Complementarities in Mergers and Acquisitions *

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Abstract

Many mergers involve firms with less-than-complementary products or technologies. This paper examines theoretically and empirically the factors that affect the expected complementarity in observed mergers. Our model demonstrates that the important determinants of expected complementarity in mergers are target's bargaining power, as well as its visibility among potential bidders, expected growth in potential bidders' profits, and the extent of competitive interaction among them. We test the model's predictions using two separate datasets, which we use to define two types of merger complementarity. The first one is based on common vocabulary in bidder's and target's product descriptions. The second is based on the relatedness of merging firms' technologies. Both sets of tests indicate that the degree of complementarity in observed mergers and acquisitions is systematically related to bidders', targets', and industry characteristics, in ways consistent with the model's predictions.

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

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1. Introduction

Many mergers and acquisitions (M&As) involve bidders and targets with less-than-complementary products or technologies. In this paper we examine theoretically and empirically the reasons for observing such mergers in the presence of more suitable matches. One recent example of such less-than-complementary merger is Facebook's $2 billion acquisition of Oculus, a young company known for its virtual reality headset "Oculus Rift", announced in March 2014. The reaction of the technology community to this acquisition 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 the better strategic acquirer [of Oculus] would have been Google.

Existing literature does not provide a satisfactory explanation as to why we may observe less-than-complementary deals, as synergies/complementarities have long been viewed as one of the main reasons for M&As.[1] Several papers document that mergers between firms with larger complementarities in products/technologies occur with a higher frequency (e.g., Rhodes-Kropf and Robinson (2008), Hoberg and Phillips (2010) and Bena and Li (2014)) and tend to result in higher realized synergy gains (e.g., Kaplan and Weisbach (1992), Maksimovic, Phillips and Prabhala (2008), Hoberg and Phillips (2010), and Bena and Li (2014)). Yet, there is substantial heterogeneity in the degree of complementarity between bidders and targets in observed M&As (e.g., Hoberg and Phillips (2010) and Bena and Li (2014)), and some targets are bought by less-than-complementary acquirers. Our paper attempts to fill this gap by examining the determinants of the degree of complementarity between bidders and targets in M&As.

Our simple but general model offers an explanation for the existence of acquisitions that do not maximize complementarities. The model features a target firm with product/technology that can be useful to potential bidders (incumbents), whose products are strategic substitutes. 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 will have discovered it later.

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

[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), Maksimovic, Phillips and Prabhala (2008), Hoberg and Phillips (2010), and Bena and Li (2014) among many others.

and is willing to give the target a sufficiently high acquisition offer, which the target optimally accepts instead of waiting to be discovered by the more complementary bidder. Thus, the model predicts that there is a positive likelihood of less-than-complementary mergers. As a result, *expected complementarity* in observed acquisitions of a given target is lower than the highest possible complementarity.

The model identifies four factors that determine the expected degree of complementarity in mergers. First, expected merger complementarity is increasing in target's bargaining power. The intuition is that targets with higher bargaining power benefit more from a situation in which they receive multiple takeover offers, and are more willing to wait to be discovered by several bidders at once. As a result, only bidders with sufficiently high degree of complementarity with the target would be willing to make acquisition offers high enough for the target to forego its option to wait for a bidder with even higher complementarity.

Second, expected merger complementarity is increasing in target's characteristics associated with the likelihood of its discovery by potential bidders. Target's discoverability raises the likelihood of multiple future bids, i.e. the likelihood of a future takeover contest, in which the bidder with higher complementarity with the target ends up acquiring it. This leads the target to be less willing to accept an offer from a bidder with lower complementarity, resulting in a positive relation between target's discoverability and expected complementarity in a merger involving that target.

Third, expected merger complementarity is increasing in expected growth in potential bidders' profits. The intuition is similar: the higher the bidders' growth, the more willing the target is to wait for future (higher) acquisition offers, and the higher the expected complementarity between the target and successful bidder.

Fourth, expected merger complementarity is increasing in the intensity of competitive interaction among potential bidders. The reason is that more intense competitive interaction magnifies the impact of a merger on the rival of the successful bidder. Thus, the stronger the competition, the larger the indirect effect of failing to acquire the target and the larger the difference between the effects of a merger on profits of successful and unsuccessful bidders, raising the acquisition price in a takeover contest. High offer value in a contest, in turn, encourages the target to wait for it, i.e. to wait for its discovery by multiple bidders. This higher value of the option to wait raises expected complementarity between the target and successful bidder.

We proceed by examining empirically the determinants of the degree of complementarity in M&As. We construct two separate measures of merger complementarity. First, following Hoberg and Phillips (2010), we consider a measure of merger complementarity that is based on common vocabulary in firms' product descriptions. Second, following Bena and Li (2014), we use a measure that is based on firms' patent overlap. These two measures aim to capture two of the crucial determinants of merger complementarity: product relatedness and technological relatedness (e.g., Henderson and Cockburn (1996), Fan and Goyal (2006), Maksimovic, Phillips and Prabhala (2008), and Hoberg and Phillips (2010)).

Each of the two approaches has its advantages and limitations. The product-relatedness-based measure is available fort virtually all public firms, while technology-relatedness-based measure is only available for mergers involving innovative firms that generate patents. On the other hand, the latter tests are not limited to publicly-traded firms and capture mergers that involve private targets as well. Finally, due to data availability, the two types of tests are performed 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 (2013)). Overall, examining both types of complementarities allows to generalize our empirical results to the general population of M&As.

Our empirical results support the model's predictions. For each complementarity measures, we find robust evidence that complementarity between a target and its acquirer (relative to complementarity between the target and other potential acquirers) is increasing in proxies for: target's bargaining power, the likelihood of target's discovery, expected growth in potential bidders' profits, and the extent of competitive interaction in bidders' industries.

The relations between these factors and relative merger complementarity are significant not only statistically but also economically. A one standard deviation increase in measures of target's bargaining power, the likelihood of its discovery, and the degree of competitive interaction in their industry is associated with 8%-20% standard deviation increase each in a product-relatedness-based measure of merger complementarity. In the case of technology-relatedness-based complementarity measure, the effect of a one standard deviation increase in each of the proxies for the model's parameters is associated with 6%-20% standard deviation increase in merger complementarity.

To ensure that our empirical findings are not driven by mechanisms exogenous to the model, we consider alternative explanations of the results. First, we verify that our complementarity measures do not proxy for market power that the merging firms could exercise, and repeat our tests within a subsample of firms operating in relatively competitive industries, in which market power considerations are less important. We find that our results are somewhat stronger within this subsample than within the full sample of mergers. Second, to address the agency hypothesis, according to which mergers may be driven by empire-building incentives of entrenched managers, resulting in mergers with low complementarity, we repeat our tests using a subsample of firms with relatively low Bebchuck, Cohen and Ferrell (2009) entrenchment index, and find that the qualitative results are unaffected. Third, we demonstrate that our results are not sensitive to the presence of "serial acquirers", whose choices of targets may be driven mostly by misvaluation considerations. Fourth, 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 (e.g., Masulis, Wang and Xie (2007)).

Overall, our paper is the first one to examine theoretically and empirically the determinants of complementarity between bidders and targets in observed M&As. Our model is related to the model in 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 examining the determinants of expected complementarity in mergers and addressing the existence of large heterogeneity in complementarity in observed M&As. Our empirical results on the determinants of merger complementarity extend the literature, which so far has focused on documenting the impact of complementarities on the incidence of M&As and on the effect of complementarities on post-merger performance of merging firms (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 variables used in product-similarity-based and technology-overlap-based empirical tests. Section 4 presents and discusses empirical results of testing the model's predictions using two distinct datasets. Section 5 concludes. Proofs are found in the Appendix.

2. Model

In this section we present a model that illustrates why less-than-complementary mergers may be observed and highlights the determinants of the expected degree of complementarity between products/technologies of targets and bidders in M&As and the likelihood of complementary mergers.

2.1. Setup

2.1.1 Incumbents

We consider two active firms (incumbents), 1 and 2. In each period t the incumbents compete in heterogenous products by producing output, while incurring a certain cost of production, and selling the output in the product market. Firm i's per-period equilibrium profit in period t is denoted by $\pi_i(\mu_t, \alpha_i, \alpha_{-i}, \gamma) \equiv \pi_i$ for $i \in \{1,2\}$. μ_t is the state of demand for the firms' products, such that $\frac{\partial \pi_i}{\partial \mu_t} > 0$.[2] α_i and α_{-i} are parameters of firm i's and its competitor's production functions, such that $\frac{\partial \pi_i}{\partial \alpha_i} > 0$.

We assume that the firms' products are strategic substitutes, therefore an increase in a firm's rival's (firm $-i$'s) production function parameter reduces the firm'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 among them. In particular, the larger the γ the stronger the negative effect of a firm's rival's production function parameter on the firm's equilibrium profit: $\frac{\partial^2 \pi_i}{\partial \alpha_{-i} \partial \gamma} < 0$. We assume that initially the two firms are symmetric in terms of their production functions, i.e. $\alpha_1 = \alpha_2$.

We also assume that the industry grows at a constant rate of g per period. In other words, μ_t increases at such a rate that firms' equilibrium profits increase at the rate of g each period, ceteris paribus (i.e. if there are no changes to firms' cost functions from period to period).[3] Finally, we assume that firms are risk-neutral, and the risk-free discount rate is $r > g$.

2.1.2 Acquisition target

In addition to the incumbents, we assume that there exists a firm ("potential target") that owns a product/technology that, if purchased by one of the existing firms, would reduce that firm's cost function parameter. In particular, we assume that the *complementarity* of this technology with firm i's production function is described by parameter δ_i, drawn from some 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 $\overline{\delta}$, such that $\frac{\partial \alpha_i}{\partial \delta_i} > 0$. To simplify the algebra, we assume that the distributions of δ_1 and δ_2 are independent. Importantly, none of the qualitative results are driven by the independence assumption. The resulting effect of δ_i on incumbents' equilibrium 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)).

Importantly, we do not assume that the target operates in the incumbents' industry. 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)), while purposely

[2] μ_t can be thought of as the intercept of a (linear) demand function or, alternatively, as the inverse of its slope.

[3] In the case of constant returns to scale and linear demand, this is equivalent to assuming that the slope of demand function is inversely related to μ_t, which grows at a rate of g per period.

abstracting from the effects of market power.

2.1.3 Discovery of the target

We assume that initially the two incumbents do not know how to integrate the potential target's product/technology in a value-enhancing way. 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 potential 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 possible integration of the target's product/technology by "target discovery".

Prior to the first (initial) discovery of the target, in any given period, each of the two incumbents may learn how to integrate the target's product/technology and the value consequences of this integration with probability $p_{before}(y) \equiv p_b$. Accounting for the fact that the target's likelihood of (subsequent) discovery by an additional bidder may be different from the likelihood of its initial discovery, we allow for a different likelihood of subsequent discovery, $p_{after}(y) \equiv p$. y are target's characteristics that are positively related to the probability of any of the incumbents discovering it: $\frac{\partial p_b}{\partial y} > 0$ and $\frac{\partial p}{\partial y} > 0$.[4,5]

If the target has been discovered by firm i at time t, the firm learns the parameters that describe the complementarities of the target's product/technology with its own and its rival's production functions, δ_i and δ_{-i}. Once discovered by incumbent i, the target's complementarity parameters are constant and remain known to firm i and to the target. We assume that δ_i and δ_{-i} are not known to firm $-i$, which would only learn these parameters if/when it discovers the target. This assumption is based on the idea that private information held by the target and by one of the bidders regarding the complementarity gains from acquiring the target cannot be verified by the other bidder.

2.1.4 Merger offers

If the target is discovered by firm i in period t, the firm may give the target an acquisition offer. (The target may receive two offers at time t if both incumbents discover it at or before time t). If the target decides to accept an offer, its product/technology is transferred to the acquiring firm and

[4] p_b and p can be assumed to be incumbent-specific. The only necessary assumption is that $p_b < 1$ and $p < 1$ for both incumbents.

[5] Note that by assuming exogenous and stochastic arrival of information regarding the target, we abstract from strategic takeover strategies, such as preemptive bidding (e.g., Fishman (1988)), which would be present in the case of endogenous (and costly) information acquisition.

the target ceases to exist as an independent entity. At that point, the complementarity parameters 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 firm i and/or from its competitor if/when it discovers the target.

The market can be in any one of the three mutually exclusive states, S_t, at time 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 as a function of the current industry structure: $\pi_i(\mu_t, \gamma, S_t)$, such that $\pi_i(\mu_t, \gamma, i) > \pi_i(\mu_t, \gamma, 0) > \pi_i(\mu_t, \gamma, -i)$. To simplify notation, we will sometimes write $\pi_i(\mu_t, S_t)$ instead of $\pi_i(\mu_t, \gamma, S_t)$.

2.1.5 Complementary and non-complementary mergers

The goal of this paper is to examine *the likelihood of complementary mergers* and *expected merger complementarity*, i.e. expected complementary between the actual (observed) bidder and the target relative to complementarities between the target and other firms (that could also have become potential acquirers). We define an acquisition by firm i of a target as *complementary merger* if firm i 's complementarity parameter is higher than that of the other potential (counterfactual) bidder. The potential bidder that has the highest complementarity with the target is the *complementary bidder.*

Definition 1. A *complementary merger* is a merger between firm i and the target when there does not exist firm j such that $\delta_i < \delta_j$. A *noncomplementary merger* is a merger between firm i and the target when there exists firm j such that $\delta_i < \delta_j$.

Definition 2. A *(non)complementary bidder* is a bidder whose acquisition of the target is an (non)complementary merger.

In what follows, we assume without loss of generality that firm 1 (2) is the (non)complementary bidder: $\delta_1 > \delta_2$.

2.2. Solution

We solve the model using the following two steps. First, we determine the i) highest offer price that a firm that discovered the target could offer to the target in period t depending on its own and its rival's complementarity parameters and on whether the rival has also discovered the target by period t, and ii) the target's reservation price above which it would accept an offer at time t depending on which firm(s) have discovered it by that time. Then we compute expected relative merger complementarity and the conditional likelihood of a complementary merger.

2.2.1 Both firms discover the target simultaneously

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

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

Since no new information is released after time τ, the bidding war is concluded at time τ by an acquisition of the target by one of the bidders, i.e. if firm i does not acquire the target then firm $-i$ does. Therefore, the benefit from an acquisition of the target by firm i is computed relative to the situation in which firm i's rival, firm $-i$, acquires the target. The benefit for the acquiring bidder is the infinite sum of the (growing) per-period profits conditional on merger with firm i net of per-period profits conditional on merger with firm $-i$.

The next result shows that the complementary bidder gains more from the merger than the non-complementary one, relative to the situation in which the target is taken over by the firm's rival:

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

Since the complementary bidder gains more from the merger every period than its rival, the former ends up acquiring the target. The surplus from this acquisition is the difference between the complementary bidder's reservation price, $B_{1_{both},\tau}$, and the target's reservation price, which equals the noncomplementary bidder's reservation price, $B_{2_{both},\tau}$. Following Alvarez and Stenbacka (2006) and Rhodes-Kropf and Robinson (2008), we assume that the division of this surplus between the complementary bidder and the target is a result of Nash bargaining game with the target's bargaining power, described by ϕ, $0 < \phi < 1$.[6] The resulting outcome of the bidding war is summarized in the following Lemma.

Lemma 2. *If both firms discover the target at time τ then*

1) the complementary bidder (firm 1) acquires the target at time τ;

2) the acquisition price following an acquisition contest at time τ, $P_{both,\tau}$, is given by

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

[6] The target's bargaining power may be microfounded by assuming random future arrival of additional firms possessing products/technologies superior to those of the target, i.e. by assuming obsolescence risk.

2.2.2 Only one firm discovers the target

Assume now that in period τ only one 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 $\tau+1$.

The target's reservation price

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

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

The first term on the right-hand side of (3) represents the scenario in which firm $-i$ does not discover the target in period $\tau+1$, in which case the target's period $\tau+1$ reservation price, $T_{i_{alone},\tau+1}$, equals $T_{i_{alone},\tau}(1+g)$. 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, $P_{both,\tau+1} = P_{both,\tau}(1+g)$, given in (2).

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

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

It follows from (4) that the target's reservation price is increasing in i) its bargaining power, since when its bargaining power is higher, it is more willing to wait for a potential future takeover contest; ii) the likelihood of firm i's rival discovering the target in the next period, p, since a higher probability of target's discovery by firm $-i$ raises the likelihood of the acquisition contest; and iii) the growth rate of per-period profits, as higher growth rate raises the acquisition price in case a takeover contest occurs in the future.

We now examine each bidder's benefit of acquiring the target when it discovers it alone. We first study the case of the complementary bidder and then that of the noncomplementary one.

The complementary bidder discovers the target first

Assume first the complementary bidder (firm 1) discovers the target 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

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

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 discounted next-period target's reservation price multiplied by the probability of the target not being discovered by firm 2 next period. The last term is the price that firm 1 would pay for the target if it is discovered next period by firm 2 leading to an acquisition contest.

Simplifying the bidder's net gain from acquiring the target in period τ leads to the following result:

Lemma 3. *If the complementary bidder is the only one to discover the target at time τ then it acquires the target at time τ for $T_{alone,\tau}(1)$.*

The reason for this result is that the complementary bidder's gain from acquiring the target immediately upon discovery is always positive. The intuition is as follows. The target trades off today's bid against next period's discounted value of expected bid. The latter is the weighted average of i) today's reservation price adjusted by inter-period growth and discounted by one period and ii) the discounted bid by the complementary bidder in case its rival discovers the target next period. For the bidder, an additional part of this trade-off is an increase in period-τ profit relative to the no-merger case, $\pi_1(\mu_\tau, 1) - \pi_2(\mu_\tau, 0) > 0$. Since the target does not internalize the latter element, its reservation price is lower than that of the bidder.

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:

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

The difference between the net benefit from acquiring the target for the noncomplementary bidder in (6) and that for the complementary bidder in (5) is the last terms in the respective equations. Unlike the complementary bidder, which by acquiring the target at time τ potentially saves the (higher) future acquisition price, $P_{both,\tau+1}$, the savings to the noncomplementary bidder in the case of a 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 rival, $B_{2_{both},\tau+1}$. Because of the target's bargaining power, $\phi > 0$, the benefit to the complementary bidder is larger than that to the noncomplementary one, $P_{both,\tau+1} > B_{2_{both},\tau+1}$, 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 4. *If the noncomplementary bidder is the only one to discover the target at time τ then it acquires the target in period τ for $T_{alone,\tau}(2)$ if and only if the noncomplementary bidder's complementarity parameter, δ_2, exceeds the threshold $0 < \delta^*(\delta_1) < \delta_1$, which solves the following equation:*

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

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 that conditional on no merger. The denominator is the difference between i) the net per-period benefit to the complementary bidder from acquiring the target relative to the case in which its rival acquires the target and ii) the net per-period benefit to the noncomplementary bidder from acquiring the target relative to the case in which its rival acquires the target. The left-hand side of (7) is monotonically increasing in the noncomplementary bidder's complementarity parameter, 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 benefit 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 a positive $\delta_2 < \delta_1$ 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.

2.2.3 Expected relative complementarity and the likelihood of complementary merger

We showed in the previous subsection that if the complementary bidder discovers the target in any given period, it always acquires it, while if the noncomplementary bidder discovers the target, it acquires it if i) the complementary bidder has not discovered the target yet, and ii) the noncomplementary bidder's complementarity with the target exceeds a certain threshold. Next, we define formally the expected relative merger complementarity.

Let us define a function $\upsilon(\delta_2, \delta_1)$, which measures the degree of relative complementarity of an acquisition by a bidder with complementarity parameter δ_2 in the presence of a complementary bidder with the complementarity parameter δ_1, such that $\frac{\partial \upsilon(\delta_2,\delta_1)}{\partial \delta_2} > 0$ and $\upsilon(\delta_1,\delta_1) = 1$. Notably, the comparative statics discussed above account for the fact that firms operate in different environments/industries and the availability of complementarities/synergies may vary across firms for reasons not considered in the model. Therefore, instead of analyzing *expected absolute complementarities*, which may be driven by a variety of omitted factors that are common to firms in particular industries, we examine *expected relative complementarities*, defined as complementarities in observed mergers relative to complementarities between the target and potential (counterfactual) bidders.

The expected relative merger complementarity conditional on observing a merger, $\mathbb{E}(\upsilon)$, is given by

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

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 for (8) is as follows. The probability with which the complementary bidder (firm 1) discovers the target first (possibly together with the noncomplementary bidder, firm 2) is p_b. In that case the merger takes place immediately (see Lemma 3) and the relative complementarity, $\upsilon(\delta_1,\delta_1)$, equals one. The probability with which the noncomplementary bidder discovers the target alone equals $p_b(1-p_b)$. In that case the likelihood of the merger happening equals $\Gamma(\delta_1)$ for any given δ_1, i.e. noncomplementary merger occurs if the complementarity parameter of the bidder is high enough relative to that of the complementary bidder.

It follows from this discussion that the conditional likelihood of a complementary merger is given by

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

The numerator of (14) is the probability of the target being discovered by the complementary bidder. The denominator is the sum of two probabilities: the probability of discovery by the complementary bidder and the probability of discovery by noncomplementary bidder *alone* multiplied by the probability of a merger conditional on the discovery by the non complementary bidder.

Note that the probabilities of target discovery by the two incumbents are conditional on $\delta_1 > \delta_2$. 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. Conditional on the noncomplementary bidder discovering the target first, The likelihood of a merger is $\Gamma(\delta_1)$ and the expected complementarity is $\Psi(\delta_1)$ for a given δ_1. Integrating over the distribution of δ_1 leads to the expected relative merger complementarity and the likelihood of a complementary merger.

In the next subsection we examine the comparative statics of the expected relative merger complementarity with respect to various model parameters.

2.3. Comparative statics

Partially differentiating the expected relative merger complementarity, $\mathbb{E}(\upsilon)$ in (8), and the probability of a complementary merger, *prob*(*comp*) in (14), with respect to the model's parameters, leads to the following results. For brevity, in the following propositions, we focus on the comparative statics with respect to expected relative merger complementarity. Importantly, we prove in the Appendix that all comparative statics for the conditional likelihood of a complementary merger are identical to those for the expected relative merger complementarity.

Proposition 1. *The expected relative merger complementarity,* $\mathbb{E}(\upsilon)$ *is increasing in the target's bargaining power,* ϕ.

The intuition is that higher target's bargaining power in the case of a takeover contest raises the target's reservation price in case it is discovered by the noncomplementary bidder only, increasing the lower complementarity threshold of the noncomplementary bidder, $\delta^*(\delta_1)$. The higher this threshold the lower the likelihood of the noncomplementary bidder's complementarity parameter, δ_2, to exceed it, and the higher the expected merger complementarity.

Proposition 2. *The expected relative merger complementarity,* $\mathbb{E}(\upsilon)$ *is increasing in the growth parameter, g.*

Higher growth rate raises the importance of future periods relative to the current period and increases the target's willingness to wait and, thus, its reservation price, again leading to higher complementarity threshold for the noncomplementary bidder, and higher expected merger complementarity.

Proposition 3. *The expected merger complementarity,* $\mathbb{E}(\upsilon)$ *is increasing in the target's characteristics positively associated with the probability of being discovered, y.*

The intuition is as follows. Target's characteristics associated with the likelihood of its discovery, y have two effects on the expected complementarity. The first one is through the effect on the threshold complementarity, $\delta^*(\delta_1)$, implicitly defined in (7). Since the likelihood of the target being discovered by the complementary bidder, p_b, which is increasing in y, raises this threshold, this effect of y on the expected complementarity is positive. Second, y has a direct effect on the likelihood of target's simultaneous discovery by the two firms, $p_b\,(1-p_b)$. However, the effect of an increase in y on p is larger than the effect on $p_b\,(1-p_b)$. Thus, the second effect of y on $\mathbb{E}(\upsilon)$ is positive as well, leading to an overall positive relation between the expected merger complementarity and target's characteristics related to the likelihood of its discovery.

Finally, if we impose additional structure on the type of interaction among 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 the expected relative merger complementarity. Assume that the demand for firms' products is linear, of the form $D(\eta_i, \eta_j) = a_i - b\eta_i + c\eta_j$, where η_i and η_j are firm i's and its rival's output market prices, $a_i = \frac{\beta\mu_i - \gamma\mu_j}{\beta^2-\gamma^2}$, $a_j = \frac{\beta\mu_j - \gamma\mu_i}{\beta^2-\gamma^2}$, $b = \frac{\beta}{\beta^2-\gamma^2}$, and $c = \frac{\gamma}{\beta^2-\gamma^2}$. Such demand function obtains in a standard model of a representative consumer with quadratic utility $U(q_i, q_j) = \sum\limits_{i=1}^{k} \mu_i q_i - \frac{1}{2}\left(\beta \sum\limits_{i=1}^{k} q_i^2 + 2\gamma \sum\limits_{j\neq i} q_i q_j\right)$, 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. Under the assumptions above, we obtain the following relation between the degree of competitive interaction in an industry and $\mathbb{E}(\upsilon)$:

Proposition 4. *There exists a value of the degree of competitive interaction in the bidder's industry, $\gamma^* < \beta$, above which the expected merger complementarity,* $\mathbb{E}(\upsilon)$*, is increasing in the degree of competitive interaction, γ.*

Table 1: Summary of comparative statics

Model parameter	Effect on expected relative merger complementarity
ϕ (target's bargaining power)	+
g (industry growth)	+
y (target's characteristics related to probability of its discovery)	+
γ (degree of competitive interaction)	+

The idea is that for sufficiently large degree of competitive interaction among incumbents, increasing it amplifies the effect of an acquisition of the target by a firm on that firm's rival's per-period profits. Thus, the larger the γ, the larger each bidder's net per-period benefit of an acquisition, which is the difference between a firm's per-period profit conditional on acquiring the target and that conditional on the target being acquired by the rival. It follows that the target's price in case of takeover contest in (2) is increasing in γ. Thus, the higher the degree of competitive interaction in the bidders' industry, the higher the target's willingness to wait for a potential takeover contest. This, in turn, increases its reservation price in the case it is discovered by just one bidder, and results in a higher complementarity threshold of the noncomplementary bidder, δ_2, leading to a positive relation between γ and the expected merger complementarity for sufficiently high level of γ.[7]

Note that another possible comparative static is the relation between the discount rate, r, and expected relative merger complementarity. It is easy to show that the effect of r on merger complementarity is negative. We do not focus on this relation, since it does not lead to cross-sectional empirical predictions. However, the 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. high expected complementarities).

Table 1 summarizes the comparative statics described in Propositions 1-4. In the next two sections, we discuss the empirical proxies for the degree of merger complementarity and for the model's parameters, and perform empirical tests of the comparative statics summarized in Table 1.

[7] It can be shown that similar result obtains under heterogenous products Cournot competition.

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.

3.2. Measures of merger complementarity

Measuring the degree of merger complementarity is a notoriously difficult task. Existing literature (e.g., Hoberg and Phillips (2010) and Bena and Li (2014)) proposes measures of merger complementarity that are based on *relatedness* 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 relatedness 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, supporting the link between product and/or technology relatedness 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 relatedness and complementarity, we examine whether the bidder-target relatedness 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 relatedness is associated with complementarity, we should observe higher relatedness between the target and the winning bidder, compared to that of the target and the losing bidder. Consistent with this hypothesis, we find that in takeover contests, winning bidders are significantly more strongly related to targets, on average, than losing bidders. In other words, bidders that are more strongly related to targets are willing to pay more in order to acquire the targets than bidders whose relation to targets is weaker, supporting the conjecture that relatedness between a bidder and target is positively associated with merger complementarity. Note, that takeover contests are an especially convenient laboratory for examining whether relatedness is positively associated with complementarity ceteris paribus, since in takeover contests all bidders have already discovered the target, which makes information environment (and possible effects of relatedness on it) less relevant. The construction of the takeover contest sample is described in detail in Section 3.4.1 below.

In light of the discussion above, we follow the existing literature and base our measures of merger complementarity on relatedness between bidders and targets. We employ two independent approaches and datasets to estimate merger complementarities and construct proxies for the model's parameters. In the first approach, we measure complementarities between actual and potential bidders and targets using text-based analysis of firms' product descriptions, as proposed by Hoberg and Phillips (2010). The second approach follows Bena and Li (2014), who rely on patent information from NBER Patent Citations data, and measures the degree of complementarity as the overlap between bidders' and targets' patent portfolios.

The advantage of an 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-relatedness-based analysis is that the data contain information on patent activity of private firms as well as that of public ones. The disadvantage 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. Another difference between the two datasets is that patent-based data are available for years 1976–2006, while data containing product descriptions span a shorter but more recent period, 1996–2011. Since each approach has its benefits and shortcomings, we perform all the empirical analyses using each dataset separately, with the idea that relying on two different approaches enhances the robustness of our results. We provide detailed descriptions of each approach and its corresponding datasets in the next two subsections.

3.2.1 Product-description-based data

To identify product-dewcription-based complementarities between bidders and targets, we use data from Hoberg and Phillips (2010), who obtain 10-K product descriptions from the Securities and Exchange Commission website (Edgar) for the period 1996–2011, translate all non-common words in each product description into a unit-length vector and compute every year cosine similarity between vectors of each two firms in Compustat. The resulting text-based similarity measure ranges between zero and one. Intuitively, the higher the proportion of words that a pair of firms' product descriptions have in common, the higher their similarity score, and the more related the products of the two firms are.[8]

To compute relative merger complementarity, we first obtain the relatedness measure 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 complementarity-unrelated considerations, we exclude all cases in which the relatedness between the bidder and target is strictly zero.

Typical relatedness of products may vary across industries due to industry-specific features of products and their descriptions. Thus, we normalize our measure of bidder-target product relatedness by the relatedness of the target with a (counterfactual) potential bidder with the highest relatedness measure. In particular, we search for the highest similarity score of the target firm with any other firm in Compustat universe. We scale the similarity score of the actual bidder-target pair by the highest similarity score of any firm with that target, and use the resulting ratio as a product-descriptions-based measure of *relative* merger complementarity for a merger involving target i, $\Theta prod_i$:

$$\Theta prod_i = \frac{\rho_{i,j}}{\sup\left(\rho_{i,1}, ...\rho_{i,k}, ...\rho_{i,K}\right)} \forall k \underline{\in TNIC(i)}, \tag{15}$$

where K is the number of Compustat firms in a given year. Higher relative complementarity indicates a better product match of the actual bidder-target pair relative to a hypothetical match between the target and the most complementary potential bidder. $\Theta prod_i$ ranges between zero (excluding strict zero) and one, where the value of one indicates that the actual bidder has the highest complementarity with the target among all potential bidders.

3.2.2 Patent-based data

To construct a patent-based proxy for relative merger complementarity, 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)) 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 obtained results to filter cases of unrelated links.

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

To validate the goodness of the match and to resolve ambiguous cases, we rely on city and state information of patent assignee and target firm, 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 firm's business.[9] As a result, we obtain a list of public and private targets, their public acquirers, and matching PDPASS numbers.

To construct a measure of relatedness 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.[10] In particular, for each patent we observe the patent technology field in which the patent was granted, defined according to one of the 36 2-digit technological subcategories developed by Hall, Jaffe, and Trajtenberg (2001). For each firm i in year t, we construct 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 ratio of the number of patents awarded to firm i in years $t-5$ to $t-1$ in class k to all patents awarded to firm i in years $t-5$ to $t-1$. In the spirit of Jaffe (1986) and Bena and Li (2014), and following Lyandres and Palazzo (2015), we calculate patent-based relatedness of firms' i and j in year t, $Patsim_{i,j,t}$:

$$Patsim_{i,j,t} = \sum_{k=1}^{K} \min[P_{i,t,k}, P_{j,t,k}] \in [0, 1]. \tag{16}$$

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.[11]

It is possible that a firm has multiple PDPASS numbers due to different name spellings and hierarchical structure. Thus, after we obtain the pairwise similarity at a PDPASS level, we aggregate the results at a firm-pair level in cases in which one or both firms have more than one PDPASS.

[9] For example, in 1997 Eaton Corp. sold its Eaton Worldwide Axle division to Dana Corp. however Eaton Worldwide Axle (the acquisition target) does not appear in the NBER database, while Eaton Corp. (the target's parent) does. In this case, we do not use the data for Eaton Corp. in the computation of patent-based similarity measure and exclude this merger from the sample.

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

[11] Jaffe (1986) and Bena and Li (2013) 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%.

Specifically, we assign 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 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 synergy from matching the target with its most complementary unit. The ability to measure division-level complementarity partially addresses the concern that multi-divisional firms may have low *average complementarity* with single-division targets, whereas the relatedness of their divisions within which the targets are integrated may be high.

As in the case of product-based relative complementarity, we scale the relatedness of the actual bidder-target pair by the highest relatedness of any firm with the target, and use the resulting ratio as the patent-based measure of relative merger complementarity, Θpat_i:

$$\Theta pat_i = \frac{Patsim_{i,j,t}}{\sup\left(Patsim_{i,1}, ...Patsim_{i,k}, ...Patsim_{i,K}\right)} \forall k, \tag{17}$$

where K is the total number of firms that were granted patents in years $t-5$ to $t-1$.

3.3. Determinants of expected merger complementarity

3.3.1 Target's bargaining power

The first prediction of the model is that the expected relative merger complementarity should be increasing in target's bargaining power, ϕ, since the higher its bargaining power, the more willing the target is to wait to be discovered by a more complementary bidder. In what follows, we describe our proxies for target's bargaining power within the two datasets that we use in the empirical tests.

Product–based data

We use the arrival rate of potential targets (*target arrival rate*) as an inverse proxy for target's bargaining power. The intuition behind this measure is as follows. The higher the number of potential future targets, the larger the risk that another firm with product/technology superior to that of the existing target would arrive in the future (obsolescence risk) and the lower the target's bargaining power.

To estimate target arrival rate, 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.[12] We calculate the number of deals by venture

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

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 and are ready to go public or to be acquired.

The industry-level target arrival rate 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 an industry level (MoneyTree defines 16 different 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 bidder, we use the natural log of the number of deals in the industry that corresponds to its 4-digit SIC code.[13]

Patent–based data

Since venture capital data, which we use to construct a measure of target arrival rate, are available only from 1996, they are not well suited for use with patent data, which span years 1976–2006. Instead, we use the number of patents that the target was granted during the 5-year period prior to the merger year as the measure of target's bargaining power. The idea is that firms that have generated a higher number of patents in the past face lower obsolescence risk, which, in turn, is negatively related to target's bargaining power.

3.3.2 Bidders' growth

The second prediction of the model is that the expected merger complementarity should be increasing in the growth rate of bidders' profits, g. Higher growth rate increases the target's willingness to wait until a more suitable bidder arrives, and as a result, raises expected merger complementarity. We proxy for the growth rate by the change in EBITDA in the winning bidder's industry. For each firm, we compute EBITDA by scaling operating income before debt and taxes by assets, and calculate the change in EBITDA between year 0 and 1 relative to the merger year.[14] We then average the resulting changes in EBITDA across 3-digit SIC industries.

We also verify that our results are robust to a forward-looking estimate of industry growth and use analyst forecasts as an alternative measure of expected growth. In particular, using I/B/E/S database, we obtain mean and median estimates (across all analysts) of long-term change in firms' earnings per share. For every bidder, we identify its industry peers and average all the forecasts for peer firms released in the year prior to the merger date.

[13]In cases in which 4-digit SIC industries corresponds to several MoneyTree industries, we average the arrival rates across the latter.

[14]We winsorize extreme observations of the change in EBITDA at values of -100% and 500%.

3.3.3 Probability of target's discovery

The third prediction of the model is that the expected merger complementarity is increasing in target's characteristics associated with the likelihood of its discovery, y, as there is a higher likelihood that more visible targets would be discovered (and acquired) by complementary bidders.

We proxy for the probability of target's discovery by the natural logarithm of one plus the number of M&A advisors of the target, with an idea that M&A advisors are beneficial for the targets and, in particular, that they may facilitate target's discovery by potential bidders (e.g., Bao and Edmans (2011) and Benou, Gleason and Madura (2007)).

3.3.4 Degree of competitive interaction

The last prediction of the model is that expected relative merger complementarity is increasing in the degree of competitive interaction among potential bidders, γ (for a high enough γ). The reason is that γ raises the target's price in the cases of a takeover contest, increasing the target's willingness to wait for a contest, i.e. for its discovery by the complementary bidder.

Product–based data

We measure the degree of a bidder's competitive interaction with its competitors as the average relatedness between bidder's product description and those of other firms operating in the bidder's industry. To identify industries, we use the Text-based Network Industry Classification (TNIC) (see Hoberg and Phillips (2010)).[15] This classification defines an industry for each firm by picking all the peers with positive pairwise relatedness with that firm. The advantage of this approach is that it overcomes some limitations of the SIC and NAICS classifications[16] and takes into account competition among 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 relatedness within its industry. The higher the average relatedness, the more substitutable the products within a given industry. Higher substitutability increases the higher the degree of competitive interaction, as well as the benefit for any bidder from acquiring the target

[15] We only examine potential bidders in the year of the actual merger in order to capture possible M&A clustering in time (e.g., Mitchell and Mulherin (1996) and Ahern and Harford (2014)).

[16] In addition to an omission of possibly complementary mergers among firms operating in different SIC or NAICS industries, 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 face of evolving product markets and/or firms entering different industries. For example, hundreds of new technology and web-related firms were assigned to the large and nondescript "business services" SIC industry through the nineties (see Hoberg and Phillips (2010)). Third, SIC and NAICS classifications impose transitivity, while it is possible that two competing firms may have different product market rivals.

relative to the situation in which the target is acquired by another potential bidder.

Patent–based data

Since product-description-based measures of relatedness are only available starting 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 idea is as follows. The wider the patent category, the less related the patented products within the associated technology field, and the higher the differentiation potential within it.

Our inverse measure of the degree of competitive interaction is constructed as follows. For every bidder, we first identify its three major 3-digit technological subcategories, based on the frequency of assignment of patents to technology fields across all patents that the bidder was granted in the 5-year period prior to the year of the merger. Separately, every year we calculate the number of patents that were granted in each 3-digit patent subcategory within the overall sample of non-withdrawn or missing patents that belong to corporations.[17] Then for each bidder we average the number of overall 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.[18]

3.4. Summary statistics

3.4.1 Product-based data

Table 2 shows the distribution of relative merger complementarity 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 1,585 observations with non-missing values of relative merger complementarity (corresponding to 1,031 distinct successful bidders).

Insert Table 2 here

The mean (median) of the dependent variable, relative merger complementarity, is 0.53 (0.51), with a standard deviation of 0.31, and it ranges through its entire possible spectrum (0.0004 to 1).

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

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

In the second and third rows of the table we report summary statistics of merger complementarity 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 the methodology by 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 contesters 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 compute relative complementarity measures between the target and both successful and 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 theoretical result, the mean value of relative complementarity between targets and bidders that win takeover contests is twice the mean relative complementarity between targets and bidders that lose the contests, the difference being statistically significant at the 1% level. This finding provides further evidence that product-description-based relatedness is positively associated with merger complementarity.

The log rate of potential targets' arrival to the industry, which serves as an inverse proxy for target's bargaining power, is 4.71 and it exhibits considerable variation – its standard deviation is 0.65. The mean (median) industry growth in EBITDA is -0.01 (0) with standard deviation of 0.04. The mean (median) logarithm of one plus the number of M&A advisors, which proxies for target's discoverability, is 1.25 (1.1) and its standard deviation is 0.39. The highest number of M&A advisors hired by a target is 10. The average (median) product-description-based relatedness of bidders with firms in their TNIC industries, serving as a proxy for the degree of competitive interaction between the winning bidder and its peers, is 0.05 (0.04). Summary statistics for the control variables are similar to the ones reported in studies that use Compustat-based samples.

Table 3 shows the correlation matrix of the product-description-based merger complementarity measure, 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 0.17 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 relative merger complementarity, proxies for model's parameters, and control variables, whereas the correlation matrix is presented in Table 5.

Insert Table 4 here

The patent-based sample has 1,127 observations and 593 different bidders. The distribution of the patent-based measure of merger complementarity is similar to that of the product-based measure. The mean (median) patent-based complementarity measure, Θpat_i, is 0.55 (0.5) and standard deviation is 0.31, indicating substantial heterogeneity in the merger complementarity measure. The measure of target's discoverability, log of target's patents in the past five years, exhibits considerable variation: the minimum number is 0.693 (1 patent), while the maximum is 7.86 (2,592 patents). The mean (median) logarithm of the number of M&A advisors is 0.55 (0.69). These numbers are lower than the corresponding ones in the product-description-based sample, since private firms, included in the patent-based sample, are less likely to hire M&A advisors than public ones. The breadth of technological fields in which the bidder tends to file patents, 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 0.9.

Insert Table 5 here

Relative merger complementarity has a negative correlation of -0.32 with bidder size, but other correlations are relatively modest, including the correlations among the proxies for the model's parameters, which range between 0.03 and 0.34 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:

$$\Theta_i = \alpha + \beta_\phi \phi_i + \beta_g g_i + \beta_y y_i + \beta_\gamma \gamma_i + \overrightarrow{\beta_B}' \overrightarrow{B_i} + \overrightarrow{\beta_T}' \overrightarrow{T_i} + \varepsilon_i. \tag{18}$$

Θ_i is a measure of relative complementarity in merger i ($\Theta prod_i$ in the case of product-description-based data and Θpat_i in the case of patent-based data). ϕ_i is a measure of target's bargaining power (target arrival rate or target's patent intensity for the case of product data and patent data respectively). g_i is the growth in bidder's industry EBITDA. y_i is target's characteristic related to the likelihood of being discovered (logarithm of the number of M&A advisors). γ_i is the degree of competitive interaction among potential bidders (computed based on average product-description-based relatedness 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 target's characteristics that serve as controls (market-to-book, tangibility, and profitability). We estimate the regression in (18) using year fixed effects. Standard errors are computed using variance-variance matrix adjusted for clustering at the firm level (see Petersen (2009)).

In addition, we examine factors that influence the conditional likelihood of observing a complementary merger. In this estimation our dependent variable is an indicator that equals one if the merger is complementary, and zero otherwise. If the observed measure of complementary were to capture the true complementarity precisely, we could use a threshold of one to separate complementary merger from non-complementary ones. However, Benner and Waldfogel (2008) show that any type merger complementarity is measured with error. Therefore, we use various thresholds for defining complementary mergers. We report the results of the specification in which the threshold for competitive merger exceeds 0.7, but the findings are robust to using other thresholds of complementarity.

4.2. Product-based analysis

Table 6 presents estimates of (18) using product-description-based data and variables. In the first column, we estimate (18) using only the proxies for the model's parameters. In the second column, we augment (18) by including control variables for the bidder, while in the third column, we also include control variables for the target. The fourth column presents the results of estimating a logistic regression in which the dependent variable is an indicator equaling one for complementary mergers and zero otherwise.

Insert Table 6 here

Overall, the signs of the coefficients on all the variables of interest, except industry growth, are consistent with the model's predictions, and the coefficients are statistically significant. Higher target arrival rate, which we use as an inverse proxy for target's bargaining power, is negatively associated with relative merger complementarity and with the conditional likelihood of a complementary merger. The logarithm of the number of M&A advisors, which captures the likelihood of target's discovery by bidders, is positively related to merger complementarity and the probability of a complementary merger. Finally, higher competitive interaction among potential bidders is also positively related to relative complementarity. All of these relations are consistent with the directional predictions of the model.

Importantly, the overall results are also economically significant. For example, a one standard deviation increase in the measure of intensity of competitive interaction, γ, is associated with an increase of 0.06 in relative merger complementarity (equivalent to 20% of its standard deviation), while the impact of one standard deviation increase in the proxy for the probability of target's discovery – scaled target's assets – is 0.04 (equivalent to 13% of the standard deviation of the merger complementarity measure). Similarly, a one standard deviation increase in the proxies for the target's bargaining power, its discoverability, and the degree of competitive interaction in bidders' industries results in a 15%-17% standard deviation increase in the conditional likelihood of a complementary merger (evaluated at mean values of all variables).

While most control variables, except size, are statistically insignificant, their inclusion helps address some concerns regarding omitted variables and alternative explanations. For example, it is possible that mergers with a low degree of complementarity 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. We add target's profitability and market-to-book ratio to account for potential mispricing, and find that their inclusion 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 (18) (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 higher relatedness between 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. Thus, to mitigate the potential market power effect, we re-estimate our baseline regression within a subsample of mergers involving targets operating in relatively competitive industries, in which 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 column 1 of Table 7. The coefficients of the main independent variables are similar to this in the full sample, and are slightly larger and more economically meaningful in the case of proxies for target's discoverability and the degree of competitive interaction in bidders' industries.

Second, we address an alternative, agency-based explanation for our results, according to which noncomplementary mergers may be driven by empire-building considerations of entrenched managers, who may acquire targets in unrelated industries (e.g., Amihud and Lev (1981)). To address this concern, we use the entrenchment index, due to Bebchuk, Cohen, and Ferrell (2009), and re-estimate (18) for the subsample of acquiring firms with low agency problems, as defined by entrenchment index of 3 and below.[19] The results, reported in the second column, demonstrate that our findings are not likely to be driven by agency reasons.

Next, we verify that our results are not driven by "serial acquirers", or firms that constantly search for M&A deals and perform multiple acquisitions during short time spans. Financial press identifies serial acquisitions as a different type of strategy, typically deals involving small, less visible, and undervalued targets. We ensure that our findings are not affected by overrepresentation of such deals, which could be driven by mispricing, rather than synergy, motives. To identify serial acquirers, we look at the history of all completed deals (both domestic and international), conducted by all acquirers during the 5-year period prior to merger year, and eliminate firms that belong to the top 10% of the distribution, which corresponds to firms that have conducted more than 6 deals during 5 years prior to the merger year. The results, presented in the last column of Table 7, demonstrate that our findings are not sensitive to the exclusion of firms with a large number of past acquisitions.

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

Lastly, we ensure that the results are not driven by the merger wave of the late 90s (e.g., Betton, Eckbo, and Thornburn (2008)), the peak of which happens in 1997-1998 and by the high-tech bubble of 1999-2000, which could drive some of our mergers, and exclude years 1997–2000 years from the analysis. The results are reported in the first 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 (18) using data and variables constructed from NBER patent data and report the results in Table 8. Since we do not have any accounting information on private targets, we use only bidder's control variables while estimating (18). The first two columns report OLS estimates of (18), while the third column presents logic estimates of a regression in which the dependent variable is an indicator equaling one (zero) for complementary (noncomplementary) mergers.[20] We also include year fixed effects.

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 number of patents owned by the target firm, which serves as a proxy for its bargaining power, is positively associated with relative merger complementarity. The breadth of bidder's industry, which we use as an inverse proxy for the intensity of competitive interaction, is negatively associated with relative merger complementarity. The probability of target discovery, proxied by the logarithm of the number of target's M&A advisors, is positively related to merger complementarity. Unlike the analysis using product-based data, growth in EBITDA has a positive impact on relative merger complementarity and the conditional likelihood of a complementary merger.

In addition to being statistically significant, the variables of interest also have an economically significant impact on relative merger complementarity and the probability of a complementary merger. For example, a one standard deviation increase in the target's bargaining power raises the relative complementarity measure by 0.06, which is equivalent to 11% of its mean value, and 20% of its standard deviation. The economic impact of the other variables is also sizable: a one standard

[20]As in the case of product-description-based data, the results reported below are based on the complementarity threshold of 0.7. The results are robust to varying the threshold.

deviation increase in each variable increases the relative merger complementarity by 0.02 − 0.03 (in absolute value), corresponding to around 6% − 11% of its standard deviation.

In Table 9 we perform the same set of robustness tests, as the ones described in the previous subsection, and ensure that the results are not driven by agency considerations, by by serial acquirers,[21] and by the merger wave of the late nineties and the high tech bubble.[22] Ensuring that our results are not driven by serial acquirers is especially important in this sample, since the strategy of serial acquisitions could be more prevalent for private and, consequently, less visible firms, which have a stronger representation in this sample, as well as for technology firms that are also over-represented in this sample.

Insert Table 9 here

Overall, the results of all robustness tests are consistent with those in the main specifications. The statistical significance of the coefficients on all the proxies for the model's parameters other than patent breadth in the first subsample is not affected by the removal of serial acquirers from the sample, and their magnitudes are similar to the ones obtained within the full sample.

5. Conclusions

Existing theoretical literature on complementarities in mergers and acquisitions demonstrates that firms with complementary products and/or technologies are more likely to become merger partners than noncomplementary ones. Existing empirical evidence indicates that complementarity among firms is positively related to the incidence of mergers between them and to post-merger performance. Yet, there is a substantial variation in the degree of complementarity in actual deals, i.e. acquirers do not seem to always merge with the most complementary targets. In this paper we analyze theoretically and empirically which factors determine the degree of complementarity between bidders and targets in observed mergers and acquisitions.

In our dynamic 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 nonzero likelihood that a merger would occur between the target and the bidder that have relatively low complementarity. We examine the determinants of expected merger complementarity, as well as of the conditional likelihood of a complementary merger, and show that they are increasing

[21] In this sample, the cutoff defining serial acquirers is 7 past acquisitions

[22] We cannot perform a subsample analysis based on industry structure, a we do not have information about TNIC industry classification of private targets and of targets of acquisitions that occurred prior to 1996.

in target's bargaining power, the likelihood of its discovery, growth in potential bidders' industries, and the extent of competitive interaction among potential acquirers.

In our empirical tests we examine relations between proxies for the model's parameters and proxies for relative merger complementarity, i.e. complementarity between bidder and target in an actual acquisition relative to that between target and the most complementary (often counterfactual) bidder. We perform the empirical tests using two datasets, which we use to define two separate proxies for merger complementarity. The first one is based on complementarity in firms' product offerings, constructed using firms' product descriptions. The second proxy is based on complementarity in firms' technologies, constructed using a measure of overlap in firms' patents' technology fields.

Both sets of tests show that target's bargaining power, the probability of target's discovery by potential bidders, and the degree of competitive interaction in their industries are positively related to the degree of complementarity in observed mergers, with the relations being significant both statistically and economically.

More generally, our paper demonstrates that noncomplementary mergers can occur among value-maximizing firms and in the absence of market power considerations, and that the degree of complementarity in observed mergers and acquisitions is systematically related to bidders', targets', and industry characteristics.

A Proofs

Proof of Lemma 1

First, note that

$$\pi_1(\mu_t,1)+\pi_2(\mu_t,1)-(\pi_1(\mu_t,2)+\pi_2(\mu_t,2)) = \int_{\underline{\delta}}^{\delta_1} \frac{\partial\left(\pi_1(\mu_t,1)+\partial\pi_2(\mu_t,1)\right)}{\partial\delta_1} d\delta_1 - \int_{\underline{\delta}}^{\delta_2} \frac{\partial\left(\pi_2(\mu_t,2)+\partial\pi_1(\mu_t,2)\right)}{\partial\delta_2} d\delta_2 \tag{19}$$

Under the assumption of initial symmetry, $\alpha_1 = \alpha_2$, (19) can be rewritten as

$$\pi_1(\mu_t,1)+\pi_2(\mu_t,1)-(\pi_1(\mu_t,2)+\pi_2(\mu_t,2)) = \int_{\delta_2}^{\delta_1} \frac{\partial\pi_1(\mu_t,1)+\partial\pi_2(\mu_t,1)}{\partial\delta_1} d\delta_1$$

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

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

Proof of Lemma 2

In the Nash bargaining game between the complementary bidder and the target, the objective function is as follows:

$$\left(B_{1_{both},\tau} - P_{both,\tau}\right)^{1-\phi}\left(P_{both,\tau} - B_{2_{both},\tau}\right)^{\phi}. \tag{20}$$

Differentiating (20) with respect to $P_{both,\tau}$ and equating the resulting expression to zero leads to

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

Proof of Lemma 3

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

$$B_{1_{alone},\tau} = -T_{alone,\tau}(1)\frac{r-g+p(1+g)}{p(1+g)} + p\frac{P_{both,\tau}(1+g)}{1+r} + \left(\pi_1(\mu_\tau,1) - \pi_1(\mu_\tau,0)\right). \tag{21}$$

Plugging $T_{alone,\tau}(1)$ from (4) into (21) leads to

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

Proof of Lemma 4

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

$$B_{2_{alone},\tau} = -T_{alone,\tau}(2)\frac{r-g+p(1+g)}{p(1+g)} + p\frac{B_{2_{both},\tau}(1+g)}{1+r} + (\pi_2(\mu_\tau, 2) - \pi_2(\mu_\tau, 0)). \quad (22)$$

Plugging $T_{alone,\tau}$ from (4) into (22) and simplifying results in

$$B_{2_{alone},\tau} = -p_1\phi\left(B_{1_{both},\tau} - B_{2_{both},\tau}\right) + (\pi_2(\mu_\tau, 2) - \pi_2(\mu_\tau, 0)). \quad (23)$$

Plugging $B_{1_{both},\tau}$ and $B_{2_{both},\tau}$ from (1) into (23) results in:

$$B_{2_{alone},\tau} = -p\phi\frac{1+g}{r-g}\left(\pi_1(\mu_\tau, 1) - \pi_1(\mu_\tau, 2) - \pi_2(\mu_\tau, 2) + \pi_2(\mu_\tau, 1)\right) + (\pi_2(\mu_\tau, 2) - \pi_2(\mu_\tau, 0)). \quad (24)$$

$B_{2_{alone},\tau}$ in (24) is positive iff

$$\frac{\pi_2(\mu_\tau, 2) - \pi_2(\mu_\tau, 0)}{\pi_1(\mu_\tau, 1) - \pi_1(\mu_\tau, 2) - \pi_2(\mu_\tau, 2) + \pi_2(\mu_\tau, 1)} > p\phi\frac{1+g}{r-g}.$$

Proof of Propositions 1–3

Lemma 1 shows that $\pi_1(\mu_\tau, 1) - \pi_1(\mu_\tau, 2) - \pi_2(\mu_\tau, 2) + \pi_2(\mu_\tau, 1) > 0$. $\frac{\partial(\pi_2(\mu_\tau,2)+\pi_1(\mu_\tau,2))}{\partial\delta_2} > 0$ by assumption. Also, $\pi_2(\mu_\tau, 2) - \pi_2(\mu_\tau, 0) > 0$ by assumption. Thus, the left-hand side of (7) is increasing in δ_2. For $\delta_2 \longrightarrow 0$, $\pi_2(\mu_\tau, 2) - \pi_2(\mu_\tau, 0) \longrightarrow 0$ and the left-hand side of (7) approaches zero. For $\delta_2 \longrightarrow \delta_1$, $\pi_1(\mu_\tau, 1) - \pi_1(\mu_\tau, 2) - \pi_2(\mu_\tau, 2) + \pi_2(\mu_\tau, 1) \longrightarrow 0$ 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 right-hand side of

(7) is increasing in ϕ, g, and p,

$$\begin{aligned} \frac{\partial\delta^*(\delta_1)}{\partial\phi} &> 0, \\ \frac{\partial\delta^*(\delta_1)}{\partial g} &> 0, \\ \frac{\partial\delta^*(\delta_1)}{\partial p} &> 0. \end{aligned} \tag{25}$$

Also, we can write

$$\begin{aligned} \frac{\partial\mathbb{E}(\upsilon)}{\partial\phi} &= \int_{\underline{\delta}}^{\overline{\delta}} \frac{\partial(\mathbb{E}(\upsilon) \mid \delta_1)}{\partial\delta^*(\delta_1)} \frac{\partial\delta^*(\delta_1)}{\partial\phi} f_{\max}(\delta_1) d\delta_1, \\ \frac{\partial\mathbb{E}(\upsilon)}{\partial g} &= \int_{\underline{\delta}}^{\overline{\delta}} \frac{\partial(\mathbb{E}(\upsilon) \mid \delta_1)}{\partial\delta^*(\delta_1)} \frac{\partial\delta^*(\delta_1)}{\partial g} f_{\max}(\delta_1) d\delta_1, \\ \frac{\partial\mathbb{E}(\upsilon)}{\partial p} &= \int_{\underline{\delta}}^{\overline{\delta}} \frac{\partial(\mathbb{E}(\upsilon) \mid \delta_1)}{\partial\delta^*(\delta_1)} \frac{\partial\delta^*(\delta_1)}{\partial p} f_{\max}(\delta_1) d\delta_1. \end{aligned} \tag{26}$$

Note that

$$\begin{aligned} \frac{\partial(\mathbb{E}(\upsilon) \mid \delta_1)}{\partial\delta^*(\delta_1)} &= p_b(1-p_b) f_{\min}(\delta^*(\delta_1)) * \\ &\quad \Big(\frac{p_b(1-\upsilon(\delta^*(\delta_1),\delta_1))}{((p_b + p_b(1-p_b))(F_{\min}(\delta_1) - F_{\min}(\delta^*(\delta_1))))^2} + \\ &\quad \frac{p_b(1-p_b)\left[\int\limits_{\delta^*(\delta_1)}^{\delta_1} f_{\max}(\delta_1)(\upsilon(\delta_2,\delta_1) - \upsilon(\delta^*(\delta_1),\delta_1)) d\delta_2\right]}{((p_b + p_b(1-p_b))(F_{\min}(\delta_1) - F_{\min}(\delta^*(\delta_1))))^2}\Big). \end{aligned} \tag{27}$$

Note that for any $\delta_1 < \overline{\delta}$:

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

by definition;

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

$$p(1-\upsilon(\delta^*(\delta_1),\delta_1)) \geq 0,$$

by assumption $(\upsilon(\delta^*(\delta_1), \delta_1) \leq 1$;

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

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,

$$\frac{\partial(\mathbb{E}(\upsilon) \mid \delta_1)}{\partial \delta^*(\delta_{\max})} > 0, \tag{28}$$

Note that

$$\frac{\partial(prob(comp) \mid \delta_1)}{\partial \delta^*(\delta_1)} = \frac{p_b f_{\min}(\delta^*(\delta_1))}{\left((p_b + p_b(1-p_b))\left(F_{\min}(\delta_1) - F_{\min}(\delta^*(\delta_1))\right)\right)^2} > 0. \tag{29}$$

(28) and (29), combined with (25) and (26), implies that $\frac{\partial \mathbb{E}(\upsilon)}{\partial \phi} > 0$, $\frac{\partial \mathbb{E}(\upsilon)}{\partial g} > 0$, $\frac{\partial \mathbb{E}(\upsilon)}{\partial p} > 0$, $\frac{\partial prob(comp)}{\partial \phi} > 0$, $\frac{\partial prob(comp)}{\partial g} > 0$, and $\frac{\partial prob(comp)}{\partial p} > 0$.

Proof of Proposition 4

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

$$U = \sum_{i=1}^{k} \mu_i q_i - \frac{1}{2}\left(\beta \sum_{i=1}^{k} q_i^2 + 2\gamma \sum_{j \neq i} q_i q_j\right), \tag{30}$$

where k is the number of available products and q_i is the quantity consumed of product i. Differentiating (30) with respect to each q_i, equating the resulting expression to product i's price, η_i, and setting the number of available products (i.e. incumbent firms) to 2 leads to the following demand function for firm 1's product:

$$q_1 = a_1 - b\eta_1 + c\eta_2, \tag{31}$$

where $a_1 = \frac{\beta\mu_1 - \gamma\mu_2}{\beta^2 - \gamma^2}$, $b = \frac{\beta}{\beta^2 - \gamma^2}$, and $c = \frac{\gamma}{\beta^2 - \gamma^2}$, and similarly for firm 2. Assuming, without loss of generality, zero marginal cost of production, firm 1's profit is given by

$$\pi_1 = (a_1 - b\eta_1 + c\eta_2)\eta_1, \tag{32}$$

and similarly for firm 2. Differentiating (32) with respect to η_1 and a similar expression for firm 2 with respect to η_2, solving the resulting system of two equations, and plugging the result into (32), leads to the following expression for equilibrium profit of firm 1:

$$\frac{\beta\left(2\beta^2\mu_1-\gamma^2\mu_1-\beta\gamma\mu_2\right)}{\left(\beta^2-\gamma^2\right)\left(4\beta^2-\gamma^2\right)^2}, \tag{33}$$

and a similar expression for firm 2. Let us refer to μ_1 in the case of an acquisition of the target by bidder 1 by $\mu(\delta_1)$, μ_2 in the case of an acquisition of the target by bidder 2 by $\mu(\delta_2)$, and μ_1 and μ_2 in the case of no merger by $\mu(0)$. Given that $\delta_1>\delta_2>0$,

$$\mu(\delta_1)>\mu(\delta_2)>\mu(0).$$

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

$$\frac{\partial\Theta}{\partial\gamma}=\frac{\left(2\beta^2-\gamma^2\right)\left(\mu\left(\delta_2\right)-\mu\left(0\right)\right)}{\left(\mu\left(\delta_1\right)-\mu\left(\delta_2\right)\right)}\Lambda, \tag{34}$$

where

$$\begin{aligned}\Lambda=\left(-2\beta^3\gamma+\beta\gamma^3\right)\mu\left(\delta_1\right)\mu\left(\delta_2\right)+\left(-2\beta^3\gamma+\beta\gamma^3\right)\mu\left(\delta_2\right)^2+\\ \left(-4\beta^4-2\beta^3\gamma+5\beta^2\gamma^2+\beta\gamma^3-\gamma^4\right)\mu\left(\delta_1\right)\mu\left(0\right)+\left(4\beta^4-2\beta^3\gamma-3\beta^2\gamma^2+\beta\gamma^3+\gamma^4\right)\mu\left(\delta_2\right)\mu\left(0\right)+\\ \left(8\beta^4-8\beta^2\gamma^2+\gamma^4\right)\mu\left(0\right)^2.\end{aligned} \tag{35}$$

Note that the sign of (34) is equal to the sign of Λ in (35). As $\gamma\to\beta$,

$$\Lambda=-\beta^4\mu\left(\delta_2\right)\left(\mu\left(\delta_1\right)+\mu\left(\delta_2\right)-2\mu\left(0\right)\right)-\beta^4\mu\left(0\right)\left(\mu\left(\delta_1\right)-\mu\left(\delta_2\right)\right). \tag{36}$$

Given that $\mu(\delta_1)>\mu(\delta_2)>\mu(0)$, Λ is negative as $\gamma\to\beta$, and so is $\frac{\partial\Theta}{\partial\gamma}$ in (34). 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 1–3, this implies that $\frac{\partial\mathbb{E}(v)}{\partial\gamma}>0$ and $\frac{\partial prob(comp)}{\partial\gamma}>0$ for $\gamma\to\beta$, i.e. there exists γ^* such that if $\gamma>\gamma^*$ then $\frac{\partial\mathbb{E}(v)}{\partial\gamma}>0$ and $\frac{\partial prob(comp)}{\partial\gamma}>0$.

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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 complementarities. Relative merger complementarity is calculated by scaling the bidder-target pairwise product description relatedness by the maximum relatedness of the target to any other firm that year. We report the statistics for the full sample, as well as for takeover contests, in which we report statistics for successful bidders and failed bidders. Target arrival rate is the natural log of the number of deals involving investment in firms at the expansion stage at an 4-digit SIC industry level. Growth in EBITDA is the difference between EBITDA-to-assets ratio in years t and $t+1$, averaged at the TNIC industry of the bidder. Log(# M&A advisors) is the natural logarithm of one plus the number of target's M&A advisors. Average relatedness is the mean of the pairwise relatedness measures 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 targets book assets in millions of 2011 $. 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
Relative merger complementarity							
Full sample		1,585	0.53	0.51	0.0004	1.00	0.31
Takeover contests: Successful bidders		40	0.60	0.56	0.00	1.00	0.27
Takeover contests: Failed bidders		40	0.30	0.35	0.00	1.00	0.33
Determinants of complementarity							
Target arrival rate	ϕ (inverse)	1,503	4.71	4.65	2.64	6.34	0.65
Growth in EBITDA	g	1,580	-0.01	0.00	-0.17	0.26	0.04
Log(# M&A advisors)	p	1,579	1.25	1.10	0.00	2.40	0.39
Average relatedness	γ	1,489	0.05	0.04	0.00	0.25	0.03
Control variables							
Log(bidder assets)		1,585	7.91	7.85	1.598	14.43	2.05
Bidder M/B		1,585	2.22	1.40	0.44	20.00	2.39
Bidder tangibility		1,585	0.20	0.09	0.00	0.94	0.24
Bidder profitability		1,578	0.09	0.09	-1.00	0.55	0.14
Log(target assets)		1,585	6.19	6.17	1.04	13.64	1.81
Target M/B		1,579	1.85	1.22	0.219	20.00	1.89
Target tangibility		1,568	0.20	0.09	0.00	0.95	0.24
Target profitability		1,563	0.03	0.04	-1.00	0.52	0.21

Table 3: Product-description-based data: Correlations

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

	Proxy for	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Relative merger comp-ty		1.00												
Determinants of comp-ty														
(2) Target arrival rate	ϕ (inverse)	-0.08	1.00											
(3) Growth in EBITDA	g	0.00	-0.02	1.00										
(4) Log(# M&A advisors)	p	0.05	-0.13	0.00	1.00									
(5) Average relatedness	γ	0.07	0.09	0.10	-0.17	1.00								
Control variables														
(6) Log(bidder assets)		-0.23	0.08	0.06	0.20	0.30	1.00							
(7) Bidder M/B		-0.02	0.04	-0.23	0.04	-0.23	-0.23	1.00						
(8) Bidder tangibility		0.08	-0.02	0.04	0.18	-0.17	-0.07	-0.05	1.00					
(9) Bidder profitability		0.01	-0.10	-0.05	0.14	-0.20	0.17	0.07	0.27	1.00				
(10) Log(target assets)		0.00	0.04	0.08	0.35	0.32	0.68	-0.23	0.04	0.06	1.00			
(11) Target M/B		-0.04	0.01	-0.20	0.09	-0.20	-0.13	0.60	-0.05	0.05	-0.23	1.00		
(12) Target tangibility		0.10	-0.03	0.05	0.20	-0.17	-0.07	-0.07	0.86	0.23	0.08	-0.06	1.00	
(13) Target profitability		0.05	-0.11	0.00	0.15	-0.01	0.19	-0.06	0.24	0.39	0.37	-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 complementarities. Relative merger complementarity is calculated by scaling the bidder-target pairwise patent-based relatedness by the maximum relatedness of the target to any other firm that year. 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. Growth in EBITDA is the difference between EBITDA-to-assets ratio in years t and $t+1$, averaged at the SIC 3-digit industry of the bidder. Log(# M&A advisors) is the natural logarithm of one plus the number of target's M&A advisors. 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 3-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
Relative merger complementarity		1,127	0.55	0.50	0.01	1.00	0.31
Determinants of complementarity							
Log(target's # patents)	ϕ	1,127	2.29	2.08	0.69	7.86	1.29
Growth in EBITDA	g	1,119	0.03	0.01	-0.17	0.34	0.07
Log(# M&A advisors)	p	1,122	0.55	0.69	0.00	1.61	0.37
Patent breadth	γ (inverse)	1,127	6.48	6.58	0.00	8.50	0.90
Control variables							
Log(bidder assets)		1,127	7.63	7.72	1.12	13.58	1.96
Bidder M/B		1,119	2.73	1.96	0.28	20.00	2.35
Bidder tangibility		1,126	0.22	0.19	0.00	0.81	0.14
Bidder profitability		1,125	0.13	0.15	-1.00	0.50	0.16

Table 5: Patent-based data: Correlations

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

	Proxy for	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Relative merger complementarity		1.00								
Determinants of complementarity										
(2) Log(target's # patents)	ϕ	0.16	1.00							
(3) Growth in EBITDA	g	0.12	-0.05	1.00						
(4) M&A advisor	p	0.04	0.34	-0.02	1.00					
(5) Average relatedness	γ (inverse)	-0.03	-0.03	0.21	-0.03	1.00				
Control variables										
(6) Log(bidder assets)		-0.32	0.20	-0.09	0.33	0.09	1.00			
(7) Bidder M/B		0.09	-0.04	0.08	0.00	0.18	-0.04	1.00		
(8) Bidder tangibility		-0.16	0.10	-0.20	0.14	-0.18	0.28	-0.22	1.00	
(9) Bidder profitability		-0.10	0.05	-0.16	0.11	-0.11	0.40	0.18	0.16	1.00

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

The first 3 columns of this table presents the results of estimating OLS regressions, in which the dependent variable is product-description-based relative merger complementarity and the independent variables are proxies for the model's parameters, and bidder (bidder and target) control variables. The 4th column reports the results of estimating a logistic regression in which the dependent variable is an indicator equalling one if product-description-based relative merger complementarity exceeds 0.7 and equals zero otherwise. See Table 2 for variable definitions. All the estimations include year fixed effects. Standard errors are reported in parentheses. In OLS regressions, the standard errors are heteroskedasticity-consistent and are adjusted for clustering at the firm level. The symbols ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	Proxy for	Predicted sign	OLS			Logit
			(1)	(2)	(3)	(4)
Intercept			0.721***	0.868***	0.879***	1.711**
			(0.102)	(0.095)	(0.096)	(0.748)
Determinants of complementarity						
Target arrival rate	ϕ (inverse)	(−)	-0.066***	-0.044***	-0.042**	-0.289**
			(0.019)	(0.017)	(0.017)	(0.133)
Growth in EBITDA	g	(+)	0.003	-0.171	-0.219	-1.372
			(0.258)	(0.261)	(0.259)	(1.753)
Log(# M&A advisors)	p	(+)	0.048*	0.105***	0.102***	0.521***
			(0.027)	(0.026)	(0.026)	(0.201)
Average relatedness	γ	(+)	0.890***	2.158***	2.056***	6.961
			(0.054)	(0.348)	(0.354)	(2.845)
Controls: Bidder						
Log(assets)				-0.050***	-0.051***	-0.289***
				(0.005)	(0.005)	(0.042)
M/B				-0.008*	-0.006	-0.042
				(0.004)	(0.005)	(0.039)
Tangibility				0.072*	-0.013	-0.029
				(0.041)	(0.073)	(0.494)
Profitability				0.158**	0.117*	0.759
				(0.066)	(0.070)	(0.508)
Controls: Target						
M/B					-0.002	-0.019
					(0.005)	(0.045)
Tangibility					0.085	0.495
					(0.074)	(0.501)
Profitability					0.091*	0.518
					(0.047)	(0.362)
Obs.			1,407	1,400	1,369	1,369
R-squared			0.03	0.12	0.12	
p(χ^2)						0.00

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 relative merger complementarity and independent variables are proxies for the model's parameters, and bidder and target control variables. See Table 2 for variable definitions. The regressions are estimated on 4 subsamples. 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. merger wave and hi-tech bubble refers to a sample that excludes years 1997-2000. Excl. entrenched firms refers to a sample of firms with Bebchuk, Cohen and Ferrell (2009) index of 3 or below. Excl. serial acquirers refers to a sample of firms that had 6 or fewer M&A transactions in the 5 years prior to merger announcement. 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	Low HHI	Excl. entrenched firms	Excl. serial acquirers	Excl. merger wave & hi-tech bubble
			(1)	(2)	(3)	(4)
Intercept			0.861***	0.871***	0.907***	0.801***
			(0.126)	(0.104)	(0.100)	(0.111)
Determinants of comp-ty						
Target arrival rate	ϕ (inverse)	(−)	-0.047**	-0.042**	-0.045**	-0.043**
			(0.019)	(0.019)	(0.018)	(0.020)
Growth in EBITDA	g	(+)	0.129	-0.213	-0.163	-0.133
			(0.497)	(0.270)	(0.269)	(0.341)
Log(# M&A advisors)	p	(+)	0.176***	0.079***	0.095***	0.130***
			(0.037)	(0.028)	(0.028)	(0.036)
Average relatedness	γ	(+)	1.848***	1.932***	1.799***	1.797***
			(0.467)	(0.386)	(0.376)	(0.448)
Controls: Bidder						
Log(assets)			-0.051***	-0.047***	-0.049***	-0.048***
			(0.007)	(0.005)	(0.005)	(0.007)
M/B			-0.007	-0.006	-0.006	0.016
			(0.008)	(0.006)	(0.005)	(0.011)
Tangibility			-0.044	-0.035	0.007	-0.013
			(0.129)	(0.078)	(0.075)	(0.100)
Profitability			0.218	0.113	0.135*	0.161*
			(0.148)	(0.071)	(0.070)	(0.096)
Controls: Target						
M/B			-0.001	-0.003	0.000	-0.010
			(0.006)	(0.005)	(0.005)	(0.010)
Tangibility			0.100	0.093	0.037	0.108
			(0.125)	(0.080)	(0.076)	(0.103)
Profitability			0.024	0.080	0.09*	0.057
			(0.100)	(0.049)	(0.047)	(0.060)
Obs.			637	1,209	1,225	768
R-squared			0.18	0.11	0.11	0.13

Table 8: Patent-based data: Main tests

The first 2 column of this table present the results of estimating OLS regressions, in which the dependent variable is patent-based relative merger complementarity and the independent variables are proxies for the model's parameters, and bidder control variables. The 3rd column reports the results of estimating a logistic regression in which the dependent variable is an indicator equalling one if patent-based relative merger complementarity exceeds 0.7 and equals zero otherwise. See Table 4 for variable definitions. All the estimations include year fixed effects. Standard errors are reported in parentheses. In OLS regressions, the standard errors are heteroskedasticity-consistent and are adjusted for clustering at the firm level. The symbols ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	Proxy for	Predicted sign	OLS		Logit
			(1)	(2)	(3)
Intercept			0.712***	0.976***	1.124
			(0.089)	(0.090)	(0.777)
Determinants of complementarity					
Log(target's # patents)	ϕ	(+)	0.039***	0.049***	0.318***
			(0.009)	(0.008)	(0.066)
Growth in EBITDA	g	(+)	0.689***	0.457***	0.049***
			(0.153)	(0.142)	(0.017)
Log(# M&A advisors)	p	(+)	0.002	0.094***	0.562
			(0.029)	(0.027)	(0.218)
Patent breadth	γ (inverse)	(−)	-0.041***	-0.022**	-0.184*
			(0.011)	(0.011)	(0.094)
Controls: Bidder					
Log(assets)				-0.059***	-0.321***
				(0.005)	(0.051)
M/B				0.008*	0.040
				(0.005)	(0.040)
Tangibility				-0.086	-0.204
				(0.075)	(0.667)
Profitability				0.076	0.017
				(0.074)	(0.550)
Obs.			1,114	1,103	1,103
R-squared			0.08	0.20	
p(χ^2)					0.00

Table 9: Patent-based data: Robustness tests

This table presents the results of estimating OLS regressions, in which the dependent variable is patent-based relative merger complementarity and independent variables are proxies for the model's parameters, and bidder control variables. See Table 4 for variable definitions. The regressions are estimated on 3 subsamples. Excl. merger wave and hi-tech bubble refers to a sample that excludes years 1997-2000. Excl. entrenched firms refers to a sample of firms with Bebchuk, Cohen and Ferrell (2009) index of 3 or below. Excl. serial acquirers refers to a sample of firms that did not have 5 or more M&A transactions in the 5 years prior to merger announcement. 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	Pred. sign	Excl. entrenched firms	Excl. serial acquirers (E index>3)	Excl. M&A wave & hi-tech bubble (1997–2000)
			(1)	(2)	(3)
Intercept			1.027***	0.986***	0.928***
			(0.101)	(0.095)	(0.111)
Determinants of comp-ty					
Log(Target's # patents)	ϕ	(+)	0.049***	0.051***	0.056***
			(0.009)	(0.008)	(0.010)
Growth in EBITDA	g	(+)	0.370**	0.484***	0.602***
			(0.159)	(0.148)	(0.170)
Log(# M&A advisors)	p	(+)	0.095***	0.093***	0.108***
			(0.028)	(0.028)	(0.030)
Patent breadth	γ (inverse)	(–)	-0.025**	-0.024**	-0.022
			(0.013)	(0.011)	(0.015)
Controls: Bidder					
Log(assets)			-0.060***	-0.059***	-0.061***
			(0.006)	(0.006)	(0.006)
M/B			0.005	0.005	0.020***
			(0.005)	(0.005)	(0.007)
Tangibility			-0.068	-0.083	-0.065
			(0.081)	(0.076)	(0.090)
Profitability			0.063	0.062	0.077
			(0.074)	(0.073)	(0.098)
Obs.			991	1,002	765
R-squared			0.20	0.20	0.24