economy is calculated over 1,001 samples. Taking the ratio gives

$$\frac{\sigma[\widehat{Y}^G(\bar{z}|\chi=0)]}{\sigma[\widehat{Y}^F(\bar{z}^F|\chi=0)]} = 1.044 = \underbrace{\frac{\sigma[\widehat{Y}^F(\bar{z}|\chi=0)]}{\sigma[\widehat{Y}^F(\bar{z}^F|\chi=0)]}}_{\text{Extensive margin}} \times \underbrace{\frac{\sigma[\widehat{Y}^G(\bar{z}|\chi=0)]}{\sigma[\widehat{Y}^F(\bar{z}|\chi=0)]}}_{\text{Intensive margin}} = 1.011 \times 1.032.$$

This implies that under constant markups, the benchmark economy with mergers is around 4.4% more volatile than the counterfactual economy without mergers. As we shall see below, the variable-markup economy delivers results with higher magnitudes. While perhaps not directly comparable, di Giovanni and Levchenko (2012) find that by opening up to trade from a state of autarky, Denmark's volatility rises by 15.6%.

We can decompose the total effect of mergers in the calculation above into the contribution of an extensive and intensive margin. As discussed in Section 2.6, the extensive margin is driven by selection effects from a change in the cutoff productivity, i.e., $\bar{z}^F < \bar{z}$, and the intensive margin by a shift in the productivity distribution from $F(z_i)$ to $G(z_i)$. Because there is a discrete number of firms, the market shares of small firms that exit due to selection effects are divided among the surviving firms, increasing market concentration. To isolate the extensive margin, we compute aggregate volatility in a hypothetical scenario where firms with $z_i < \bar{z}$ are dropped from the counterfactual economy, holding fixed the productivity distribution at $F(z_i)$ for $z_i \geqslant \bar{z}$. This is denoted as $\sigma[\widehat{Y}^F(\bar{z}|\chi = 0)]$. Its ratio to the counterfactual volatility $\sigma[\widehat{Y}^F(\bar{z}^F|\chi = 0)]$ is equal to 1.011. Hence, the extensive margin and selection effects account for one-quarter (i.e., 1.1/4.4) of the rise in aggregate fluctuations from mergers. The remaining 75% is accounted for by the intensive margin, indicated by the ratio of $\sigma[\widehat{Y}^G(\bar{z}|\chi = 0)]$ in the benchmark economy to $\sigma[\widehat{Y}^F(\bar{z}|\chi = 0)]$. This ratio compares two productivity distributions holding fixed the productivity threshold. Therefore, the major driving force behind the increase in macroeconomic volatility is the shift in productivity distribution. The firm-size distribution becomes more fat tailed, thereby amplifying granular fluctuations.[29]

Now, we relax the assumption of i.i.d. productivity shocks, and suppose that there is a negative relationship between size and volatility because larger firms face shocks with lower variance. In particular, we set $\chi = 0.14$ in Eq. (18). Recall from the discussion in Section 2.6 that this gives an ambiguous prediction with regards to whether volatility is amplified or mitigated. Nonetheless, performing the same calculations as above gives:

$$\frac{\sigma[\widehat{Y}^G(\bar{z}|\chi = 0.14)]}{\sigma[\widehat{Y}^F(\bar{z}^F|\chi = 0.14)]} = 1.037 = \frac{\sigma[\widehat{Y}^F(\bar{z}|\chi = 0.14)]}{\sigma[\widehat{Y}^F(\bar{z}^F|\chi = 0.14)]} \times \frac{\sigma[\widehat{Y}^G(\bar{z}|\chi = 0.14)]}{\sigma[\widehat{Y}^F(\bar{z}|\chi = 0.14)]} = 1.010 \times 1.027.$$

Aggregate volatility is lower, and again, the shift in the productivity accounts for the majority of the total effect. Although smaller firms have higher variance in sales growth, selection effects imply that the smallest, most volatile firms exit the market. Moreover, mergers create larger, less volatile firms. Results from the counterfactual exercises are summarized in Table 3.

4.4 Counterfactuals under variable markups

4.4.1 Solving the equilibrium

From the previous steps in Section 4.1, we obtain the Pareto shape parameters ξ_k, productivity distributions $G_k(z_{ki})$, and market shares s_{ki} for each of 1,001 random samples. With i.i.d. productivity shocks, we approximate firms' expected profits using a Taylor expansion: $\pi^E_{ki}(z_{ki}) = \pi_{ki}(z_{ki}) + \frac{1}{2}\frac{\partial^2 \pi_{ki}(z_{ki})}{\partial z^2_{ki}}\bar{v}^2_z$. The second-order partial derivative is calculated numerically, and we set $\bar{v}_z = 0.1$ (e.g., di Giovanni and Levchenko, 2012). The computation of markups m_{ki}, pass-through rates α_{ki}, and profits $\pi_{ki}(z_{ki})$ follows directly from Eqs. (20), (21), and (8).

The value of a firm is determined by current expected profits $\pi^E_{ki}(z_{ki})$ and expected merger gains net of search costs. We use the same method as the constant-markup economy to solve the merger market here for each of the random samples. Because market shares in the Cournot equilibrium are computed for a specific set of firms, when defining the merger matrix $s[z^a_{ki}, z^t_{ki}]$,

[29] The alternative decomposition is $\frac{\sigma[\widehat{Y}^G(\bar{z}^F|\chi=0)]}{\sigma[\widehat{Y}^F(\bar{z}^F|\chi=0)]} \times \frac{\sigma[\widehat{Y}^G(\bar{z}|\chi=0)]}{\sigma[\widehat{Y}^G(\bar{z}^F|\chi=0)]}$, where mergers shift the productivity distribution holding fixed the counterfactual economy's cutoff productivity, and selection effects change the cutoff productivity while maintaining the Pareto distribution. In this case, we obtain 1.023×1.020, and intensive margin continues to account for the majority of the total effect.

Table 3: Results from Counterfactual Exercises

Variance of shocks		Panel A: Constant-markup economy Constant $\chi = 0$ (1)	 Decreasing in size $\chi = 0.14$ (2)
Total effect of mergers	$\frac{\sigma[\widehat{Y}^G(\bar{z}\|\chi)]}{\sigma[\widehat{Y}^F(\bar{z}^F\|\chi)]}$	1.044	1.037
Extensive margin	$\frac{\sigma[\widehat{Y}^F(\bar{z}\|\chi)]}{\sigma[\widehat{Y}^F(\bar{z}^F\|\chi)]}$	1.011	1.010
Intensive margin	$\frac{\sigma[\widehat{Y}^G(\bar{z}\|\chi)]}{\sigma[\widehat{Y}^F(\bar{z}\|\chi)]}$	1.032	1.027

Variance of shocks		Panel B: Variable-markup economy Constant $\chi = 0$ (1)	 Decreasing in size $\chi = 0.14$ (2)
Total effect of mergers			
Incomplete pass-through	$\frac{\sigma[\widehat{Y}^G(\bar{z}_k\|\alpha_{ki}<1,\chi)]}{\sigma[\widehat{Y}^F(\bar{z}_k^F\|\alpha_{ki}<1,\chi)]}$	1.124	1.093
Complete pass-through	$\frac{\sigma[\widehat{Y}^G(\bar{z}_k\|\alpha_{ki}=1,\chi)]}{\sigma[\widehat{Y}_k^F(\bar{z}_k^F\|\alpha_{ki}=1,\chi)]}$	1.184	1.138

Notes: The standard deviation of idiosyncratic productivity shocks is defined by $v_z(s_{ki}) = \bar{v}_z s_{ki}^{-\chi}$ for $\chi = 0$ or 0.14.

we restrict merged entities to the same grid points as the initial draw of firm productivities.[30] For each sector, the counterfactual productivity distribution $F_k(z_{ki})$ is constructed for $z_{ki} \geqslant \bar{z}_k$. Fixed costs of production c_k^d and sunk costs of entry c_k^e are derived accordingly. Their (median) values are shown in Appendix Table A.5.

As in the constant-markup economy, we extrapolate the productivity distribution for $z_{ki} < \bar{z}_k$. However, because firms charge variable markups, we can no longer use the free entry condition to directly solve for the cutoff productivity. Instead, we must simulate and solve the equilibrium in each sector. The price index, number of firms, and cutoff productivity are all endogenous variables in the counterfactual economy. To solve them, we first guess a candidate sectoral price index, denoted as P_k^F. For a given productivity cutoff in the counterfactual economy $\bar{z}^F$, we can find the value of M_k^F that satisfies the definition of the price index in Eq. (5). We do so by guessing M_k^F, simulating the economy with random draws, and solving for firm market shares, markups, and prices under Cournot competition. This step is analogous to the benchmark economy. Next, we check the zero profit condition (i.e., Eq. (14)) and update $\bar{z}^F$ (along with M_k^F) until this condition is satisfied. Then, we check the free entry condition and update our guess of the price index P_k^F. This process is repeated until both the zero profit condition and free entry condition are satisfied. In the end, this gives us the endogenous variables P_k^F, $\bar{z}_k^F$, M_k^F, and $F_k(z_{ki})$ $\forall z_{ki} \geqslant \bar{z}_k^F$ for every sector in the counterfactual economy.

[30] If the value of $s[z_{ki}^a, z_{ki}^t]$ between two firms is not an element of the set of drawn productivities in the random sample, the next highest value is used instead.

4.4.2 Results

The steps taken above also provide us with market shares s_{ki} and pass-through rates α_{ki} for the counterfactual economy. Using Eq. (27), we compute aggregate volatility $\sigma[\widehat{Y}]$, where sectoral market shares $\mathcal{S}_k$ are fixed because of Cobb-Douglas preferences. Again, we first consider the case of idiosyncratic shocks with constant variance. We allow for the incomplete pass-through of shocks to prices with $\alpha_{ki} < 1$. The ratio of aggregate volatilities in the benchmark economy under $G_k(z_{ki})$ and the counterfactual economy under $F_k(z_{ki})$ is:

$$\frac{\sigma[\widehat{Y}^G(\bar{z}_k|\alpha_{ki} < 1, \chi = 0)]}{\sigma[\widehat{Y}^F(\bar{z}_k^F|\alpha_{ki} < 1, \chi = 0)]} = 1.124.$$

Thus, in the multi-sector economy under variable markups, mergers increase aggregate fluctuations by around 12.4%. This is larger than the result obtained in the constant-markup economy. Even though Eq. (27) takes into account the size of each sector in computing aggregate volatility, mergers have a greater impact when the number of firms is smaller.[31]

As before, we can decompose the overall effect to examine the individual contributions arising from selection effects and the shift in the productivity distribution, respectively:

$$\frac{\sigma[\widehat{Y}^F(\bar{z}_k|\alpha_{ki} < 1, \chi = 0)]}{\sigma[\widehat{Y}^F(\bar{z}_k^F|\alpha_{ki} < 1, \chi = 0)]} \times \frac{\sigma[\widehat{Y}^G(\bar{z}_k|\alpha_{ki} < 1, \chi = 0)]}{\sigma[\widehat{Y}^F(\bar{z}_k|\alpha_{ki} < 1, \chi = 0)]} = 1.020 \times 1.101.$$

The majority of the rise in aggregate volatility continues to be accounted for by the intensive margin, with the firm-size distribution becoming more fat tailed.

Next, we investigate how the total effect of mergers is influenced by a negative firm size-volatility relationship. Under variable markups, the sales of larger firms may fluctuate less either due to strategic market power and incomplete pass-through, or the lower variance of productivity shocks. First, we maintain the assumption of i.i.d. shocks and consider another hypothetical scenario where firms charge constant markups in the multi-sector economy. This affects the prices and market shares of all firms, and pass-through is complete, i.e., $\alpha_{ki} = 1$. The ratio of volatility is:

$$\frac{\sigma[\widehat{Y}^G(\bar{z}_k|\alpha_{ki} = 1, \chi = 0)]}{\sigma[\widehat{Y}^F(\bar{z}_k^F|\alpha_{ki} = 1, \chi = 0)]} = 1.184.$$

This is significantly higher than our baseline result for the variable-markup economy, and can be explained by two (interconnected) factors. For a given function α_{ki}, the market shares of large firms are higher when setting constant markups at $\varepsilon/(\varepsilon - 1)$, as opposed to variable markups, so the market tends to be more concentrated. Moreover, for given market shares, increasing α_{ki} to 1 directly removes the dampening effect of markups (i.e., Eq. (22)). Our result indicates that even when shocks have constant variance, the market power of large firms formed through mergers limits their firm-level price fluctuations, and by extension, movements in the sectoral and aggregate price indices. By hypothetically assuming constant markups and complete pass-

[31] For example, if M is lowered to 19900, the largest M_k observed across sectors, aggregate volatility in the constant-markup economy rises by 8.5% with mergers.

through, we effectively turn off the channel of variable markups and find that aggregate volatility increases. Taking the ratio between the scenarios with complete and incomplete pass-through informs us that by neglecting variable markups and incomplete pass-through, the change in aggregate volatility is overestimated by almost 50% (i.e., 18.4/12.4). Thus, the strategic market power effect on firm-level volatility plays an important role in mitigating aggregate volatility and the impact of large firms created through mergers.

In Table 3 Panel B column 2, we repeat the exercise above by assuming that $\chi = 0.14$ instead of zero. Similar findings are obtained. The effects of mergers are further dampened, as aggregate volatility rises by around 9.3% with incomplete pass-through. Again, turning off the channel of variable markups increases fluctuations by nearly 50%.

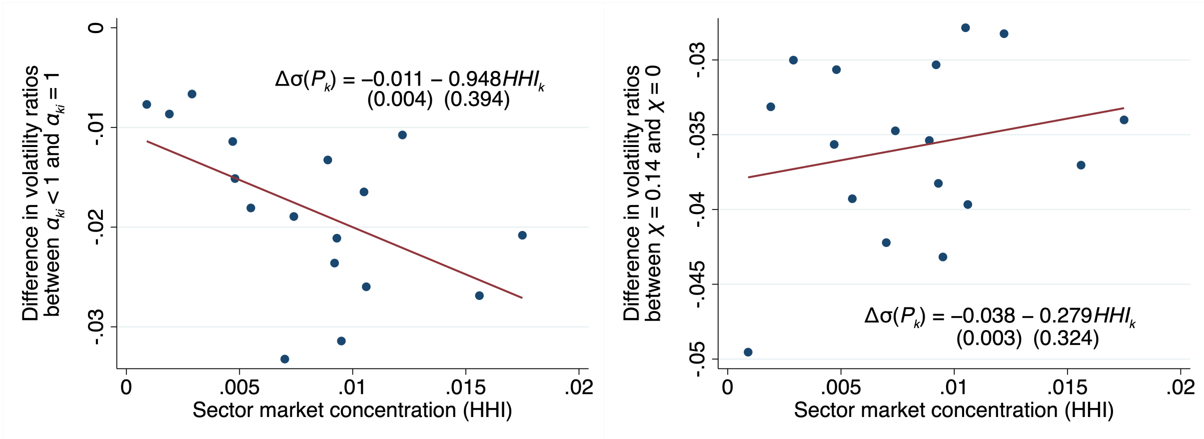
To gauge the importance of each channel, we can also compare the results across the columns of Panel B by row. Moving from χ equals zero to 0.14 in the case of incomplete (complete) pass-through indicates that aggregate volatility is 33.3% (32.5%) smaller when the heterogeneity of shocks is taken into account. Thus, compared to the size-variance relationship of shocks, variable markups have an even larger quantitative effect in mitigating the impact of mergers on aggregate fluctuations. Nonetheless, our findings suggest that ignoring the effects of either channel on firm-level volatility leads to an significant overestimate of the impact of mergers on the variance of output growth.

4.4.3 Sector heterogeneity

The results presented in Table 3 Panel B provide estimates of the aggregate effect of mergers as the sales-weighted average over sectors. However, the outcomes also differ across sectors, and exploring this heterogeneity can be helpful in further understanding the mechanisms involved. In particular, some sectors are more concentrated than others. These differences in market concentration are driven by variation in the underlying productivity distribution. In Appendix Table A.4, the Herfindahl indices of the 17 sectors are strongly negatively correlated with the estimated Pareto shape parameters ξ_k at -0.89.

Our analysis in Section 2.5 showed that the reduction in volatility from variable markups is increasing in firm size. In Figure 4(b), the curve representing the linear combination of the log-log and log-linear functional forms becomes steeper as market shares rise. In sectors with higher market concentration, there are relatively more and/or more dominant large players in the market. Hence, this suggests that the dampening effect from the variable markup channel would be relatively more important. In other words, firm-level volatility falls more for the merged entities, which in turn has a stronger effect in mitigating the rise in aggregate fluctuations.

To test this hypothesis, we take the ratios of volatilities between the benchmark and counterfactual economies by sector. We do this separately for the cases of incomplete pass-through $\alpha_{ki} < 1$ and complete pass-through $\alpha_{ki} = 1$. Then, for each sector, we subtract the ratio of the



(a) (b)

Figure 9: This figure plots the model-implied difference in volatility ratios between (a) the cases of variable and constant markups, and (b) the cases where the variance of shocks declines with size (i.e., $\chi = 0.14$) and where shocks are i.i.d., against sector market concentration measured by Herfindahl index in the data.

incomplete pass-through case by the complete pass-through case. That is, we compute:[32]

$$\frac{\sigma[\widehat{P}_k^G(\bar{z}_k|\alpha_{ki} < 1, \chi = 0.14)]}{\sigma[\widehat{P}_k^F(\bar{z}_k^F|\alpha_{ki} < 1, \chi = 0.14)]} - \frac{\sigma[\widehat{P}_k^G(\bar{z}_k|\alpha_{ki} = 1, \chi = 0.14)]}{\sigma[\widehat{P}_k^F(\bar{z}_k^F|\alpha_{ki} = 1, \chi = 0.14)]}$$

and multiply by 100 to obtain the percentage point difference. At the aggregate level with $\sigma[\widehat{Y}]$, we know from Table 3 Panel B that this difference between the variable and constant markup outcomes is negative. This is also true with $\sigma[\widehat{P}_k]$. Importantly, we expect sectors with higher market concentration to have a more negative difference. Figure 9(a) plots the difference in ratios against Herfindahl indices for the 17 sectors, and we find a strong negative correlation as predicted. This provides further evidence consistent with our theory that firm-level volatility falls disproportionately by size, due to firms' strategic market power and variable markups.

We can repeat this exercise to examine whether differences in sector market concentration can also be explained by heterogeneity in the variance of shocks. In Figure 9(b), we plot

$$\frac{\sigma[\widehat{P}_k^G(\bar{z}_k|\alpha_{ki} < 1, \chi = 0.14)]}{\sigma[\widehat{P}_k^F(\bar{z}_k^F|\alpha_{ki} < 1, \chi = 0.14)]} - \frac{\sigma[\widehat{P}_k^G(\bar{z}_k|\alpha_{ki} < 1, \chi = 0)]}{\sigma[\widehat{P}_k^F(\bar{z}_k^F|\alpha_{ki} < 1, \chi = 0)]}$$

against market concentration. Firm-level volatility is a weighted average of the log-log and log-linear components, and the former dominates when $\mathcal{S}_{ki}$ is small. Thus, in contrast to the variable markup channel, mergers between small firms play a more important role in mitigating aggregate volatility when market concentration is low. The expression above is expected to be more negative in this case. Conversely, the contribution of χ as a dampening force is smaller

[32]Note that with $\phi = 1$, sectoral market sizes $\mathcal{S}_k PY$ are also fixed and $\widehat{Y}_k = -\phi \widehat{P}_k$. We assume $\chi = 0.14$, but the results are quantitatively with $\chi = 0$.

when there are many large firms, so we predict the expression to be closer to zero. Indeed, Figure 9(b) shows a positive correlation, albeit weak and statistically insignificant. The assumed log-log (i.e., power law) relationship implies that volatility declines proportionally with firm size, which may explain why strong differences are not observed across sectors.

4.5 Welfare

We conclude by briefly discussing the welfare implications of mergers. In the case of constant markups, our result mirrors the findings of David (2020) that consumption rises. Mergers induce productivity gains for the merged entity and selection effects drive up the average productivity of firms in the market. In our setting, we find that output and consumption increases by 0.18%. Because aggregate profits under constant markups is zero and the market size is exogenous, labor supply is also held fixed. Thus, welfare improves by the same amount. Our result is qualitatively similar to David (2020), but our estimate for welfare gains is smaller. As mentioned, the merger rate in our sample of the universe of Danish firms is an order of magnitude smaller than in David (2020), who uses a sample of Compustat firms. At the aggregate level, fewer mergers implies less productivity gains.

Under variable markups, we obtain a slightly larger estimate that output and consumption rise by 0.90%. Appendix B demonstrates that aggregate profits are equal to the difference between expected and realized profits. Hence, labor supply adjusts accordingly to satisfy the household's budget constraint, where the market size is again fixed. Taking this into account, welfare increases by 0.22%. In summary, mergers generate efficiency gains which improves welfare, but at the same time, increases aggregate volatility. This suggests that countries face a trade-off, where higher (static) welfare is offset a more volatile business cycle.

5 Conclusion

In this paper, we study the implications of domestic M&A at the firm and aggregate levels. We show that, in addition to the first moment of firm-level sales and aggregate output growth, mergers have a significant impact on the second moment. In order to quantify the effects of mergers on firm-level and aggregate volatility, we build a multi-sector model of horizontal mergers that features a discrete number of firms with market power charging variable markups.

We show that mergers reduce firm-level volatility through an increase in firm size, and this negative relationship is characterized by the linear combination of log-log and log-linear functions. In contrast to the log-log component, the novel log-linear component implies that volatility declines disproportionately with size. Firms adjust their markups in response to shocks such that prices and sales fluctuate less. Thus, the incomplete pass-through of shocks implies a rapid decay of volatility when firms' market shares grow large. Despite the decline in firm-level volatility of acquirer firms, we demonstrate that mergers actually increase macroeconomic fluctuations in a granular economy. The creation of large firms through M&A intensifies selection effects and shifts the productivity distribution such that the firm-size distribution becomes more fat tailed. Ultimately, these effects raise market concentration and aggregate volatility.

Using Danish register data from 1993 to 2015, we provide empirical evidence for the effect of variable markups on volatility, and perform a quantitative assessment of our model. Comparing the benchmark economy with mergers to a counterfactual economy without mergers, we find that mergers increase aggregate volatility by 3.7 to 9.3%. The negative firm size-volatility relationship considerably dampens the impact of mergers. Our results also suggest that policymakers and antitrust authorities face an important trade-off in evaluating mergers. While productivity gains from mergers generate welfare gains, they must also tolerate greater macroeconomic fluctuations, as the business cycle becomes more sensitive to the shocks of large firms created through mergers.

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Appendix to "Mergers and Aggregate Fluctuations in a Granular Economy"

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A Additional figures and tables

Figure A.1: Fraction of total domestic sales accounted for by the top 50 and 100 Danish firms in each year from 1993 to 2015. *Note:* Authors' calculations using Danish register data.

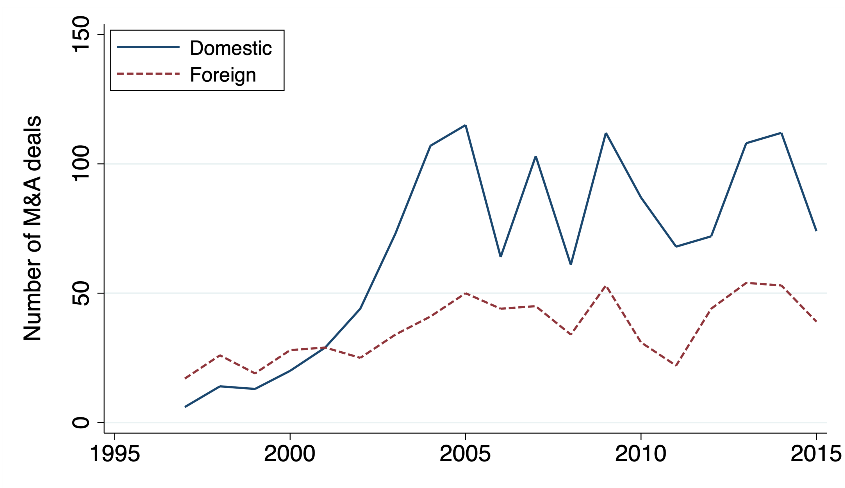

Figure A.2: Number of domestic and foreign acquisitions of Danish target firms from 1997 to 2015. The sample includes completed horizontal mergers in which the final ownership stake is 100%. *Note:* Authors' calculations using data from Zephyr from Bureau van Dijk.

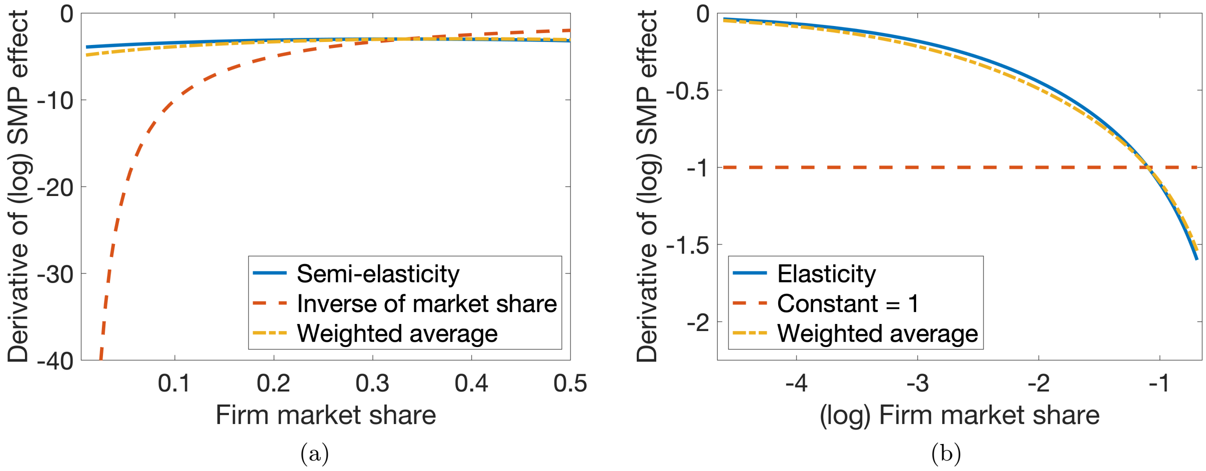

Figure A.3: This figure plots the derivative of the (log) strategic market power (SMP) effect on volatility in Eq. (24) against firm market share in (a) levels, and (b) logarithms. This is denoted by the weighted average. We also decompose each derivative into two components, the semi-elasticity and inverse of the market share in (a), and the elasticity and the constant 1 in (b). For purposes of illustration, we assume $\phi = 1$ and $\varepsilon = 5$, $\sum_{i'=1}^{M_k}(s_{ki'}\alpha_{ki'})^2 = 1$, and $\sum_{i'=1}^{M_k} s_{ki'}\alpha_{ki'} = 1$.

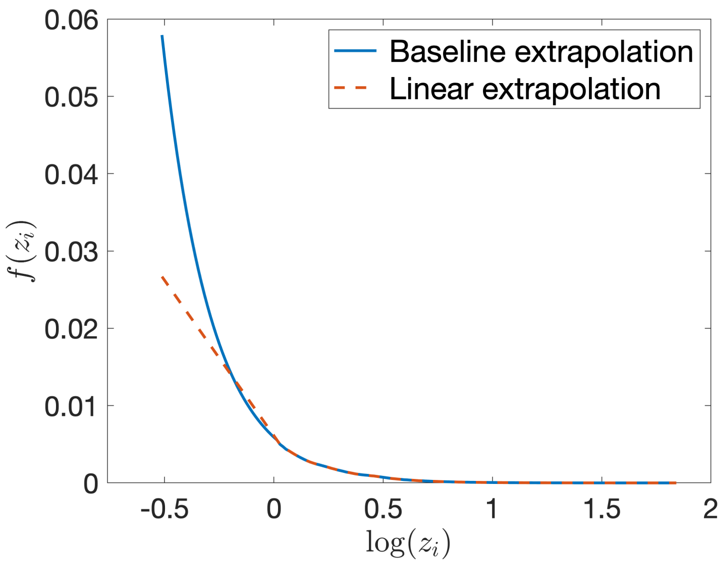

Figure A.4: This figure plots the productivity distribution in the counterfactual economy without mergers $f(z_i)$ for $10^{-0.2} < z_i < 10^{0.8}$. Two different extrapolations are shown. Above $\log(\bar{z}) = 0$, the two curves are identical. Below $\log(\bar{z})$, $f(z_i)$ is extrapolated. The baseline extrapolation is described in Footnote 28 and Appendix D, while linear extrapolation uses the slope from the neighboring grid points.

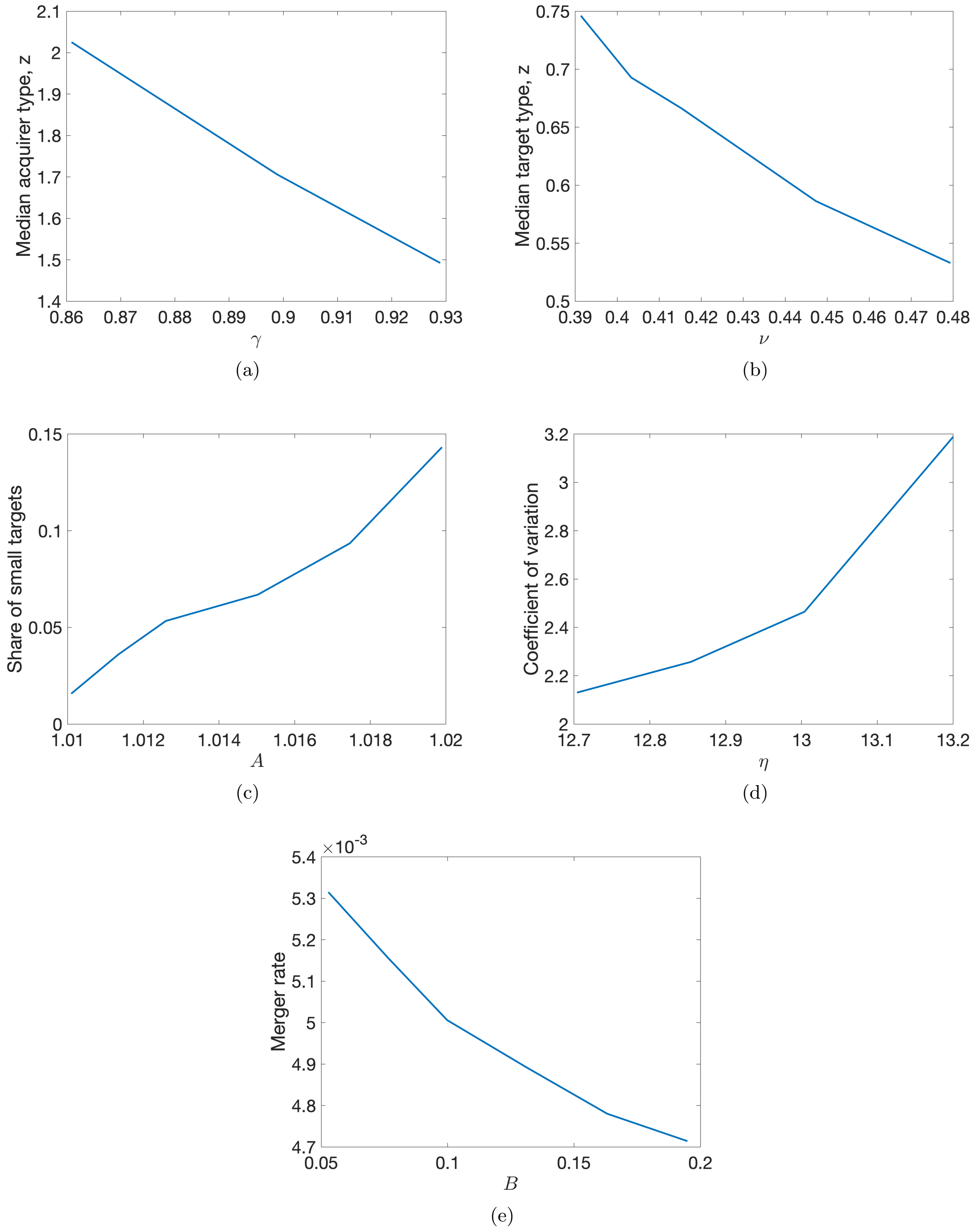

Figure A.5: This figure plots, for various values of the parameters: (a) the median deviation of (log) acquirer sales from the sector median against γ in the merger technology function; (b) the median deviation of (log) target sales from the sector median against ν in the merger technology function; (c) the share of targets in the bottom quintile of the firm-size distribution against A in the merger technology function; (d) the aggregate merger rate against B in the search cost function; and (e) the coefficient of variation of target sales against η in the search cost function.

Table A.1: Cross-sectional Regression Results Across Threshold Percentiles

	Panel A: Period 1995-9									
Threshold percentile	0	10	20	30	40	50	60	70	80	90
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(log) Market share	-0.0052	0.0061	-0.0009	-0.0055	-0.0110	-0.0181*	-0.0265**	-0.0310**	-0.0518***	-0.0546*
	(0.0066)	(0.0072)	(0.0078)	(0.0084)	(0.0091)	(0.0103)	(0.0119)	(0.0143)	(0.0189)	(0.0281)
N	14,858	13,373	11,887	10,401	8,915	7,429	5,944	4,458	2,972	1,486
R^2	0.105	0.116	0.111	0.111	0.107	0.110	0.113	0.115	0.095	0.092

	Panel B: Period 2000-4									
Threshold percentile	0	10	20	30	40	50	60	70	80	90
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(log) Market share	-0.0306***	-0.0428***	-0.0578***	-0.0766***	-0.0913***	-0.0992***	-0.1054***	-0.1058***	-0.1064***	-0.1477***
	(0.0065)	(0.0071)	(0.0077)	(0.0083)	(0.0090)	(0.0100)	(0.0114)	(0.0135)	(0.0176)	(0.0278)
N	15,366	13,830	12,293	10,757	9,220	7,683	6,147	4,610	3,074	1,537
R^2	0.080	0.085	0.084	0.087	0.090	0.092	0.104	0.107	0.100	0.122

	Panel C: Period 2005-9									
Threshold percentile	0	10	20	30	40	50	60	70	80	90
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(log) Market share	-0.0503***	-0.0677***	-0.0782***	-0.0999***	-0.1148***	-0.1243***	-0.1390***	-0.1553***	-0.1769***	-0.2147***
	(0.0057)	(0.0062)	(0.0067)	(0.0072)	(0.0079)	(0.0087)	(0.0099)	(0.0121)	(0.0156)	(0.0247)
N	16,797	15,118	13,438	11,758	10,079	8,399	6,719	5,040	3,360	1,680
R^2	0.115	0.124	0.129	0.137	0.155	0.169	0.164	0.157	0.168	0.196

	Panel D: Period 2010-4									
Threshold percentile	0	10	20	30	40	50	60	70	80	90
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(log) Market share	-0.0354***	-0.0543***	-0.0710***	-0.0942***	-0.1147***	-0.1382***	-0.1604***	-0.1855***	-0.2185***	-0.2597***
	(0.0056)	(0.0061)	(0.0066)	(0.0072)	(0.0078)	(0.0086)	(0.0098)	(0.0114)	(0.0147)	(0.0228)
N	19,924	17,932	15,940	13,947	11,955	9,962	7,970	5,978	3,985	1,993
R^2	0.128	0.134	0.135	0.148	0.168	0.185	0.180	0.164	0.164	0.195

Notes: The dependent variable is (log) volatility. All regressions include sector fixed effects. Robust standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.

Table A.2: Change in Volatility after a Merger

Volatility computation	Excludes $\tau = +1$			Includes $\tau = +1$	
Estimation method	OLS	OLS	Imputation estimator	OLS	Imputation estimator
	(1)	(2)	(3)	(4)	(5)
Merger >+5	-0.1380*	-0.1508***		-0.4581***	
	(0.0712)	(0.0341)		(0.0459)	
Merger +5	-0.1612**	-0.1643***	-0.1739***	-0.4713***	-0.2910***
	(0.0600)	(0.0409)	(0.0382)	(0.0501)	(0.0395)
Merger +4	-0.1117**	-0.1136***	-0.1151***	-0.4191***	-0.2328***
	(0.0460)	(0.0324)	(0.0286)	(0.0374)	(0.0289)
Merger +3	-0.1820***	-0.1821***	-0.1870***	-0.0604**	0.0884***
	(0.0442)	(0.0385)	(0.0311)	(0.0238)	(0.0227)
Merger +2	-0.0831**	-0.0829***	-0.0693***	-0.0092	0.1363***
	(0.0294)	(0.0244)	(0.0232)	(0.0186)	(0.0198)
Merger +1	-0.0846***	-0.0839***	-0.0423***	0.0098	0.1497***
	(0.0216)	(0.0225)	(0.0154)	(0.0131)	(0.0189)
Merger year	–	–	-0.0110	–	0.2471***
			(0.0322)		(0.0348)
Merger −1	-0.0563**	-0.0564**	-0.0634**	-0.0383***	0.2245***
	(0.0208)	(0.0223)	(0.0282)	(0.0119)	(0.0288)
Merger −2	0.0203	0.0195	0.0097	-0.2628***	-0.0027
	(0.0254)	(0.0233)	(0.0253)	(0.0332)	(0.0266)
Merger −3	-0.0153	-0.0226	-0.0322	-0.3021***	-0.0399
	(0.0347)	(0.0271)	(0.0251)	(0.0240)	(0.0260)
Merger −4	0.0112	-0.0013	-0.0067	-0.2807***	-0.0145
	(0.0388)	(0.0301)	(0.0256)	(0.0287)	(0.0253)
Merger −5	0.0147	-0.0029	-0.0032	-0.2782***	-0.0081
	(0.0343)	(0.0222)	(0.0234)	(0.0247)	(0.0226)
Merger <−5	0.0376	0.0068		-0.2628***	
	(0.0544)	(0.0305)		(0.0336)	
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
N	21,033	691,872	685,863	691,872	685,863
R^2	0.473	0.610		0.610	

Notes: The dependent variable is (log) volatility. In columns 1 to 3, the computation of volatility excludes $\tau = +1$ for $\tau \in \{-1, 0, +1, +2, +3\}$. Standard errors in parentheses are clustered at the sector level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.

Table A.3: Sectoral Distribution of Firms, Domestic Sales, Exit Rates, and Survival Rates

Codes	Sector	Share of firms (M_k) (1)	Share of sales (D_k) (2)	Exit rate (δ_k) (3)	Survival rate (M/M^e) (4)
10-12	Food, beverages, and tobacco	0.026	0.047	0.109	0.593
13-15	Textiles and apparel	0.010	0.005	0.119	0.658
16-18	Wood and paper	0.028	0.024	0.105	0.316
19-23	Chemicals, plastics, and non-metallic mineral products	0.023	0.039	0.067	0.540
24-25	Metal and fabricated metal products	0.041	0.028	0.082	0.600
26-27	Computers, electronics, and electrical equipment	0.014	0.017	0.078	0.510
28	Machinery	0.027	0.025	0.069	0.628
29-33	Transport equipment, furniture, and other manufacturing	0.030	0.022	0.103	0.596
41-43	Construction	0.194	0.097	0.118	0.532
45-46	Wholesale trade	0.199	0.355	0.089	0.611
47	Retail trade	0.115	0.095	0.127	0.568
49-53	Transportation and storage	0.064	0.072	0.117	0.473
55-56	Accommodation and food service activities	0.050	0.018	0.170	0.496
58-63	Information and communication	0.040	0.052	0.120	0.518
68	Real estate	0.016	0.010	0.172	0.531
69-75	Professional, scientific, and technical activities	0.084	0.061	0.120	0.581
77-82	Administrative and support service activities	0.039	0.033	0.158	0.476

Notes: Authors' calculations using Danish register data. Averages over the sample period are computed. 2-digit industry codes follow the NACE Rev. 2 statistical classification of economic activities. For a given year, exit rates are defined as the share of firms with no production for 3 years straight. Survival rates are defined as the share of new firms that survive for at least five years. Data on new firms is retrieved from the register *IVNV*, beginning in year 2001.

Table A.4: Market Concentration and Estimated Pareto Shape Parameters

Codes	Sector	HHI (1)	ξ_k (2)	$\frac{\xi_k}{(\varepsilon-1)}$ (3)
10-12	Food, beverages, and tobacco	0.0092	4.73	1.18
13-15	Textiles and apparel	0.0156	4.59	1.15
16-18	Wood and paper	0.0093	4.71	1.18
19-23	Chemicals, plastics, and non-metallic mineral products	0.0089	4.78	1.20
24-25	Metal and fabricated metal products	0.0055	5.04	1.26
26-27	Computers, electronics, and electrical equipment	0.0175	4.33	1.08
28	Machinery	0.0105	4.61	1.15
29-33	Transport equipment, furniture, and other manufacturing	0.0106	4.65	1.16
41-43	Construction	0.0019	5.32	1.33
45-46	Wholesale trade	0.0009	5.80	1.45
47	Retail trade	0.0029	5.18	1.29
49-53	Transportation and storage	0.0047	4.97	1.24
55-56	Accommodation and food service activities	0.0070	4.81	1.20
58-63	Information and communication	0.0074	4.77	1.19
68	Real estate	0.0122	4.60	1.15
69-75	Professional, scientific, and technical activities	0.0048	4.92	1.23
77-82	Administrative and support service activities	0.0095	4.58	1.15

Notes: Authors' calculations of the Herfindahl-Hirschman index (HHI) using the Danish register data and estimates of the Pareto shape parameter ξ_k. Averages of the HHI over the sample period are computed.

Table A.5: Estimated Costs Across Sectors

Codes	Sector	Fixed cost of production (c_k^d, $\times 10^{-5}$)	Sunk cost of entry (c_k^e, $\times 10^{-4}$)
10-12	Food, beverages, and tobacco	7.51	1.83
13-15	Textiles and apparel	2.02	0.58
16-18	Wood and paper	3.49	0.47
19-23	Chemicals, plastics, and non-metallic mineral products	7.33	1.57
24-25	Metal and fabricated metal products	3.28	0.66
26-27	Computers, electronics, and electrical equipment	4.05	1.16
28	Machinery	3.56	1.02
29-33	Transport equipment, furniture, and other manufacturing	2.84	0.76
41-43	Construction	2.63	0.41
45-46	Wholesale trade	11.4	1.56
47	Retail trade	4.10	0.74
49-53	Transportation and storage	5.14	0.87
55-56	Accommodation and food service activities	1.51	0.30
58-63	Information and communication	5.40	1.14
68	Real estate	2.50	0.58
69-75	Professional, scientific, and technical activities	3.16	0.70
77-82	Administrative and support service activities	3.14	0.70

Notes: Estimated fixed costs of production and sunk costs of entry from model estimation. The median value over 1,001 random samples is computed and shown.

B Firm profits

We derive sectoral firm profits Π_k here; the computation of aggregate profits is straightforward by adding up profits across all sectors. The firm's realized productivity after learning its transitory shock is $z_{ki}\epsilon_{ki}$. We use $\pi_{ki}(z_{ki}|\epsilon_{ki})$ to denote the firm's realized profits. Below, we minimize notation and use $\sum\limits_{z_{ki}}$ to denote the summation $\sum_{z_{ki}=\bar{z}_k}^{z_k^m}$. Thus,

$$\Pi_k \equiv M_k \sum_{z_{ki}} \pi_{ki}(z_{ki}|\epsilon_{ki}) g_k(z_{ki}) - M_k^e c_k^e - M \sum_{z_{ki}} \left[C\big(\lambda_{ki}(z_{ki})\big) + C\big(\mu_{ki}(z_{ki})\big)\right] g_k(z_{ki}).$$

Define the difference between realized and expected profits of a firm as $\Delta\pi_{ki}(z_{ki}) \equiv \pi_{ki}(z_{ki}|\epsilon_{ki}) - \pi_{ki}^E(z_{ki})$. Then, by Eqs. (12) and (16):

$$\begin{aligned}
\Pi_k &= M_k \sum_{z_{ki}} \left[\Delta\pi_{ki}(z_{ki}) + \pi_{ki}^E(z_{ki})\right] g_k(z_{ki}) - M_k^e c_k^e - M \sum_{z_{ki}} \left[C\big(\lambda_{ki}(z_{ki})\big) + C\big(\mu_{ki}(z_{ki})\big)\right] g_k(z_{ki}) \\
&= M_k \sum_{z_{ki}} \Delta\pi_{ki}(z_{ki}) g_k(z_{ki}) + M_k \sum_{z_{ki}} \Big\{ \delta_k V_{ki}(z_{ki}) - \lambda_{ki}(z_{ki}) \theta_k^a \mathbb{E}_{z_{ki}^t} \left[\Sigma_{ki}^a(z_{ki}, z_{ki}^t)\right] \\
&\quad - \mu_{ki}(z_{ki}) \theta_k^t \mathbb{E}_{z_{ki}^a} \left[\Sigma_{ki}^t(z_{ki}^a, z_{ki})\right] \Big\} g_k(z_{ki}) - M_k \sum_{z_{ki}} V_{ki}(z_{ki}) \frac{M_k^e}{M_k} f_k(z_{ki}).
\end{aligned}$$

From the stationary condition in Eq. (15), we have

$$\begin{aligned}
\sum_{z_{ki}} V_{ki}(z_{ki}) \frac{M_k^e}{M_k} f_k(z_{ki}) = \sum_{z_{ki}} V_{ki}(z_{ki}) \Big\{ & \lambda_{ki}(z_{ki}) \theta_k^a g_k(z_{ki}) \sum_{z_{ki}^t} \mathbf{1}\left[\Sigma_{ki}(z_{ki}, z_{ki}^t) \geqslant 0\right] \Gamma_k(z_{ki}^t) \\
& + \mu_{ki}(z_{ki}) \theta_k^t g_k(z_{ki}) \sum_{z_{ki}^a} \mathbf{1}\left[\Sigma_{ki}(z_{ki}^a, z_{ki}) \geqslant 0\right] \Lambda_k(z_{ki}^a) + \delta_k g_k(z_{ki}) \\
& - \sum_{z_{ki}^a} \lambda_{ki}(z_{ki}^a) \theta_k^a \mathbf{1}\left[\Sigma_{ki}(z_{ki}^a, s^{-1}[z_{ki}, z_{ki}^a] \geqslant 0)\right] \Gamma_k(s^{-1}[z_{ki}, z_{ki}^a]) g_k(z_{ki}^a) \Big\}.
\end{aligned}$$

Without loss of generality, suppose acquirers are on the short side of the market (i.e., $\sum\limits_{z_{ki}} \mu_{ki}(z_{ki}) g_k(z_{ki}) > \sum\limits_{z_{ki}} \lambda_{ki}(z_{ki}) g_k(z_{ki})$), which implies $\theta_k^a = 1$. By the definition of merger gains, we have

$$\begin{aligned}
& \sum_{z_{ki}} \Big\{ \lambda_{ki}(z_{ki}) \theta_k^a \beta \sum_{z_{ki}^t} \Sigma_{ki}(z_{ki}, z_{ki}^t) \Gamma_k(z_{ki}^t) + \mu_{ki}(z_{ki}) \theta_k^t \sum_{z_{ki}^a} (1-\beta) \Sigma_{ki}(z_{ki}^a, z_{ki}) \Lambda_k(z_{ki}^a) \Big\} g_k(z_{ki}) \\
&= \beta \sum_{z_{ki}^a} \sum_{z_{ki}^t} \Sigma_{ki}(z_{ki}^a, z_{ki}^t) \frac{\lambda_{ki}(z_{ki}^a) \mu_{ki}(z_{ki}^t)}{\sum_{z_{ki'}} \mu_{ki}(z_{ki'}) g_k(z_{ki'})} g_k(z_{ki}^t) g_k(z_{ki}^a) \\
&\quad + (1-\beta) \sum_{z_{ki}^a} \sum_{z_{ki}^t} \Sigma_{ki}(z_{ki}^a, z_{ki}^t) \frac{\lambda_{ki}(z_{ki}^a) \mu_{ki}(z_{ki}^t)}{\sum_{z_{ki'}} \mu_{ki}(z_{ki'}) g_k(z_{ki'})} g_k(z_{ki}^t) g_k(z_{ki}^a) \\
&= \sum_{z_{ki}^a} \sum_{z_{ki}^t} \Sigma_{ki}(z_{ki}^a, z_{ki}^t) \frac{\lambda_{ki}(z_{ki}^a) \mu_{ki}(z_{ki}^t)}{\sum_{z_{ki'}} \mu_{ki}(z_{ki'}) g_k(z_{ki'})} g_k(z_{ki}^t) g_k(z_{ki}^a).
\end{aligned}$$

Excluding the difference between realized and expected profits, Π_k is therefore equal to

$$
\begin{aligned}
&- M_k \sum_{z^a_{ki}} \sum_{z^t_{ki}} \Big[V_{ki}(s[z^a_{ki}, z^t_{ki}]) - V_{ki}(z^a_{ki}) - V_{ki}(z^t_{ki}) \Big] \frac{\lambda_{ki}(z^a_{ki}) \mu_{ki}(z^t_{ki})}{\sum_{z_{ki'}} \mu_{ki}(z_{ki'}) g_k(z_{ki'})} g_k(z^t_{ki}) g_k(z^a_{ki}) \\
&- M_k \sum_{z_{ki}} V_{ki}(z_{ki}) \Big\{ \sum_{z^t_{ki} = \bar{z}_k}^{z^m_k} \frac{\lambda_{ki}(z_{ki}) \mu_{ki}(z^t_{ki})}{\sum_{z_{ki'}} \mu_{ki}(z_{ki'}) g_k(z_{ki'}))} \mathbf{1} \left[\Sigma_{ki}(z_{ki}, z^t_{ki}) \geqslant 0 \right] g_k(z^t_{ki}) g_k(z_{ki}) \\
&+ \sum_{z^a_{ki}} \frac{\lambda_{ki}(z^a_{ki}) \mu_{ki}(z_{ki})}{\sum_{z_{ki'}} \mu_{ki}(z_{ki'}) g_k(z_{ki'})} \mathbf{1} \left[\Sigma_{ki}(z^a_{ki}, z_{ki}) \geqslant 0 \right] g_k(z^a_{ki}) g_k(z_{ki}) \\
&- \sum_{z^a_{ki}} \frac{\lambda_{ki}(z^a_{ki}) \mu_{ki}(s^{-1}[z_{ki}, z^a_{ki}])}{\sum_{z_{ki'}} \mu_{ki}(z_{ki'}) g_k(z_{ki'})} \mathbf{1} \left[\Sigma_{ki}(z^a_{ki}, s^{-1}[z_{ki}, z^a_{ki}] \geqslant 0) \right] g_k(s^{-1}[z_{ki}, z^a_{ki}]) g_k(z^a_{ki}) \Big\}.
\end{aligned}
$$

The terms exactly cancel out, which means

$$
\Pi_k = M_k \sum_{z_{ki}} \Delta \pi_{ki}(z_{ki}) g_k(z_{ki}).
$$

Remark: In the derivation above, we have used a discount factor of δ_k. If the discount factor is instead $r + \delta_k$, then aggregate firm profits are simply the aggregate value of firms captured as a result of the difference in the perceived discount factor (i.e., $r + \delta_k$) and the actual (exogenous) exit rate (i.e., δ_k). This is equal to $M_k \sum_{z_{ki}} r V_{ki}(z_{ki})$, and is added on top of the difference in expected and realized profits.[33] However, this does not affect our main results.

C Model estimation

We use a simulated method of moments (SMM) estimator to estimate our model. In the first step, the Pareto shape parameters ξ_k of the observed productivity distributions are estimated for the multi-sector variable-markup version of the model. For each sector k, we discretize the productivity distribution of z_{ki} over a (log) grid space with 500 points in the interval between $\bar{z}_k$, normalized to 1, and $z^m_k = 10^3$. This implies that the largest firm is around 10^7 times bigger in sales than the smallest, which is in the same order of magnitude as in the data. Given M_k and $\mathcal{S}_k$ from the data (see Appendix Table A.3), $\phi = 1$, and $\varepsilon = 5$, we use the following algorithm to estimate ξ_k for each sector and each of the random 1,001 samples drawn:

1. For candidate ξ_k, construct the productivity distribution from the Pareto distribution $G_k(z_{ki}) = 1 - z_{ki}^{-\xi_k}$.
2. Draw M_k random numbers and compute the simulated productivity distribution, $G^{sim}_k(z_{ki})$, and the corresponding probability mass function $g^{sim}_k(z_{ki})$.
3. Solve for market shares as a fixed point problem:
   (a) Guess market shares $\mathcal{s}_{ki}$, and update using Eqs. (19) and (20).
   (b) Normalize such that the updated market shares add up to 1; iterate on $\mathcal{s}_{ki}$.
4. Compute the Herfindahl index $HHI = M_k \sum_{z_{ki} = \bar{z}_k}^{z^m_k} \mathcal{s}^2_{ki} g^{sim}_k(z_{ki})$.

[33] To understand this point, suppose firms perceive the exogenous rate to be δ'_k, but the actual exit rate is δ_k. Then, the number of firms will be smaller than that implied under a stationary equilibrium, and the remaining firms that do not exit will capture a portion of the firms' aggregate value as profits today.

The process is iterated until the model-implied market concentration (given by the median over the random samples) matches the data.

From Eq. (20), firm-level markups are determined. Sector and aggregate level markups are defined by:

$$\mathscr{M}_k = \left[\sum_{z_{ki}=\bar{z}_k}^{z_k^m} s_{ki} m_{ki}^{-1} \right]^{-1}, \quad \mathscr{M} = \left[\sum_{k=1}^{N} \mathcal{S}_k \mathscr{M}_k^{-1} \right]^{-1}$$

In the constant-markup economy, firms charge a markup equal to $\frac{\tilde{\varepsilon}}{\tilde{\varepsilon}-1}$, which we set equal to $\mathscr{M}$. Thus, $\tilde{\varepsilon} = \frac{\mathscr{M}}{\mathscr{M}-1} = 4.85$. The algorithm above is also utilized to set the Pareto shape parameter ξ of the aggregate productivity distribution. Then, we construct the productivity distribution by drawing 1 million firms from $G(z_i) = 1 - z_i^{-\xi}$ for the simulation. We calculate firm-level prices, the price index, and firm-level profits and sales (note $\pi_i(z_i) = \pi_i^E(z_i)$). From this random sample, we also compute the size of the median firm and the productivity level at the 10th percentile, which are used to compute the model-implied moments.

Next, we estimate the merger market parameters $\Theta = \{\gamma, \nu, A, B, \eta\}$ with the following algorithm:

1. Guess candidate γ, ν, and A from the merger technology function Eq. (9) and B and η from the merger search cost function Eq. (11).
2. Construct the merger matrix $s[z_i^a, z_i^t]$.
3. Guess candidate $V_i(z_i)$ and evaluate the merger matrix (i.e., determine whether $\Sigma_{ki}(z_i^a, z_i^t)$ in Eq. (10) is positive).
4. Guess candidate $\mu_i(z_i)$ and θ_k^a. Given $\Sigma_{ki}(z_i^a, z_i^t)$, solve for $\lambda_i(z_i)$ and θ_k^t. Iterate on θ_k^a and $\mu_i(z_i)$ until convergence.
5. Compute $V_i(z_i)$ from Eq. (12).
6. Solve for c^d such that $V_i(\bar{z}) = 0$ (i.e., Eq. (14)). Iterate on $V_{ki}(z_{ki})$.

After this procedure, the merger market is simulated with random meeting rates between acquirer and target firms. A merger is successful if merger gains are positive. Then, we construct the five target moments and compute the objective function $\left(m - \widehat{m}(\Theta)\right)' W \left(m - \widehat{m}(\Theta)\right)$, where m is the vector of five target moments from the data, $\widehat{m}(\Theta)$ is the vector of corresponding moments constructed using the simulated economy with parameters $\Theta = \{\gamma, \nu, A, B, \eta\}$, and W is a matrix of weights. We use the generalized inverse of the estimated variance-covariance matrix of the moments computed from the data. This process is iterated until convergence.

D Counterfactuals

D.1 Constant markups

By the stationary condition in Eq. (15), we construct $F(z_i)$ for $z_i \geqslant \bar{z}$. From Eqs. (14) and (16), we compute the values of c^d and c^e. In order to extrapolate $f(z_i)$ for $z_i < \bar{z}$, we regress $\log[f(z_i)]$ on $\log(z_i)$. Note that if the productivity distribution follows the Pareto distribution, then we have a perfect fit in the regression (i.e., $R^2 = 1$).[34] The fit will not be perfect because $F(z_i)$

[34] For example, $G(z_i)$ follows the Pareto distribution with shape parameter ξ. In a continuous setting, $\log[g(z)] \propto -(\xi+1)\log(z)$. Given our definition of the probability mass function (i.e., $g(z_j) = G(z_j) - G(z_{j-1})$), in a discrete setting with evenly log-spaced grid points, we have $\log[g(z_i)] \propto -\xi \log(z_i)$. This means the slope is equal to $-\xi$.

does not follow the Pareto distribution. Nonetheless, this regression provides an approximation for the shape of the productivity distribution where it is (by definition) unobserved. The slope coefficient is $\hat{\beta}_1 = -4.46$, which is slightly lower in magnitude than ξ, with an R^2 of 0.9997. In order to guarantee that $F(z_i)$ is strictly increasing, we do not use the coefficient of the constant term from the regression. Instead, for the grid point below $\bar{z}$, we compute $exp\{\log[f(z_i)]+\hat{\beta}_1 \times Stepsize\}$, where $Stepsize$ is the step size between grid points in logarithms, and so on. This gives us $F(z_i)\ \forall z_i < \bar{z}$.

In the constant-markup economy without mergers, we have the zero profit condition and free entry condition, respectively:

$$\pi_i(\bar{z}^F) = 0,$$

$$\sum_{z_i=\bar{z}^F}^{z^m} \frac{\pi_i(z_i)}{\delta} f(z_i) = wc^e.$$

Given c^d and c^e, we search for the point $\bar{z}^F$ that satisfies both conditions, and compute the equilibrium number of firms M^F accordingly. Analogous to the benchmark economy with mergers, the counterfactual economy without mergers is simulated.

D.2 Variable markups

From Appendix D, we obtain ξ_k, $G_k(z_{ki})$ (or equivalently, $G_k^{sim}(z_{ki})$), and s_{ki}. Pass-through rates α_{ki}, markups m_{ki}, prices p_{ki}, operating profits π_{ki}^o follow immediately from Eqs. (21), (20), (7), and (8). The value function depends on expected profits, which we approximate with a Taylor expansion under the assumption of i.i.d. productivity shocks. Because we normalize the mean of the shocks to 1 (i.e., $\mathbb{E}_\epsilon[(z_{ki}\epsilon_{ki})^{\varepsilon-1}] = z_{ki}^{\varepsilon-1}$), and $\bar{v}_z^2 = 0.01$, expected operating profits are approximated by:

$$\pi_{ki}^{o,E}(z_{ki}) = \pi_{ki}^o(z_{ki}) + \frac{1}{2}\frac{\partial^2 \pi_{ki}^o(z_{ki})}{\partial z_{ki}^2}\bar{v}_z^2.$$

The second-order partial derivative is computed numerically.

Next, we follow the same steps as the in constant-markup economy to solve the merger market, back out $F_k(z_{ki})$ for $z_{ki} \geqslant \bar{z}_k$, and compute c_k^d and c_k^e. Likewise, for each sector and random sample, we extrapolate $f_k(z_{ki})$ for $z_{ki} < \bar{z}_k$. However, because markups are not constant, the number of firms M_k^F cannot be determined by simply combining the zero profit and free entry conditions. Instead we follow the following algorithm to solve the counterfactual economy without mergers:

1. Guess candidate sectoral price index P_k^F.
2. Guess candidate cutoff productivity for the counterfactual economy, $\bar{z}_k^F$. The probability mass function $f_k(z_{ki})\ \forall\ z_{ki} \geqslant \bar{z}_k^F$ is obtained from the extrapolation above.
3. Guess candidate M_k^F.
4. Construct the simulated counterfactual productivity distribution $F_k^{sim}(z_{ki})$.
5. As in the benchmark economy, solve for firm-level market shares as a fixed point problem:
   (a) Guess market shares s_{ki}^F, and update using Eq. (19) and (20).
   (b) Normalize such that the updated market shares add up to 1; iterate on s_{ki}^F.

6. Compute markups, prices, and based on the guess of P_k^F, update M_k^F from Eq. (5); iterate on M_k^F until convergence.

7. Using c_k^d, compute expected profits at the cutoff productivity level $\pi_{ki}^{F,E}(\bar{z}_k^F)$. Iterate on $\bar{z}_k^F$ until convergence. For example, if $\pi_{ki}^{F,E}(\bar{z}_k^F)$ is negative, move $\bar{z}_k^F$ up.

8. Using $F_k(\bar{z}_k^F)$, $f_k^{sim}(z_{ki})$, c_k^d, c_k^e, and expected profits $\pi_{ki}^{F,E}(z_{ki})$, check the free entry condition in Eq. (16). Update P_k^F using the free entry condition, and iterate on P_k^F until convergence.

It is then straightforward to compute pass-through rates α_{ki}^F from Eq. (21) and subsequently, aggregate volatility $\sigma[\widehat{Y}^F]$ from Eq. (27).