Strategic and Financial Bidders in Takeover Auctions

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Abstract

Using data on auctions of companies, we estimate valuations (maximum willingness to pay) of strategic and financial bidders from their bids. We find that a typical target is valued higher by strategic bidders. However, 22.4% of targets in our sample are valued higher by financial bidders. These are mature poorly-performing companies. We also find that (i) valuations of different strategic bidders are more dispersed, (ii) valuations of financial bidders are correlated with aggregate economic conditions. Our results suggest that different targets appeal to different types of bidders, rather than that strategic bidders always value targets more because of synergies.

Keywords: mergers and acquisitions, strategic bidders, financial bidders, takeover auctions
JEL Classification Numbers: D44, G32, G34

The market for corporate control is one of the largest corporate markets. In 2007 alone, the value of M&A transactions worldwide was a staggering $4.8 trillion. While some takeovers proceed as negotiations of a target with a single acquirer, many takeovers face competition among several bidders.[1] The set of bidders is comprised of two groups: strategic and financial. Strategic bidders are usually companies in a related type of business, such as competitors, suppliers, or customers. They tend to look for targets that offer long-term operational synergies and integrate them into their own business. In contrast, financial bidders, typically private equity firms, look for undervalued targets with a potential to generate high cash flow, often after a reorganization. After the acquisition, a financial bidder treats the target as a part of its financial portfolio and sells it once exit opportunities become sufficiently appealing.

Despite their recognized importance,[2] the differences between strategic and financial bidders remain largely unexplored. A common view is that strategic bidders are systematically willing to pay more than financial bidders. For example, as Mark E. Thompson and Michael J. O'Brien, practitioners in the private equity industry, summarize: "Strategic buyers have traditionally had the advantage over private equity funds, particularly in auctions, because strategic buyers could pay more because of synergies generated from the acquisition that would not be enjoyed by a fund."[3] Taken to the extreme, this view implies that strategic bidders have systematically higher valuations of targets than financial bidders: in the worst case, they can implement the same changes as financial bidders, but they can also be willing to pay more due to synergies. Furthermore, the maximum willingness to pay of strategic bidders can be

even higher because of empire-building private benefits of their managers. In this paper, we evaluate this and other views about strategic versus financial bidders by estimating valuations of participating bidders in auctions of companies. We find that an average participating strategic bidder values a typical target more than an average financial bidder. At the same time, strategic and financial bidders appear to be inherently very different. In particular: (1) a significant subset of targets is systematically valued more by financial bidders, contrary to the above view; (2) valuations of different financial bidders are considerably less dispersed than valuations of different strategic bidders; and (3) valuations of financial bidders are more correlated with aggregate economic conditions.

A major obstacle to the empirical analysis of bidders' valuations is the lack of data on all bidders in takeover auctions. Unless bidding is public, which is rare, a researcher typically observes only the outcome of the auction: the identity of the winning bidder and her payment to the shareholders of the target. A naive approach to compare valuations of strategic and financial bidders would be to compare takeover premiums paid by strategic and financial acquirers for similar targets. This approach, however, is problematic for two reasons. First, there is a selection bias: valuations of winning bidders are likely to be very different from valuations of average bidders. Second, and perhaps more importantly, the takeover premium is different from the bidder's valuation, which is her maximum willingness to pay for the target. Because the winning bidder must outbid all other participating bidders, the takeover premium depends not only on the valuation of the winning bidder, but also on the valuations of other bidders.

To deal with the first problem, we use data on all participating bidders in auctions of

companies that took place between 2000 and 2008. We follow Boone and Mulherin (2007a, 2007b) and manually collect these data from deal backgrounds in the SEC filings, distinguishing between strategic and financial bidders. Our data set includes information on all participating bidders, defined as bidders who signed confidentiality agreements, their informal and formal bids, and in many cases their type, strategic or financial. Our final sample consists of 349 takeover auctions and covers all takeover auctions of U.S. public companies in which the acquirer paid in cash.

To deal with the second problem, we propose a methodology to estimate valuations of strategic and financial bidders from the data on their bids. The major challenge with such estimation is that one has to impose reasonable assumptions about the mapping of unobserved bidders' valuations into the observed auction outcomes. Unfortunately, existing models of takeover auctions rely on rather restrictive assumptions, which are inconsistent with their typical free-form nature. For example, the assumption that auctions of companies proceed as "button" auctions with a continuously increasing price, as in Milgrom and Weber (1982), is inconsistent with informal bids, jump bids, and re-entries, which occur in practice. While these features can be explained by many different models, there is no consensus about which model, if any, is the most reasonable.[4] Thus, rather than commit to a particular model, we build on Haile and Tamer (2003) and impose three assumptions that are consistent with a large variety of bidding patterns in takeover auctions:

Assumption 1. Bidders do not bid more than they are willing to pay.

Assumption 2. Bidders do not allow opponents to win at a price they are willing to beat.

Assumption 3. Bidders do not make informal noncommitting bids, if their valuation is

below the value of the target under its current management.

Haile and Tamer (2003) use Assumptions 1 and 2 to build lower and upper bounds on the bidders' valuations. To obtain point estimates, we also impose parametric assumptions. Specifically, we assume that each bidder's valuation is a combination of the observable component, which depends on the observed characteristics of the target, and the unobservable private component. While the observable component is common for all bidders of the same type, unobservable components differ across bidders and reflect the heterogeneity within the bidder's type. Assuming that valuations, conditional on bounds, have a truncated lognormal distribution, we obtain point estimates of the sensitivities of average valuations of strategic and financial bidders to observable target and economy characteristics, as well as the variances of unobservable components. Our empirical strategy allows for differences between strategic and financial bidders but does not assume them.

Our findings suggest that the view that strategic bidders are willing to pay more due to potential synergies may be true for the average target. However, this view is far from capturing the whole picture. The difference in average valuations of strategic and financial bidders varies widely across targets. While strategic bidders have higher valuations for targets with higher investment opportunities, as proxied by R&D expenditures and cash balances, financial bidders are willing to pay higher premiums for poorly performing targets, as reflected in substantial negative cash flows. The average, across all targets, valuation of a strategic (financial) bidder is 16.7 % (11.7 %) above the stand-alone market value of the target. However, a large subsample of targets, comprising 22.4% of our sample, is valued more by an average financial bidder than by an average strategic bidder.

Our results are consistent with the alternative view of segmentation of the takeover market, whereby different targets appeal to different bidders. According to this view, financial bidders have an advantage over strategic bidders in dealing with poorly performing mature targets. In contrast, strategic bidders have an advantage in generating synergies out of targets' investment opportunities. The advantage of financial bidders can come from different sources, for example, from having expertise in restructuring targets or from having access to debt at a lower cost than strategic bidders. The latter argument is consistent with the findings of Demiroglu and James (2010) and Ivashina and Kovner (2011) that leveraged buyout firms' reputation and bank relationships are related to the cost of debt of their portfolio companies. The positive effect of investment opportunities on valuations of strategic bidders is also consistent with strategic bidders' managers extracting private benefits from investments. It is also consistent with mergers being combinations of acquirers with low operating costs and targets with good investment opportunities but high operating costs (e.g., Levine (2013)).

The difference in the willingness to pay of strategic and financial bidders appears to change with aggregate economic conditions. Specifically, higher valuations of financial, but not strategic, bidders are associated with a lower cost of debt, as measured by the aggregate credit spread, and lower stock market performance over the 12 months preceding the transaction. The former result relates to the recent findings of Axelson et al. (2013) that financial bidders use more leverage to finance deals when debt is cheap.

In addition to differences in average valuations of strategic and financial bidders, we find a large difference in the dispersion of their valuations. Variation in valuations of financial bidders is captured to a large extent by observable target and economy-wide characteris-

tics. In contrast, valuations of strategic bidders are less tied to observables: the estimated standard deviation of their unobserved valuation component is almost twice as high as that of financial bidders. This result is consistent with different financial bidders applying similar post-acquisition strategies and each strategic bidder having relatively unique synergies. This finding suggests that different financial bidders appear to be more interchangeable than strategic bidders from the target's point of view.

Importantly, the above results cannot be obtained using a naive approach in which takeover premiums are interpreted as valuations. Premiums paid by strategic and financial acquirers change similarly with target and economy characteristics. The only significant difference is that the former pay more on average: 46.4% versus 36.5% of the premium to the market value of the target. Moreover, the magnitude of unexplained variation is roughly identical for both types of acquirers. These results are a consequence of endogenoneity of winning bidders and takeover premiums: if strategic and financial bidders compete against each other, the takeover premium reflects valuations of both bidder types no matter the winner's type. In light of this, our paper makes a methodological contribution by providing a sensible way to estimate bidders' valuations from all bids in takeover auctions. This approach is general and can be applied to other questions that require knowledge of valuations in takeovers.

Our approach allows us to estimate and study acquirers' winning slack, that is, how much acquirers underpay relative to their valuations. We find that while financial acquirers usually pay close to their valuations, keeping on average 7.3% of their maximum willingness to pay, strategic acquirers tend to have substantial winning slack, which averages 14.9% of their maximum willingness to pay. Given that acquisitions by strategic bidders generate acquirers'

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abnormal returns that are close to zero on average (e.g., Betton, Eckbo, and Thorburn (2008)), this result suggests either significant stock market anticipation of acquisitions by strategic bidders or large private benefits of their managers, consistent with empirical evidence on merger-induced CEO compensation (Grinstein and Hribar (2004), Harford and Li (2007)).[5]

Our work is related to several papers. Boone and Mulherin (2007b) analyze 400 takeovers for large public U.S. companies and show that approximately half of them can be classified as auctions given competition at the pre-public takeover stage. We follow their methodology to identify auctions. Our sample is different because it covers a more recent period and a broader range of companies. Betton and Eckbo (2000), Dimopoulos and Sacchetto (2011), and Li (2012) estimate sequential competition in takeovers based on public bids. Several recent papers look at how announcement returns are associated with the type of the acquirer, but none of them empirically studies competition and all bids within each auction, which is important for recovering valuations. Bargeron at el. (2008) examine the difference in announcement returns for targets acquired by public and private acquirers (including private equity), and find that announcement returns are higher for targets acquired by public acquirers. Dittmar, Li, and Nain (2012) find that strategic acquirers that follow a first bid by a financial bidder have higher returns than those that follow a first bid by a strategic bidder. Hege et al. (2012) examine returns to companies selling their assets to private equity and strategic buyers. Fidrmuc et al. (2012) compare the selling process of firms acquired by financial and strategic buyers. Martos-Vila, Rhodes-Kropf, and Harford (2013) present a theory of oscillations in activity between strategic and financial acquirers based on debt misvaluation. Finally, our paper is related to Axelson et al. (2013), who find a substantial relation between economy-wide credit

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spreads and leverage in leveraged buyouts, and Demiroglu and James (2010) and Ivashina and Kovner (2011), who suggest that PE funds' portfolio companies can have better access to debt financing.[6] To our knowledge, our paper is the first to study competition between financial and strategic bidders for the same targets and estimate their maximum willingness to pay.

The remainder of the paper is organized as follows. Section I describes the process of a typical auction of a company. Section II lays down the assumptions that link bids to bidders' valuations, as well as the estimation procedure. Section III presents data and summary statistics. Section IV reports the estimates and discusses the intuition behind them and the impact of identification assumptions. Section V uses the estimates of the model to estimate the distribution of takeover gains between targets and financial and strategic acquirers. Section VI discusses approach validity and reports various robustness checks. Section VII concludes.

I. Institutional Background

Insert Figure 1 About Here.

Before setting up the model and estimation procedure, we describe how auctions of companies are usually conducted. The process of a typical takeover auction, shown in Figure 1, is described and studied by Hansen (2001) and Boone and Mulherin (2007b). It usually starts when the firm (typically, its board of directors) decides to sell itself to a potential buyer. At or before this stage, the firm hires an investment bank, which examines potential strategic and financial buyers and presents a list of potentially interested parties to the firm. The

firm and its investment bank contact the parties who, in their view, might be interested in acquiring the company. The interested potential bidders sign confidentiality agreements upon which they may receive access to nonpublic information about the target. After studying this information, some of the bidders submit preliminary bids in several rounds. The bids at this stage are nonbinding (or informal) in the sense that bidders do not commit to them and frequently renegotiate them in the future. Between rounds of bidding, qualified bidders are provided with additional information through presentations by senior management, plant and site visits, and review of documents assembled in a "data room." After several rounds of preliminary bids, the selling firm and its investment bank ask a smaller number of the most interested bidders to submit final-round bids. Upon receiving the final-round bids, the firm sometimes negotiates with the bidders and raises the price. The final-round bids are usually binding, and the takeover agreement is usually signed soon after receiving the final-round bids (in many cases, within two to three days). Sometimes, the target accepts a formal offer from a bidder even beyond the final-round deadline if it is sufficiently high. Before the first takeover agreement is signed, the takeover process is private in the sense that bidders and their bids are not publicly announced. In the rest of the paper, we refer to the preliminary nonbinding bids as informal bids and to the final-round bids and public bids after the takeover agreement is signed as formal bids, unless it is stated explicitly that the final-round bid is subject to additional due diligence or approval of financing.

No standard model captures all features of a typical takeover auction. On the one hand, because of multiple rounds of bidding and post-bid negotiations, a takeover auction is similar to an English (ascending-bid) auction, in which the bidders offer higher prices until only one

of them remains, winning the asset and paying according to her offer. On the other hand, takeover auctions differ from English auctions in several respects. First, there are usually several rounds of informal bids. The exact number of rounds is not predetermined, and bidders do not commit to their informal bids, often decreasing them in subsequent rounds. Second, while bidders are often informed if their current bid is the highest, they usually do not know the exact bids of their competitors. Third, bidders sometimes exit and later reenter the sale process. Fourth, jump bids and negotiations between the selling firm and bidders are common. Finally, while the auction process describe above is typical, deviations are frequent. Given these peculiarities, it is difficult to come up with a formal model that is close to the true process of takeover auctions. We address this issue in our empirical strategy.

II. Model Specification

We now turn to assumptions about bidding in a takeover auction. Given the free-form structure of a typical takeover auction, our goal is to avoid significant abstractions and at the same time provide sufficient structure to estimate bidders' valuations.

A. Strategic and Financial Bidders

Consider an auction for target i. Suppose that the auction has N_i participating bidders. Participating bidders are defined as bidders that agree to sign confidentiality agreements and thereby may obtain access to nonpublic information about the target. Each bidder belongs to

one of two categories, strategic and financial, denoted by s and f, respectively. Let $t_{i,j} \in \{s, f\}$ denote the type of bidder j in the auction for target i.

After observing nonpublic information about the target, each bidder learns her valuation, which is the maximum amount that the bidder is willing to pay to acquire the target.[7] We assume that the valuation of bidder j is given by

$$V_{i,j} = M_i \exp\left\{X_i' \beta_{t_{i,j}} + \sigma_{t_{i,j}} \varepsilon_{i,j}\right\}. \tag{1}$$

Here, M_i refers to the value of the target under its current management, and $\exp\left\{X_i' \beta_{t_{i,j}} + \sigma_{t_{i,j}} \varepsilon_{i,j}\right\}$ refers to the bidder-specific premium (or discount, if it is below one). The premium of each bidder is the sum of a public common component, $X_i' \beta_{t_{i,j}}$, which is the same for all bidders of the same type (financial or strategic), and a private component, $\sigma_{t_{i,j}} \varepsilon_{i,j}$, which is specific to each bidder. The public common component captures common factors that affect the attractiveness of the target to all bidders of the same type. This component depends on the vector X_i of publicly observable characteristics of the target and aggregate economic conditions at the time of the auction. The common factors can be different between the two classes of bidders: β_s can be different from β_f. The private component captures such factors as synergy and suitability of the target for each potential acquirer. We assume that all $\varepsilon_{i,j}$ are independently distributed according to the standard Normal distribution. Section VI presents robustness checks and discussions of this and other assumptions.

This model embeds, as a particular case, the view that strategic bidders can implement the same changes as financial bidders but can also generate synergies. In case this view

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is true, $X_i'\beta_f$ captures the value that a financial bidder generates by implementing changes in the target, σ_f is small relative to $X_i'\beta_f$ because all financial bidders implement similar changes, $X_i'(\beta_s - \beta_f)$ corresponds to average synergies that a strategic bidder generates, and $\varepsilon_{i,j}$ measures the degree to which synergies vary across strategic bidders. Under this view, $X_i'(\beta_s - \beta_f)$ is positive for all targets, perhaps with rare exceptions. In general, however, $X_i'(\beta_s - \beta_f)$ can take either sign, because either group of bidders can have an advantage in bidding for a particular target. In addition, σ_f can be high, because financial bidders can also differ in their expertise, envisioned changes in the target, and access to debt financing.

For notational simplicity, we normalize bidders' valuations by the value of the target under the current management:

$$\log v_{i,j} \equiv \log\left(\frac{V_{i,j}}{M_i}\right) = X_i'\beta_{t_{i,j}} + \sigma_{t_{i,j}}\varepsilon_{i,j}. \tag{2}$$

Two points are worth noting about our specification. First, we avoid making assumptions about the exact sources of valuations. Specifically, willingness to pay can come not only from synergies but also from private benefits, and we do not assume away one or the other. Second, the form of valuations (1) implies that there are three potential sources of differences between financial and strategic bidders. Strategic and financial bidders can differ because they value different targets, because their valuations respond differently to changes in aggregate economic conditions, or because the importance of the private component of valuations is different across types. The first two effects are captured by the potential differences between β_s and β_f. The third effect is captured by the potential difference between σ_s and σ_f. While the model allows

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for differences between strategic and financial bidders, it does not impose them.

B.   Bidding Behavior

Instead of committing to interpretation of bids implied by any particular model, we rely on the following assumptions, previewed in the introduction:

ASSUMPTION 1: *Bidders do not make formal bids exceeding their willingness to pay.*

ASSUMPTION 2: *Bidders do not allow an opponent to win at a price they are willing to beat.*

ASSUMPTION 3: *Bidders do not make informal noncommitting bids if their valuation is below the value of the target under its current management.*

Assumptions 1 and 2 come from Haile and Tamer (2003), who deal with nonparametric estimation of bidders' valuations in English auctions without clearly identifiable rules. Their motivation is straightforward. Because, independent of the underlying structure of the auction, every formal bid is potentially a winning bid, it is irrational for a bidder to bid above her valuation. This motivates Assumption 1. Assumption 2 means that as long as there is a chance of winning the auction and paying below the valuation, a rational bidder will take this opportunity.[8] In takeover auctions, targets often inform bidders whose current bids are high but below the highest bid that there is a better offer. Thus, bidders have the opportunity to respond to the current highest bid.[9] Given this, Assumption 2 means that a bidder does not miss this opportunity, if she can make a positive surplus. Finally, Assumption 3 is natural in the context of takeover auctions. If a rational bidder learns that she values the target below

its value under the current management, she will not continue to invest time and resources to submit formal or informal bids, as the target's shareholders will not agree to sell the company at a price attractive to the bidder.

These restrictions on bidding strategies allow for a large variety of bidding patterns observed in auctions of companies. For example, these restrictions are compatible with jump bidding, bidders reentering the takeover process, and bidders not bidding at all. In addition, the implied ranking of bids does not necessarily map one-to-one with the ranking of bidders' valuations, except for the winning bidder, who must be the bidder with the highest valuation.

C. Estimation Strategy

Consider an auction for target i. Let $b_{i,j}$ denote the formal bid submitted by bidder j during the process of auction i and let $t_{i,j}$ denote the bidder's type (s or f).[10] If bidder j submits only an informal bid, then Assumption 3 implies that her informal bid is equivalent to a formal bid of M_i. Hence, we can set $b_{i,j} = M_i$. Similarly, if the bidder does not submit any bid, then this is equivalent to having a formal bid of zero. Hence, we can set $b_{i,j} = 0$.

Without loss of generality, we sort bidders within each auction in descending order by their highest bid: $b_{i,1} \geq b_{i,2} \geq ... \geq b_{i,N_i}$. The first bidder is thus the winner. We need to write the likelihood of auction i's outcome given the realization of bids $b_i = (b_{i,1}, b_{i,2}, ..., b_{i,N_i})'$, types $t_i = (t_{i,1}, t_{i,2}, ..., t_{i,N_i})'$, and model parameters $\theta = (\beta_S, \beta_F, \sigma_S^2, \sigma_F^2)'$. Assumptions 1–3 put bounds on the valuations of each bidder. Because we do not take a further stand on the underlying bidding model and valuations, by observing bids we (as researchers) update bounds on valuations but not other properties of the distribution. Several events constitute

this likelihood. By way of example, we only provide the expression for the likelihood of one of the events (the rest are provided in Section A of Appendix B):

1. Bidder 1 *submits formal bid* $b_{i,1}$ and *wins*. By Assumption 1, the likelihood of this event is

$$l_{i,1}(v_{i,1}|X_i, b_{i,1}, t_{i,1}; \theta) = \mathbb{P}\{b_{i,1} \le v_{i,1}|X_i, t_{i,1}; \theta\} = 1 - \Phi\left(\frac{\log \frac{b_{i,1}}{M_i} - X_i\beta_{t_{i,1}}}{\sigma_{t_{i,1}}}\right), \qquad (3)$$

   where $\Phi(\cdot)$ is the c.d.f. of the standard Normal distribution.

2. Bidder $j > 1$ *submits formal bid* $b_{i,j}$ and *loses* to bidder 1.

3. Bidder $j > 1$ *submits informal bid* of any size and *loses* to bidder 1.

4. Bidder $j > 1$ *does not submit any bid.*[11]

Because the identity of the winning bidder is public information, we always know whether bidder 1 is strategic or financial. However, information on a losing bidder's type is not always provided in deal backgrounds and thus is not always known to the researcher. To deal with non-observability of some of losing bidders' types, we use a two-step estimation procedure, the details of which are outlined in Sections B and C of Appendix B. In the first step, we estimate the probability $\mathbb{P}\{t_{i,j}|Z_i\}$ that a losing bidder's unobservable type is $t_{i,j} \in \{s, f\}$ using observable data Z_i, which contains target and economy characteristics X_i and outcomes of the auction (winning bid, winning bidder's type, and total number of bidders). The important assumption here is that, conditional on the characteristics of the target and auction outcomes, the distribution of losing bidders' types is unrelated to whether these types are reported in deal

backgrounds. In the second step, the *expected* likelihood $\mathbb{E}\left[l_{i,j}(v_{i,j}|X_i, b_{i,j}, t_{i,j}; \theta)\right]$ of the event is calculated as the weighted sum of the likelihoods conditional on type $t_{i,j}$, with probability weights of each $t_{i,j}$ given by the first-step estimate.

By independence, the likelihood function for auction i can be written as

$$L_i(v_i|N_{s,i}, N_{f,i}, N_{u,i}, X_i, b_i, t_i; \theta) = \prod_{j=1}^{N_i} \mathbb{E}\left[l_{i,j}(v_{i,j}|X_i, b_{i,j}, t_{i,j}; \theta) \mid t_{i,j}\right], \tag{4}$$

where $N_{s,i}$, $N_{f,i}$, and $N_{u,i}$ are the number of strategic bidders, financial bidders, and bidders with unobservable type, respectively, such that $N_{s,i} + N_{f,i} + N_{u,i} = N_i$.

Let $\mathfrak{L}_i(v_i|N_{s,i}, N_{f,i}, N_{u,i}, X_i, b_i, t_i; \theta) = \log L_i(v_i|N_{s,i}, N_{f,i}, N_{u,i}, X_i, b_i, t_i; \theta)$. Define $b = (b_1, b_2, ..., b_I)'$ and $t = (t_1, t_2, ..., t_I)'$, where I is the number of auctions in our sample. Also, define N_s, N_f, and N_u to be the sum of the corresponding number of bidder types across all auctions. The complete likelihood function of the model is given by

$$\begin{aligned}
\mathfrak{L}(v|N_s, N_f, N_u, X, b, t; \theta) &= \frac{1}{\sum_{i=1}^{I} N_i} \sum_{i=1}^{I} \mathfrak{L}_i(v_i|N_{s,i}, N_{f,i}, N_{u,i}, X_i, b_i, t_i; \theta) \\
&= \frac{1}{\sum_{i=1}^{I} N_i} \sum_{i=1}^{I} \sum_{j=1}^{N_i} \mathbb{E}\left[\log l_{i,j}(v_{i,j}|X_i, b_{i,j}, t_{i,j}; \theta)|t_{i,j}\right]. \tag{5}
\end{aligned}$$

The estimates are obtained by maximizing (5) over the set of parameters θ. Additional details on the analytical properties and numerical implementation of the above maximum likelihood method are given in Appendix B. In Section B of Appendix C, we use simulations to examine the performance of the estimator, we compare it to a number of alternatives, and we argue that it performs well at recovering valuation parameters.

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III.   Data and Summary Statistics

A.   Data Description

We analyze a sample of corporate takeovers announced and completed in the period from January 1, 2000[12] to September 6, 2008 (the most recent data entry at the moment of data collection). The sample comes from the mergers and acquisitions database of the Securities Data Corporation (SDC). We require that targets and bidders satisfy the following set of conditions:

- The target is a publicly traded nonfinancial (SIC codes 6000–6999 excluded) U.S. company;

- Bidders seek 100% of target shares;

- Winning bids are made in cash only;

- The deal is not a spin-off, recap, self-tender, exchange offer, repurchase, minority stake purchase, acquisition of remaining interest, or privatization;

- The deal is an auction. We define the deal as a negotiation if only one potential bidder signs a confidentiality agreement and as an auction if two or more potential bidders sign confidentiality agreements;

- Final deal value (value of the winning bid) is included in the database;

- Deal backgrounds are available in SDC.

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Whenever the final two requirements are not satisfied, we try to complement the data using other sources (EDGAR filings on the SEC, MergerMetrics).

We impose two important constraints on the deal to include it in our sample. First, we focus on cash-only deals because in this case the value of the deal is known with certainty. Our estimation strategy requires knowledge of the value of the winning bid to bound valuations of all bidders. If the winning bid is in securities, its equivalent cash value depends on unobservable characteristics of the bidder and thus cannot be reliably compared to cash-only deals or to other bids in securities without imposing a realistic model of security pricing and observing identities and characteristics of all auction participants. We discuss the difficulties with using data on noncash bids in more detail in the Internet Appendix and the potential selection effect in Section VI.[13] Second, we focus on takeovers in the form of auctions for two reasons. First, if a takeover is a negotiation with a single bidder, its outcome depends on expected competition should the bidder's offer be rejected. Because this expected competition is not observed, including negotiations in the sample is not feasible. Second, the quality of some deal backgrounds classified as negotiations is low: these deal backgrounds are significantly shorter and include less information on the takeover process. As a result, some deals classified as negotiations can actually be auctions with missing information on losing bidders. These two factors prevent us from including negotiations in the sample.

The background documents allow us to manually collect information on participating bidders in each auction. We define participating bidders as bidders who sign a confidentiality agreement with the target, thereby obtaining access to confidential data. For each takeover i, we collect the total number of bidders N_i, the number of bidders known to be financial

bidders $N_{f,i}$, and the number of bidders known to be strategic bidders $N_{s,i}$, as defined in the deal background. The types of $N_i - N_{s,i} - N_{f,i}$ bidders are unknown.

After signing a confidentiality agreement, a bidder can drop out of the auction, submit only a nonbinding offer (an informal bid), or submit a binding offer in the final round of the auction (a formal bid). Sometimes bidders submit competitive bids publicly after the takeover announcement; we also treat these bids as formal bids. If a bidder submits multiple bids, we use the highest formal bid submitted in the course of the auction, which is also typically the last bid of the bidder.

Appendix A provides an example of a takeover auction. In particular, it contains extracts from the SEC deal background that we use to collect the data. Manor Care, a target in the healthcare industry, decided at the meeting of the board of directors on April 10, 2007 to explore strategic opportunities to enhance shareholder value, possibly through selling itself. Over the course of the next several weeks, JP Morgan, the investment bank of Manor Care, contacted 48 potential bidders, 23 of which (two strategic and 21 financial) signed confidentiality agreements and thereby received access to nonpublic information about the company. Two strategic and eight financial bidders made informal offers during several rounds of informal bidding, and two bidders, one strategic and one financial, made formal offers at the end of the process. The eventual acquirer, Carlyle, a financial bidder, made an offer of \$67 per share and won the auction. The other bidder that submitted a formal bid offered \$65 and lost the auction. On July 2, 2007, Manor Care and Carlyle issued a joint press release announcing the deal. The data we collect from this auction consist of the number of bidders that signed confidentiality agreements, the type of each bidder, a binary indicator for whether each bidder

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submitted a bid (formal or informal), and the bidder's formal bid, if any.

Following other empirical research on mergers and acquisitions, we collect data on the market values of the targets[14] *(i)* four weeks prior to the date of the takeover announcement and *(ii)* one day prior to the date of any press release that states that the company is for sale or is exploring strategic alternatives (only if the press release occurred no less than four weeks and no more than one year before the takeover announcement).[15] Whenever there is a press release, we use *(ii)* as a measure of M_i in the model; otherwise, we use *(i)* as a measure of M_i.[16]

Characteristics of the targets come from the quarterly COMPUSTAT database. We collect and construct the following target characteristics: firm size defined as the book value of the target's total assets, market leverage, average q-ratio (market-to-book), cash flow over the last four quarters, cash and short-term investments, R&D expenses, and intangible assets (all measured as ratios to the target's book value). Economy-wide variables are the market return, defined as the cumulative return on the S&P 500 index over the 12 months prior to the announcement date, and the credit spread, defined as the rate on Moody's Baa bonds preceding the date on which the snapshot of the market value was taken minus the rate on 10-year Treasury bonds on the same date.

We use standard assumptions in the literature to filter out unreasonable values of exogenous variables that are likely to be mistakes. Specifically, we remove observations with market leverage below zero and above 100%, q-ratio in excess of 10, cash flow in excess of 10, and negative cash. In addition, we remove eight instances in which the ratio of the winning bid to the target's value under the current management is below one, and two instances in which it

is above four. The latter cases are clearly outliers; the former cases (all except one auction) correspond to takeovers in which the auction process did not proceed "by the book," most often because time constraints prohibited the target from soliciting the highest offer (either the target was in deep distress or its blockholder influenced the immediate sale of the company at a low price). After applying the above filters, we are left with 349 takeover auction and 4,365 bidder observations.

B. Summary Statistics

Insert Table I About Here.

Table I shows bidder participation for the full sample of auctions and the auctions won by strategic versus financial bidders, as well as across 11 industries defined as in Fama and French (1997).[17] On average, an auction won by a financial bidder attracts approximately six more participants. The bidder's type is known for approximately 45% of bidder observations. On average, financial bidders participate in auctions more often but win less often (in approximately 40% of the cases). An auction won by a strategic bidder has more observed strategic bidders, while an auction won by a financial bidder has more observed financial bidders. The winning bid paid when a strategic bidder wins the auction is on average 9.9 percentage points higher than the winning bid paid when a financial bidder wins the auction: 46.4% versus 36.5%. This result is consistent with Bargeron et al. (2008), who show that targets' announcement returns are higher for targets acquired by public rather than private (in particular, private equity) acquirers.

Approximately 40% of auctions in the sample are for targets that belong to the "Business

Equipment" industry, which includes business and computer services and software companies. The two other industries with the highest number of takeover auctions are "Wholesale, Retail" and "Healthcare, Medical, etc.," with each accounting for 13% to 14% of the sample. Auctions in the "Chemicals," "Business Equipment," and "Healthcare, Medical, etc." industries have on average a smaller number of bidders. On the other hand, for the latter two industries, the composition of competitors is skewed towards strategic bidders and the winning bid is relatively high, which suggests that these targets are especially valued by strategic bidders.

Insert Table II About Here.

Table II complements Table I by presenting descriptive statistics of target characteristics. The average target's size is $654 million; the total sample accounts for $228 billion worth of transactions. On average, financial bidders tend to win in auctions for slightly larger companies (average size is $1,168 million) with higher recent cash flows that also have higher leverage ratios. Strategic bidders end up acquiring targets with higher q-ratios, greater R&D expenditures, and more cash and short-term investments. The magnitudes of two target characteristics, leverage and cash and short-term investments, markedly differ from the COMPUSTAT averages. This is not surprising given the composition of our sample: 53% of the sample are firms from the "Business Equipment" and "Healthcare, Medical, etc." industries. Table II shows that these are growth firms that, consistent with prior research, are more likely to have low leverage and large cash balances.

Insert Table III About Here.

Table III presents descriptive statistics for bids made by strategic and financial bidders, as well as by bidders whose type we do not observe. An average auction has between 12

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and 13 bidders who sign confidentiality agreements. These numbers are higher than those in Boone and Mulherin (2007a, 2007b), likely because their sample includes only auctions for large targets, which are on average less competitive, while we consider auctions for all public companies. Approximately one-third of bidders make informal bids, and an average auction contains approximately four informal and 1.36 formal bids. Strategic bidders are more likely to submit both informal and formal bids. Consistent with Table I, the average of all (including losing) formal bids is higher for strategic bidders. In our sample 33 formal bids are impossible to classify by bidder type. These bids appear to be higher than the average of formal bids made by both strategic and financial bidders. However, due to a small number of these unclassified bids, these statistics are not meaningful.

IV. Estimation Results

A. Recovering Bidder Types for Bidders with Missing Information

In the first step, we recover the probability that a bidder whose type we do not observe is strategic to use this information as an input when estimating valuations. For this purpose, as we describe in Section II.C, we estimate the equation

$$\mathbb{P}\left(t_{i,j} = s | Z_i\right) = \Gamma\left(Z_i'\gamma\right), \; j > 1. \tag{6}$$

Equation (6) determines the probability with which a losing bidder j in an auction for target i is strategic as a function of the observable characteristics of the target, the economic environment

at the moment of the takeover, and the properties of the auction (number of bidders, type of winning bidder, and winning bid). Because the type of the winning bidder is always known, we estimate equation (6) only on the sample of losing bidders to avoid selection bias. Assuming that in auctions for similar targets with similar outcomes losing bidders whose type is unknown are not different from losing bidders whose type is known, $\Gamma\left(Z_i'\hat{\gamma}\right)$ is the estimated probability that a losing bidder of an unknown type is strategic, where $\hat{\gamma}$ is the vector of estimates.

Insert Table IV About Here.

Table IV reports the results of the binary Logit model, which we use to estimate equation (6).[18] Table IV shows that most observable characteristics are significant in predicting the probability that an unobserved bidder is strategic. For example, a bidder with unobserved type is more likely to be strategic if the auction has a lower number of participating bidders and the winner is a strategic bidder.

B. Valuations of Strategic and Financial Bidders

Insert Table V About Here.

Having recovered the probabilities that bidders with unobserved type are strategic or financial, we can estimate the parameters of the valuation model–β_s, β_f, σ_s, σ_f–using maximum likelihood. Before doing so, it is instructive to see what results can be obtained using a naive approach that regresses the takeover premium on characteristics of the target and the economy separately for the targets acquired by strategic and financial bidders. The right panel of Table V presents the results. As we can see, the target and economy-wide characteristics do not appear to have differential effects on the premiums paid by strategic and financial bidders.

Many coefficients are not statistically significant, and the statistically significant coefficients do not appear to be different for strategic and financial bidders. Similarly, the magnitude of unobserved variation in the takeover premium is almost identical for strategic and financial bidders. At the same time, strategic acquirers pay on average 9.9% more of the market value of the target than financial acquirers, as shown in Table I. Taken together, these results may lead one to believe that strategic bidders are indeed systematically willing to pay more than financial bidders for any target, likely due to potential synergies and agency conflicts.

Results of our valuation model are very different. The estimates are reported in Table V. Model I illustrates the most basic comparison of the valuations of the two groups of bidders, unconditional on target and economy characteristics. Model II presents our main specification. To see whether the sensitivity of bidders' valuations to observable characteristics of targets is driven by industry effects, Model III expands Model II to include industry dummies following the five-industry classification of Fama-French (1997).[19]

Consistent with higher takeover premiums, we find that strategic bidders have higher average valuations in the sample. According to Model II, the average valuation of a strategic (financial) bidder of an average target in the sample is 16.7% (11.7%) above its value under the current management. However, this difference varies across targets and economy-wide characteristics. The estimates of Models II and III suggest that valuations of strategic and financial bidders have different patterns. Valuations of strategic bidders are positively associated with R&D expenditures, cash balances, and moderate leverage of the target. In contrast, valuations of financial bidders are negatively associated with cash flows and intangibles of the target. Valuations of strategic bidders are also negatively associated with size, but this is

likely due to our focus on auctions in which the winning bid is in cash.[20]

Insert Table VI About Here.

Table VI illustrates how average valuations of strategic and financial bidders vary from target to target. We sort targets in our sample based on each characteristic and calculate average valuations of strategic and financial bidders implied by Model II for targets in the bottom and top quantiles of the sample. While average valuations of strategic bidders across all targets in the sample are higher, many targets are valued more by an average financial bidder than by an average strategic bidder. These targets comprise a significant fraction of the sample: according to the estimates of Model II, a typical financial bidder values the target more than a typical strategic bidder in approximately one out of four takeover auctions (precisely, 22.64%). This result contradicts the view that strategic bidders are always willing to pay more because they can implement the same changes as financial bidders, but can also generate potential synergies or are willing to pay more due to agency conflicts.

The findings of Tables V and VI suggest the segmentation view of the takeover market. Under this view, neither strategic nor financial acquirers have a systematic advantage over the other group. Instead, some targets are a better match for financial bidders, and some – for strategic bidders. This segmentation arises due to different advantages of strategic and financial bidders. Financial bidders are better than strategic bidders at reorganizing targets and providing incentives to the management team. In addition, financial bidders can use their relationships and reputation to obtain debt financing at more favorable terms, in line with the evidence in Demiroglu and James (2010) and Ivashina and Kovner (2011) and the model of Malenko and Malenko (2014). In contrast, strategic bidders can realize synergies from

combining their operations with the target. Additionally, even without synergies, they may be willing to pay more due to agency problems, such as managerial empire building. Because both synergies and agency conflicts are likely to be created in investment, this view implies that strategic bidders have higher valuations than financial bidders for targets with greater investment opportunities. In contrast, financial bidders have higher valuations than strategic bidders for targets that perform worse and have fewer investment opportunities. Our findings are consistent with this view, because both R&D expenditures and cash balances are correlated with investment opportunities (see, for example, Erickson and Whited (2000, 2006)), and cash flows measure performance.[21]

The ranking of valuations of strategic and financial bidders not only varies from target to target but also changes with aggregate economic conditions. We employ two measures of aggregate economic conditions, the return on the S&P 500 in the 12 months preceding the takeover and the credit spread at the time of the takeover. While estimates of coefficients for strategic bidders are insignificant, both coefficients are significantly negative for financial bidders, suggesting that financial bidders are willing to pay higher premiums over market value after a period of low market returns and when debt is "cheap." The result for the credit spread is consistent with recent findings of Axelson et al. (2013) that both buyout leverage and buyout pricing are negatively related to the market-wide credit risk premium of leveraged loans at the time of the buyout. The result for past market returns is surprising but is consistent with the view that financial bidders are able to identify undervalued targets and initiate contests for them. If a market downturn makes more targets undervalued relative to fundamentals and financial bidders have the expertise to spot them and initiate takeover

auctions, their average valuations will be higher in downturns. Thus, financial bidders can provide a cushion to the market in downturns.[22]

If financial bidders have an advantage over strategic bidders in debt financing, their valuations should be associated with the target's leverage differently. According to Table V, valuations of strategic bidders are approximately 2.5 times more sensitive to target leverage than valuations of financial bidders. This result is consistent with the idea that financial bidders find it easier to adjust the leverage of the target. We find an inverted U-shaped relation between leverage and valuations of both strategic and financial bidders, and the shape (but not the magnitude of the effect) is surprisingly similar for both types of bidders. According to Model II, a marginal increase in leverage increases the valuation of a strategic (financial) bidder if leverage is below 41.35% (45.99%), and decreases the valuation if it is above this amount. One potential explanation for this effect is that bidders value reasonable leverage in targets more than the market because an acquisition helps lift the bidder's debt overhang. On the other hand, too high leverage increases default risk of the merged company and is thus undesirable. A caveat here is that, because a strategic bidder combines its debt with the debt of the target, it is reasonable to expect that for such bidders, the joint rather than target leverage matters for valuations. In results reported in the Internet Appendix, we estimate the model with both target and joint leverage and find that only joint leverage is significant for valuations of strategic bidders, and the relation is again inverted U-shaped.[23]

Finally, the results in Table V suggest that the importance of the unobserved component of valuations is substantially different for strategic and financial bidders. According to Model II, we find that the average impact of the private component of the valuation is 15.3% of

the market value for financial bidders and 25.8% for strategic bidders.[24] This difference is little affected by adding industry dummies in the valuation model. This result suggests that valuations of financial bidders are rather closely tied to the observable characteristics of the target, while valuations of strategic bidders are mostly based on whether a particular target is a good fit for a particular strategic bidder, which is not reflected in the observable characteristics of the target. In the Internet Appendix, we also estimate an extended model in which the variance of the private component of valuations may be a function of target and economy-wide characteristics. We find the private component of strategic bidders to be more important (i.e., have a higher variance) for targets that are smaller and have high R&D expenditures, that is, in situations in which the fit of a particular bidder with the target is likely to be more important.

The above result also has implications for theoretical modeling of bidder values in takeover contests. If strategic bidders are the dominant contestants, as in models of mergers driven by industry concentration, then the assumption of private values is more valid. If financial bidders are the major contestants, as in models of acquisitions driven by the underperformance of the target's current management, then the assumption of public common values may be more appropriate. Finally, models that allow for bidder asymmetries are likely to be more appropriate to settings in which the two groups of bidders compete against each other. Accounting for potential asymmetries between bidders is important because those can lead to different implications for the efficiency and optimality of selling procedures.

V. Distribution of Takeover Gains

A question of utmost importance in the M&A literature is how the surplus from takeovers is split between the acquirer and the target. Most of the existing literature addresses this question by looking at the average returns to the acquirer and the target upon the takeover announcement. The common conclusion is that average returns to targets are large and positive, while average returns to acquirers are close to zero or even negative.[25] These results seem to suggest that most if not all gains from takeovers are accrued to targets. In addition to the well-known concern that expectation of acquisition activity is already incorporated in the acquirer's stock price,[26] this approach does not allow for evaluation of gains to private acquirers, which comprise a significant group of strategic bidders and almost all financial bidders. Because our empirical strategy estimates valuations of all bidders and does not use data on the acquirer's stock price, it allows us to address these concerns.

To analyze the distribution of takeover gains between targets and acquirers, we compare the observed winning bids with the expected valuations of the winning bidders, conditional on the characteristics of the target, the economy-wide variables, and the outcome of the auction:[27]

$$\mathbb{E}\left[v_i^{(1)}|X_i, b_i^1, t_i^1\right] = \mathbb{E}\left[v_i^{(1)}|X_i, v_i^{(1)} \geq b_i^1, v_i^{(2)} \leq b_i^1, t_i^1\right]. \tag{7}$$

By properties of order statistics, (7) can be computed as the expectation of a random variable distributed according to a lognormal distribution with parameters $X_i'\beta_{t_i^1}$ and $\sigma_{t_i^1}^2$, truncated at b_i^1 from below. We use the estimation results of Model II to compute the estimates of the expected valuations of the winning bidders, $E\hat{v}_i^{(1)}$, for each takeover auction i in the sample.

This gives us the estimate of each acquirer's maximum willingness to pay for the target. By comparing this figure with the actual winning bid for each takeover, we quantify the "winning slack" of the winning bidder.

Insert Figure 2 About Here.

Figure 2 plots the distribution of the ratio of the winning bid to the estimate of the expected valuation of the winning bidder for the samples of takeovers undertaken by strategic and financial acquirers. Strategic acquirers pay between 65.5% and 92.9% (on average, 85.1%) of their expected maximum willingness to pay. Financial acquirers pay between 84.7% and 97.9% (on average, 92.7%) of their expected maximum willingness to pay. These results have two implications. First, it appears that financial bidders often pay close to their maximum willingness to pay when acquiring the target. If a financial bidder's valuation corresponds to the present value of future proceeds from selling the reorganized company, discounted by the appropriate cost of capital, this result suggests that financial bidders are able to generate returns only slightly above the required return. This interpretation is in line with the finding of Kaplan and Schoar (2005) that average LBO fund returns (net of fees) are slightly below the S&P 500 return.

Second, unlike financial acquirers, strategic acquirers appear to have substantial winning slack, underpaying on average 14.92% of their maximum willingness to pay (or, equivalently, 24.7% of the value of the target under the current management). Not only do strategic acquirers pay on average higher premiums than financial acquirers, but the maximum premiums that they are willing to pay are considerably higher. If valuations of strategic acquirers are solely defined by potential synergies from the acquisition and there is no anticipation

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of the takeover, we would expect to obtain the average acquirer's announcement returns of approximately 3%.[28] This figure contrasts with the evidence of approximately zero acquirer announcement returns in takeovers.[29] The difference between these findings is likely due to two factors. First, future acquisition activity is likely partially captured in the acquirer's stock price, before the acquisition occurs. For example, Song and Walkling (2008) find that the average acquirer returns are significantly positive at 0.69% for the sample of acquisitions that are the first in the industry in the last 12 months, which are arguably unanticipated. However, because this number is significantly below 3%, the anticipation effect alone is unlikely to explain the absence of acquirer announcement returns. The second factor that can help explain the difference is private benefits of control. If managers of strategic bidders obtain private benefits from undertaking acquisitions, then we would expect their maximum willingness to pay for the target to be above the price at which the acquirer shareholders' gains from the acquisition are zero.[30] In this case, strategic bidders are willing to overpay for targets, which would lead to substantial winning slack that is not reflected in the shareholders' wealth.

VI.   Approach Validity

In this section, we examine the validity of our empirical approach. First, we study the overall fit of the model. We simulate auction outcomes using the estimation results and find that the simulated outcomes are similar to what we observe in the data. Thus, we conclude that the model performs reasonably well at capturing the takeover outcomes observed in the data. A detailed description of the simulations and results is provided in Appendix C.

Next, we present several robustness checks of the estimation procedure. Our estimation results are based on four assumptions: Assumptions 1 to 3 and normality of the distribution of private component of valuations. While Assumption 1 must hold in all auctions by the definition of the maximum willingness to pay, the other assumptions can be violated in some contexts. We alter these assumptions one by one and re-estimate Model II. We find that our results are largely robust.

First, we alter Assumption 2. If submitting a bid is costly, a bidder can choose to let the opponent win at a price below the bidder's valuation. For example, if a bidder's valuation is only slightly above the opponent's bid, potential gains from submitting a higher bid can be below the bidding cost. Alternatively, the winning bid is not necessarily an upper bound on losing bidders' valuations if the winner has made a strategic preemptive bid. To see whether our results are robust to these concerns, we relax Assumption 2: instead of assuming that a bidder does not allow an opponent to win at a price below the bidder's valuation, we assume that a bidder does not allow an opponent to win if the bidder's valuation exceeds the opponent's bid by more than five percentage points of the target's value under the current management. This increases the upper bound on the valuation of a losing bidder from $b_{i,1}$ to $b_{i,1} + 0.05$. Table VII, Model IV presents estimates of the modified model and shows that the results of Section IV are robust to this modification.

Insert Table VII About Here.

Second, we alter Assumption 3. If there is a chance that the target's shareholders agree to sell the company at a price below the value under the current management, then bidding behavior can violate Assumption 3. This may happen, for example, in the presence of pressure

from a large shareholder of the target. In addition, our measure of the target's value under the current management can be imprecise. To see whether our estimation results are robust to these concerns, we relax Assumption 3: instead of assuming that a bidder does not make an informal bid if her valuation is below the target's value under the current management, we assume that a bidder does not make an informal bid if her valuation is below 90% of the target's value under the current management. This decreases the lower bound on the valuation of a losing bidder who submitted an informal bid from one to 0.9. Table VII, Model V presents the modified estimates, which indicate that our results are also robust to this modification.

Finally, we alter the assumption that the private component of valuations, $\varepsilon_{i,j}$, is distributed normally. This assumption is a natural starting point of the analysis but can be criticized if one believes that the distribution of potential synergies exhibits fat tails. To check the robustness of our results to presence of fat tails, we replace the assumption of a Normal distribution of $\varepsilon_{i,j}$ with that of a central t-distribution with known degrees of freedom ν. We assume $\nu_s = \nu_f = 5$.[31] The estimates, presented in Table VII, Model VI, suggest that most results of the baseline model are robust to the distributional assumption.

In the Internet Appendix, we provide further discussion of other less explicit identification assumptions and sample selection, and argue that most of our results are unlikely to be overturned with reasonable alternative assumptions in place.

VII.   Concluding Remarks

Potential acquirers are usually classified into two broad groups, strategic bidders and

financial bidders. This paper studies how the two groups of bidders differ with respect to valuations of potential takeover targets. We use hand-collected data from SEC filings on formal and informal bids as well as on bidders' types to estimate valuations of participating strategic and financial bidders in auctions of companies. We find that while strategic bidders on average have higher valuations than financial bidders across all targets, the two types of bidders are inherently different. First, a significant subset of targets is systematically valued more by financial bidders. These appear to be targets that perform poorly and have few investment opportunities. Higher target valuations of financial bidders can stem from greater expertise in dealing with poorly-managed mature companies and from access to cheaper debt financing. Second, valuations of different financial bidders are considerably less dispersed than valuations of different strategic bidders. Finally, valuations of financial bidders appear to be correlated more by aggregate economic conditions, such as the cost of debt and recent stock market performance. Taken together, our results support the market segmentation view, according to which which different targets appeal to different groups of bidders.

Several potential avenues for future research could be interesting. First, one could look at further links between bidders' valuations and the takeover premiums paid by strategic and financial bidders. It is well known that strategic acquirers pay more for targets they acquire than financial acquirers. In this paper, we show that this observation is consistent with two of our results. First, it is consistent with higher valuations of strategic bidders. Second, it is consistent with higher heterogeneity of strategic bidders: because valuations of strategic bidders within the auction are more different from each other, the winning bidder's valuation exceeds the valuation of the average strategic bidder by a larger amount, resulting

in a higher takeover premium. Future research could evaluate the importance of each of these effects in explaining the observed difference in takeover premiums paid by strategic and financial bidders. Second, there exists considerable heterogeneity in the number of bidders in each auction. A potential avenue for future research would be to look at the sources of this heterogeneity, and at the differences in participation decisions between strategic and financial bidders. Finally, it could be interesting to study what selling mechanisms are optimal in the presence of two distinct categories of bidders. Symmetric auction formats are typically suboptimal for the seller in the presence of bidder asymmetries. However, it is not obvious how the optimal selling mechanisms would look like in the complex takeover market.[32]

Appendix A. Example of a Takeover Auction

This appendix provides extracts from the background of the sale process of Manor Care. The text is taken from the SEC filings.

At a meeting of the board held on April 10, 2007, our board of directors considered a review of our strategic plan and potential alternatives to maximize shareholder value. ... After further discussions between members of the board and our management, the board determined at the meeting that it was advisable and in the best interests of Manor Care and our stockholders to further explore strategic alternatives to enhance shareholder value, including through a potential sale of Manor Care. We retained JPMorgan as financial advisor, and Cravath, Swaine & Moore LLP ("Cravath") as legal counsel, to Manor Care and the board. We announced our board's determination to explore strategic alternatives to enhance shareholder value in an April 11, 2007 press release.

JPMorgan also began to contact potential strategic and financial acquirors to gauge their interest in acquiring Manor Care. Over the course of the following weeks, JPMorgan contacted 48 potential acquirors, including 10 potential strategic acquirors, to assess their interest in acquiring Manor Care. ... We subsequently executed confidentiality agreements with 21 potential financial acquirors and two potential strategic acquirors. At the regular meeting of our board of directors on May 8, 2007, ... representatives of JPMorgan also updated the board on the progress of the potential sale of the company process, noting that, of the 23 parties that had entered into confidentiality agreements, eight potential financial acquirors and two potential strategic acquirors had provided preliminary indications of interest to JPMorgan. ... During the course of their due diligence process and prior to the submission of final acquisition proposals, all but two of the potential buyers dropped out of the process. On June 8, 2007, JPMorgan distributed a bid procedures letter and a draft merger agreement to the seven potential financial acquirors and one potential strategic acquiror that were still actively engaged in the process.

By June 25, 2007, Carlyle and one continuing strategic acquiror submitted proposals for the acquisition of Manor Care, together with debt financing commitments and comments on the draft merger agreement and, in the case of Carlyle, an equity financing commitment and sponsor guarantee. Carlyle offered merger consideration of $67.00 per share in cash, while the potential strategic acquiror offered merger consideration of $65.00 per share divided equally between cash and the acquiror's common stock. ... With respect to the potential sale of the company process, representatives of JPMorgan and Cravath discussed with the board, in light of the proposals made by each of the potential acquirors, the process to solicit improved terms from the potential acquirors. ... The board also directed JPMorgan and Cravath to seek improved terms from each of the potential acquirors. ... Prior to the meeting of the board on the morning of June 28, 2007 described below, Carlyle orally

informed JPMorgan that it was increasing its proposal to a best and final offer of $67.50 per share ... . The potential strategic acquiror informed Manor Care in writing that it was not willing to increase its offer price any further.

Management and JPMorgan informed the board that, in responding to questions raised by Carlyle in the course of the due diligence process, management and JPMorgan had determined that a sale of Manor Care would give rise to additional costs in connection with the termination of certain options purchased and warrants issued by Manor Care with respect to its common stock in connection with Manor Care's 2.125% convertible senior notes due 2035. ... In order to offset the option value cost in the context of a sale of Manor Care (which cost Manor Care and its hedge counterparty had agreed to fix at $47 million), Carlyle submitted a revised offer to purchase Manor Care for $67.00 per share.

On the evening of July 1, 2007, our board met to review Manor Care's strategic alternatives and the revised financial and legal terms that had been proposed by Carlyle. ... Following additional discussion and deliberation, our board of directors determined that, based on all information available to the board, a sale of Manor Care to Carlyle at $67.00 per share would provide our stockholders with greater value than any of Manor Care's other strategic alternatives, and the board unanimously ... approved the merger agreement with an entity sponsored by Carlyle, the merger and the other transactions contemplated by the merger agreement, authorized Manor Care to enter into the merger agreement and resolved to recommend that our stockholders vote to adopt the merger agreement. The merger agreement was executed by Manor Care, Inc. and MCHCR-CP Merger Sub Inc. as of July 2, 2007. On July 2, 2007, before the opening of trading on the NYSE, Manor Care and Carlyle issued a joint press release announcing the merger.

Appendix B.   Estimation Methodology

A.   Estimation of Fully Observable Bidder Types

Consider auction i. First, suppose that information on the type of all N_i bidders is observed by the researcher,[33] and thus, there are $N_{s,i}$ strategic bidders and $N_{f,i}$ financial bidders, such that $N_{s,i} + N_{f,i} = N_i$. Suppose further that bidders within each auction are sorted in descending order by the maximum bid, as described in Section II.C. Let $b_{i,j}$ and $t_{i,j}$ denote their maximum bids and types correspondingly.

The likelihoods of events from Section II for each auction i are then:

1. Bidder 1 *submits formal bid* $b_{i,1}$ and *wins* an auction. By Assumption 1, the likelihood of this event is

$$
\begin{aligned}
l_{i,1}(v_{i,1}|X_i, b_{i,1}, t_{i,1}; \theta) &= \mathbb{P}\{b_{i,1} \leq v_{i,1}|X_i, t_{i,1}; \theta\} = \mathbb{P}\left\{ \frac{\log \frac{b_{i,1}}{M_i} - X_i\beta_{t_{i,1}}}{\sigma_{t_{i,1}}} \leq \varepsilon_{i,1} \right\} \\
&= 1 - \Phi\left(\frac{\log \frac{b_{i,1}}{M_i} - X_i\beta_{t_{i,1}}}{\sigma_{t_{i,1}}} \right).
\end{aligned}
\tag{B1}
$$

2. Bidder $j > 1$ *submits formal bid* $b_{i,j}$ and *loses* to bidder 1. By Assumptions 1 and 2,

$$
\begin{aligned}
l_{i,j}(v_{i,j}|X_i, b_{i,j}, t_{i,j}; \theta) &= \mathbb{P}\{b_{i,j} \leq v_{i,j} \leq b_{i,1}|X_i, t_{i,j}; \theta\} = \mathbb{P}\left\{ \frac{\log \frac{b_{i,j}}{M_i} - X_i\beta_{t_{i,j}}}{\sigma_{t_{i,j}}} \leq \varepsilon_{i,j} \leq \frac{\log \frac{b_{i,1}}{M_i} - X_i\beta_{t_{i,j}}}{\sigma_{t_{i,j}}} \right\} \\
&= \Phi\left(\frac{\log \frac{b_{i,1}}{M_i} - X_i\beta_{t_{i,j}}}{\sigma_{t_{i,j}}} \right) - \Phi\left(\frac{\log \frac{b_{i,j}}{M_i} - X_i\beta_{t_{i,j}}}{\sigma_{t_{i,j}}} \right).
\end{aligned}
\tag{B2}
$$

3. Bidder $j > 1$ *submits informal bid* of any size and *loses* to bidder 1. By Assumptions 1–3,

$$
\begin{aligned}
l_{i,j}(v_{i,j}|X_i, b_{i,j}, t_{i,j}; \theta) &= \mathbb{P}\{M_i \le v_{i,j} \le b_{i,1}|X_i, t_{i,j}; \theta\} = \mathbb{P}\left\{\frac{-X_i\beta_{t_{i,j}}}{\sigma_{t_{i,j}}} \le \varepsilon_{i,j} \le \frac{\log\frac{b_{i,1}}{M_i} - X_i\beta_{t_{i,j}}}{\sigma_{t_{i,j}}}\right\} \\
&= \Phi\left(\frac{\log\frac{b_{i,1}}{M_i} - X_i\beta_{t_{i,j}}}{\sigma_{t_{i,j}}}\right) - \Phi\left(\frac{-X_i\beta_{t_{i,j}}}{\sigma_{t_{i,j}}}\right).
\end{aligned} \tag{B3}
$$

4. Bidder $j > 1$ *does not submit any bid.* If the bidder *does not inform the target* about this decision, then by Assumptions 1 and 2,

$$
\begin{aligned}
l_{i,j}(v_{i,j}|X_i, b_{i,j}, t_{i,j}; \theta) &= \mathbb{P}\{0 \le v_{i,j} \le b_{i,1}|X_i, t_{i,j}; \theta\} = \mathbb{P}\left\{-\infty \le \varepsilon_{i,j} \le \frac{\log\frac{b_{i,1}}{M_i} - X_i\beta_{t_{i,j}}}{\sigma_{t_{i,j}}}\right\} \\
&= \Phi\left(\frac{\log\frac{b_{i,1}}{M_i} - X_i\beta_{t_{i,j}}}{\sigma_{t_{i,j}}}\right).
\end{aligned} \tag{B4}
$$

If the bidder *informs the target* that her valuation is below the market value of the company under its current management m_i, then by Assumption 1,

$$
\begin{aligned}
l_{i,j}(v_{i,j}|X_i, b_{i,j}, t_{i,j}; \theta) &= \mathbb{P}\{0 \le v_{i,j} \le M_i|X_i, t_{i,j}; \theta\} = \mathbb{P}\left\{-\infty \le \varepsilon_{i,j} \le \frac{-X_i\beta_{t_{i,j}}}{\sigma_{t_{i,j}}}\right\} \\
&= \Phi\left(\frac{-X_i\beta_{t_{i,j}}}{\sigma_{t_{i,j}}}\right).
\end{aligned} \tag{B5}
$$

The likelihood function for auction i with observable bidder types can be written as

$$
L_i(v_i|N_{s,i}, N_{f,i}, N_{u,i}, X_i, b_i, t_i; \theta) = \prod_{j=1}^{N_i} l_{i,j}(v_{i,j}|X_i, b_{i,j}, t_{i,j}; \theta), \tag{B6}
$$

so that the complete log-likelihood function of the model with fully observable data is given by

$$
\begin{aligned}
\mathfrak{L}(v|N_s, N_f, N_u, X, b, t; \theta) &= \frac{1}{\sum_{i=1}^{I} N_i} \sum_{i=1}^{I} \mathfrak{L}_i(v_i|N_{s,i}, N_{f,i}, N_{u,i}, X_i, b_i, t_i; \theta) \\
&= \frac{1}{\sum_{i=1}^{I} N_i} \sum_{i=1}^{I} \sum_{j=1}^{N_i} \log l_{i,j}(v_{i,j}|X_i, b_{i,j}, t_{i,j}; \theta).
\end{aligned}
\tag{B7}
$$

Denote $N = \sum_{i=1}^{I} N_i$. From the theory of ML estimators, and slightly abusing notation $(\mathfrak{L}_i(v_i|N_{s,i}, N_{f,i}, N_{u,i}, X_i, b_i, t_i; \theta) \equiv \mathfrak{L}_i(\theta))$,

$$
\sqrt{N}(\hat{\theta} - \theta) \xrightarrow{d} \mathcal{N}(0, I^{-1}(\theta))
\tag{B8}
$$

$$
I(\theta) = -p \lim_{N \to \infty} \sum_{i=1}^{N} \frac{d^2 \mathfrak{L}_i(\theta)}{d\theta d\theta'} = p \lim_{N \to \infty} \sum_{i=1}^{N} \frac{d\mathfrak{L}_i(\theta)}{d\theta} \frac{d\mathfrak{L}_i(\theta)}{d\theta'}.
\tag{B9}
$$

The asymptotic confidence interval for parameter $\theta_k \in \theta$ is given by

$$
\left[\hat{\theta} + q_{\alpha/2}^{\mathcal{N}(0,1)} \sqrt{\frac{1}{N} I^{-1}(\hat{\theta})}; \hat{\theta} + q_{1-\alpha/2}^{\mathcal{N}(0,1)} \sqrt{\frac{1}{N} I^{-1}(\hat{\theta})} \right].
\tag{B10}
$$

B.   Estimation with Partially Unobservable Bidder Types

Consider the estimation framework of Section II.C, but now suppose that bidder type is unobservable for some bidders. Let $N_{s,i}$ and $N_{f,i}$ be the observable number of strategic and financial bidders in auction i, and $N_{u,i} = N_i - N_{s,i} - N_{f,i} \geq 0$ be the number of bidders with unobservable type. Denote by U_i and O_i the set of unobservable and observable bidders in auction i. With partially unobservable data, O_i contains at least bidder 1 – the winner's identity and type are always known. The rest of the framework follows that of Section II.C.

One straightforward way to deal with unobserved data is to maximize the likelihood function

(B7), treating all possible unobservable types $t_{i,j}$ as additional parameters of estimation that can take values $\{s, f\}$, and find the set of types that provides the highest function value. This approach is computationally unfeasible in all but the most simple setups. As an alternative, we use a method similar to the expectation maximization (EM) algorithm, which dates back to Dempster, Laird, and Rubin (1977) and in recent years has been extended in many ways to deal with the unobserved latent data.[34] The method allows us to iteratively solve the following two-step problem. In the first step, the probability $\mathbb{P}\{t_{i,j}|Z_i; \gamma\}$ that a bidder of type $t_{i,j} \in \{s, f\}$ enters an auction is calculated from the observable data. The vector of target characteristics Z_i that affects this probability includes X_i. It also contains the information about auction outcomes available to the researcher (e.g., winning bid, winning bidder's type, total number of bidders). In the second step, the *expected* likelihood function is maximized with respect to structural parameters. In this function, the likelihood of each missing observation is substituted with the expected likelihood $\mathbb{E}\left[l_{i,j}(v_{i,j}|X_i, b_{i,j}, t_{i,j}; \theta)|t_{i,j}\right]$, which is the weighted sum of the likelihoods conditional on the type $t_{i,j}$ being observable with probability weights of each $t_{i,j}$ given by the first step's estimate.

The two-step EM algorithm for a model with partially unobservable data proceeds as follows:

1. Calculate fitted values $\hat{\mathbb{P}}_s(Z_i'\hat{\gamma}) = \mathbb{P}\left(t_{i,j} = s|Z_i, \hat{\gamma}\right) \in [0, 1]$ of the flexible parametric regression for the probability that a losing bidder is strategic,

$$\mathbb{P}_{s,i,j} = \Gamma(Z_i'\gamma, \nu_{i,j}), \ j > 1, \tag{B11}$$

where $\mathbb{P}_{s,i,j}$ is equal to one if the observed type of bidder j in auction i is strategic, and is equal to zero if its type is financial. Also, compute $\hat{\mathbb{P}}_f(Z_i'\hat{\gamma}) = 1 - \hat{\mathbb{P}}_s(Z_i'\hat{\gamma})$. For our purposes, Γ can be any function that limits its values to [0,1], for example, Logistic or Probit-like function. We

provide more details on the likelihood function that is estimated in the first step in Section C of this appendix.

2. (a) Construct the expected log-likelihood function for auction i as

$$\mathcal{L}_i(v_i|N_{s,i}, N_{f,i}, N_{u,i}, X_i, b_i, t_i; \theta) = \log \mathbb{E}[L_i(v_i|N_{s,i}, N_{f,i}, N_{u,i}, X_i, b_i, t_i; \theta)|t_i], \quad \text{(B12)}$$

where, because types are independent across all the bidders in the economy,

$$\mathbb{E}[L_i(v_i|N_{s,i}, N_{f,i}, N_{u,i}, X_i, b_i, t_i; \theta)|t_i] = \prod_{j=1}^{N_i} \mathbb{E}[l_{i,j}(v_{i,j}|X_i, b_{i,j}, t_{i,j}; \theta)|t_{i,j}] \text{ (B13)}$$

$$= \prod_{j \in O_i} l_{i,j}(v_{i,j}|X_i, b_{i,j}, t_{i,j}; \theta) \prod_{j \in U_i} \sum_{t_{i,j} \in \{s,f\}} l_{i,j}(v_{i,j}|X_i, b_{i,j}, t_{i,j}; \theta) \mathbb{P}_{t_{i,j}}(Z_i'\hat{\gamma}).$$

That is, the likelihood function of auction i is the product of the likelihoods of bidders with observable and unobservable types, such that the likelihood of the unobservable type is the weighted sum of the likelihoods conditional on type $t_{i,j}$ being observable with probability weights obtained on the first step.

(b) Maximize

$$\mathcal{L}(v|N_s, N_f, N_u, X, b, t; \theta) = \frac{1}{\sum_{i=1}^I N_i} \sum_{i=1}^I \mathcal{L}_i(v_i|N_{s,i}, N_{f,i}, N_{u,i}, X_i, b_i, t_i; \theta) \quad \text{(B14)}$$

with respect to θ.

The winning bidder is excluded from the calculations of $\hat{\mathbb{P}}_s(Z_i'\hat{\gamma})$ and $\hat{\mathbb{P}}_f(Z_i'\hat{\gamma})$ because of the potentially large bias that perfect knowledge of the winner in each auction introduces to the estimation. Consider a simple example. For every i, suppose that $X_i'\beta_s \gg X_i'\beta_f$, $\sigma_s = \sigma_f$, and $O_i = \{1\}$,

that is, only the winning bidder's type is observed. Also, suppose that the true probability that a bidder's type is strategic is $\mathbb{P}_s = \Gamma((1 \; Z_i)' \cdot (\gamma_1 \; 0 \ldots 0))$ – a constant. As Z varies, similar fractions of strategic and financial bidders participate, but the estimation of the probability of the bidder's type will always give $\hat{\mathbb{P}}_s(Z_i'\hat{\gamma}) \simeq 1$ and $\hat{\mathbb{P}}_f(Z_i'\hat{\gamma}) \simeq 0$, as valuations of strategic bidders dominate those of financial bidders in this example. As a result, the first step estimation predicts unobserved bidder types with bias.

C. Recovering Types of Bidders for Bidders with Missing Information

Suppose that in auction i, a losing bidder is strategic with probability $\mathbb{P}_s = \Gamma(Z_i'\gamma)$. The number of losing strategic bidders in an auction with N_i bidders, $N_{u,i}$ of which have unobserved type, is distributed as $Bernoulli\,((N_i - N_{u,i})\Gamma(Z_i'\gamma), (N_i - N_{u,i})\Gamma(Z_i',\gamma)\,(1 - \Gamma(Z_i',\gamma)))$. The probability that $N_{s,i}$ losing bidders are strategic in such an auction is then

$$\mathbb{P}\{N_{s,i}|N_i, N_{u,i}, Z_i; \gamma\} = C_{N_i}^{N_{s,i}}\Gamma(Z_i'\gamma)^{N_{s,i}}\left(1 - \Gamma(Z_i'\gamma)\right)^{N_i - N_{u,i} - N_{s,i}}. \tag{B15}$$

Define $N_s = (N_{s,1}, N_{s,2}, ..., N_{s,I})'$, $N = (N_1, N_2, ..., N_I)'$, and $N_u = (N_{u,1}, N_{u,2}, ..., N_{u,I})'$. The complete likelihood function of the model that recovers the bidder type for losing bidders with missing information is

$$L(N_s|N, N_u, Z; \gamma) = \prod_{i=1}^{I} C_{N_i}^{N_{s,i}}\Gamma(Z_i'\gamma)^{N_{s,i}}\left(1 - \Gamma(Z_i'\gamma)\right)^{N_i - N_{u,i} - N_{s,i}}. \tag{B16}$$

Taking the logarithm,

$$
\begin{aligned}
\mathfrak{L}(N_s | N, N_u, Z; \gamma) &= \sum_{i=1}^{I} C_{N_i}^{N_{s,i}} \Gamma(Z_i'\gamma)^{N_{s,i}} \left(1 - \Gamma(Z_i'\gamma)\right)^{N_i - N_{u,i} - N_{s,i}} \\
&= const + \sum_{i=1}^{I} N_{s,i} \log \Gamma(Z_i'\gamma) + \sum_{i=1}^{I} (N - N_{u,i} - N_{s,i}) \log(1 - \Gamma(Z_i'\gamma)) \\
&= const + \sum_{i=1}^{I} \sum_{j=1}^{N_{s,i}} \log \Gamma(Z_i'\gamma) + \sum_{i=1}^{I} \sum_{j=1}^{N_{f,i}} N_{f,i} \log(1 - \Gamma(Z_i'\gamma)), \qquad \text{(B17)}
\end{aligned}
$$

because $N_{s,i} + N_{f,i} + N_{u,i} = N_i$ for every i. Maximizing (B17) with respect to γ, we obtain the ML estimate $\hat{\gamma}$ and the projected probability of a losing bidder being strategic $\hat{\mathbb{P}}_s(Z_i'\hat{\gamma})$.

D.   Details of Numerical Procedures

Because of the unobservability of types, the complete likelihood of the model may be nonconvex and as such may have multiple local maxima. To address this problem, we use the following two-step numerical procedure to find the global maximum:

1. The original starting point $\theta^{(0)}$ is obtained from economic considerations. The likelihood is first optimized using the simulated annealing method, which allows us to safely escape local maxima that are substantially far away from the global maximum. This step simulates the set of parameters $\theta^{(k)}, k = 1, ..., 30,000$ using the modified Accept-Reject method and finds the intermediary optimum θ^*.[35]

2. Use θ^* as the starting point for the simplex method optimization (see, for example, Nelder and Mead (1967)). This method can also escape local maxima and is in general efficient in finding the global maximum if the starting point is sufficiently close to it, which is ensured by the first numerical step. The optimization continues until a new intermediary optimum is found, and

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then is repeatedly restarted using the newly obtained optimum as the starting point until the sequential optima coincide. The final iteration of the simplex method gives $\hat{\theta}$.

The combination of methods performs consistently well in the simulated data, for which the true valuation parameters are known, even for original starting points substantially far away from the true maximum.

Appendix C.   Discussion of Approach Validity

A.   Overall Performance of the Model

Table CI examines the fit of the model.[36] We use the estimates of Model II to simulate valuations and outcomes of $34,900$ takeover auctions (100 simulated auctions for each target in the sample). More specifically, for each auction we simulate the uninformed bidder types using the estimates of the Logit model in Table IV and valuations of all participating bidders using the estimates of the valuations model in Table V. Then, for each simulated auction we determine its outcome: the type of the winning bidder and the takeover premium. By Assumptions 1 to 3, the type of the winning bidder is equal to the type of the bidder with the highest valuation. The takeover premium is not uniquely determined, because our assumptions imply only bounds on it. The lower bound on the winning bid (normalized by the value of the target under the current management) is the maximum of the second-highest bidder's valuation among all participants and one:

$$\text{Winning Bid LB}_i = \max\left[v_i^{(2)}, 1\right], \tag{C1}$$

where $v_i^{(j)}$ denotes the jth-highest valuation in simulated auction i. The winning bid must

be above the second-highest valuation by Assumption 2, as otherwise the bidder with the second-highest valuation would be willing to beat the winner's offer. In addition, the winning bid must be above one, as otherwise the shareholders of the target are better off not selling the company at all. The upper bound on the winning bid is the valuation of the winning bidder, which is the highest bidder's valuation among all participants:

$$\text{Winning Bid UB}_i = v_i^{(1)}. \tag{C2}$$

The winning bid must be below the winner's valuation by Assumption 1, as otherwise the winner would pay more than she is willing to. Having recorded the outcomes of the simulated auctions, we compare their summary statistics (presented in Table CI) with the corresponding sample values presented in Table I.

Table CI shows that the simulations produce outcomes that are similar to what we observe in the data. Strategic bidders win auctions more often than financial bidders, despite the fact that a typical auction has more financial bidders than strategic bidders. As in the data, there are fewer bidders in takeovers won by strategic bidders than in takeovers won by financial bidders: 11.7 versus 14.5 bidders on average compared to 9.9 versus 16.5 bidders in the data. The average winning premium in the data is within the bounds for the samples of all auctions and auctions won by strategic bidders, and slightly above the upper bound in auctions won by financial bidders.[37] More precisely, the model predicts the average target premium in takeover auctions to be between 30.2% and 52.4%, which is consistent with the observed average takeover premium of 42.5%. For the sample of takeovers undertaken by strategic

(financial) acquirers, the model predicts the average takeover premium to be between 32.9% and 59.1% (23.5% and 35.5%), while the sample average takeover premium in the data is 46.4% (36.5%).

Thus, we conclude that the model performs reasonably well at capturing the takeover outcomes observed in the data. Note that our estimation procedure relies on all bids rather than only winning bids, so the fact that simulations produce takeover outcomes that are similar to what we observe in the data is not trivial.

B. Our Model of Takeover Auctions versus Linear Regression of the Takeover Premium versus The Button Model

In this section, we examine performance of the estimator obtained using our incomplete model of English auctions with three assumptions on bidding behavior. We simulate artificial data with bidding patterns that are poorly approximated by any particular structure and that to some extent resemble bidding patterns in takeover auctions. For simplicity, we continue to use the terms "strategic" and "financial" to differentiate between the two types of bidders. In the course of each simulated auction, we allow strategic and financial bidders to arrive with new offers in random sequence and submit bids (both informal and formal) with discrete increment of random size. To focus on the performance of the valuation model only, we keep bidder type known in the resulting data set.[38] We consider three different parameterizations of the simulation procedure that differ in the distribution of observable target characteristics across auctions and the number of auction participants. Specifically, we simulate three data sets, each

containing $I = 200$ auctions, and each corresponding to the following three parameterizations:

1. All auctions have from $\underline{N}_i = 2$ to $\overline{N}_i = 8$ bidders with equal probability; two valuation shifters (observable target characteristics) $X_i = (X_{i,1}, X_{i,2})'$ are $X_{i,1} = 1$ (fixed component of valuation) and $X_{i,2} \sim \mathcal{N}(\mu_X, \sigma_X^2)$, where $(\mu_X, \sigma_X) = (0, 0.4)$.

2. $(\mu_X, \sigma_X) = (0, 1.2)$, with the rest of the parametrization the same as in the first parametrization;

3. $\overline{N}_i = 4$, with the rest of the parametrization the same as in the first parametrization.

For each bidder, the probability of being strategic is $\mathbb{P}_s = 0.3$. The market value of the target is simulated as $M_i = \exp(\mathcal{N}(\mu_M, \sigma_M^2))$, where $(\mu_M, \sigma_M) = (4, 0.5)$. The true parameter set is $\beta_s = (\beta_{s,1}, \beta_{s,2})' = (0.1, 0.1)'$, $\beta_f = (\beta_{f,1}, \beta_{f,2})' = (0.1, 0.5)'$, $\sigma_s = 0.25$, and $\sigma_f = 0.15$.

Bidders start to make offers knowing that M_i is the lowest bid that will be accepted, and are chosen to come up with new offers at random. To capture discreteness of bid increments, we set the minimum bid increment equal to $M_i/100$. Bidders choose the size of the increment at random, uniformly from a discrete set of values $\{M_i/100, 2M_i/100, ..., 10M_i/100\}$. If bidder j's valuation is such that $v_{i,j} < b_{i,\max} + kM_i/100$, where $k \leq 10, k \in \mathbb{N}$, and $b_{i,\max}$ is the current highest bid, the bidder will rationally choose from a subset $\{M_i/100, 2M_i/100, ..., (k-1)M_i/100\}$. If $k < 1$, the bidder drops out of the auction.

The simulated data are estimated using three empirical methods: our model, a linear OLS model of takeover premiums, and a button model, which assumes that each bidder continuously increases its offers up to the valuation. The results are presented in Table CII.

The results produced by the incomplete model of English auctions are close, both economically and statistically, to the true valuation parameters. In contrast, the results of the linear model and the structural button model are widely inconsistent.

First, consider a linear model. Because takeover premiums are complex functions of all bidders' valuations, this takeover premium regression lacks identification to reliably distinguish among different factors that separately shape valuations of strategic and financial bidders. Takeover premiums tend to be above the average bidder valuations, more so if the number of bidders in the auction is higher. This is evidenced by overestimated mean valuations, $\beta_{s,1}$ and $\beta_{f,1}$, for every parametrization of the simulated data, and by overall higher coefficients for the parametrization presented in Table CII, Panel A as compared to Panel B, in which the average number of participants across auctions is smaller. Moreover, a simple change in the data properties can substantially affect all coefficients: an increase in the variance of X_2 in the parametrization presented in Table CII, Panel C, as compared to Panel A, increases (decreases) both the average and the variance of takeover premiums paid by financial (strategic) bidders,[39] which under the linear model results in an inverse relationship between the estimated magnitudes of private valuations, σ_s and σ_f, for the two types of bidders. Finally, takeover premiums paid by strategic and financial bidders tend to differ by approximately the same amount across auctions, as reflected in a reduced and almost insignificant difference between $\beta_{s,2}$ and $\beta_{f,2}$, compared to true values, for the two parameterizations. Second, to a smaller extent, the same problems plague estimation results of the button model in which, for all bidders with formal offers except the winner, valuations are still assumed to be equal to their bids.

Notes

[1] For example, Boone and Mulherin (2007b) find that the fraction of takeovers in the form of auctions in their sample is 50%. Even though public competing bids are rare, a more detailed analysis of deal backgrounds reveals substantial competition via nonpublic bids.

[2] For example, see "Selling to a strategic or financial buyer" by Rebecca Pomering in *Financial Advisor*'s May 2006 issue.

[3] Thompson, Mark E., and Michael O'Brien, "Who has the advantage: Strategic buyers or private equity funds?" *Financier Worldwide*, November 2005.

[4] See Chowdhry and Nanda (1993), Bulow, Huang and Klemperer (1999), and Povel and Singh (2010), who model takeover contests as button auctions, and Fishman (1988, 1989), Avery (1998), and Daniel and Hirshleifer (1998) for models, in which jump bids occur in equilibrium.

[5] It is also consistent with the finding by Ahern (2012) that targets and strategic acquirers share merger gains.

[6] Related, Haddad, Loualiche, and Plosser (2013) find a negative relation between buyout activity and aggregate expected excess returns. See also Axelson, Strömberg, and Weisbach (2009), who rationalize the financial structure of private equity transactions. Axelson et al. (2013) point that this theory can explain their findings.

[7]Some bidders, for example, strategic bidders operating in the same industry as the target or financial bidders with expertise in the industry, can learn their valuations to a large extent even prior to the due diligence process.

[8]Without loss of generality, rational bidders in this paper include bidders with behavioral values for the target (i.e., bidders can be overoptimistic about the target), as long as such bidders do not overbid above their behavioral valuations, and will want to outbid anyone who is about to win an auction at a lower price.

[9]Sometimes targets do not inform bidders about a better offer. Even in this case, bidders have an opportunity to respond to the highest bid by making a public offer once the private stage of the auction is over. Such response is likely to entail additional costs. Thus, a bidder may allow an opponent to win at a price below the valuation if the difference is not too big. In Section VI, we present a robustness check that alters Assumption 2 this way.

[10]If bidder j submitted several formal bids in the course of the auction, $b_{i,j}$ denotes the highest formal bid.

[11]Almost always, the bidder does not inform the target about the reason for not submitting a bid. However, in several cases in our sample, a bidder who does not submit a bid informs the target that this is because her valuation is below the company's market value m_i. We differentiate between these two groups during the estimation. Section A of Appendix B provides the details.

[12]Before 2000, detailed information on the composition of competition was rarely provided

in deal backgrounds; whenever it was provided, the pool of competitors was more often divided into public and private bidders than strategic and financial bidders. Although private bidders are more likely to be financial bidders, the absence of a one-to-one correspondence and lower overall quality prevent us from using older data.

[13]The Internet Appendix is available in the online version of the article on the Journal of Finance website. An even safer approach would be to eliminate all auctions with at least one noncash bid. However, a noncash losing bid provides information about the valuation of only this bidder, while a noncash winning bid provides information about the valuations of all bidders in the auction, since it serves as an upper bound on those valuations. Thus, a noncash losing bid introduces a much smaller econometric problem. The downside of eliminating auctions with any non-cash bids is the reduction in the number of bidders in the sample. As a robustness check, we estimated the model on a sample of auctions in which all formal bids are in cash and obtained similar results.

[14]Whenever the target has dual-class stock (six cases) or a stock split after the snapshot of the market price is taken but before the takeover announcement (two cases), we compute the market value as the weighted average of dual-class stock prices or the proportion of the price before the stock split, respectively.

[15]A press release occurred for 100 out of 349 targets. In almost all cases it increased the stock price of the target.

[16]As a robustness check, we also calculated M_i as the market value three months prior to

the day of the takeover announcement and obtained similar results.

[17]The "Finance" industry from the standard 12-industry classification does not contain any firms due its exclusion from the sample of targets.

[18]In the first specification, vector Z_i contains X_i and auction outcomes; in the second one, Z_i is updated with industry fixed effects following the classification of Fama and French (1997). We also estimated (6) using the Probit model and obtained similar results.

[19]In Model III we follow the five-industry classification instead of the 11-industry classification because many industries in the 11-industry classification have few observations in our sample, as evident from Table I.

[20]As a robustness check, we also collected data on auctions in which the winning bid is in combination of cash and stock with the fraction of cash in the total bid exceeding 50%. Consistent with selection driving the size coefficient, the coefficient on size for strategic bidders decreases to -0.024. The other coefficients are largely unaffected. Alternatively, size coefficients can be different because synergies from mergers of two operating companies can have decreasing returns to scale, while an increase in efficiency from acquisition by a financial bidder can be multiplicative.

[21]Following Harford (1999), we normalize cash balances by dividing them by the book value of assets. We also estimated the model dividing cash balances by the market value of assets and obtained similar results. All coefficients are similar in magnitude, but the coefficients on cash for financial bidders becomes significant.

[22]We also simulate auction outcomes without financial bidders participating in takeover auctions. We estimate that in the absence of financial bidders, the average takeover premium decreases by 6% to 8% of the market value of the target, and the effect is greater in downturns and for targets valued more by financial bidders. See the Internet Appendix for details.

[23]Because we do not observe the identity and hence the characteristics of a strategic bidder unless it makes a public bid, such estimation has to rely on strong assumptions. Our estimation strategy is based on the assumption that a strategic bidder of unknown identity is drawn randomly from the set of U.S. public corporations in the same two-digit SIC industry as the target. See the Internet Appendix for a description of methodology and results.

[24]Because valuations of bidders are log-normally distributed, conditional on publicly observable characteristics of the target, their conditional standard deviations are equal to $\sqrt{e^{\sigma_t^2} - 1}$, $t \in \{S, F\}$. For the base model, this implies a conditional standard deviation of $\sqrt{e^{0.258^2} - 1} = 26.24\%$ for valuations of strategic bidders and $\sqrt{e^{0.153^2} - 1} = 15.39\%$ for valuations of financial bidders.

[25]See, for example, Jarrell, Brickley, and Netter (1988) for early evidence and Andrade, Mitchell, and Stafford (2001) and Betton, Eckbo, and Thorburn (2008) for recent updates.

[26]See Betton, Eckbo, and Thorburn (2008) for a discussion, and Song and Walkling (2000), Fuller, Netter, and Stegemoller (2002), and Cai, Song, and Walkling (2011) for approaches to address this problem.

[27]Number of strategic bidders, number of financial bidders, type of the winning bidder, and

size of the winning bid.

[28]The acquirer's abnormal return would be the difference between its maximum willingness to pay and the price paid, multiplied by the relative size of the target. Given that the median size of a target is around 12% of the size of the acquirer in the sample of acquisitions of public U.S. companies by public U.S. companies (Andrade, Mitchell, and Stafford (2001)), the implied announcement return is around $0.12 \times 24.7\% \approx 3\%$.

[29]See Betton, Eckbo, and Thorburn (2008) for a review of the evidence. The announcement returns for public acquirers in our sample are in line with those in the prior literature. For example, the CAPM-adjusted average abnormal announcement return in our sample is -0.231% in the (-1,+1) window around the announcement date and -0.018% in the (-3,+3) window. Both values are statistically insignificantly different from zero.

[30]The private benefits of managers could be due to empire building (Jensen (1986)) or effects on compensation through M&A bonuses and future stock and option grants. See Grinstein and Hribar (2004) and Harford and Li (2007) for empirical evidence.

[31]Liu (2004) shows that ML estimators of so-called "robit" models, to which ours is similar, are robust if the number of degrees of freedom in the t-distribution is known, and suggests the use of five to seven degrees of freedom.

[32]Povel and Singh (2006) make a contribution in this direction, showing that when two bidders are asymmetrically informed about the target, a sequential procedure in which the target first offers an exclusive deal to a better informed bidder is optimal.

[33]By assuming complete type observability, this section lays down basic building blocks of our identification strategy. Section B of Appendix B deals with the more complicated case in which some losing bidders' type is not observable.

[34]See McLachlan and Krishnan (2008) for a comprehensive overview of EM methods.

[35]More details on the parametrization of the simulated annealing procedure are available from the authors upon request.

[36]Because we use all the bids, not just the winning bids, in our estimation, bidders' intrinsic valuations are estimated more precisely. However, the fit of the winning bid alone implied by the model might diverge from that observed in the data, if the losing bids carry substantially different information than the winning bids. Therefore, the fit of the model can be checked by looking at whether simulations of the model produce auction outcomes that closely resemble the data.

[37]Both sample and simulated takeover premiums have high standard deviations, so the fact that the observed average of the takeover premium is slightly above the upper boundary implied by the model is not surprising.

[38]The results are similar if we implement partially unobservable types, that is, randomly "forget" the true type for a subset of losing bidders in the simulated data, consistent with our assumption about the actual data.

[39]Financial bidders start to win more often and on average more easily against strategic bidders due to a higher sensitivity of their valuations to X_2.

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Table I.
Descriptive Statistics of Bidder Participation in All Auctions, Auctions Won by Strategic versus Financial Bidders, and Across Industries

The table shows descriptive statistics (mean, standard deviation, and median) of bidder participation for auctions won by different types of bidders and across 11 industries, as classified by Fama and French (1997). *Number* is the number of auctions. *Total* is the number of bidders who signed confidentiality agreements, which is composed of *Strategic* bidders, *Financial* bidders, and *Unknown* bidders, those for whom information about their type is not provided in deal backgrounds. The winning bid is in units of the target's value under the current management. Standard deviations are reported in parentheses. Medians are reported in brackets. The sample covers 01/01/2000 to 09/06/2008.

	Number	Total	Strategic	Financial	Unknown	Winning Bid
All Auctions	349	12.507	2.269	3.453	6.785	1.425
		(15.493)	(2.910)	(8.236)	(12.574)	(0.323)
		[6.000]	[1.000]	[1.000]	[1.000]	[1.339]
Won by Strategic Bidder	211	9.886	2.706	1.370	5.810	1.464
		(12.637)	(2.486)	(4.154)	(11.251)	(0.324)
		[5.000]	[2.000]	[0.000]	[1.000]	[1.380]
Won by Financial Bidder	138	16.514	1.601	6.638	8.275	1.365
		(18.390)	(3.360)	(11.356)	(14.279)	(0.315)
		[9.000]	[1.000]	[2.000]	[1.000]	[1.306]
t-statistic of Difference		3.991	-3.524	6.143	1.796	-2.827
Consumer Nondurables	13	17.154	1.000	9.308	6.846	1.492
		(17.573)	(0.707)	(17.895)	(6.926)	(0.593)
Consumer Durables	4	18.250	4.000	7.000	7.250	1.415
		(16.520)	(1.633)	(9.695)	(13.200)	(0.650)
Manufacturing	25	29.360	3.480	7.120	18.760	1.308
		(26.372)	(5.636)	(15.584)	(21.495)	(0.251)
Oil, Gas, and Coal	7	16.286	0.714	0.857	14.714	1.398
		(13.376)	(0.756)	(0.900)	(12.932)	(0.296)
Chemicals etc.	9	11.111	3.778	4.778	2.556	1.361
		(23.235)	(5.848)	(11.777)	(5.897)	(0.198)
Business Equipment	138	9.616	2.297	1.891	5.428	1.434
		(11.708)	(2.297)	(4.131)	(10.614)	(0.320)
Telephone & Television	10	10.400	2.000	0.500	7.900	1.348
		(8.897)	(1.826)	(0.972)	(9.386)	(0.154)
Utilities	2	21.000	8.500	12.500	0.000	1.122
		(24.042)	(7.778)	(16.263)	(0.000)	(0.146)
Wholesale, Retail	47	17.574	1.213	6.468	9.894	1.400
		(18.838)	(2.021)	(9.915)	(17.328)	(0.297)
Healthcare, Medical etc.	48	6.479	2.646	1.396	2.438	1.418
		(6.823)	(2.771)	(3.780)	(4.617)	(0.270)
Other	46	11.109	2.152	3.630	5.326	1.524
		(11.861)	(2.521)	(7.628)	(10.009)	(0.354)

Table II.
Descriptive Statistics of Target Characteristics in All Auctions, Auctions Won by Strategic versus Financial Bidders, and Across Industries

The table shows descriptive statistics (mean, standard deviation, and median) of target characteristics for auctions won by different types of bidders and across 11 industries, as classified by Fama and French (1997). *Size* is equal to book value (in $ millions); *Leverage* is the ratio of book value of debt to the sum of market value of equity and book value of debt; *q-ratio* is the ratio of the sum of market value of equity and book value of debt to book value of the target; *Cash Flow* is the sum of the last four quarterly cash flows; and *Cash* is the sum of cash, short-term investments, and marketable securities. *Cash Flow, Cash, R&D*, and *Intangibles* are normalized by target size. Standard deviations are reported in parentheses. Medians are reported in brackets. The sample covers 01/01/2000 to 09/06/2008.

	Size	Leverage	q-ratio	Cash Flow	Cash	R&D	Intangibles
All Auctions	654.3	0.148	1.498	0.008	0.260	0.017	0.149
	(2327.4)	(0.211)	(1.139)	(0.270)	(0.242)	(0.031)	(0.189)
	[164.4]	[0.040]	[1.233]	[0.070]	[0.194]	[0.000]	[0.059]
Won by Strategic Bidder	318.4	0.101	1.703	-0.029	0.324	0.025	0.146
	(786.7)	(0.177)	(1.295)	(0.329)	(0.243)	(0.037)	(0.178)
	[128.6]	[0.010]	[1.356]	[0.058]	[0.305]	[0.015]	[0.073]
Won by Financial Bidder	1167.8	0.220	1.184	0.064	0.161	0.005	0.154
	(3517.3)	(0.238)	(0.749)	(0.119)	(0.203)	(0.012)	(0.206)
	[258.9]	[0.129]	[1.000]	[0.082]	[0.078]	[0.000]	[0.047]
t-statistic of Difference	3.383	5.324	-4.262	3.164	-6.541	-6.259	0.387
Consumer Nondurables	476.1	0.219	1.161	0.067	0.114	0.000	0.155
	(821.7)	(0.259)	(0.579)	(0.051)	(0.087)	(0.000)	(0.207)
Consumer Durables	289.7	0.283	1.253	0.089	0.118	0.009	0.060
	(238.4)	(0.318)	(0.476)	(0.125)	(0.208)	(0.017)	(0.070)
Manufacturing	362.5	0.190	1.219	0.105	0.085	0.004	0.105
	(577.5)	(0.187)	(0.408)	(0.075)	(0.091)	(0.008)	(0.156)
Oil, Gas, and Coal	211.1	0.268	1.431	0.143	0.030	0.001	0.039
	(189.5)	(0.261)	(0.639)	(0.103)	(0.027)	(0.001)	(0.103)
Chemicals etc.	1390.8	0.183	1.410	0.072	0.149	0.005	0.118
	(3421.1)	(0.230)	(0.521)	(0.097)	(0.208)	(0.005)	(0.128)
Business Equipment	516.9	0.058	1.519	-0.050	0.399	0.032	0.183
	(2812.2)	(0.114)	(1.005)	(0.356)	(0.228)	(0.039)	(0.193)
Telephone & Television	2021.9	0.207	1.338	0.109	0.234	0.004	0.248
	(5476.8)	(0.229)	(0.543)	(0.071)	(0.187)	(0.007)	(0.248)
Utilities	2971.5	0.162	0.748	0.062	0.028	0.000	0.017
	(2556.0)	(0.229)	(0.035)	(0.040)	(0.015)	(0.000)	(0.024)
Wholesale, Retail	771.8	0.222	1.082	0.068	0.080	0.000	0.084
	(1501.1)	(0.261)	(0.613)	(0.105)	(0.077)	(0.000)	(0.130)
Healthcare, Medical etc.	417.1	0.137	2.530	-0.028	0.312	0.026	0.173
	(500.6)	(0.216)	(1.965)	(0.235)	(0.260)	(0.034)	(0.218)
Other	959.7	0.260	1.143	0.025	0.190	0.002	0.126
	(2359.3)	(0.252)	(0.795)	(0.267)	(0.229)	(0.007)	(0.198)

<div align="center">**Table III.**</div>

<div align="center">**Descriptive Statistics of Formal and Informal Bids by Strategic, Financial, and Unknown Types of Bidders (per auction)**</div>

The table shows descriptive statistics (mean and standard deviation) of formal and informal bids by strategic, financial, and unknown types of bidders per auction. The formal bid size is in units of the target's value under the current management. The sample covers 01/01/2000 to 09/06/2008.

	Total Number	Per Auction	Informal Bids	Formal Bids	Size of Formal Bid
Strategic Bidder	792	2.269	1.330	0.736	1.456
		(2.910)	(1.261)	(0.643)	(0.332)
Financial Bidder	1205	3.453	1.295	0.533	1.344
		(8.236)	(2.020)	(0.701)	(0.319)
Bidder of Unknown Type	2368	6.785	1.370	0.095	1.461
		(12.574)	(2.839)	(0.401)	(0.294)
Total	4365	12.507	3.994	1.364	1.413
		(15.493)	(3.255)	(0.688)	(0.328)

Table IV.
Determinants of Types of Losing Bidders

The table shows the estimation results of the Logit model $\mathbb{P}(t = s|Z)$ used to recover the probability of a losing bidder with unobservable type being strategic. The model is outlined in Section II.C. In the first specification, Z contains observable target characteristics, characteristics of the economy, and auction outcomes. In the second specification, Z is updated with industry fixed effects following the five-industry classification by Fama and French (1997). The sample size (total number of losing bidders with observable type) is 1,648. Standard errors are reported in parentheses. Statistical significance is indicated by ***,**, and * for the 0.01, 0.05, and 0.10 levels. The sample covers 01/01/2000 to 09/06/2008.

	Baseline model	With industry f.e.
Const	3.932***	–
	(0.751)	–
log(Size)	-0.075	-0.052
	(0.047)	(0.049)
q-ratio	0.139	0.100
	(0.095)	(0.104)
Leverage	-1.393***	-1.337***
	(0.375)	(0.395)
Cash flow	-1.953***	-2.351***
	(0.596)	(0.666)
Cash	0.197	0.134
	(0.416)	(0.511)
Intangibles	-7.451***	-10.231***
	(2.124)	(2.313)
R&D	-0.680**	-1.065***
	(0.310)	(0.387)
Market Return	-2.502***	-2.024**
	(0.830)	(0.889)
Credit Spread	-29.041*	-31.949*
	(16.112)	(17.262)
log(# bidders)	-0.650***	-0.674***
	(0.067)	(0.075)
Won by F dummy	-1.082***	-0.918***
	(0.131)	(0.137)
Winning bid	-0.385*	0.073
	(0.227)	(0.251)
McFadden R^2	19.37%	23.27%

Table V.
Estimation Results of the Valuations Model, Models I to III, and Regression of Takeover Premiums

The table shows the estimation results for the determinants of strategic and financial bidders' valuations. Model I is the basic comparison of means and standard deviations of valuations. Model II is the baseline model. Model III expands the baseline model to include industry dummies following five-industry classification by Fama and French (1997) and industry concentration. Model II is compared to a simple linear OLS regression of scaled winning bids on characteristics of the target and the economy. Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels. The sample covers 01/01/2000 to 09/06/2008.

	Model I			Model II			Model III			OLS on winning bids		
	Strategic	Financial	Diff.	Strategic	Financial	Diff.	Strategic	Financial	Diff.	Strategic	Financial	Diff.
St. Dev. of PV	0.275***	0.166***	0.109***	0.258***	0.153***	0.105***	0.238***	0.152***	0.086***	0.295	0.279	0.016
	(0.009)	(0.002)	(0.009)	(0.009)	(0.003)	(0.010)	(0.008)	(0.002)	(0.009)			
Const	0.113***	0.043***	0.070***	0.106	0.142***	-0.036	–	–	–	0.879***	0.772***	0.107
	(0.014)	(0.007)	(0.016)	(0.072)	(0.023)	(0.077)	–	–	–	(0.155)	(0.208)	(0.259)
log(Size)	–	–	–	-0.028***	0.000	-0.028***	-0.033***	-0.006*	-0.027***	-0.055***	-0.034**	-0.021
	–	–	–	(0.007)	(0.003)	(0.008)	(0.007)	(0.003)	(0.008)	(0.019)	(0.017)	(0.026)
Leverage	–	–	–	0.483***	0.195***	0.288	0.354**	0.189***	0.165	0.280	-0.119	0.399
	–	–	–	(0.161)	(0.063)	(0.177)	(0.155)	(0.066)	(0.173)	(0.378)	(0.314)	(0.493)
Leverage^2	–	–	–	-0.584***	-0.212***	-0.372	-0.439**	-0.248***	-0.191	-0.568	0.672*	-1.240*
	–	–	–	(0.221)	(0.077)	(0.238)	(0.219)	(0.081)	(0.239)	(0.550)	(0.399)	(0.680)
q-ratio	–	–	–	0.001	0.003	-0.002	-0.006	-0.004	-0.002	-0.058***	-0.018	-0.040
	–	–	–	(0.010)	(0.008)	(0.013)	(0.009)	(0.008)	(0.013)	(0.017)	(0.038)	(0.042)
Cash Flow	–	–	–	-0.063**	-0.380***	0.317***	-0.037	-0.340***	0.304***	-0.018	-0.374	0.356
	–	–	–	(0.028)	(0.052)	(0.060)	(0.027)	(0.054)	(0.061)	(0.072)	(0.254)	(0.264)
Cash	–	–	–	0.154***	0.058*	0.096	0.072	-0.022	0.093	0.028	-0.155	0.184
	–	–	–	(0.054)	(0.035)	(0.067)	(0.057)	(0.038)	(0.070)	(0.112)	(0.154)	(0.191)
R&D	–	–	–	1.593***	-0.037	1.630***	1.562***	-0.072	1.634***	-0.016	-0.157	0.141
	–	–	–	(0.332)	(0.481)	(0.601)	(0.318)	(0.498)	(0.607)	(0.128)	(0.128)	(0.181)
Intangibles	–	–	–	0.028	-0.093***	0.121**	-0.039	-0.155***	0.116*	0.771	-0.812	1.583
	–	–	–	(0.054)	(0.025)	(0.061)	(0.055)	(0.029)	(0.064)	(0.640)	(2.390)	(2.475)
Market Return	–	–	–	-0.010	-0.250***	0.241*	-0.014	-0.168***	0.153	-0.622***	-0.662**	0.041
	–	–	–	(0.115)	(0.045)	(0.126)	(0.107)	(0.047)	(0.120)	(0.223)	(0.283)	(0.361)
Credit Spread	–	–	–	2.308	-2.446***	4.754**	3.144	-3.348***	6.492***	-1.891	-5.182	3.291
	–	–	–	(2.102)	(0.744)	(2.275)	(1.962)	(0.930)	(2.217)	(4.250)	(6.272)	(7.576)

Table VI.
Average Valuations of Strategic and Financial Bidders in Different Subsamples

The table shows average valuations of strategic and financial bidders (restored according to Model II) in different subsamples of targets. We sort all targets in our sample based on each characteristic, select the 10% of the sample with the lowest (highest) characteristic, calculate average valuations of a strategic and a financial bidder for each target in the subsample, and report their averages over the subsample. The average valuations of strategic and financial bidders over the entire sample of targets are 1.167 and 1.117. The sample covers 01/01/2000 to 09/06/2008.

| | Bottom Quantile of the Sample | | Top Quantile of the Sample | |
	Strategic	Financial	Strategic	Financial
log(Size)	1.291	1.201	1.047	1.073
Leverage	1.196	1.120	1.115	1.106
q-ratio	1.249	1.236	1.226	1.138
Cash Flow	1.382	1.464	1.126	1.028
Cash	1.118	1.066	1.323	1.283
R&D	1.116	1.091	1.383	1.284
Intangibles	1.205	1.153	1.122	1.049
Market Return	1.264	1.304	1.129	1.047
Credit Spread	1.112	1.072	1.261	1.254

Table VII.
Estimation Results of the Valuations Model, Models IV to VI (robustness checks)

The table provides robustness checks of estimation results for the baseline model (Model II). Model IV relaxes Assumption 2, so that the upper bound on valuations from losing formal bids is equal to 105% of the target's value under the current management. Model V relaxes Assumption 3, so that the lower bound on valuations from informal bids is equal to 90% of the target's value under the current management. Model VI checks the robustness of the estimation results to the potential presence of fat tails in the distribution of unobservable component of valuations (by assuming that they come from a t-distribution with five degrees of freedom). Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels. The sample covers 01/01/2000 to 09/06/2008.

	Model IV			Model V			Model VI		
	Strategic	Financial	Diff.	Strategic	Financial	Diff.	Strategic	Financial	Diff.
St. Dev. of PV	0.252***	0.159***	0.093***	0.272***	0.167***	0.105***	0.245***	0.112***	0.133***
	(0.009)	(0.004)	(0.011)	(0.010)	(0.004)	(0.011)	(0.009)	(0.004)	(0.010)
Const	0.128*	0.169***	-0.041	0.073	0.117***	-0.044	0.073	0.097***	-0.023
	(0.075)	(0.034)	(0.084)	(0.078)	(0.043)	(0.091)	(0.064)	(0.037)	(0.077)
log(Size)	-0.027***	0.000	-0.027***	-0.028***	0.001	-0.029***	-0.018**	0.001	-0.019**
	(0.007)	(0.004)	(0.009)	(0.008)	(0.004)	(0.009)	(0.007)	(0.003)	(0.008)
Leverage	0.470***	0.204***	0.265	0.490***	0.197***	0.292	0.333**	0.429***	-0.097
	(0.165)	(0.072)	(0.183)	(0.172)	(0.070)	(0.190)	(0.151)	(0.056)	(0.166)
Leverage²	-0.563**	-0.221**	-0.343	-0.572**	-0.213**	-0.359	-0.345	-0.670***	0.325
	(0.229)	(0.088)	(0.248)	(0.239)	(0.085)	(0.257)	(0.211)	(0.075)	(0.230)
q-ratio	-0.001	0.003	-0.005	0.002	0.004	-0.002	0.004	0.002	0.002
	(0.010)	(0.009)	(0.014)	(0.010)	(0.009)	(0.014)	(0.008)	(0.007)	(0.011)
Cash Flow	-0.070**	-0.394***	0.325***	-0.068**	-0.397***	0.329***	-0.081**	-0.362***	0.281***
	(0.028)	(0.060)	(0.067)	(0.030)	(0.059)	(0.067)	(0.029)	(0.044)	(0.053)
Cash	0.146***	0.059	0.087	0.157***	0.061	0.095	0.112**	0.082***	0.030
	(0.055)	(0.040)	(0.071)	(0.057)	(0.040)	(0.072)	(0.049)	(0.031)	(0.061)
R&D	1.621***	-0.033	1.654**	1.673***	-0.084	1.757***	1.489***	0.114	1.375***
	(0.339)	(0.559)	(0.670)	(0.350)	(0.543)	(0.662)	(0.287)	(0.429)	(0.531)
Intangibles	0.027	-0.105***	0.133**	0.034	-0.102***	0.136**	0.007	-0.092***	0.099*
	(0.055)	(0.029)	(0.064)	(0.058)	(0.029)	(0.066)	(0.049)	(0.023)	(0.057)
Market Return	-0.028	-0.276***	0.248*	-0.011	-0.269***	0.258*	0.028	-0.079*	0.107
	(0.117)	(0.055)	(0.132)	(0.122)	(0.059)	(0.138)	(0.105)	(0.046)	(0.119)
Credit Spread	2.192	-3.327***	5.519**	2.533	-2.944**	5.477**	2.213	-1.274	3.487
	(2.142)	(0.736)	(2.288)	(2.231)	(1.147)	(2.570)	(1.885)	(1.073)	(2.268)

Table CI.

Simulated Economy, 100x Original Sample, at Estimated Valuation Parameters

The table shows descriptive statistics (mean, standard deviation, and median) of the composition of competition, as well as bounds on the outcome of takeover auctions in a simulated economy in which bidders value targets according to Model II, Table V. Each target in the sample is replicated 100 times; for each replication, a different set of bidder valuations is simulated. Standard deviations are reported in parentheses. Medians are reported in brackets.

	Number	Total	Strategic	Financial	Winning LB	Winning UB
All Auctions	34900	12.507	4.619	7.888	1.302	1.524
		(15.471)	(4.524)	(12.978)	(0.235)	(0.316)
		[6.000]	[3.000]	[3.000]	[1.283]	[1.477]
Won by Strategic Bidder	24987	11.724	5.391	6.333	1.329	1.591
		(15.204)	(4.655)	(12.028)	(0.250)	(0.330)
		[5.000]	[4.000]	[1.000]	[1.313]	[1.551]
Won by Financial Bidder	9913	14.481	2.675	11.806	1.235	1.355
		(15.956)	(3.486)	(14.385)	(0.176)	(0.192)
		[8.000]	[1.000]	[5.000]	[1.226]	[1.342]

Table CII.
Estimation Results of the Simulated Model with Stochastic Jump Bids, Our Model vs. Linear OLS Model vs. Button model

S and F columns correspond to true and estimated parameters (with standard errors) of strategic and financial bidders. σ_t is the variance of private components; $\beta_{t,1}$ and $\beta_{t,2}$ are sensitivities of type $t \in \{s, f\}$ to the two observable target characteristics. * denotes estimates for which the true parameter lies within 95% confidence bounds.

Panel A: $N \in [2, 8]$, $X_2 \sim N(0, 0.4^2)$.

	True		Incomplete model		"Button" model		Linear model	
t	S	F	S	F	S	F	S	F
σ_t	0.25	0.15	0.308*	0.164*	0.181	0.141*	0.106	0.103
			(0.031)	(0.008)	(0.023)	(0.010)	(0.012)	(0.006)
$\beta_{t,1}$	0.1	0.1	0.077*	0.112*	0.157	0.141	0.229	0.199
			(0.022)	(0.008)	(0.020)	(0.009)	(0.013)	(0.012)
$\beta_{t,2}$	0.1	0.5	0.094*	0.546*	0.152*	0.436	0.272	0.386
			(0.061)	(0.026)	(0.050)	(0.023)	(0.041)	(0.031)

Panel B: $N \in [2, 4]$, $X_2 \sim N(0, 0.4^2)$.

	True		Incomplete model		"Button" model		Linear model	
t	S	F	S	F	S	F	S	F
σ_t	0.25	0.15	0.244*	0.167*	0.144	0.123	0.087	0.100
			(0.029)	(0.011)	(0.020)	(0.009)	(0.010)	(0.008)
$\beta_{t,1}$	0.1	0.1	0.129*	0.121	0.168	0.162	0.195	0.140
			(0.023)	(0.010)	(0.017)	(0.008)	(0.013)	(0.011)
$\beta_{t,2}$	0.1	0.5	0.033*	0.452*	0.036*	0.353	0.201	0.303
			(0.056)	(0.032)	(0.053)	(0.021)	(0.031)	(0.028)

Panel C: $N \in [2, 8]$, $X_2 \sim N(0, 1.2^2)$.

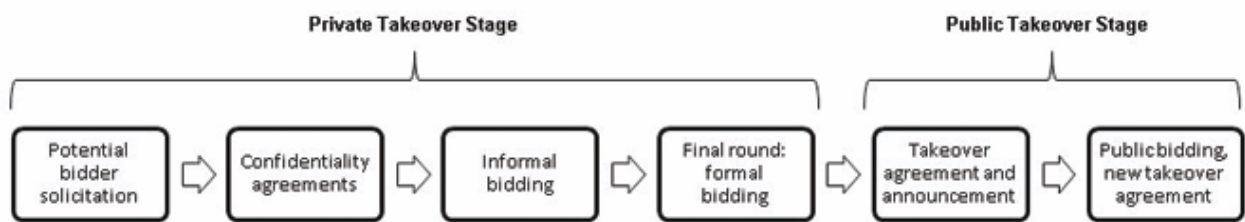|	True		Incomplete model		"Button" model		Linear model	
t	S	F	S	F	S	F	S	F
σ_t	0.25	0.15	0.318*	0.139*	0.138	0.183	0.087	0.150*
			(0.035)	(0.006)	(0.017)	(0.013)	(0.011)	(0.008)
$\beta_{t,1}$	0.1	0.1	0.127*	0.124	0.177	0.151	0.221	0.188
			(0.023)	(0.009)	(0.014)	(0.017)	(0.014)	(0.028)
$\beta_{t,2}$	0.1	0.5	0.111*	0.528	0.064	0.471	0.106*	0.465*
			(0.022)	(0.010)	(0.017)	(0.014)	(0.013)	(0.024)

Figure 1: Timing of the takeover auction process. This figure shows the most common timing structure of a takeover auction process, starting from the bidder solicitation stage.
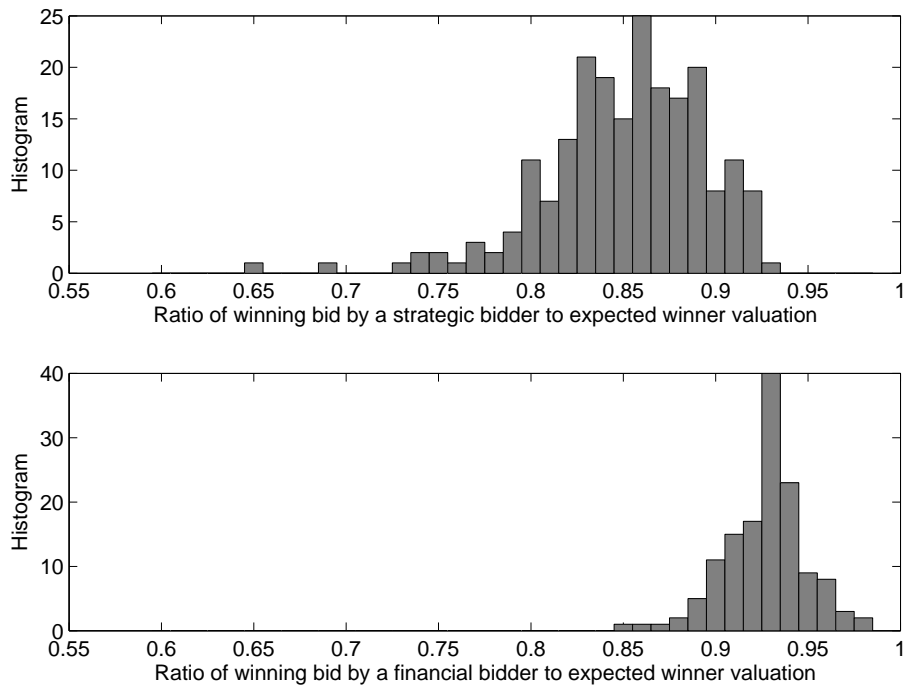
Figure 2: Distribution of the winning slack. The figure shows the distribution of 1-*Winning Slack*, which is defined as the ratio of the winning bid to the ex-post mean valuation by the winner, conditional on the observable winning bid. Higher winning slack corresponds to lower effective competition in an auction and to higher ability of the winner to pay more if stronger competition arises or target characteristics change adversely.