Inefficient Mergers

November 10, 2015

Abstract

Although complementarity between products or technologies of bidders and targets is considered a key driver of M&A deals, many observed mergers are inefficient: Complementarity gains in actual mergers are lower than the gains that could have been obtained were the targets acquired by different bidders. In this paper we propose a possible reason for the existence of inefficient mergers, which is based on information frictions. Our model identifies three factors that are associated with expected inefficiency of a merger involving a given target: its obsolescence risk, the likelihood of the target's discovery by potential acquirers, and the extent of competitive interaction among potential bidders. We test the model's predictions using two types of merger complementarities: product similarity and technological overlap. Both sets of tests indicate that the degree of inefficiency in observed M&As is systematically related to targets' and bidders' characteristics in ways consistent with the model's predictions.

Key words: M&As; complementarities; product similarity; technological overlap

JEL Codes: G32, L13

1. Introduction

Aggregating complementary assets under common ownership is one of the main sources of gains in mergers and acquisitions.[1] Consistent with this view, empirical evidence shows that mergers between firms with larger complementarities in products/technologies are more likely to occur and lead to higher average realized gains (e.g., Kaplan and Weisbach (1992), Rhodes-Kropf and Robinson (2008), Hoberg and Phillips (2010), Maksimovic, Phillips and Prabhala (2011), and Bena and Li (2014)). Yet, in actual merger pairings, the realized gains from complementarities between target's and acquirer's products and/or technologies are often lower than hypothetical gains that could have been achieved were the target acquired by a different bidder.

One recent example of a merger that is not expected to realize the full potential of the target's technology is Facebook's $2 billion acquisition of Oculus, a young company known for its virtual reality headset "Oculus Rift". The reaction of the technology community to this acquisition, announced in March 2014, was lukewarm. For example, a popular technology blog Tech.pinions featured a story "Why Google should have bought Oculus Rift", suggesting that Oculus will not realize its real world-changing potential under Facebook, and that Google could have achieved higher gains from incorporating Oculus' technology in its product offerings.

In this paper we propose a reason for the existence of *inefficient mergers*, which we define as merger deals in which complementarity gains are lower than gains that could have been achieved were the target acquired by a different (hypothetical) bidder. We then examine theoretically and empirically which factors are associated with the likelihood of observing an inefficient merger and with the degree of merger inefficiency.

Our simple model features a target and two potential bidders (incumbents). The target possesses a product/technology that can be useful to each bidder. The degree of usefulness of the target to each of the incumbents is determined by exogenously given complementarity of the target's product/technology with those of that incumbent. In every period each incumbent may discover the target (i.e. learn the value implications of acquiring and integrating the target's product/technology) with a positive probability. Once an incumbent has discovered the target, it can make a merger offer, which the target can accept or reject. In the latter case, the target remains in play and may receive future offers from any firm that would discover it later. The incumbents' products are strategic substitutes, implying that the acquisition of the target by one of the incumbents has a negative impact on the

[1] See Bradley, Desai and Kim (1988), Kaplan and Weisbach (1992), Healy, Palepu and Ruback (1992), Andrade, Mitchell and Stafford (2001), Maksimovic and Phillips (2001), Betton, Eckbo and Thorburn (2008), Hoberg and Phillips (2010), Maksimovic, Phillips and Prabhala (2011), and Bena and Li (2014) among many others.

other incumbent's profits.

In equilibrium, the bidder that has the highest degree of complementary with the target does not always acquire it. It is possible that the bidder with lower complementarity discovers the target first and is willing to make a sufficiently high acquisition offer, which the target optimally accepts, leading to an inefficient merger. This scenario can happen if one incumbent's information about the degree of complementarity between the target's product/technology and those of the incumbents is nonverifiable, i.e. it cannot be transferred to the other incumbent. If the information discovered by one of the incumbents were verifiable, then gains from transferring this information to the bidder with the highest complementarity with the target would be possible, and only efficient mergers would take place.

Our model highlights three factors that influence *expected inefficiency* of a merger involving a given target, which is a decreasing function of combined merger gains, relative to combined gains that could have been achieved in a acquisition of the target by the most complementary bidder. First, expected inefficiency is increasing in the target's obsolescence risk. The intuition is that a target whose product/technology is more likely to become obsolete is less willing to wait for future acquisition offer from a bidder with higher complementarity and is more likely to accept an existing offer from a less suitable bidder. The target's increased willingness to settle for the second-best bidder increases the likelihood of observing inefficient merger.

Second, expected merger inefficiency is decreasing in target's characteristics associated with the likelihood of its discovery by potential bidders. The easier it is for any bidder to discover the target, the higher the chances of multiple future bids are, leading to a takeover contest where the acquisition price is higher than in the single-bid scenario. Thus, an easily discoverable target is more likely to reject an offer from a bidder with lower complementarity and to wait for an acquisition offer from a bidder with more complementary product/technology. This results in a negative relation between the likelihood of target's discovery by bidders on one hand and expected merger inefficiency on the other hand.

Third, expected merger inefficiency is negatively related to the intensity of competitive interaction among potential bidders. The reason is that the target's acquisition not only raises the value of the acquirer, but also reduces the value of the other incumbent. The latter effect is stronger when the competitive interaction between the incumbents is more intense. As a result, higher degree of competitive interaction between potential bidders increases the offer prices that both bidders are willing to pay in an acquisition contest. The attractiveness of an acquisition contest, in turn, encourages the target to wait for this scenario to happen in the future. This leads to negative relation between the degree of competitive interaction between potential bidders and expected merger inefficiency.

To capture the inefficiency of observed mergers empirically, we examine the degree of product/technology complementarity between the target and all potential bidders. Our empirical measures of the degree of inefficiency in observed M&As are based on the ratio of the estimated complementarity between bidder and target in observed mergers and the highest possible complementarity between the target and any counterfactual bidder, i.e. any firm whose products/technologies are complementary to those of the target. We employ two separate measures of complementarity between a pair of firms. First, following Hoberg and Phillips (2010), we construct a measure of complementarity that is based on common vocabulary in the two firms' product descriptions. Second, we use a measure that is based on patent overlap, as suggested by Bena and Li (2014). These two measures aim to capture two of the crucial determinants of merger complementarities: product similarity and technological overlap (e.g., Henderson and Cockburn (1996), Fan and Goyal (2006), Hoberg and Phillips (2010), and Maksimovic, Phillips and Prabhala (2011)).

Each of the two approaches has its advantages and limitations. The product-based measure of complementarity is available for virtually all public firms, while technology-based measure is only available for pairs of innovative firms that generate patents. On the other hand, the latter measure is not limited to publicly-traded firms and can be constructed for privately-held targets as well. Overall, using both types of complementarity in computing measures of merger inefficiency allows to generalize our empirical results to the overall population of M&As.

To capture the determinants of merger inefficiency empirically, we use the following proxies. For the product-based sample, we use the scope of VC activity in the target's industry as a proxy for the target's obsolescence risk, with the idea that more intense VC activity speeds up the introduction of new, potentially superior, products/technologies, which could hurt the target. We use the number of analysts as a proxy for the likelihood of target discovery, as analysts reduce the degree of information asymmetry between the target and potential acquirers. Finally, we calculate the mean similarity among products of all firms in the bidder's industry, and use it as a proxy for the degree of competitive interaction among potential bidders. We rely on an alternative set of proxies in the patent-based sample. We use the number of patents that the target firm has an inverse proxy for its obsolescence risk, the target's publicly-traded status as a measure of target visibility, and patent breadth in the bidder's patent filing category as an inverse measure of competitive interaction in the bidder's industry.

Our empirical results support the model's predictions. For both measures of complementarity, we find robust evidence that the degree of inefficiency of a merger involving a given target is positively related to our proxies for the target's obsolescence risk and is negatively related to the likelihood of its discovery by possible acquirers and to the degree of competitive interaction among potential bidders. The relations between these factors and merger inefficiency are significant both statistically and economically. A one standard deviation increase in measures of target's obsolescence risk, the likelihood of its discovery, and the extent of competitive interaction among potential acquirers is associated with 10%-20% standard deviation change each in our measures of merger inefficiency.

To ensure that our empirical findings are not driven by mechanisms outside the scope of our model, we consider alternative explanations for the results. First, we verify that our complementarity measures do not proxy for market power that the merging firms could exercise. We repeat our tests for firms operating in relatively competitive industries, where market power considerations are less important, and also within a sample of non-horizontal mergers. Second, we address the agency hypothesis, according to which mergers may be driven by empire-building incentives of entrenched managers, potentially resulting in inefficient mergers. We repeat our tests using a subsample of firms with low Bebchuck, Cohen and Ferrell (2009) entrenchment index and find that the qualitative results are unaffected. Third, we verify that our results are not driven by the merger wave of the late nineties and by the hi-tech bubble of the turn of the millennium, in which abnormally high incidence of (inefficient) mergers could be driven by reasons unrelated to complementarities between bidders' and targets' products/technologies (e.g., Masulis, Wang and Xie (2007)).

Overall, our paper is the first to examine theoretically and empirically factors that are related to the degree of inefficiency in observed mergers. Our model is related to the model by Rhodes-Kropf and Robinson (2008), which features scarce targets and costly search, and is rooted in the property rights theory of the firm (e.g, Grossman and Hart (1986), Hart and Moore (1990), and Hart (1995)). We complement Rhodes-Kropf and Robinson (2008) by proposing an explanation for the existence of inefficient mergers. Our theoretical and empirical results highlight some of the determinants of the degree of inefficiency in observed mergers and extend the literature that has so far focused on the effect of complementarities on the incidence of M&As and on post-merger performance (e.g., Hoberg and Phillips (2010) and Bena and Li (2014)).

The remainder of the paper is organized as follows. The next section presents the model and its comparative statics. Section 3 describes the data and construction of variables. Section 4 presents and discusses empirical tests. Section 5 concludes. Proofs are found in the Appendix.

2. Model

In this section we present a model that illustrates why some of the observed merger pairings are inefficient, i.e. why not all mergers maximize the combined value of all firms in the bidder's industry. The model highlights some of the factors that influence the likelihood of observing inefficient mergers and the expected degree of inefficiency in observed mergers.

2.1. Setup

2.1.1 Incumbents

We consider two firms (incumbents), 1 and 2. In each period t the incumbents compete in heterogenous products. Firm i's per-period equilibrium profit is denoted by $\pi_i(\alpha_i, \alpha_{-i}, \gamma) \equiv \pi_i$ for $i \in \{1, 2\}$. α_i is a variable that affects firm i's profit, such that $\frac{\partial \pi_i}{\partial \alpha_i} > 0$. The firms' products are strategic substitutes, therefore an increase in a firm's rival's (firm $-i$'s) profit variable, α_{-i}, reduces firm i's equilibrium per-period profit: $\frac{\partial \pi_i}{\partial \alpha_{-i}} < 0$. Parameter γ defines the degree of product substitutability between the incumbents and, therefore, the extent of competitive interaction between them. In particular, when γ is higher, the negative effect of a firm's rival's profit variable on the firm's equilibrium profit is stronger: $\frac{\partial^2 \pi_i}{\partial \alpha_{-i} \partial \gamma} < 0$. To simplify the exposition, we assume that initially the two firms are symmetric in terms of their profit variables, i.e. $\alpha_1 = \alpha_2$.

2.1.2 Acquisition target

In addition to the incumbents, there exists a firm ("potential target") that owns a product/technology that, if purchased by one of the incumbents, would increase the acquirer's per-period profit, either through higher demand for the incumbent's product/technology or through lower production costs. In particular, we assume that the complementarity of the target's product/technology with that of firm i is described by parameter δ_i, drawn from a distribution with the p.d.f. $f(\delta)$ and c.d.f $F(\delta)$ with a lower bound $\underline{\delta} = 0$ and an upper bound $\overline{\delta}$. If firm i acquires the target, its profitability variable becomes $\alpha_i'(\delta_i)$, where $\frac{\partial \alpha_i'}{\partial \delta_i} > 0$ and $\alpha_i'(0) = \alpha_i$. Thus, the higher the complementarity between the bidder's and target's products/technologies, the larger the per-period profits of the merged entity. To simplify the algebra, we assume that the distributions of δ_1 and δ_2 are independent. However, none of the qualitative results are driven by the independence assumption. The resulting effect of δ_i on the incumbents' equilibrium per-period profits following an acquisition of the target by firm i are $\frac{\partial \pi_i}{\partial \delta_i} > 0$ and $\frac{\partial \pi_{-i}}{\partial \delta_i} < 0$. As is common in the industrial organization literature, we assume that the direct effect of δ_i on firm i's profit is stronger than its (indirect) effect on firm $-i$'s profit: $|\frac{\partial \pi_i}{\partial \delta_i}| > |\frac{\partial \pi_{-i}}{\partial \delta_i}|$ (e.g., Vives (2000)).

The effects of the acquisition of the target's product/technology on the two incumbents' per-period profits are not infinitely-lived. In particular, we assume that the target's product/technology may become "obsolete" with probability ψ in any period. If it becomes obsolete in period τ, it remains obsolete forever, that is in every period $t > \tau$. Once obsolete, the target's complementarity parameters, δ_1 and δ_2 revert to zero, i.e. the winning bidder's profit variable returns to the initial state, $\alpha_i'(0) = \alpha_i$, and the incumbents' equilibrium per-period profits revert to their pre-merger values.

Importantly, we do not assume that the target operates in the incumbents' product market. In other words, our model encompasses any merger with potential complementarities, such as horizontal mergers (e.g., Eckbo (1983, 1985), Fee and Thomas (2004), Shahrur (2005), and Bernile and Lyandres (2015)), or vertical mergers (e.g., Fan and Goyal (2006) and Kedia, Ravid, and Pons (2011)). We purposely abstract from the effects of market power to highlight the non-market-power-related determinants of inefficiency in observed M&As.

2.1.3 Discovery of the target

We assume that initially the two incumbents do not know the complementarity parameters, δ_1 and δ_2. A possible interpretation of this assumption is that initially the incumbents are unaware of the existence of the target. Alternatively, and more plausibly, the incumbents could be unfamiliar with the details of the target's product/technology and/or with value implications of acquiring the target and integrating it within their operations. In what follows, we will refer to the realization of the value effects of the merger by "target discovery".

In any given period, each of the two incumbents may learn the value consequences of integrating the target's product/technology with probability $p_{before}(y) \equiv p_b$. It is possible that once discovered by one incumbent, the probability of future discovery by the other incumbent changes. For example, it may increase if the information about past merger negotiations is released to the market. To allow for that possibility, we denote the likelihood of subsequent discovery as $p_{after}(y) \equiv p$. y is any characteristic of the target that is positively related to the probability of an incumbent discovering it: $\frac{\partial p_b}{\partial y} > 0$ and $\frac{\partial p}{\partial y} > 0$.[2]

If the target has been discovered by firm i at time τ, the firm learns the complementarity parameters of the target's product/technology with its own product/technology and with that of its rival, δ_i and δ_{-i} respectively. We assume that δ_i and δ_{-i} are not revealed to firm $-i$, which would only learn their

[2]The process of target's discovery can be further generalized by allowing p_b and p to be incumbent-specific. The only necessary assumption is that $p_b < 1$ and $p < 1$ for both incumbents.

realizations if it discovers the target itself in the future. This assumption is based on the idea that private information held by the target and by one of the incumbents regarding the complementarity gains from acquiring the target cannot be verified by the other incumbent.

2.1.4 Merger offers

If the target is discovered by firm i in period t, it may receive an acquisition offer. (The target may receive two offers in period t if both incumbents discover it at or before t). If the target decides to accept the offer, its product/technology is transferred to the acquiring firm and the target ceases to exist as an independent entity. At that point, the realizations of complementarity with the incumbents become public knowledge. If the target decides to reject the offer(s) at time t, it remains in play and may receive future offers from the same firm and/or the other firm once it discovers the target.

As a result, at time t the market can be in any one of the three mutually exclusive states, S_t: the target was acquired by firm 1 ($S_t = 1$); the target was acquired by firm 2 ($S_t = 2$); and the target has not been acquired yet ($S_t = 0$). Given our assumptions on the production functions, we can write each firm's per-period profit (conditional on the target's product/technology not being obsolete) as a function of current industry structure: $\pi_i(\gamma, S_t)$, such that $\pi_i(\gamma, i) > \pi_i(\gamma, 0) > \pi_i(\gamma, -i)$. To simplify notation, we will sometimes write $\pi_i(S_t)$ instead of $\pi_i(\gamma, S_t)$.

2.2. Solution

We solve the model by determining 1) the highest offer price that a firm that discovered the target at or before period t could offer, depending on the realizations of its own and its rival's complementarities with the target and on whether the rival has also discovered the target by period t, and 2) the target's reservation price above which it would accept that offer.

In what follows, we refer to the incumbent with the higher complementarity parameter as the "complementary bidder" and the incumbent with the lower complementarity parameter as the "non-complementary bidder". Without loss of generality, we assume that firm 1 is the complementary bidder and firm 2 is the noncomplementary one, $\delta_1 > \delta_2$. The comparison of the reservation prices of the incumbents and the target results in the '*equilibrium complementarity threshold*. This threshold determines the value of the complementarity parameter of the noncomplementary bidder above which it is able to give the target an acquisition offer that the target would accept in equilibrium.

2.2.1 Both firms discover the target simultaneously

If both firms discover the target simultaneously at time τ, a bidding war ensues. The benefit to firm i from acquiring the target, i.e. firm i's reservation price, is

$$B_{i_{both}} = \sum_{t=\tau}^{\infty} \frac{(1-\psi)^{t-\tau}(\pi_i(i) - \pi_i(-i))}{(1+r)^{t-\tau}} = (\pi_i(i) - \pi_i(-i))\,\frac{1+r}{r+\psi}. \tag{1}$$

The bidding war is always concluded at time τ by an acquisition of the target by one of the incumbents. The intuition is as follows. No new information regarding the realizations of target's complementarities with the two incumbents is revealed to the incumbent after time τ as long as the target's product/technology do not become obsolete. The target's expected present value to each of the two incumbents in the next period is lower than that in the current period (both because of discounting and because of obsolescence risk). As a result, there are no benefits for postponing the resolution of the bidding war.

In this scenario, the benefit from acquisition of the target by firm i is computed relative to the situation in which firm $-i$, acquires the target. This benefit to firm i is the infinite sum of per-period profits conditional on merger with firm i net of firm i's per-period profits conditional acquisition of the target by firm $-i$, accounting for the fact that this difference may become zero with probability ψ starting from any period $t > \tau$ in which the target's product/technology becomes obsolete.

The next result shows that the complementary bidder always gains more from the merger than the noncomplementary one, relative to the situation in which the target is taken over by the other incumbent.

Lemma 1. $\pi_1(1) - \pi_1(2) > \pi_2(2) - \pi_2(1)$.

Since the complementary bidder gains more from the merger than the noncomplementary one in every period, the former ends up acquiring the target. The surplus from this acquisition is the difference between the complementary bidder's reservation price, $B_{1_{both}}$, and the target's reservation price, which equals the noncomplementary bidder's reservation price, $B_{2_{both}}$. The division of the surplus, $B_{1_{both}} - B_{2_{both}}$ between the complementary bidder and the target depends on the target's bargaining power, ϕ, vis a vis the bidder, which can take any value, $0 < \phi \leq 1$. Target's bargaining power may be determined as an outcome of a Nash bargaining game (e.g., Alvarez and Stenbacka (2006) and Rhodes-Kropf and Robinson (2008)) or, alternatively, according to the target's Shapley value (e.g., Fulghieri and Sevilir (2011)). While the target's bargaining power determines the share of the merger surplus that it receives, it does not affect the outcome of the bidding war. In other words, in case of simultaneous discovery of the target by both bidders, the complementary bidder is always the one to acquire the target, and the acquisition price, P_{both}, equals

$$P_{both} = B_{2_{both}} + \phi \left(B_{1_{both}} - B_{2_{both}} \right). \tag{2}$$

2.2.2 Only one firm discovers the target

Assume now that in period τ only firm i discovers the target. We first compute the target's reservation acquisition price, i.e. the price at which the target is indifferent between being acquired in period τ and waiting to period $\tau + 1$. We then examine each incumbent's benefit of acquiring the target when the incumbent discovers it alone.

The target's reservation price

When discovered by just one firm, i, the target's reservation price solves the following equation:

$$T_{alone}(i) = (1 - \psi) \left((1 - p) \frac{T_{alone}(i)}{1 + r} + p \frac{P_{both}}{1 + r} \right). \tag{3}$$

The first term inside the brackets represents the scenario in which firm $-i$ does not discover the target in period $\tau + 1$. In that case, the target's period $\tau + 1$ reservation price equals $T_{alone}(i)$. The second term represents the case in which firm $-i$ discovers the target in period $\tau + 1$. If that happens, then the target is acquired at the price of an acquisition contest, P_{both}, given in (2). The target's expected reservation price is multiplied by the probability of its product/technology not becoming obsolete next period, $1 - \psi$.

Solving (3) for $T_{alone}(i)$ leads to the following target's reservation price:

$$T_{alone}(i) = \left(B_{2_{both}} + \phi \left(B_{1_{both}} - B_{2_{both}} \right) \right) \frac{p(1 - \psi)}{r + \psi + p(1 - \psi)}. \tag{4}$$

It follows from (4) that the target's reservation price is increasing in the likelihood of firm $-i$ discovering the target in the next period, p, since a higher probability of target's discovery by firm $-i$ raises the likelihood of acquisition contest. The target's reservation price is decreasing in its obsolescence risk, ψ, since higher obsolescence risk reduces the target's expected value next period.

The complementary bidder discovers the target first

Assume first that the complementary bidder (firm 1) discovers the target alone at time τ. The net benefit to firm 1 from acquiring the target immediately upon discovery in period τ for price $T_{alone,\tau}$ is

$$B_{1_{alone}} = -T_{alone}(1) + (\pi_1(1) - \pi_1(0)) + (1-\psi)\left((1-p)\frac{T_{alone}(1)}{1+r} + p\frac{P_{both}}{1+r}\right). \tag{5}$$

The first (negative) term on the right-hand side of (5) is the target's reservation price. The second term is the difference between the current-period profit conditional on acquiring the target net of the profit conditional on waiting. The third term is the target's discounted expected reservation price next period multiplied by the probability of the target's product/technology not becoming obsolete next period. Simplifying the bidder's net gain from acquiring the target in period τ leads to the following result:

Lemma 2. *If the complementary bidder is the only one to discover the target at time τ then it acquires the target at time τ for price $T_{alone}(1)$.*

Once the complementary bidder discovers the target, waiting until the noncomplementary bidder discovers it in the future, which would lead to a bidding war, becomes suboptimal. The reason is as follows. Although the complementary bidder always wins the bidding war, the total surplus from an immediate acquisition by the complementary bidder is larger than the expected surplus from possible acquisition in the future, both because of the obsolescence risk and due to the time value of money. Thus, waiting is Pareto-inefficient: There always exists an acquisition price that makes both the bidder and the target better off in the case of immediate acquisition.

In other words, the target trades off today's bid against next period's discounted value of expected bid. The latter is the weighted average of 1) today's reservation price multiplied by the likelihood of the target's product/technology not becoming obsolete next period and discounted by one period, and 2) the discounted bid by the complementary bidder in case its rival discovers the target next period and its product/technology is not obsolete by then. For the bidder, an additional part of this trade-off is an increase in period-τ profit relative to the no-merger case, $\pi_1(1) - \pi_2(0) > 0$.

The noncomplementary bidder discovers the target first

Assume now that the noncomplementary bidder (firm 2) is the only one to discover the target at time τ. The noncomplementary bidder's net benefit of acquiring the target in period τ is:

$$B_{2_{alone}} = -T_{alone}(2) + (\pi_2(2) - \pi_2(0)) + (1-\psi)\left((1-p)\frac{T_{alone}(2)}{1+r} + p\frac{B_{2_{both}}}{1+r}\right). \tag{6}$$

The difference between the net benefit from acquiring the target to the noncomplementary bidder in (6) and that to the complementary bidder in (5) is the last terms of the respective equations. Unlike the complementary bidder, which by acquiring the target at time τ avoids paying higher acquisition price, P_{both}, in the future, the savings to the noncomplementary bidder in the case of future takeover contest amount to the present value of the difference between its profits conditional on acquiring the target to those conditional on the target being acquired by the complementary bidder, $B_{2_{both}}$. Because of target's bargaining power, $\phi > 0$, the benefit to the complementary bidder is larger than that to the noncomplementary one, $P_{both} > B_{2_{both}}$, and the noncomplementary bidder's net benefit from acquiring the target immediately upon discovery is lower than that of the complementary bidder.

Simplifying the noncomplementary bidder's net benefit from acquiring the target at time τ leads to the following result.

Lemma 3. *If the noncomplementary bidder is the only one to discover the target at time τ then it acquires the target in period τ for $T_{alone}(2)$ if and only if its complementarity with the target, δ_2, exceeds the threshold $0 < \delta^*(\delta_1) < \delta_1$, which solves the following equation:*

$$\frac{\pi_2(2) - \pi_2(0)}{\pi_1(1) - \pi_1(2) - \pi_2(2) + \pi_2(1)} = \frac{p\phi\,(1-\psi)}{r+\psi}. \tag{7}$$

The numerator on the left-hand side of (7) is the difference between the noncomplementary bidder's current-period profit conditional on acquiring the target and its profit conditional on no merger. The denominator is the difference between 1) the net per-period benefit to the complementary bidder from acquiring the target relative to the case in which the noncomplementary bidder acquires the target, and 2) the net per-period benefit to the noncomplementary bidder from acquiring the target relative to the case in which the complementary bidder acquires the target. The left-hand side of (7) is monotonically increasing in the noncomplementary bidder's complementarity with the target, δ_2. In particular, the per-period benefit to firm 2 from acquiring the target relative to the situation in which the target remains in play (i.e. the numerator of the left-hand-side of (7)) is increasing in δ_2. The difference between the two bidders' per-period benefits of acquiring the target relative to the situation in which the rival bidder acquires it (i.e. the denominator of the left-hand-side of (7)) is decreasing in δ_2. The left-hand side approaches zero as $\delta_2 \longrightarrow 0$ and it approaches infinity as $\delta_2 \longrightarrow \delta_1$ (as in this case the denominator approaches zero). The right-hand side is finite. Therefore, there always exists $0 < \delta_2 < \delta_1$ for which the net benefit to the noncomplementary bidder from acquiring the target at time τ is higher than the target's reservation price. Thus, for any δ_1 and $\delta_2 < \delta_1$, if the target has not been acquired prior to time τ, there exists a non-zero probability that the noncomplementary bidder (firm 2) would acquire the target at time τ.

The intuition is simple. If the target rejects the noncomplementary bidder's merger offer, there are three possible scenarios in the next period. First, the target may be discovered by the complementary bidder, raising the equilibrium acquisition price. Second, the target's product/technology may become obsolete, making it worthless to both bidders. Third, the target may remain undiscovered by the complementary bidder, in which case the target's value in terms of today's dollars is reduced by a factor of $1/(1+r)$. The target's decision to accept or reject the noncomplementary bidder's best offer depends on the tradeoff between the benefits of the first possibility on one hand and the costs of the last two possibilities on the other hand. Lower likelihood of discovery by the complementary bidder along with higher obsolescence risk and discount rate discourage the target from waiting and increases its willingness to merge with the noncomplementary bidder.

2.3. Expected merger inefficiency and the likelihood of inefficient merger

The goal of this paper is to examine the determinants of the *likelihood of inefficient mergers* and *expected inefficiency in observed mergers.* Our definition of an (in)efficient merger is as follows.

Definition 1. An acquisition of a target by firm i upon its discovery at time τ is (in)efficient if the combined value of firm i, the target, and firm $-i$, which does not acquire the target, is higher (lower) than their combined value if incumbent $-i$ would acquire the target at time τ.

The next result shows that the merger between the target and the complementary bidder is efficient, whereas the acquisition of the target by the noncomplementary bidder is inefficient.

Lemma 4. *The combined values of the two incumbents and the target at time τ is higher if the complementary bidder (1) acquires the target at time τ than if the noncomplementary bidder acquires the target at time τ.*

The friction that leads to the possibility of inefficient mergers is the non-verifiability of bidder's information about the complementarity parameters of the target. In other words, the incumbent that discover the target first cannot share the complementarity parameters it has learned with the other incumbent. If this information were verifiable, gains from trade could be obtained. In particular, there would exist a price at which the noncomplementary bidder and/or the target would transmit their information regarding the target's complementarity parameters to the complementary bidder, making efficient merger possible.

We now define formally the expected merger inefficiency and the likelihood of observing an inefficient merger. Let us define a function $\upsilon(\delta_2, \delta_1)$, which measures the degree of inefficiency when a bidder with complementarity δ_2 acquires the target in the presence of complementary bidder with complementarity δ_1, such that $\frac{\partial \upsilon(\delta_2,\delta_1)}{\partial \delta_2} < 0$ and $\upsilon(\delta_1,\delta_1) = 0$. Merger inefficiency is increasing as the bidder's complementarity parameter with the target decreases, and the inefficiency of a merger between the target and the bidder with complementarity parameter δ_1 equals zero.

Expected merger inefficiency conditional on observing a merger, $\mathbb{E}(\upsilon)$, is given by

$$\mathbb{E}(\upsilon) = \int_0^{\overline{\delta}} f_{\max}(\delta_1) \frac{p_b (1 - p_b) \Psi(\delta_1)}{p_b + p_b (1 - p_b) \Gamma(\delta_1)} d\delta_1, \tag{8}$$

where

$$\Psi(\delta_1) = \int_{\delta^*(\delta_1)}^{\delta_1} f_{\min}(\delta_2) \upsilon(\delta_2, \delta_1) d\delta_2, \tag{9}$$

$$\Gamma(\delta_1) = \int_{\delta^*(\delta_1)}^{\delta_1} f_{\min}(\delta_2) d\delta_2 = F_{\min}(\delta_1) - F_{\min}(\delta^*(\delta_1)), \tag{10}$$

and

$$f_{\max}(\delta) = 2F(\delta) f(\delta), \tag{11}$$

$$f_{\min}(\delta) = 2f(\delta)(1 - F(\delta)), \tag{12}$$

$$F_{\min}(\delta) = 2F(\delta) - F^2(\delta). \tag{13}$$

The intuition behind the definition of expected merger inefficiency (8) is as follows. The probability of observing a merger in any given period is the sum of the probability of the target's discovery by the complementary bidder (firm 1), p_b, and the probability with which the noncomplementary bidder (firm 2) discovers the target alone, which equals $p_b(1 - p_b)$, multiplied by the conditional likelihood of the merger with firm 2, which equals $\Gamma(\delta_1)$ for any given δ_1. An inefficient merger occurs if two conditions are satisfied. First, the noncomplementary bidder has to discover the target alone, which happens with probability $p_b(1 - p_b)$. Second, the complementarity of the noncomplementary bidder has to be high enough relative to that of the complementary bidder to enable the noncomplementary bidder to make an offer that the target would accept. The conditional merger inefficiency is $\Psi(\delta_1)$ for a given δ_1.

It follows from this discussion that the likelihood of inefficient merger is given by

$$prob(ineff) = \int_{\underline{\delta}}^{\overline{\delta}} f_{\max}(\delta_1) \frac{p_b (1-p_b) \Gamma(\delta_1)}{p_b + p_b (1-p_b) \Gamma(\delta_1)} d\delta_1. \tag{14}$$

The numerator of (14) is the probability of the target being discovered by the noncomplementary bidder with a sufficiently high complementarity parameter, $\delta_2 > \delta^*(\delta_1)$. The denominator is the sum of two probabilities: the probability of discovery by the complementary bidder and the probability of discovery by only the noncomplementary bidder multiplied by the probability of a merger conditional on the discovery by only the noncomplementary bidder.

Note that the probabilities of the target's discovery by the two incumbents are conditional on δ_1. In particular, the p.d.f. of δ_1, $f_{\max}(\delta)$, is the p.d.f. of the supremum of two independent identical distributions, as in (11); the p.d.f. of δ_2, $f_{\min}(\delta)$, is the p.d.f. of the infimum of two independent identical distributions, as in (12); and $F_{\min}(\delta)$ in (13) is the c.d.f. of the infimum of two independent identical distributions. Integrating over the distribution of δ_1 leads to the expected merger inefficiency in (8) and the likelihood of inefficient merger in (14).

2.4. Comparative statics

Partially differentiating expected merger inefficiency, $\mathbb{E}(\upsilon)$ in (8), and the probability of inefficient merger, $prob(ineff)$ in (14), with respect to the model's parameters, leads to the following results.

Proposition 1. *Expected merger inefficiency, $\mathbb{E}(\upsilon)$, and the likelihood of inefficient merger, $prob(ineff)$, are increasing in the target's obsolescence risk, ψ.*

Higher obsolescence risk lowers the value of potential gains in future periods relative to the current period and reduces the target's willingness to wait and, thus, its reservation price, leading to lower complementarity threshold in equilibrium. The lower this threshold, the higher the likelihood that the noncomplementary bidder's complementarity with the target, δ_2, would exceed it. This leads to higher expected merger inefficiency and higher likelihood of observing inefficient merger.

Proposition 2. *Expected merger inefficiency, $\mathbb{E}(\upsilon)$, and the likelihood of inefficient merger, $prob(ineff)$, are decreasing in target's characteristics positively related to the probability of being discovered, y.*

Target's characteristics associated with the likelihood of its discovery by potential acquirers, y, have two effects on expected merger inefficiency. First, conditional on the discovery of the target by the noncomplementary bidder, the threshold complementarity, $\delta^*(\delta_1)$, implicitly defined in (7), is increasing in p, since the probability of target's discovery by the other incumbent next period is increasing in p. Since p is increasing in y, expected merger inefficiency is decreasing in y, conditional on initial discovery by the noncomplementary bidder. Second, the unconditional probability of target's discovery by the noncomplementary bidder alone relative to the probability of discovery by the complementary bidder is $1 - p_b$, thus decreasing in p_b as well. Therefore, the effect of y on $\mathbb{E}(\upsilon)$ and $prob(ineff)$ through its impact on the probability of discovery by the noncomplementary bidder alone is also positive.

If we impose additional structure on the type of interaction between potential bidders in the output market, in particular Bertrand competition in heterogenous products with linear demand and constant marginal costs, we can analyze the relation between the degree of competitive interaction, γ, and expected merger inefficiency. Assume that the demand for firms' products is linear, of the form

$$D(\eta_i, \eta_j) = a - b\eta_i + c\eta_j, \tag{15}$$

where η_i and η_j are firm i's and its rival's output market prices, $a = \frac{\mu(\beta-\gamma)}{\beta^2-\gamma^2}$, $b = \frac{\beta}{\beta^2-\gamma^2}$, and $c = \frac{\gamma}{\beta^2-\gamma^2}$. Such demand function obtains in a standard model of a representative consumer with quadratic utility

$$U(q_i, q_j) = \sum_{i=1}^{k} \mu q_i - \frac{1}{2}\left(\beta \sum_{i=1}^{k} q_i^2 + 2\gamma \sum_{j \neq i} q_i q_j\right), \tag{16}$$

where q_i and q_j are quantities consumed of products produced by firms i and j. In this setting, to ensure stability of equilibrium, γ is bounded by 0 and β. Assume also constant marginal cost, s_i for firm i, which is affected by the merger between firm i and the target: $\frac{\partial s_i}{\partial \delta_i} < 0$. Under these assumptions, we obtain the following relation between the degree of competitive interaction between the incumbents, γ on one hand and $\mathbb{E}(\upsilon)$ and $prob(ineff)$ on the other hand:

Proposition 3. *There exists a value of the competitive interaction parameter, $\gamma^* < \beta$, above which expected merger inefficiency, $\mathbb{E}(\upsilon)$, and the likelihood of inefficient merger, $prob(ineff)$, are decreasing in the degree of competitive interaction, γ.*

The intuition is that for sufficiently strong competitive interaction between incumbents, increasing it further amplifies the effect of acquisition of the target by an incumbent on the other incumbent's per-period profit. Thus, the larger the γ, the larger each incumbent's net per-period benefit of an acquisition, which is the difference between that incumbent's per-period profit conditional on acquiring the target and that conditional on the target being acquired by the other incumbent. It follows that the target's price in the case of takeover contest in (2) is increasing in γ. Thus, the higher the degree of competitive interaction between potential bidders, the higher the target's willingness to wait for potential takeover contest. This, in turn, increases its reservation price in the case it is discovered by just one bidder, and results in higher complementarity threshold required for the acquisition of the target by the noncomplementary bidder, δ_2. This leads to negative relation between γ on one hand and expected merger inefficiency and the probability of observing inefficient merger on the other hand, for sufficiently high level of γ.[3]

There are other comparative statics that follow from the model. The first one is the relation between the discount rate, r, and expected merger inefficiency. It is easy to show that the effect of r on expected merger inefficiency is positive. We do not focus on this relation, since it does not lead to cross-sectional empirical predictions. However, this comparative static is consistent with Rhodes-Kropf and Robinson (2008), who argue that low discount rates proxy for low search costs, which are associated with more assortative matching (i.e. lower merger inefficiency). The second comparative static is the negative relation between target's bargaining power, ϕ, and expected merger inefficiency. While it is hard to measure target's bargaining power empirically, it is plausible that it is decreasing in target's obsolescence risk, reinforcing the positive relation between the latter and expected inefficiency of a merger involving the target.

Table 1 summarizes the comparative statics described in Propositions 1-3. In the next two sections, we discuss the empirical proxies for the degree of merger inefficiency and the model's parameters, and perform empirical tests of the comparative statics summarized in Table 1.

3. Data and variables

3.1. Mergers and acquisitions data

The data on mergers and acquisitions are obtained from Thomson Financial's SDC Database. We start by retrieving information on all completed deals during the period 1980–2012, in which the acquirer is a publicly-traded U.S.-based firm. We then limit our sample to U.S.-based targets (including public, private, and subsidiaries), and acquisitions of at least 50% of the target firm's shares. We further require that the deal is completed within 1,000 days of the announcement, and that the transaction value is at least $1 million. Finally, we retain acquirers with available CRSP/Compustat link and asset values (in dollars of 2011) of at least $1 million.

[3]Similar result obtains under heterogenous products Cournot competition.

Table 1: Summary of comparative statics

Model parameter	Effect on expected merger inefficiency
ϕ (target's obsolescence risk)	$+$
y (target's characteristics related to probability of its discovery)	$-$
γ (degree of competitive interaction)	$-$ (above γ^*)

3.2. Measures of merger inefficiency

In our setting, an acquisition of a target by a bidder is inefficient if there exists a firm (counterfactual bidder) whose products/technologies are more complementary with those of the target. Thus, low complementarity of the target with the actual bidder relative to complementarity of the target with the most complementary counterfactual bidder translates into high merger inefficiency.

Measuring the degree of merger complementarity is a notoriously difficult task. Existing studies (e.g., Hoberg and Phillips (2010) and Bena and Li (2014)) propose measures of merger complementarity that are based on *similarity* of bidder's and target's product descriptions or patent portfolios. While conceptually it is plausible that unrelated product/technologies may be complementary, existing evidence supports the use of product and/or technology similarity as measures of complementarity. Hoberg and Phillips (2010) and Bena and Li (2014) show that mergers between related firms tend to result in better post-merger performance than mergers between less related ones, consistent with the link between product and/or technology similarity and merger complementarity. In addition, a large body of industrial organization literature uses industry-specific settings, such at pharmaceutical research and drug development (e.g., Henderson and Cockburn (1996)) or market for cereal (e.g., Nevo (2000)), to show that related products and technologies generate complementarities.

To zero in on the relation between similarity and complementarity in the context of our model, we examine whether bidder-target similarity differs between successful and failed takeover bids. According to our model, a bidder with higher complementarity with the target wins the takeover contest. Therefore, if similarity is a good proxy for complementarity, we should observe higher similarity between targets and winning bidders, compared to that between targets and losing bidders. Consistent with this hypothesis, we find that in takeover contests, the products of winning bidders are more closely related to targets' products than products of losing bidders. In other words, bidders with a stronger relation to targets are willing to pay more than bidders whose relation to targets is weaker, supporting the conjecture that similarity between bidder and target is positively associated with merger complementarity. Takeover contests are an especially suitable laboratory for examining whether similarity is positively associated with complementarity ceteris paribus, since in takeover contests all bidders have already discovered the target. As a result, in this setting the concern that more related targets are easier to discover by more complementary bidders is eliminated. The construction of the takeover contest sample is described in detail in Section 3.4.1 below.

In light of the discussion above, we base our measures of merger inefficiency on similarity between bidders and targets. We employ two independent approaches to estimate the degree of merger inefficiency and to construct proxies for the model's parameters. In the first approach, we estimate merger inefficiency by comparing similarity of a target to actual and counterfactual bidders, where similarity is estimated using text-based analysis of firms' product descriptions, as proposed by Hoberg and Phillips (2010). Our second approach to estimating firms' pairwise similarities relies on Bena and Li (2014), who utilize patent information from NBER Patent Citations data, and define pairwise similarity as the overlap between bidders' and targets' patent portfolios.

The advantage of the analysis based on firms' product descriptions is that data are available for 97% of Compustat firms, operating in a wide spectrum of industries. The drawback is that product descriptions are obtained from firms' 10-K filings, which are only available for publicly-traded firms. The benefit of patent-based data is that they contain information on patent activity of private as well as public firms. The disadvantage of the patent-based sample is that the data are limited to firms that generate patents and do not include industries and firms that by nature of their business do not have patents. Due to data availability, the two types of measures can be constructed over different, partially overlapping, sample periods, which mitigates the concern that our results may be driven by merger waves that dominate one or the other sample period (e.g., Mitchell and Mulherin (1996), Maksimovic and Phillips (2001), Rhodes-Kropf, Robinson and Viswanathan (2005) and Ahern and Harford (2014)). Since each approach has its benefits and shortcomings, and in order to enhance the robustness of our results, we perform all the empirical analyses using each dataset separately. We provide detailed descriptions of each approach and its corresponding datasets in the next two subsections.

3.2.1 Product-description-based data

To estimate product similarity among firms, we use data from Hoberg and Phillips (2010). Their approach relies on 10-K product descriptions from the Securities and Exchange Commission website (Edgar) for the period 1996–2011. They translate all non-common words in each product description into a unit-length vector and compute every year cosine similarity between vectors of product descriptions of each pair of Compustat firms. The resulting text-based similarity measure ranges between zero and one. Intuitively, the higher the proportion of common words in product descriptions of two firms, the more related the products of the two firms.[4]

To compute merger inefficiency, we first obtain similarity scores for every target (i)–bidder (j) pair for the year preceding the merger year, which we denote by $\rho_{i,j}$. To ensure that our sample does not include unrelated mergers driven by agency, value extraction, and other considerations unrelated to complementarities, we exclude all cases in which the similarity between the bidder and target is strictly zero. Second, we calculate the similarity score of the target firm with every firm in Compustat, and pick the firm with the highest score, which we consider to be the bidder whose (hypothetical) acquisition of the target would be classified as efficient merger. We then scale the similarity score of the target with the actual bidder by the similarity score of the target and the most related hypothetical bidder, subtract the resulting ratio from one, and use the result as the product-description-based measure of inefficiency in a merger involving target i, $\Theta prod_i$:

$$\Theta prod_i = 1 - \frac{\rho_{i,j}}{\sup\left(\rho_{i,1}, \ldots\rho_{i,k}, \ldots\rho_{i,K}\right)} \forall k, \tag{17}$$

where K is the number of Compustat firms in a given year. $\Theta prod_i$ ranges between zero and one (excluding strict one), where the value of zero indicates that the actual bidder is the efficient one, and higher values of $\Theta prod_i$ correspond to higher degrees of merger inefficiency.

3.2.2 Patent-based data

To construct a patent-based proxy for merger inefficiency, we first match publicly-traded targets and bidders to their patent assignee numbers (PDPASS) using the dynamic assignee matching file, provided by NBER. To include private targets, we match their names in SDC with standardized assignee names from the patent database. To increase the likelihood of a correct match, we use all possible spellings of assignee names, available in the NBER database, and standardize spellings and abbreviations of commonly used words (such as “Technology” (Tech), “Information” (Info) and “Chemical” (Chem))

[4]We are grateful to Gerard Hoberg and Gordon Phillips for sharing the data with us.

before implementing the matching procedure. We match the names of target firms and assignees based on the similarity of the first two words of the name, and manually screen the results to filter cases of unrelated links.

To validate the goodness of the match and to resolve ambiguous cases, we rely on city and state information of patent assignee and the target, as well as the target's business description from SDC. In some cases, we find that a private target is a subsidiary, a division, or a unit of a larger firm, which has patents in the NBER database. While patent characteristics of the overall firm could provide some general information regarding the similarity of its specific division with the bidder, it is unclear which subset of patents is transferred to the acquiring firm as part of the merger deal. Therefore, we exclude these cases, and restrict the sample to matches in which assignee name represents the scope of the target's business.

To construct a measure of similarity between two PDPASS numbers, for every PDPASS we obtain information on all the patents granted within a 5-year period prior to the year of the observation.[5] In particular, for each patent we observe the technology field in which the patent was granted, defined according to one of the 36 two-digit technological subcategories developed by Hall, Jaffe, and Trajtenberg (2001). For each firm i in year t, we convert its patent portfolio into a vector $P_{i,t} = [P_{i,t,1}, ..., P_{i,t,k}, ...P_{i,t,K}]$, where $k = 1, ..., K = 36$ are 2-digit technological subcategories. $P_{i,t,k}$ is the proportion of the number of patents awarded to firm i in years $t-5$ to $t-1$ in class k out of all patents awarded to firm i in years $t-5$ to $t-1$. In the spirit of Jaffe (1986) and Bena and Li (2014), we calculate patent-based similarity of firms' i and j in year t, $Patsim_{i,j,t}$:

$$Patsim_{i,j,t} = \sum_{k=1}^{K} \min[P_{i,t,k}, P_{j,t,k}] \in [0, 1]. \tag{18}$$

If $Patsim_{i,j,t}$ equals one, then firms i and j have the exact same proportions of patents across the 36 technology fields. On the other hand, if $Patsim_{i,j,t}$ equals zero, then the two firms do not share any patents in two-digit technological subcategories.[6]

It is possible that a firm has multiple PDPASS numbers due to different name spellings and hierarchical structure. Thus, after we obtain pairwise similarities at a PDPASS level, we aggregate them at a firm level by assigning the highest patent-based similarity score among all combinations of the two firms' PDPASSes as the pair's similarity score. This aggregation method is based on the idea

[5] Benner and Welldfogel (2008) show that measures of similarity between firms with few patents are both biased and noisy. They propose that aggregating patents across years mitigates these problems.

[6] Jaffe (1986) and Bena and Li (2014) define the measure of similarity as $Patsim_{i,j,t} = \frac{\sum_{k=1}^{K} P_{i,t,k} P_{j,t,k}}{\sum_{k=1}^{K} P_{i,t,k} \sum_{k=1}^{K} P_{j,t,k}}$. The correlation between this measure and our measure is in excess of 90%.

that a separate PDPASS represents a unit, or division, of a firm. If a multi-divisional firm allocates resources in an efficient way, it should derive the highest gain from matching the target with its most complementary unit. The ability to measure division-level similarity partially addresses the concern that multi-divisional firms may have low average similarity with targets, but the similarity of some of their specific divisions with targets may be high.

As in the case of product-based merger inefficiency, we scale the similarity of the actual bidder-target pair by the highest similarity of the target with any other firm, subtract this ratio from one, and use the result as the patent-based measure of merger inefficiency, Θpat_i:

$$\Theta pat_i = 1 - \frac{Patsim_{i,j,t}}{\sup\left(Patsim_{i,1}, ...Patsim_{i,k}, ...Patsim_{i,K}\right)} \forall k, \tag{19}$$

where K is the total number of firms that were granted patents in years $t-5$ to $t-1$. As in the case of product-based similarity, $\Theta pat_i = 0$ corresponds to efficient merger, and the degree of inefficiency is increasing in Θpat_i.

3.3. Determinants of expected merger inefficiency

3.3.1 Target's obsolescence risk

The first prediction of the model is that expected merger inefficiency increases in target's obsolescence risk, ψ, since higher obsolescence risk discourages the target from waiting to be discovered by a more complementary bidder in the future. In what follows, we describe our proxies for target's obsolescence risk within the two datasets that we use in the empirical tests.

Product–based data

We use the venture capitalist (VC) activity in the target's industry as a proxy for target obsolescence risk. Venture capitalists play an important role in picking firms with potential for innovation, and help these firms to advance further through financing their R&D and new product development (e.g., Hellmann and Puri (2000), Engel and Keilbach (2007), and Peneder (2008)). Therefore, the higher the level of VC activity within a certain industry, the larger the risk that a VC-backed firm would develop a product/technology superior to that of the existing target, potentially making the target's product/technology obsolete.[7]

[7] The scope of VC activity is determined not only by the arrival of new start-ups, but also by the levels of funding available to VC firms. Since the availability of capital is primarily driven by overall economic conditions, we include year dummy variables in all our regressions to capture time-series trends.

To measure the level of VC activity, we use MoneyTree reports, which provide quarterly information on venture capital activity in the U.S. The reports are managed by PriceWaterhouseCoopers and are based on information from Thomson Reuters.[8] We calculate the number of deals by venture capitalists in a given industry-year, and use it as a proxy for the number of firms that have reached an advanced stage of their product development.

The industry-level VC activity variable is constructed as follows. First, we collect the number of deals involving investments in firms at the expansion stage (i.e. firms that are active for more than three years, show revenue growth, but do not necessarily have profits) at the industry level (MoneyTree defines 16 industries). Second, we obtain all VC deals from Thomson Reuters and construct a mapping bridge between 4-digit SIC industries and MoneyTree industries. For every target, we use the natural log of one plus the number of deals in the industry that corresponds to its 4-digit SIC code.[9]

Patent–based data

Since venture capital data from our data source are available only from 1996, they are not well suited for the patent sample, which spans years 1976–2006. Instead, following Pakes and Schankerman (1979) and Grabowski and Vernon (1990), we use the number of patents that the target was granted during the 5-year period prior to the merger year as an inverse measure of target's obsolescence risk. The idea is that the more patents the target has generated in the past, the broader its technological portfolio, and the more difficult it is to make its technology obsolete.

3.3.2 Probability of target's discovery

The second prediction of the model is that expected merger inefficiency is decreasing in target's characteristics associated with the likelihood of its discovery. As described in Section 2, our discoverability definition is broad, and includes a variety of possible scenarios. Thus, the bidder could be aware of the target's existence, but not have the resources required to evaluate its complementarity. This can happen, for example, if the M&A team is busy finalizing another merger deal or analyzing a different acquisition candidate. Another, possibly broader, interpretation of target discoverability is the target's opaqueness to outside investors. Thus, it may be possible that the target has technological potential, but it is difficult for potential bidders to evaluate its value.

[8] We obtain the reports from MoneyTree website at https://www.pwcmoneytree.com/MTPublic/ns/index.jsp.

[9] In cases where 4-digit SIC industries corresponds to several MoneyTree industries, we average the VC activity across the SIC industries.

Product–based data

We use the number of analysts following the target as a proxy for its discoverability. Investment analysts have the ability to reduce information asymmetry by producing information about the value of the firm (e.g., Brennan and Subrahmanyam (1995); Hong, Lim, and Stein (2000); Frankel and Li (2004)). Thus, a higher number of analyst forecasts is expected to be positively related to target's discoverability. To construct the measure, we use the I/B/E/S database and calculate the number of distinct analysts that have produced at least one annual forecast of firm performance during the three-month window prior to the fiscal year-end. Our discoverability measure is the logarithm of one plus the number of analysts.

Patent–based data

Since I/B/E/S database covers only public firms, we cannot use the number of analysts when constructing a patent-based proxy for target discoverability. To capture the aspects of target discoverability in a way that is consistent with the information asymmetry channel, we construct a dummy variable that equals one if the target is publicly-traded, and zero if it is privately-held or a subsidiary. Annual and quarterly reports of financial performance of public firms are the key source of information to market participants, substantially reducing the degree of information asymmetry. Therefore, we expect public firms to be more less opaque and more discoverable than the private ones.

3.3.3 Degree of competitive interaction

The third prediction of the model is that merger inefficiency is likely to be decreasing in the degree of competitive interaction among potential bidders, γ. The reason is that γ raises the target's price in the case of takeover contest, increasing the target's willingness to wait for discovery by the complementary bidder, which, in turn, would lead to a contest.

Product–based data

We measure the degree of a bidder's competitive interaction with its competitors as the average similarity between bidder's product description and those of other firms operating in the bidder's industry. To identify industries, we use Text-based Network Industry Classification (TNIC) (see Hoberg and Phillips (2010)). This classification defines an industry for each firm by picking all the peers with positive pairwise similarity with that firm. The advantage of this approach is that it overcomes some limitations of the SIC and NAICS classifications[10] and takes into account competition among

[10] SIC and NAICS classifications suffer from a number of limitations. First, they are based on production processes, not on products that firms supply. Second, they are static, in the sense that they are rarely adjusted over time in the

firms that have traditionally been assigned into different SIC or NAICS industries (e.g., publishing and broadcasting; or electronic components and software industries). Specifically, for each bidder we average all the pairwise similarity within its industry. The higher the average similarity, the more substitutable the products within a given industry. Higher substitutability increases the degree of competitive interaction, as well as the benefit for any bidder from acquiring the target relative to the situation in which the target is acquired by another potential bidder.

Patent–based data

Since product-description-based measures of similarity are only available starting from 1996 and are limited to public firms, we construct an alternative measure of the degree of competitive interaction. Our (inverse) proxy is based on patent breadth in each patent subcategory. The wider the patent category, the less related the patented products within the associated technology field. As a result, there is higher differentiation potential within the field, and lower degree of competitive interaction.

Our inverse measure of the degree of competitive interaction is constructed as follows. For every bidder, we first identify its three major technological subcategories. Specifically, we take all patents that the bidder was granted in the 5-year period prior to the year of the merger, allocate them into technological categories, and pick the three most frequent ones. Separately, every year we calculate the number of patents that were granted in each two-digit patent subcategory within the overall sample of non-withdrawn or missing patents that belong to corporations.[11] Then for each bidder we average the overall number of patents granted in each of its top three patent subcategories in the past 5 years. The natural logarithm of this average is the measure of patent breadth in the bidder's top technology fields. The higher the patent breadth, the more widespread the product categories in which the bidder operates, and the lower the expected degree of competitive interaction between the bidder and its peers.[12]

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face of evolving product markets and/or firms entering different industries. Third, SIC and NAICS classifications impose transitivity, while it is possible that two competing firms may have different product market rivals.

[11] We count both U.S. and non-U.S.-based corporations. We also include patents with missing values for assignee type.

[12] Our results are robust to using an alternative measure of competitive interaction, which we obtain by averaging patent-similarity-based measure across all the bidders' peers. To define peers, we look at all the firms that have positive measure of patent-based similarity with the bidder. Next, we average pairwise similarity measures of the bidder with its peers, and use it as an alternative measure of competitive interaction.

3.4. Summary statistics

3.4.1 Product-based data

Table 2 shows the distribution of merger inefficiency measures, as well as the distributions of proxies for the model's parameters. We also present descriptive statistics of bidder and target characteristics that we use as control variables. The final sample includes 1,665 observations with non-missing values of merger inefficiency.

Insert Table 2 here

The mean (median) of the dependent variable, merger inefficiency, is 0.47 (0.5), with a standard deviation of 0.31, and it ranges through its entire possible spectrum (0 to 0.9996). In the second and third rows of the table we report summary statistics of merger inefficiency in takeover contests. To construct the sample of takeover contests, we extract all deals in which the target is a U.S.-based firm; deal status is recorded as "Completed" or "Withdrawn"; and the bidder acquired or intended to acquire at least 50% of the target's shares. We refine the bidding event window by requiring that the announcement date of each bid falls within a 365-day window of the deal completion. If a bidder submits multiple bids for the same target within that time window, we consider the earliest date of the bid submission as the valid one. Following Malmendier, Moretti and Peters (2014), we exclude bidders that are white knights, as well as all cases in which the winner is the target's ultimate or immediate parent company, as those could not be considered equal contestants in the bidding wars. After applying all the filters, and merging the SDC data with CRSP and Compustat, we obtain a sample of 62 cases of bidding wars, where both the bidder and target are publicly traded. In 40 of these cases we can estimate the inefficiency of both the actual mergers and the counterfactual acquisitions of the target by failed bidder(s).

Lemma 2 shows that in the case of a takeover contest, the bidder with the highest complementarity with the target acquires it in equilibrium. Consistent with this result, the mean value of inefficiency in actual mergers is 0.4, which is almost half the mean inefficiency in counterfactual acquisitions of targets by bidders that lose the contests, 0.7. The difference is also statistically significant at 1% level (not reported). This result demonstrates that bidding wars lead to more efficient mergers. This finding provides further evidence that product-description-based similarity is a good proxy for merger complementarity and as a result, for merger inefficiency.

The log rate of VC activity in the industry, which serves as a proxy for target's obsolescence risk, is 4.67 and it exhibits considerable variation – its standard deviation is 0.67. The mean (median) logarithm of one plus the number of analysts, which proxies for target's discoverability, is 1.32 (1.39) and its standard deviation is 0.96. Thus, the average (median) number of analysts following a certain target is 4.85 (3). The average (median) product-description-based similarity of product descriptions of bidders and those of firms in their TNIC industries – our proxy for the degree of competitive interaction between the bidder and its industry competitors, is 0.05 (0.04). Summary statistics for the control variables are similar to the ones reported in M&A studies that use Compustat-based samples.

Table 3 shows the correlation matrix of the product-description-based merger inefficiency measure, our proxies for model parameters, and control variables.

Insert Table 3 here

The correlations among the proxies for the model's parameters are low – they range between 0 and 0.23 in absolute value, suggesting that each of them captures different information about the bidder, target, and their competitive environment. On the other hand, there is relatively high correlation between bidder's and target's characteristics (0.60 in the case of the market-to-book ratio, 0.86 in the case of tangibility, and 0.39 in the case of profitability), consistent with the "like buys like" theory of Rhodes-Kropf and Robinson (2008).

3.4.2 Patent-based data

Table 4 shows the descriptive statistics of the patent-based measure of merger inefficiency, our proxies for model's parameters, and control variables. The correlation matrix is presented in Table 5.

Insert Table 4 here

The patent-based sample has 1,319 observations. The distribution of the patent-based measure of merger inefficiency is similar to that of the product-based measure. The mean (median) patent-based inefficiency measure, Θpat_i, is 0.46 (0.48) and its standard deviation is 0.3, indicating substantial heterogeneity. The inverse measure of target's obsolescence risk, log of target's patents in the past five years, exhibits considerable variation: the minimum number is 0.69 (1 patent), while the maximum is 7.88 (2,644 patents). Half of our target firms are publicly-traded. The breadth of technological fields, which serves as an inverse proxy for the degree of competitive interaction the bidder is exposed to, also exhibits substantial heterogeneity: it ranges between 0 and 8.5 with standard deviation of 0.97.

Insert Table 5 here

As evident from Table 5, the correlations among the proxies for the model's parameters, which range between 0.03 and 0.28 in absolute value, are relatively modest, as are the correlations among control variables, which do not exceed 0.26 in absolute value.

4. Empirical results

4.1. Empirical specification

To test the predictions of our model regarding the determinants of relative complementarity in mergers, we estimate the following regression:

$$\Theta_i = \alpha + \beta_\psi \psi_i + \beta_y y_i + \beta_\gamma \gamma_i + \overrightarrow{\beta_B}' \overrightarrow{B_i} + \overrightarrow{\beta_T}' \overrightarrow{T_i} + \varepsilon_i. \tag{20}$$

Θ_i is a measure of inefficiency in merger i ($\Theta prod_i$ in the case of product-description-based data and Θpat_i in the case of patent-based data). ψ_i is a measure of target's obsolescence risk (VC activity (product-based data) or target's patent intensity (patent-based data)). y_i is target's characteristic related to the likelihood of being discovered (logarithm of the number of analysts in product-description-based data, and a publicly-traded indicator in the patent-based data). γ_i is the degree of competitive interaction among potential bidders (computed based on average product-description-based similarity between the bidder and its product market competitors or based on the average breadth of bidder's main technology fields). $\overrightarrow{B_i}$ is a vector of bidder's characteristics that serve as controls (size, market-to-book, tangibility, and profitability) and $\overrightarrow{T_i}$ is a vector of controls for target's characteristics (market-to-book, tangibility, and profitability). We estimate the regression in (20) using year fixed effects. Standard errors are computed using variance-covariance matrix adjusted for clustering at firm level (see Petersen (2009)).

4.2. Product-based analysis

Table 6 presents estimates of (20) using product-description-based data and variables. In the first column, we estimate (20) using only the proxies for the model's parameters. In the second column, we augment (20) by including control variables for the bidder, while in the third column, we also add control variables for the target. In columns 4-6, we regress our measure of merger inefficiency on each of the three proxies for the model's parameters at a time, while excluding proxies for the other two parameters. These regressions serve two purposes. First, even though the correlations among the proxies for the model's parameters are relatively low, we would like to ensure that the signs of the coefficients on the variables of interest are not driven by potential multicollinearity. Second, we want to mitigate the impact of potential measurement errors, which may alter the magnitudes and signs of estimated coefficients.

Insert Table 6 here

Overall, the signs of the coefficients on all the variables of interest are consistent with the model's predictions, and the coefficients are statistically significant. Higher VC activity, proxying for target's obsolescence risk, is positively associated with merger inefficiency. The logarithm of the number of analysts, which captures the likelihood of target's discovery by bidders, is negatively related to merger inefficiency. Finally, higher similarity among potential bidders, proxying for the degree of competitive interaction among them, is also negatively related to merger inefficiency. All these results are consistent with the directional predictions of the model.

Importantly, the results are also economically significant. A one standard deviation increase in VC activity (0.67), which proxies for the target's obsolescence risk, is associated with an increase of 0.03 in merger inefficiency, an equivalent of almost 10% of its standard deviation. The impact of one standard deviation increase in the number of analysts – a proxy for the probability of target's discovery – is -0.06 (equivalent to 19% of the standard deviation of merger inefficiency). A one standard deviation increase in the measure of intensity of competitive interaction, γ, is associated with a decrease of 0.05 in merger inefficiency (equivalent to 17% of its standard deviation).

While most control variables, except bidder size and target profitability, are statistically insignificant, their inclusion helps address some concerns regarding alternative explanations for our results. For example, it is possible that inefficient mergers happen due to mispricing of target firms (e.g., Servaes (2001) and Shleifer and Vishny (2003)). In this case, a bidder may decide to acquire a firm with lower complementarity potential if it is relatively cheap. Adding target's profitability and market-to-book ratio to account for potential mispricing does not change the coefficients of the main variables of interest in a material way.

In Table 7 we examine the robustness of the main results by re-estimating the regression in (20) (including all the control variables) within different subsamples.

Insert Table 7 here

First, we examine whether our results are driven by potential market power effects of horizontal mergers (e.g., Eckbo (1983, 1985)). The concern is that high similarity between products of bidder and target operating in the same industry may lead to higher gains due to increased market power of the merged firm, even in the absence of complementarities in firms' production functions.

To mitigate the potential market power effect, we re-estimate our baseline regression within two subsamples. The first one is a sample of mergers between bidders and targets that operate in different four-digit SIC industries. The second is a sample of mergers involving targets operating in relatively competitive industries, where market power considerations are expected to be less important. In particular, we restrict the sample to bidders operating in TNIC industries in which the Herfindahl index is below median in a given year. The results are reported in the first two columns of Table 7. The coefficients on the main independent variables are similar to those in the full sample, suggesting that it is unlikely that the results are driven by market-power-motivated mergers, and that our merger inefficiency measure indeed captures non-market-power dimensions of complementarity between targets on one hand and actual and counterfactual bidders on the other hand.

Second, we address an alternative, agency-based explanation for our results, according to which inefficient mergers may be driven by empire-building considerations of entrenched managers, who acquire targets in unrelated industries (e.g., Amihud and Lev (1981)). If this is the case, then competitive interaction may serve a role of a disciplining device and reduce potential agency conflicts, leading to negative relation between competitive interaction and relative merger inefficiency, which is not driven by equilibrium pairing between bidders and targets that our model highlights. To address this concern, we use Bebchuk, Cohen and Ferrell's (2009) entrenchment index and re-estimate (20) for the subsample of acquiring firms with low agency problems, as defined by entrenchment index of 3 and below.[13] The results, reported in the third column, remain similar to the main ones, demonstrating that our findings are not likely to be driven by agency reasons.

Third, we ensure that the results are not driven by the merger wave of the late 90s (e.g., Betton, Eckbo, and Thorburn (2008)), the peak of which happens in 1997-1998 and by the high-tech bubble of 1999-2000, which could also drive some of our results, and exclude years 1997–2000 years from the analysis. The results are reported in the last column of Table 7. While the number of observations is substantially lower than in the full sample, the results are robust to excluding the merger wave and the high-tech bubble from the sample.

4.3. Patent-based analysis

Next, we repeat the estimation of equation (20) using variables constructed from NBER patent data and report the results in Table 8. Since we do not have any accounting information on private targets,

[13]The index is obtained from Lucian Bebchuk's website at http://www.law.harvard.edu/faculty/bebchuk/data.shtml.

we use only bidder's control variables while estimating (20). The regressions are estimated using year fixed effects, and standard errors are clustered at a bidder level.

Insert Table 8 here

All the coefficients on the proxies for the model's parameters have signs consistent with the model's predictions and are statistically significant. The log of number of target's patents, which serves as an inverse proxy for its obsolescence risk, is negatively associated with merger inefficiency. The probability of target discovery, proxied by the indicator variable for publicly-traded firms, is negatively related to merger inefficiency. The breadth of bidder's industry, which we use as an inverse proxy for the intensity of competitive interaction, is positively associated with merger inefficiency.

In addition to statistical significance, the variables of interest also have an economically sizeable impact on merger inefficiency. For example, a one standard deviation increase in the log of target's number of patents (an inverse proxy for its obsolescence risk), reduces the inefficiency measure by 0.07, which is equivalent to 15% of its mean value and 23% of its standard deviation. The other variables also have a significant economic impact: a one standard deviation increase in measures of target discoverability and competitive interaction among potential bidders change merger inefficiency by $0.025 - 0.03$ in absolute value, corresponding to $8\% - 9\%$ of its standard deviation.

In Table 9 we perform robustness tests similar to those in the previous subsection, to ensure that the results are not driven by market power (column 1), agency considerations (column 2), and the merger wave of the late nineties and the high tech bubble (column 3).

Insert Table 9 here

Overall, the results of all robustness tests are consistent with those in the main specifications. The magnitudes of the coefficients in column 1, in which mergers among bidder and target in the same industry are excluded, are similar to those in the overall sample and are statistically significant with the exception of the probability of target discovery. The results in columns 2 and 3, in which we exclude mergers involving agency-prone firms and mergers belonging to a wave, are also robust, and with the exception of one case, statistically significant.

5. Conclusions

Existing theoretical literature demonstrates that firms with complementary products and/or technologies are more likely to become merger partners. Existing empirical evidence indicates that the potential for complementarity gains from putting assets of two firms under common ownership has a positive effect on the incidence of a mergers and on post-merger performance. Yet, there is substantial variation in complementarity between bidders and targets in actual deals. Targets are seldom acquired by bidders with the potential for achieving highest complementarity gains, resulting in inefficient mergers. In this paper we propose a reason for the existence of inefficient mergers and examine theoretically and empirically some of the factors that affect the degree of inefficiency in observed mergers.

In our model, two potential bidders randomly discover a target with product/technology that may increase a bidder's value if placed under its ownership. The model shows that in equilibrium there is a positive likelihood of acquisition of the target by the bidder whose complementarity with the target is lower than that of the other, counterfactual, bidder. Such inefficient merger is possible because of an information friction: A bidder only learns its complementarity with the target after discovering it. This leads to cases in which the target agrees to be acquired by the bidder with relatively low complementarity because of the uncertainty regarding its future discovery by the bidder with higher complementarity. Factors that affect expected inefficiency of a merger involving a given target include the target's obsolescence risk, the likelihood of its discovery by potential bidders, and the extent of competitive interaction among potential acquirers.

In our empirical tests, we construct two separate measures of merger inefficiency. The first one is based on similarity of bidder's and target's product offerings. The second proxy is based on overlap between bidder's and target's technologies. Tests using both measures show that the target's obsolescence risk is positively related to inefficiency of observed mergers, while the probability of target's discovery by potential bidders and the degree of competitive interaction among them are negatively related to merger inefficiency.

More generally, our paper demonstrates that inefficient mergers can occur among value-maximizing firms and in the absence of market power considerations, and that inefficiency of observed mergers and acquisitions is systematically related to the merging firms' characteristics.

A Proofs

Proof of Lemma 1

First, note that

$$\pi_1(1)+\pi_2(1)-(\pi_1(2)+\pi_2(2))=\int\limits_{\underline{\delta}}^{\delta_1}\frac{\partial\left(\pi_1(1)+\partial\pi_2(1)\right)}{\partial\delta_1}d\delta_1-\int\limits_{\underline{\delta}}^{\delta_2}\frac{\partial\left(\pi_2(2)+\partial\pi_1(2)\right)}{\partial\delta_2}d\delta_2. \tag{21}$$

Under the assumption of initial symmetry, $\alpha_1=\alpha_2$, (21) can be rewritten as

$$\pi_1(1)+\pi_2(1)-(\pi_1(2)+\pi_2(2))=\int\limits_{\delta_2}^{\delta_1}\frac{\partial\pi_1(1)+\partial\pi_2(1)}{\partial\delta_1}d\delta_1.$$

Since we assume that $|\frac{\partial\pi_1}{\partial\delta_1}|>|\frac{\partial\pi_2}{\partial\delta_1}|$, $\frac{\partial\pi_1(1)+\partial\pi_2(1)}{\partial\delta_1}>0$ for any δ_1. Thus, since $\delta_1>\delta_2>0$, it follows that

$$\pi_1(1)+\pi_2(1)-(\pi_1(2)+\pi_2(2))>0.$$

Proof of Lemma 2

$B_{1_{alone}}$ in (5) can be simplified as

$$B_{1_{alone}}=-T_{alone}(1)\frac{r+\psi+p(1-\psi)}{p(1-\psi)}+p\frac{P_{both}(1-\psi)}{1+r}+\left(\pi_1(1)-\pi_1(0)\right). \tag{22}$$

Plugging $T_{alone}(1)$ from (4) into (22) leads to

$$B_{1_{alone}}=\pi_1(1)-\pi_1(0)>0.$$

Proof of Lemma 3

$B_{2_{alone}}$ in (6) can be simplified as

$$B_{2_{alone}}=-T_{alone}(2)\frac{r+\psi+p(1-\psi)}{p(1-\psi)}+p\frac{B_{2_{both}}(1-\psi)}{1+r}+\left(\pi_2(2)-\pi_2(0)\right). \tag{23}$$

Plugging T_{alone} from (4) into (23) and simplifying results in

$$B_{2_{alone}}=-p\phi\left(B_{1_{both}}-B_{2_{both}}\right)+\left(\pi_2(2)-\pi_2(0)\right). \tag{24}$$

Plugging $B1_{both}$ and $B2_{both}$ from (1) into (24) results in:

$$B2_{alone} = -p\phi \frac{1-\psi}{r+\psi} \left(\pi_1(1) - \pi_1(2) - \pi_2(2) + \pi_2(1)\right) + \left(\pi_2(2) - \pi_2(0)\right). \tag{25}$$

$B2_{alone}$ in (25) is positive iff

$$\frac{\pi_2(2) - \pi_2(0)}{\pi_1(1) - \pi_1(2) - \pi_2(2) + \pi_2(1)} > p\phi \frac{1-\psi}{r+\psi}.$$

Proof of Lemma 4

The combined value at time τ of the two incumbents and the target conditional on acquisition of the target at time τ by incumbent i is

$$\sum_{t=\tau}^{\infty} \frac{\pi_i(i) + \pi_{-i}(i)}{(1+r)^{t-\tau}} (1-\psi)^{t-\tau} = \frac{\pi_i(i) + \pi_{-i}(i)}{r+\psi}. \tag{26}$$

It follows from Lemma 1 that

$$\frac{\pi_1(1) + \pi_2(1)}{r+\psi} - \frac{\pi_1(2) + \pi_2(2)}{r+\psi} > 0. \tag{27}$$

Proof of Propositions 1–2

Lemma 1 shows that $\pi_1(1) - \pi_1(2) - \pi_2(2) + \pi_2(1) > 0$. $\frac{\partial(\pi_2(2)+\pi_1(2))}{\partial\delta_2} > 0$ by assumption. Also, $\frac{\partial(\pi_2(2)-\pi_2(0))}{\partial\delta_2} > 0$ by assumption. Thus, the left-hand side of (7) is increasing in δ_2. For $\delta_2 \longrightarrow 0$, $\pi_2(2) - \pi_2(0) \longrightarrow 0$ and the left-hand side of (7) approaches zero. For $\delta_2 \longrightarrow \delta_1$, $\pi_1(1) - \pi_1(2) - \pi_2(2) + \pi_2(1) \longrightarrow 0$ and the left-hand side of (7) approaches ∞. Thus, there exists a threshold, $\delta^*(\delta_1)$, such that for $\delta_2 > \delta^*(\delta_1)$, the left-hand side of (7) is larger than the right-hand side of (7), while for $\delta_2 < \delta^*(\delta_1)$ the opposite is true. Since the RHS of (7) is decreasing in ψ and is increasing in p,

$$\begin{aligned} \frac{\partial\delta^*(\delta_1)}{\partial\psi} &< 0, \\ \frac{\partial\delta^*(\delta_1)}{\partial p} &> 0. \end{aligned} \tag{28}$$

Also, we can write

$$
\begin{aligned}
\frac{\partial \mathbb{E}(\upsilon)}{\partial \psi} &= \int_{0}^{\overline{\delta}} \frac{\partial (\mathbb{E}(\upsilon) \mid \delta_1)}{\partial \delta^*(\delta_1)} \frac{\partial \delta^*(\delta_1)}{\partial \psi} f_{\max}(\delta_1) d\delta_1, \\
\frac{\partial \mathbb{E}(\upsilon)}{\partial p} &= \int_{0}^{\overline{\delta}} \frac{\partial (\mathbb{E}(\upsilon) \mid \delta_1)}{\partial \delta^*(\delta_1)} \frac{\partial \delta^*(\delta_1)}{\partial p} f_{\max}(\delta_1) d\delta_1. \qquad (29)
\end{aligned}
$$

Note that

$$
\begin{aligned}
\frac{\partial (\mathbb{E}(\upsilon) \mid \delta_1)}{\partial \delta^*(\delta_1)} &= p_b(1-p_b) f_{\min}(\delta^*(\delta_1)) * \Big(\frac{-p_b \upsilon(\delta^*(\delta_1), \delta_1)}{\left((p_b + p_b(1-p_b))\left(F_{\min}(\delta_1) - F_{\min}(\delta^*(\delta_1))\right)\right)^2} + \\
&\frac{p_b(1-p_b)\left[\int_{\delta^*(\delta_1)}^{\delta_1} f_{\min}(\delta_2)\left(\upsilon(\delta_2, \delta_1) - \upsilon(\delta^*(\delta_1), \delta_1)\right) d\delta_2\right]}{\left((p_b + p_b(1-p_b))\left(F_{\min}(\delta_1) - F_{\min}(\delta^*(\delta_1))\right)\right)^2} \Big). \qquad (30)
\end{aligned}
$$

Also, for any $\delta_1 < \overline{\delta}$:

$$(1-p_b) p_b f_{\min}(\delta^*(\delta_1) > 0,$$

by definition;

$$\left((p_b + p_b(1-p_b))\left(F_{\min}(\delta_1) - F_{\min}(\delta^*(\delta_1))\right);\right)^2 > 0,$$

$$-p(\upsilon(\delta^*(\delta_1), \delta_1)) \leq 0,$$

by assumption $(\upsilon(\delta^*(\delta_1), \delta_1) \geq 0)$; and

$$\int_{\delta^*(\delta_1)}^{\delta_1} f_{\min}(\delta_2)\left(\upsilon(\delta_2, \delta_1) - \upsilon(\delta^*(\delta_1), \delta_1)\right) d\delta_2 < 0$$

since $\frac{\partial \upsilon(\delta_2, \delta_1)}{\partial \delta_2} < 0$ by assumption and $\delta_2 > \delta^*(\delta_1)$ as defined by the bounds of the integral. Therefore,

$$\frac{\partial (\mathbb{E}(\upsilon) \mid \delta_1)}{\partial \delta^*(\delta_{\max})} < 0. \qquad (31)$$

Note that

$$\frac{\partial (prob(ineff) \mid \delta_1)}{\partial \delta^*(\delta_1)} = \frac{-(1-p_b) f_{\min}(\delta^*(\delta_1))}{\left((1 + (1-p_b))\left(F_{\min}(\delta_1) - F_{\min}(\delta^*(\delta_1))\right)\right)^2} < 0. \qquad (32)$$

(31) and (32), combined with (28) and (29), imply that $\frac{\partial \mathbb{E}(\upsilon)}{\partial \psi} > 0$, $\frac{\partial \mathbb{E}(\upsilon)}{\partial p} < 0$, $\frac{\partial prob(ineff)}{\partial \psi} > 0$, and $\frac{\partial prob(ineff)}{\partial p} < 0$.

Proof of Proposition 3

Assume that the utility of a representative consumer takes the following form:

$$U = \sum_{i=1}^{2} \mu q_i - \frac{1}{2}\left(\beta \sum_{i=1}^{2} q_i^2 + 2\gamma \sum_{j\neq i} q_i q_j\right), \tag{33}$$

where q_i is the quantity consumed of product i. Differentiating (33) with respect to each q_i, and equating the resulting expression to product i's price, η_i leads to the following demand function for firm i's product:

$$q_1 = a - b\eta_1 + c\eta_2, \tag{34}$$

where $a = \frac{\mu(\beta-\gamma)}{\beta^2-\gamma^2}$, $b = \frac{\beta}{\beta^2-\gamma^2}$, and $c = \frac{\gamma}{\beta^2-\gamma^2}$. Assuming constant marginal cost of production, s_i for firm i, firm i's profit is given by

$$\pi_1 = (a - b\eta_i + c\eta_{-i})(\eta_i - s_i). \tag{35}$$

Differentiating (35) with respect to η_i where i takes the values of 1 and 2, solving the resulting system of two equations, and plugging the result into (35), leads to the following expression for equilibrium profit of firm i:

$$\frac{\beta\left(\mu(2\beta^2-\beta\gamma-\gamma^2) - c_i(2\beta^2-\gamma^2) + c_{-i}\beta\gamma\right)}{(\beta^2-\gamma^2)\left(4\beta^2-\gamma^2\right)^2}. \tag{36}$$

Let us refer to s_1 in the case of an acquisition of the target by bidder 1 by $s(\delta_1)$, s_2 in the case of an acquisition of the target by bidder 2 by $s(\delta_2)$, and s_1 and s_2 in the case of no merger by $s(0)$. Given that $\delta_1 > \delta_2 > 0$,

$$s(\delta_1) < s(\delta_2) < s(0).$$

Denoting $\frac{\pi_2(s(\delta_2))-\pi_2(s(0))}{\pi_1(s(\delta_1))-\pi_1(s(\delta_2))-\pi_2(s(\delta_2))+\pi_1(s(\delta_1))}$ by Θ, and differentiating Θ with respect to γ results in

$$\frac{\partial\Theta}{\partial\gamma} = -\frac{2\beta(2\beta^2+\gamma^2)(s(0)-s(\delta_2))}{s(\delta_2)-s(\delta_1)}\Lambda. \tag{37}$$

As $\gamma \to \beta$,

$$\Lambda \to \beta^4(2s(0)-s(\delta_1)-s(\delta_2))(2\mu-c(0)-c(\delta_2)). \tag{38}$$

Given that $s(\delta_1) < s(\delta_2) < s(0)$, Λ is positive and $\frac{\partial\Theta}{\partial\gamma}$ in (37) is negative as $\gamma \to \beta$. Given that the right-hand side of (7) is independent of γ, and $\frac{\partial\Theta}{\partial\delta_2} > 0$, $\frac{\partial\delta^*(\delta_1)}{\partial\gamma} > 0$. As shown in the proof to Propositions 1–2, this implies that $\frac{\partial\mathbb{E}(v)}{\partial\gamma} < 0$ and $\frac{\partial prob(ineff)}{\partial\gamma} < 0$ for $\gamma \to \beta$, i.e. there exists γ^* such that if $\gamma > \gamma^*$ then $\frac{\partial\mathbb{E}(v)}{\partial\gamma} < 0$ and $\frac{\partial prob(ineff)}{\partial\gamma} < 0$.

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Table 2: Product-description-based data: Descriptive statistics

This table presents summary statistics of variables used in the tests of product-description-based merger inefficiency. Merger inefficiency is calculated by scaling the bidder-target pairwise product description similarity by the maximum similarity of the target with any other firm that year, and subtracting the resulting ratio from one. We report the statistics for the full sample, as well as for the sample of takeover contests, in which we report statistics for successful bidders and failed bidders. See subsection 3.4.1 for the description of construction of the takeover contests sample. Log (#VC deals) is the natural log of one plus the number of deals involving venture capital investment in firms at the expansion stage at an 4-digit SIC industry level. Log (#analysts) is the natural logarithm of one plus the number of distinct analysts that have produced at least one annual forecast of firm performance during the three-month window prior to the fiscal year-end. Average similarity is the mean of the pairwise similarity within bidder's TNIC industry. Log(bidder assets) is the natural logarithm of acquirer's book assets in millions of 2011 $US. Log (target assets) is the natural logarithm of target's book assets in millions of 2011 $US. Bidder (target) M/B is bidder's (target's) market-to-book ratio, computed as book assets + market cap – book value of equity (CEQ) – deferred taxes (TXDB (if available; zero otherwise)), all scaled by book assets. Bidder (target) tangibility is bidder's (target's) ratio of PP&E to assets. Bidder (target) profitability is bidder's (target's) EBITDA-to-assets ratio.

	Proxy for	N	Mean	Median	Min	Max	Std Dev
Merger inefficiency							
Full sample		1,665	0.47	0.50	0.0	0.9996	0.31
Takeover contests: Successful bidders		40	0.40	0.44	0.0000	1.00	0.27
Takeover contests: Failed bidders		40	0.70	0.65	0.0000	1.00	0.33
Determinants of merger inefficiency							
Log(#VC deals)	ψ	1,583	4.67	4.62	2.64	6.34	0.67
Log(# analysts)	p	1,665	1.32	1.39	0.00	3.66	0.96
Average similarity	γ	1,665	0.05	0.04	0.002	0.22	0.03
Control variables							
Log(bidder assets)		1,665	7.92	7.87	1.598	14.43	2.04
Bidder M/B		1,661	2.19	1.38	0.44	20.00	2.35
Bidder tangibility		1,593	0.20	0.09	0.00	0.94	0.24
Bidder profitability		1,603	0.09	0.09	-1.00	0.55	0.14
Log(target assets)		1,665	6.21	6.20	1.04	13.64	1.80
Target M/B		1,660	1.83	1.21	0.219	20.00	1.86
Target tangibility		1,606	0.20	0.08	0.00	0.99	0.25
Target profitability		1,601	0.03	0.04	-1.00	0.52	0.20

Table 3: Product-description-based data: Correlations

This table presents Pearson correlation matrix of variables used in the tests of product-description-based merger inefficiency. See Table 2 for the description of the variables.

	Proxy for	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Merger inefficiency		1.00											
Determinants of merger inefficiency													
(2) Log(#VC deals)	ψ	0.08	1.00										
(3) Log(# analysts)	p	-0.04	0.03	1.00									
(4) Average similarity	γ	-0.04	0.12	-0.16	1.00								
Control variables													
(5) Log(bidder assets)		0.23	0.08	0.35	0.25	1.00							
(6) Bidder M/B		0.02	0.06	0.10	-0.23	-0.23	1.00						
(7) Bidder tangibility		-0.08	-0.01	0.18	-0.24	-0.07	-0.05	1.00					
(8) Bidder profitability		-0.01	-0.10	0.19	-0.23	0.16	0.07	0.27	1.00				
(9) Log(target assets)		0.00	0.03	0.50	0.27	0.68	-0.23	0.04	0.06	1.00			
(10) Target M/B		0.04	0.03	0.08	-0.21	-0.13	0.60	-0.05	0.05	-0.23	1.00		
(11) Target tangibility		-0.09	-0.03	0.20	-0.23	-0.08	-0.07	0.86	0.24	0.07	-0.06	1.00	
(12) Target profitability		-0.04	-0.11	0.20	-0.02	0.18	-0.06	0.24	0.39	0.36	-0.10	0.26	1.00

Table 4: Patent-based data: Descriptive statistics

This table presents summary statistics of variables used in the tests of patent-based merger inefficiency. Merger inefficiency is calculated by scaling the bidder-target pairwise patent-based similarity by the maximum similarity of the target to any other firm that year and subtracting the resulting ratio from one. Log (target's # patents) is the natural logarithm of one plus the number of patents that the target was granted during 5 years prior to the merger. Dummy(public=1) is an indicator variable that equals one if the target firm is publicly-traded and equals zero if it is privately-held. Patent breadth is the average of the total number of patents in the 5-year period prior to the merger in the bidder's 3 main two-digit patent subcategories. Log(bidder assets) is the natural logarithm of acquirer's book assets in millions of 2011 $US. Bidder M/B is bidder's market-to-book ratio, computed as book assets + market cap – book value of equity (CEQ) – deferred taxes (TXDB (if available; zero otherwise)), all scaled by book assets. Bidder tangibility is its ratio of PP&E to assets. Bidder profitability is its EBITDA-to-assets ratio.

	Proxy for	N	Mean	Median	Min	Max	Std Dev
Merger inefficiency		1,319	0.46	0.48	0.00	0.997	0.30
Determinants of merger inefficiency							
Log(target's # patents)	ψ (inverse)	1,319	2.35	2.20	0.69	7.88	1.31
Dummy(public=1)	p	1,319	0.51	1.00	0.00	1.00	0.50
Patent breadth	γ (inverse)	1,319	6.32	6.43	0.00	8.50	0.97
Control variables							
Log(bidder assets)		1,319	7.63	7.74	1.124	13.58	1.95
Bidder M/B		1,311	2.52	1.83	0.35	20.00	2.17
Bidder tangibility		1,318	0.24	0.22	0.00	0.82	0.15
Bidder profitability		1,317	0.14	0.16	-1.00	0.50	0.14

Table 5: Patent-based data: Correlations

This table presents Pearson correlation matrix of variables used in the tests of patent-based merger inefficiency. See Table 4 for the description of the variables.

	Proxy for	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Merger inefficiency		1.00							
Determinants of merger inefficiency									
(2) Log(target's # patents)	ψ (inverse)	-0.22	1.00						
(3) Dummy(public=1)	p	-0.13	0.28	1.00					
(4) Patent breadth	γ (inverse)	-0.05	-0.04	-0.03	1.00				
Control variables									
(5) Log(bidder assets)		0.01	0.26	0.29	0.04	1.00			
(6) Bidder M/B		-0.14	-0.01	0.02	0.22	-0.11	1.00		
(7) Bidder tangibility		0.06	0.11	0.05	-0.21	0.30	-0.26	1.00	
(8) Bidder profitability		0.03	0.04	0.05	-0.06	0.33	0.13	0.18	1.00

Table 6: Product-description-based data: Main tests

This table presents the results of estimating OLS regressions, in which the dependent variable is product-description-based merger inefficiency and the independent variables are proxies for the model's parameters, and bidder (bidder and target) control variables. See Table 2 for variable definitions. The regressions are estimated with year fixed effects. Standard errors are heteroskedasticity-consistent, adjusted for clustering at the firm level, and reported in parentheses. The symbols ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	Proxy for	Predicted sign	(1)	(2)	(3)	(4)	(5)	(6)
Intercept			0.272***	-0.004	-0.007	-0.0003	0.135**	0.179***
			(0.086)	(0.083)	(0.084)	(0.091)	(0.059)	(0.059)
Determinants of merger inefficiency								
Log(#VC deals)	ψ	(+)	0.058***	0.045***	0.043***	0.037**		
			(0.017)	(0.015)	(0.015)	(0.016)		
Log(# analysts)	p	(−)	-0.021**	-0.065***	-0.062***		-0.046***	
			(0.009)	(0.010)	(0.010)		(0.010)	
Average similarity	γ	(−)	-0.620**	-1.757***	-1.678***			-1.234***
			(0.281)	(0.294)	(0.297)			(0.294)
Controls: Bidder								
Log(assets)				0.055***	0.056***	0.038***	0.047***	0.044***
				(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
M/B				0.009**	0.008	0.007	0.010*	0.004
				(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Tangibility				-0.067*	0.004	0.026	0.040	0.025
				(0.041)	(0.071)	(0.073)	(0.071)	(0.072)
Profitability				-0.128*	-0.091	-0.019	-0.020	-0.088
				(0.066)	(0.069)	(0.065)	(0.067)	(0.068)
Controls: Target								
M/B					0.001	0.003	0.004	0.000
					(0.005)	(0.005)	(0.005)	(0.005)
Tangibility					-0.072	-0.098	-0.071	-0.133*
					(0.072)	(0.072)	(0.071)	(0.072)
Profitability					-0.087**	-0.122***	-0.104**	-0.112**
					(0.044)	(0.044)	(0.044)	(0.044)
Obs			1,583	1,501	1,472	1,472	1,553	1,553
R-squared			0.02	0.12	0.13	0.09	0.10	0.09

Table 7: Product-description-based data: Robustness tests

This table presents the results of estimating OLS regressions, in which the dependent variable is product-based merger inefficiency and independent variables are proxies for the model's parameters, and bidder and target control variables. See Table 2 for variable definitions. Different SIC codes refers to a subsample of mergers between firms with different 4-digit SIC codes. Low HHI refers to a subsample of targets operating in TNIC industries in which the Herfindahl index is lower than the median Herfindahl index that year. Excl. entr. firms refers to a sample of firms with Bebchuk, Cohen and Ferrell (2009) index of 3 or below. Excl. wave and bubble refers to a sample that excludes years 1997-2000. We estimate the regressions with year fixed effects. Heteroskedasticity-consistent standard errors, reported in parentheses, are adjusted for clustering at the firm level. The symbols ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	Proxy for	Predicted sign	Different SIC codes	Low HHI	Excl. entrenched firms	Excl. wave & bubble
			(1)	(2)	(3)	(4)
Intercept			-0.062	0.021	0.014	0.033
			(0.115)	(0.114)	(0.088)	(0.099)
Determinants of merger inefficiency						
Log(# VC deals)	ψ	(+)	0.043**	0.043**	0.041**	0.042**
			(0.019)	(0.017)	(0.016)	(0.019)
Log(# analysts)	p	(−)	-0.067***	-0.097***	-0.060***	-0.054***
			(0.014)	(0.014)	(0.011)	(0.014)
Average similarity	γ	(−)	-1.747***	-2.282***	-1.510***	-1.48***
			(0.383)	(0.454)	(0.308)	(0.382)
Controls: Bidder						
Log(assets)			0.064***	0.058***	0.053***	0.053***
			(0.007)	(0.007)	(0.005)	(0.007)
M/B			0.005	0.004	0.008	-0.01
			(0.006)	(0.009)	(0.005)	(0.011)
Tangibility			-0.040	0.024	0.032	0.016
			(0.103)	(0.162)	(0.075)	(0.1)
Profitability			-0.129	-0.134	-0.084	-0.144
			(0.090)	(0.182)	(0.070)	(0.095)
Controls: Target						
M/B			0.002	0.002	0.001	0.009
			(0.006)	(0.008)	(0.005)	(0.01)
Tangibility			-0.046	-0.106	-0.095	-0.105
			(0.100)	(0.151)	(0.076)	(0.1)
Profitability			-0.050	-0.145	-0.082*	-0.074
			(0.052)	(0.131)	(0.045)	(0.059)
Obs.			785	621	1,327	815
R-squared			0.16	0.20	0.11	0.12

Table 8: Patent-based data: Main tests

This table presents the results of estimating OLS regressions, in which the dependent variable is patent-based merger inefficiency and the independent variables are proxies for the model's parameters, and bidder control variables. See Table 4 for variable definitions. The are estimated with year fixed effects. Standard errors are heteroskedasticity-consistent, adjusted for clustering at the firm level, and reported in parentheses. The symbols ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	Proxy for	Predicted sign	(1)	(2)	(3)	(4)	(5)
Intercept			0.422***	0.366***	0.631***	0.571***	0.309**
			(0.146)	(0.132)	(0.060)	(0.064)	(0.139)
Determinants of merger inefficiency							
Log(target's # patents)	ψ (inverse)	(−)	-0.051***	-0.054***	-0.057***		
			(0.007)	(0.008)	(0.008)		
Dummy(public=1)	p	(−)	-0.045**	-0.050**		-0.077***	
			(0.020)	(0.020)		(0.021)	
Patent breadth	γ (inverse)	(+)	0.024	0.030**			0.032**
			(0.016)	(0.014)			(0.015)
Controls: Bidder							
Log(assets)				0.006	0.003	-0.001	-0.008
				(0.006)	(0.006)	(0.007)	(0.007)
M/B				-0.019***	-0.019***	-0.020***	-0.021***
				(0.006)	(0.006)	(0.007)	(0.007)
Tangibility				0.008	0.026	0.008	0.026
				(0.075)	(0.075)	(0.080)	(0.080)
Profitability				0.085	0.104*	0.130**	0.153**
				(0.060)	(0.060)	(0.063)	(0.062)
Obs			1,319	1,308	1,308	1,308	1,308
R-squared			0.09	0.11	0.10	0.07	0.06

Table 9: Patent-based data: Robustness tests

This table presents the results of estimating OLS regressions, in which the dependent variable is patent-based merger inefficiency and independent variables are proxies for the model's parameters, and bidder control variables. See Table 4 for variable definitions. Different SIC codes refers to a subsample of mergers between firms with different 4-digit SIC codes. Excl. entr. firms refers to a subsample of firms with Bebchuk, Cohen and Ferrell (2009) index of 3 or below. Excl. wave and bubble refers to a subsample that excludes years 1997-2000. The regressions are estimated with year fixed effects. Heteroskedasticity-consistent standard errors, reported in parentheses, are adjusted for clustering at the firm level. The symbols ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	Proxy for	Predicted sign	Bidders and targets in different SIC codes	Excl. entrenched firms	Excl. merger wave & hi-tech bubble
			(1)	(2)	(3)
Intercept			0.377**	0.242	0.191
			(0.166)	(0.177)	(0.199)
Determinants of merger inefficiency					
Log(target's # patents)	ϕ	(−)	-0.046***	-0.053***	-0.056***
			(0.010)	(0.009)	(0.010)
Dummy(public=1)	p	(−)	-0.029	-0.059***	-0.032
			(0.024)	(0.021)	(0.025)
Patent breadth	γ (inverse)	(+)	0.039**	0.038*	0.054**
			(0.018)	(0.020)	(0.022)
Controls: Bidder					
Log(assets)			-0.002	0.011	0.003
			(0.007)	(0.007)	(0.007)
M/B			-0.028***	-0.015**	-0.024***
			(0.008)	(0.006)	(0.008)
Tangibility			0.014	-0.018	0.048
			(0.092)	(0.079)	(0.083)
Profitability			0.068	0.101	0.099
			(0.086)	(0.065)	(0.077)
Obs.			949	1,177	965
R-squared			0.11	0.11	0.13