Bidder Pools in Mergers and Acquisitions

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Abstract

Allocation mechanisms in M&A deals are complex, but a main feature is that a target board controls who to invite to the sale. In a theoretical model, we show that the optimal size of the bidder pool is negatively related to the correlation among potential acquirers, and that greater correlation (and hence a smaller bidder pool) yields the target a higher surplus from the sale (i.e., higher premium). We test the model empirically and show that M&A deals with smaller bidder pools are associated with higher target returns. This is not a result of synergies in the deals: the target's share of the surplus is simply higher in deals with smaller bidder pools. Finally, we show that cash deals are associated with larger, whereas stock deals have smaller, pools of bidders.

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1 Introduction

Ever since the seminal case *Paramount Communications, Inc. v. Time, Inc.* (1989), targets have had more control over the merger process (Brown, Liu, and Mulherin, 2022). Bidder-initiated takeovers are less common, and target boards are tasked with choosing allocation mechanisms that maximize wealth for their shareholders. Many notable researchers have opined on the optimal way to structure these sales, mostly focusing on the comparison between auctions and negotiations (e.g., Bulow and Klemperer, 1996; Boone and Mulherin, 2007; Hoffmann and Vladimirov, 2025).

However, the distinction between auctions and negotiations is not so clear cut in practice as it is in theory. Most deals involve a complex allocation process in which auctions and negotiations are combined in multiple rounds over an extended time-frame (Hansen, 2001; Subramanian, 2020). Furthermore, the number of buyers participating in the M&A process varies significantly across deals, even when restricting attention to deals in which at least two prospective buyers are involved. Thus, classifying all sales involving two or more bidders as "auctions" overlooks significant heterogeneity, and this heterogeneity remains understudied in the extant literature.

The purpose of this paper is to investigate how the structure of the bidder pool is determined in M&A transactions, characterize how this affects the target's premium, and report empirical tests of classic theories in the academic literature regarding auctions in the M&A setting. We first develop a theoretical model of M&A auctions in which the target can control the bidder pool, and then study these auctions empirically with a large, granular dataset of successful acquisitions between 2005 and 2019.

In our model, N buyers with private, correlated values are interested in acquiring a target. The target chooses how many buyers to invite to the sale and how the sale proceeds. We assume that inviting more buyers is costly to the target, e.g., because participants get access to proprietary information about the target firm or because maintaining active discussions requires costly effort.

We first study the target's choice of how many potential buyers to invite, assuming that the sale proceeds as a standard second-price auction (SPA). We show that it is optimal to invite fewer buyers when their private values are more correlated. Furthermore, if we hold constant the total expected gains from trade, the target enjoys a higher share of the surplus when buyers' valuations are more correlated. This implies empirically that if the size of bidder pools depends on bidder correlation, then the target's expected revenues increase when the size of the bidder pool is smaller.

We then go beyond standard auctions and consider what happens when a target has the option to augment the auction with a round of negotiation. That is, the sale proceeds with an initial round of bidding, but the target has discretion whether to end the process with the auction or proceed to place a take-it-or-leave-it counteroffer to the highest bidder.[1] This mechanism maximizes the revenue for the target among all ex-post incentive compatible and individually rational mechanisms (Segal, 2003; Roughgarden and Talgam-Cohen, 2016). It improves upon a standard SPA because the take-it-or-leave-it counteroffer reduces the winning bidder's information rent. This counteroffer is set after observing the bids of the other $N-1$ bidders, which is particularly valuable when bidder valuations are correlated, and we show that the target is more likely to make it when fewer buyers participate in the sale.

Our primary empirical analysis includes 604 M&A transactions from the Thomson One Banker SDC database that were announced from 2005-2019, each with a definitive merger agreement in the SEC's EDGAR database. These merger agreements provide detailed information about each non-public sale process and the bidding behavior of potential acquirers. To test our model, we observe the number of firms included in each complex auction, which is endogenously chosen by each target.

[1]The take-it-or-leave-it offer (TIOLI) has been used extensively as a building block in the bargaining literature. For example, Rubinstein (1982) is a classic model of sequential, alternating TIOLI offers. Duffie, Garleanu, and Pedersen (2003) provides an application of TIOLI offers in OTC financial markets. See Muthoo (1999) for a nice description of TIOLI offers in bargaining models.

The empirical tests reveal that higher correlation among the bidders is associated with smaller bidder pools. This is a robust finding that arises with three different measures of correlation, and is present with varied metrics for the size of bidder pools (e.g., relative to median, by quartiles, or by the raw number of bidders). We also find that targets that choose smaller bidder pools often explicitly use the mechanism outlined by our theory. Specifically, these targets are more likely to make final counter-offers at the end of the allocation process.

Following this, we study the returns to targets and bidders in these deals. Importantly, we show that the size of the bidder pool is unrelated to the degree of synergy that is expected from a given deal, that is, the total return earned through the merger. However, the share of the surplus that the target earns is higher with a smaller number of bidders, even after controlling for industry correlation, industry fixed effects, the depth of potential suitors, and whether the deal is made in cash or stock. Thus, targets who limit the size of their bidder pool do not have access to better deals – they simply get better terms.

This empirical finding might seem puzzling at first, as auction theory usually predicts that the seller's revenue is increasing in the number of bidders. Intuitively, more participants should result in more competition and a higher expected price paid by the "winner." However, that logic relies heavily on the exogeneity of the number of auction participants. In M&A transactions over the last three decades the number of auction participants is almost surely not exogenous: the target has greater control over the deal process and can choose how many buyers to invite to a sale.

Thus, if we observe a sale that only involved a few buyers, this is not necessarily bad news for the target—it simply means the target did not find it profitable to invite many buyers. There are two key reasons that could explain that choice: either (i) the cost associated with having more participants was high, or (ii) the benefit was low because few buyers were enough for the target to get a high return. Our empirical findings support the latter explanation, as only the latter predicts that higher target returns are associated with a smaller number of participants in the sale. Our results emphasize one particular feature that reduces the benefit from having more participants, namely, correlation between buyers' valuations. Targets with more correlated buyers need not invite as many to get the same expected return: they optimally invite fewer buyers, save on the associated cost, and get a higher share of the surplus.[2]

One important caveat to our empirical results is that we do not claim causality between bidder pool size and target returns. Indeed, our theory supports the optimal choice made by a target to limit the bidder pool size when potential bidders are more correlated, and the target earns higher surplus when doing so. However, the regressions that we use in the paper do not control for this source of endogeneity. We have been unable to find a source of exogenous variation, natural experiment, or instrument that does not violate an exclusion restriction in an instrumental variables approach. Such is the nature of the M&A setting. Notwithstanding, the associations that we document among bidder correlation, bidder pool size, and target returns are novel, and are in fact consistent with our theory.

Finally, our empirical results also help reconcile two papers in the academic literature regarding the optimal size of the bidder pool and the payment mechanism used. Bulow and Klemperer (1996) study *cash* auctions and conclude that a simple auction with one extra bidder is always superior to any other complex auction mecahnism involving negotiation. In contrast, Hoffmann and Vladimirov (2025) posit that the opposite arises when *stock* deals take place. Based on our analysis, we find evidence that supports both theories: cash deals are more likely to involve larger bidder pools and stock deals are associated with more intimate mechanisms.

The rest of the paper proceeds as follows. In Section 2, we present a review of the related literature. In Section 3, we provide a parsimonious model and

[2]In a model of preemptive bidding, Fishman (1988) finds a similar comparative static: "auctions" with a single bidder are associated with higher target revenue than auctions with multiple bidders. Indeed, if an auction has a single bidder, it means that bidder made a sufficiently high preemptive bid to scare away the competitors, which benefits the target. This is a very different mechanism than the one we uncover, and one that is not present in our empirical setting since bids are not made public.

characterize its empirical implications. We describe our large dataset of M&A transactions in Section 4 and present our empirical results in Section 5. Section 6 concludes. The Appendix contains all proofs and empirical robustness checks.

2 Literature Review

Because M&A deals often involve multiple potential acquirers, much of the emphasis in the academic literature has focused on whether targets should engage in auctions or negotiations. This was first emphasized by Bulow and Klemperer (1996) who examine the problem of how a seller should maximize their expected revenue when potential buyers are privately informed about their valuations. The central insight that they derive is that attracting one additional bidder to an auction always yields higher expected revenue than any negotiation strategy the seller might design. This result set a benchmark in the literature by suggesting that breadth of competition dominates depth of negotiation tactics when bids are restricted to cash.

Hoffmann and Vladimirov (2025) revisit these results by considering the role of auctions and negotiations when buyers also have private information about the potential synergy offered via merger. The authors show that negotiation may be preferred to solve this asymmetric information problem for the seller, allowing them to offer a menu of deal contracts that screen buyers. As such, they argue that the optimality of one mechanism over another depends on the way in which the seller will be compensated during the transaction.

On the empirical front, several papers have examined whether takeover premiums or bidder returns differ between auction and negotiation processes. Boone and Mulherin (2007, 2008) show that both target shareholder gains and bidder returns are similar across the two mechanisms, which they interpret as inconsistent with an agency-cost explanation for why some target managers choose negotiations over auctions. Similarly, Aktas, De Bodt, and Roll (2010) document comparable bid premiums in their negotiation and auction subsamples. They further show that latent competition raises premiums in negotiated deals, whereas the costs associated with running an auction tend to reduce premiums.

In light of the previous literature, the main contribution of our paper is to study the role of the bidder pool in M&A deals, beyond the binary comparison between auctions and negotiations. We first study this theoretically in a model in which the target can choose the size of the bidder pool. We then bring our theoretical predictions to the data. Our empirical analysis uncovers a significant relationship between target premiums and the number of buyers invited to the sale, which contrasts with the above-mentioned empirical studies. Thus, our results suggest that the binary distinction between auctions and negotiations misses important heterogeneity between all the deals classified as "auctions" (i.e., deals that involve two or more potential acquirers).

Furthermore, we also speak to the literature that emphasizes the "free-form" nature of M&A transactions. Hansen (2001) describes several stylized facts that are often present during M&A deals. In particular, these deals involve complex processes in which auctions and negotiations are combined over multiple rounds. Subramanian (2020) terms these complex processes "negotiauctions" and documents that they are extremely common, not only during M&A activity, but also during any conflict resolution, asset or service procurement (e.g., investment banking, consulting, or construction), or licensing deals. There is theoretical support for adding some negotiation, either before (Quint and Hendricks, 2018) or after an auction (Bulow and Klemperer, 1996; Roughgarden and Talgam-Cohen, 2016). Indeed, the seller can benefit from making a TIOLI offer to the auction winner when the second-highest bid is too low, as shown in Myerson (1981) and Bulow and Klemperer (1996). Furthermore, when bidders' valuations are correlated, the optimal TIOLI offer depends on the bids submitted by the losing bidders, as characterized by Segal (2003) and Roughgarden and Talgam-Cohen (2016). We consider this possibility in our theoretical framework and show empirical support for it in the data.

Lastly, we provide an extensive empirical analysis that tests many of the theories listed in this review, which allows us to reconcile what appears to be true about the complex auctions in M&A transactions.

3 A Model

Consider an M&A setting in which there is one target firm with fixed value v_0. Upon choosing to be sold, the target hires an advisor who functions as a de facto auctioneer and helps generate a list of potential buyers. Suitors could include competitors, suppliers, customers, or leveraged buyout entities.

For each buyer that participates in the sale, assume that the seller incurs a cost $c \geq 0$. This may capture the time it takes to have active discussions with counterparties or that the target has sensitive information that declines in value once more outsiders gain access to it during due diligence. The size of the bidder pool $n \in \{0, \dots, N\}$ is chosen optimally by the target, where N is the number of potential buyers in the market.

Each buyer i's valuation for the target is denoted by $v_i \in [\underline{v}, \overline{v}]$. We assume $v_0 \leq \underline{v}$ such that all potential buyers are serious, in the sense that they value the company weakly more than the target. From now on, we normalize v_0 to zero. Buyers' valuations are identically distributed but correlated across buyers. We assume that each buyer's valuation is a linear combination between some common component $\omega \in [\underline{v}, \overline{v}]$ and some buyer-specific component $\varepsilon_i \in [\underline{v}, \overline{v}]$. That is,

$$v_i = \alpha\omega + (1 - \alpha)\varepsilon_i,$$

where $\alpha \in [0, 1]$ captures the amount of correlation across buyers' valuations. One can interpret α as capturing how homogeneous potential buyers of the target firm are, with a high α indicating, for example, that they are all comparable firms in the same industry. Homogenous bidders (for example, firms in the same industry) are likely to have similar business plans for the integration of the target firm into their operations, and thus place similar private values on that target firm (connecting similarity of the bidders with correlation in private values). Let $\omega \sim F_\omega$ and $\varepsilon_i \overset{i.i.d.}{\sim} F_\varepsilon$. Thus, the buyer-specific components are independent across buyers and any correlation in buyers' valuations is driven by the common component.

The main goal of the model is to investigate how many buyers the target should invite to the sale, and how that depends on the correlation in buyers' values α. To align with our empirical analysis, we assume that the target invites at least two buyers to the sale, so $n \geq 2$. Of course, the target's return depends not only on how many buyers it invites but also on how the sale proceeds. However, a well-known result in auction theory is that many standard sale processes lead to the same equilibrium outcome, namely the target is acquired by the highest-value bidder and expected revenue equals the expected second-highest value among the bidders (Myerson, 1981). For instance, this is the case if the target runs a sealed-bid second-price auction, or an open-cry ascending auction. It is also the case if the target goes to bidders one-by-one, asking them whether they want to outbid the highest offer he currently has.[3] In what follows, we start by assuming that the target commits to using one of these standard sale processes. Thus, when deciding how many buyers to invite, the target solves

$$\max_{2 \leq n \leq N} \mathbb{E}[v_{(2:n)}] - cn,$$

where $v_{(2:n)}$ denotes the realized second-highest value among the n invited buyers. That is, the target trades-off more competition, and thus higher expected revenue, with the cost of attracting more buyers.

Proposition 1. *The optimal number of buyers to invite n^* is decreasing in the correlation level α and decreasing in c.*

Intuitively, if buyers' values are more correlated, then they impose higher competitive pressure on each other, and the target does not need to invite many buyers to extract a large share of the surplus. Thus, fewer bidders are invited to the sale.

[3] A first-price auction also leads to the same outcome in this setting, provided buyers know which part of their valuation is due to the common component and which part is specific to them.

Based on this, we investigate how correlation affects the target's expected revenue. The level of correlation α can impact the target's revenue in two ways: it can change the overall gains from trade (i.e., total surplus) as well as how those gains are shared between the seller and the buyers. In this setting, the gains from trade are equal to $\max_i v_i - v_0 = \alpha\omega + (1-\alpha)\max_i \varepsilon_i - v_0$. Thus, if the distribution of ω is less favorable than that of $\max_i \varepsilon_i$, then higher correlation reduces the gains from trade. We do not find any relationship between correlation and overall trade value in our empirical analysis, so, for the next result, we focus on how correlation affects the division of the surplus. To that end, we assume that $\mathbb{E}(\omega) \geq \mathbb{E}(\varepsilon_{(2:N)})$, which guarantees that expected total surplus does not decrease too much with α.[4]

Proposition 2. *Suppose* $\mathbb{E}(\omega) \geq \mathbb{E}(\varepsilon_{(2:N)})$*. Then, the target's expected revenue is increasing in* α *and decreasing in* c*.*

This result yields an important, testable empirical implication. If the observed heterogeneity in the number of inviting buyers n^* across M&A deals is driven by heterogeneity in the correlation among potential acquirers, then the target's expected revenue is *negatively* correlated with the size of the bidder pool. This contrasts with the effect of costs (Hansen, 2001): if the size of the bidder pool were only driven by heterogeneity in the cost of inviting more buyers, then the target's expected revenue would be *positively* correlated with the observed number of bidders. Specifically, if the target faced lower costs, then it would invite more bidders, increase competition, and enjoy higher proceeds from the sale. We test these competing hypotheses below in Section 4.

We emphasize that these predicted correlations operate through the target's optimal choice of bidder pool size, and so should not be interpreted as causal effects per se.

So far, we have assumed the sale takes the form of a standard auction. Now, we consider a more complex allocation mechanism in which the target is able to

[4]Alternatively, we could assume that the distribution of total surplus is independent of α, that is that ω follows the same distribution as $\max_i \varepsilon_i$. This is a stronger assumption than the one in Proposition 2, but a natural one.

make counteroffers following the auction. Making such counteroffers generally benefits the target. For instance, when buyers' values are uncorrelated ($\alpha = 0$), a standard second-price auction with a *predetermined* reserve price maximizes the target's revenue among all possible allocation mechanisms (Myerson, 1981). The reserve price can be equivalently thought of as a TIOLI offer that the target makes to the highest bidder if the second highest bid is too low. When buyers' valuations are correlated, the seller can benefit from conditioning the counteroffer he makes to the auction winner on the bids submitted by the losing buyers. Importantly, we assume that the target can commit to how it will make counteroffers.[5]

Let F_v be the CDF of v_i, which can be derived from the distributions of the common and idiosyncratic components. Furthermore, let $F_v(\cdot \mid v_{-i})$ be the CDF of v_i conditional on v_{-i} and $f_v(\cdot \mid v_{-i})$ its pdf. We assume that for every realization of v_{-i}, the distribution $F_v(\cdot \mid v_{-i})$ is regular. That is, the function $x - (1 - F_v(x \mid v_{-i}))/f_v(x \mid v_{-i})$ is weakly increasing in x. For a given choice of $n \leq N$, the following proposition characterizes the selling mechanism that maximizes revenue for the seller among all ex-post incentive compatible and individually rational mechanisms.

Proposition 3. ***Complex Auctions*** *Suppose N buyers have been invited to join the sale. The revenue-maximizing selling mechanism involves proceeds as follows:*

(i) All invited buyers submit a bid b_i.

(ii) The highest-bidder $i^* \in \arg\max_i b_i$ wins if his bid is above

$$r(b_{-i^*}) = \frac{1 - F_v(r(b_{-i^*}) \mid b_{-i^*})}{f_v(r(b_{-i^*}) \mid b_{-i^*})}.$$

[5] Absent commitment power, the target has an incentive to misrepresent losing bids so as to make a higher counteroffer to the winner. In that case, the target can still use a first-price or ascending auction with predetermined reserve, as these auctions are credible and do not require commitment (Akbarpour and Li, 2020).

If she wins and the second-highest bid $\max_{j \neq i^*} b_j \geq r(b_{-i^*})$*, then the auction ends and the seller earns* $\max_{j \neq i^*} b_j$*. Otherwise, the seller earns* $r(b_{-i^*})$ *by making a take-it-or-leave-it offer to the highest bidder.*

The above optimal selling mechanism allows the seller to use information strategically and offers discretion over conducting a follow-on negotiation. Suppose, in a first round, the seller elicits bids from all buyers. If the second-highest bid is high enough (specifically, if $\max_{j \neq i^*} b_j \geq r(b_{-i^*})$), then the sale goes through as a standard SPA: the highest-bidder wins and pays the second highest-bid. If this is not the case, the seller has discretion to continue the process and make the highest bidder a TIOLI offer at $r(b_{-i^*})$.

So, compared to standard auction mechanisms, this process is murky in the sense that it offers discretion to the target. No reserve price is pre-set. And the allocation mechanism may end with only an SPA or the target can add a round of negotiation to it. In practice, allocation during M&A transactions are even more convoluted, which is beyond the bounds of formal theoretical modeling. But Proposition 3 captures the essence of the discretion that targets have in running the selling process.

This mechanism is similar to that in Segal (2003) and a special case of Roughgarden and Talgam-Cohen (2016). It admits an equilibrium where all buyers bid their values truthfully. The asset then goes to the highest-value bidder, but that bidder need not pay the second-highest bid, nor a predetermined reserve price. The reserve price he faces is personalized in the sense that it depends on the submitted bids of all losing buyers. In particular, the higher the losing bids, the higher the personalized reserve price.

As such, the target learns through bidding about the correlated component among the bidders' values. This allows the target to tailor a reserve price for the top bidder that is more advantageous than a pre-specified reserve price before any learning takes place.

Proposition 4. *There exists* $\overline{\alpha} > 0$ *such that, if* $\alpha \leq \overline{\alpha}$*, then the probability that the seller makes a counter-offer decreases in the number of participants in* *the sale n.*

The benefit of using counteroffers is non-monotonic in α. For $\alpha = 0$, the seller does not learn anything about the highest bidder from the losing bids, so the reserve price that is set is the same as that in a standard second price auction. For $\alpha = 1$, all of the bids are the same, so there is no need to make a counteroffer. As such, the result in Proposition 4 regarding the use of counteroffers and the number of bidders is also non-monotonic. However, there does exist an interval for α such that increasing the number of bidders lowers the probability that a counteroffer will be used. We test this relationship in the empirical work that follows.

4 The M&A sample and summary statistics

4.1 Sample formation

To construct our sample, we begin with M&A transactions announced from 2005 to 2019 from the Thomson One Banker SDC database (hereafter, SDC). We impose the following standard filters: 1) the deal is classified as a "Merger (stock or asset)"; 2) the target public status is "Public"; 3) the deal value reported by SDC is at least $1 million; 4) the acquirer holds less than 50% of the shares of the target firm before the deal announcement and seeks to purchase 50% or more of the shares of the target firm after the deal; and 5) the deal status is "completed." We then merge this sample with the Center for Research in Security Prices (CRSP) to obtain target-firm stock prices and returns, and with the Compustat database to obtain basic accounting information.

In addition, we require that the definitive merger agreement is available on the SEC's EDGAR website, as this document provides the detailed information necessary to analyze the private sale process and bidding behavior.

We further constrain our sample to include only target firms in the S&P 1500, and we justify this constraint with two reasons: 1) S&P 1500 firms often transact in large deals that are economically significant and involve substantial transfers of value. It is not uncommon for researchers to focus on the largest M&A deals and investigate their outcomes due to their economic importance.[6] 2) The restriction to S&P 1500 firms produces a manageable sample size, which allows us to thoroughly investigate each transaction and collect the detailed information described below.

4.2 Key variables

4.2.1 Number of participated bidders and valuation correlation

For each completed deal in our sample, we carefully read the definitive merger agreement to identify the number of bidders involved in the private merger negotiation process. Since our main research question focuses on the role of the bidder pool, we restrict the sample to deals with at least two participating bidders. This yields a final sample of 604 completed deals.

Following Boone and Mulherin (2008), we define the potential depth of the takeover market for a target firm as the set of firms within the target's industry that have a larger market capitalization.

With the number of participating buyers identified, we then construct measures to capture the degree of correlation across potential buyers' valuations. As discussed in the exposition of our model, a key parameter of the model is the correlation in private values among potential acquirers. Homogenous bidders, for example firms in the same industry, are likely to have similar business models and plans for the future integration of the target firm into their operations. Bidder homogeneity is, therefore, likely to be strongly associated with higher correlation in private values between those bidders.

We base our measures of bidder homogeneity on the correlation in daily stock returns between firms in the same industry as the target firm. Our first measure of potential bidders' homogeneity, *Corr_SIC*, is computed as the average pair-

[6]For example, Ahern and Sosyura (2014) start with the largest 1,000 deals in the SDC database and end up having 507 acquisitions in their final sample. Aktas, De Bodt, and Roll (2010) require deals in their sample to be larger than $100 million.

wise correlation of daily stock returns over the one-year period preceding the deal initiation date among all firm pairs sharing the target's two-digit SIC code and exceeding its size. The other two measures, *Corr_FF48* and *Corr_TNIC2*, are constructed similarly, except that potential bidders are defined based on the Fama–French 48 industry classification or the target's TNIC2 peer group, respectively.

4.2.2 Deal outcomes

To capture negotiation outcomes, we compute abnormal returns for both the target and acquirer around the merger announcement, the estimated synergies of the combined firm, and the target's gains relative to those of the acquirer.

We employ the standard event study methodology to calculate the cumulative abnormal returns (CARs) for target firms over the event window from day -105 to deal completion, following Eaton, Liu, and Officer (2021).[7] CARs are computed as returns in excess of the CRSP value-weighted market index. For acquirers, abnormal returns are measured over the (-5, +5) window surrounding the merger announcement.[8]

To measure the estimated synergies of the combined firm, we follow the literature and use the value-weighted combined bidder-target cumulative CARs around merger announcements (e.g., Bradley, Desai, and Kim, 1988; Houston, James, and Ryngaert, 2001). We begin by using an eleven-day window (-5, 5) for both the acquirer and the target to calculate our first measure of deal synergy, *Synergy (-5, +5)*. This measure is computed as the weighted average of the acquirer's CAR (-5, +5) and the target's CAR (-5, +5), with the weights being their respective market capitalization measured one day prior to the target of the event window. As a robustness check, we also consider alternative event

[7] As a robustness check, we compute target CARs over the window from day -63 to deal completion, following Schwert (2000). We also adopt the approach of Brown, Liu, and Mulherin (2022), which defines the event window from one trading day prior to the private deal initiation date through deal completion. Our results remain similar.

[8] We also calculate acquirer CARs using narrower event windows, (-1, +1) and (-10, +10), and the results remain qualitatively unchanged.

windows. While the eleven-day window is generally appropriate for estimating the acquirer CARs, it may not be suitable for estimating the target CARs due to the well-documented pre-announcement price run-up and post-announcement mark-up for target firms. To address this, we adopt two alternative event windows, (-42, +42) and (-42, +126), and construct two additional synergy measures, *Synergy (-42, +42)* and *Synergy (-42, +126)*, accordingly.

Following the construction of our synergy measures, we next examine how these gains are distributed between acquirers and targets. We follow the approach of Ahern (2012) and compute the target's relative gain as the difference in abnormal dollar returns between the target and the acquirer, scaled by the sum of their market capitalization measured 50 trading days prior to the announcement date. Specifically, abnormal dollar returns are calculated by multiplying each firm's CAR by its market capitalization one day prior to the event window. This measure reflects the deal gain by target shareholders relative to the gain by acquirer shareholders. Consistent with our synergy analysis, we calculate this measure using the same three event windows: (-5, +5), (-42, +42), and (-42, +126).

4.3 Sample overview and summary statistics

4.3.1 Sample distribution and deal characteristics

Panel A of Table 1 presents the temporal distribution of our sample. There are no obvious merger waves (e.g., Andrade, Mitchell, and Stafford, 2001; Harford, 2005) in our data because our sample is from 2005 to 2019 and the level of merger activity in that time period had little variability. The average (median) number of bidders contacted during the auction process ranges from 9 (3) to 27 (11), with lower numbers observed during the 2008–2009 financial crisis.[9]

Panel B of Table 1 reports summary statistics for the key variables used in

[9]To ensure that our results are not driven by potential abnormalities in the auction process during the financial crisis, we conduct robustness tests for all our main results by excluding the crisis years (2008–June 2009). The results are reported in Appendix Table 6.

the analysis. The relative size of the target to the acquirer averages 0.43, indicating that targets are typically less than half the size of their acquirers, though the interquartile range (0.08 to 0.54) suggests substantial variation across deals. Roughly 41% of targets in the sample make at least one counteroffer during the negotiation process. About 62% of acquirers are publicly listed firms, and cash financing is the predominant payment method, used in 64% of transactions. Pure stock deals account for only 7% of the sample, with the remainder involving a mix of stock and cash payments. Tender offers represent 16% of all transactions, while approximately 38% of mergers occur between firms operating in the same industry. Bidder toeholds are relatively uncommon, averaging just 1% across the sample.

Figure 1 presents the frequency distribution of the number of contacts made with potential bidders during the auction process. The x-axis categorizes the number of contacts into six bins: 2–4, 5–7, 8–10, 11–15, 16–20, and 20+. The y-axis shows the corresponding frequency for each bin. The most common number of contacts falls within the 2–4 range, with 194 occurrences, representing 31% of all deals involving two or more bidders. This suggests that many auctions engage only a small number of potential buyers. The 5–7 contact range is also frequent, accounting for 113 cases or 19% of the sample. Combined, deals involving between two and seven bidders comprise approximately half of the total, highlighting a common practice of limiting the auction to a manageable group. Industry practitioners note that auctions become increasingly difficult to manage beyond this point.[10]

4.3.2 Bidder correlations

Table 2 presents summary statistics and comparative analyses for three measures of bidder correlations using different industry classification schemes: Corr_SIC, Corr_FF48, and Corr_TNIC2. Panel A reports descriptive statistics for these measures across the full sample. All three correlation measures show similar

[10]As Xerium CEO Tom Gutierrez explains, "You can't really handle more than seven serious bidders. It's incredibly time-consuming," (Subramanian, 2020).

distributions, with mean values ranging from 0.338 to 0.351 and standard deviations between 0.12 and 0.13.

Figure 2 presents the time series patterns of average bidder correlations from 2005 to 2019, based on three different industry based correlation measures. Across all three measures, bidder correlations exhibit broadly similar dynamics over time. Correlations remain relatively stable from 2005 to 2008, rise during the 2009 to 2012 period, coinciding with the global financial crisis and subsequent recovery, and then stabilize thereafter.

Panel B of Table 2 examines how bidder correlations relates to the number of buyers invited during the negotiation process. We split the sample at the median number of contacts and compare the average correlation values across the two groups. Across all three measures, we observe that bidder similarity is significantly higher when fewer contacts are made and the differences are statistically significant at the 1% level.

Panel C further investigates this relationship by dividing deals into quartiles based on the number of contacts. The results exhibit a clear monotonic decline in bidder correlations as the number of contacts increases. For all three correlation measures, the mean correlation in the lowest contact quartile is significantly higher than in the highest contact quartile. These findings provide initial empirical support for our Proposition 1 that predicts a negative relationship between the optimal number of buyers invited to participate in the bidding process and the level of correlation among bidders.

5 Empirical results

5.1 Payment structure, bidder correlations, and number of participants

Hoffmann and Vladimirov (2025) highlights the important role of payment structure in shaping the seller's choice between auctions and negotiations. Their model shows that cash deals are more likely to induce an auction-like setting, encouraging competitive bidding and broader buyer participation. In contrast, stock deals are more conducive to negotiations, as they allow for risk-sharing, long-term alignment, and greater contractual flexibility. This framework implies that sellers may tailor their outreach strategy based on the form of consideration, broadening the search in cash transactions and narrowing it in stock-based deals.

To empirically test how payment structure affects the scope of buyer search, we construct two indicator variables: one for all-cash deals and another for all-stock deals, using mixed-payment deals as the benchmark group. The dependent variable is the natural logarithm of the number of contacts.[11] We control for a comprehensive set of target firm characteristics that may affect the size of the potential bidder pool. These controls include the potential number of buyers, firm age, firm size, past stock returns, return volatility, profitability (ROA), sales growth, leverage, R&D expenditure, and liquidity.

Table 3 reports the regression results examining the relationship between payment structure, bidder correlations, and the number of buyer contacts. Consistent with the predictions of Hoffmann and Vladimirov (2025), we find that cash deals are associated with a significantly higher number of contacts, while stock deals are associated with fewer contacts. These results support the notion that payment structure is closely tied to the underlying sale mechanism, with cash enabling more competitive processes and stock favoring selective, strategic engagement.

More importantly, across all specifications, we find a robust and significant negative relationship between bidder correlation and the number of contacts. Even after controlling for the payment structure and all other observable firm characteristics, deals with higher bidder correlation are consistently associated with fewer contacts. The negative relation is not only statistically significant,

[11] Given that the dependent variable is non-negative, we also employ a Poisson regression as a robustness check, following the approach advocated by Cohn, Liu, and Wardlaw (2022). In addition, we use alternative dependent variables, including a binary indicator for whether the number of contacts falls below the median and indicators for contact quartiles. Appendix Table 1 shows that our results remain robust.

but also economically meaningful. For example, based on the regression result in Column (6), a one–standard-deviation increase in Corr_TNIC2 is associated with a 19.82% decrease in the number of contacts. This finding not only reinforces the descriptive evidence presented in Table 2 but also provides direct empirical support for our Proposition 1, which predicts that the optimal number of buyers invited decreases with bidder correlation.

Lastly, among the control variables, we find that the number of contacts is generally positively associated with the total number of potential acquirers and negatively associated with firm size. This pattern suggests that firms tend to engage more bidders when they have a broader set of viable acquirers or when they are smaller in size. Most other firm characteristics do not appear to significantly influence the size of the bidder pool, except that firms with less liquid stock tend to contact more bidders.

5.2 Size of the bidder pool and merger announcement returns

We next examine whether and how target returns vary with the selling mechanism and the extent of bidder participation. Table 4 presents the regression results. The dependent variable is *Target CAR(-105, Completion)*, defined as the target's cumulative abnormal return over the 105 trading days prior to the deal announcement through deal completion, adjusted by the market value–weighted return.[12] Our key independent variable, $\leq$ *median(contact)*, equals one if the number of contacts is at or below the median number of contact (seven), and zero otherwise.[13]

Across all specifications, the coefficient on $\leq$ median(contact) is positive

[12]The literature has employed various event windows to measure target abnormal returns. Following Eaton, Liu, and Officer (2021), we use a five-month window before the announcement to capture potential price run-ups. As robustness checks, we also consider two- and three-month windows, as well as a window from the initiation date to deal completion. The results, reported in Appendix Table 2, remain qualitatively unchanged.

[13]The results (reported in Appendix Table 7) are robust to alternative specifications that use contact quantiles rather than the binary median split.

and statistically significant at the 1% level, indicating that targets that contact fewer bidders are associated with significantly higher announcement-to-completion abnormal returns. The economic magnitude is meaningful: the coefficient estimates range from 0.067 to 0.075, suggesting that lower-contact targets outperform high-contact targets by roughly 6.7%-7.5% over the event window.

The relation remains robust after controlling for bidder correlations in industry classification using SIC codes (*Corr_SIC*), Fama-French 48 industry classification (*Corr_FF48*), and text-based industry classification (*Corr_TNIC2*), as well as deal and firm characteristics including size, public acquirer status, deal form, and toehold ownership. The inclusion of industry fixed effects and additional controls does not materially affect the estimated relation.

This empirical fact can seem surprising at first, as sales with more bidders are usually thought to be more competitive, resulting in higher revenue for the target. However, in M&As, the number of participating buyers is not exogenously given, but endogenously chosen by the target. Thus, the estimates in Table 4 should not be interpreted as the causal impact of inviting fewer bidders, but as evidence that targets who choose to invite fewer bidders differ from those that choose to invite more bidders. Our model considers two different explanations that might lead some targets to invite fewer bidders than others: it can be (i) costlier for them to invite more bidders, or (ii) less valuable because their pool of potential acquirers is more correlated (Proposition 1). If the former explanation dominates, then the model predicts that targets who invite fewer bidders get lower returns, while the opposite is true under the latter explanation (Proposition 2). The data supports the latter explanation: targets who invite fewer bidders get higher returns on average.

Table 5 reports the results examining how the number of contacts during the sale process relates to bidder shareholders' announcement-period returns. The dependent variable is *Acquirer CAR(-5, +5)*, defined as the bidder's cumulative abnormal return over the 11-trading-day window centered on the merger announcement date, adjusted by the market value–weighted return.[14] The sample size is smaller than in Table 4 because bidder returns are observable only for public acquirers.

Across all specifications, the coefficient on $\leq$ *median(contact)* is negative and statistically significant at the 5% level. This finding indicates that deals with fewer bidder contacts are associated with lower bidder announcement returns. The relation remains robust after controlling for bidder correlations, as well as other deal and firm characteristics and industry fixed effects.

Overall, the results suggest a contrasting pattern relative to target returns (Table 4): while fewer contacts are associated with higher target gains, they correspond to lower bidder returns. This pattern is consistent with the model's predictions. When potential acquirers are more similar, their equilibrium bids are also more correlated, leaving a lower expected rent to the winner. Provided greater correlation does not reduce total gains from trade, this results in higher returns for the target but lower returns for the bidders.

5.3 Size of the bidder pool, merger synergy, and target relative gains

In this section, we investigate whether the size of the bidder pool is related to the degree of merger synergies and the share of surplus among the target and the acquirer.

Table 6 reports how the number of bidder contacts relates to merger synergy after controlling for bidder correlations and other deal characteristics. The dependent variable, *Synergy*, is the value-weighted average of the acquirer's and target's cumulative abnormal returns (CARs) over the [-5,+5] announcement window, where the weights are the firms' market capitalizations one day prior to the merger announcement.

Across all specifications, the coefficient on the indicator for transactions

[14] The literature typically employs a shorter event window to measure acquirer returns because price runups are less of a concern for acquirers.

with a number of contacts below the sample median ($\leq$ median contact) is small and statistically insignificant. This suggests that, once accounting for firm size, deal financing, and other deal characteristics, the number of contacts during the deal process does not have a statistically discernible effect on the total merger synergy. Importantly, the absence of a positive relation between contacts and synergy also reinforces our earlier evidence that targets earn higher announcement returns primarily because they extract more rent from acquirers, and not because these transactions generate higher expected synergies.

We now explore more explicitly how the number of bidder contacts relates to the distribution of merger gains between targets and acquirers. In Table 7, the dependent variable, *Target Gains Relative to Acquirer*, is defined as the difference between the target's and acquirer's abnormal announcement-period dollar returns, scaled by the combined market value of both firms as in Ahern (2012).

Across all specifications, deals with a below-median number of contacts are associated with significantly higher target-relative gains, with coefficients between 0.035 and 0.041 and t-statistics around 4. These results imply that target firms in deals with a smaller number of bidder contacts tend to capture a larger share of total value. The economic magnitude is meaningful: moving from above- to below-median contact intensity increases the target's gain relative to the acquirer by roughly four percentage points.

Taken together with the findings in Table 6, these results point to a clear interpretation. While the total merger synergy is unrelated to the number of contacts, the division of that synergy systematically depends on it. Targets who choose a more restricted bidder pool generate the gains from trade as targets who invite more bidders. They however get better deals, thus shifting a larger share of the surplus toward target shareholders. As explained above, this is consistent with a model in which targets who restrict the bidder pool precisely do so because they do not need many competing bidders to extract a large share of the surplus.

5.4 Size of the bidder pool and target counteroffers

The final set of empirical tests examines whether target firms that select a smaller bidder pool are more likely to make explicit counteroffers during negotiations. The dependent variable, Counteroffer, equals one if the target makes one or more counteroffers during the negotiation process and zero otherwise. Table 8 presents the regression results.

Across all specifications, the indicator for deals with a below-median number of contacts is positive and highly significant, with coefficients between 0.16 and 0.17, indicating that target firms that contact fewer bidders are significantly more likely to make counteroffers. Economically, the magnitudes imply that the likelihood of a target making a counteroffer increases by roughly 16–17 percentage points when the bidder pool is small.

As emphasized in our model, targets can benefit from making a counteroffer to the highest bidder when competition between bidders does not drive up the price high enough. In general, this is more likely to be the case when the number of competing bidders is small. In our setting, the number of bidders is endogenous, making the comparative statics more nuanced. Still, our model predicts that targets who invite fewer bidders are more likely to make counteroffers, provided correlation between their bidders is not too large (Proposition 4). The results in Table 8 are consistent with that prediction. They also provide further evidence on the mechanism linking bidder contacts to the distribution of surplus documented in Tables 6 and 7. While total merger synergy is unrelated to the number of contacts (Table 6), targets in small-pool deals capture a larger share of the total value (Table 7). Table 8 shows that these same targets are also more likely to make counteroffers, consistent with stronger bargaining power driving the higher target returns rather than differences in expected synergies.

6 Conclusion

The previous academic literature has focused on the distinction between negotiations and auctions in M&A deals. However, this distinction hides significant heterogeneity in all the deals classified as "auctions," with some deals involving only two potential acquirers and others more than twenty. In this paper, we investigate the role of the bidder pool in M&A deals, from both theoretical and empirical perspectives.

Theoretically, we show that targets optimally restrict the size of bidder pools, and do so more when bidders have more correlated values. Additionally, targets are more likely to use counteroffers within the allocation mechanism when the number of bidders is smaller. Overall, targets who choose smaller bidder pools tend to enjoy a higher share of the surplus. We show empirical evidence that supports these results in a large granular dataset of successful M&A deals.

There is still a lot of work for academic investigators to uncover regarding auctions in M&A deals because of their inherent complex nature. In particular, the role of indicative rounds and the optionality granted to the seller regarding the mechanism used are fruitful directions for future research. Our work in this paper takes a step forward in this regard.

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Figure 1: Frequency distribution: Number of contacts during the auction process

This figure displays the frequency distribution by number of contacts made along the auction process. The "2-4" group includes number of deals where the target has contacted two to four bidders during the sale process. The "5-7" group includes number of deals where the target has contacted five to seven bidders during the sale process. The "8-10" group includes number of deals where the target has contacted eight to ten bidders during the sale process. The "11-15" group includes number of deals where the target has contacted eleven to fifteen bidders during the sale process. The "16-20" group includes number of deals where the target has contacted sixteen to twenty bidders during the sale process. The "20+" group includes number of deals where the target has contacted more than twenty bidders during the sale process. The sample includes 604 deals announced between 2005 and 2019.

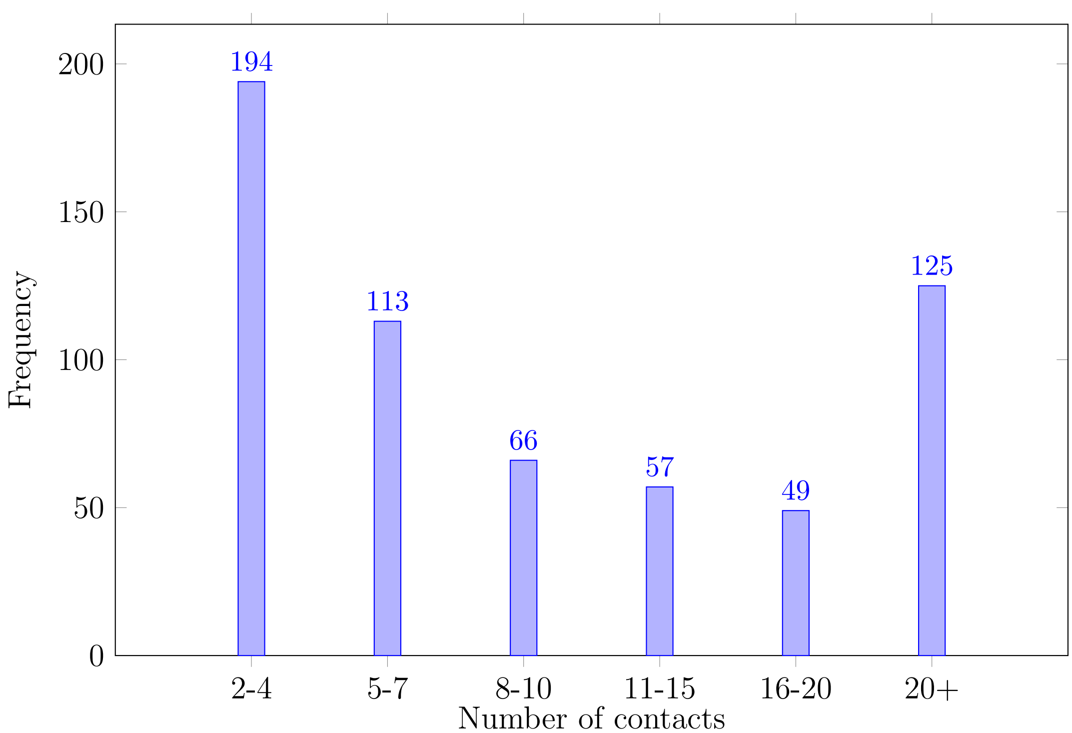

Figure 2: Time trend of correlation measures

This figure displays the average correlation measures across years from 2005 to 2019. Corr_SIC is calculated as the mean correlation of daily returns over the one-year window prior to the deal initiation date between all pairs of firms that have the same two-digit SIC code as the target firm and have a larger market capitalization than the target firm. Corr_FF48 is calculated in a similar way but requires the firms to share the same FF48 classification as the target firm. Corr_TNIC2 represents the bidder correlation calculated based on target firm's TNIC2 peers.

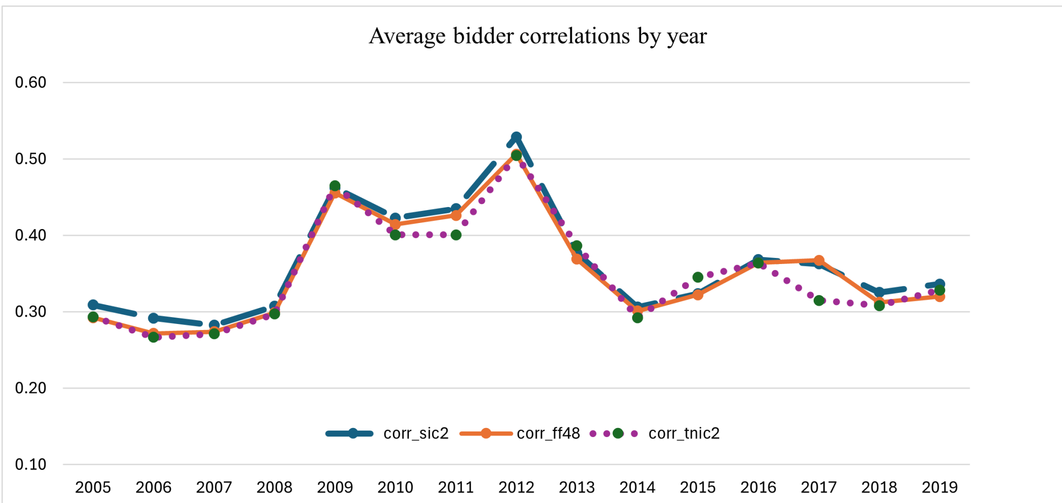

Table 1: Sample distribution and summary statistics

This table presents the sample distribution by year. We draw a sample of completed deals from 2005 to 2019 and require that the form of the deal is coded as a'merger'. We require that the targets be public companies and the deal value reported by the SDC is greater than \$1 million. We also require that bidders seek to purchase 50% or more of the ownership of the target. We restrict the target firms to be S&P1500 firms to manage the extensive manual data collection. Lastly, we restrict deals to having at least two potential buyers with whom the target firm was in contact during the negotiation process. Panel A presents the temporal distribution for the full sample of 604 M&A deals. Percent of deals in each year is calculated using the number of deals announced during that year divided by the total number of deals during the sample period. We also report summary statistics in each year for the number of potential bidders during the process. Panel B presents summary statistics for deal and firm characteristics. Definitions of all variables are in Appendix A.

Panel A. Sample distribution

Year	Number of deals	% deals	Mean n. of contacts	Median	25^{th} Pctl.	75^{th} Pctl.
2005	43	7.1%	27.6	10	3	36
2006	57	9.4%	15.0	8	5	20
2007	72	11.9%	19.8	8.5	4	24
2008	29	4.8%	13.9	5	3	11
2009	23	3.8%	12.0	3	2	5
2010	37	6.1%	9.2	4	2	10
2011	37	6.1%	16.2	10	5	23
2012	30	5.0%	11.7	6.5	3	13
2013	32	5.3%	13.9	11	4	16.5
2014	38	6.3%	10.2	7.5	3	13
2015	45	7.5%	12.2	8	4	16
2016	45	7.5%	19.1	7	4	22
2017	36	6.0%	15.5	8	3.5	19
2018	41	6.8%	11.7	6	4	11
2019	39	6.5%	16.8	9	3	22
Total	604	100%				

Table 1: Continued

Panel B. Summary statistics						
Variable	N	Mean	Median	Std	25 th Pctl.	75 th Pctl.
Target CAR (-105, completion)	604	0.27	0.24	0.25	0.11	0.41
Acquirer CAR (-5, +5)	313	-0.01	-0.01	0.08	-0.06	0.03
Synergy (-5, +5)	311	0.03	0.02	0.08	-0.02	0.07
Target relative gains (-5, +5)	310	0.05	0.04	0.07	0.00	0.09
Counteroffer	604	0.41	0	0.49	0	1
Potential bidders_SIC	604	78.00	55	84.65	19	108
Potential bidders_FF48	604	90.14	54	110.48	27	116
Potential bidders_TNIC2	604	65.68	44	65.58	19	91
Deal Value	604	4573.67	1929.29	8372.67	855.80	4599.85
Target total assets	604	3932.59	1471.16	7375.74	554.15	3622.30
Acquirer total assets	313	38157.89	9220.40	91527.92	2968.06	34672.20
Relative size	313	0.43	0.24	0.57	0.08	0.54
Public acquirer	604	0.62	1	0.49	0	1
Cash deal	604	0.64	1	0.48	0	1
Stock deal	604	0.07	0	0.25	0	0
Tender offer	604	0.16	0	0.36	0	0
Same industry	604	0.38	0	0.48	0	1
Toehold	604	0.01	0	0.12	0	0
Age	604	22.01	19	12.67	12	31
Past return	604	0.04	0.02	0.33	-0.18	0.20
Return volatility	604	1.93	1.81	0.80	1.33	2.33
ROA	604	0.04	0.04	0.09	0.01	0.07
Sales growth	604	0.09	0.06	0.19	-0.01	0.16
Leverage	603	0.23	0.21	0.20	0.02	0.37
R&D	604	0.04	0	0.06	0	0.07
Illiquidity	604	0.69	0.12	2.21	0.04	0.39

Table 2: Bidder correlation and number of contacts

This table presents summary statistics for our three measures of bidder correlation (Panel A). We also compare the bidder correlations across deals sorted by the number of contacts the target made during the negotiation process in Panels B and C. Corr_SIC is calculated as the mean correlation of daily returns over the one-year window prior to the deal initiation date between all pairs of firms that have the same two-digit SIC code as the target firm and have a larger market capitalization than the target firm. Corr_FF48 is calculated in a similar way but requires the firms to share the same FF48 classification as the target firm. Corr_TNIC2 represents the bidder correlation calculated based on target firm's TNIC2 peers. In Panel B, deals are grouped based on whether the number of contacts is above or below the median in our sample (i.e., seven). In Panel C, deals are grouped into quartiles based on the number of contacts. We report the number of observations, mean, median, and standard deviation of our three measures of bidder correlations. The last two columns of the table report the tests of differences in means and medians.

Panel A. Summary statistics

Variable	N	Mean	Median	Std	25^{th} Pctl.	75^{th} Pctl.
Corr_SIC	596	0.351	0.334	0.129	0.259	0.433
Corr_FF48	594	0.341	0.322	0.121	0.253	0.419
Corr_TNIC2	591	0.338	0.317	0.122	0.251	0.402

Table 2: Continued

Panel B. Bidder correlations sorted by number of contacts relative to median										
	$\leq$ Median (no. of contact)				$>$ Median (no. of contact)				Low - High	
Variable	N	Mean	Median	SD	N	Mean	Median	SD	Mean	Median
Corr_SIC	303	0.374	0.354	0.138	293	0.327	0.316	0.115	0.05^{***}	0.04^{***}
Corr_FF48	301	0.366	0.353	0.130	293	0.315	0.303	0.106	0.05^{***}	0.05^{***}
Corr_TNIC2	297	0.359	0.340	0.128	294	0.317	0.303	0.113	0.04^{***}	0.04^{***}

Panel C. Bidder correlations sorted by quartiles of number of contacts														
	Low (no. of contact)			2			3			High (no. of contact)			Low - High	
Variable	Mean	Med.	SD	Mean	Med.	SD	Mean	Med.	SD	Mean	Med.	SD	Mean	Med.
Corr_SIC	0.393	0.385	0.129	0.340	0.305	0.147	0.339	0.328	0.109	0.313	0.298	0.120	0.08^{***}	0.09^{***}
Corr_FF48	0.386	0.369	0.119	0.333	0.302	0.140	0.325	0.315	0.102	0.304	0.291	0.110	0.08^{***}	0.08^{***}
Corr_TNIC2	0.377	0.358	0.128	0.328	0.297	0.122	0.331	0.308	0.122	0.301	0.299	0.100	0.08^{***}	0.06^{***}

Table 3: Regression analysis: Bidder correlation and number of contacts

This table reports regression results on how bidder correlations are related to the number of contacts. The dependent variable is *ln(contact)*, the natural logarithm of the number of contacts. Corr_SIC is calculated as the mean correlation of daily returns over the one-year window prior to the deal initiation date between all pairs of firms that have the same two-digit SIC code as the target firm and have a larger market capitalization than the target firm. Corr_FF48 is calculated in a similar way but requires the firms to share the same FF48 classification as the target firm. Corr_TNIC2 represents the bidder correlation calculated based on target firm's TNIC2 peers. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var			ln (contact)			
Corr_SIC	-0.771**	-1.073**				
	(-2.21)	(-2.50)				
Corr_FF48			-1.116***	-1.154***		
			(-3.15)	(-2.60)		
Corr_TNIC2					-1.131***	-1.482***
					(-3.49)	(-3.71)
Potential bidders_SIC	0.002***	0.003***				
	(3.28)	(3.60)				
Potential bidders_FF48			0.001***	0.002***		
			(3.19)	(3.64)		
Potential bidders_TNIC2					0.001	0.001
					(1.24)	(0.73)
Size	-0.108***	-0.051	-0.115***	-0.096**	-0.147***	-0.141***
	(-2.74)	(-1.02)	(-2.95)	(-2.13)	(-3.96)	(-3.21)
Cash deal	0.235**	0.227**	0.261***	0.228**	0.256***	0.243**
	(2.50)	(2.33)	(2.76)	(2.33)	(2.68)	(2.42)
Stock deal	-0.398***	-0.497***	-0.363**	-0.450***	-0.348**	-0.436***
	(-2.69)	(-3.10)	(-2.50)	(-2.74)	(-2.39)	(-2.60)
Age	-0.000	0.001	0.001	0.001	0.000	0.003
	(-0.04)	(0.20)	(0.30)	(0.26)	(0.04)	(0.77)
Past return	-0.148	-0.084	-0.131	-0.097	-0.153	-0.159

Table 3 (Continued)						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	ln (contact)					
	(-1.30)	(-0.69)	(-1.15)	(-0.78)	(-1.36)	(-1.26)
Return volatility	-0.008	-0.059	-0.013	-0.069	-0.041	-0.055
	(-0.14)	(-0.88)	(-0.22)	(-1.03)	(-0.69)	(-0.81)
ROA	-0.974*	-0.837	-0.773	-1.009*	-0.866	-0.965
	(-1.78)	(-1.50)	(-1.37)	(-1.70)	(-1.50)	(-1.63)
Sales growth	0.005	0.202	0.031	0.174	-0.063	0.095
	(0.02)	(0.81)	(0.13)	(0.68)	(-0.27)	(0.37)
Leverage	0.189	0.314	0.345	0.421	0.432*	0.447
	(0.84)	(1.15)	(1.54)	(1.53)	(1.86)	(1.60)
R&D	-1.334*	0.148	-0.796	-0.266	-0.743	-0.219
	(-1.87)	(0.15)	(-1.12)	(-0.28)	(-1.05)	(-0.22)
Illiquidity	0.048*	0.042	0.051*	0.048*	0.058**	0.058**
	(1.65)	(1.60)	(1.81)	(1.82)	(2.03)	(2.15)
Constant	2.947***	2.983***	3.022***	3.412***	3.391***	1.995***
	(7.80)	(5.97)	(8.10)	(7.06)	(9.48)	(4.95)
Industry FE	No	Yes	No	Yes	No	Yes
Observations	595	595	593	593	590	590
R-squared	0.163	0.262	0.173	0.267	0.157	0.258

Table 4: Number of contacts and target returns

This table examines how the number of contacts is related to the target returns after controlling for bidder correlations. The dependent variable is *Target CAR(-105, Completion)*, measured as the target cumulative abnormal return, adjusted by the market value-weighted return, over the period from 105 trading days prior to deal announcement date through deal completion date. The main independent variable is $\leq median(contact)$, an indicator variable that equals one if the number of contacts is equal or below the median in our sample (i.e., 7), and zero otherwise. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	Target CAR (-105, Completion)					
≤ median (contact)	0.074***	0.068***	0.073***	0.073***	0.075***	0.067***
	(3.53)	(3.00)	(3.54)	(3.24)	(3.67)	(3.02)
Corr_SIC	-0.025	0.019				
	(-0.28)	(0.16)				
Corr_FF48			-0.003	0.005		
			(-0.03)	(0.04)		
Corr_TNIC2					0.010	0.042
					(0.11)	(0.40)
Potential bidders_SIC	-0.000	-0.000				
	(-1.50)	(-0.47)				
Potential bidders_FF48			-0.000*	0.000		
			(-1.65)	(0.21)		
Potential bidders_TNIC2					-0.000	-0.000
					(-0.72)	(-0.76)
Size	-0.002	0.001	-0.004	0.003	-0.003	-0.001
	(-0.20)	(0.10)	(-0.36)	(0.28)	(-0.26)	(-0.10)
Public acquirer	0.074***	0.074***	0.073***	0.071***	0.078***	0.075***
	(3.25)	(3.10)	(3.16)	(2.94)	(3.36)	(3.11)
Cash deal	0.084***	0.062**	0.080***	0.059**	0.079***	0.058**
	(3.36)	(2.27)	(3.23)	(2.17)	(3.18)	(2.10)
Stock deal	-0.092*	-0.067	-0.094*	-0.069	-0.111**	-0.072
	(-1.73)	(-1.22)	(-1.78)	(-1.26)	(-2.01)	(-1.26)

Table 4 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	Target CAR (-105, Completion)					
Tender offer	0.055*	0.044	0.053*	0.048	0.054*	0.048
	(1.93)	(1.45)	(1.85)	(1.57)	(1.90)	(1.56)
Same industry	0.015	0.014	0.010	0.015	0.007	0.008
	(0.69)	(0.61)	(0.46)	(0.64)	(0.30)	(0.35)
Toehold	0.035	0.055	0.057	0.049	0.042	0.058
	(0.30)	(0.42)	(0.49)	(0.37)	(0.35)	(0.43)
Age	0.001	-0.000	0.000	-0.000	0.000	-0.000
	(0.67)	(-0.04)	(0.48)	(-0.12)	(0.37)	(-0.43)
Past year return	-0.058*	-0.074**	-0.053	-0.069*	-0.051	-0.075**
	(-1.72)	(-2.05)	(-1.58)	(-1.88)	(-1.53)	(-2.02)
Return volatility	0.033*	0.035	0.032	0.034	0.034*	0.034
	(1.67)	(1.59)	(1.63)	(1.53)	(1.75)	(1.55)
ROA	0.130	0.134	0.089	0.134	0.141	0.142
	(0.85)	(0.86)	(0.59)	(0.83)	(0.94)	(0.91)
Sales growth	-0.025	-0.031	-0.028	-0.030	-0.034	-0.031
	(-0.38)	(-0.43)	(-0.42)	(-0.41)	(-0.51)	(-0.43)
Leverage	0.040	0.037	0.038	0.039	0.055	0.053
	(0.67)	(0.51)	(0.64)	(0.54)	(0.90)	(0.73)
R&D	0.451**	0.250	0.398*	0.234	0.430**	0.297
	(2.08)	(0.85)	(1.89)	(0.79)	(2.04)	(0.99)
Illiquidity	0.013*	0.011	0.012*	0.011	0.012*	0.011
	(1.79)	(1.55)	(1.72)	(1.44)	(1.69)	(1.58)
Constant	0.049	0.369***	0.067	0.363**	0.040	-0.001
	(0.45)	(2.69)	(0.62)	(2.56)	(0.38)	(-0.01)
Industry FE	No	Yes	No	Yes	No	Yes
Observations	595	595	593	593	590	590
R-squared	0.140	0.216	0.140	0.220	0.140	0.223

Table 5: Number of contacts and bidder returns

This table examines how the number of contacts is related to the bidder returns after controlling for bidder correlations. The dependent variable is *Acquirer CAR (-5, +5)*, measured as the cumulative abnormal return, adjusted by the market value-weighted return, over 11-day window surrounding the merger announcement. The main independent variable is $\leq median(contact)$, an indicator variable that equals one if the number of contacts is equal or below the median in our sample (i.e., 7), and zero otherwise. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	Acquirer CAR (-5, +5)					
≤ median (contact)	-0.024**	-0.022**	-0.022**	-0.022**	-0.025**	-0.025**
	(-2.40)	(-2.17)	(-2.15)	(-2.16)	(-2.45)	(-2.37)
Corr_SIC	-0.009	0.064*				
	(-0.25)	(1.68)				
Corr_FF48			0.012	0.077**		
			(0.33)	(1.99)		
Corr_TNIC2					0.020	0.070*
					(0.57)	(1.89)
Potential bidders_SIC	-0.000	0.000				
	(-1.17)	(0.24)				
Potential bidders_FF48			0.000	0.000		
			(0.48)	(1.32)		
Potential bidders_TNIC2					-0.000	-0.000
					(-0.75)	(-0.68)
Acquirer size	-0.000	0.001	0.000	0.002	-0.001	-0.001
	(-0.07)	(0.20)	(0.10)	(0.50)	(-0.25)	(-0.13)
Relative size	0.001	-0.003	0.003	-0.001	-0.002	-0.008
	(0.05)	(-0.24)	(0.21)	(-0.07)	(-0.16)	(-0.55)
Cash deal	0.039***	0.049***	0.038***	0.046***	0.040***	0.050***
	(3.41)	(3.75)	(3.31)	(3.57)	(3.36)	(3.76)
Stock deal	-0.007	-0.008	-0.010	-0.007	-0.006	-0.008
	(-0.39)	(-0.42)	(-0.58)	(-0.41)	(-0.34)	(-0.43)
Tender offer	-0.003	-0.011	-0.001	-0.007	-0.002	-0.008

Table 5 (Continued)						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	Acquirer CAR (-5, +5)					
	(-0.22)	(-0.74)	(-0.04)	(-0.45)	(-0.12)	(-0.55)
Same industry	0.004	0.001	0.006	0.004	0.007	0.004
	(0.44)	(0.12)	(0.60)	(0.35)	(0.68)	(0.40)
Toehold	0.003	0.018	-0.005	0.000	0.010	0.026
	(0.06)	(0.42)	(-0.09)	(0.00)	(0.18)	(0.60)
Constant	-0.007	0.074	-0.029	0.056	-0.014	0.099**
	(-0.19)	(1.57)	(-0.79)	(1.16)	(-0.36)	(2.01)
Industry FE	No	Yes	No	Yes	No	Yes
Observations	305	305	304	304	301	301
R-squared	0.082	0.259	0.076	0.262	0.083	0.267

Table 6: Number of contacts and merger synergy

This table examines how the number of contacts is related to merger synergy after controlling for bidder correlations. The dependent variable is *Synergy*, measured as the value-weighted average of acquirer's and the target's CARs, with the weights being their respective market capitalizations one day prior to their respective CAR event windows. We calculate the measure over the event windows (-5, +5), where day 0 is the announcement date. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var			Synergy [-5, +5]			
$\leq$ median (contact)	0.006	0.008	0.009	0.009	0.008	0.005
	(0.68)	(0.73)	(1.05)	(0.86)	(0.88)	(0.43)
Corr_SIC	0.018	0.030				
	(0.51)	(0.61)				
Corr_FF48			0.042	0.054		
			(1.19)	(1.06)		
Corr_TNIC2					0.058*	0.084*
					(1.70)	(1.72)
Potential bidders_SIC	-0.000**	-0.000				
	(-2.44)	(-0.23)				
Potential bidders_FF48			-0.000	0.000		
			(-0.44)	(0.32)		
Potential bidders_TNIC2					-0.000	-0.000
					(-0.56)	(-1.03)
Acquirer size	-0.011***	-0.012***	-0.011***	-0.012**	-0.011***	-0.014***
	(-3.30)	(-2.61)	(-3.25)	(-2.52)	(-3.36)	(-2.80)
Relative size	0.014	0.003	0.015	0.002	0.012	-0.003
	(1.34)	(0.20)	(1.40)	(0.12)	(1.10)	(-0.18)
Cash deal	0.032***	0.033***	0.031***	0.032***	0.032***	0.035***
	(3.15)	(2.76)	(3.06)	(2.66)	(3.07)	(2.88)
Stock deal	-0.017	-0.016	-0.021	-0.017	-0.019	-0.014
	(-1.03)	(-0.86)	(-1.28)	(-0.95)	(-1.11)	(-0.76)
Tender offer	0.002	-0.005	0.004	-0.005	0.004	-0.004
	(0.17)	(-0.35)	(0.35)	(-0.38)	(0.32)	(-0.29)

Table 6 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var			Synergy [-5, +5]			
Same industry	0.000	0.003	0.002	0.005	0.003	0.004
	(0.03)	(0.22)	(0.26)	(0.40)	(0.38)	(0.33)
Toehold	-0.003	0.011	0.007	0.003	0.003	0.021
	(-0.07)	(0.40)	(0.13)	(0.10)	(0.07)	(0.75)
Age	-0.000	0.000	0.000	0.000	0.000	0.000
	(-0.13)	(0.49)	(0.12)	(0.53)	(0.13)	(0.21)
Past year return	0.039***	0.035**	0.039***	0.035**	0.039***	0.033**
	(2.72)	(2.28)	(2.78)	(2.32)	(2.77)	(2.14)
Return volatility	-0.002	0.001	-0.001	0.001	-0.001	-0.001
	(-0.24)	(0.19)	(-0.11)	(0.09)	(-0.15)	(-0.07)
ROA	-0.044	-0.071	-0.050	-0.085	-0.058	-0.085
	(-0.68)	(-1.03)	(-0.78)	(-1.28)	(-0.90)	(-1.27)
Sales growth	-0.007	0.006	-0.003	0.006	0.002	0.009
	(-0.25)	(0.24)	(-0.10)	(0.23)	(0.06)	(0.35)
Leverage	0.012	0.022	0.020	0.022	0.018	0.012
	(0.45)	(0.64)	(0.76)	(0.65)	(0.62)	(0.34)
R&D	-0.008	-0.078	-0.026	-0.096	-0.022	-0.038
	(-0.10)	(-0.73)	(-0.32)	(-0.89)	(-0.27)	(-0.36)
Illiquidity	-0.003*	-0.005***	-0.003**	-0.005***	-0.003**	-0.004**
	(-1.87)	(-2.81)	(-2.47)	(-3.20)	(-2.23)	(-2.25)
Constant	0.113***	0.476***	0.088**	0.465***	0.092**	0.506***
	(2.70)	(7.57)	(2.06)	(7.18)	(2.14)	(7.87)
Acq Industry FE	No	Yes	No	Yes	No	Yes
Target Industry FE	No	Yes	No	Yes	No	Yes
Observations	304	304	303	303	300	300
R-squared	0.148	0.457	0.137	0.459	0.141	0.478

Table 7: Number of contacts and target gains relative to acquirer

This table examines how the number of contacts is related to target gains relative to acquirers after controlling for bidder correlations. The dependent variable is *Target's gain relative to the acquirer*, defined as the difference between target abnormal dollar returns and acquirer abnormal dollar returns over the event window, scaled by the sum of the market values of the two parties at a date prior to the event window. We calculate the measure over the event windows (-5, +5), where day 0 is the announcement date. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	Target Gains Relative to Acquirer [-5, +5]					
≤ median (contact)	0.034***	0.039***	0.033***	0.038***	0.036***	0.041***
	(3.75)	(3.41)	(3.69)	(3.22)	(3.92)	(3.49)
Corr_SIC	0.030	-0.007				
	(0.85)	(-0.12)				
Corr_FF48			0.022	0.005		
			(0.63)	(0.09)		
Corr_TNIC2					0.021	0.035
					(0.64)	(0.78)
Potential bidders_SIC	-0.000	-0.000				
	(-0.86)	(-1.28)				
Potential bidders_FF48			-0.000*	-0.000		
			(-1.92)	(-1.39)		
Potential bidders_TNIC2					-0.000	-0.000
					(-0.18)	(-0.09)
Acquirer size	-0.006*	-0.010**	-0.006*	-0.010**	-0.006*	-0.009*
	(-1.77)	(-1.99)	(-1.81)	(-1.97)	(-1.71)	(-1.78)
Relative size	0.018	0.010	0.017	0.010	0.019	0.013
	(1.39)	(0.60)	(1.36)	(0.61)	(1.44)	(0.73)
Cash deal	-0.023**	-0.022	-0.025**	-0.021	-0.024**	-0.021
	(-2.12)	(-1.57)	(-2.28)	(-1.50)	(-2.10)	(-1.45)
Stock deal	0.004	0.008	0.005	0.007	0.004	0.004
	(0.31)	(0.44)	(0.40)	(0.42)	(0.28)	(0.23)
Tender offer	0.007	0.013	0.003	0.011	0.006	0.011

Table 7 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	Target Gains Relative to Acquirer [-5, +5]					
	(0.54)	(0.85)	(0.28)	(0.75)	(0.48)	(0.77)
Same industry	-0.013	-0.012	-0.015*	-0.013	-0.012	-0.012
	(-1.50)	(-1.04)	(-1.72)	(-1.11)	(-1.38)	(-1.09)
Toehold	-0.026	-0.066*	0.008	-0.030	-0.025	-0.069*
	(-0.50)	(-1.88)	(0.17)	(-0.80)	(-0.47)	(-1.87)
Age	0.000	-0.000	-0.000	-0.000	0.000	-0.000
	(0.15)	(-0.35)	(-0.10)	(-0.25)	(0.26)	(-0.48)
Past year return	-0.002	0.000	-0.002	0.001	-0.003	0.004
	(-0.15)	(0.02)	(-0.18)	(0.09)	(-0.24)	(0.21)
Return volatility	-0.001	-0.009	-0.001	-0.009	-0.000	-0.011
	(-0.11)	(-1.08)	(-0.11)	(-1.03)	(-0.01)	(-1.27)
ROA	0.021	0.033	0.017	0.052	0.010	0.034
	(0.32)	(0.42)	(0.25)	(0.69)	(0.14)	(0.44)
Sales growth	0.003	-0.032	0.001	-0.036	0.006	-0.028
	(0.14)	(-1.20)	(0.02)	(-1.34)	(0.23)	(-1.05)
Leverage	-0.018	-0.007	-0.024	-0.006	-0.015	0.006
	(-0.70)	(-0.18)	(-0.92)	(-0.16)	(-0.52)	(0.17)
R&D	0.061	0.068	0.044	0.080	0.039	0.071
	(0.80)	(0.62)	(0.58)	(0.71)	(0.51)	(0.64)
Illiquidity	0.003	0.005**	0.003	0.005**	0.002	0.004
	(1.42)	(2.17)	(1.61)	(2.18)	(1.09)	(1.65)
Constant	0.082**	0.252***	0.096**	0.240***	0.078*	0.219***
	(1.99)	(3.92)	(2.25)	(3.75)	(1.84)	(3.36)
Acq Industry FE	No	Yes	No	Yes	No	Yes
Target Industry FE	No	Yes	No	Yes	No	Yes
Observations	304	304	303	303	300	300
R-squared	0.133	0.397	0.140	0.394	0.130	0.397

Table 8: Number of contacts and target making explicit counteroffers

This table examines how the number of contacts is related to whether the target firm makes counteroffer(s). The dependent variable is *Counteroffer*, an indicator variable that equals one if the target firm makes counteroffer(s) during the negotiation process, and zero otherwise. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	Counteroffer					
$\leq$ median (contact)	0.173***	0.162***	0.172***	0.165***	0.171***	0.172***
	(3.96)	(3.50)	(3.93)	(3.55)	(3.93)	(3.71)
Corr_SIC	0.212	0.270				
	(1.15)	(1.14)				
Corr_FF48			0.345*	0.470**		
			(1.79)	(2.07)		
Corr_TNIC2					0.365**	0.415*
					(1.99)	(1.94)
Potential bidders_SIC	-0.000	-0.000				
	(-1.51)	(-1.34)				
Potential bidders_FF48			-0.000	-0.000		
			(-0.44)	(-0.20)		
Potential bidders_TNIC2					-0.000	0.000
					(-1.24)	(0.28)
Size	-0.032	-0.016	-0.028	-0.010	-0.024	-0.001
	(-1.41)	(-0.60)	(-1.26)	(-0.37)	(-1.13)	(-0.06)
Public acquirer	-0.017	-0.042	-0.021	-0.044	-0.004	-0.029
	(-0.36)	(-0.86)	(-0.44)	(-0.89)	(-0.09)	(-0.57)
Cash deal	0.002	-0.038	0.002	-0.034	-0.004	-0.048
	(0.04)	(-0.71)	(0.05)	(-0.64)	(-0.08)	(-0.89)
Stock deal	-0.059	0.035	-0.065	0.034	-0.056	0.045
	(-0.68)	(0.38)	(-0.75)	(0.37)	(-0.61)	(0.45)
Tender offer	-0.006	0.017	-0.005	0.017	-0.004	0.017
	(-0.10)	(0.28)	(-0.08)	(0.27)	(-0.07)	(0.27)
Same industry	-0.003	0.015	-0.005	0.019	-0.008	0.011

Table 8 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var			Counteroffer			
	(-0.07)	(0.33)	(-0.11)	(0.41)	(-0.19)	(0.23)
Toehold	0.087	0.208	0.102	0.205	0.116	0.208
	(0.52)	(1.19)	(0.61)	(1.17)	(0.68)	(1.19)
Age	-0.002	-0.003*	-0.002	-0.003	-0.003*	-0.004*
	(-1.40)	(-1.67)	(-1.31)	(-1.62)	(-1.69)	(-1.81)
Past year return	0.026	0.020	0.011	0.015	0.014	0.013
	(0.40)	(0.30)	(0.18)	(0.23)	(0.21)	(0.19)
Return volatility	0.009	0.004	0.011	-0.001	0.019	-0.007
	(0.29)	(0.13)	(0.35)	(-0.02)	(0.62)	(-0.20)
ROA	-0.046	-0.001	-0.030	-0.028	-0.073	0.041
	(-0.17)	(-0.00)	(-0.11)	(-0.09)	(-0.26)	(0.14)
Sales growth	0.046	-0.050	0.065	-0.004	0.068	-0.005
	(0.41)	(-0.40)	(0.57)	(-0.03)	(0.59)	(-0.04)
Leverage	0.039	-0.157	0.007	-0.177	0.021	-0.121
	(0.33)	(-1.11)	(0.06)	(-1.23)	(0.18)	(-0.83)
R&D	0.764*	-0.062	0.684*	0.022	0.652	0.055
	(1.87)	(-0.12)	(1.70)	(0.04)	(1.59)	(0.10)
Illiquidity	-0.009	0.000	-0.010	-0.001	-0.010	-0.002
	(-0.95)	(0.02)	(-1.09)	(-0.05)	(-1.01)	(-0.16)
Constant	0.518**	-0.145	0.434**	-0.347	0.419**	-0.114
	(2.52)	(-0.51)	(2.07)	(-1.23)	(2.06)	(-0.48)
Industry FE	No	Yes	No	Yes	No	Yes
Observations	595	595	593	593	590	590
R-squared	0.054	0.154	0.054	0.160	0.059	0.165

Appendices

A Empirical Appendix

Appendix A. Variable definitions

Variable	Definition
A.1. Bidder correlation	
Corr_SIC	The mean correlation of daily returns over the one-year window prior to the deal initiation date between all pairs of firms that have the same two-digit SIC code as the target firm and have a larger market capitalization than the target firm.
Corr_FF48	Similar to Corr_SIC but requires the firms to share the same FF48 classification as the target firm.
Corr_TNIC2	Similar to Corr_SIC but requires the firms to be targe firm's TNIC2 peer group.
A.2. Sale process variables	
$\leq$ median (contact)	An indicator variable that equals one if the number of contacts is equal to or below the sample median (i.e., 7), and zero otherwise.
ln (contact)	The natural logarithm of the number of contacts.
Counteroffer	An indicator variable that equals one if the target firm makes counteroffer(s) during the negotiation process, and zero otherwise.
A.3. Deal outcome variables	
Target CAR (-105, completion)	The target cumulative abnormal return, adjusted by the market value-weighted return, over the period from 105 trading days prior to deal announcement date through deal completion date.
Acquirer CAR (-5, +5)	The cumulative abnormal return, adjusted by the market value-weighted return, over 11-day window surrounding the merger announcement
Synergy (a, b)	The value-weighted average of acquirer's and the target's CARs, with the weights being their respective market capitalizations one day prior to their respective CAR event windows (a, b), where day 0 is the announcement date.
Target gains relative to acquirer (a, b)	The difference between target abnormal dollar returns and acquirer abnormal dollar returns over the event window, scaled by the sum of the market values of the two parties at a date prior to the event window (a, b).
A.4. Deal/firm characteristics	

Appendix A (Continued)	
Variable	Definition
Size	The natural logarithm of target firm's total assets, measured at the most recent fiscal year end prior to the deal initiate date.
Acquirer size	The natural logarithm of acquiring firm's total assets, measured at the most recent fiscal year end prior to the deal initiate date.
Relative size	The ratio between target market capitalization and acquirer market capitalization.
Cash deal	An indicator variable that equals 1 if the method of payment is cash only, and zero otherwise.
Stock deal	An indicator variable that equals 1 if the method of payment is stock only, and zero otherwise.
Tender offer	An indicator variable that equals 1 if the deal is a tender offer, and zero otherwise.
Same industry	An indicator variable that equals one if the acquirer and the target share the same three-digit Standard Industrial Classification Code (SIC), and zero otherwise.
Public acquirer	An indicator variable that equals 1 if the acquirer's public status is 'Public', and zero otherwise.
Toehold	An indicator variable that equals 1 if the acquirer has an ownership stake of 5% or more in the target, and zero otherwise.
Age	The time in years since the first date of the target firm's total assets data in Compustat.
Past year return	Buy-and-hold stock return from month -12 to month -1 relative to the deal initiate month.
Return volatility	Idiosyncratic volatility, calculated as the standard deviation of residual returns from regressing daily excess stock returns onto contemporaneous Fama-French three factors. The regression is performed using daily returns over 252 days prior to the deal initiate date.
ROA	Net income, scaled by total assets.
Sales growth	Growth rate of sales.
Leverage	Book value of debt divided by the book value of assets.
R&D	R&D expenditures, scaled by total assets.
Illiquidity	Amihud's illiquidity ratio over 252 days prior to the deal initiate date.

Appendix A (Continued)	
Variable	Definition
Potential bidders_SIC	The number of firms that have the same two-digit SIC code but with a larger market capitalization than the target firm measured at the most recent month-end prior to the deal initiate date.
Potential bidders_FF48	Similar to Potential bidders_SIC but requires the firms to share the same FF48 classification as the target firm.
Potential bidders_TNIC2	Similar to Potential bidders_SIC but requires the firms to be targe firm's TNIC2 peer group.

Appendix Table 1. Robustness: Bidder correlation and number of contacts

This table reports results of robustness tests on how bidder correlations are related to the number of contacts. Columns (1) to (3) present OLS regression results where the dependent variable is $\leq$ *median*(*contact*), an indicator variable that equals one if the number of contacts is equal to or below the sample median (i.e., 7). Columns (4) to (6) present OLS regression results where the dependent variable is *quartile (contact)*, a ranking variable that ranges from 1 to 4 based on the number of contacts. Column (7) to (9) present Poisson regression results with fixed effects, where the dependent variable is *Contact*, the count of the number of contacts. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var	≤ median (contact)			Quartile rank (contact)			Contact		
	OLS						Poisson		
Corr_SIC	0.409*			-1.291**			-1.287**		
	(1.79)			(-2.53)			(-2.29)		
Corr_FF48		0.400*			-1.416***			-1.235**	
		(1.76)			(-2.68)			(-2.15)	
Corr_TNIC2			0.416**			-1.598***			-2.091***
			(1.97)			(-3.36)			(-4.35)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	595	593	590	595	593	590	595	593	590
R-squared	0.207	0.210	0.193	0.237	0.238	0.228			

Appendix Table 2. Robustness: Number of contacts and target returns

This table presents results of robustness tests on target returns. In Columns (1) to (3), the dependent variable is *Target CAR(-63, Completion)*, measured as the target cumulative abnormal return, adjusted by the market value-weighted return, over the period from 63 trading days prior to deal announcement date through deal completion date. In Columns (4) to (6), the dependent variable is *Target CAR(initiation, Completion)*, measured as the target cumulative abnormal return over the period from deal initiation to deal completion date. The main independent variable is $\leq median(contact)$, an indicator variable that equals one if the number of contacts is equal or below the median in our sample (i.e., 7), and zero otherwise. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	Target CAR (-63, Completion)			Target CAR (Initiation, Completion)		
≤ median (contact)	0.066***	0.071***	0.065***	0.050**	0.052**	0.046**
	(3.28)	(3.48)	(3.31)	(2.16)	(2.22)	(2.02)
Corr_SIC	0.001			-0.010		
	(0.01)			(-0.10)		
Corr_FF48		-0.012			-0.011	
		(-0.11)			(-0.09)	
Corr_TNIC2			0.029			0.031
			(0.32)			(0.29)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	595	593	590	595	593	590
R-squared	0.215	0.219	0.224	0.236	0.237	0.243

Appendix Table 3. Robustness: Number of contacts and bidder returns

This table reports results of robustness tests on bidder returns. In Columns (1) to (3), the dependent variable is *Acquirer CAR (-1, +1)*, measured as the cumulative abnormal return, adjusted by the market value-weighted return, over three-day window surrounding the merger announcement. In Columns (4) to (6), the dependent variable is *Acquirer CAR (-10, +10)*, measured as the cumulative abnormal return, adjusted by the market value-weighted return, over 21-day window surrounding the merger announcement. The main independent variable is $\leq$ *median*(*contact*), an indicator variable that equals one if the number of contacts is equal or below the median in our sample (i.e., 7), and zero otherwise. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	Acquirer CAR (-1, +1)			Acquirer CAR (-10, +10)		
$\leq$ median (contact)	-0.012	-0.011	-0.015*	-0.027**	-0.025*	-0.030**
	(-1.30)	(-1.23)	(-1.65)	(-1.99)	(-1.86)	(-2.14)
Corr_SIC	0.042			0.057		
	(1.29)			(1.13)		
Corr_FF48		0.018			0.086*	
		(0.56)			(1.67)	
Corr_TNIC2			0.061**			0.081
			(2.00)			(1.64)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	305	304	301	305	304	301
R-squared	0.276	0.274	0.283	0.235	0.239	0.243

Appendix Table 4. Robustness: Number of contacts and merger synergy

This table examines the robustness of regressions on the merger synergy. The dependent variable is *Synergy*, measured as the value-weighted average of acquirer's and the target's CARs, with the weights being their respective market capitalizations one day prior to their respective CAR event windows. We calculate the measure over two alternative event windows: (-42, +42), and (-42, +126), where day 0 is the announcement date. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	Synergy [-42, +42]			Synergy [-42, +126]		
$\leq$ median (contact)	0.016	0.024	0.019	0.013	0.021	0.009
	(0.70)	(1.03)	(0.84)	(0.46)	(0.77)	(0.34)
Corr_SIC	0.084			0.073		
	(0.93)			(0.62)		
Corr_FF48		0.084			0.040	
		(0.96)			(0.34)	
Corr_TNIC2			0.098			0.163
			(1.11)			(1.35)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Acq Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Target Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	304	303	300	304	303	300
R-squared	0.434	0.436	0.452	0.420	0.423	0.433

Appendix Table 5. Robustness: Number of contacts and target gains relative to acquirer

This table examines the robustness of regressions on target gains relative to acquirer. The dependent variable is *Target Relative Gains*, defined as the difference between target abnormal dollar returns and acquirer abnormal dollar returns over the event window, scaled by the sum of the market values of the two parties at a date prior to the event window. We calculate the measure over two alternative event windows: (-42, +42), and (-42, +126), where day 0 is the announcement date. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	Target Relative Gains [-42, +42]			Target Relative Gains [-42, +126]		
$\leq$ median (contact)	0.035*	0.031	0.032	0.044*	0.039	0.047*
	(1.70)	(1.48)	(1.51)	(1.69)	(1.52)	(1.84)
Corr_SIC	-0.065			-0.030		
	(-0.75)			(-0.27)		
Corr_FF48		-0.046			0.002	
		(-0.57)			(0.02)	
Corr_TNIC2			0.039			-0.020
			(0.53)			(-0.20)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Acq Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Target Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	304	303	300	304	303	300
R-squared	0.360	0.351	0.357	0.378	0.381	0.380

Appendix Table 6. Robustness: Removing financial crisis periods

This table examines the robustness of regressions in Table 4 to 7 by removing deals announced during financial crisis periods (i.e., from Dec 2007 to June 2009). Columns (1) to (3) present results of target returns. Columns (4) to (6) present results of acquirer returns. Columns (7) to (9) present results of merger synergy. Columns (10) to (12) present results of target gains relative to acquirer. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dep. Var	Target CAR (-105, Completion)			Acquirer CAR (-5, +5)			Synergy (-5, +5)			Target Relative Gains (-5, +5)		
$\leq$ median (contact)	0.045**	0.047**	0.046**	-0.021**	-0.020**	-0.023**	0.010	0.012	0.007	0.039***	0.038***	0.040***
	(2.15)	(2.31)	(2.28)	(-2.03)	(-2.06)	(-2.17)	(0.91)	(1.00)	(0.65)	(3.46)	(3.22)	(3.51)
Corr_SIC	0.105			0.033			-0.004			0.027		
	(0.99)			(0.83)			(-0.08)			(0.50)		
Corr_FF48		0.065			0.038			0.001			0.031	
		(0.63)			(0.92)			(0.02)			(0.59)	
Corr_TNIC2			0.118			0.034			0.045			0.055
			(1.27)			(0.88)			(0.87)			(1.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	551	549	547	277	276	273	276	275	272	276	275	272
R-squared	0.232	0.240	0.243	0.303	0.301	0.308	0.514	0.512	0.519	0.457	0.455	0.454

Appendix Table 7. Robustness: Alternative independent variable

This table replicates the regression analysis in Appendix Table 6, replacing $\leq$ median (contact) with its quartile ranking as the independent variable. Columns (1) to (3) present results of target returns. Columns (4) to (6) present results of acquirer returns. Columns (7) to (9) present results of merger synergy. Columns (10) to (12) present results of target gains relative to acquirer. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dep. Var	Target CAR (-105, Completion)			Acquirer CAR (-5, +5)			Synergy (-5, +5)			Target Relative Gains (-5, +5)		
Quartile (contact)	-0.025***	-0.026***	-0.026***	0.007	0.006	0.008*	-0.007	-0.008	-0.005	-0.016***	-0.015***	-0.016***
	(-2.74)	(-2.92)	(-2.89)	(1.53)	(1.49)	(1.70)	(-1.32)	(-1.46)	(-0.92)	(-2.97)	(-2.79)	(-3.14)
Corr_SIC	0.094			0.035			-0.009			0.027		
	(0.89)			(0.87)			(-0.17)			(0.50)		
Corr_FF48		0.051			0.037			-0.004			0.032	
		(0.50)			(0.88)			(-0.07)			(0.60)	
Corr_TNIC2			0.097			0.035			0.042			0.052
			(1.04)			(0.90)			(0.80)			(1.09)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	551	549	547	277	276	273	276	275	272	276	275	272
R-squared	0.237	0.246	0.248	0.299	0.295	0.303	0.517	0.515	0.521	0.448	0.448	0.447

B Proofs

Proof of Proposition 1
The optimal number of buyers to invite then solves

$$n^* \in \arg\max\ \mathbb{E}[v_{(2:n)} \mid \alpha] - cn.$$

Note that $\mathbb{E}[v_{(2:n)} \mid \alpha] = \mathbb{E}[\alpha\omega + (1-\alpha)\varepsilon_{(2:n)} \mid \alpha] = \alpha\mathbb{E}[\omega] + (1-\alpha)\mathbb{E}[\varepsilon_{(2:n)}]$. Thus the seller's problem rewrites as

$$n^* \in \arg\max\ (1-\alpha)\mathbb{E}[\varepsilon_{(2:n)}] - cn.$$

The seller's objective function has increasing differences in $(-\alpha, n)$. By Topkis's theorem, the optimizer n^* is then weakly decreasing in α. Similarly, the seller's objective function has increasing differences in $(-c, n)$, such that n^* is then weakly decreasing in c. ■

Proof of Proposition 2
We want to show that

$$Rev(\alpha) := \mathbb{E}_\alpha[v_{(2:n^*(\alpha))}] - cn^*(\alpha) = \alpha\mathbb{E}(\omega) + (1-\alpha)\mathbb{E}(\varepsilon_{(2:n^*(\alpha))}) - cn^*(\alpha)$$

is weakly increasing in α. Let $\alpha > \alpha'$. By Proposition 3.3, we have $n^*(\alpha) \leq n^*(\alpha')$. Since inviting $n^*(\alpha)$ buyers is optimal when the correlation level is α, it must be that

$$Rev(\alpha) \geq \mathbb{E}_\alpha[v_{2:n^*(\alpha')}] - cn^*(\alpha').$$

Then,

$$\begin{aligned} Rev(\alpha) - Rev(\alpha') &\geq \mathbb{E}_\alpha[v_{2:n^*(\alpha')}] - cn^*(\alpha') - \mathbb{E}_{\alpha'}[v_{2:n^*(\alpha')}] + cn^*(\alpha') \\ &= (\alpha - \alpha')[\mathbb{E}(\omega) - \mathbb{E}(\varepsilon_{(2:n^*(\alpha'))})] \\ &\geq 0, \end{aligned}$$

where the last inequality comes from the fact that $\mathbb{E}(\omega) \geq \mathbb{E}(\varepsilon_{(2:N)})$ implies $\mathbb{E}(\omega) > \mathbb{E}(\varepsilon_{(2:n)})$ for any $n < N$. ■

Proof of Proposition 3

By the revelation principle, we can restrict attention to direct revelation mechanisms without loss of optimality (Myerson, 1981). In a direct disclosure mechanism, all participating buyers report their values v_i and the mechanism specifies the probability that each buyer receives the good $x_i(\mathbf{v}) \in [0, 1]$ and his payment $p_i(\mathbf{v}) \in \mathbb{R}$. Of course, the allocation proposed by the mechanism must be feasible: $\sum_i x_i(\mathbf{v}) \leq 1$ for all possible realizations of $\mathbf{v}$. We are interested in characterizing mechanisms that maximize expected revenue among all mechanisms that satisfy ex-post individual rationality (IR) and incentive compatibility (IC) constraints. A mechanism satisfies ex-post IR if

$$v_i x_i(v_i, v_{-i}) - p_i(v_i, v_{-i}) \geq 0 \qquad \forall i, v_i, v_{-i}.$$

A mechanism satisfies ex-post IC if

$$v_i x_i(v_i, v_{-i}) - p_i(v_i, v_{-i}) \geq v_i x_i(v_i', v_{-i}) - p_i(v_i', v_{-i}) \qquad \forall i, v_i, v_i', v_{-i}.$$

Ex-post IC guarantees that a buyer with value v_i never wants to misreport his type to be v_i', irrespective of other buyers' realized values v_{-i}.

Roughgarden and Talgam-Cohen (2016) extend the analysis of Myerson (1981) to settings with correlated and interdependent values. They show (Proposition 5.1) that a mechanism is ex-post IR and IC if and only if, for every i and v_{-i}, buyer i's allocation $x_i(v_i, v_{-i})$ is weakly increasing in v_i and the following payment equality and inequality hold:

$$\begin{aligned} &p_i(v_i, v_{-i}) = v_i x_i(\mathbf{v}) - \int_{\underline{v}}^{v_i} x_i(s, v_{-i}) ds - (\underline{v} x_i(\underline{v}, v_{-i}) - p_i(\underline{v}, v_{-i})), \\ &p_i(\underline{v}, v_{-i}) \leq \underline{v} x_i(\underline{v}, v_{-i}). \end{aligned}$$

Note that that last inequality is simply the ex-post IR constraint of a buyer with the lowest possible value $v_i = \underline{v}$. A mechanism that maximizes the seller's expected revenue must bind that constraint. If not, all payments could be increased by a fixed amount up until it binds: doing so would not violate ex-post IC and would strictly increase expected revenue. Thus, $p_i(\underline{v}, v_{-i}) = \underline{v} x_i(\underline{v}, v_{-i})$, and the payment equality becomes

$$p_i(v_i, v_{-i}) = v_i x_i(\mathbf{v}) - \int_{\underline{v}}^{v_i} x_i(s, v_{-i}) ds \quad \forall i, v_i, v_{-i}.$$

Taking stock, maximizing expected revenue subject to ex-post IR and IC constraints is equivalent to solving:

$$
\begin{aligned}
\max_{x,p} \quad & \mathbb{E}[\sum_i p_i(\mathbf{v})] \\
\text{s.t.} \quad & x_i(\cdot, v_{-i}) \text{ non-decreasing for all } i, v_{-i} \\
& p_i(v_i, v_{-i}) = v_i x_i(\mathbf{v}) - \int_{\underline{v}}^{v_i} x_i(s, v_{-i}) ds \quad \forall i, v_i, v_{-i}, \\
& \sum_i x_i(\mathbf{v}) \leq 1 \quad \forall \mathbf{v}.
\end{aligned}
$$

Plugging the equality payment into the objective function and rearranging using integration by part as in Myerson (1981), this problem can be rewritten as

$$
\begin{aligned}
\max_{x} \quad & \mathbb{E}\left[\sum_i x_i(\mathbf{v}) \left(v_i - \frac{1 - F_v(v_i \mid v_{-i})}{f_v(v_i \mid v_{-i})}\right)\right] \\
\text{s.t.} \quad & x_i(\cdot, v_{-i}) \text{ non-decreasing for all } i, v_{-i}, \\
& \sum_i x_i(\mathbf{v}) \leq 1 \quad \forall \mathbf{v}.
\end{aligned}
$$

Theorem 5.3 in Roughgarden and Talgam-Cohen (2016) shows that the monotonicity constraint does not bind when the distribution F_v satisfies two conditions—regularity and affiliation. We can then focus on the relaxed problem that ignores the monotonicity constraint and solve that problem point-wise: for each $\mathbf{v}$, the revenue-maximizing mechanism allocates the good to the buyer with the highest virtual value if that value is positive and to no-one otherwise:

$$
x_i^*(\mathbf{v}) = \mathbb{1}\left\{ i = \arg\max_j v_j - \frac{1 - F_v(v_j \mid v_{-j})}{f_v(v_j \mid v_{-j})} \text{ and } v_i - \frac{1 - F_v(v_i \mid v_{-i})}{f_v(v_i \mid v_{-i})} \geq 0 \right\}.
$$

Regularity of F_v requires that, for every v_{-i}, the virtual value function $v_i - (1 - F_v(v_i \mid v_{-i}))/f_v(v_i \mid v_{-i})$ is increasing in v_i. Affiliation requires that

$$
f(\mathbf{v} \wedge \mathbf{t}) f(\mathbf{v} \vee \mathbf{t}) \geq f(\mathbf{v}) f(\mathbf{t}) \quad \forall \mathbf{v}, \mathbf{t},
$$

where $(\mathbf{v} \vee \mathbf{t})$ is the component-wise maximum of $\mathbf{v}$ and $\mathbf{t}$ and $(\mathbf{v} \wedge \mathbf{t})$ the component-wise minimum. Roughgarden and Talgam-Cohen (2016) show that these conditions guarantee that an increase in v_i weakly increases buyer i's virtual value and weakly decreases all other buyers' virtual values. This directly implies that the solution to the relaxed problem x^* satisfies the monotonicity constraint, and is thus a solution to the overall problem.

The optimal payments associated with x^* are pinned down by the payment equality:

$$p_i^*(v_i, v_{-i}) = v_i x_i^*(\mathbf{v}) - \int_{\underline{v}}^{v_i} x_i^*(s, v_{-i})ds = \begin{cases} 0 & \text{if } x_i^*(\mathbf{v}) = 0 \\ \min\{s \mid x_i^*(s, v_{-i}) = 1\} & \text{if } x_i^*(\mathbf{v}) = 1 \end{cases}.$$

In words, a buyer's payment is positive only if he wins the good, in which case he pays the lowest value he could have reported and still won the object. That value is either the highest value among the losing buyers or the optimal TIOLI offer, depending on which is higher. Indeed, the optimal TIOLI offer solves

$$r^*(v_{-i}) - \frac{1 - F_v(r^*(v_{-i}) \mid v_{-i})}{f_v(r^*(v_{-i}) \mid v_{-i})} = 0,$$

and so corresponds to the value v_i at which buyer i's virtual value function becomes positive. At any other realizations of v_i, it is optimal not to allocate the good to buyer i (nor to any other buyers).

The two-step mechanism described in Proposition 3 is a two-step implementation of the optimal direct-revelation mechanism: it induces the same allocation x^* and the same payments p^* in every state of the world $\mathbf{v}$, and thus the same expected revenue. ■

Proof of Proposition 4

Under the selling mechanism described in Proposition 3, it is a weakly dominant strategy for buyers to bid their true valuations in the auction. Thus, the submitted bids simply coincide with the buyers' values, and the target makes a counteroffer if and only if

$$v_{(2:n)} < r^*((v_i)_{i \neq (1:n)}).$$

In words, given realized values $(v_i)_i$, the buyer with $j = (1 : n)$ is the buyer with the highest realized value. The optimal counteroffer depends on the bids (and so on the values) of all losing buyers, and thus on the vector $(v_i)_{i \neq (1:n)}$. The optimal counteroffer is made if and only if it is higher than the second-highest bid, which coincides the second-highest value in equilibrium.

We want to understand how the probability of that event varies with n. Note that

n has two effects. First, higher n means that there are more draws of buyer values, thus pushing the distribution of the second-highest value $v_{(2:n)}$ upward. Second, higher n means that the optimal counteroffer can be conditioned on more draws, and thus be better targeted. We can distinguish between two effects by writing the effect of an increase in n as:

$$\begin{aligned}\Pr\left(v_{(2:n+1)} < r^*((v_i)_{i\neq(1:n+1)})\right) - \Pr\left(v_{(2:n)} < r^*((v_i)_{i\neq(1:n)})\right)\\ = \Pr\left(v_{(2:n+1)} < r^*((v_i)_{i\neq(1:n)})\right) - \Pr\left(v_{(2:n)} < r^*((v_i)_{i\neq(1:n)})\right)\\ + \Pr\left(v_{(2:n+1)} < r^*((v_i)_{i\neq(1:n+1)})\right) - \Pr\left(v_{(2:n+1)} < r^*((v_i)_{i\neq(1:n)})\right)\end{aligned}$$

where the first difference is the effect on the second-highest value, fixing the optimal counteroffer, while the second difference is the learning effect. The first effect is necessarily negative: the distribution of $v_{(2:n+1)}$ first-order stochastically dominates the distribution of $v_{(2:n)}$, which depresses the probability of counteroffers. However, the second effect has ambiguous sign: higher n means the seller can condition on more draws to make the counteroffer, making counteroffers more dispersed. Being able to learn from one additional draw v_{n+1} can push the optimal counteroffer up or down, depending on the realized $\mathbf{v}$. Nevertheless, if the second effect is small relative to the first effect, then higher n necessarily decreases the probability of counteroffers. This is the case when the correlation α is small enough, as there is then not much to learn from additional losing bids.

To complete the proof of Proposition 4, we show that

$$\Pr\left(v_{(2:n+1)} < r^*((v_i)_{i\neq(1:n+1)})\right) < \Pr\left(v_{(2:n)} < r^*((v_i)_{i\neq(1:n)})\right)$$

when $\alpha = 0$. Combined with the fact that $\Pr\left(v_{(2:n)} < r^*((v_i)_{i\neq(1:n)})\right)$ is continuous is α for each n, this establishes the claim.

When $\alpha = 0$, buyers' valuations are independently distributed and $F_v(\cdot \mid v_{-i}) = F_v(\cdot)$. The optimal counteroffer is then independent of the losing bids, as shown in Myerson (1981), and also independent of the number of bidders n. Indeed, it solves

$$r^* = \frac{1 - F_v(r^*)}{f_v(^*)},$$

which neither depends on the losing bids nor on how many bidders participate in the sale. The probability that the seller makes a counteroffer is then $\Pr(v_{(2:n)} < r^*)$. This probability is decreasing in n since

$$\begin{aligned}\Pr(v_{(2:n+1)} < r^*) &= \Pr(v_{(2:n+1)} < r^* \mid v_{(2:n)} < r^*)\Pr(v_{(2:n)} < r^*) \\ &\quad + \underbrace{\Pr(v_{(2:n+1)} < r^* \mid v_{(2:n)} > r^*)}_{=0}\Pr(v_{(2:n)} > r^*) \\ &\leq \Pr(v_{(2:n)} < r^*),\end{aligned}$$

strictly so when the seller makes a counteroffer with strictly positive probability (that is, when $r^* > \underline{v}$).