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ARTICLE

Mergers and acquisitions and the aggregate markup

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Abstract

The measured markups in the U.S. have been increasing since the 1980s. This paper quantitatively evaluates the impact of surging mergers and acquisitions (M&As) on the aggregate markup. We propose a dynamic general equilibrium model featuring heterogeneous firms, endogenous markups, and an M&A market to explore the aggregate implications of M&As under different antitrust policy regimes. Firms are heterogeneous in productivity, while more productive firms are larger in size and charge a higher markup, and the M&A market is characterized by a search and matching process. Successful purchases of other firms improve the productivity of the acquirer but also raise its markup. We calibrate the impact of M&As on markups at the firm level to the data counterpart. Our quantitative results show that surging M&As account for about 60% of the 9.75 percentage points increase in aggregate markup in the U.S. from the 1980s to the 2010s. The quantified model also generates changes in the markup distribution comparable to the data.

Keywords: markup; mergers and acquisitions; antitrust policy

JEL classifications: D42; E22; G34; K21; L11; L40

1. Introduction

In the U.S., the measured markups (i.e., the difference between price and marginal cost as a percentage of the cost) have been increasing since the early 1980s (Barkai, 2020; de Loecker *et al.* 2020). The recent literature has investigated the impact of increasing markups on other aggregate variables, such as industrial concentration and labor share. However, there is no consensus on what forces have driven the increase in markups over the past four decades (Grossman & Oberfield, 2022). Our paper thus examines and quantitatively evaluates one such force: the relaxation of antitrust policies and the ensuing surging M&A activities since the 1980s. Over time, M&As have become an increasingly important strategy for firms to gain a competitive edge, acquire new technology and skills, or expand to new markets.

We first measure the firm-level markups of Compustat firms using the method proposed by de Loecker and Warzynski (2012) and de Loecker *et al.* (2020), and construct an aggregate-level markup using the cost-weighted average. As strong evidence for rising market power, the measured aggregate markup has increased from 13.93% in 1981–1985 to 23.68% in 2013–2017. On the other hand, obtaining competitive advantage is typically both a reason for and a consequence of M&As. Since the Reagan administration took office in the early 1980s, antitrust policy implementation has been drastically relaxed in the U.S. (Mueller, 1984; Philippon, 2019), allowing for a surge in M&A activities. Using the Compustat public firms database along with the Thompson Financial SDC Platinum M&As database, we find that the aggregate M&A rate, defined as the

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ratio of M&As to the number of Compustat firms in our merged sample, increases from 11.52% in 1981–1985 to 19.11% in 2013–2017.

We then build a dynamic general equilibrium model with heterogeneous firms, endogenous markups, and an M&A market, to analyze the economic consequences of increasing M&A activities. Our model builds on the M&A market setup proposed by David (2021) under a heterogeneous firm dynamics framework. M&A is characterized by a two-sided search and matching process. Firms endogenously decide their search intensities bearing search costs. M&As are assumed to improve the acquirer's post-merger productivity, and the magnitude of the increase depends on the pre-merger productivity of both parties to capture the technological or managerial complementarity between the acquiring firm and the target. Potential acquirer and target firms jointly decide whether to consummate the M&A deal, as they split the surplus through Nash bargaining.

We extend the model of David (2021) that assumes a competitive goods market to one that features endogenous and heterogeneous market power by introducing a Kimball aggregator. Larger firms face lower elasticity of demand, hence optimally charging a higher markup. M&As raise the acquirers' productivity and sizes, and consequently, their post-merger markups. Given that an individual firm's monopoly power is affected by the ease of finding M&A opponents and consummating deals, the proposed model allows us to study the impact of different antitrust policy regimes on the evolution of the aggregate markup and the markup distribution.

To quantitatively evaluate the impact of M&As on the aggregate markup, we discipline the benchmark model parameters with moments from the 1981–1985 U.S. economy. In particular, parameters are calibrated such that the model-generated increase in post-merger markups at the firm level matches the data counterpart. The equilibrium properties of the quantified model match stylized facts documented in the literature. For example, large (and productive) firms search more intensively as acquirers, and raise their bar for synergistic targets, which is consistent with empirical findings in Andrade *et al.* (2001 and Rhodes-Kropf and Robinson (2008). Then, we vary the value of search costs to target the 2013–2017 U.S. M&A rate, as in the model, search costs can reflect the strictness of antitrust policies. The counterfactual exercise generates a 5.80 percentage points increase in the economy's aggregate markup, while that in the data is 9.75 percentage points. That gives the main conclusion of our paper: changes in the M&A market account for 59.45% of the observed rise in the aggregate markup.

As mentioned earlier, the paper is most closely related to David (2021) among the literature studying the aggregate implications of M&As. Beyond that, Xu (2017) studies how M&As contribute to economic growth under an endogenous growth framework, while Fons-Rosen *et al.* (2024) examines the impact of M&As on the innovation incentives of both incumbent firms and startups. However, neither paper studies the evolution of markups as we do. A large number of studies empirically investigate the impact of M&As on acquirers' performance, typically using stock returns as a measurement for merger gains (Andrade *et al.* 2001; Bhagata *et al.* 2005). Our paper focuses on the market power dimension.

The paper is also related to the recent literature (Grullon *et al.* 2019; Barkai, 2020; de Loecker *et al.* 2020) that documents rising market powers in the U.S. since the 1980s. Philippon (2019) systematically collects evidence on rising concentration and market powers and declining investment in the U.S. and argues that they indicate a (inefficiently) decreasing domestic competition rather than a rise of (efficient) superstar firms over the past few decades, especially after 2000. He points to the weakening of merger reviews and the decline in entry associated with the rise of entry regulations as the main drivers. In particular, the author concludes that "What is undeniable, however, is that mergers have been allowed to proceed at an unprecedented pace, which has significantly contributed to a rise in the concentration in the U.S.". Our research contributes to the literature by quantitatively evaluating the impact of a more active M&A market, triggered by the relaxation of antitrust policies, on the rise in aggregate markup.

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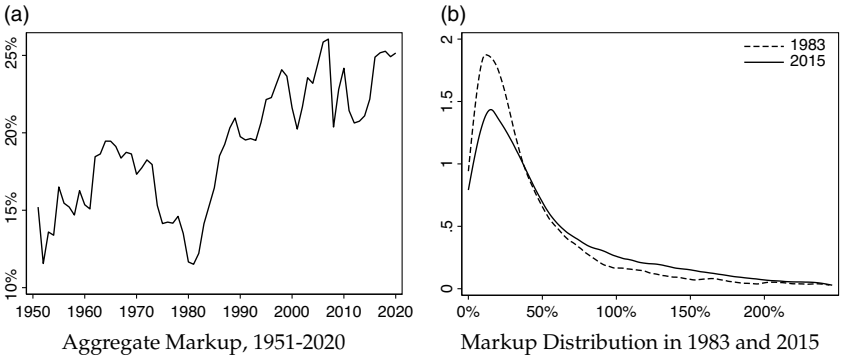


Figure 1. The aggregate markup and changes in markup distribution.
Note: This figure shows the time series of the aggregate markup, defined as the cross-firm weighted average with weights equal to the cost of goods sold, among public firms (Panel (a)), and change in the markup distribution restricting to values between 0% and the 95th percentile (Panel(b)). *Data source*: Compustat.

The rest of the paper is organized as follows. In Section 2, we present the evolution of markups and M&A activities, and show a positive correlation between M&As and changes in firm-level markups. The dynamic general equilibrium model is proposed in Section 3. Section 4 presents quantification and quantitative evaluations of the model. Concluding remarks are provided in Section 5.

2. Motivational facts

This section provides the main motivation facts. We first document that the measured markups — the difference between price and marginal cost as a percentage of the cost — have been rising since the early 1980s, among Compustat public firms.[1] We provide the aggregate as well as distributional comparisons of markups in the 1980s and the 2010s, and then present the facts on surging M&A activities, from the same period.

Rising markups

The rise in markups in the U.S. is documented by various studies in the literature (Barkai, 2020; de Loecker *et al.* 2020). We measure markup using the method proposed by De Loecker and Warzynski (2012).[2] The measurement is based on the following observation: at the firm level, the ratio of price to marginal cost equals the ratio of the output elasticity to an input without significant adjustment cost, to the cost share of this input.[3] The input cost share can be directly calculated from firms' balance sheets, while the elasticity is estimated by using a control function approach following the productivity estimation literature (Olley and Pakes, 1996; Levinsohn and Petrin, 2003).[4]

There are a total of 341,540 *firm* × *year* valid observations from 1951–2020 in Compustat.[5] The aggregate markup is calculated as a cost-weighted average

$$\bar{\mathcal{M}}_t = \sum_i \omega_{i,t} \times \mathcal{M}_{i,t},$$

where $\mathcal{M}_{i,t}$ is firm i's measured markup at year t, and the weight $\omega_{i,t}$ equals to its cost of goods sold.[6]

Panel (a) of Figure 1 presents the evolution of aggregate markup in our data period. Variations considered, the aggregate markup in the early 1980s is at about the same level as in the 1950s. However, over the following three to four decades, the measured aggregate markup has increased sharply from around 14% to close to 24% in the 2010s.

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Table 1. Aggregate M&A rate among compustat firms

	1981–1985	2013–2017
M&A rate	11.52%	19.11%

Note: The aggregate M&A rate is the ratio of total M&As to total number of Compustat firms.
Data source: The merged Compustat-SDC sample.

Panel (b) of Figure 1 presents the distribution of estimated markups among Compustat public firms in 1983 v.s. that in 2015. The markup distributions for both years are characterized by a fat upper tail but also demonstrate clear differences. In particular, the 2015 distribution has more firms with markups on the upper tail, while the 1983 distribution featured significantly more firms with low-to-medium markups. Consistent with what's documented in the literature, the rise in aggregate markup is mainly driven by the fattening upper tail of the distribution.

Another widely used measurement of markup and market power is the Lerner index, which relies less on assumptions about the production function. Like German and Philippon (2017) and Grullon *et al.* (2019), we measure firm-level Lerner index as operating income after depreciation divided by sales using Compustat data, then aggregate them using sales as weight.[7] Figure A.1 in the appendix plots the aggregate Lerner index from 1951 to 2020. Consistent with the evolution of aggregate markup in Figure 1, the Lerner index was relatively stable until the 1980s and shows a clear rising trend after that.

Surging M&As

Since the Reagan administration took office in the early 1980s, the antitrust policy implementation in the U.S. has been drastically relaxed. More lenient antitrust policies are reflected by a surge in M&A activities. We combine the Compustat public firms database and the Thompson Financial SDC Platinum M&As database, and construct a Compustat-SDC merged sample using the CUSIP identifier recorded in both databases.[8] A Compustat firm in a year is labeled as an acquirer if it has acquired at least one other firm in the SDC database, and as a target if it was acquired by other firms in that year.

Table 1 shows the ratio of M&As to the number of Compustat firms in our merged sample, which we dub the aggregate "M&A rate," in 1981–1985 and 2013–2017.[9] The M&A rate has seen a significant rise over the decades—an increase of 7.59 percentage points in levels and of about 66% in relative terms.[10]

Obtaining competitive advantage is typically both a reason for and a consequence of M&A transactions. Using our Compustat-SDC merged sample, we empirically establish a correlation between M&As and changes in a firm's markup. Formally, we run the following firm-year regression

$$\Delta \ln (1+\mathcal{M}_{i,j,t+1}) = \delta_0 + \underbrace{0.0174^{***}}_{(s.e.\ 0.0028)} \times MA_{i,j,t} + \mathcal{M}_{i,j,t} + D_t + D_j + v_{i,j,t}. \tag{1}$$

The term $\mathcal{M}_{i,j,t}$ is the markup of firm i in industry j in year t, and $\Delta \ln (1+\mathcal{M}_{i,j,t+1})$ is the change in the logarithmic ratio of price to marginal cost from year t to $t+1$. $MA_{i,j,t}$ is an indicator variable and equals to 1 for firm i if it has acquired at least one other firm in year t. The year and 2-digit industry dummies, D_t and D_j, are added to account for any time trend or industrial heterogeneity. The estimated coefficient for $MA_{i,j,t}$, 0.0174, is significant at the 1% level. That is, the acquiring firm's price-to-marginal cost ratio increases after the M&A transaction, by a magnitude of 1.74% in relative terms. That is, for an average firm with a markup of 14%, M&A increases its markup to about 15.98%. As firms' merger decisions are endogenous, the correlation pattern shown in equation (1) is not causal. Later, we use the correlation implied by equation (1) as a target moment to discipline parameters in the model with endogenous merger decisions of

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firms, such that the model-generated post-merger increase in the markups of acquirers matches that in the data.

3. The model

We now present the modeling framework to evaluate the impact of M&As on the aggregate markup. A firm is characterized by its productivity, which determines the firm's optimal size. Firms of different sizes face different elasticities of demand, allowing for an endogenous markup distribution. Firms find potential targets to acquire on a market featuring two-sided search and matching. Successfully matched pairs jointly decide whether to consummate an M&A deal, through a Nash bargaining of the surplus. To capture the technological and managerial complementarity between acquirers and targets, we allow acquiring firms to increase their productivity by merging worthy opponents.

3.1 Production

Time is continuous and denoted by t. The economy consists of two sectors—an intermediate goods sector where each single firm monopolizes in producing an intermediate variety, and a final good sector where firms produce competitively by aggregating over intermediate varieties. We start with the competitive final good sector.

Final good

The final good is produced competitively by aggregating over intermediate varieties according to the following aggregator

$$\int_{\Omega_t} \sigma\left(\frac{y_t(\omega)}{Y_t}\right) d\omega = 1, \tag{2}$$

where Y_t and $y_t(\omega)$ denote the quantity of the final good and intermediate variety ω at time t, respectively. Ω_t is the set of varieties available at time t, whose size M_t is determined endogenously by the number of incumbent intermediate firms. Following Kimball (1995), the function $\sigma(q)$ is assumed to be strictly increasing, strictly concave, and satisfy $\sigma(1) = 1$.

Use the final good as the numeraire and denote by $p_t(\omega)$ the price of an intermediate variety ω. Competitive final good producers optimally choose the quantity of intermediate varieties to maximize profit, that is

$$\max_{y_t(\omega)} \quad Y_t - \int_{\Omega_t} p_t(\omega) y_t(\omega) d\omega,$$

subject to the production technology specified in equation (2). The maximization problem gives the demand function facing the producer of variety ω as

$$p_t(\omega) = \sigma'\left(\frac{y_t(\omega)}{Y_t}\right) D_t, \tag{3}$$

where D_t is a common term facing all intermediate producers, defined as

$$D_t \equiv \left(\int_{\Omega_t} \sigma'\left(\frac{y_t(\omega)}{Y_t}\right) \frac{y_t(\omega)}{Y_t} d\omega\right)^{-1}.$$

One useful property of this demand function is that, depending on the functional form of $\sigma(q)$, the elasticity of demand facing the producer of an intermediate variety can vary across its relative size $q \equiv y/Y$. This property allows the model to generate an endogenous markup distribution among intermediate firms.

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For the $\sigma(q)$ function, we follow Klenow and Willis (2016) and Edmond *et al.* (2023) to choose the following specification

$$\sigma(q) = 1 + (\beta - 1)\exp\left(\frac{1}{\alpha}\right)\alpha^{\frac{\beta-\alpha}{\alpha}}\left[\Gamma\left(\frac{\beta}{\alpha}, \frac{1}{\alpha}\right) - \Gamma\left(\frac{\beta}{\alpha}, \frac{q^{\frac{\alpha}{\beta}}}{\alpha}\right)\right],$$

where $\alpha > 0$, $\beta > 1$, and $\beta > \alpha$. $\Gamma(a, b) \equiv \int_b^\infty x^{a-1}e^{-x}dx$ is the upper incomplete Gamma function.

Using this specification, the term $\sigma'(q)$ in the intermediate goods demand function can be written as

$$\sigma'(q) = \frac{\beta - 1}{\beta}\exp\left(\frac{1 - q^{\frac{\alpha}{\beta}}}{\alpha}\right), \tag{4}$$

which is a decreasing function of the relative size q. Consequently, larger firms face smaller demand elasticity and charge a higher markup.

Intermediate goods

Each intermediate variety is produced monopolistically by a single firm. An intermediate firm with productivity $z > 0$ uses labor as the sole input and has access to the following linear production technology

$$y_t = z\ell_t. \tag{5}$$

The intermediate monopolist optimally chooses the quantity and price of its product, and the amount of labor to employ, to maximize profit

$$\pi_t(z) \equiv \max_{p_t, y_t, \ell_t} p_t y_t - W_t \ell_t,$$

subject to the demand function and production technology specified in equations (3) and (5). W_t is the competitive wage rate at time t.

Drop the time subscript t and substitute away price and labor, we can rewrite the intermediate firm's profit maximization problem as

$$\pi(z) = \max_q \quad \left[\sigma'(q)q - \frac{w}{z}q\right]DY,$$

where $w \equiv W/D$ represents the "effective wage rate." With our specification of $\sigma'(q)$ in equation (4), the optimality condition yields

$$\frac{\beta - 1}{\beta}\exp\left(\frac{1 - q^{\frac{\alpha}{\beta}}}{\alpha}\right)\left(\frac{\beta - q^{\frac{\alpha}{\beta}}}{\beta}\right) = \frac{w}{z}. \tag{6}$$

From the first-order condition, one can solve for the equilibrium relative size q^* as a function of the productivity z, and the markup satisfies

$$\mathcal{M} \equiv \frac{p}{MC} - 1 = \frac{q^{*\frac{\alpha}{\beta}}}{\beta - q^{*\frac{\alpha}{\beta}}}. \tag{7}$$

As $\alpha, \beta > 0$, equation (7) indicates a positive correlation between firm sizes and markups.

Understanding the correlation between productivity and markups requires further analysis of the equilibrium relative size function $q^*(z)$. The following proposition shows important properties of the function.

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Proposition 1. *The equilibrium relative size $q^*(z)$ is strictly increasing in z, and "convex-concave." That is, there exist $0 < \underline{z}_q \leq \bar{z}_q$ to such that, $q^*(z)$ is strictly convex on $(0, \underline{z}_q)$ and strictly concave on $(\bar{z}_q, \infty)$. Furthermore, $q^*(z)$ is bounded above by a constant $\beta^{\frac{\beta}{\alpha}}$.*

Proposition 1 states that firms with higher productivity have larger market shares. Since the markup is an increasing function of market share, more productive firms also charge a higher markup.

The following proposition summarizes the convexity of the profit function. Proofs for both propositions can be found in Appendix B.

Proposition 2. *The intermediate firm's profit $\pi(z)$ is strictly increasing in z, and "convex-concave." That is, there exist $0 < \underline{z}_\pi \leq \bar{z}_\pi$ such that, $\pi(z)$ is strictly convex in $(0, \underline{z}_\pi)$ and strictly concave in $(\bar{z}_\pi, \infty)$.*

3.2 The M&A Market

In the previous layout of the model, productivity determines a firm's market share, as well as the markup it charges. To single out the effect of M&As on markups, we assume that productivity changes only through M&As, and stays constant otherwise.

Following the setup in David (2021), which builds on the canonical framework of Shimer and Smith (2000), M&As are introduced to the economy as a process of search and matching, and bargaining over the surplus. Firms search on both sides of the market simultaneously.[11] Once met, the pair of potential acquirer and target jointly decide whether to consummate the deal, through a Nash bargaining over the surplus. In a backward order, we start by introducing the merger technology and bargaining.

Merger technology

Individual firms use M&As to gain a competitive edge, acquire new technology and skills, or expand to a new market. In our model, though, the synergy between firms is characterized by the following merger technology: upon a successful matching with a potential target firm of productivity z_T, an acquirer firm with pre-merger productivity z_A can expect post-merger productivity of

$$z_M = A z_A^{\kappa} z_T^{\varepsilon}, \tag{8}$$

given that the M&A is consummated. If not, both parties leave with their productivity unaffected. We further assume that $A > 1$, $\kappa + \varepsilon > 1$, and $\kappa > \varepsilon > 0$.[12]

The merger technology captures productivity improvement from technological or managerial complementarity between firms. In the Cobb-Douglas form that we use, parameter A represents a general scale of synergy, that is, improvement regardless of pre-merger productivity. Parameters κ and ε govern the elasticity with respect to the acquirer's and the target's pre-merger performance, respectively. $\kappa > \varepsilon$ implies that the post-merger productivity relies more heavily on the productivity of acquirers. David (2021) gives an excellent discussion on how this assumption makes it more likely for large firms to acquire small ones,[13] which is consistent with empirical findings in Andrade *et al.* (2001) and Rhodes-Kropf and Robinson (2008).

Let $V(z)$ denote the value of an intermediate firm of productivity z. Since an M&A changes the acquirer's post-merger productivity, the associated change of value is given by

$$\Delta V(z_A, z_T) \equiv V(z_M) - V(z_A) - V(z_T),$$

where z_M is specified in equation (8). Naturally, we assume that an M&A will be consummated if and only if $\Delta V(z_A, z_T) > 0$, that is, with a positive surplus.

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Bargaining

The surplus from the M&A, if any, is split between the acquirer and the target through Nash bargaining. Let $\gamma \in (0, 1)$ represent the bargaining power of the acquirer. In a consummated M&A transaction, the acquiring firm pays the target

$$P(z_A, z_T) = V(z_T) + (1 - \gamma) \times \Delta V(z_A, z_T), \tag{9}$$

and continues with post-merger productivity z_M, while the target firm exits the economy.[14] For the purpose of this paper, we omit possible contractual constraints and assume that an acquirer can always commit to paying such $P(z_A, z_T)$, either by a lump-sum transfer or through a long-term contract.

We further define G_A and G_T as the gain from matching as an acquirer and a target, respectively. It follows that

$$G_A(z_A, z_T) = \max\left\{\gamma \times \Delta V(z_A, z_T)\,,\ 0\right\};$$
$$G_T(z_A, z_T) = \max\left\{(1 - \gamma) \times \Delta V(z_A, z_T)\,,\ 0\right\}.$$

These two terms will prove useful when we write down the intermediate firm's value function.

Search and matching technology

Next, we explain how firms meet on the M&A market through a two-sided search and matching process. A firm can search on both sides of the market simultaneously with separate search intensities. In particular, denote μ_A and μ_T as its search intensities on the acquirer and the target side, respectively. Search is costly, to maintain a search intensity of μ_i, the firm must pay a cost of

$$C(\mu_i) = \frac{B}{\phi}\mu_i{}^{\phi}, \quad i = A, T, \tag{10}$$

where $B > 0$ and $\phi > 1$.

In equilibrium, the search intensities of a firm depend on its current productivity level. We denote the optimal choices $\mu_A(z)$ and $\mu_T(z)$, and assume a matching technology characterized by the following matching rate[15]

$$\min\left\{\int \mu_A(z)dF(z), \int \mu_T(z)dF(z)\right\},$$

where $F(z)$ denotes the endogenous productivity distribution of firms.

This matching technology implies that if the two sides of the market are not equally populated, the short side will determine the number of matches, while the long side is rationed. Correspondingly, the market tightnesses on the acquirer and the target side are given by

$$\theta_A = \min\left\{\frac{\int \mu_T(z)dF(z)}{\int \mu_A(z)dF(z)}, 1\right\}; \quad \theta_T = \min\left\{\frac{\int \mu_A(z)dF(z)}{\int \mu_T(z)dF(z)}, 1\right\}.$$

We assume undirected (or random) search, so the rates at which a type z_A acquirer meets a type z_T target, and vice versa, are given by

$$\underbrace{\mu_A(z_A)}_{\text{search intensity}} \times \underbrace{\theta_A}_{\text{market tightness}} \times \underbrace{\frac{\mu_T(z_T)dF(z_T)}{\int \mu_T(z)dF(z)}}_{\text{conditional probability}} \quad ; \quad \mu_T(z_T) \times \theta_T \times \frac{\mu_A(z_A)dF(z_A)}{\int \mu_A(z)dF(z)}.$$

In the end, the rate at which M&As are consummated in the economy, i.e., the aggregate M&A rate, can be written as

$$\int\int \mu_A(z_A)\theta_A \frac{\mu_T(z_T)}{\int \mu_T(z)dF(z)} \times \mathbb{1}\left\{\Delta V(z_A, z_T) > 0\right\} dF(z_T)dF(z_A),$$

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where $\mathbb{1}\{\cdot\}$ is the standard index function. That is, potential M&A parties meet each other through undirected search and matching, then consummate the deal if and only if such a transaction incurs a positive change of value, or, surplus.

3.3 Equilibrium

Next, we present the value function, the evolution of productivity distribution, and the definition of a stationary equilibrium of the economy.

Value function

Assume a time discount rate of $\rho > 0$ and all incumbent firms exit at an exogenous rate $\eta > 0$. The value of an intermediate firm with productivity z can be written as

$$\begin{aligned}(\rho+\eta)V(z) = \pi(z) &+ \max_{\mu_A}\left\{\mu_A\theta_A\mathbb{E}_{z_T}[G_A(z,z_T)] - C(\mu_A)\right\} \\ &+ \max_{\mu_T}\left\{\mu_T\theta_T\mathbb{E}_{z_A}[G_T(z_A,z)] - C(\mu_T)\right\},\end{aligned} \tag{11}$$

i.e., the flow value of the firm equals the instantaneous profit $\pi(z)$, plus the expected net gains from searching in the M&A market. With the search cost specified in equation (10), the optimal search intensities are given by

$$\mu_A(z) = \left\{\frac{\theta_A\mathbb{E}_{z_T}[G_A(z,z_T)]}{B}\right\}^{\frac{1}{\phi-1}}; \quad \mu_T(z) = \left\{\frac{\theta_T\mathbb{E}_{z_A}[G_T(z_A,z)]}{B}\right\}^{\frac{1}{\phi-1}}. \tag{12}$$

Entry, exit, and equilibrium

Incumbent firms exit the economy either by being merged, or being hit by an exogenous shock at rate η. On the other hand, a firm enters the economy by paying an entry cost $c_E > 0$ upfront, then draws initial productivity from an exogenous distribution $H(z)$. We assume that $H(z)$ follows a Pareto distribution with shape parameter $\xi > 1$. Free entry implies that the expected value of entrants equals the cost, i.e.,

$$\int V(z)dH(z) = c_E. \tag{13}$$

Let M_E denote the total mass of new entrants, and M is that of incumbent firms.[16] The distribution of firm productivity, $F(z)$, evolves according to the following Kolmogorov forward equation

$$\begin{aligned}\dot{dF}(z) = &\underbrace{\int \mu_A(z_A)\theta_A\frac{\mu_T\left(z_T^{-1}(z,z_A)\right)}{\int\mu_T(z)dF(z)}\mathbb{1}\left\{\Delta V\left(z_A,z_T^{-1}(z,z_A)\right)>0\right\}dF\left(z_T^{-1}(z,z_A)\right)dF(z_A)}_{\text{inflow through M\&As}} \\ &\underbrace{- dF(z)\times\mu_A(z)\theta_A\left[\int\frac{\mu_T(z_T)}{\int\mu_T(z)dF(z)}\mathbb{1}\{\Delta V(z,z_T)>0\}dF(z_T)\right]}_{\text{outflow through merging}} \\ &\underbrace{- dF(z)\times\mu_T(z)\theta_T\left[\int\frac{\mu_A(z_A)}{\int\mu_A(z)dF(z)}\mathbb{1}\{\Delta V(z_A,z)>0\}dF(z_A)\right]}_{\text{outflow through being merged}} \\ &- \underbrace{dF(z)\times\eta}_{\text{outflow through exogenous exit}} + \underbrace{dH(z)\times\frac{M_E}{M}}_{\text{inflow through entry}}.\end{aligned}$$

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In the equation above, we define

$$z_T^{-1}(z, z_A) \equiv \left(\frac{z}{A z_A^{\kappa}}\right)^{\frac{1}{\varepsilon}}.$$

That is, for an acquirer firm of productivity z_A, a target of productivity $z_T^{-1}(z, z_A)$ is needed to make the post-merger productivity right at level z.

This law of motion decomposes changes at the density of any state z into five possible channels: firms previously of lower productivity might acquire others and obtain post-merger productivity of z; firms originally with productivity z might acquire others and arrive at a new (and higher) productivity level; firms originally with productivity z might be acquired by others and exit the economy; firms originally with productivity z might be hit by the exogenous exit shock; and entrants might draw an initial productivity of z. In a stationary equilibrium, the distribution at each state must remain constant. That gives the stationary conditions

$$\dot{dF}(z) = 0, \quad \forall z.$$

To close the model, we assume that the economy admits a representative household who owns all firms. It is endowed with 1 unit of labor and supplies it inelastically. The household consumes all its income every period, as saving is not allowed. Formally, the equilibrium in our model is defined as follows:

Definition 1. *A **S**tationary **E**quilibrium of the economy consists of: aggregate variables of the economy,* $\{Y, C, W, M, M_E, F(z), \theta_A, \theta_T\}$*; firm's policy function and profit from the static profit maximization problem,* $\left\{q^*(z), \pi(z)\right\}$*; and firm's policy functions and value function in the M&A market,* $\{\mu_A(z), \mu_T(z), \mathbb{1}\{\Delta V > 0\}, V(z)\}$*, so that:*

1. *Policy functions solve their corresponding optimization problems;*
2. *The goods and labor markets clear;*
3. *The free entry condition is met;*
4. *The evolution of firm productivity distribution is consistent with the stationary conditions.*

4. Quantitative analysis

In this section, we first calibrate the model's benchmark parameters to the 1981–1985 U.S. economy, using moments from our Compustat-SDC merged sample. Then we evaluate the impact of surging M&A activities on the aggregate markup through a counterfactual exercise, in which we reduce firms' search costs to the 2013–2017 level. We also show that the quantified model successfully replicates several stylized patterns in the U.S. M&A market.

4.1 Calibration Strategy

We calibrate the model's benchmark economy with our Compustat-SDC merged sample in 1981–1985, that is, when the surge of M&As and the rise of markups began to happen. We start with those that can be externally calibrated, directly inferred, or taken from the literature.

We follow the literature and normalize the lower bound of firm productivity to $z_{min} = 1$.[17] Moreover, we set the time discount rate ρ to match an annual interest rate of 5%. For the exogenous exit rate, η, we use the average exit rate of 7.17% calculated from the Compustat database. We assume a 50–50 split of surplus between the acquirer and target in their Nash bargaining, which is close to the estimate in David (2021). Table 2 summarizes the values of all externally calibrated parameters and their sources.

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Table 2. Externally calibrated parameters

Param	Value	Equation	Meaning	Source
z_{min}	1		productivity support	normalization
ρ	0.05	(11)	time discount rate	annual interest rate
η	7.17%	(11)	exogenous exit rate	Compustat exit rate
γ	0.50	(9)	acquirer's bargaining power	assumption

Note: See detailed explanations of the parameter values in the main text.

The rest of the parameters are calibrated internally. We jointly estimate all remaining 9 parameters to minimize the total sum of distances between model-generated and data moments

$$\sum_i \left| \frac{\text{model}(i) - \text{data}(i)}{\text{data}(i)} \right| \times 100\%.$$

In particular, we pick 9 moments that are standard to the literature. While these parameters are jointly estimated, some moments are particularly informative about the corresponding parameters. Next, we briefly outline the logic.

The first subset of parameters regards the aggregate economy. Our specification of the Kimball aggregator contains two parameters, α and β. In the theoretical layout, we showed that β affects the aggregate markup level, while α governs how fast markups rise with firms' relative sizes. Correspondingly, we use the economy's cost-weighted aggregate markup ($\bar{\mathcal{M}}$) to discipline β, and the difference in markup levels between firms of the 90^{th} and 50^{th} size percentiles ($\Delta\mathcal{M}$) to discipline α.[18] The former moment amounts 13.93%, while the latter is 8.60% in the 1981–1985 sample period.

For the entry cost, Hopenhayn (1992) discussed how it affects firms of different sizes differently. In our model, it affects the equilibrium wage rate, thereby influencing the firm size distribution. In particular, we pick the size ratio between firms of the 90^{th} and 50^{th} percentiles ($s_{F_{90}/F_{50}}$), 24.10, to discipline c_E. We use that ratio among entrants ($s_{H_{90}/H_{50}}$), 18.05, to discipline the shape parameter ξ of entrant firms' productivity distribution $H(z)$.[19]

Next, we turn to parameters in the search cost function. For the scale parameter, B, we use the aggregate M&A rate ($\overline{MA}$), defined as the number of consummated M&As divided by that of Compustat firms. We use the ratio of acquirer rates between firms at the 90^{th} and 50^{th} size percentiles ($Acq_{F_{90}/F_{50}}$) to discipline the curvature parameter, ϕ.[20] These two moments are 11.52% and 1.92, respectively, in the 1981–1985 sample period.

The last 3 parameters, A, κ and ε, are from the merger technology. Parameter A represents the general scale of M&A synergy. The higher A is, the faster a firm's productivity improves through the lens of M&As, as well as its size and markup. Consequently, we use the average increase in ln(1+markup) for post-merger firms ($\Delta\mathcal{M}_{MA}$), as estimated empirically by regression equation (1), to discipline the parameter.[21] As for the elasticity on pre-merger productivity, David (2021) gives an excellent explanation on how they determine the size of acquirers and targets in consummated M&A transactions. We thus use the size ratio between median acquirers and median firms ($s_{A_{50}/F_{50}}$), and the median size ratio between matched acquirer-target pairs in consummated M&A transactions ($s_{(A/T)_{50}}$), to discipline these two parameters. The value of the former is 4.30, while that of the latter is 4.43 in the 1981–1985 sample period. Table 3 summarizes the parameters and their corresponding target moments.

4.2 Model Fit

As explained in the calibration strategy, we have in total 9 parameters jointly estimated by minimum distance. We start by checking their values and the model fit on targeted moments.

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Table 3. Parameters calibrated by minimum distance

Param	Equation	Meaning	Target
Aggregate Economy			
α	(4)	para. in Kimball aggregator	top-to-median markup difference
β	(4)	para. in Kimball aggregator	aggregate markup
c_E	(13)	entry cost	top-to-median firm size ratio
ξ		entrants' prod. distribution	top-to-median entrant size ratio
M&A Market			
B	(10)	scale of search cost	aggregate M&A rate
ϕ	(10)	curvature of search cost	top-to-median acquirer rate ratio
A	(8)	scale of general synergy	average post-merger rise in markups
κ	(8)	elasticity on acquirer's prod.	size ratio of median acquirers and firms
ε	(8)	elasticity on target's prod.	median size ratio of matched M&A pairs

Note: See detailed explanations of target moments in the main text.

Table 4. Benchmark parameters and moments

	α	β	c_E	ξ	B	ϕ	A	κ	ε
	4.79	10.84	0.27	12.14	370.86	6.50	1.03	0.87	0.48
	$\Delta\mathcal{M}$	$\bar{M}$	$s_{F_{90}/F_{50}}$	$s_{H_{90}/H_{50}}$	$\overline{MA}$	$Acq_{F_{90}/F_{50}}$	ΔM_{MA}	$s_{A_{50}/F_{50}}$	$s_{(A/T)_{50}}$
Data	8.60%	13.93%	24.10	18.05	11.52%	1.92	1.74%	4.30	4.43
Model	8.44%	13.95%	23.93	17.94	11.57%	1.93	1.77%	4.36	4.31

Note: Detailed information on each moment can be found in Section 4.1. All numbers are rounded to two decimal places for better presentation.

Targeted moments

Table 4 presents estimation results and model fit, showing that the benchmark model replicates targeted moments well. The total sum of data-model distances is about 10 percentage points, or an average distance of 1.14 percentage points per moment. We further illustrate the identification of the model parameters in Appendix C.2.

The estimate of β is close to what's reported in Edmond *et al.* (2023), while our estimate of α is higher,[22] which implies a steeper increase in markup when a firm's productivity and size increase. We then run a regression of ln(1+markup) on ln(size) in both the quantified model and the Compustat-SDC merged sample. The obtained coefficient in the model is 0.016, which is reasonably close to the value of 0.019 estimated from the data.[23]

The estimated entry cost c_E is about a third of the average firm value, and the share of total output used in paying the entry cost is 8.42% in the stationary equilibrium. The value of ξ indicates a skewed productivity distribution. Note that, as discussed in Proposition 1, firm productivity does not translate proportionally into size. To compare the model-generated size distribution with data,[24] we further estimate a Pareto shape coefficient by regressing the logarithmic frequency on the logarithmic size, and find a slope of –1.79, or a Pareto shape coefficient of 0.79, which is close to the value of 1 found in the literature (Axtell, 2001).[25]

Our estimate of the search costs implies an aggregate matching rate of around 18% on the M&A market. About two-thirds of the matched pairs eventually consummate the deal, while the rest willingly forgo the opportunity as their matches generate no surplus. In the model, firms of different sizes choose search intensities endogenously, thus bearing different search costs. On average, search costs take around 7% of the firm's profit.

Though using different target moments, our estimates of the merger technology parameters are close to David (2021).[26] The value of A implies that in general, merged firms enjoy a productivity

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Table 5. Search intensities and rates across firm sizes

Percentiles	10^{th}	30^{th}	50^{th}	70^{th}	90^{th}	99^{th}
μ_A	0.12	0.14	0.17	0.21	0.26	0.29
μ_A/μ_T	0.71	0.78	0.83	0.89	1.05	1.40
$Acq/(\mu_A\theta_A)$	37%	51%	64%	81%	77%	46%
$Tag/(\mu_T\theta_T)$	80%	89%	80%	61%	30%	7%

Note: The percentiles are ranked in terms of firm size. μ_A and μ_T denote search intensities, θ_A and θ_T denote market tightness. *Acq* and *Tag* denote the rates of becoming acquirers and targets, respectively. All numbers are rounded for better presentation.

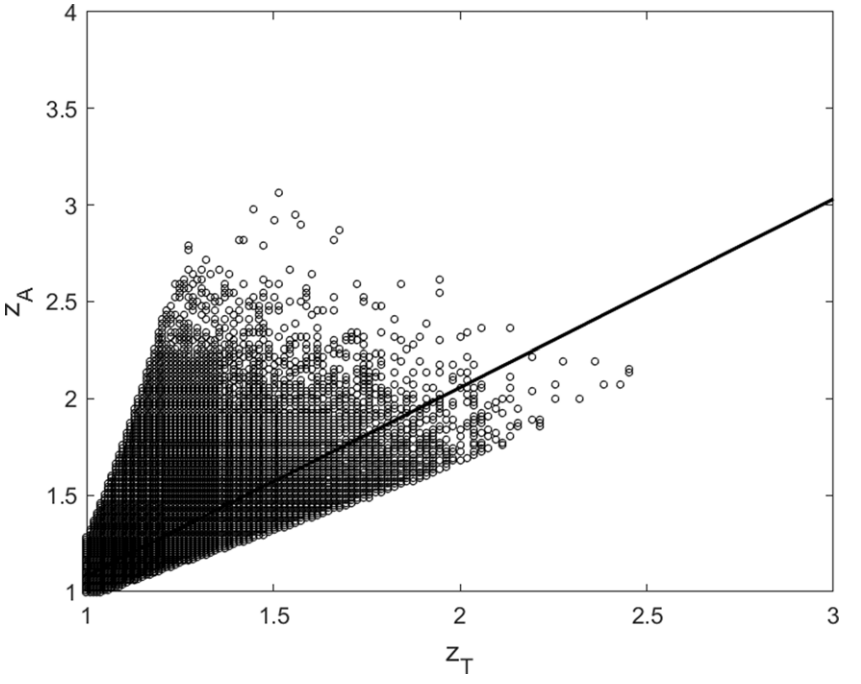


Figure 2. Simulated M&A transactions.
Note: The vertical (horizontal) axis represents the productivity of the acquirer (target). Each dot represents a consummated M&A from the simulation, and the solid line is the OLS fit.

improvement of 3%, regardless of pre-merger performance. Estimates of κ and ε confirm that post-merger productivity relies more on the productivity of acquirers. As a consequence, larger firms search more intensively, especially as acquirers, a point that is shown by rows 1 & 2 in the following Table 5.[27]

On the other hand, the conditional probabilities of finding a synergistic opponent are hump-shaped on both the acquirer's and the target's side, peaking at different percentiles (rows 3 & 4). In the end, it is firms that are large but still have the potential to grow that are more likely to be acquirers, and those that are relatively small become targets. Another important feature of merging firms is positive sorting. As size (and productivity) grows, an acquiring firm will raise its bar for the targets it is willing to merge with, and vice versa. We simulate 1 million matches on the M&A market and scatter those that are eventually consummated in Figure 2. The simulation shows a clear and positive correlation between the sizes (and productivity) of the acquirer and the

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Table 6. Surging M&As and the aggregate markup

	B	$\bar{M}_{model}$	$\bar{M}_{data}$	explanation Power
1981-1985	370.86	13.95%	13.93%	—
2013-2017	11.40	19.75%	23.68%	
change	—	5.80 p.p.	9.75 p.p.	59.45%

Note: The explanation power is calculated as the model-generated change in the aggregate markup divided by that in the data. All numbers are rounded to two decimal places for better presentation.

target. These numerical properties of the quantified model are consistent with empirical findings in the literature (Andrade *et al.* 2001; Rhodes-Kropf and Robinson, 2008; David, 2021).

Next, we turn to the situation in which firms' search cost on the M&A market is reduced to the 2013–2017 level, to see how much rise in aggregate markup the quantified model can generate.

4.3 Surging M&As and the Aggregate Markup

As reported in Table 1, the aggregate M&A rate has increased from 11.52% for 1981–1985 to 19.11% for the 2013–2017 period in our Compustat-SDC merged sample. Equation (12) shows that a decrease in B raises the search intensities so as the aggregate M&A rate, and can be used as a proxy for more lenient antitrust policies which fail to keep M&A activities at bay.[28] To examine the impact of surging M&A activities on the aggregate markup, we study a counterfactual economy where the scale parameter of the search cost function, B, is recalibrated to match the M&A rate in 2013–2017, while all other parameters are kept at their benchmark values. Table 6 summarizes the results.[29]

Compared to the benchmark, the counterfactual economy features lower search costs, and consequently, higher search intensities and aggregate M&A rate.[30] The aggregate markup in the model increases by 5.80 percentage points, which explains about 60% of the observed change in the data. In the model, the (cost-weighted) aggregate markup $\bar{\mathcal{M}}$ can be written as

$$\bar{\mathcal{M}}\big(F(z), q^*(z)\big) = \int \frac{q^*(z)^{\frac{\alpha}{\beta}}}{\beta - q^*(z)^{\frac{\alpha}{\beta}}} \frac{\big[q^*(z)/z\big]\, dF(z)}{\int \big[q^*(z)/z\big]\, dF(z)}.$$

Hence, changes in the aggregate markup can be attributed to two channels: (i) changes in the productivity distribution $F(z)$; and (ii) changes in the map between productivity and firm size, as characterized by the $q^*(z)$ function.[31] A further decomposition exercise shows that channel (i) contributes 99.21% to the change in the aggregate markup, i.e., the rise in aggregate markup is mainly driven by a fattening productivity distribution.[32]

Next, we examine the distributional impact of surging M&A activities. In particular, we look at changes in the markup distribution of firms. We first record the markup levels of different percentiles of the 1981–1985 distribution, then calculate the fraction of firms with a markup greater than those levels in the 2013–2017 distribution. For the X^{th} percentile markup level in the 1981-1985 distribution, that more than $(100 - X)$% of firms in 2013–2017 have markups greater than it indicates a fattening distribution.

Table 7 presents the comparison, our model produces changes in the markup distribution at various percentiles that are comparable to the data. Moreover, the fattening of markup distribution mainly happens around the upper percentiles, a pattern consistent with empirical findings both in De Loecker *et al.* (2020 and that documented in panel (b) of Figure 1.

Overall, our quantified model suggests that surging M&A activities can cause the aggregate markup to rise. And the fattening of the markup distribution can be largely explained by the fattening of firms' productivity distribution.[33]

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Table 7. Changes in cost-weighted markup distribution

Percentiles, 1981-1985	fraction, 2013-2017	fraction, model
$\geq 10^{th}$ pct	87.78%	94.05%
$\geq 30^{th}$ pct	71.91%	81.29%
$\geq 50^{th}$ pct	60.61%	67.96%
$\geq 70^{th}$ pct	41.46%	52.59%
$\geq 90^{th}$ pct	21.40%	30.38%

Note: The comparison is based on the cost-weighted markup distribution. We restrict to non-negative markups for all firms and all years in the data.

5. Conclusion

This paper evaluates the impact of M&As on the evolution of aggregate markup under a dynamic general equilibrium framework. We construct a model featuring heterogeneous firms, endogenous markups, and an M&A market characterized by search, matching, and Nash bargaining. We calibrate the benchmark economy to empirical moments from a Compustat-SDC merged sample in the 1981–1985 period, and then, to evaluate the impact of more lenient antitrust policies, counterfactually reduce the search costs on the M&A market to match the aggregate M&A rate in the 2013–2017 period. The counterfactual economy successfully generates a fattening markup distribution, and a 5.80 percentage points increase in the aggregate markup, which accounts for around 60% of the change observed in the U.S. economy from the 1980s to the 2010s.

Our model incorporates both the efficiency-enhancing and markup-raising effects of M&A activities. However, both effects are characterized by a single parameter — productivity. One needs to disentangle these two factors, to give a reliable implication on welfare, which we view beyond the scope of this paper. The model can be extended by including other productivity-enhancing activities such as innovation (Fons-Rosen *et al.* 2024). The aggregate impact of more lenient M&A policies could be strengthened or weakened, depending on whether self-innovation complements or substitutes M&As at the firm level. The paper also abstracts from reasons for lenient antitrust policies. International trade and globalization could be one driver. A globalized economy might encourage more domestic M&As, as firms strategically merge with domestic competitors to be better positioned in the international market. We leave these interesting questions to future research.

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Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S1365100525100199

Notes

1 We do not have access to other firm-level datasets (such as the Census data) that can be used to compute markups. Hence, we use the Compustat public firm sample as the universe and aim to explain the rise of markups in this universe. Public firms in Compustat account for about 30% of total employment (Davis *et al.* 2006), though it should be pointed out that it is not a representative sample of the whole economy.
2 A detailed description of the method is provided in Appendix A.
3 This equivalence can be seen in a firm's cost minimization problem, as shown in Appendix A.
4 Following de Loecker *et al.* (2020), we chose the "cost of goods sold" in Compustat as input and estimated the output elasticity to this input for each two-digit NAICS sector.
5 This number includes *firm* × *year* observations for which data are available for the estimation of markups, thus excluding observations with missing data. We also exclude the public administration sector.
6 Alternative weights such as sales would produce a larger increase in the aggregate markup over the past decades (de Loecker *et al.* 2020). We follow Edmond *et al.* (2023) and use the cost-weighted one as it uses what's on the denominator as weight.
7 Sales is the natural weight to use as it is in the denominator in calculating the Lerner index.

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8 SDC is a comprehensive source of data on U.S. M&As, covering all corporate transactions involving at least 5% of the ownership of a company where the transaction is valued at 1 million or more (after 1992, all deals are covered) or where the value of the transaction was undisclosed. SDC covers both public and private transactions.
9 If a firm merges twice in a year, it is counted as two M&As in that year. From 1981-1985 to 2013-2017, the share of acquirers among Compustat firms increases from 8.10% to 11.28%, and the annual average number of M&As for acquirers increases from 1.40 to 1.69.
10 The left panel of Figure A.2 in the appendix presents the economy-wide total number of M&As from 1851 to 2015. The post-1980 period stands out over the long historical horizon. In the right panel, we show the ratio of M&As to the total number of firms in the U.S. from 1977 to 2015, which also shows a clear surge from the 1980s to the 2010s. As we study markups but only have data for public firms, in the paper we focus on moments calculated for public firms.
11 The continuous time setup allows us to avoid the situation where a firm meets more than one counterparty.
12 This merger technology highlights the importance of productivity improvement as a critical driving force behind M&A activity, as emphasized in the recent macro literature (Jovanovic and Rousseau, 2002; David, 2021). Combining the merger technology with equation (7) reveals that in the model, M&As always increase productivity and markups simultaneously. The results from the related empirical literature are mixed. Some studies find a positive impact of M&As on productivity, markups, and profitability (Braguinsky *et al.* 2015), some conclude that M&As increase prices and markups but not necessarily productivity (Ashenfelter *et al.* 2014; Blonigen and Pierce, 2016; Bhattacharya *et al.* Bhattacharya *et al.*, 2022), while others document substantial post-merger efficiency improvement without significant markup effect (Demirer and Karaduman, 2024). We acknowledge that markups are determined by productivity and consummated M&As necessarily increase both is a limitation of our model. A model with two separate state variables, one governing productivity and the other markups, which we view beyond the scope of the current work, would connect closer to reality.
13 A one-line proof for this statement: suppose $z_{high} > z_{low}$, if $\Delta V(z_{low}, z_{high}) > 0$, then $\Delta V(z_{high}, z_{low}) > 0$ for sure, but not vice-versa. The definition for $\Delta V(z_A, z_T)$ is given immediately.
14 This is the reason why we restrict to transactions involving no less than 50% of the target firm's ownership when presenting Table 1.
15 That is, the total number of matches divided by the total number of (searching) firms.
16 M is also the total number of intermediate varieties in the economy, as each is monopolized by a single firm.
17 The upper bound of productivity, z_{max}, is set to be large enough to avoid any truncation issues.
18 The default measure for firm size is sales in the paper. Under the Kimball aggregator specification that we adopt, the output of low-productivity firms could be close to or even equal to zero. Given that concern, we always use moments regarding top- and median-sized firms in the calibration.
19 In the Compustat-SDC merged sample, a firm is defined as an entrant in a year if the firm appears for the first time in the dataset in that year. While a greater top-to-median size ratio among incumbents than entrants could be due to factors such as large firms facing a greater opportunity to survive (Klette and Kortum, 2004), the driving force in our model is that larger firms are more likely to acquire others and grow over time.
20 The acquirer rate is defined as the number of acquirers divided by that of Compustat firms. To be consistent with the aggregate M&A rate, repeated acquirers are counted multiple times here.
21 We calculate the model counterpart as the average increase in ln(1+markup) for acquiring firms.
22 Their paper studies the variation of markups across firms using Compustat data, and gives an estimate of $\alpha = 2.18$, $\beta = 11.55$.
23 In the regression using the Compustat-SDC merged sample, we control for year and industry fixed effects.
24 In the model, incumbent firms' size distribution is jointly determined by the exogenous entrants' productivity distribution, the merger process, and parameters affecting the map between productivity and size. The model-generated size distribution is not exactly Pareto and admits an upper bound of $\beta^{\beta/\alpha}$.
25 Only in the limiting case when $\alpha = 0$, we can have a closed-form solution of $q^*(z) = \text{constant term} \times z^{\beta}$. It is then ξ/β, which is close to 1 based on the calibrated values, that governs the tail of the size distribution.
26 David's paper uses the same database covering a longer period and reports $A = 1.05, \kappa = 0.91, \varepsilon = 0.54$ in the benchmark case.
27 Though not seen in the table, μ_A eventually drops as the firm size grows.
28 Note a decrease in B in the model can reflect either an improvement in the M&A intermediary's efficiency in finding matches or more importantly, a fall-off in the government's effort to fight market power. Alternatively, we can impose a proportional tax on merger gains and reduce the tax rate to capture weakening antitrust policies. In the model, a reduction in the M&A cost, or a decrease in the M&A tax rate, produces similar results.
29 Under the linear production technology specified by equation (5), low-productivity firms in the economy might choose an optimal size of zero. We resolve the issue by assuming a decreasing return to scale production technology in Appendix C.3, the results remain similar.
30 In the search cost, the estimate of the curvature parameter is as high as $\phi = 6.50$. Hence, a large reduction in the scale parameter is necessary for generating the observed rise in the aggregate M&A rate.
31 A reduction in search costs raises the equilibrium wage rate, thereby reducing firm sizes $q^*(z)$.

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32 The contribution of channel (i) is calculated by changing $F(z)$ to the counterfactual while keeping $q^*(z)$ at the benchmark: $\bar{\mathcal{M}}(F_{cf}(z), q^*_{bm}(z))$, and see how it affects the aggregate markup. A similar procedure applies to channel (ii): $\bar{\mathcal{M}}(F_{bm}(z), q^*_{cf}(z))$.

33 In Appendix C.4, we report the impact of surging M&As on total output and welfare within our modeling framework.

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