Buy, Invent, or Both?

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November, 2021

Abstract: Why do firms purchase technology instead of developing it internally? This paper studies two main motives behind technology-driven acquisitions: synergies and competition. We argue that the key determinant for the firm's choice of organic growth or acquisition of innovation is its profit shock volatility. Higher volatility leads to more acquisitions and less in-house R&D. In addition, profitability of the firm's physical investment influences what types of benefits it achieves from acquisitions. Less profitable firms are more likely to acquire competitors while more profitable ones look for synergies. We also find that shutting down the acquisition market completely has a significant and negative impact on the firm's own innovation. Not being able to make either synergy- or competition-driven acquisitions reduces firm value by 12.53% and 20.24%, respectively. Overall, mergers mitigate barriers to innovation and technology growth.

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1. Introduction

When do firms prefer to develop technology internally over obtaining it through acquisitions? This question is nuanced because there are multiple reasons for the acquisition of technology via mergers. Traditionally, mergers are motivated by the desire to achieve technological synergies through the combination of complementary assets of the merging firms. More recently, Cunningham, Ederer, and Ma (2021) and Kamepalli, Rajan, and Zingales (2020) highlight the anti-competitive role of technology acquisitions whereby incumbent firms terminate or preempt the innovation from rival firms. Thus, a related issue is understanding the conditions under which firms acquire technology for reasons of either synergy or competition.

These questions are empirically challenging. M&A decisions depend on many variables that are hard to measure: for example, acquisition costs or bargaining power. Moreover, these decisions are endogenous outcomes determined jointly with other decisions such as physical investment, and exogenous variation in any of these decisions is rare. These data limitations preclude traditional regression analysis and lead us to an alternative method. Specifically, we construct and estimate the parameters of a dynamic partial equilibrium model based on Gu (2017). The main benefit of a structural approach is that it represents a feasible method for addressing these serious data limitations and allows us to answer important questions regarding the interactions between firm profitability, risks, competition, and innovation. An auxiliary benefit of this approach is that we can couch our research questions in a broader framework that also allows us to understand the impact of the existence of the acquisition market on a firm's technology growth. In addition, this framework allows us to quantify the extent to which acquisitions crowd out in-house R&D.

Briefly, we find that uncertainty about a firm's future cash flows has a quantitatively important effect on its choice between developing technology in-house or acquiring it from the market. This second-moment effect is accompanied by a related first-moment effect in which low-profit firms favor acquisitions that squelch competition over those that provide synergies. Interestingly, the very existence of the acquisition market boosts overall R&D productivity, as acquisitions arising from synergies boost the productivity of the acquirer. Finally, we find that in-house R&D and acquisitions are nearly always complementary, with lower costs of one spurring the other.

To provide intuition for these results, we briefly sketch the model, which features a firm whose profits are determined by its stock of physical capital, patents, and the realization of a profit shock. The profit shock captures the uncertainty in the firm's product market that arises because of unexpected political, technological, and economic changes. The firm also faces competition from other innovative firms in the industry and bears the risk of losing a fraction of its market share unless it acquires its rivals. The firm maximizes its equity value by choosing its investment, finance, and innovation policies. R&D policies are discrete and uncertain in their outcomes, with the firm deciding every period to take on an R&D project, acquire the technology from the market, both, or neither. If the firm chooses to acquire, it selects between two mutually exclusive types of technology acquisitions: a synergy acquisition where acquired innovation is used to enhance the productivity of existing patents, and ii) a competition acquisition where acquired innovation is not used but instead helps reduce the market competition for acquirers. Thus, in our model, acquisitions are motivated either to achieve asset complementarities or to maintain market share.

In the model, all firms innovate in-house and this risky activity by nature elevates future volatility and thus increases expected future financing costs, as more volatility raises the likelihood that firms will need to tap costly external finance. However, only those firms that are sufficiently profitable do acquisitions, which require large outlays. More broadly, acquiring firms are those that have performed better, innovated more, and held larger patent portfolios. When profit shocks are more volatile, these firms acquire more often because the likelihood of a shock large enough to spur an acquisition is more likely in a volatile environment. Thus, in a more volatile environment, we observe less R&D

relative to acquisitions.

Next, we find that a firm's performance in the product market influences the type of acquisition it makes. While only high-profit firms make any acquisitions at all, the lower-profit end of this group favors acquisitions that squelch competition over those that provide synergies. The economic mechanism involves substitution between a firm's physical investment and assets acquired via acquisitions. When internal investment prospects are limited, the firm shifts attention outside the firm and tries to generate profits by taking over competitors' market share. In sum, more profitable firms look for synergies while less profitable ones acquire to expand market share.

One of the benefits of estimating a model is that we can ask counterfactual questions. In particular, we can shut off the acquisition market and observe what happens to R&D. The results depend on whether firms favor synergistic or competition-squelching acquisitions. For the high-performing firms that seek acquisitions that provide synergies, losing the opportunity to make synergy acquisitions has a large impact on their innovation, thereby reducing their Tobin's q by 12.53%. Not being able to achieve synergies from the market also discourages these firms from innovating themselves. Because synergy acquisitions augment the productivity the outputs of R&D investments (patents), not achieving synergies makes R&D less attractive. The firm's R&D and total patents drop by 7.28% and 4.72%, respectively.

For firms that chase after their competitors, shutting down their opportunities to purchase younger firms that are potential rivals reduces their Tobin' q by 20.24%. Not being able to acquire rivals also discourages these firms from innovating themselves, as any potential gains in market share could eventually be eroded away by rivals. Their R&D and total patents drop by 7.22% and 5.90%, respectively. Therefore, we show that both synergy and competition acquisitions play a crucial role in developing corporate innovation. More importantly, our results demonstrate that existence of the acquisition market does not crowd out acquiring firm's incentives for in-house R&D. On the contrary, our results show that the firm's innovation suffers without the acquisition market.

We also dig deeper and quantify the benefits for acquirers in competition acquisitions. These are hard to capture using typical merger abnormal returns, where the challenge is to establish a valid counterfactual. Ideally, one should compare the firm's subsequent performance to the hypothetical scenario in which the acquisition does not occur, and in which the potential acquirer loses market share to a rival. Using our model, we can compute this hypothetical benchmark. We find that acquirers can to save 2.88% of their total market share per acquisition. On aggregate, removing the acquisition market completely results in a 38.52% drop in patent productivity of these potential acquirers because of peer competition.

Finally, we examine two important sources of complementarity between R&D and acquisitions. The first is the cost of engaging in R&D. Naturally, when R&D is more costly, the firm uses fewer R&D inputs and generates patents organically. Yet, the relation between these costs and acquisitions is U-shaped. Initially, rising R&D costs spur firms to acquire technology via acquisitions more and more often. However, after a certain point, the lack of in-house R&D leads to lower capital productivity, which dampens the complementarities that lead to synergy innovations. In addition, lower capital productivity discourages all acquisitions because the firm lacks the resources to make them without accessing external financial markets. Second, we study the effect of target bargaining power, which also has a nonlinear effect on R&D and acquisitions. Mechanically, a rise in bargaining power makes acquisitions more costly for acquirers, reducing their stock of patents and R&D investments. However, if bargaining power starts to rise from a very low base, more firms make synergy acquisitions because a higher deal price attracts potential targets and thus more deals. However, if bargaining power keeps increasing, acquirers' deal profits fall, so they acquire fewer firms. To summarize, our results demonstrate that more in-house R&D leads to more acquisitions and vice versa. That is, R&D and acquisitions are complementary in most cases. However, in two relatively rare occasions, they behave as substitutes, that is when R&D costs or target bargaining power are low.

Most of this literature emphasizes the role of asset complementarities in the technology space as a driver of synergies (Bena and Li 2014). Sevilir and Tian (2012) show that takeovers involving innovative targets create more value. Phillips and Zhdanov (2013) find that anticipated merger activity can lead to increased R&D spending by innovative firms, showing that small firms respond the strongest to this incentive. Besides the desire to achieve synergy gains, our paper highlights the role that profit shock volatility and product-market competition play in a firm's decision to acquire technology. Importantly, we find that a firm's decision between types of acquisitions depends heavily on its performance in the product market, including its investment prospects and uncertainty.

A second strand of the literature emphasizes the role that competition acquisitions play in the innovation of current targets (Cunningham et al. 2021) or future entrants (Segal and Whinston 2007; Phillips and Zhdanov 2013; Kamepalli et al. 2020). In a related study, Fulghieri and Sevilir (2009) theoretically demonstrates how a reduction in competition through mergers reduces employees' incentive to innovate. Yet, whether competition-driven acquisitions affect acquirers' incentives to invest in R&D remains an open question. On the one hand, the consolidation of market share dominance itself results in inefficiencies arising from less competition. On the other hand, market share consolidation can, in turn, increase the value of existing innovation (Blundell, Griffith, and Van Reenen 1999; Aghion, Bloom, Blundell, Griffith, and Howitt 2005) or expand the acquirer's portfolio of innovate ventures (Letina, Schmutzler, and Seibel 2020), thereby resulting in synergies.

We add to this literature in two different ways. First, we show that competition acquisitions enhances acquirers' incentives to conduct in-house R&D by allowing firms to retain full rents from their innovation. Thus, while technology acquisition can result in inefficiencies that may harm incentives to innovate (Seru 2014; Federico, Langus, and Valletti 2017; Cabral 2018), our model provides a new channel through which competition-driven acquisitions influence in-house R&D positively. In particular, we study the firm's choice to either make or acquire technology when *both* types of acquisitions are feasible. More importantly, our work examines the effect of competition acquisitions by establishing a counterfactual scenario where such acquisitions are infeasible and provides a new empirical explanation for the effect of acquisitions on R&D. Second, we show that such competition acquisitions are value-enhancing despite their anti-competitive nature. That is, while the average market reaction to such deal announcement is indistinguishable from zero, our analysis reveals that firm valuation are lower absent the takeover. One caveat of our results, however, is that our model does not incorporate other frictions such as agency conflicts within the firm that may also affect its choice to undertake acquisitions.

As reviewed in Li and Wang (2020), another strand of this literature also studies how innovation outputs change following an acquisition. Li, Qiu, and Wang (2019), Zhao (2009) and Sevilir and Tian (2012) show that corporate takeovers or strategic alliances lead to superior innovation outputs, with the relationship being larger (and causal) among pair of firms sharing a degree of technological overlap (Bena and Li 2014). Using inventor-level data, Li (2017) shows that such a positive effect is mainly driven by the recombination and acquisition of talent, finding that target inventors produce more patents post-completion and that and a M&A also allows firms to tap into people and knowledge that otherwise would be inaccessible for them. We add to this literature by showing that a market for corporate takeover does not crowd-out innovation incentives. On the contrary, firm's innovation suffers without the acquisition market.

The remainder of this paper is as follows. Section 2 presents the model while Section 3 presents the data used for the estimation. Section 4 illustrates the estimation procedures while Section 5 discusses the results. Section 6 concludes. A detailed explanation of the constructions of the patent data is included in the Appendix.

2. Model

In this section, we present the dynamic model. In the model, firms operate in a discrete time, infinite horizon, and partial equilibrium framework. Firms maximize their equity value each period by choosing optimal physical investments, R&D, financing, and acquisition policies. The mostly closely related model is Gu (2017). We build on and extend the model by also incorporating endogenous R&D investments and acquisitions of technology from the market. The added complexity in the setting is needed to approximate empirical patterns in corporate innovation.

2.1 Sequence of Events

We focus on a firm that operates in high-tech industries and is a potential acquirer. The sequence of events is as follows. Initially, the firm observes a realization of its profit shock and its endowments of capital and technology. Given these factors, it decides how much to invest in R&D. Simultaneously, the firm decides whether to purchase technology through acquisitions. If the firm decides to acquire technology, it engages in costly search for a potential target. After paying a search cost, the firm identifies a target and pays a price for the target that is agreed by both parties. Finally, the acquiring firm competes in the product-market and equilibrium profits are collected.

2.2 Technology and Production

This section describes a firm's operation and technology. The firm produces with capital k_t via a decreasing return to scale Cobb-Douglas production function:

$$y_t(k_t, h_t, z_t) = e^{z_t} h_t^{\phi} (1 - m_c) k_t^{\alpha} \tag{1}$$

where α refers to the firm's output elasticity of capital. The output level is also a function of an exogenous profit shock z_t, which can be thought as sudden changes in the demand from the product market or as a regulatory shock at time t. h_t refers to the firm's stock of patents at time t and h_t^{ϕ} captures the firm's productivity at time t. The firm can augment its own productivity by investing in R&D or by obtaining technology via acquisitions.

In the model, the firm faces constant competition from other innovative firms in the industry.[1] We capture this by assuming that a fraction m_c of the firm's market share is lost every period due to competition. However, the firm can choose to acquire its potential rivals and recover the lost market when the condition permits.

Following Aw, Roberts, and Xu (2011) and Doraszelski and Jaumandreu (2013), the profit shock z_t evolves over time as a Markov process:

$$z_t = \rho_z z_{t-1} + \sigma_z \varepsilon_t \quad \text{where} \quad \varepsilon_t \sim N(0,1) \tag{2}$$

where z_t in (2) denotes the accumulated historical profit shocks at time t and ρ_z captures its degree of persistence. We assume that the stochastic shocks ε_t are i.i.d. across time and firms and are drawn from a normal distribution with mean zero and variance σ_z. Thus, a firm's profitability is also affected by stochastic demand or regulatory shocks that reflect the inherent randomness in the product market. The firm's accumulated level of innovative assets at time t, summarized by h_t, evolves over time according to the following process:

$$h_t = \rho_h h_{t-1} + w_t \tag{3}$$

In equation (3), w_t captures the outputs generated from the firm's R&D in period t. The firm's innovation output is assumed to persist over time with the degree of persistence captured by ρ_h. The accumulated output h_t is allowed to systematically shift the distribution of future firm productivity and the magnitude of this effect is captured by ϕ as in equation (1). We measure h_t using the firm's stock of patents. The firm incurs a cost $C(w_t) = cw_t$ for producing w_t units of R&D outputs, where c is the unit cost of R&D.

[1]We do not model this for parsimony given that we focus on partial equilibrium framework.

The specification in (1), (2), (3) captures the relation between the output from a firm's innovation and the economic return to the output in the form of higher future productivity. It also captures the fact that the evolution of productivity is a noisy process. While innovation alters the firm's future productivity, it may be offset by other random factors in the product market.

We assume that there are two types of R&D projects that the firm can choose from to develop internally: a type-L project that has low risk and a type-H project that is riskier but leads to a larger number of patents than the type-L project if it succeeds. Following Chen and Xu (2021) and Phillips and Zhdanov (2013), we introduce the output function for these R&D projects as follows:

$$w_t = \begin{cases} \Delta h_L & \text{with probability } \theta_L \\ \Delta h_H & \text{with probability } \theta_H \end{cases} \tag{4}$$

where θ_L and θ_H captures the success rates of the type-L and type-H projects, respectively. The level of outputs produced in the low-risk and high-risk project are Δh_H and Δh_L, respectively. We assume that $\Delta h_H \theta_H > \Delta h_L \theta_L$ to capture the fact that the riskier type-H project also generates higher returns. Each period, the firm chooses to invest in either the low-risk or high-risk R&D projects, or nothing. The specifications in (2), (3), and (4) capture the endogenous evolution process for firm productivity. As such, there are different levels of uncertainty in both the random shock and innovation evolution processes. The model recognizes both sources of uncertainty that affect a firm's profitability.

The firm's capital stock is governed by the following law of motion:

$$k_{t+1} = (1 - \delta)k_t + I_t \tag{5}$$

where I_t denotes the gross investment at period t and δ is the depreciation rate of capital. The firm purchases or sells capital at a normalized price of 1 and incurs capital stock adjustment costs governed by:

$$\Psi(I_t, k_t) = \frac{a}{2}(\frac{I_t}{k_t})^2 k_t \tag{6}$$

This functional form of adjustment costs follows Cooper and Haltiwanger (2006) and is standard in the investment literature. The parameter a governs the smoothness of investment and is set to zero in the model. We do so because firms in our sample are highly innovative and hold largely tangible assets and human capital. It is relatively easier for these firms to adjust their operational sizes by changing k_t.

Thus, the after-tax profits for a standalone firm in period t are:

$$\Pi(k_t, h_t, z_t) = (1 - \tau_c)e^{z_t} {h_t}^{\phi}(1 - m_c)k_t^{\alpha} \tag{7}$$

where τ_c is the corporate tax rate.

2.3 The Search Process

There exists a market for the firm to acquire another firm for its technology. We make several assumptions concerning the acquisition market. First, firms cannot contract on the potential surplus generated by combining their resources, and so, the only way to realize the synergies is to place their resources under common control. Second, the acquisition is initiated by the acquirer. Third, the acquisition is an decentralized and uncoordinated economic activity. Therefore, its deal price is negotiable between the acquirer and target, which allows for a negotiated outcome that depends on each party's ability to locate another suitable merger partner.[2]

If the firm decides to acquire technology from the market, the firm incurs the search cost and starts searching for a target. We denote as D the search cost the firm has to pay every period it looks for a target. The search cost may include managerial efforts in locating

[2]This is consistent with the classic search model of Diamond-Mortensen-Pissarides (Diamond 1993; Mortensen and Pissarides 1994; Petrongolo and Pissarides 2001).

and evaluating potential targets, interruption to ongoing operations, and consulting and investment banking fees. Besides these, the search cost also includes the delay in finding a partner and the time firms spend for researching, searching, conducting due diligence and negotiating in order to look for a target.

After incuring the search cost, the firm makes an offer to acquire the target. The offer price has to be high enough to attract the target who chooses between the gains from accepting the current offer and the expected gains from waiting. The offer price also has to be low enough to generate positive NPVs for the acquirer. If both parties agree on a price, the acquisition is implemented. The acquirer takes over all the patents from the target and continues to operate. The target firm liquidates and exits the market. If both parties cannot reach an agreeable price, the deal fails and both parties continue to operate as stand-alone firms.

2.4 Technology Acquisition

When two parties agree on the deal, they bargain over the potential surplus from the acquisition. How the surplus is split between the two parties depends on their bargaining power. In line with Phillips and Zhdanov (2013), we assume that the target firm gets a fraction η of the acquisition surplus. In other words, η reflects the relative bargaining power of the target while $1-\eta$ is the relative bargaining power of the acquirer. The price paid to the target is then:

$$P_t = V_{T,t} + \eta(V_{A,t+1} - V_{A,t} - V_{T,t} - D * k_{A,t}) \tag{8}$$

where $V_{T,t}$ refers to the standalone value of target firm prior to acquisition. $V_{A,t}$ and $V_{A,t+1}$ refer to the acquirer's firm value before and after acquisition, respectively. $D * k_{A,t}$ represents the cost for searching the target. That is, larger firms incur a higher cost to locate a suitable target. Accordingly, $V_{A,t+1} - V_{A,t} - V_{T,t} - D * k_{A,t}$ represents the surplus created from the merger. The price in (8) captures the fact that the price is determined by the two parties' relative bargaining power; the higher the target's bargaining power η, the higher its share of the available surplus and the higher the payment it receives from the bidder.

If the firm chooses to acquire innovation, the gains from acquisition should at least cover the cost, i.e., the payment to the target plus the search cost. The individual rationality constraint for the acquirer is then:

$$V_{A,t+1} - V_{A,t} \geq P_t + D * k_{A,t}. \tag{9}$$

If the inequality in (9) is not satisfied, the acquirer is better off walking away from the deal. Once an offer is made to the target, the target decides whether to accept it based on the following,

$$P_t \geq (1 + \mu)V_T. \tag{10}$$

where the coefficient μ captures the minimum returns that the target is willing to accept for it to give up future opportunities, which are determined by the gains from potential acquisitions and the quality and complementarity of potential bidders. The condition in (10) states that the payment to the target should surpass its firm value by at least $(1 + \mu)$ times. Otherwise, the target firm is better off postponing the deal because by accepting the current offer, the target forgoes potential gains from future acquisition opportunities. Thus, it may be optimal for the target to reject a positive NPV offer today when more qualified bidders are anticipated tomorrow. This condition reflects the trade-off between the equilibrium merger share and the value of waiting.

If the target agrees to accept the offer, it takes the payment from the acquirer and exits the market. The acquirer, on the other hand, takes over the target and continues to operate. The acquirer also decides the type of acquisition. If it chooses to make a *synergy* acquisition, complementary assets obtained in such an acquisition augment the productivity of the firm's patents, creating synergies. Once the acquisition is completed, the firm's output elasticity of patents is elevated by m_s. The after-tax profits for the acquirer after *synergy* acquisitions are:

$$\Pi(k_t, h_t, z_t) = (1-\tau_c)e^{z_t}{h_t}^{\phi+m_s}(1-m_c)k_t^{\alpha} \tag{11}$$

Alternatively, in a *competition* acquisition, the firm preemptively takes over the potential rival and "kills" it before it becomes a threat and steals its market. Hence, the potential loss of market share, m_c, is recovered in such an event. The after-tax profits for the acquirer after competition acquisitions are:

$$\Pi(k_t, h_t, z_t) = (1-\tau_c)e^{z_t}{h_t}^{\phi}k_t^{\alpha} \tag{12}$$

Every period, the firm chooses to either acquire for synergies, or its competitor, or neither.[3] Given this setup, gains from acquisitions are related to the acquirer's own performance (z_t and h_t). Better performing bidders may offer a higher price for the same target since the available surplus from the potential acquisition is higher.[4]

2.5 External Financing

For simplicity, we assume that firms do not keep cash reserves. Thus, the investments and acquisitions at time t, if any, are funded using the profits from the same period. When the profits are not sufficient to finance the firm's investments, it raises external funds. The amount of external finds required at time t, referred to as the *financing gap* is defined as:

$$\begin{aligned} Financing\ Gap_t = C(w_t) + [k_{t+1} - (1-\delta)k_t] + \Psi(k_t, k_{t+1}) + D * k_t * \mathbb{1}_{m_t=1} \\ + P_t\mathbb{1}_{m_t=1} - \Pi(k_t, h_t, z_t) - \delta k_t \tau_c \end{aligned} \tag{13}$$

where $C(w_t)$ denotes the cost of producing innovation outputs w_t. $[k_{t+1} - (1-\delta)k_t]$ and $\Psi(k_t, k_{t+1})$ is the change in the stock of capital and the capital stock adjustment cost,

[3]We assume that the firm does not make the synergy and competition acquisitions simultaneously as we allow one acquisition per period.

[4]The fact that firms look for complementarity in acquisition is documented in recent work by Sevilir and Tian (2012), Bena and Li (2014), and Phillips and Zhdanov (2013).

respectively. $D * k_t$ and P_t represent the search cost and the price paid to acquire the target where $\mathbb{1}_{m_t=1}$ is an indicator function that equals one if the firm chooses to make an acquisition in period t and zero otherwise. $\Pi(k_t, h_t, z_t)$ represent the firm's profits at time t and $\delta k_t \tau_c$ captures the free-cash-flow saved because of depreciation. As in Nikolov and Whited (2009), we do not distinguish between debt and equity financing. External funds can therefore be thought of as a mix of equity and debt that is determined outside the model.

If the firm's financing gap is positive, the firm has to raise funds from outside the firm. Conversely, if the financing gap is negative, the firm pays dividends to shareholders. The cash flows to shareholders can thus be expressed as:

$$e(k_t, h_t, z_t) = -Financing\ Gap_t \tag{14}$$

The cost of external funds is given by,

$$\Phi(e(.)) = \frac{1}{2}\boldsymbol{\phi}_{e<0}\lambda e(.)^2 \tag{15}$$

where λ refer to the quadratic cost of external finance. $\boldsymbol{\phi}_{e<0}$ is the indicator that takes the value of 1 if $e(.) < 0$ (i.e., the firm needs to raise external funds) and zero otherwise. For every dollar raised outside, firms must pay costs that are monotonic in the amount raised. This is consistent with the existence of flotation costs for equity and public debt as well as origination fees for loans and possible adverse selection costs. We omit the fixed component of external finance costs as firms are likely to lower fixed costs using credit lines or other low-cost sources for the first dollar they raise.

2.6 The Maximization Problem

The firm chooses (k_{t+1}, w_t, m_t) in period t to maximize the value of its expected future cash flows, discounted at the opportunity cost of funds, r. Then the Bellman equation for the firm's dynamic programming problem is:

$$
\begin{aligned}
V(k_t, h_t, z_t) = \max_{I_t, w_t, m_t} \{ & e(k_t, h_t, z_t, k_{t+1}, h_{t+1}, m_t) \\
& + \Phi(e(k_t, h_t, z_t, k_{t+1}, h_{t+1}, m_t)) \\
& + \frac{1}{1+r} \int V(k_{t+1}, h_{t+1}, z_{t+1}) dF(z_{t+1}) \}
\end{aligned} \tag{16}
$$

As we show in Proposition 1 and prove in the Appendix, Equation (16) has a unique solution.

Proposition 1. There exists a unique function $V(k, h, z)$ that solves the Bellman equation above. The value function is continuous, increasing in k, h, and z.

3. Data

3.1 Sample Overview

Our data comes from various sources. First, we obtain from SDC Platinum the list of completed acquisitions of 50% or more of the target firm from 1977-2019. We require the acquirer to be a U.S. public firm and the deal to have a non-missing information on its value in SDC. Second, we obtain financial and stock price information from CRSP/COMPUSTAT. We supplement this with Capital IQ to obtain financial information when not available in COMPUSTAT. Third, we obtain patent and citation information from the USPTO patent assignment files, hosted by Google Patents. The data includes the information on the assignment date, assignee(s), and technology class among others. We merge the USPTO data with the NBER and KPSS patent database to identify the *gvkey* for each patent granted. [5] Fourth, we obtain from WRDS-Eventus, the abnormal returns for each deal announcement using a one-factor model in a two-year window around the event date.

[5]A detailed description of our patent dataset is included in the Internet Appendix.

To form our sample, we retain the deals where both firms are classified as being in the "high-technology" space.[6] We require targets to have at least one patent granted in any of the 20 years prior to the deal consistent with patents having a 20 year term on average.[7] We also choose not to include diversifying mergers as most technology-driven acquisitions are not diversifying in nature. Lastly, we retain the deals for which the acquirer and the target have at least one patent in the same technology class. This last filter captures the degree of technological proximity between the two firms. Our final sample consists of 738 deals.

3.2 Technology and Product Proximity Measures

Technology and product market consideration have a first order effect on firm's decision to acquire. To capture this, we first provide a measure of the degree technological overlap between the target and the acquirer. We measure this proximity by using the Jaffee (1986) measure. The USPTO allocates each patent into 453 different technology classes during our sample period 1985 to 2019. For each firm i and time t, we define the vector $T_{i,t} = \left(T_{i1,t}, T_{i2,t}, ..., T_{i\tau,t}\right)$, where $T_{i\tau,t}$ is the share of the patents of firm i in the technology class τ using all available information up to year t. The technological proximity measure is calculated as the uncentered correlation between any pair of firms (i, j) at time t as:

$$TECH_{ij,t} = \frac{T_{i,t}T_{j,t}^{'}}{\left(T_{i,t}T_{i,t}^{'}\right)^{0.5}\left(T_{j,t}T_{j,t}^{'}\right)^{0.5}}$$

This measure captures the closeness of any two firms' innovation activities' in the technology space using patent counts in different technology classes.

[6]We follow Loughran and Ritter (2004) and classify a firm as "High-Tech" if the 3-digit SIC code is one of 283, 357, 366, 367, 382, 384, 481 or 737.

[7]For applications filed on or after June 8, 1995, the term of a patent ends on the date that is twenty years from the date on which the application for the patent was filed in the United States or, if the application contains a specific reference to an earlier filed application or applications under 35 U.S.C. 120, 121, or 365(c), twenty years from the filing date of the earliest of such application(s). See https://www.uspto.gov/web/offices/pac/mpep/s2701.html

We also follow Bloom, Schankerman, and Van Reenen (2013) and compute the product market proximity for any paring of firms i and j. From the Compustat Segment Data, we obtain each firm's sales, broken down into lines of business defined by 4-Digit SIC codes. In total, the Segment Data spans 1,330 industries across our entire sample. For each firm i at time t, we define the vector $S_{i,t} = \left(S_{i1,t}, S_{i2,t}, ..., S_{i\delta,t}\right)$, where $S_{i\delta,t}$ is the share of sales of firm i in the 4-Digit SIC industry δ. We compute the uncentered correlation between all firms pairings in an exactly analogous way to the technology closeness measure:

$$PM_{ij,t} = \frac{S_{i,t}S'_{j,t}}{\left(S_{i,t}S'_{i,t}\right)^{0.5}\left(S_{j,t}S'_{j,t}\right)^{0.5}}$$

3.3 Classification of Deals

An important aspect of our analysis is the classification of deals into those that are motivated by the desire to increase productivity (labeled as "synergy acquisitions") and those that are motivated by the obsolescence of patents because of competition (labeled as "competition acquisitions").

Distinguishing between both types of acquisitions ex ante is challenging. A classification of deals based on whether the target discontinues a project or its patents are not marketed is difficult to achieve. For one, identifying which projects are discontinued is often not observable. Second, it is common for firms to discontinue product lines and development projects. Even in an acquisition, the interruption or termination of product development can be a rational business decision that is unrelated to competition concerns. Specifically, when there is any degree of acquirer-target product overlap, acquirers have stronger incentives to discontinue development than target firms because some of their existing profits will be cannibalized by the substitute product (Cunningham et al. 2021).

We follow Bena and Li (2014) and classify our deals based on the realized synergies, and technological and product market proximity between the merging pair. Technology overlap plays a major role in the transaction incidence. Firms that participate in same technology classes are more likely realize synergies from a potential combination. Yet, as pointed out by Ahuja and Katila (2001), the overall effect of a merger on innovative capabilities is lower among merging with similar technological capabilities. They also study the relationship between expected synergies gains from technology acquisitions and product-market rivalry and find that the incidence of pair formation is lower when such firms are also product market rivals. One implication of their findings is that when both firms are related in their product offerings and innovation, expected synergies are smaller.

We examine the distribution of the expected synergy gains for the deals in our sample based on the degree of technological and product-market overlap between the target and acquirer. Figure 2 presents the relationship between the cumulative abnormal returns upon the deal announcement and the degree of acquirer-target technology proximity (in deciles). For completeneness, we also depict the announcement returns for deals without any overlap in the technology between firms (which are excluded from our main sample). The dashed line represents the 95% confidence interval. Interestingly, while the announcement returns are greater for deals where there is an overlap in the patents between firms, the effect is more pronounced and significant only for those deals that exhibit a degree of overlap in the bottom 30% of the in-sample distribution.

Figure 3 depicts the relationship the product market proximity and technology proximity in our sample, controlling for acquirer and deal relative size. Deals for which the acquirer returns are positive and significant (i.e., bottom 30% of the distribution in terms of technology overlap) are also those deals where both have a lower correlation in their sales across lines of business. Similarly, deals with a large technology proximity and low CAR also exhibit a high product market proximity measure. This is consistent with Hoberg and Phillips (2010) who show that the synergy gains are smaller when targets are more similar to the pool of potential acquirers.

Taken together, our results suggest that those deals with large technology overlap are likely motivated by product market consideration as opposed to technology synergies. Based on this, we classify the deals as being "*synergy acquisitions*" as those where the technology correlation is in the bottom 30% of the $TECH_{ij,t}$ measure (this corresponds to a technology proximity measure of 13.1% or less) and those above such threshold as "*competition acquisitions*".

3.4 Summary Statistics

In Figure 1 we plot the number of transactions per year of technology-driven M&A transactions. As in Bena and Li (2014), a larger number of deals is observed around the year 2000. Importantly, synergy-driven deals exhibit the same cyclicality as deals in general.

Table 1 presents descriptive statistics. Column (1)-(3) present the descriptive statistics for the 738 deals in our sample. Columns (4)-(6) report the summary statistics for the entire set of completed deals in SDC for which there is financial information about the acquirer as a basis for comparison. To avoid over weighting acquirers with multiple transactions, we exclude duplicates of acquirer-year combinations when computing the summary statistics and moments. In our sample, we have 681 unique acquirer-year pairs. For each of these deals, we include the financial information up to 10 years prior to the deal announcement, leading to 7,491 observations.

While the average acquirer and target size in our sample is similar to that of the average deal in the SDC sample, acquirers and targets in our sample exhibit a larger number of patents (granted and in their stock) as well as R&D Expenditures. This is not surprising given that we require our sample to include a a technology overlap between both firms, which only occurs when both firms have at least one patent granted. In terms of deal-level variables, our deals in our sample exhibit a larger premium paid and a larger relative size. Targets and acquirers in our sample also exhibit a larger product market and technology proximity.

Table 2 presents the differences for high and low technological proximity deals. Consistent with our classification, deals that have a lower technological overlap exhibit higher announcement returns in a one-, two-, and three-day window around the announcement date. Moreover, the difference in the CARs is statistically significant across deals.

4. Estimation and Simulation

4.1 Estimation Procedures

We estimate the model using simulated minimum distance. Given a set of parameters, the model yields optimal policy rules that prescribe optimal choices of $(k', w', m'))$ next period given the state of the firm in the current period (k, h) and the realization of the shock, z'. These optimal policy rules are used to generate a panel of simulated firms by recording the firms' optimal choices in response to simulating a series of shocks. Next, I select moments that can identify the structural parameters of the model. These moments are calculated using both real data and the simulated data from the model. The estimation then determines the parameter values that minimize the distance between the model-generated moments and the corresponding real moments from the empirical data. Details of the model solution and estimation are in Appendices B and C.

Although we estimate most parameters via SMM, some are directly calibrated using prior studies and empirical data. The tax rate τ_1 is set to 26%, which is the effective U.S. corporate tax rate. The interest rate r is set to 6.05%, which is the average return on a five-year Treasury bond during the sample period. Consequently, the discount factor is calculated as $1/(1+r)$. Consistent with the literature, the capital depreciation rate δ is set to 0.10. In addition, we set ρ_h to 0.80 as the term of patents is 20 years under current U.S. patent law. We compute the average premium that the firm pays in acquisitions as 0.3182 and use it to represent μ. This parameter thus captures the outside opportunities for the average target firm.

Moreover, we compute the success rates of the low-risk R&D project θ_1 and high-risk project θ_2 using all the history of patents granted of each acquirer prior to the acquisition. θ_1 (θ_2) is the implied probability of success based a binary distribution over the outcome of the innovation for the acquirer (target). We assume that with probability θ_1 (θ_2), the innovation projects succeeds and results in an outcome of Δh_1 for the acquirer or Δh_2 for the target, and with the complement probability it yields 0. Δh_1 (Δh_2) is computed as the average ratio of the yearly patents granted for the acquirer (target)– including only the years where there is at least one patent assigned. Using computed Δh_1 and Δh_2 as such, we set θ_1 and θ_2 to match the expected value of this binomial distribution and obtain a value of θ_1 and θ_2 of 0.6725 and 0.2973, respectively. This is consistent with our argument that the firm chooses to take on the low-risk R&D project itself and outsource the high-risk one to the market. In addition, we identify the effectiveness of patents ϕ as 0.0341 by regressing firm productivity on its stock of patents. We also compute the median relative size of target firm over its corresponding acquirer (V_{tar}) as 1/74. Acquirers in our sample hold 976.5624 patents on average. We scale it by 105 to get 9.3006 as the number of patent stock for the firm. Similarly, we scale the acquirer's and target's yearly granted patents by 105 as the values for Δh_1 and Δh_2, respectively. Finally, we set the bargaining power of target η to 0.5 due to lack of data to simultaneously estimate η and D.

4.2 Parameters and Selected Moments

Simulated moment estimators are identified when the selected moments equal the simulated moments if and only if the structural parameters are at their true values. A sufficient condition for identification is a one-to-one mapping between a subset of structural parameters and the selected moments. Nevertheless, since real and financial decisions are intertwined, we over-identify the structural parameters by selecting more moments than the estimated parameters to fully characterize both the financial and real sides of the firm. Another advantage of over-fitting the model is that one can employ a general over-identification test of model fit to ensure that the model is a close approximation of the data.

Using SMM, we estimate the following parameters: ρ_z, serial correlation of income; σ_z, variance of income shocks; α, curvature of the profit function; λ, quadratic external financing cost; c_w, unit cost of R&D; D, acquisition cost ; m_s, augmented output elasticity of patents in *synergy* acquisitions, and m_c, salvaged market share in *competition* acquisitions.

To identity these parameters, we select the following moments and try to match simulated moments from our model to their empirical counterparts. To identify ρ_z and σ_z, we choose moments related to the production side of the firm. We use the Holtz-Eakin, Newey, and Rosen (1988) methodology to estimate a first-order panel autoregression of operating income on lagged operating income. The autoregressive coefficient and the standard deviation of the residual from this regression are used as moments to identify ρ_z and σ_z, respectively. We also include the first and second moments of the rate of investment to identify α. Higher α makes investment larger and more volatile as optimal capital is more volatile for high-profitability firms.

In order to identify external finance costs λ, we use the mean and variance of external financing. As the model does not distinguish between debt and equity, we do not use moments pertaining to the composition of external finance. Instead, we aggregate both debt and equity issuance. Our model does not incorporate cash holdings. But, the majority of high-tech acquirers sits on large cash reserves and many use all-cash offers for acquisitions. Hence, we also add cash holdings to the aggregate of debt and equity issuance to compute the sum of both external and internal financing. We identify acquisition costs D using the likelihood of acquisitions. Larger costs lead to a lower probability of acquisitions. We also use the average and variance of R&D investments to identify the unit cost of R&D, c_w. Higher c_w increases the dollar amount of R&D expenditures but decreases R&D inputs. We also include the stock of patents to capture the unit cost c_w. Larger c_w makes generating patents more costly and lowers the total outputs. Finally, we use the likelihood of *synergy* and *competition* acquisitions to identify the gains in these two types of acquisitions (m_s

and m_c), respectively. Higher m_s or m_c makes acquisitions more profitable, leading to more deals accomplished.

5. Results

5.1 Estimation Results

The results of the SMM estimation are presented in Table 4. Panel A reports the results of a comparison between empirical and simulated moments while Panel B reports the parameter point estimates. The results show that most simulated moments are close to their corresponding real moments. Importantly, the model is able to match firm R&D, patents, and likelihood of acquisitions that are the focus of this paper. The likelihood of synergy (competition) acquisitions is 6.44% (14.63%), which is close to its corresponding empirical estimate of 6.60% (14.70%). R&D investment is 8.30%, close to its empirical counterpart of 8.55%. The number of patents (scaled in the model) is estimated as 9.21, close to corresponding empirical value of 9.30. The rest of the simulated moments including the serial correlation of income, variance of income shocks, external finance, and investment are also closely matched with their empirical counterparts.

Parameter estimates for the production parameters (ρ, σ, a) are largely consistent with prior estimates in the literature. We thus focus on the parameters that are unique to our model. Firms incur a search cost of 0.9% when they make acquisitions. The estimated deadweight costs D reflect both direct and indirect costs of an acquisition. The unit cost of R&D (c_w) is estimated as 1.10% of total assets. This is scaled to reflect the cost of producing 105 patents in the firm. In addition, synergy acquisitions increase the firm's output elasticity of innovation by 8.13%, while competition acquisitions help recover the firm's market share by 2.875%. Finally, the standard errors in Panel B show that all but one of the parameters are accurately estimated, suggesting successful identifications of the structural parameters with the selected moments. The J-statistics for this estimation is

24.51 with degree of freedom 3.

5.2 Organic Growth or Acquiring Innovation?

Why does the firm choose to acquire innovation as opposed to organic growth of innovation? Prior literature argues that many acquiring firms achieve synergies by combining complementary assets of the two merging firms. Others argue that firms preemptively acquire younger rivals to which firms may lose market share eventually. But why and when are these options more profitable than organic growth via in-house R&D? Under what circumstances is acquiring innovation optimal? In our model, the firm holds two types of assets (physical and innovative assets) and makes two types of investments (physical and R&D investments) accordingly. While physical investment increases firm size, R&D investment generates patents and boosts firm productivity. We find that the firm's choice of innovation is heavily influenced by its production side, especially the volatility in its profit shocks, σ_z. σ_z captures the uncertainty in the firm's cash flows due to unexpected political, economic, and technological changes in its product market. When its profit shock is more volatile or more persistent, the firm makes less R&D but more acquisitions. When we lower σ_z to a minimum level of 0.001, the firm no longer makes any acquisition but chooses to focus entirely on its own R&D. The results are shown in Figure 4 (Panel B and C).

Volatility, σ_z, is a key determinant for the firm's choice of innovation as higher σ_z raises the costs of innovation for both R&D and acquisitions, but much more for the former. This is because the firm is more likely to tap costly external financing when investment opportunities show up unexpectedly. This is especially true for R&D investments as R&D projects are highly risky, the outcome of which is hard to predict. When σ_z is higher, since acquiring innovation involves much less risks, the firm chooses to outsource more of its innovation to the acquisition market. In fact, large external finance is not only costly but also increases the firm's default risk. The firm tries to balance its pursue of profitability with the concerns of high financing costs and likelihood of default.

We also find that acquiring and non-acquiring firms are different in terms of their performance and innovation policies. Our results show that acquiring firms have performed better than non-acquiring firms. Their Tobin's q is roughly two times as large as the non-acquiring ones'. Thus, these firms have enough funds for costly acquisitions. Acquisitions are also more beneficial for them as more synergies are generated when the acquirer is more profitable or already holds more patents. Additionally, we find that compared to non-acquiring ones, R&D investment of acquiring firms is less sensitive to changes in their profit shock volatility, σ_z. Specifically, increasing σ_z from 0.21 to 0.23 reduces R&D investments by 10.84% for the acquiring firms and by 26.09% for the non-acquiring firms. When σ_z is higher, both firms cut down their R&D. But the effect is less pronounced for acquiring firms. This is because if profit shock is more volatile, acquiring firms make more acquisitions, resulting in higher productivity of firm patents and in-house R&D. Since acquired innovation inflates R&D productivity, acquiring firms are able to cut down less R&D investments by making more acquisitions. This piece of evidence indicates that corporate acquisitions are, to some extent, used as a buffer that protects the firm's internal innovation from unexpected market shocks.

We also examine how profitability of physical investment (α) affects the firm's innovation policies. In Figure 4 (Panel A), we find that when physical investment is more profitable, the firm increases in-house R&D and makes more acquisitions simultaneously. First, profitable firms are less likely to tap costly external financing, rendering innovation effectively cheaper. Second, given the firm's profit function, one unit of patent generates more profits for a firm that has better investment opportunities. In other words, patents are more productive for profitable firms. As a result, more profitable firms also make more innovation, either via R&D or acquisitions.

5.3 Acquire for Synergies or Market Control?

Next, we investigate the corporate motives behind technology-driven acquisitions by classifying these motives into two groups. The first group includes acquisitions that aim at creating synergies by combining complementary resources of the two merging firms. We call this *synergy* acquisitions. The second group includes acquisitions that aim at maintaining market share by preemptively acquiring potential rivlas and killing them. We call this *competition* acquisitions. We take all merger deals as independent events even if they are conducted by the same firm in the same year. Therefore, these two types of acquisitions are treated as mutually exclusive in each period. In this subsection, we ask how the firm chooses to make one type of acquisitions over the other.

How are synergies generated from the acquisition market? Due to agency issues inside the firm, innovators as internal employees or as outside entrepreneurs have distinctive compensation contracts and are rewarded differently from their innovation outcomes. Since entrepreneur innovators enjoy much higher upside gains when their projects succeed, they tend to be more motivated and innovate more efficiently. Therefore, innovating outside the firm (as an entrepreneur) might be more efficient in the scenario of high-risk patents and severe agency issues. In this case, acquiring high-risk patents from the market could be cheaper, even though the firm needs to pay a premium for these patents [8]. Therefore, the acquisition market create synergies where firms outsource riskier R&D to the market and buy it back with a premium. Consistent with this, we find that the acquirer mostly chooses to invest in low-risk R&D in-house and acquire successful outcomes of high-risk R&D from the market.

The benefits associated with each type of acquisitions influence the firm's ultimate choice. We find that the firm' choice of acquisition is heavily influenced by the profitability (α) and financing costs (λ) of its physical investment. In other words, how the firm performs

[8] The premium is defined as the extra amount paid on top of the cost incurred to produce these patents by the entrepreneur.

on the product market determines what types of benefits it is likely to enjoy from making acquisitions. As shown in Figure 5, when profitability of physical investment is low or financing costs are high, the firm reduces its *synergy* acquisitions (and R&D investments), but increases *competition* acquisitions instead. On one hand, this implies that when the firm has limited investment opportunities on the product market, it also innovate less. This is sensible as innovation is less productive for firms that are not profitable. On the other hand, this implies that when the firm has limited investment opportunities on the product market, it makes more *competition* acquisitions. This speaks to a substitution effect between the firm's physical investment and *competition* acquisitions. While physical investment is one way to increase firm size and expand market share, *competition* acquisition is another. If investment prospects are not promising internally, the firm substitutes part of physical investments with its outside options, i.e., expanding via mergers and acquisitions. Hence, our results demonstrate that more profitable firms look for synergies while less profitable ones are more likely to acquire competitors. This is because although both types of acquisitions bring value, their mechanisms differ fundamentally. While benefits associated with *synergy* acquisitions rely heavily on the firm's exisitng levels of innovation and performance, *competition* acquisitions add value even when internal investment opportunities are constrained.

In the model, *synergy* acquisitions augment the firm's output elasticity of patents by m_s and thus create synergies, while *competition* acquisitions help eliminate potential rivals and replenish the firm's market share by m_c. As shown in Figure 7 Panel B, we find that with larger m_s, the firm makes more *synergy* acquisitions and also innovate more internally. In the meanwhile, the firm makes less *competition* acquisitions because capital is used to achieve synergies. Also in Panel C, we find that with larger m_c, the firm makes more *competition* acquisitions. But its internal innovation declines as shrinking market sure renders R&D less profitable. In the meanwhile, the firm makes less *synergy* acquisitions as capital is used to maintain market share.

5.4 How Important is the Acquisition Market?

In this subsection, we examine the importance of the acquisition market in a firm's technology growth. We begin with explaining the existence of *competition* acquisitions by quantifying the benefits for firms acquiring their competitors. Prior literature shows that the cumulative abnormal return for these acquirers is insignificantly different from zero. Establishing a valid counterfactual is challenging in this case. Instead of comparing the scenario after the acquisition with the one before, one should compare it with the hypothetical scenario that the acquisition didn't happen. These two benchmarks systematically differ because in a competitive environment, the firm may preemptively take over another firm to eliminate the potential threat that the target (either growing organically or acquired by other firms) could eventually steal its market with better technology. In other words, if the firm does nothing, it is possible that it would lose its market share and end up with declining profits and firm value. It is exactly those firms who are going to be worse off and lose market share that are more likely to acquire potential competitors. Therefore, these acquisitions, if compared to the scenario before the firm loses its market share, might not generate positive returns for acquirers.

Identifying such a hypothetical benchmark necessitates finding an exogenous shock to the firm's *competition* acquisitions that does not directly affect any other corporate decisions. Since physical investment, R&D, and financing decisions are all intertwined, this is difficult. Using a structural approach, we are able to estimate the hypothetical benchmark, that is, how the firm would perform if the acquisition didn't happen, with which we identify the benefits of *competition* acquisitions. We engineer such an exogenous shock by manually setting off *competition* acquisitions in the model. As shown in Table 5 (Panel A), we find that for firms that chase after their competitors, not being able to do so truncates their Tobin's Q by 20.24%, which means billions of dollars are lost if they are forbidden to purchase younger firms that are potential rivals. Not being able to acquire rivals also discourages these firms from innovating themselves as part of the outcomes could eventually be overpowered by rivals. As a result, their own R&D drops by 7.22%. Our estimation results also demonstrate that acquirers are able to replenish 2.875% of their market share per competition acquisition. This translates into 38.52% loss of patent productivity under threat of competition if the acquisition make did not exist. Therefore, we demonstrate that *competition* acquisitions add substantial value to the acquirers even though it is hard to observe empirically. Put differently, the firm maximizes its value by optimally choosing to acquire its competitors.

We also ask what would happen if the firm innovates in a perfect world with no peer competition (see Table 5, Panel B). We find that the firm increases R&D investment by 2.72% and make synergy acquisitions more frequently. Its total patents increase by 2.15%. All the evidence points to the fact that the competitive nature of innovation makes R&D riskier and negatively affects the acquirer's own R&D. However, thanks to the existence of the acquisition market, the firm is able to curtail some of these risks from market competition by acquiring its competitors. In this paper, we focus on the behavior of potentail acquirers which are big firms that play important roles in shaping the high-tech industries. However, how such *competition* acquisitions may impact potential target firms in the industry remains an open question. On one hand, it is likely that without the market for taking over younger and smaller rivals, not only the acquirers suffer major drawbacks in their innovation, these targets are also discouraged from coming up with new ideas because they no longer enjoy the alternative exit option of being bought out. On the other hand, without the market for being acquired, these young start-ups no longer face the risk of external interruption of their development of new technology. Hence, it is possible that we see more start-ups and new technology coming up in the industry. Studying how these target respond, while important and interesting, is beyond the scope of our paper.

Similarly, we examine the firm's responses after shutting down *synergy* acquisitions. As shown in Table 5 (Panel A), it is the good performers in the industry that look for synergies from the market as for them, larger synergies are achieved. For these firms, not being able to do so truncates their Tobin's Q by 12.53%. The results also show that these firms reduce R&D investment by 7.28%, causing a 4.72% decline of total patents. Hence, not being able to make *synergy* acquisitions discourages firms from innovating themselves. This is because acquired technology boosts firm productivity by rendering their existing patents more productive.

To summarize, we document that the acquisition market is crucial for firms' technology growth and overall performance. Both *synergy* and *competition* acquisitions play a key role in the development of corporate innovation, especially for the leading firms in the industry. As described above, shutting down the acquisition market truncates these firms' Tobin's Q by 12.53% and 20.24%, respectively. To put things into perspective, we set this side by side with the effect on firm value from shutting down in-house R&D. Tobin's Q declines by 14.93% if firms cannot innovate in-house. On that account, for high-tech firms, the acquisition market is as important as in-house R&D in terms of their overall growth and performance.

5.5 Does Acquisition Crowd Out R&D?

In this subsection, we ask whether the existence of the acquisition market crowds out acquiring firms' incentives for in-house R&D. Previously, we have discussed the hypothetical scenarios if the acquisition market did not exist. Here, we closely examine how in-house R&D and technology-driven acquisitions influence each other. We start by examining how acquisition costs (D) affect the firm's R&D decisions. The results are shown in Figure 6 (Panel A). Larger acquisition costs result in less acquisitions, which in turn causes declining patents and shrinking R&D investments. Since acquisition leads to more productive patents, R&D investments become less attractive with less acquisitions. Li, Qiu, and Wang (2019), Zhao (2009) and Sevilir and Tian (2012) show that corporate takeovers lead to superior innovation outputs, with the relationship being larger among pair of firms sharing a degree of technological overlap (see Bena and Li (2014)). Our result is consistent with the findings in this strand of literature.

Next, we investigate how R&D costs (c_w) affect the firm's acquisition decisions. In Figure 7 (Panel A), when R&D is more costly, the firm uses less R&D inputs even though the dollar amount the firm spends on R&D is larger. Consequently, less outputs (i.e., patents) are produced. The firm also acquires more frequently as it cuts down internal R&D and uses the saved amount on the acquisition market. However, if R&D costs keep increasing, the firm's likelihood of making an acquisition starts to drop. This is because if R&D costs become too high, declining patents makes acquisitions less attractive as innovative firms get more out of the acquired technology. As a consequence, less in-house R&D also leads to less technology-driven acquisitions.

We also look at the effect of target bargaining power (η) on innovation (see Figure 6, Panel B). Higher η makes acquisitions more costly for acquirers, eventually reducing their R&D investments and stock of patents. It is interesting to see that with increasing η, more firms make synergy acquisitions at first. This is because more targets agree to be taken over when price is higher. With more targets on the market, more firms jump in and become acquirers. However, if η becomes too high, the profit margin becomes too thin for many acquirers. They acquire less and innovate less accordingly. To summarize, our results support the view that R&D and acquisitions are mostly complements, with a couple of exceptions. That is, when unit cost of R&D or target bargaining power is low, R&D and acquisitions substitute each other. But other than these cases, more in-house R&D leads to more acquisitions, and vice versa.

Last but not least, we discuss the relation between *synergy* and *competition* acquisitions. In our sample, 91% of all acquirers conduct only one acquisition each year, while 99% conduct no more than two acquisitions each year. Hence, for simplicity, we allow the firm to make one type of acquisiton each period. This setup partially contributes to the observed substitution effect between these two types of acquisitions in our results. Overall, we find that the firm is inclined to make both types of acquisitions more often when the firm has higher profitability or better profit shocks. The firm also acquires more often if the firm itself is more innovative. However, as discussed earlier, the underlying mechanisms for these acquisitions are different. Our results indicate that it is possible for a poorly-performing firm to acquire its competitors but only the good performers search for synergies from the market. This is because synergies that can be achieved from the merger deal utterly depend on the firm's own level of innovation. However, gained market share is particularly useful when the firm has constrained internal opportunities.

6. Conclusion

It is very common for firms in the technology space to acquire other innovative firms. Companies such as *Alphabet* or *Cisco*, to name a few, have reached rates of acquisitions of about one firm per month. This large frequency of acquisitions has attracted the attention of lawmakers calling for more regulation on the concern that such acquisitions limit not only prospective challengers but also distort innovation incentives of incumbents and entrants. For example, the Subcommittee on Antitrust, Regulatory, and Administrative Law of the U.S. House of Representatives Committee on the Judiciary culminated in 2021 a 16-month investigation of competition in digital markets by issuing a report calling for significantly greater regulation of these companies. We contribute to this debate by studying the role that a market for acquisitions has on incumbents' incentives to innovate.

Specifically, we argue that technology-driven acquisitions provide acquiring firms stronger incentives for in-house R&D as acquired innovation magnifies the benefits of R&D. However, it is possible that technology-driven acquisitions can limit innovation, either by acquiring start-ups in order to terminate the development of innovations that threaten their continued dominance (Cunningham et al. 2021) or by creating areas of the market in which they exert dominance to the extent others won't invest in these areas (Kamepalli et al. 2020). Reduced competition, in turn, can result in fewer incentives to innovate for incumbents, especially in industries where entry costs are low or that are "neck-and-neck" (Aghion et al. 2005). These arguments are rooted in the assumptions that agency conflicts inside the firm are so severe that reduced market competition leads to less in-house R&D. One caveat in this paper is that our model does not explicitly incorporate agency issues between the firm's management and shareholders. Hence, even though our paper identifies the channels through which technology-driven acquisitions promote innovation, it does not necessarily exclude the possibility of innovation distortion, especially for firms with severe agency problems.

Appendix A: Proof of Proposition 1

The proof uses the Contraction Mapping Theorem. For the detailed proof of monotonicity, see Lucas, Prescott, and Stokey (1989). Let C(k,p,h,s,z) be the space of all continuous and bounded functions in the state space (k,p,h,s,z). The Contraction Mapping Theorem requires two steps to show the existence of a unique fixed point that satisfies the Bellman equation:

T: C(k,p,h,s,z) -> C(k,p,h,s,z);

T is a contraction in C(k,p,h,s,z). Q.E.D.

Appendix B: Model Solution & Estimation

Since the theoretical model does not yield a closed-form mapping, the state space for (k, h, z) is divided intro discrete intervals in order to find a numerical solution for the model. The value function and policy functions are solved via interations with the Bellman equation on these grid points. When optimal values have been computed at each grid point (k, h, z), values at other points of the value and policy functions are inferred by interpolation.

Specifically, the simulation procedures are conducted by taking a random draw of (k, h, z) for each firm and then computing $V(k, h, z)$ and the policy functions $u(I, w, m)$. The model simulation proceeds by taking a random draw from the distribution of z' (conditional on z) and repeating the previous computations every peiod. We use these computations to generate an artificial panel of firms. We simulate 1,000 independent firms for 100 time periods and retain the last 10 time periods as a panel. We then collect 10 such panels to use for estimating the structural parameters via SMM.

Next, we estimate the model via SMM by choosing a good set of moments that identify the structural parameters. The estimation procedure follows Lee and Ingram (1991). Let x_i be an *i.i.d.* data vector, where i equals $1, ..., n$. Let $y_{is}(\beta)$ be an *i.i.d.* simulated vector from simulation s, where i equals $1, ..., n$ and s equals $1, ..., S$. n and S indicate the size of simulated sample and the number of simulations performed, respectively. Michaelides and Ng (2000) find that good finite-sample performance of a simulation estimator requires a simulated sample size to be ten times as big as the actual data sample size. The simulated vector $y_{is}(\beta)$ depends on a vector of structural parameter $\beta = (\alpha, \rho_z, \sigma_z, \lambda, c_w, D, m_s, m_c)$. The goal is to estimate β by matching a vector of moments, $H(y_{is}(\beta))$, to the corresponding real moments $H(x_i)$. The moments may include summary statistics and coefficient estimates from reduced-form models. The objective function to be minimized is defined as follows:

$$\hat{\beta} = \underset{\beta}{\text{argmin}} G_n(\beta)' \hat{W}_n G_n(\beta)$$

$$G_n(\beta) = \frac{1}{n} \sum_{i=1}^{n} [H(x_i) - \frac{1}{S} \sum_{s=1}^{S} H(y_{is}(\beta))]$$

A simplex method called the Nelder-Mead algorithm is used to achieve minimization. $\hat{W}_n$ is a positive definite matrix that converges in probability to a deterministic positive definite matrix. We use the optimal weighting matrix:

$$\hat{W}_n = [n \times \text{Cov}(H(x_i))]^{-1}$$

I compute the 11×11 covariance matrix of $H(x_i)$ using the seeming unrelated regression approach. The moments can be expressed as the coefficients from a system of regression equations. Each regression has the form:

$$Y_i = X_i h_i + \epsilon_i$$

where Y_i and X_i are both $n \times 1$ and h_i is a scalar vector, where $i = 11$. The covariance between moment estimators h_i and h_j is:

$$\text{Cov}(\hat{h}_i, \hat{h}_j) = (X_i^\top X_i)^{-1} X_i{}^\top \Omega_{ij} X_j (X_i^\top X_i)^{-1}$$

where the covariance matrix Ω_{ij} for each pair of moments i and j is calculated as $\text{Cov}(\epsilon_i, \epsilon_j)$, the $n \times n$ matrix whose element t, s is $\text{Cov}(\epsilon_{it}, \epsilon_{js})$.

Applying the result of Pakes and Pollard (1989) with the efficient weighting matrix, we obtain:

$$\sqrt{n}(\hat{\beta} - \beta_0) \xrightarrow{d} \mathcal{N}(0,\, avar(\hat{\beta}))$$

$$avar(\hat{\beta}) = (1 + \frac{1}{s})(\Gamma^\top \hat{W}_n \Gamma)^{-1} \Gamma^\top \hat{W}_n \hat{\Omega} \hat{W}_n \Gamma (\Gamma^\top \hat{W}_n \Gamma)^{-1}$$

where $\Gamma = \lim_{n \to \infty} \frac{\partial G_n(\beta_0)}{\partial \beta}$. I estimate Γ by numerically differentiating $G_n(\beta)$ with respect to β. I also have:

$$\sqrt{n} G_n(\beta_0) \xrightarrow{d} \mathcal{N}(0,\, (1 + \frac{1}{S}) \hat{W}_n^{-1})$$

SMM provides the following J-test of the model's over-identifying restrictions with degrees of freedom calculated by substracting number of parameters from number of moments:

$$\frac{nS}{1+S} G_n(\beta)^\top \hat{W}_n G_n(\beta) \xrightarrow{d} \chi^2.$$

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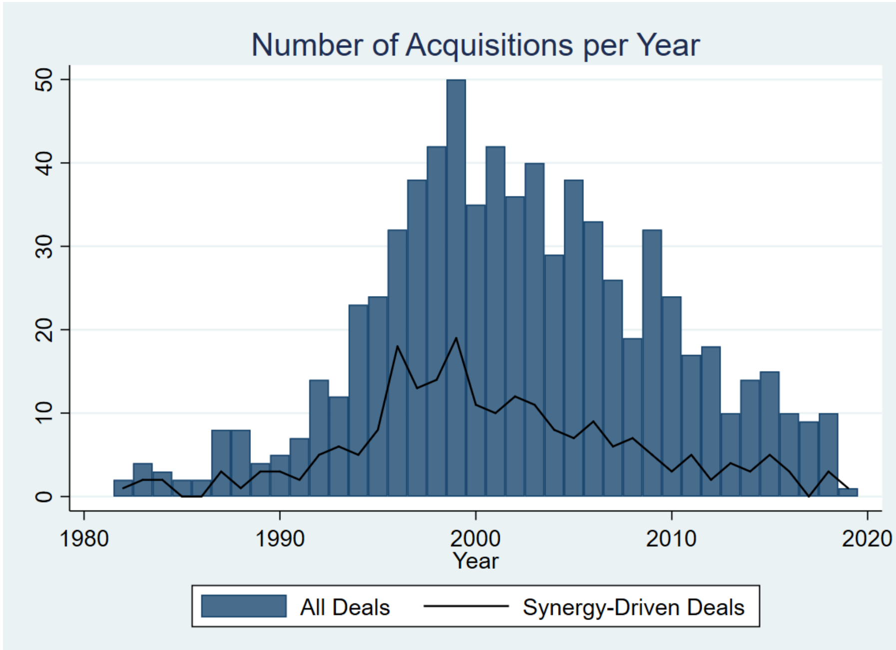
Figure 1. Number of Transactions per Year



This figure presents the distribution in event-time of the number of deals per year in our sample. Our sample includes all the completed M&A deals from 1975–2019 where: (1) both the target and the acquirer are in the "high-technology" space (see Loughran and Ritter (2004)); (2) the patent has at least one patent granted in any of the 20 years prior to the deal; and (3), both firms in the deal share at least one patent in a technology class. We classify as "synergy acquisitions" the deals where both the target and the acquirer measure of technological rivalry is in the bottom 30% of the distribution, and it is classified as a "competition acquisition" otherwise.

Figure 2. Announcement Returns and Technology Proximity

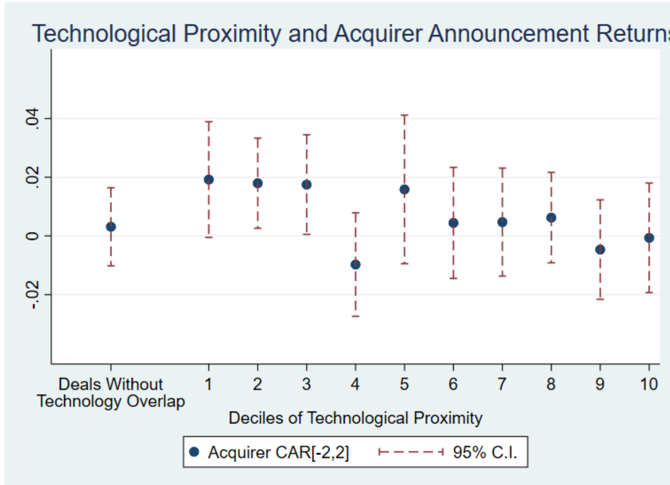
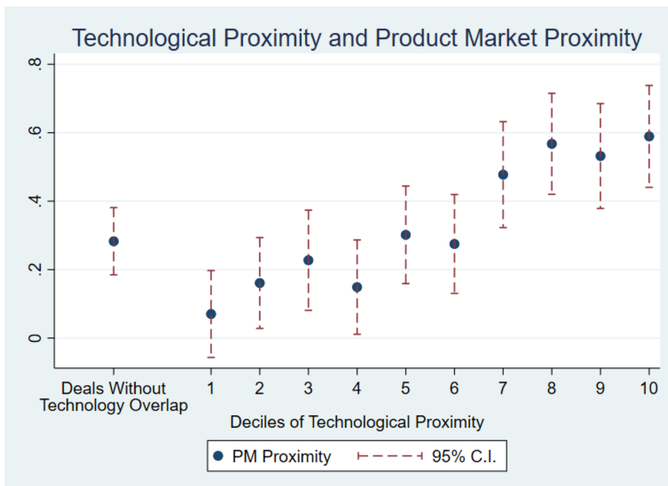


Figure 3. Product Market Proximity and Technological Proximity



Figures 2 and 3 present the distribution of the announcement returns and market-rivalry measure for the 738 deals in our sample. The vertical dashed-line represents the 95% confidence interval. The measure of technological proximity is calculated as the uncentered correlation between any pair of firms (i, j) at time t in terms of their share of patents across technology classes as in Jaffee (1986). The product market Proximity measure is calculated in a similar manner following Bloom, Schankerman, and Van Reenen (2013). The cumulative abnormal returns are computed using a one-factor model over a two-day window around the event date.

Table 1. Summary Statistics

This table presents the summary statistics. *Main Sample* includes all the completed M&A deals from 1975–2019 where: (1) both the target and the acquirer are in the "high-technology" space (see Loughran and Ritter (2004)); (2) the patent has at least one patent granted in any of the 20 years prior to the deal; and (3), both firms in the deal share at least one patent in a technology class. Our final sample includes 738 completed deals and 681 unique firm-year deals. *All SDC* includes all the completed M&A deals from 1975–2019 for which there is financial information about the acquirer without any of the previous filters. Panel A presents all the firm-year observations (without duplicates) for the acquirer up to 10 years prior to the deal. Panel B presents all the firm-year observations for the target up to 10 years prior to the deal. Panel C presents the deal-level variables. To account for firm heterogeneity, the standard deviation is computed using firm fixed effects. All variables are winsorized at the 1th and 99th percentiles. Variable definitions are in the Appendix.

	Main Sample			All SDC		
	Mean	Std.Dev.	N	Mean	Std.Dev.	N
	(1)	(2)	(3)	(4)	(5)	(6)
			Acquirer			
Size	13,049.585	26,629.900	7,491	18,076.313	63,667.902	84,128
Patents per Year	112.250	250.442	7,491	32.825	105.093	84,128
Stock of Patent (Normalized)	11.970	23.295	7,491	4.228	9.724	84,128
Leverage	0.235	3.582	7,491	0.280	1.152	84,128
Sales Growth	0.199	0.339	7,491	0.182	0.341	84,128
Net Income	0.076	0.091	7,491	0.069	0.049	84,128
Capital Expenditures	0.054	0.030	7,491	0.053	0.033	85,128
R&D Expenditures	0.086	0.058	7,491	0.017	0.018	84,128
External Finance	0.338	0.206	7,491	0.162	0.140	84,128
			Target			
Size	8,845.710	16,013.140	5,070	14,348.180	66,844.450	79,058
Patents per Year	126,4249	276.231	5,070	17.021	81.985	79,058
			Deal			
Premium Paid	33.474	26.525	292	26.946	27.345	2,335
Relative Size	73.669	156.290	715	21.776	49.163	6,559
CAR[-1,1]	0.005	0.065	639	0.004	0.052	5,078
CAR[-2,2]	0.007	0.076	639	0.005	0.061	5,078
CAR[-3,3]	0.007	0.084	639	0.006	0.068	5,078
Technological Proximity	0.374	0.304	738	0.184	0.252	1,690
Product-Market	0.396	0.461	724	0.304	0.421	5,821

This table presents the differences across deals with high and low technology proximity between the acquirer and the target. Our sample includes all the completed M&A deals from 1975–2019 where: (1) both the target and the acquirer are in the ”high-technology” space (see Loughran and Ritter (2004)); (2) the patent has at least one patent granted in any of the 20 years prior to the deal; and (3), both firms in the deal share at least one patent in a technology class. Our final sample includes 738 completed deals. *synergy acquisitions* are the deals for which the technology proximity measure between the target and the acquirer is in the bottom 30% of the distribution (equivalent to a technological proximity of 13.1% or less). *competition acquisitions* are the deals for which the technology proximity measure between the target and the acquirer is in the top 70% of the distribution. The last column reports the mean difference across types of deals. All variables are winsorized at the 1th and 99th percentiles. Variable definition are in the Appendix.

Table 2. Differences Across Deals

	Synergy Acquisitions			Competition Acquisitions			
	Mean	Std.Dev.	N	Mean	Std.Dev.	N	
	(1)	(2)	(3)	(4)	(5)	(6)	(1)-(4)>0
Premium Paid	29.337	24.277	69	34.754	27.107	223	-5.417
Relative Size	85.761	172.766	211	68.606	148.743	504	17.152*
CAR[-1,1]	0.012	0.065	180	0.002	0.065	459	0.010**
CAR[-2,2]	0.018	0.073	180	0.003	0.077	459	0.015**
CAR[-3,3]	0.014	0.081	180	0.004	0.085	459	0.009*
Technological Proximity	0.059	0.040	221	0.509	0.265	517	
Product-Market Proximity	0.214	0.385	218	0.475	0.469	506	

This table presents the estimate of the probability of success and the likelihood of default for the acquirers and potential targets. We define as acquirers the firms that acquire a firm in any of our 738 deals. We define as potential targets all the U.S. assignees in the USPTO data (excluding the firms that are acquirers and targets in SDC). Moreover, we only retain the assignees that have a technological overlap with each acquirer, and split the sample into two based on whether the assignee and the acquirer technology correlation is above/below 13.1%. We compute the probability of success as the as the probability that matches the expected value of the binomial distribution when the upside is defined as the average number of patents granted when at least one patent is granted and the downside is defined as 0 (see Section **??**). The probability of exit is computed as the frequency of a firm that stops appearing in COMPUSTAT (for acquirers) or in the USPTO (for potential targets) in a given year t. //

Table 3. Probability of Success

			Potential Targets (All Firms in the USPTO)			
	Acquirer		Tech Proximity<0.13		Tech Proximity≥0.13	
	Mean	N	Mean	N	Mean	N
	(1)	(2)	(3)	(4)	(5)	(6)
Prob. Success (θ)	0.715	7491	0.369	111,800,993	0.369	338,754,626
Prob. Exit	0.059	6514	0.194	111,800,993	0.193	338,754,626

Table 4. SMM Estimation

Panel A reports the simulated and estimated moments and t-statistics for differences between the corresponding moments. Panel B reports the estimated structural parameters and their standard errors (in parentheses). Estimation is done with the simulated moment estimator in Gourieroux and Monfort (1993), which chooses structural parameters by matching the simulated moments to the corresponding moments from the real data. The real moments are based on a sample of high-tech firms from the 1980-2018 Compustat industrial files. The simulated panel of firms is generated by the dynamic model from Section 2. Moments in Panel A and parameters in Panel B are defined in Section 4.

Panel A: Moments from SMM Estimation

	Simulated Moments	Real Moments	t-statistics
Serial Correlation of Income	0.8017	0.8061	-0.0076
Variance of Innovation to Income	0.0105	0.0043	0.4349
Average External Finance (incl. Cash)	0.3290	0.3382	-0.0483
Variance of External Finance (incl. Cash)	0.0272	0.0366	-0.1149
Average Investment	0.0575	0.0543	0.1136
Variance of Investment	0.0011	0.0008	0.1775
Likelihood of Synergy Acquisitions	0.0660	0.0608	0.2147
Likelihood of Competition Acquisitions	0.1470	0.1412	0.1213
Average Stock of Patents	9.2125	9.3006	-0.0051
Average R&D Investment	0.0830	0.0855	-0.0430
Variance of R&D Investment	0.0021	0.0033	-0.1675

Panel B: SMM Parameter Estimates

α	ρ_z	σ_z	$\lambda(10^{-7})$	c_w	D	m_s	m_c
0.990	0.940	0.210	0.001	0.011	0.009	0.002773	0.028750
(0.003)	(0.030)	(0.031)	(0.001)	(0.003)	(0.004)	(0.000587)	(0.011812)

Table 5. Counterfactuals

This table provides changes in the firm's innovation policies in various hypothetical scenarios. Panel A presents changes in the firm's innovation policies if 1) the synergy acquisitions are manually set off or 2) the competition acquisitions are manually set off. Panel B shows changes in the firm's innovation policies if 1) industry competition is set to zero or 2) firms are manually disallowed to conduct internal R&D. Moments in both panels are defined in Appendix E. The simulated results are computed based on parameter values from Table 4. * represents Tobin's Q of a subset of acquiring or non-acquiring firms.

Panel A: The Acquisition Market

	No Synergy Acquisitions			No Competition Acquisitions		
	Before	After	Changes	Before	After	Changes
Stock of Patents	10.7266	10.2198	-4.73%	10.1243	9.5270	-5.90%
R&D	0.1003	0.0930	-7.28%	0.0898	0.0860	-7.22%
Tobin's Q	8.4283*	7.3720*	-12.53%	6.6990*	5.3430*	-20.24%

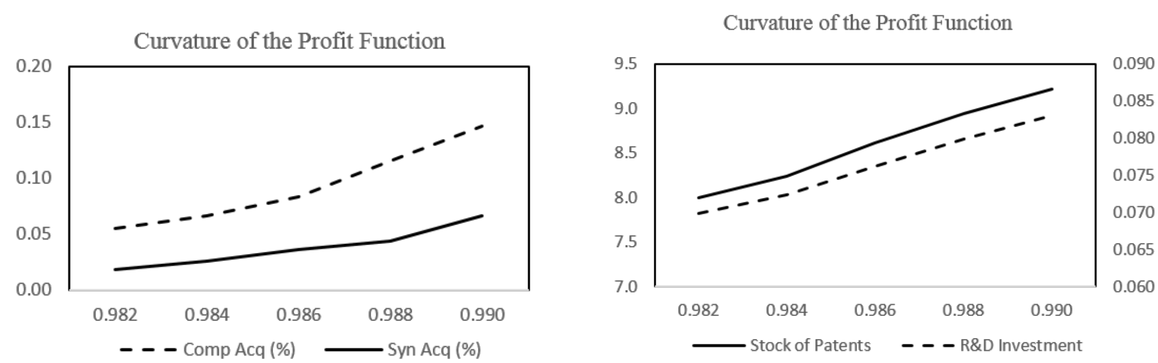
Panel B: Internal R&D

	No Peer Competition			No R&D		
	Before	After	Changes	Before	After	Changes
Stock of Patents (Tobin's Q)	9.2125	9.4107	2.15%	4.4288*	3.8534*	-14.93%
Synergy Acquisitions	0.0660	0.1855	180.92%	0.0660	0.0120	-81.81%
R&D ($Comp$ Acquisitions)	0.0830	0.0853	2.72%	0.1470	0.0736	-49.93%

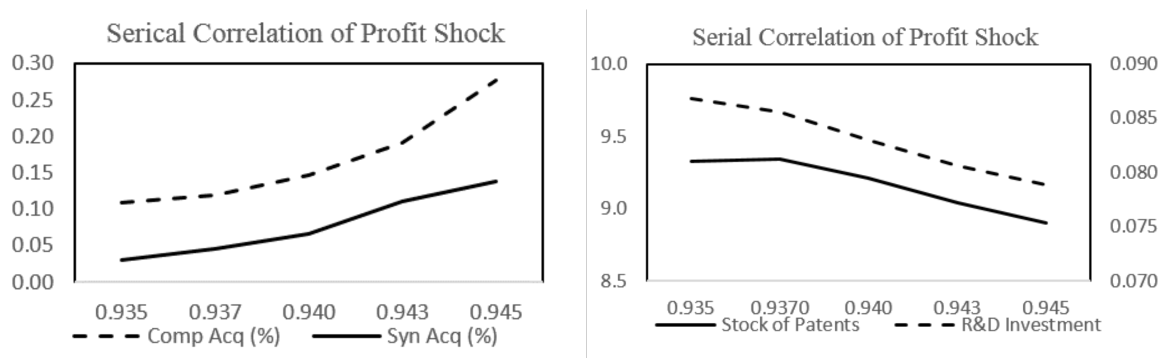
Figure 4. Production and Innovation

This figure shows the relationship between the innovation policies (R&D and acquisitions) of firms and the following parameters: curvature of the profit function (α) (Panel A), serial correlation of the profit shock (ρ) (Panel B), and standard deviation of the profit shock (σ_z) (Panel C). These results are from simulations of the model using parameter values from Table 2. Syn Acq (%) is the likelihood that firms make synergy acquisitions, while Comp Acq (%) is the likelihood that firms make competition acquisitions.

Panel A: Curvature of the Profit Function



Panel B: Serial correlation of Profit Shock



Panel C: Volatility of Profit Shock

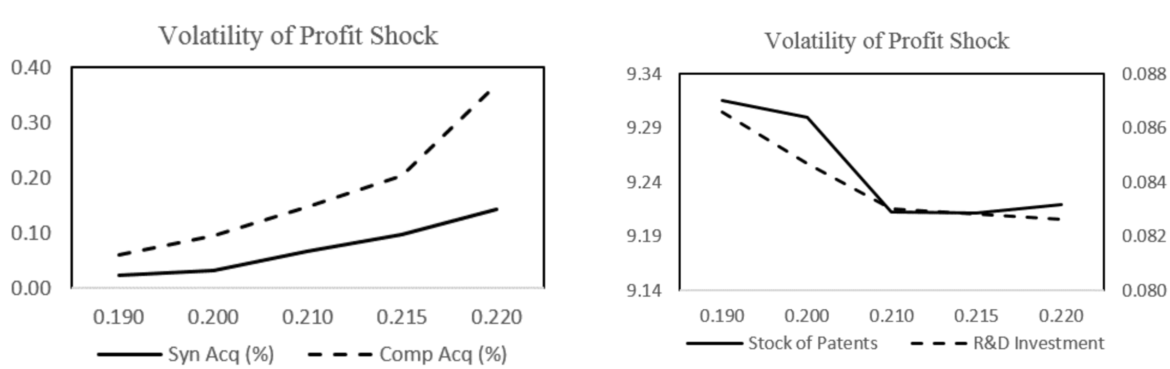
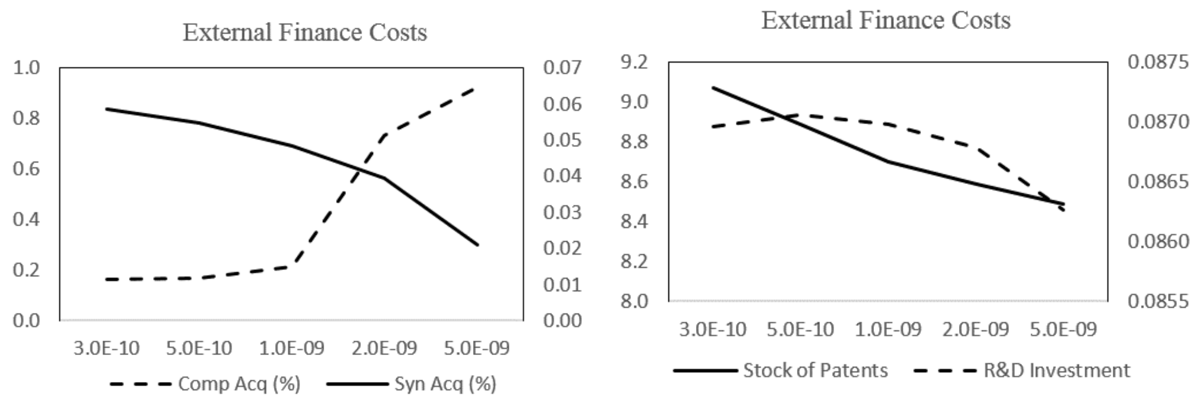


Figure 5. Finance and Innovation

This figure shows the relationship between the innovation policies (R&D and acquisitions) of firms and the following parameters: external finance costs (λ) (Panel A) and curvature of the profit function (α) (Panel B). These results are from simulations of the model using parameter values from Table 2. Syn Acq (%) is the likelihood that firms make synergy acquisitions, while Comp Acq (%) is the likelihood that firms make competition acquisitions.

Panel A: External Finance Costs



Panel B: Curvature of the Profit Function

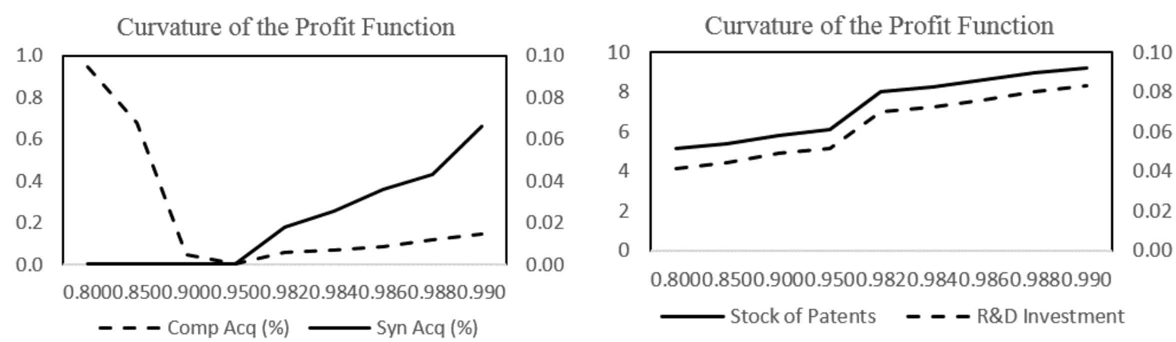
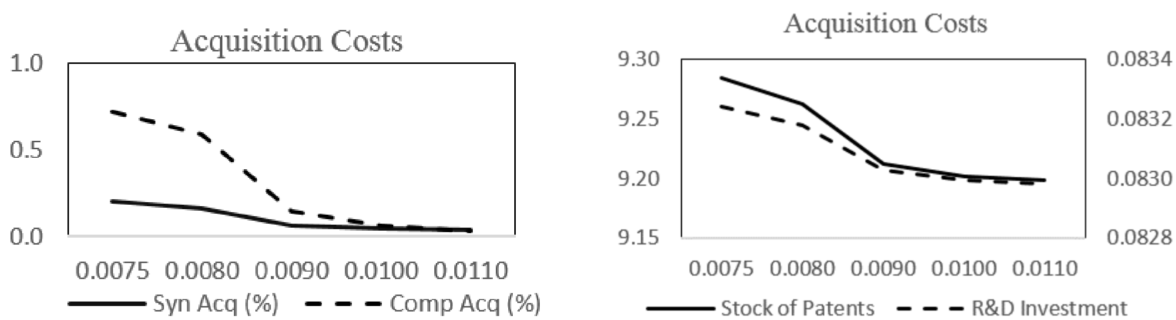


Figure 6. Acquisition Market and Innovation

This figure shows the relationship between the innovation policies (R&D and acquisitions) of firms and the following parameters: search costs of acquisition (D) (Panel A) and bargaining power of the target firms (η) (Panel B). These results are from simulations of the model using parameter values from Table 2. Syn Acq (%) is the likelihood that firms make synergy acquisitions, while Comp Acq (%) is the likelihood that firms make competition acquisitions.

Panel A: Acquisition Costs



Panel B:Target Bargainning Power

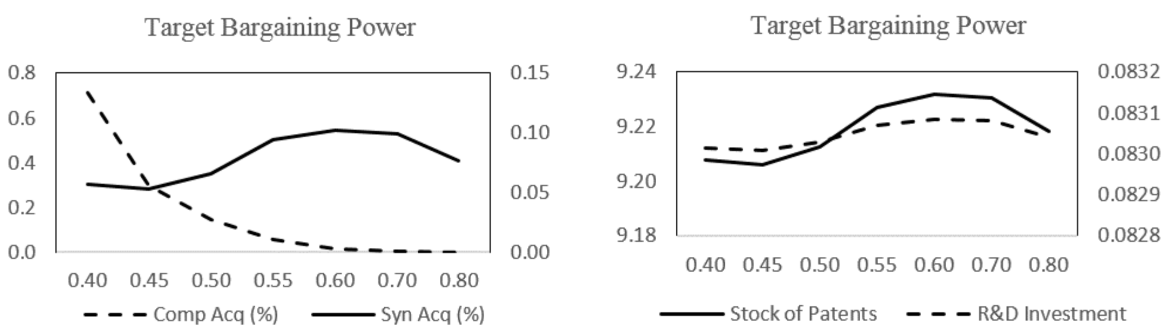
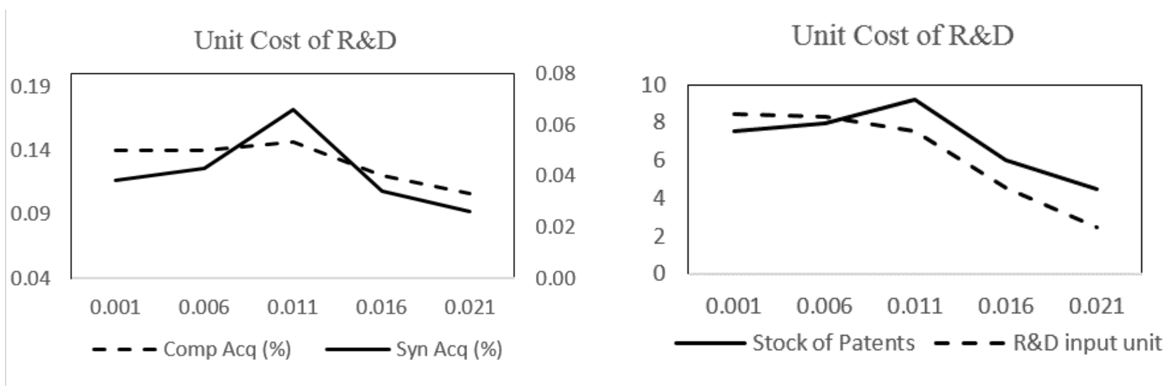


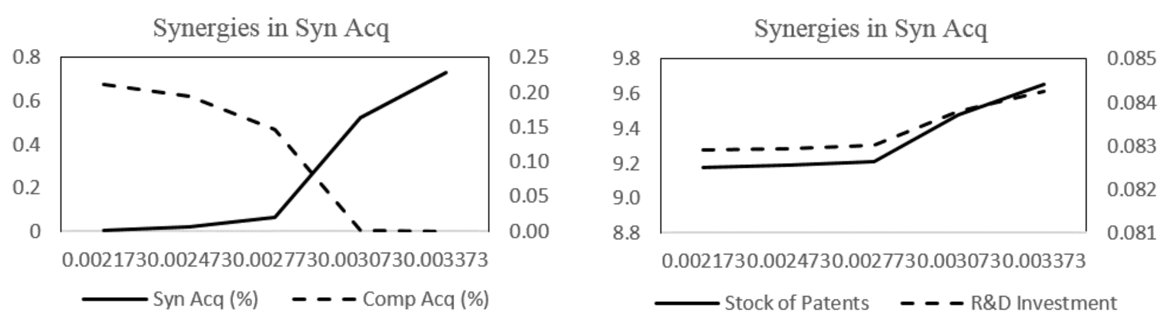
Figure 7. R&D and Acquisitions

This figure shows the relationship between the innovation policies (R&D and acquisitions) of firms and the following parameters: unit cost of R&D investment (c_w) (Panel A), patents acquired in synergy acquisitions (Δ_H) (Panel B), and percentage of firm patents that regain effectiveness from competition acquisitions (h_c) (Panel C). These results are from simulations of the model using parameter values from Table 2. Syn Acq (%) is the likelihood that firms make synergy acquisitions, while Comp Acq (%) is the likelihood that firms make competition acquisitions.

Panel A: Unit Cost of R&D



Panel B: Synergies in Synergy Acquisitions



Panel C: Rescued Market Share in Competition Acquisitions