Innovation and Competition Policy

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ABSTRACT

It has become increasingly apparent to policymakers that optimal antitrust policy requires looking beyond traditional static analyses and considering the dynamic effects of policy. Such analysis is challenging as limited studies exist concerning dynamic competition policy. This paper attempts to bridge this knowledge gap by developing a novel structural growth model containing the major motivations of mergers and acquisitions (M&A) activity. To enable estimation of the model, frontier natural language processing (NLP) techniques are employed to classify whether parties to an M&A transaction are currently operating in similar markets or whether acquirers are using M&A as an entry mechanism into new markets. Examining the overall impact of M&A on growth reveals a double-edged sword: policies that either completely shut down M&A or allow unrestricted M&A both result in significantly lower growth rates than the baseline estimate. This motivates an optimal antitrust policy that accounts for dynamic effects.

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1 Introduction

In 2004, the world of online mapping and navigation was dominated by a company named MapQuest. At the same time, a small tech company called Where 2 Technologies had also developed a competitor product called Expedition — one that would prove vastly superior to the existing products. Where 2 secured an initial funding deal from a venture capital firm, but any hope of a deal was lost as Yahoo! entered the market the next day. The consensus from venture firms was that it would require too much investment and risk to enable Where 2 to compete with an internet giant like Yahoo. However, one of those VC funds connected Where 2 with another client interested in bringing Where 2's product to the market and out-compete Yahoo. That client was Google and Expedition was re-branded as Google Maps. It is fair to say that, without having been acquired, the return on investment for Where 2 Technologies' product would have been scarce.

This story is not just an anecdote of one tech startup. Mergers and Acquisitions (M&A) have become the primary channel for startup companies to receive a return on their investments. Figure 1 displays methods of VC firm exits, the point where venture capital firms exit their investments and receive returns on their investment. It shows that from 2010 to 2019, on average, 78% of VC firms exited via acquisitions compared to 8%,which were exits through public offerings. This trend is a reversal of the VC exit outcomes of the 1990s. Looking back to the 1990s, that pattern is reversed. From the acquirers' perspective, M&A is a significant channel of investment. Data on M&A transactions, is detailed in Section 3.1, shows that M&A transaction values, on average, exceed $300 billion a year. However, M&A is a channel rarely considered in the endogenous growth literature. By excluding M&A activity, the literature is missing a significant incentive for investment and a central mechanism for firm growth.

However, in addition to being a source of significant investment incentives, M&A is also one of the primary sources for firms to consolidate markets and gain monopoly power. Monopolies and and antitrust authorities have always been a traditional concern of the government. However, recent developments in market consolidation and the rise of large tech companies have brought renewed scrutiny. In 2020, the House Judiciary Committee's antitrust panel issued a congressional report following investigation into the big four tech companies: Amazon, Apple, Google and Facebook. In particular, the report raised concerns that the tech companies were no longer confined to their original scope and instead had become multi-headed corporations with arms in many different markets. Another key concern is killer acquisitions, as documented by Cunningham, Ederer and Ma (2021), where a company attempts to maintain their current level of market power by buying a competitor within the same market with the sole purpose of retiring the competing product and shutting down its further development.

Another aspect of current interest in antitrust policy is the consideration of dynamic factors versus the traditional analysis. As Crandall and Winston (2003) points out, "the substantial and growing challenges of formulating and implementing effective antitrust policies in a new economy characterized by dynamic competition, rapid technological change and important intellectual property." These challenges are difficult to address given the existing literature because the study of antitrust dynamic competition policy is incredibly limited. This sentiment is echoed in the remarks of J. Thomas Rosch, a commissioner from the Federal Trade Commission as such:

> If you were to get together a group of antitrust and patent experts, everyone would likely agree broadly that antitrust and intellectual property are complementary in that both areas of law seek to protect and encourage innovation. When it comes to antitrust law, however, promoting innovation is good in theory, but hard in practice.

Thus, the goal of this paper is to help develop a useful tool for consideration of different dynamic antitrust concerns and policies.

The first contribution of this paper is to develop a dynamic, endogenous growth model which captures the majority of stories of M&A and their relationships to economic growth. This model can simultaneously capture the q-theoretic motivations for M&A proposed by Jovanovic and Rousseau (2002) and product complimentary motivation studies by Rhode-Kropf and Robinson (2008). Incorporating oligopolistic competition, the model also captures the motives for and consequences of market consolidation. The inclusion of numerous potential motives and consequences for M&A allows the model to provide a rich laboratory for experimentation on U.S. antitrust policy.

While the model's richness provides significant power in studying the aggregate effects of mergers and acquisitions, it presents several measurement challenges. The second contribution of this paper is to offer solutions for two of the most significant challenges. One challenge posed by the model is determining whether an M&A transaction is between firms currently operating in the same market or whether the acquiring company is using the transaction to enter the market. An accurate estimate is critical since these two cases have different market consolidation consequences. Transaction data does not indicate this relationship between the transacting parties. However, it does provide a textual description of the acquired firm. State-of-the-art natural language processing combined with a broad textual description of the acquiring firm in the form of corporate annual reports was used to estimate the relation between the parties. The results show that 61% of M&A transactional value is for transactions between firms in the same market. The second measurement challenge is providing an accurate depiction of US antitrust policy. Quantitative data on antitrust decision-making is extremely limited, making strictly empirical estimates of the antitrust policy function nearly impossible. This paper proposes a novel approach to this problem by utilizing a simple discrete choice model to bridge the gaps in data. The resulting antitrust policy function provides increased accuracy to this paper's results as well as providing an estimate applicable beyond this project.

The paper's third contribution is to employ the estimated model to illustrate the impact of M&A on growth. The key result is to show that M&A is a double-edged sword: a complete ban on MA results in a -10.2% decrease in growth and a 8% decrease in consumption equivalence welfare. For the case where there is no M&A, the results show that the lack of an outside option causes a significant decline in expansion rates for low- and medium-productivity firms. On the other hand, when there are no restrictions on M&A, there is a nearly 700% increase in the number of monopolies.

Literature Review

Despite the significant concern surrounding the dynamic effects of antitrust policy, the literature is incredibly sparse and rarely considers the growth angle. The closest prior research to this paper in goal and approach is Cavenaile, Celik and Tian (2021b). This paper used the Cavenaile et al. (2021b) model as a base and then made several key advancements to increase its applicability. In the Cavenaile et al. (2021b) paper, M&A opportunities arrive exogenously at a common rate for all pairs of firms in a market. The pair of potential merger partners then negotiate bilaterally. Their decision to have a rate be exogenous results in limited ability of firms to respond to changes in antitrust policy. One advancement of the current paper is to replace the exogenous opportunities with endogenous search. The impact of an exogenous versus endogenous rate is most apparent when considering an antitrust policy shutdown, i.e., all M&A transactions occur freely. In this situation, Cavenaile et al. (2021b)'s model demonstrates that there is only a -0.88% change in the growth rate and a minor impact on market concentration. When running the identical experiment, the current paper's model[1] results stand in

[1]Located in section **??**

stark contrast with a 14.4% decrease in growth and a 700% increases in the number of monopolies, which more realistically reflects both historical changes.

Another significant improvement that this paper makes is to estimate the true U.S. antitrust policy function. Their paper makes the assumption that all transactions above the screening threshold[2] are obstructed with equal probability — an assumption that does not hold true in the empirical data. The consequence of their assumption is to underestimate antitrust enforcement for transactions that result in a high degree of market consolidation since transactions with extremely high HHIs and significant impact on market concentration would have the same probability of being blocked as a transaction that is just over the screening threshold and minimally impacts market concentration. This choice of model assumption would both bias their estimation (the parameter values are chosen to match the distribution of markups of the United States while allowing a higher frequency of large increase in markup transactions) as well as their result that shutting down antitrust enforcement has modest welfare consequences.

Other studies have considered specific aspects of dynamic antitrust policy. Fons-Rosen, Roldan-Blanco and Schmitz (2021) focuses on the impact of banning startup acquisitions and finds a positive growth effect. Mermelstein, Nocke, Satterthwaite and Whinston (2020) studies the theory side of dynamic optimal antitrust policy.

A closely related strand of the literature focuses on the interaction of markup and innovation: Peters (2020); Cavenaile, Celik and Tian (2021a); Phillips and Zhdanov (2013); Akcigit, Celik and Greenwood (2016); Cavenaile et al. (2021b); and Pearce and Wu (2022). Peters (2020) shows that R&D activity can have both pro- and anti-competitive effects by increasing markup by improving a firm's product and decreasing competitive effects by creating new products and displacing market incumbents. This paper's model has a very similar finding to Peters (2020). Cavenaile et al. (2021a) found that R&D provides firms with an increased ability to charge markups, resulting in in static welfare losses for consumers. However, they found that the dynamic welfare gains were more significant than the static welfare loss. These findings echo the increasing need for a dynamic antitrust policy.

This paper contributes to techniques on employing unstructured data to answer macroeconomic questions in the spirit of Hoberg and Phillips (2010), who used SEC 10-K filings to examine public-to-public mergers. Additional references are Higgins and

[2]For the latest published guidelines, the screening threshold is an HHI of more than 0.15 and a change in HHI of more than 0.01.

Rodriguez (2006), Wang, Wu and Lai (2022), Gerard and Phillips (2021)

2 Model

The model developed by this paper is a continuous-time, endogenous-growth model with endogenous M&A both between competitors and across markets. For M&A, the model simultaneously captures the q-theoretic mechanism of Jovanovic and Rousseau (2002) and the product market complementary mechanism of Rhode-Kropf and Robinson (2008). Oligopolistic competition is another feature of the model, which incentivizes firms to consolidate markets to gain market power. This section describes the environment and describes equilibrium. Careful derivations of results are reserved for Appendix A.

2.1 Environment

Household: There is a single infinitely-lived representative household who discounts the future at rate ρ. The household is endowed with one unit of labor which it supplies to the labor market at wage rate w_t. The household owns all the assets in the economy which evolves according to:

$$\dot{A}_t = r_t A_t + w_t - P_t C_t.$$

where A_t is the household's assets with rate of return r_t, and where C_t is the consumption good with price P_t. The household determines its consumption-savings plan to maximize its discounted lifetime utility of:

$$U = \int_0^\infty e^{-\rho t} \log C_t \, \mathrm{d}t.$$

Firms: The economy is populated by a measure m of multi-product firms indexed by f. Firms can be multi-product. Across all of a firm's product markets, it has a common, time-invariant productivity z_f drawn from a distribution Z. The set of product markets in which a firm f competes at time t is denoted by $I_{f,t}$. Within each of these product markets $i \in I_{f,t}$, the firm produces a single good with quality $q_{f,i,t}$.

Product Markets: The economy contains a unit measure of differentiated product markets indexed by $i \in [0, 1]$. For each product market i, there is a set of firms $F_{i,t}$ and a competitive fringe, each producing differentiated varieties of products. These product varieties each have their qualities denoted $q_{f,i,t}$ for a firm $f \in F_{i,t}$, and $q_{c,i,t}$ for a fringe firm. Within a product market i, the firms' goods are aggregated together by a competitive firm employing technology:

$$y_{i,t}^{\frac{\theta-1}{\theta}} = \frac{1}{|F_{i,t}|+1}\left(\sum_{f\in F_{i,t}} q_{f,i,t}y_{f,i,t}^{\frac{\theta-1}{\theta}} + q_{c,i,t}y_{c,i,t}^{\frac{\theta-1}{\theta}}\right)$$

where $y_{i,t}$ is the total quantity of aggregated goods, $y_{f,i,t}$ is a firm f's output, and $y_{c,i,t}$ is the competitive fringe's output[3].

While the competitive fringe are price takers, the firms strategically compete with each other in Cournot competition, similar to Atkeson and Burstein (2008). This structure enables the firms to set an endogenous markup based on market conditions including the relative quality of their goods. The endogenous markup provides incentive for a firm to improve product quality in order to increase profits. However, it is also a source of misallocation: the higher a firm's market share, the higher the markup it can charge.

Final Goods: All product markets' goods $y_{i,t}$ are aggregated into a final good Y_t by a competitive final goods firm. This final goods firm employs a unitary elasticity of substitution aggregator function[4] specified by:

$$\log Y_t = \int_0^1 \log y_{i,t}, \mathrm{d}i.$$

Production: For a firm f to produce their output $y_{f,i,t}$ in market $i \in I_{f,t}$, they combine their productivity $z_{f,t}$ with a labor input $h_{f,i,t}$, hired at a wage rate w_t, according to

$$y_{f,i,t} = z_{f,t}h_{f,i,t}.$$

The competitive fringe employs an identical technology where their productivity is identically one.

Research and Development: The firms conduct research and development to achieve two goals: (1) to improve the quality of their current products and (2) to expand into

[3]The right-hand side is divided by the number of firms plus one (for the competitive fringe) in order to cancel the love of variety effect within a market. If it was included, there would have been welfare gains from a market having more firms, regardless if the extra firms caused any reduction in misallocation.

[4]The assumption that the aggregator has unitary elasticity is not critical when computing the solution to the model — it can be easily replaced with a flexible constant elasticity of substitution aggregator. However, the unitary case provides an increased degree of clarity in welfare analysis and is consistent with the previous literature.

new markets by creating new products. Each good's quality sits on a quality ladder with step size λ. Each time a firm improves its product, the good's quality takes a single step up the ladder; its quality goes from $q_{f,i,t}$ to $\lambda q_{f,i,t}$. Improvements arrive to the firm exogenously according to a Poisson arrival process at an endogenous rate $\mathcal{I}_{f,i,t}$. The cost of achieving that rate is $c_{\mathcal{I}}\left(\mathcal{I}_{f,i,t}\right) Y_t$ units of goods. The improvements are market-specific, and the firm can simultaneously attempt to improve all its products. If a firm's product quality in a market falls more than the quality gap threshold of $\bar{n}$ steps behind the highest quality product, the product becomes obsolete, and the firm can no longer produce in that market. This mechanism captures the creative destruction channel of growth.

Recall that firms can have a single product in each market. Therefore, expansion into new markets is achieved by generating new products, which occurs similarly to improvements. New products arrive to the firm according to a Poisson arrival process at an endogenous rate $\mathcal{X}_{f,t}$. The cost of achieving that rate is $c_{\mathcal{X}}\left(\mathcal{X}_{f,t}\right) Y_t$ units of goods. The research effort is undirected because the firm cannot target which market to enter. When they develop a new product, the firm receives a uniform random draw of which market it enters. Upon entering the new market, the quality of the new good is a step above the maximum quality currently existing in that market. The new product quality q' is

$$q'_{i,t} = \lambda \max\left\{q_{f,i,t} : f \in F_{i,t}\right\}.$$

This is intended to capture new products being superior versions of existing products. In each product market, there is a maximum size cap of $\bar{F}$ firms. If the market is drawn, and it already has $\bar{F}$ firms, then the firm with the least profitable product[5], in terms of sales minus wages paid to production workers, exits as another victim of creative destruction[6].

The competitive fringe does not perform research and development. Instead, their good's quality is a function of the market leader's quality. Specifically,

$$q_{c,i,t} = \psi \max\left\{q_{f,i,t} : f \in F_{i,t}\right\}.$$

[5]If multiple firms are tied for least profitable, one is picked with equal probability to exit the market.

[6]A common, alternative assumption is that the market is closed to new entry after reaching the size cap. However, this framework leads to an unrealistic result where the firm with the highest quality will cut research if one of its competitors is $\bar{F}$ steps behind. Recall that firms leave a market if their product quality is too far from the leading firm, and that new market entrants emerge with a product with superior quality to the current market leader. As a result, current market leaders can ensure that they are not overtaken by new entrants by stopping innovation in order to not force additional firms out.

That means innovations by the market leaders result in a positive spillover by increasing good quality for the competitive fringe.

Mergers and Acquisitions: The second source of firm growth is through mergers and acquisitions. Firms can perform M&A both within markets where they currently operate and across markets where they use M&A to enter into new markets. In the model, M&A transactions are for a single product. While M&A transactions are traditionally thought of as one company buying the entirety of another, it is also frequently observed in the data that one company buys only a portion of another[7].

Beginning with transactions where the buyer is not currently active in the market (the entry margin), there is a decentralized M&A market for potential buyers and sellers. Since this paper focuses on product market dispersions, the paper attempts to minimize the impact of M&A market distortions by setting an endogenous arrival assumption. The market opportunities for a buyer or a seller to enter the market arrive exogenously at an endogenous rate. Beginning with the sellers, if a firm f wants to sell its good in market i, it picks an opportunity arrival rate $\eta_{f,i,t}$ at a cost $c_b\left(\eta_{f,i,t}\right)Y_t$. If a seller wants to sell multiple products, they pick individual arrival rates and pay the associated cost for each. Let $s = \left(q_{f,i,t}, \{(z_{f',i,t}, q_{f',i,t})\}_{f \neq f'}\right)$ denote the quality of the good and the competition in the market. When an opportunity arrives, the seller observes all the potential buyers and the competitive price schedule $p_t^q(z|z', s)$ where z is the productivity of the buyer they sell the good to, and z' is the productivity of the seller. The seller then picks a buyer in order to solve

$$\max_{z' \in Z} \{p_t^q(z'|s) - D_t(z, s)\}$$

where D is the value of a firm with productivity z producing a good with state s. The buyers have a similar process to identify opportunities for M&A. They pick an arrival rate $\psi_{f,t}$ at a cost $c_b\left(\phi_{f,t}\right)Y_t$. When those opportunities do arrive, the buyer observes all the sellers in the market and a competitive price schedule $p_t^q(z', s|z)$ where z' is the productivity of the seller, s is the state of the good, and z is the buyer's productivity. The buyer then picks which product line to buy in order to solve

$$\max_{(z', s)} \{D_t(z, s) - p_t^q(z', s|z)\}$$

When the firm sells its good, it exits the market, and the buying firm takes its place. A key distinction between this mechanism and the within-market mechanism is that the

[7] For example, Google purchased only Motorola's cell phone division.

number of firms does not change as a result of an M&A transaction — the buyer simply takes the seller's place.

Next, we look at how the buyer is operating in the market. Since there are only finite firms in a market, the buyer is assumed to know all of their competitors. A firm can attempt to acquire any other firm operating in that market. If the selling firm is multi-product, then it can only sell the product within that specific market. When a firm f operating in market i wants to acquire firm f''s market i good, they pick an opportunity arrival rate $\theta_{f',f,i,t}$ at a cost $c_w\left(\theta_{f',f,i,t}\right)$. The firm can attempt to simultaneously generate an M&A opportunity for multiple of its competitors, independently setting rates and paying the associated cost. Since there is a finite number of firms in each market, there is no equivalent competitive price schedule. Instead, the two parties enter into Nash bargaining where the acquirer has bargaining power β. If negotiations are successful, the seller transfers their good to the buyer and exits the market. This time, there is no replacement for the seller — the market has one fewer firm as a result. When the buyer receives the new product, they then combine their current product and their own product to produce a new product. The quality of the new product is given by $\zeta q_a^{\alpha} q_t^{1-\alpha}$ where q_a is the acquiring firm's good, q_t is the acquired firm's good and the parameter ζ is the quality growth resulting from combining the two goods while α is the product share of acquires existing product.

Both types of transactions are subject to antitrust regulation prior to being allowed to commence. The antitrust regulator is assumed to be able to accurately predict the post-merger Herfindahl-Hirschman index (HHI) and the change in HHI. Given those estimates, the antitrust regulator will choose to block a transaction with probability $B(hhi, \Delta hhi)$ where hhi is the post-merger HHI and Δhhi is the change following the transaction. This function is an input to the model and will be estimated in Section 4.1. If the regulator blocks a transaction, nothing is transferred between the parties and the market remains in the state it was in prior to the merger cost. Their only loss is the wasted effort of attempting the transaction. Additionally, it is assumed that once the regulator blocks the transaction, the parties can not re-attempt a modified version of the transaction.

The structure placed on the M&A process by the model is very flexible. Before moving on, it is worth taking a minute to detail a selection of the different M&A stories allowed by the model. The classic story of "buying your competitors in order to consolidate markets" is present in the within market mechanism. The within-market mechanism also allows two firms to combine their goods and produce a single superior good. The q-theoretic mechanism is covered by a high-productivity firm using the across-market mechanism to purchase a product from a low-productivity firm. While across-market transactions do not result in the market having one less firm, they are not necessarily competitive. A high-productivity firm could buy a low-productivity firm operating in a neck-and-neck market and disrupt the market. These are just a sample of the set of motivations and stories that the flexible form of the M&A process allows the model to encapsulate.

Firm's Value Function: Each firm's full state is an infinite dimensional object — each firm needs to track not only its own state but also the state of its competitors, and the state of its competitor's competitors, and so on. Each state can be solved separately since decisions in one firm's market does not spill over to other markets. The firm f's state consists of its productivity z and a collection of other variables representing information about each market in which it competes. Thus, the state is defined as $s_{f,i,t} = \left(q_{f,i,t}, \{(z_{f',i,t}, q_{f',i,t})\}_{f \neq f'}\right)$. Then, the firm's value function $V_{f,t}\left(z, \{s_{f,i,t}\}\right)$ can be written as[8]

$$V_{f,t}\left(z, \{s_{f,i,t}\}\right) = F\left(z\right) + \sum_{i \in I_{f,t}} D\left(z, s_{f,i,t}\right)$$

where $D\left(z, s_{i,f,t}\right)$ represents the value function for firm f's operations in market i and $F(z)$ represents the value function for other components that are only dependent on the productivity level. The easiest way to conceptualize both value functions is to imagine $D\left(z, s_{i,f,t}\right)$ as the different divisions of the firm while $F(z)$ is the head-quarters. At the division level, decisions are made regarding that division's specific product, such as investing in product improvements and making M&A decisions within their product market. On the other hand, the headquarters is responsible for expansion decisions either through R&D innovation or across-market M&A activities.

The division's value function is presented next. For increased clarity, the state will be omitted and only changes to the state (indicated by $\rightarrow$) will be shown. Also, let

[8] This is formally shown in Appendix A.

$T(i,f,f')$ represent the outcome of firm f acquiring firm f' within market i.

$$
\begin{aligned}
r_t D - \dot{D} = &\underbrace{\pi(z_f, s_{f,i,t})}_{\text{Gross Profits}} \\
&+ \underbrace{\max_{\mathcal{I}_{f,i,t}} \left\{ \mathcal{I}_{f,i,t} \left(D \left(q_{f,i,t} \to \lambda q_{f,i,t} \right) - D \right) - c_{\mathcal{I}} \left(\mathcal{I}_{f,i,t} \right) Y_t \right\}}_{\text{Own R\&D Improvements}} \\
&+ \underbrace{\sum_{\substack{f' \in F_{i,t} \\ f' \neq f}} \mathcal{I}_{f',i,t} \left(D \left(q_{f',i,t} \to \lambda q_{f',i,t} \right) - D \right)}_{\text{Other Firm's R\&D Improvements}} \\
&+ \underbrace{\sum_{z} X_t(z) \left(D \left(\{ (z_{f',i,t}, q_{f',i,t}) \} \to \{ (z_{f',i,t}, q_{f',i,t}) \} \cup \{ (z, \lambda q_{\ell,i,t}) \} \right) - D \right)}_{\text{Outside Firm's R\&D Entry}} \\
&+ \underbrace{\sum_{f' \neq f} \max_{\theta_{f',f,i,t}} \left\{ \theta_{f',f,i,t} \mathbb{E} \left[1 - B \right] \left(D \left(T(i,f,f') \right) - D \right) - c_w \left(\theta_{f',f,i,t} \right) Y_t \right\}}_{\text{Own Within Market M\&A}} \\
&+ \underbrace{\sum_{f', \tilde{f} \neq f} \theta_{f',\tilde{f},i,t} \mathbb{E} \left[1 - B \right] \left(D \left(T(i,\tilde{f},f') \right) - D \right)}_{\text{Other Firms' Within Market M\&A}} \\
&+ \underbrace{\max_{\eta_{f,i,t}} \left\{ \eta_{f,i,t} \max_{z'} \mathbb{E} \left[1 - B \right] \left[p^q(z' | z_{f,i,t}, s_{f,i,t}) - D \right] - c_b \left(\eta_{f,i,t} \right) Y_t \right\}}_{Own Across Market M\&A} \\
&+ \underbrace{\sum_{f' \neq f} \eta_{f',i,t} \mathbb{E} \left[1 - B \right] \left(D \left(z_{f',i,t} \to \tilde{z} \right) - D \right)}_{\text{Other Firm's Across Market M\&A}}
\end{aligned}
$$

along with boundary conditions that result in a firm exiting from the market: when the firm falls $\bar{n}$ step behind the technology leader or when the firm is the least profitable firm when there is a new firm entrant in a full market. The problem that the headquarters solves for is to manage the firm's expansion, whether through R&D or M&A. The value of the headquarters is given by

$$
\begin{aligned}
r_t F(z_{f,t}) - \dot{F}(z_{f,t}) = &\max_{\mathcal{X}_{f,t}} \left\{ \mathcal{X}_{f,t} \mathbb{E}_s \left[D(z_{f,t}, s) \right] - c_{\mathcal{X}} \left(\mathcal{X}_{f,t} \right) Y_t \right\} \\
&+ \max_{\theta_{f,t}} \theta_{f,t} \left\{ \max_{(z',s)} \left[D\left(z, s\right) - q(z', s | z_{f,t}) \right] \right\}
\end{aligned}
$$

2.2 Balanced Growth Path

The equilibrium concept for this environment is a balanced growth path. Determining the price schedules $p^q(z', s|z)$ and $p^q(z|z', s)$ is the only less standard part of solving for the equilibrium. Given that the two price schedules have been endowed with very little structure in the model, it seems like a nearly impossible challenge. However, the theory of optimal transport problems[9] provides a tractable solution. The surplus for a productivity z firm acquiring a product whose state is $s = (q, \{(\tilde{z}, \tilde{q})\})$ from a productivity z' firm is

$$X(z, z', s) = D\left(z, q, \{(\tilde{z}, \tilde{q})\}\right) - D\left(z', q, \{(\tilde{z}, \tilde{q})\}\right).$$

Let $\pi(z)$ be the measure of buyers of productivity in the market and let $\pi\left(z', s\right)$ be the measure of products in the M&A market available for sale. Consider the market planner's problem

$$\begin{aligned}
\max_{\pi(z,z',s)} \; & \sum_{(z,z',s)} \pi(z, z', s) X(z, z', s) \\
s.t. \; & \sum_{z} \pi(z, z', s) \leq \pi\left(z', s\right) && (1) \\
& \sum_{(z',s)} \pi(z, z', s) \leq \pi(z) && (2) \\
& \pi\left(z', s\right), \pi(z) \geq 0
\end{aligned}$$

where $\pi(z, z', s)$ is the measure of products of state s transferred between productivity z and z' firms[10]. Optimal transport theory shows that the allocations from this planner problem corresponds to the equilibrium allocation. It also shows that the dual value $\nu_s(z', s)$ of (1) and $\nu_b(z)$ of (2) are equal to the market value for each party. That means they satisfy

$$\begin{aligned}
\nu_b(z) &= \max_{(z',s)} \left(X(z, z', s) - \nu_s(z', s)\right) \\
\nu_s(z', s) &= \max_{z} \left(X(z, z', s) - \nu_b(z)\right).
\end{aligned}$$

[9]The theory of optimal transport problems is beyond the scope of this paper. Galichon (2016) provides an excellent introduction.

[10]Under the assumption of this problem, everyone must trade and there is no opting out once they reach the market. However, attempting to enter the market is an endogenous choice of the firms which means that firm which will not want to trade will not enter the market

Using those relationships, the equilibrium price schedules are

$$p^q(z', s|z) = X(z, z', s) - \nu(z', s)$$
$$p^q(z|z', s) = X(z, z', s) - \nu(z).$$

2.3 Numerical Solution

The model does not admit an analytical solution and must be solved numerically. Throughout estimation and for all of the results, the model was discretized such that every market could have a maximum of five firms (excluding the competitive fringe), a maximum of six quality steps between competitors, and every firm can take on one of three distinct productivity states. This results in 32,131 potential markets and 133,980 unique firm states for which solving a value function is required. While this results in a large system, it contains several convenient numerical properties that enable relatively rapid solutions — especially if utilizing parallel processing via a GPU.

3 M&A Data

The model described in the previous subsection made a distinction for M&A activity between competitors within a market and as an across-market mechanism for firms to enter into new markets. While this does allow the model to analyze a wide variety of M&A situations, it also creates a difficult measurement challenge of how to distinguish between the two types of transactions. Approaches that compare industry codes — such as NAICS or SIC codes — are insufficient since neither is specific enough to determine if two firms are in a similar market, nor can they capture the multi-product nature of modern firms. This section develops an alternative approach that applies state of the art natural language processing (NLP) techniques to compare textual descriptions of both the target and the firm acquiring it.

3.1 M&A Transaction Data

The most comprehensive dataset on M&A transactions in the United States is SDC Platinum data set by Refinitiv. After 1992, it covers all corporate transactions involving at least 5% of a company's equity. For each transaction, the dataset contains financial variables on the acquired firm prior to the transaction, information on the terms of the deal, and — if they are a public company — identifier information that allows for linking to other datasets, including Compustat and SEC filings. From these transactions, filter for transactions where the following criteria are met:

1. The acquiring company is a US publicly traded corporation,
2. The transaction resulted in the acquiring firm acquiring a majority stake in the company,
3. The parties were unrelated,
4. The transaction was completed.

This sample consists of over 38k transactions with a total market value of $7.8 trillion between 1997 and 2019. If the acquiring firm listed in a transaction record is the subsidiary of another corporation, then the ultimate parent is set as the acquirer. When discussing the goals of the requirements, the first criterion is critical for this approach since, as discussed int he next section, there exists high quality textual descriptions of US publicly traded corporations.

The goal of the second criterion is to ensure that control was transferred to the acquiring firm and to exclude the purchases of minority positions. The final two criteria attempt to exclude actions such as corporate reorganizations that appear like M&A transactions for legal reasons.

After subsetting for these four criteria, the next step is to link the transactions with the corporate annual report of the acquirer's company. On an annual basis, US publicly traded corporations are required to submit a detailed report of their business and operations along with their financial statements to the Securities and Exchange Commission (SEC). These annual reports, known as 10-Ks, are freely accessible from the SEC's Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) which, staring in 1997, is a near-complete record of all corporate filings with the SEC. The transactions from the SDC Platinum data set are matched with the acquiring corporation's 10-K form for the year prior to the transaction date. The previous year's date is chosen in order to obtain an accurate depiction of the acquiring business prior to the transaction and to minimize the number of documents that directly refer to the specific M&A transaction[11].

Given the availability restrictions of EDGAR data, the data is restricted to transactions from 1997-2019. Not every transaction claiming to be acquired by a public

[11] Since the approach undertaken will be to compare text similarity, having references to the transaction in the comparison text will add noise

corporation in a specific year is able to be linked. This likely seems to be due to mistaken labels such as having been purchased by a public corporation or there was clerical error when recording the acquirer's identifying information.

3.2 Comparing Companies Using Natural Language Processing

An example of a company description in the SDC Platinum data set that demonstrates the multi-product nature of firms is Phase Shift Technology, which was acquired by ADE Corportion in 1998. Phase Shift Technology's description in the SDC Platinum data reads: [12]:

> Manufacture high-performance, non-contact surface metrology equipment using advanced optical interferometric technology; its products are used in data storage, optics, metals, and related research for production control, failure analysis, and advanced research of surface shape and surface microstructure.

The descriptions of target companies in the SDC Platinum data are high quality and rich with product-level information, product purpose, and markets. Crucially, the SDC Platinum data provides descriptions for private companies that do not file 10-K forms. Thus, target company descriptions in the SDC dataset are ideal for semantic similarity methods, which classify with a significantly higher level of both granularity and accuracy than industry classification methods used in past literature, such as NAIC or SIC.

An excerpt of ADE Corporation's business description provided in its SEC 10-K filing from 1998 is as follows:

> The Company's metrology and inspection products use its proprietary non-contact capacitive, magnetic and optical technologies to measure the dimensional, magnetic and surface characteristics of semiconductor wafers and devices and computer hard disks.

Comparing these two statements between Phase Shift Technologies and ADE Corporation, it is easy for a human reader to digest the context of the statements and conclude

[12] There is no uniform format or length for company descriptions. Some company descriptions are populated with a few words, while others involve highly detailed and multi-paragraph descriptions. Accounting for the seemingly-infinite variety of ways that company descriptions are written is nearly intractable without modern machine learning approaches.

that this acquisition occurred within the same market since both firms are involved in the production of non-contact optical technologies and in some type of data storage device, such as hard disks. However, context-based analysis of semantic similarity has been an intractable problem until advancements in the last decade around machine learning and, in particular, a new frontier approach in NLP named Google's BERT, which became the underlying model powering Google Search and was released as open source software in 2019.

Contextual sentence similarity involves not only identifying keywords and product names that help characterize whether two firms are working on identical areas, but also identifying context that provides information about company purpose and market intent, as well as identifying synonyms and related words for highly specific products. Furthermore, the comparison needs to be able to account for the multi-product nature of modern firms.

By being able to implement BERT to analyze company descriptions between the acquiring company's SEC 10-K filings and the target company's descriptions sourced from SDC Platinum data, this paper demonstrates a new context-based approach to classify each M&A transaction as either (1) a transaction between two firms in the same market to consolidate market power or (2) a transaction between firms in different markets such that the acquiring firm seeks to enter a new market.

3.3 Natural Language Processing

The classification of semantic similarity as "within market" or "across markets" is performed for over 38,000 transactions.

In order to classify transactions, I implemented a variant of Bidirectional Transformers for Language Understanding (BERT) to search for the company description from the AUP's annual reports, specifically finBERT which was specifically trained on reading and performing sentiment analysis from reading financial reports such as 10-Ks and other sources of financial news[13].

The procedure for finBERT is as follows:

1. Extract one sentence of the target company's description from the SDC Platinum

[13] Conceptually, BERT is a language representation model developed by Google that learns contextual relations between words (or sub-words) in a text both left-to-right and right-to-left ("bidirectional"). The bidirectional pre-training results in significantly improved accuracy over prior language models that were only pre-trained on reading sentences left-to-right. Further, BERT achieves state-of-the-art performance for a large suite of both sentence-level and token-level tasks.

data.

2. Compare the sentence against each sentence from the acquirer's SEC 10-K filing for the previous year.

3. The model outputs a score on how similar the two sentences are.

4. Repeat the process for each sentence in the target company's description to get a similarity score for each sentence.

If finBERT outputs a score indicating that the target's company description is highly similar to any sentences in the acquirer's 10-K, then the transaction is classified as "within market." If all sentences in the target's company description have a low similarity score compared to the acquirer's 10-K, then the transaction is classified as "across markets"[14].

Across all transactions, M&A activity by acquirers already existing in the target firm's market comprised 61% of all M&A value. For acquisitions in the tech and pharmaceutical sectors, it was 42% and 84%, respectively.

From an accuracy perspective, the performance was tested on a sample of 150 acquisitions within the same market, and 150 acquisitions across different markets. This sample was manually labeled by the author of this paper. The accuracy was 80% within the same market and 83% across markets. This approach is an improvement over past macroeconomic attempts to compare textual data, such as Hoberg and Phillips (2010) which used a vector space model on the SEC 10-K filings to compute similarity between firms by counting the keyword density of each company description. However, Hoberg and Phillips (2010) acknowledge three primary challenges:

1. Counting the frequency of keywords is less accurate if the firm is a multi-product conglomerate, as are most tech firms, while BERT demonstrates significantly greater accuracy at 80% and above.

2. Keyword density struggles with understanding synonyms and context whereas BERT excels in understanding context.

[14] An acquiring firm may still have operations in the same market as the target company despite the acquiring firm not listing it in its 10-K. However, if the market is not listed in the acquiring firm's 10-K, then it is not a major business line of the company and therefore it is assumed that the acquiring firm does not have significant market power in the market where the target company operates

3. The method does not provide accurate labeling if the text data has fewer than 1000 characters. However, the majority of target descriptions in the SDC Platinum data are single-sentence descriptions with fewer than 1000 characters.

Although there is still roughly a 20% degree of error with BERT, the author viewed the accuracy of this method as a reasonable first step and hopes that readers will find this approach to be a fruitful area for further research. There remains further work to do around natural language processing in the area of processing 10-Ks and applying NLP methods to industrial organization tasks.

4 Estimation

4.1 Capturing US Antitrust Policy

Accurately modeling antitrust policy is crucial for estimating the model and providing realistic policy analysis. In the United States, the primary form of antitrust policy is the premerger notification program, where the parties to a M&A transaction, whose value exceeds a legal threshold[15], must seek approval from the antitrust regulator[16] for the transaction prior to it commencing. This process has three basic steps:

1. The transacting parties submit information to the regulator about their proposed transaction.

2. The antitrust regulator reviews the submission and can approve the transaction or request additional information related to anti-competitive concerns. The request for additional information is called "entering second review."

3. The regulator assesses the second review material determines whether it will attempt to legally block the transaction or allow it to transact legally.

A significant challenge when studying antitrust policy is a lack of transparent data surrounding the decision-making process. The United States antitrust authorities release

[15]The threshold is defined by Hart-Scott-Rodino Antitrust Improvements Act and changes annually. For transactions occurring in 2022, the threshold $101 million.

[16]In the United State, antitrust regulation is the dual duties of the Federal Trade Commission and the Department of Justice Antitrust Division. While there are differences between the two agencies, those differences are beyond the scope of this paper. In general, the two will be referred together as the antitrust regulator.

two quantitative resources, both limited in scope. The first resource is the *Hart-Scott-Rodino Annual Report* (HSR report) in which the Federal Trade Commission and the Department of Justice Antitrust Division are required to report information related to that year's actions for the premerger notification program. Quantitatively, it contains:

- the number of transactions reported to the antitrust regulator
- the number of requests for second reviews
- the number of transactions that the regulator attempted to block[17]

The report also qualitatively describes the reasoning behind selected actions — frequently discussing concerns about market concentration — but lacks information about the measures of market concentration, such as HHI, in both those selected transactions and the overall sample of transactions. However, the second source, *Horizontal Merger Investigation Data, Fiscal Years 1996-2011*[18], provides enough of a glimpse to push forward. The report provides summary statistics on every second request investigation between 1996 and 2011, where the antitrust regulator's reason for performing the investigation was concerns about horizontal theories of competitiveness concerns. Crucially, Table 3.1 of the report (reproduced as Table **??** in the appendix of this paper) provides, for bins of HHI and change in HHI, counts on the number of transactions which were and were not blocked. The remainder of this section will discuss how to turn this data into an antitrust policy function.

Recall from the model that antitrust policy is characterized as a Bernoulli random variable $B(hhi, \Delta hhi)$ where $B(hhi, \Delta hhi) = 1$ means the regulator blocks the merger and $B(hhi, \Delta hhi) = 0$ means the regulator allows the transaction. Let P_B be the probability mass function of B. The mass function, conditional on a transaction $(hhi, \Delta hhi)$, can be written as

$$P_B\left(B|hhi, \Delta hhi\right) = P_B\left(B|hhi, \Delta hhi, S=1\right) P_S\left(S=1|hhi, \Delta hhi\right) \tag{3}$$

where $P_B\left(B|hhi, \Delta hhi, S=1\right)$ is the probability that a transaction is blocked, conditional on having received a second review[19] and $P_S\left(S=1|hhi, \Delta hhi\right)$ is the probability of

[17] A table of these counts for the sample years is included in the appendix as Table **??**

[18] Commission (2013)

[19] A transaction can not be blocked without first getting a second review. Thus $P_B\left(B|hhi, \Delta hhi, S=0\right) = 0$.

a transaction receiving a second review conditional on having characteristics $(hhi, \Delta hhi)$. These objects will be considered separately.

Consider the problem of the antitrust regulator, after having entered a second review, determining if they want to challenge a transaction with characteristics $(hhi, \Delta hhi)$. The simplest way to analyze this problem is to set it up as a discrete choice problem where the value of denying the transaction is given by

$$G\left(hhi, \Delta hhi\right) + \varepsilon$$

and the value of approving the transaction is zero. The G function can be thought specifying the regulator's goal to prevent concentration, while ε accounts for non-concentration factors influencing the regulator's decision. Table 3.1 of the *Horizontal Merger Investigation Data* report can be considered the outcome of this discrete choice problem. Assuming that ε is logistically distributed, a logistics regression on Table 3.1 characterizes the solution to the government's discrete choice problem. Prior to performing that regression, a linear functional form of G must be chosen. Given there is limited research into the form of G, a fourth-degree polynomial is chosen

$$G\left(hhi, \Delta hhi\right) = \sum_{n=0}^{4} \sum_{k=0}^{n} \beta_{n,k} \left(hhi\right)^{n-k} \left(\Delta hhi\right)^{k}$$

to allow for maximum flexibility in representing the solution. The result of the regression, the representation of the regulator's choice function $P_B\left(B | hhi, \Delta hhi, S = 1\right)$[20].

Estimating the probability of a firm entering a second review is much more challenging. There is no comparable version of Table 3.1 for entering secondary review and no other data source allowing for a similar estimation exercise. In fact, the only available data on the choice of sending a transaction to secondary review is the fraction of transactions, on average 3.1%, over 1997 to 2019, that received secondary review[21]. Given that, the approach will be to exploit the discrete choice problem from the previous exercise and combine it with the aggregate counts. Suppose that the antitrust regulator is capacity-constrained and cannot send more than 3.1% of transactions to secondary review. Furthermore, suppose that the regulator can observe every merger they will need to pick between for sending to secondary review. The question is, who would they choose? This question can be answered by connecting back to the discrete choice problem.

[20]The coefficients can be found in Appendix B

[21]These counts are also sliced by major industry and transaction size, either of which is useful for this project.

Let $T = \{(hhi_j, \Delta hhi_j)\}$ be the set of all transactions submitted to the regulator for review. The regulators problem is to choose at most 3.1% of them to review. It will select a set of transactions $\tilde{T}$ to maximize the total expected value of its second-stage problem

$$\int_{\tilde{T}} \mathbb{E}_{\varepsilon} \left[\max\left\{G\left(hhi, \Delta hhi\right) + \varepsilon, 0\right\}\right] \, \mathrm{d}f_T\left(hhi, \Delta hhi\right)$$

where f_T is the measure of transactions. While this problem appears challenging at first, the solution can be characterized as finding a threshold R such that transactions where $P_B\left(B|hhi, \Delta hhi\right) \geq R$ are selected for secondary review and the total number of transactions reviewed is subject to the capacity constraint. While being able to observe both the capacity constraint and $P_B\left(B|hhi, \Delta hhi\right)$, the threshold condition is not able to be directly estimated since there is no information on the distribution of M&A transactions f_T. However, it can be estimated indirectly through the model, as detailed in the next subsection.

4.2 Estimation

In addition to the threshold condition R, the model has 17 parameters (A_a, $A_{\mathcal{I}}$, A_w, $A_{\mathcal{X}}$, α, β, γ_a, $\gamma_{\mathcal{I}}$, γ_w, $\gamma_{\mathcal{X}}$, λ, m, ψ, ρ, θ, ω, ζ) as well as the productivity distribution for z. Except for the discount rate ρ, the fringe's goods quality ψ, and α, the remaining parameters are estimated. For the discount rate ρ, the model assumes a 6% interest rate. Since the economy is growing at 2.4% in the baseline, that implies the discount rate is $\rho = 0.036$. For the fringe's quality ψ, the assumption is that the fringe's good is always lower quality when compared to a strategic firm. The easiest way to implement this assumption is to set ψ such that it is one step further down the quality ladder than the maximum allowed gap of $\bar{n}$. That parameter α is intended to enable the model to the like-buys-like story of Rhode-Kropf and Robinson (2008) and is thus set at half. Also, to correspond with the M&A data set detailed in Section 3.1, data is restricted to 1997-2019.

Prior to discussing the estimation moments, it is crucial to establish the units of measurement in the model. The moments will either be aggregates or firm-level statistics. While within the model, the divisions' and headquarters' problems were solved independently, they are still part of a single unit of measurement: the firms. During simulations, the firms need to keep track of their divisions and add up their divisions' variables into firm-level ones. This is critical when utilizing identification moments such as average profits. If the division values are dollar values from real world financial statements such as sales or profits, then the dollars are summed into a single firm-level value. For other values, like markup or market share, they are sales-weighted averages between all the firm's divisions.

Functional Forms: The model section allows for arbitrary function forms on the cost functions. For quantitative exercises, a standard convex cost function is employed. Specifically, the cost functions are

- **Improvement R&D:** $c_{\mathcal{I}}(\mathcal{I}) = A_{\mathcal{I}}\mathcal{I}^{1+\gamma_{\mathcal{I}}}$,
- **Expansion R&D:** $c_{\mathcal{X}}(\mathcal{X}) = A_{\mathcal{X}}\mathcal{X}^{1+\gamma_{\mathcal{X}}}$,
- **Within Market M&A:** $c_w(\theta) = A_w\theta^{1+\gamma_w}$,
- **Across Market M&A:** $c_b(\eta) = A_b\eta^{1+\gamma_b}$.

Data Moments: A brief description of the identifying data moments utilized to discipline the model follows. The moments' values, as well as the values of the estimated parameters, can be found in Table 1. A more detailed description of the identifying moments, and how to construct model objects to match the data, is provided in Appendix **??**.

To capture the U.S.'s growth dynamics, the model is estimated to match the US growth rate and the ratio of the National Income and Product Accounts' estimates of research and development, investment and GDP. Given the paper's interest, it is critical to accurately depict the interaction of competition and research effort. For almost all parameter sets, this model will produce an inverted-U relationship between the level of competition and R&D spending. The goal is to match the inverted-U shape in the data. Following Cavenaile et al. (2021a), the model is estimated to match a quadratic regression of relative sales on the log of RD spending[22]. The model is also estimated on the sales-weighted average and standard deviation of markup reported in De Loecker, Eeckhout and Unger (2020).

Moving onto M&A process, the model is set to match the ratio of the sum of M&A

[22] In Cavenaile et al. (2021a), they used patent counts and improvement arrival rates. Given the multi-product nature of this model, R&D spending adds up to a firm-level variable more easily than the arrival rates.

equity values[23] to GDP and the within-sector MA ratio established in Section 3. To match the pattern of trade, the model matches the mean of the M&A premium as observed in the SDC Data.

Finally, the primary goal for the productivity values z is to match the skewness of the US sales distribution. There are three productivity states z_1, z_2, z_3 meant to represent firms under the 50th percentile in sales, firms between the 50th and 90th percentiles, and firms in the top decile of sales. After normalizing $z_2 = 1$, z_1 and z_3 are chosen to match the share of sales for the bottom 50% and top 10% Compustat firms, respectively. This grouping was chosen to match key groups for mergers and acquisitions. Panel B of Figure 2 displays the share of M&A transnational value by sales decile of Compustat firms. It shows that the top decile of acquiring firms represents 75.7% of the total M&A transactional value, the 50th-90th percentile represents 20.3% of the value, while the bottom 50th percentile represents the remaining 3.9%. Separating out the top 10% of acquiring firms allows for a more accurate characterization of MA trade patterns. It also enables the model to understand the consequences of having, presumably, highly productive being responsible for the vast majority of M&A spending.

5 Growth and M&A

5.1 Illustrative Example

To elucidate the impact of M&A on economic growth, it is best to consider a simple illustrative example that compares a baseline economy with an economy where the antitrust authority imposes a blanket ban on M&A activity.

Consider a duopoly market where one firm's productivity is equal to the highest productivity in the model, and the other firm's productivity is equal to the lowest. These firms represent the extreme ends of productivity and allow us to examine the corresponding impact of productivity on two variables: (1) gross profit and (2) revenue minus wages paid to production labor. For each firm, Figure 3 displays the baseline case for the level and the change for gross profit, and revenue minus wages paid to production labor. The figure clearly shows that for the low-productivity firm, the marginal gross profit gain from moving a step up the quality ladder is extremely small. If gross profits from production were the only possible return on the R&D investment, then the low-productivity

[23] There are several measures of M&A transactions values. Equity value is the total transaction value net of debt. Since the paper abstracts from financial issues, it is the appropriate measure.

firm would have very little incentive to perform any R&D. Panel A of Figure 4 illustrates this lack of incentive, which contrasts the firm's research intensity between the baseline economy and the fully-restricted economy with no M&A activity permitted[24] activity. Panel A reveals that under a complete M&A ban, the low-productivity firm, relative to its peak, performs 83% less innovation R&D than in the baseline case.

This reduction in R&D spending is not just limited to the low-productivity firm. Turning to the research intensity for the high-productivity firm, Panel B of Figure 4 shows that the high-productivity firm performs 68% less innovation R&D in this market compared to the baseline. Unlike the low-productivity firm in the baseline case, the high-productivity firm is not performing R&D in hopes of a future M&A transaction. In fact, the firm is attempting to reduce the likelihood that an M&A transaction occurs within their market since new firms that enter the market via acquisition have a productivity that supersedes the current high-productivity firm.

5.2 The Impact of M&A Across The Firm Distribution

The previous example was just the story of one market. The model's high degree of heterogeneity allows it to simultaneously capture a wide variety of incentives and consequences of M&A at the micro level. One of the clearest ways to appreciate these micro effects is by using the model to calculate micro-elasticities. There are many candidate elasticities that could be considered, but the one that fits most clearly with the overall topic of competition policy is the regulator's blocking elasticity. Recall the blocking probability of an arbitrary M&A transaction is $B\left(hhi, \Delta hhi\right)$. The elasticity is calculated by taking a small additive perturbation of that probability — as if every transaction in the economy became slightly more likely to be blocked.

Beginning with expansion R&D elasticity, the average elasticity is -0.22. Breaking this down by a firm's productivity type, the elasticities are:

Productivity z	Low	Medium	High
Elasticity $\varepsilon_B^{\mathcal{X}}$	-0.36	-0.12	0.09

Only the high-productivity firms increase their expansion R&D spending in response to an increase in the blocking probability. In other words, 90% of firms in this economy reduce their expansion R&D spending in response to an increase in the blocking rate. The

[24]While general equilibrium effects change the profit functions in Figure 3, the changes are minor between the baseline and the case of fully restricted M&A activity. The result remains that the low-productivity firm has minimal profit growth.

reason for the decrease is identical to the example, the increase in blocking probability leads to a decrease in the outside option for the low and medium productivity firms. It also limits those firms' options when competing in markets against high productivity firm. For the high productivity firm, the increase in blocking probability can be seen as an increase in the cost of expanding through M&A. The firm firms thus compensate by increasing their spending in a substitute: expansion R&D.

Moving to the improvement elasticity, Figure 5 shows the distribution across all divisions of the improvement elasticity $\varepsilon_B^{\mathcal{I}}$. The average elasticity is slightly negative at -0.01. Firms which increased their effort the most typically are higher productivity firms with similar product quality to their lower productivity counterparts. Firms that decreased their effort the most are also typically higher productivity firms competing against a set of lower productivity firms. However, the high productivity firms are several steps higher on the quality ladder than their lower productivity competitors.

5.3 Aggregate Growth

These micro-effects results aggregate into substantial macro-effects. In the balanced-growth path, the growth rate is defined by a combination of R&D improvements, R&D expansions, and M&A synergies.

5.4 M&A is a Double-Edged Sword

The previous sections have shown how reduced M&A activity can significantly dampen growth. A reasonable hypothesis is that loosening antitrust policy may therefore increase the growth rate. A version of this hypothesis is an experiment with no antitrust restrictions on M&A such that any firm can trade with any firm regardless of market concentration. The result from this experiment is shown in Table 2 alongside the results from the estimated baseline and the fully restricted M&A policy that was previously considered. Similarly to the fully restricted M&A case, unrestricted M&A activity also causes a drop in the growth when compared 43to the baseline estimate — in this case, a drop of 0.31pp. While the drop in growth in the fully restricted MA experiment was also caused by limited outside options for firms to sell their divisions, the drop here is due to too much M&A resulting in a significant number of monopolies. Table 2 reveals that the number of markets in monopolies increases 8x, from around one percent to 24 percent of all firms. The lack of competition severely reduces the motive for a firm to perform R&D. These two extremes motivate the importance of optimal antitrust policy considering dynamic factors.

6 Competition Policy

In Progress

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Figures and Tables

Table 1: Estimation Moments and Estimated Parameters

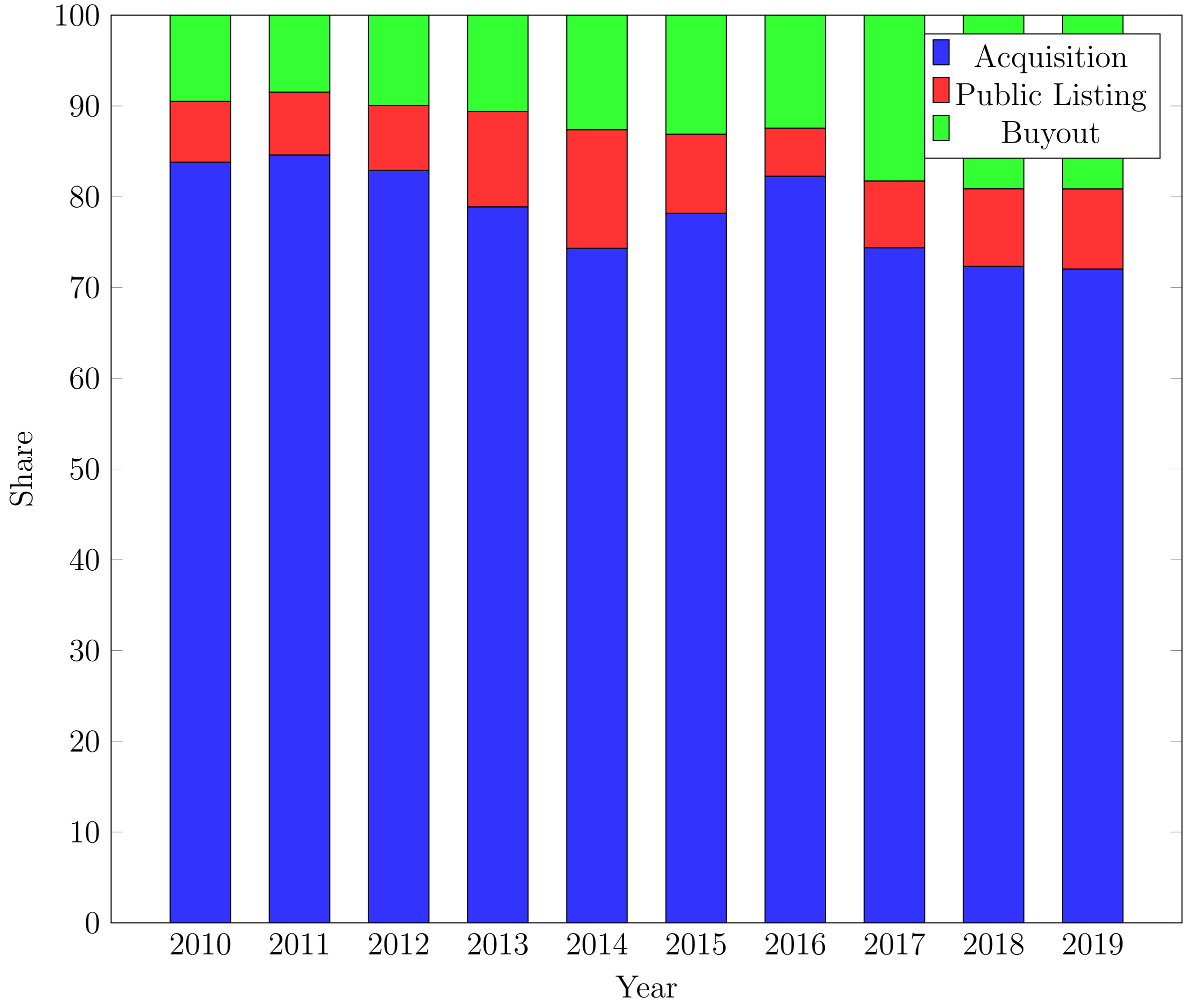
Parameter	Value	Moment	Data	Model
A_a		M&A-GDP Ratio	5.00%	
$A_{\mathcal{I}}$		R&D-GDP Ratio	3.48%	
A_w		Within Market M&A Ratio	61.03%	
$A_{\mathcal{X}}$		Markup Standard Deviation	34.60%	
β		Avg. Merger Premium	41.56%	
λ		GDP Growth Rate	2.41%	
m		Labor Share	0.65	
θ		Avg. Markup	34.98%	
ω		Killer Acquisition Rate	5.3%	
ζ		Merger Premium Standard Deviation	0.4491	
z_1		Bottom 50 Share of Sales	1.4%	
z_3		Top 10 Share of Sales	80.73%	

Note: The current estimation is an approximation.

Table 2: The Estimated, No M&A, and No Blocking

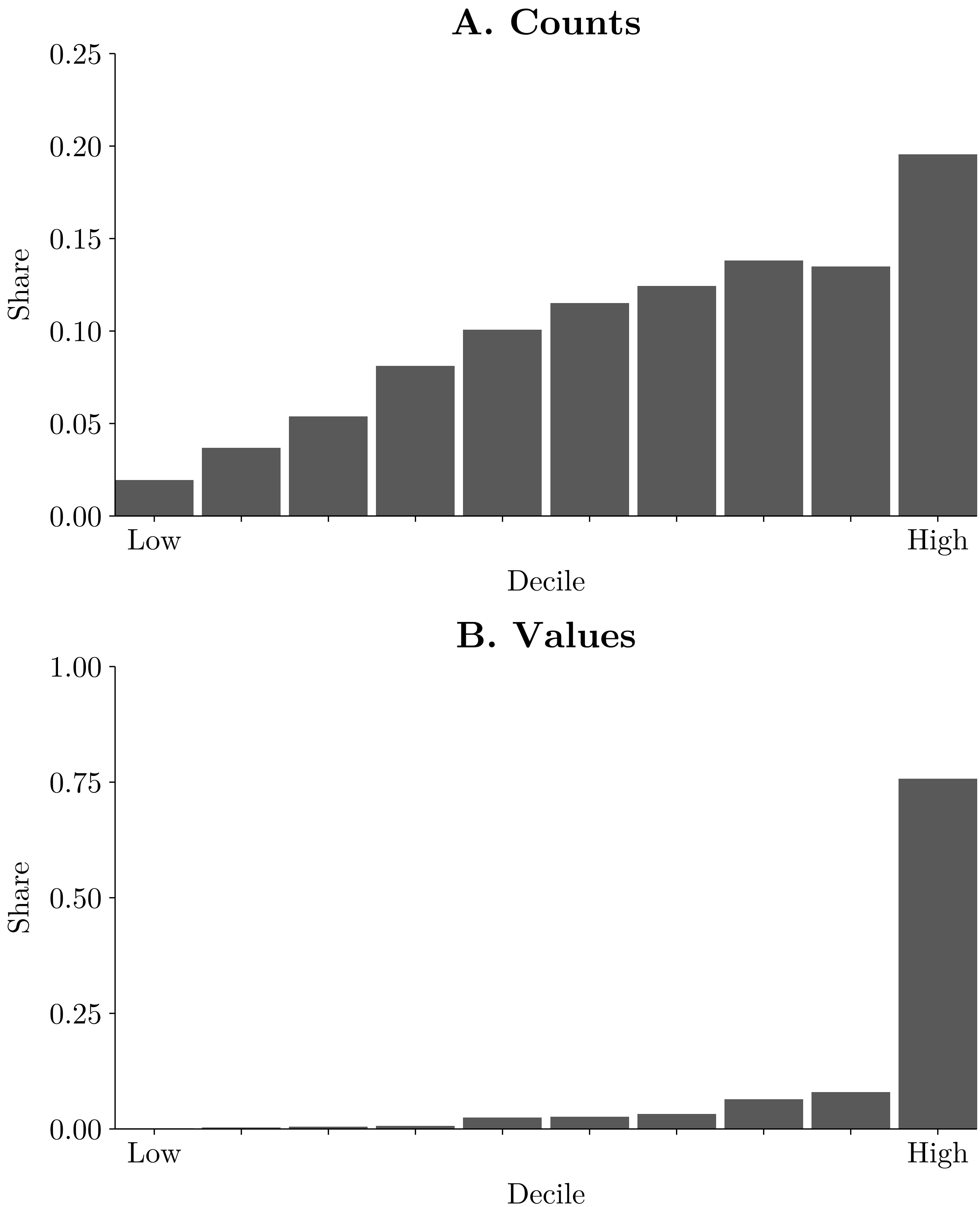
	Estimated	No M&A	No Blocking
Growth Rate	2.15	1.93	1.84
R&D Intensity	2.0	1.8	1.4
Avg. Markup	34	25	48
Market Size:			
1	3	0.5	24
2	8	2	18
3+	89	97	58
C.E. Welfare		-8%	-23%

Figure 1: Venture Capital Exits By Type of Exit



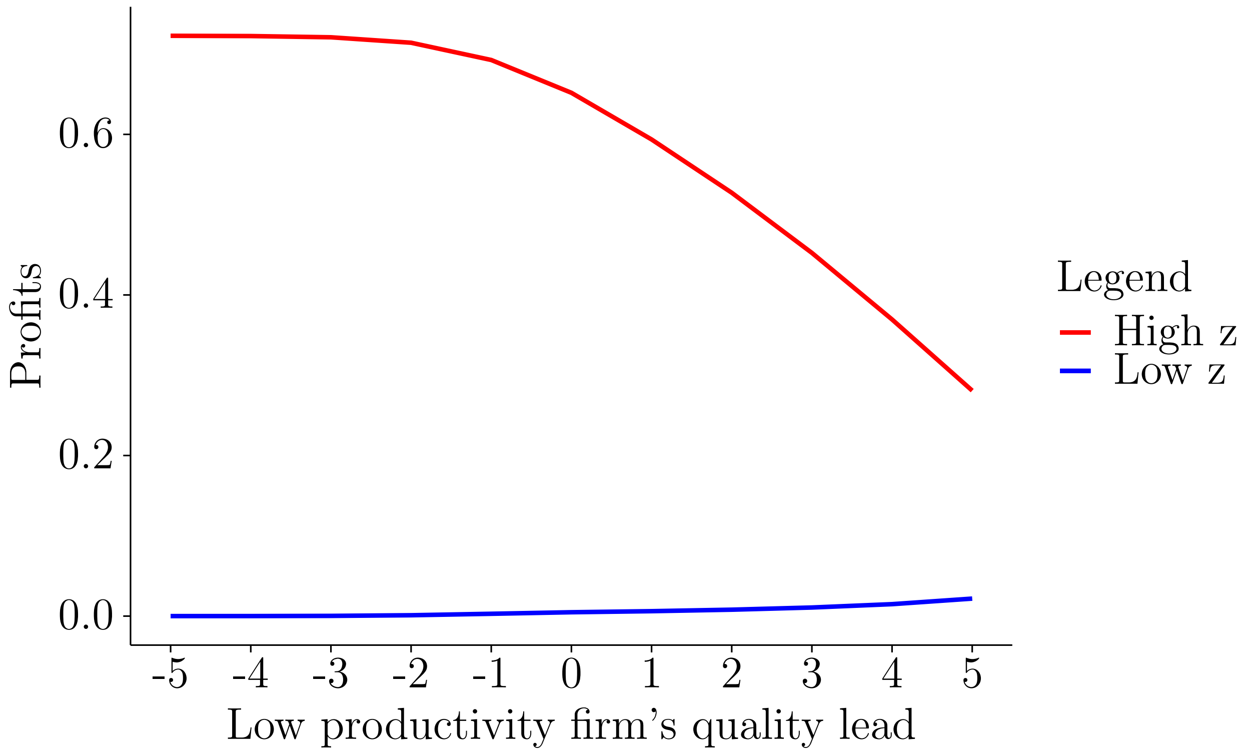
Note: This data was retrieved from the Q3 2022 Pitchbook-NVCA Venture Monitor.

Figure 2: Share of Acquirers and Transaction Value



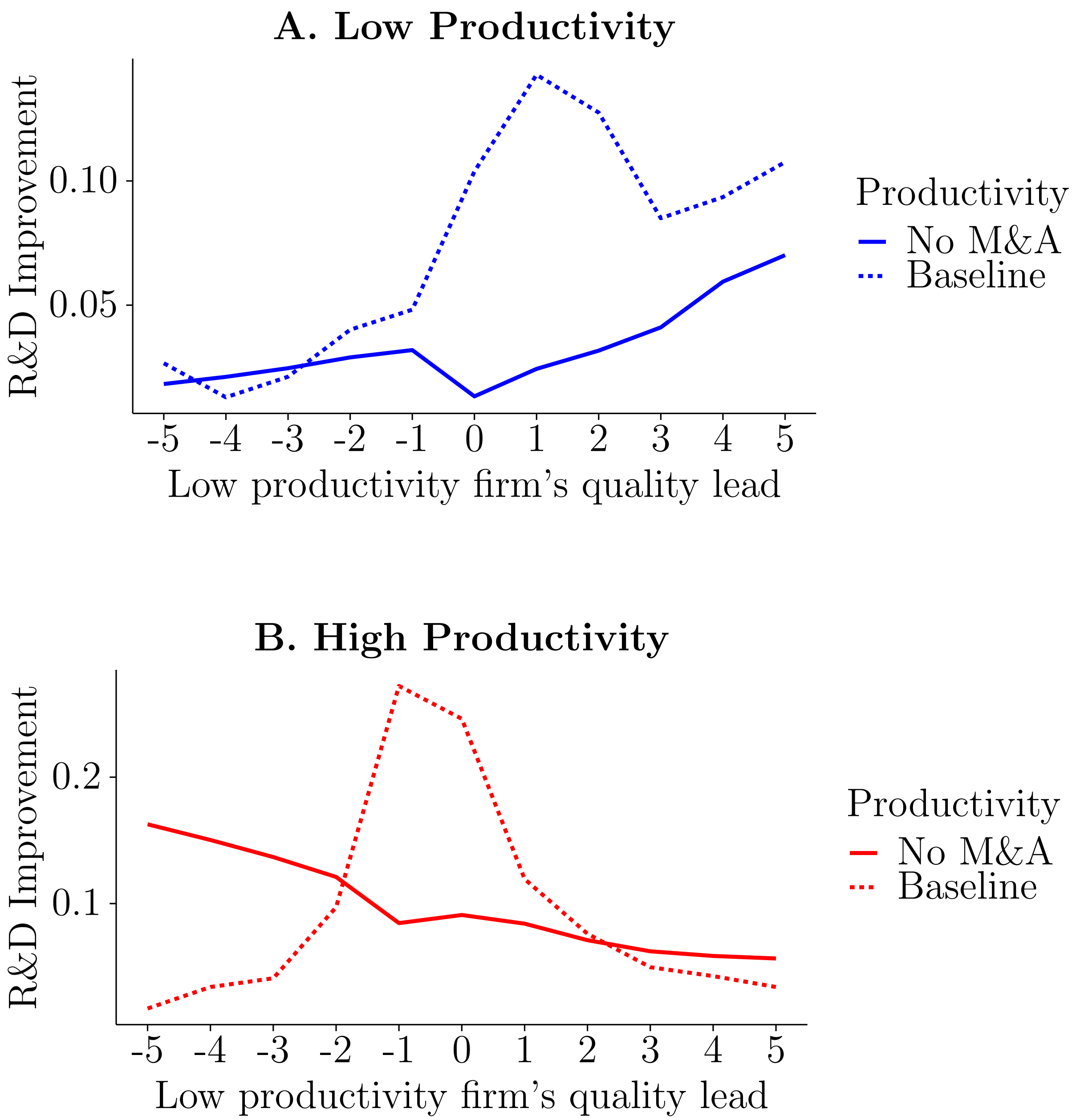
Note:

Figure 3: Illustrative Example, Gross Profits



Note: A firm's product quality sits on a quality ladder. The quality lead is the number of steps the low-productivity firm's product is above (or, if negative, below) the low-productivity firm.

Figure 4: Illustrative Example, R&D Effort: Innovation ($\mathcal{I}_{f,i,t}$)



Note: A firm's product quality sits on a quality ladder. The quality lead is the number of steps the low-productivity firm's product is above (or, if negative, below) the low-productivity firm.

Figure 5: Innovation Elasticity Distribution