Online Appendix

to accompany

Inefficiencies and Externalities from Opportunistic Acquirers

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A.1. Discussion of Auction Protocols

We model the M&A process as a modified sealed second-price auction (SP) in which bidders simultaneously submit their bids in combinations of cash and equity, and the winner pays a settlement whose value assessed by the target is no smaller than the second-highest bid (again ranked by the target). Alternatively, the M&A process can be modeled as an ascending English auction (EA) (Gorbenko and Malenko, 2016), in which the bidders repeatedly make offers in terms of the value of consideration they promise to deliver to the target if they win the competition. These offers continue until all but one bidder drops out, and the winner (the remaining bidder) then chooses a combination of cash and equity whose value assessed by the target is no smaller than the value offered by the last bidder who drops out. The EA protocol has many desirable features. It arguably resembles the actual M&A transaction process more closely, because we do occasionally observe multiple-round bid revisions among several bidders for a target. This dynamic bidding is missing in the static SP protocol. In addition, mapping the SP model's second-price settlement to actual M&A transactions requires more work, compared to EA.

Despite these differences, choosing between the SP and EA auction protocols is not of great importance in our setting. The reason is that SP and EA share several essential features that we need for our theoretical and empirical analysis. Within our model's private-value paradigm, the two auction protocols have equilibriums that are strategically equivalent. To see the equivalence, in the EA auction let the equilibrium valuation (scoring) rule used by the target be $z(C, \alpha, M)$, and let $\mathcal{A}(\Phi)$ be the set of (C, α) combinations that are feasible for a bidder given its state. In equilibrium, a bidder drops out when the price reaches $\max_{(C,\alpha)\in\mathcal{A}(\Phi)} z(C, \alpha, M)$, which occurs on the boundary of $\mathcal{A}(\Phi)$ where the offer, (C, α), exhausts the bidder's true valuation of the target. Intuitively, in EA a bidder exits if the highest value that it can deliver to the target should it win the competition reaches its maximum willingness to pay (i.e., its valuation of the target). This outcome for the EA auction is the same as the SP auction's outcome that the bidders structure their bids to offer their true valuation of the target. More important, in EA the winner needs to deliver a value (assessed by the target) equal to the last competitor who drops out. Given the above discussion, the expected value paid by the winner is also equal to the bidder who has the second-highest valuation. As a result, the winning bidder's ultimate payment (C_i^*, α_i^*) in this EA model is equivalent to the settlement described in our model, and in both models, the target expects to receive a gross revenue equal to the greater of (a) its reservation value (i.e., 1) and (b) the losing bidder's valuation assessed rationally by the target.

Despite EA's more straightforward mapping to reality, we choose the SP format, because the EA has a disadvantage in the empirical analysis. To carry out the structural estimation, we need to numerically solve the model (whether based on EA or SP), and EA calls for a solution for both choice variables, cash and equity, simultaneously, which greatly increases the computational difficulty. Different from EA, this computational difficulty can be mitigated in SP since the cash and equity components in the SP equilibrium bids satisfy the relation $\alpha_i^*(X_i + V_i - C_i^*) + C_i^* = V_i$, which allows us to solve the model over only one choice variable C and then obtain the equity payment using the settlement rule. The seemingly complicated protocol and settlement in SP actually decomposes the process to solve for the EA equilibrium into two steps, each of which, however, is easier to carry out computationally. We essentially get the ultimate payment $(C_i^*, \tilde{\alpha}_i^*)$ that is strategically equivalent to that in EA.

Using the SP auction protocol, we need to specify a settlement rule for the winner to make an ultimate payment according to a second-price rule. We assume that the winner keeps the cash component of its bid unchanged and lowers the equity component so that the ultimate settlement is worth (assessed by the target) at least the higher between the target's stand-alone value and the value of the losing bid (again assessed by the target): $z(C_i, \tilde{\alpha}_i, M_i) = \max\{1, z(C_j, \alpha_j, M_j)\}$. Theoretically, there may be multiple feasible settlement rules that satisfy a second-price rule. Specifically, any $(\tilde{C}, \tilde{\alpha})$ such that $z(\tilde{C}_i, \tilde{\alpha}_i, M_i) = \max\{1, z(C_j, \alpha_j, M_j)\}$ can be used as a valid settlement. However, given a specific settlement rule in place, the bidders choose a corresponding bidding strategy such that the resulting ultimate payment achieves the same expected profit. In other words, as long as the equilibrium described in Definition 1 is unique with a given settlement rule, the choice of settlement rule is not critical, because, though the equilibrium bids (C_i, α_i) is different (since they are contingent on the settlement rule), the expected ultimate payment is the same. From the practical perspective, however, the specific settlement rule that we choose has two advantages. First, information asymmetry about the acquirer's stock value is the source of the target's confusion. Therefore, the target may have a preference for cash over equity, which in turn requires the winning bidder to lower its nominal equity bid while leaving the cash part unchanged for settlement. Second, though not being considered in our model, in practice bidders sometimes face pressure from competing financial bidders to pay cash, and this pressure creates another reason for adjusting the bid's equity part rather than the cash part in the settlement.

A.2. Proof of Proposition 1

Since the acquirer knows its own value X_i and the valuation of the target V_i, the optimization problem (2) can be written as

$$b_i^* = \underset{b=(C,\alpha)}{\operatorname{argmax}} \; E\left\{ (X_i + V_i - \tilde{C}) \cdot \left[\frac{V_i - \tilde{C}}{X_i + V_i - \tilde{C}} - \tilde{\alpha}^* \right] \cdot 1_{\{\tilde{\alpha}^* \leqslant \alpha\}} \middle| \Phi_i \right\},$$

subject to $C \leqslant k_i$, where $\tilde{C} = \min\{C, \max\{1, z(b^*(\Phi_j), M_j)\}\}$ and the substitution of $1_{\{\tilde{\alpha}^* \leqslant \alpha\}}$ for $1_{\{\max\{1, z(b^*(\Phi_j), M_j)\} \leqslant z(C,\alpha,M_i)\}}$ is based on the definition of the equity settlement and the fact that given C, the scoring function is nondecreasing in α.

Note that given C and that the rival follows the optimal equilibrium bidding rule, the transformed share $\tilde{\alpha}^*$ does not depend on α. We may have the following discussion to establish the equilibrium relation specified in Proposition 1.

We first consider the case where $C \geqslant \max\{1, z(b^*(\Phi_j), M_j)\}$. Let $\mathcal{S}_1$ be the support of Φ_j on which this relation is true. In this case the integrand degenerates to $V_i - \max\{1, z(b^*(\Phi_j), M_j)\} \geqslant 0$ which does not depend on α. This simplification is based on the fact that $\tilde{\alpha}_i^* = 0$ on $\mathcal{S}_1$ so that $1_{\{\tilde{\alpha}^* \leqslant \alpha\}} = 1$ for all $\alpha \geqslant 0$. Therefore, the deviation of α from $(V_i - C)/(X_i + V_i - C)$ does not improve the objective function value on $\mathcal{S}_1$. Next we focus on the cases where $C < \max\{1, z(b^*(\Phi_j), M_j)\}$ and $\tilde{C} = C$.

If $(V_i - C)/(X_i + V_i - C) > \tilde{\alpha}^*$ (let $\mathcal{S}_2$ be the support of Φ_j for this relation), the integrand of the expectation operator is positive and the part in front of the indicator function does not depend on α. The deviation of α only changes the likelihood of winning the auction. The deviation to $\alpha' > (V_i - C)/(X_i + V_i - C)$ or $(V_i - C)/(X_i + V_i - C) > \alpha' \geqslant \tilde{\alpha}^*$ does not change the value of the objective function since the winning probability is not affected, and the deviation to $\alpha < \tilde{\alpha}^*$ reduces the value of the objective function since it reduces the winning probability on this support. Therefore, the deviation of α from $(V_i - C)/(X_i + V_i - C)$ does not improve the objective function value on $\mathcal{S}_2$.

If $(V_i - C)/(X_i + V_i - C) < \tilde{\alpha}^*$ (let $\mathcal{S}_3$ be the support of Φ_j for this relation), the integrand of the expectation operator is non-positive and at $\alpha = (V_i - C)/(X_i + V_i - C)$, the integrand is zero. The deviation to $\alpha' < (V_i - C)/(X_i + V_i - C)$ or $(V_i - C)/(X_i + V_i - C) < \alpha' \leqslant \tilde{\alpha}^*$ does not change the value of the objective function. And the deviation to $\alpha > \tilde{\alpha}^*$ makes the integrand negative and reduces the value of the objective function. Again, the deviation of α from $(V_i - C)/(X_i + V_i - C)$ does not improve the objective function value on $\mathcal{S}_3$.

If $(V_i - C)/(X_i + V_i - C) = \tilde{\alpha}^*$ (let $\mathcal{S}_4$ be the support of Φ_j for this relation), the integrand of the expectation operator is zero regardless the value of the indicator function. Therefore, any deviation from $\alpha = (V_i - C)/(X_i + V_i - C)$ does not change the value of the objective function on $\mathcal{S}_4$.

In sum, on the whole support of Φ_j the deviation of α from $(V_i - C)/(X_i + V_i - C)$ does not improve the objective function value. Therefore, in the equilibrium it is weakly dominant that the optimal bids satisfy the relation $\alpha_i^* = (V_i - C_i^*)/(X_i + V_i - C_i^*)$.

Given this equilibrium relation between the cash and equity components of the bid, the value of the bid submitted to the target is $\alpha_i^*(X_i + V_i - C_i^*) + C_i^* = V_i$ should the bid be executed, which means that it is a weakly dominant strategy in the equilibrium for the acquirers to bid their true valuation of the target.

Substitute the equilibrium relation between the cash and equity components in a bid into the scoring rule (1) and use the equilibrium implication of truthful bid $V_i = \alpha_i^*(X_i + V_i - C_i^*) + C_i^*$. We can easily drive the updated scoring rule that incorporates the equilibrium implications:

$$z(C, \alpha, M) = \frac{\alpha M}{1 - \alpha} (1 - E[\varepsilon | C, \alpha, M; b^*(\cdot)]) + C.$$

□

It is theoretically interesting to show that an equilibrium with the above features is unique. However, formally proving the equilibrium's uniqueness is difficult and beyond the scope of this paper given its empirical focus. Nevertheless, it is reassuring that for any parameters we have considered, we have searched numerically and found no evidence of multiple equilibria.

A.3. Numerical Solution of Model

A.3.1. Solving the Equilibrium

The solution to the equilibrium described in Definition 1 is a functional fixed point $b^*(\cdot)$ defined on the space of (s, ε, k, M) that satisfies (2). We know from Proposition 1 that the optimal α and C satisfy the relation $\alpha_i^*(X_i + V_i - C_i^*) + C_i^* = V_i$. Therefore, we only need to solve the optimal cash offer $C^*(\cdot)$ and derive the optimal equity share $\alpha^*(\cdot)$ using this equilibrium relation. We adopt the following iterative procedure to solve for the optimal bidding rule $C^*(\cdot)$ and the implied scoring rule $z(\cdot)$.

We start with an initial guess of the bidding rule $C_0(\cdot) = k$, assuming that the acquirers exhaust their cash capacity k.[A1] In the subsequent iterations, based on the optimal bidding rule solved in iteration $t-1 \geqslant 0$, we derive the implied joint distribution $h_{t-1}(s, C, \alpha, M)$ and compute the target scoring rule $z_{t-1}(\cdot)$ as

$$z_{t-1}(C, \alpha, M) = 1 + \frac{\int_s s \cdot h_{t-1}(s, C, \alpha, M)\mathtt{d}s}{\int_s h_{t-1}(s, C, \alpha, M)\mathtt{d}s}.$$

We carry this scoring rule into iteration t and solve the optimal bidding rule using the equilibrium condition pertaining the bids:

$$\begin{aligned} C_t(s, \varepsilon, k, M) \quad = \quad \underset{C}{\text{argmax}} \int_{\Phi'} & [M(1-\varepsilon) + (1+s) - \tilde{C}_{t-1}] \times (\alpha - \tilde{\alpha}_{t-1}) \\ & \times \mathbb{I}_{t-1}(C, \alpha, M, \Phi')\mathtt{d}\mathcal{F}(\Phi'), \end{aligned}$$

where all variables with an apostrophe superscript belong to the rival acquirer; $\Phi = (s, \varepsilon, k, M)$ and $\mathcal{F}(\cdot)$ is the joint distribution of Φ; $\tilde{C}_{t-1} = \min\{C, \max\{1, z_{t-1}(b_{t-1}(\Phi'), M')\}\}$, $C \leq k$; α satisfies the equilibrium relation $\alpha = [(1+s) - C]/[M(1-\varepsilon) + (1+s) - C]$; $\tilde{\alpha}_{t-1} = 0$ if $C \geqslant \max\{1, z_{t-1}(b_{t-1}(\Phi'), M')\}$ and otherwise $\tilde{\alpha}_{t-1}$ is determined by $z_{t-1}(C, \tilde{\alpha}_{t-1}, M) = \max\{1, z_{t-1}(b_{t-1}(\Phi'), M')\}$; and indicator function $\mathbb{I}_{t-1}(\cdot)$ is defined as

$$\mathbb{I}_{t-1}(C, \alpha, M, \Phi') = \begin{cases} 1 & \text{if} \quad z_{t-1}(C, \alpha, M) \geqslant \max\{1, z_{t-1}(b_{t-1}(\Phi'), M')\} \\ 0 & \text{if} \quad \text{otherwise.} \end{cases}$$

We repeat this procedure until $\|C_t(\cdot) - C_{t-1}(\cdot)\| < \delta$, where δ is the criterion of convergence. To carry out the above iterative procedure, we discretize the state variable space as well as the space of (C, α, M) and iterate the computation on the grid.

A.3.2. Scoring Rule

After we solve the model numerically, we plot the scoring rule of the target in Fig. A.1 as a function of cash payment C (Panel a), equity fraction α (Panel b), and acquirer relative size M

[A1] Note that the model does not necessarily construct a contraction mapping equilibrium, so the initial guess of the optimal bidding rule is critical to the convergence of the fixed point algorithm. We pick the initial guess of the optimal bidding rule as to make the bidders follow a pecking order decision: they use as much cash as possible in the bids, and if the target value is larger than their cash capacity, they make the remaining payment with equity.

(Panel c). The blue solid lines depict the score assigned by the target, determined by Eq. (4) in the paper.

As discussed in the paper, cash payment and equity payment may induce different revelation effects, reflected by the term $E[\varepsilon|C, M, \alpha]$ in Eq. (4) in the paper. To illustrate the revelation effect, we construct a hypothetical score with the revelation effect held constant when we allow C or α to change (i.e., assume revelation effect is $E[\varepsilon|C = 0, M, \alpha]$ and $E[\varepsilon|C, M, \alpha = 0]$ in Panel (a) and (b), respectively). We compare this hypothetical score (red dash line) with the true score the target assigns to a bid (blue solid line), and the difference between the lines indicates the revelation effect. Fig. A.1 shows that the hypothetical score lies below the true score when C increases, indicating that more cash payment has a positive revelation effect. The hypothetical score lies above the true score when α increases, indicating that equity payment has a negative revelation effect.

The rest of this subsection explains the paper's claim that equity bids made by highly overvalued acquirers appear to be worth more than they truly are. In other words, the target assigns these bids a score Z that exceeds the bids' true value. We provide a simple numerical example followed by a plot from the full model.

Consider an example in which two bidders are drawn from the model distribution, $\mathcal{F}(\cdot)$, such that (1) they have the same relative size of one ($M_1 = M_2 = 1$), the same synergy of one ($s_1 = s_2 = 1$), and the same zero cash capacity ($k_1 = k_2 = 0$); (2) bidder one is overvalued and its true stand-alone value is 0.5; and (3) bidder two is undervalued and its true stand-alone value is 1.5. This precise information is private and not available to the target or the rival bidder. In the equilibrium, they both bid the true valuation and hence bidder one offers $\alpha_1 = 2/(0.5+2) = 4/5$ and bidder two offers $\alpha_2 = 2/(1.5 + 2) = 4/7$. Apparently, though they have the same synergy and their bids have the same true value, the bid made by the overvalued bidder (bidder one) appears more attractive to the target, because all else equal, a sweetened bid (higher equity offer given the same cash component) appears more valuable in the eyes of the target in the equilibrium.

In Fig. A.2 we show how the target's assessment of a bid's value (i.e., the score) varies with the bidder's misvaluation, assuming that the bidder submits its optimal bid (C, α, and M) and the target evaluates the bid based on its scoring rule. The red line depicts the score when the bidder has sufficient cash capacity for the bid and the blue line depicts the score when the bidder has zero cash capacity. The black dash line represents the true deal value $1 + s$. We assume the bidder has a $s = 0.62$ and a M equal to the median size.

When a bidder has sufficient cash (i.e., the red line), it chooses to pay all cash when its misvaluation ε is low. Since cash payment has no ambiguity, the score it receives equals to the true bid value $1 + s$. As its equity becomes more and more overvalued, the bidder starts to pay more and more equity even though it can afford to pay all cash. The score it receives increases and becomes higher than the true value of the bid, indicating that overvalued bidders make bids that appear more attractive than they really are, and in this way they manage to take advantage of their overvaluation. When the bidder has zero cash (i.e., the blue line), it has to pay all equity regardless of its misvaluation. When its equity is undervalued, the score it receives lies well below the true bid value, $1 + s$. That is, the bids from undervalued bidders appear less attractive than they really are. When its equity is overvalued, the score it receives becomes higher than the true bid value.

The red line and the blue lines converge once the two bidders' overvaluations are high enough, because with high overvaluation the bidders would optimally choose to pay all in equity regardless of their cash capacity. Since the two bidders have the same s and M, their bids would be exactly the same in this case. Note that the two lines meet when the misvaluation is around 0.11 instead of 0, because the bidder with sufficient cash capacity would begin choosing to use no cash at that point.

A.3.3. Announcement Returns

In most acquisitions, only one bidder is publicly announced. In our sample, 89% of initial bidders successfully acquired their targets. Therefore, to map our model to the data we assume that in our simulation the winning bidder becomes the initial bidder with a probability of 89% and the losing bidder becomes the initial bidder with a probability of 11%. Between the two bidders i and j, let bidder i be the announced bidder. To compute the abnormal announcement returns to the initial bidder and the target, as well as the combined abnormal abnormal return, we consider the following three cases.

1. No bidder eventually wins. Let $I_1 = I_1(M_{jn}, b_{jn}; M_{in}, b_{in})$ be the indicator of this case, where $b_{in} = (C_{in}, \alpha_{in})$. Then $E[I_1|M_{in}, b_{in}] = \Pr(\max\{Z_{in}, Z_{jn}\} < 1|M_{in}, b_{in})$. In this case, the abnormal return to the initial bidder is

$$AR^a_{in,1} = E[(1 - \varepsilon_{in})|M_{in}, b_{in}, I_1 = 1] - 1.$$

That is, the abnormal return only reflects the revision of the market value of the bidder given the announced bid. Since no bidder wins, the abnormal return to the target is zero. That is, $AR^t_{in,1} = 0$. And finally, the combined abnormal return is

$$AR^c_{in,1} = \frac{M_{in}E[(1 - \varepsilon_{in})|M_{in}, b_{in}, I_1 = 1]}{1 + M_{in}} - 1.$$

2. Bidder i eventually wins. Let $I_2 = I_2(M_{jn}, b_{jn}; M_{in}, b_{in})$ be the indicator of this case. Then

$$E[I_1|M_{in}, b_{in}] = \Pr(Z_{in} \geqslant \max\{1, Z_{jn}\}|M_{in}, b_{in}).$$

In this case, the abnormal return to the initial acquirer is

$$AR^a_{in,2} = (1 - \tilde{\alpha}_{in}) \cdot \frac{M_{in}E[(1 - \varepsilon_{in})|M_{in}, b_{in}, I_2 = 1] + E[(1 + s_{in})|M_{in}, b_{in}, I_2 = 1] - \tilde{C}_{in}}{M_{in}} - 1,$$

where $\tilde{C}_{in} = \min\{C_{in}, \max\{1, Z_{jn}\}\}$ and $\tilde{\alpha}_{in}$ is the equity share determined by the settlement rule discussed in Section 2.1. The abnormal return to the target is

$$AR^t_{in,2} = \tilde{C}_{in} + \tilde{\alpha}_{in}\left\{M_{in}E[(1 - \varepsilon_{in})|M_{in}, b_{in}, I_2 = 1] + E[(1 + s_{in})|M_{in}, b_{in}, I_2 = 1] - \tilde{C}_{in}\right\} - 1.$$

And finally, the combined abnormal return is

$$AR^c_{in,2} = \frac{M_{in}E[(1-\varepsilon_{in})|M_{in}, b_{in}, I_2 = 1] + E[(1+s_{in})|M_{in}, b_{in}, I_2 = 1]}{1+M_{in}} - 1.$$

3. Bidder j eventually wins. Let $I_3 = I_3(M_{jn}, b_{jn}; M_{in}, b_{in})$ be the indicator of this case. Then

$$E[I_3|M_{in}, b_{in}] = \Pr(Z_{jn} \geqslant \max\{1, Z_{in}\}|M_{in}, b_{in}).$$

In this case, the abnormal return to the initial bidder again only reflects the revision of its market value given the announced bid since it loses the contest.

$$AR^a_{in,3} = E[(1-\varepsilon_{in})|M_{in}, b_{in}, I_3 = 1] - 1.$$

The abnormal return to the target is

$$\begin{aligned} AR^t_{in,3} &= \tilde{C}_{jn} + \tilde{\alpha}_{jn}\Big\{M_{jn}E[(1-\varepsilon_{jn})|M_{jn}, b_{jn}, I_3 = 1] \\ &\quad + E[(1+s_{jn})|M_{jn}, b_{jn}, I_3 = 1] - \tilde{C}_{jn}\Big\} - 1, \end{aligned}$$

following the second-price auction setting, where $\tilde{C}_{jn} = \min\{C_{jn}, \max\{1, Z_{in}\}\}$ and $\tilde{\alpha}_{jn}$ is determined by the settlement rule discussion in Section 2.1. And the combined abnormal return in this case is

$$AR^c_{in,3} = \frac{M_{in}(1 + AR^a_{in,3}) + 1 + AR^t_{in,3}}{1+M_{in}} - 1 = \frac{M_{in}}{1+M_{in}}AR^a_{in,3} + \frac{1}{1+M_{in}}AR^t_{in,3}.$$

Since by the time of bid announcement the market does not know which case will happen, the announcement returns are computed as the weighted average of abnormal returns across different states. That is, we can compute the ex-ante abnormal announcement returns as follows.

$$\begin{aligned} AR^a_{in} &= E_j\left[I_1 \cdot AR^a_{in,1} + I_2 \cdot AR^a_{in,2} + I_3 \cdot AR^a_{in,3}|M_{in}, b_{in}\right] \\ AR^t_{in} &= E_j\left[I_1 \cdot AR^t_{in,1} + I_2 \cdot AR^t_{in,2} + I_3 \cdot AR^t_{in,3}|M_{in}, b_{in}\right] \\ AR^c_{in} &= E_j\left[I_1 \cdot AR^c_{in,1} + I_2 \cdot AR^c_{in,2} + I_3 \cdot AR^c_{in,3}|M_{in}, b_{in}\right] \end{aligned}$$

where the subscript j of the expectation operator indicates that the expectation is taken with respect to the state variables of the bidder j. Note, bidder j's state is given within the expectation operator of $E_j(\cdot)$. So the conditions of I_1, I_2, and I_3 in the announcement returns are redundant.

Empirically, the announced initial bidder wins with a probability of 89%. The market takes this information into account when they evaluate the deals. Therefore, the expectations above must be computed with the joint distribution conditional on this perception. Let $h(\Phi_j|b_i, M_i, J_i)$ be the joint distribution of the state variables of bidder j ($\Phi_j = \{s_j, \varepsilon_j, k_j, M_j\}$) conditional on the observation of the bid by bidder i and the fact that i is announced (J_i is the indicator). Then,

$$h(\Phi_j|b_i, M_i, J_i) = h(\Phi_j, Z_i > Z_j|b_i, M_i, J_i) + h(\Phi_j, Z_i < Z_j|b_i, M_i, J_i)$$

$$
\begin{aligned}
&= h(\Phi_j|b_i, M_i, J_i, Z_i > Z_j)\Pr(Z_i > Z_j|b_i, M_i, J_i) \\
&\quad + h(\Phi_j|b_i, M_i, J_i, Z_i < Z_j)\Pr(Z_i < Z_j|b_i, M_i, J_i) \\
&= h(\Phi_j|b_i, M_i, Z_i > Z_j) \times 0.87 + h(\Phi_j|b_i, M_i, Z_i < Z_j) \times 0.13
\end{aligned}
$$

where the last equality holds because conditional on $Z_i < Z_j$ or $Z_i > Z_j$, J_i does not have additional information on Φ_j. To complete the computation, note

$$
\begin{aligned}
h(\Phi_j|b_i, M_i, Z_i > Z_j) &= \frac{h(\Phi_j)\mathbb{I}(Z(b(\Phi_j), M_j) < Z(b_i, M_i))}{\Pr(Z(b(\Phi_j), M_j) < Z(b_i, M_i))} \\
h(\Phi_j|b_i, M_i, Z_i < Z_j) &= \frac{h(\Phi_j)\mathbb{I}(Z(b(\Phi_j), M_j) > Z(b_i, M_i))}{\Pr(Z(b(\Phi_j), M_j) > Z(b_i, M_i))}
\end{aligned}
$$

where $h(\Phi)$ is the unconditional joint distribution of the state variables, $\mathbb{I}(\cdot)$ is an indicator function that equals one if the argument is true and zero otherwise, $b(\cdot)$ the optimal bidding rule, and $Z(\cdot)$ is the scoring rule used by the target.

In the real data, in most cases we observe the cash as percentage of the *transaction value*. To translate it into a dollar amount, we need to define what the transaction value means in our model setting. For case two, it is unambiguous that the transaction value is the higher of the loser's score and the target's standalone value, $\max\{1, Z_{jn}\}$. In cases one and three, since the bidder loses, we map the transaction value as the own score, Z_{in}. The rationale is that in an ascending English auction, the last observed *bid* of the loser is its own valuation of the target. And with private valuation, the second-price sealed auction is equivalent to the ascending English auction both ex ante and ex post. As a summary, let c_{in} be the percentage of cash reported in the data, then

$$
C_{in} = \begin{cases} c_{in} \times \max\{1, Z_{jn}\} & \text{if } i \text{ wins,} \\ c_{in} \times Z_{in} & \text{if } i \text{ loses.} \end{cases}
$$

A.4. Comparing the Variances of Misvaluations and Synergies

One of our paper's main findings is that the high-synergy bidder almost always wins the auction. The explanation given in the paper is that $Stdev(s) \gg Stdev(\varepsilon)$, so it is almost always synergies rather than misvaluations that determine the auction's winner. This section explains why this explanation is correct.

The target chooses the bid with the higher score Z. The expression for Z is shown in the main paper's Eq. (1). If variation in synergies (s) rather than misvaluations (ε) drives most of the variation in Z, then it is almost always synergies rather than misvaluations that determine the auction's winner. To show that variation in synergies (s) rather than misvaluations (ε) drives most of the variation in Z, it would be sufficient (but not necessary) to show that (a) $Stdev(s) \gg Stdev(\varepsilon)$ and (b) Z is equally sensitive to ε and s. However, Z is not equally sensitive to ε and s, and in fact ε and s are not measured in the same units. (Variable s is measured as a fraction of target size, and ε is unitless, as we explain in the paper.) To compare the sensitivity of Z to s and ε, we ask how Z would change in response to a one-standard-deviation change in ε combined with a one-standard-deviation change in s. The change in Z would be approximately

$$\Delta Z = \frac{\partial z}{\partial \varepsilon} Stdev(\varepsilon) + \frac{\partial z}{\partial s} Stdev(s).$$

Eq. (1) in the paper shows that ε and s affect Z via their effects on the choice of C and α, and this relation depends also on M. We cannot compute the partial derivatives above in closed form, and their values vary across the state space. We therefore compute the derivatives' values numerically, and we summarize their values across a simulated sample from the estimated baseline model. We find that the ratio $\left|\frac{\partial z/\partial \varepsilon}{\partial z/\partial s}\right|$ has a mean of 1.3 and a standard deviation of 0.7. Its value almost never exceeds 2.5. This result implies that, on average, Z is 1.3 times more sensitive to ε than to s, and it is almost never more than 2.5 times more sensitive. Recall we estimate $Stdev(\varepsilon) = 7\%$ and $Stdev(s) = 44\%$. Even if we use the ratio's upper bound of 2.5, we still find that $Stdev(s) \gg 2.5 \times Stdev(\varepsilon)$. It follows that most of the variation in scores Z, and hence auction outcomes, comes from variation in synergies rather than misvaluations.

A.5. Results Without Bayesian Updating by the Target

In Section 4.3 of the main paper, we ask how the average synergy loss would change if targets did not update their beliefs about bidder misvaluation upon seeing the bid's method of payment. First, we assume targets score bids as in Eq. (1), except targets set $E[\varepsilon_i|C_i, \alpha_i, M_i] = 0$. In other words, targets behave as if bidders were fairly valued. Second, we solve for bidders' optimal response to the target's revised scoring rule. We plot the optimal bidding rule in Fig. A.3, which is analogous to Fig. 1 in the main paper. Bidders respond to targets' naïve behavior by bidding with all equity if the bidder is overvalued (i.e., $C^* = 0$ if $\varepsilon > 0$), and by bidding with as much cash as possible when the bidder is undervalued (i.e., $C^* = \min(1 + s, k)$ if $\varepsilon < 0$). Intuitively, if targets no longer penalize bidders for paying with equity, overvalued bidders will try to dump as much equity as possible onto the target. We simulate data from this revised model, keeping all parameters at their estimated values. With naïve targets, we find that 9.75% of deals are inefficient, and the average synergy loss among these inefficient deals is 14.16% of the target's size. The unconditional average synergy loss is 1.38% of target size, which equals 9.75% × 14.16%. For comparison, in our main results with rational targets, we find that 7.01% of deals are inefficient, the average synergy loss in inefficient deals is 9.02% of target size, and the unconditional average synergy loss is 0.63% of target size (Table 5).

A.6. Results from Overidentified SMM

In the paper's main analysis we use eight moments to identify eight model parameters (i.e., exact identification). To assess the robustness of our results to the choice of moments, we consider an overidentified model that includes three additional moments from the subsample of all-cash bids. These moments are the mean and conditional variance of offer premium and the mean acquirer announcement return, all computed within the subsample in which the initial bidder offers an all-cash bid.

We choose these additional moments for the following reasons. In all-cash bids, the target does not need to learn about the degree of acquirer misvaluation, because the value of cash is unambiguous. Also, we know the bidder's cash constraint is not binding. Therefore, the distribution of offer premiums and acquirer announcement returns in this subsample may be especially informative about the distribution of synergies. Also, the all-cash subsample represents the outcome of an endogenous selection effect in our model—bidders optimally choose their bids and the method of payment based on their characteristics, i.e., misvaluation, cash capacity, and synergy. These variables' distributions affect which bidders choose to pay all in cash, so the properties of the all-cash subsample are informative about the parameters controlling these distributions.

Table A.3 confirms the intuition above by showing the sensitivity of the extra moments to the model's parameters. We show that, as expected, the average offer premium and acquirer announcement return within the all-cash bids are indeed sensitive to the parameter μ_s (i.e., the mean of the synergy), and the variance of offer premium within the all-cash bids is sensitive to the parameter σ_s (i.e., the standard deviation of the synergy). The table also indicates that the average offer premium in the all-cash subsample is sensitive to the standard deviations of misvaluation and cash capacity. This sensitivity results from the endogenous selection effect described above. To see this, note that the difference in average offer premium between the full sample and the all-cash subsample to some extent reflects the full-sample dispersion in bidder characteristics. For the same reason, we find that the subsample average of acquirer announcement return is also informative about the dispersion of misvaluation.

Comparing Tables A.3 and 2, we see that the magnitudes of the sensitivities for the eight original moments used in our main analysis decrease when we add the three extra moments. This change, however, does not indicate that the eight moments become less sensitive to the parameters when we include the three extra moments. Note that the tables' sensitivity measures are adjusted by the standard deviation of the parameters divided by the standard deviation of the moments. The decrease in magnitude is almost completely due to the decrease in parameters' standard deviations that occurs when we include extra moments in the SMM procedure.

We report SMM results from the overidentified model in Table A.4. In Panel A, we show the model fit by reporting both the data moments used in the estimation and their model counterparts. The original eight moments and the three extra moments are all matched reasonably well. None of the differences between the data moments and their model counterparts is statistically significant.

More important, the economic magnitudes of the differences are all quite small. It is comforting that the model can match properties of the offer premium and acquirer announcement return in both the full sample and the all-cash subsample. This result suggests that the model does a good job of capturing the endogenous selection effects described above. With three more moments than parameters, we can now assess the overall model fit using a J-test. The test shows that our model can be rejected at the 5% confidence level but not at the 1% level. However, the rejection of the model is mainly due to the high precision (i.e. low standard errors) of the empirical moments, not large gaps between the empirical and simulated moments.

In Panel B of Table A.4, we report the parameter estimates, which we have transformed as in Table 4 to make them easier to interpret. Using the expanded set of moments has almost no effect on our parameter estimates. Comparing the estimates between Table 4 and Table A.4, we see that the parameter estimates barely change. The largest percent change in a parameter's value is for $Stdev(\varepsilon)$, which decreases in value from 0.070 to 0.065. Adding the extra moments increases the standard errors for some parameters while decreasing the standard errors of others.

We also report the estimated inefficiencies in Panel C of Table A.4. Compared with the baseline results, we find that the percentage of inefficient deals, the average loss in inefficient deals, and the average loss in all deals all become slightly smaller. For example, the average synergy loss decreases from 0.63% to 0.52%. This decrease is due to the slight decrease in the estimated value of $Stdev(\varepsilon)$.

To summarize, adding three additional moments to the SMM estimation does not significantly change the model fit, parameter estimates, or estimated inefficiency. Our paper's main conclusions are therefore robust to adding these extra moments.

A.7. Additional Details on Paper's Table 8

This section provides additional details about the robustness exercises from Table 8 in the main paper.

- Specification 2 extends our main model to account for the effect of target misvaluation on the target's reservation price. We add the following assumptions to our main model. The target's fundamental value equals its market value times by $1-\delta$. The bidder observes δ but the market does not. Everyone understands that δ follows a normal distribution $\mathcal{N}_\delta(\mu_\delta, \sigma_\delta^2)$. For the target to accept a bid, the bid must exceed the target's market value and fundamental value. Therefore, the target's reservation price equals its market value times $\max\{1,\ 1-\delta\}$. The winning bidder must pay whichever is greater, the second highest bid or the target's reservation price.

- Specification 3: When measuring our moments, we supplement *Controls* with eight bidder characteristics, three proxies for the target's information about the bidder's value, and two proxies for the external pressure to pay in cash. Bidder characteristics include the bidder's size (log of book assets), leverage, cash holdings scaled by assets, market to book equity ratio, a dividend-payer dummy, R&D expenditure scaled by assets, asset tangibility, and return on assets. All eight characteristics are constructed exactly following Eckbo et al. (2017). Our proxies for the target's information include a local deal dummy that indicates whether the target and the bidder are located within 25 miles of each other, a recent SEO and acquisition dummy that indicates whether the bidder has SEOs or other acquisitions 24 months around the bid announcement, and a horizontal merger dummy that indicates whether the target and the bidder are in the same Fama-French 48 industry. Our two proxies for external pressure to pay in cash capture the competition from private buyers and competition among industry peers. The former is the fraction of all merger bids in the target's Fama-French 48 industry and year in which the bidder is private, and the latter is measured by the Herfindahl Hirschman Index (HHI) for the bidder's industry. We re-estimate the model using the updated moments, then compute the new model implications.

- Specification 4 allows more than two bidders. To do so, we keep the parameter estimates and model solution unchanged except in each contest we simulate multiple bidders (3, 4, or 5, as shown in the table).

- Specification 5 uses our main model's assumptions but simulates contests with a random number of bidders, i.e., random N. We assume $\Pr\{N=1\}=0.5$, $\Pr\{N=2\}=0.25$, and $\Pr\{N=4\}=0.25$. Using these altered assumptions, we re-estimate the model's parameters.

- Specification 6 allows negative synergies by moving the model's lower bound of synergies (s) from 0 to -0.2. We then re-estimate the model and compute the model implications. When s can be negative, there are two types of inefficiencies. The first type of inefficiency is the same as in our baseline model: the winner has a non-negative s, but the winner's s is lower than the loser's s. The second type of inefficiency is that the winner has a negative s. We define efficiency loss as the difference between the winner's s and the loser's s in the first type of inefficient deals, and as the gap between the winner's s and the maximum of zero and the loser's s in the second type of inefficient deals. The table reports the sum of the two inefficiencies.

- Specification 7 assumes that the synergy of competing bidders are correlated. We keep the parameter estimates and model solution unchanged, except we simulate bidders with correlated synergies s.

- Specification 8 allows the bidder's misvaluation to be correlated with its cash capacity. We set the correlation to the value shown in the table, then we re-estimate the model and recompute its implications.

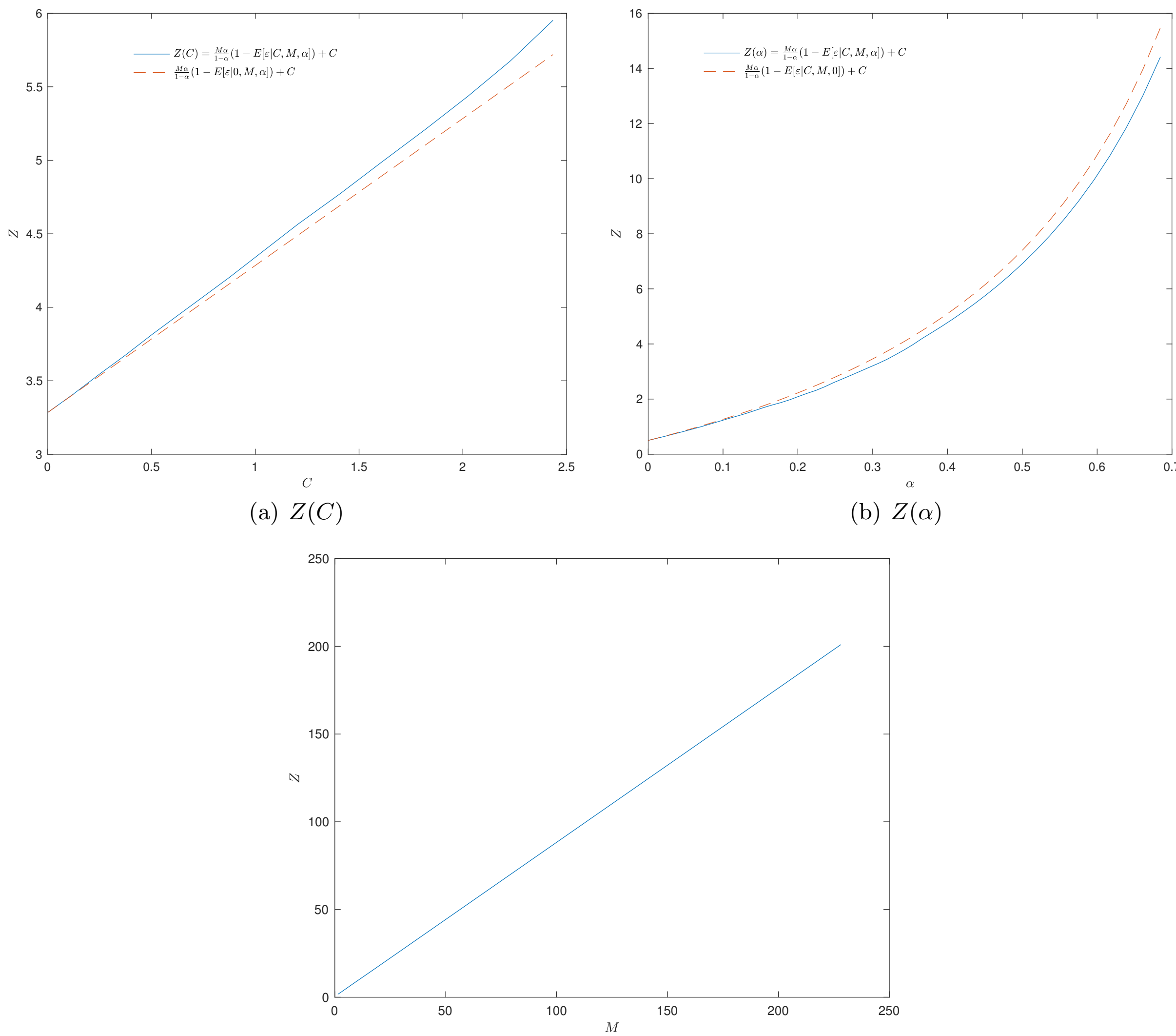
- Specification 9 controls for the negative price pressure induced by M&A arbitrageurs on acquirers' announcement returns in equity or mixed deals. We use the method of Mitchell et al. (2004) to estimate the predicted change in short interest of acquirer stocks for equity or mixed bids, and we include the predicted change in the vector *Controls* in regression (6). We also cut the average acquirer announcement returns to half following Mitchell et al. (2004). We re-estimate the model using the updated data moments and characterize the model implications based on the new parameters.

- Specification 10 estimates the model after replacing the offer premium with the target's announcement return. This change affects the values of both the simulated and data moment.

- Specification 11 re-estimates the model using 11 moments instead of 8. The extra 3 moments are the mean and conditional variance of offer premium and the mean of the acquirer's announcement return, all computed within the sample of all-cash bids. Additional details and estimation results from this exercise are in Online Appendix Section A.6.

- Specification 12 replaces the offer premium reported by SDC with an alternative measure computed following Officer (2003). Specifically, we first obtain different components of payment offered to target shareholders from SDC (cash, equity, debt, etc). Then we compute a premium measure using the aggregate amount of each form of payment, scaled by the target's market value of equity 23 trading days prior to the bid announcement. Finally, we follow Officer (2003) and calculate the offer premium as the combined premium as follows: It is equal to the premium from the component data if that number is between zero and two; if it is not, the combined premium is set to the premium reported by SDC if this provides a number between zero and two; if neither condition is met, the combined premium is left as missing. We also update the observations in SDC with missing data on the method of payment whenever they become available based on Officer (2003). We re-estimate the model using the updated data moments and characterize the model implications based on the new parameters.

- Specification 13 re-estimates the model after reducing the conditional variance of offer premium measured in data by half. We also reduce the loading of offer premium on $\log(M)$ by $1/\sqrt{2}$. We re-estimate the model using the updated data moments and characterize the model implications based on the new parameters.



(a) $Z(C)$

(b) $Z(\alpha)$

(c) $Z(M)$

Figure A.1: Scoring Rule

This figure illustrates how the target's assessment of a bid's value (i.e., the scoring rule) varies with the observed bid characteristics, C (Panel a), α (Panel b), and M (Panel c). The red dash lines in Panel (a) and Panel (b) represent the hypothetical score if the revelation effect is held constant when C and α change. The blue solid lines depict the true score with the target's rational expectation of the revelation effect.

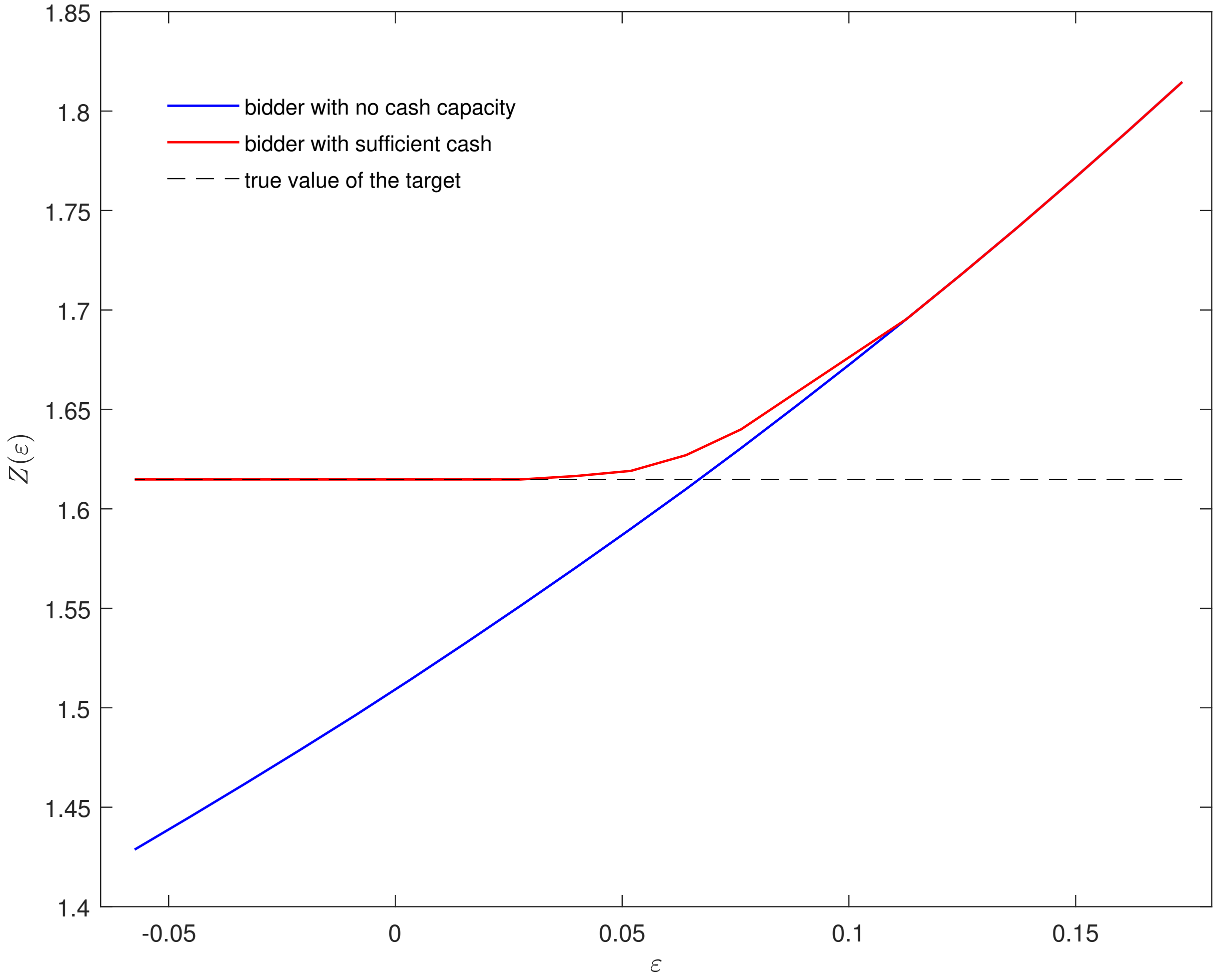


Figure A.2: Score of the Bid with Different Bidder's Misvaluation

This figure illustrates how the target's assessment of a bid's value (i.e., the scoring rule) varies with the bidder's misevaluation ε, assuming that the bidder submits its optimal bid (C, α, and M) and the target evaluates the bid based on its scoring rule. The red line depicts the score when the bidder has sufficient cash capacity for the bid and the blue line depicts the score when the bidder has zero cash capacity. The black dash line represents the true deal value $1 + s$. We assume the bidder has a $s = 0.6$ and a M equal to the median size.

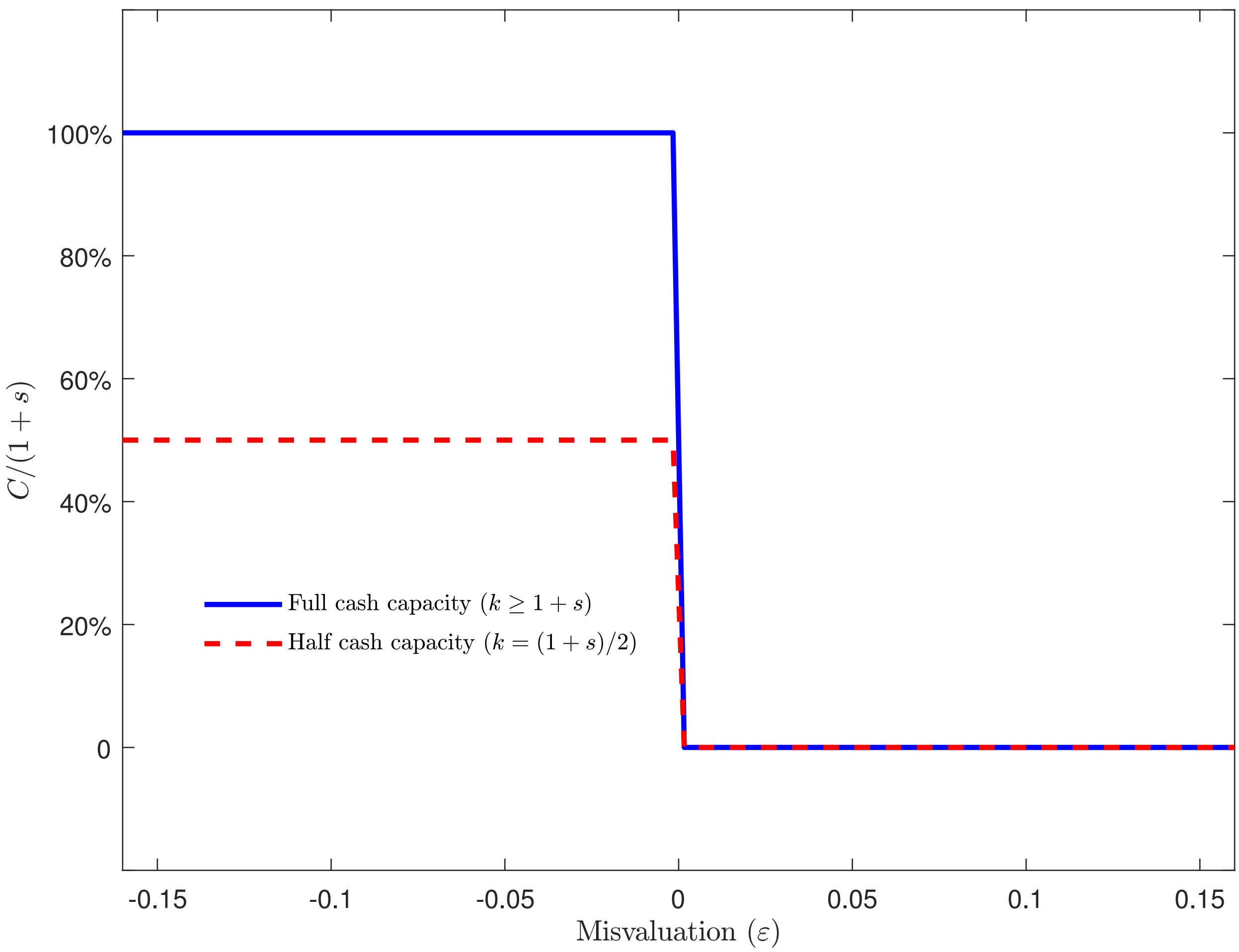


Figure A.3: Cash Fraction in the Optimal Bid When Targets Are Naive

This figure is the same as Fig. 1 in the main paper, except we assume that targets do not use Bayes' Rule to update beliefs about bidder misvaluation upon observing the bid's method of payment.

Table A.1: Robustness - Moments with Additional Controls

This table reports how the data moments used in SMM estimation would change if we added additional variables to the vector *Controls* in regression (5)-(7) in the main paper. The columns under Full Sample are the moments based on the baseline method; the columns under E-index Sample are the moments computed with and without *E*-index included as a control variable; the columns under Blockholder Sample are the moments computed with and without the percentage of shares held by blockholders included as a control variable; and the columns under TarFounder CEO Sample are the moments computed with and without the dummy indicating whether the target CEO is the founder CEO included as a control variable. The first moment, Mean *OfferPrem*, is the average offer premium. The second moment is the conditional variance of offer premia, measured using regression (5). The third moment is a_1, the slope coefficient of offer premium on the logarithm of relative firm size, also from regression (5). The fourth moment, Mean *AcqAR*, is the average acquirer announcement return. The fifth moment is b_1, the slope coefficient of acquirer announcement return on the fraction of cash used in the bid, from regression (6). The sixth moment, Mean *CashFrac*, is the average fraction of cash in bids. The seventh moment is the conditional variance of *CashFrac*, measured using regression (7). The eighth moment is c_1, the slope coefficient of cash usage on the logarithm of relative firm size, from regression (7).

		E-index Sample		Blockholder Sample		TarFounder CEO Sample	
Moment	Full Sample	excld. as ctrl	incld. as ctrl	excld. as ctrl	incld. as ctrl	excld. as ctrl	incld. as ctrl
Mean *OfferPrem*	0.437	0.393	0.393	0.431	0.431	0.411	0.411
Cond. Var. of *OfferPrem*	0.085	0.050	0.050	0.081	0.081	0.042	0.042
Slope of *OfferPrem* on $\log(M)$	0.033	0.039	0.040	0.032	0.033	0.014	0.014
Mean *AcqAR*	−0.023	−0.026	−0.026	−0.024	−0.024	−0.032	−0.032
Slope of *AcqAR* on *CashFrac*	0.031	0.041	0.040	0.027	0.027	0.032	0.031
Mean *CashFrac*	0.306	0.419	0.419	0.298	0.298	0.228	0.228
Cond. Var. of *CashFrac*	0.119	0.093	0.092	0.115	0.115	0.062	0.062
Slope of *CashFrac* on $\log(M)$	0.050	0.069	0.076	0.052	0.052	0.022	0.022
Number of Observations	2,503	459	459	2,236	2,236	249	249

Table A.2: Robustness – Implied Bidder Characteristics in Additional Subsample Analysis

This table reports the bidder characteristics implied by the estimated parameters from estimating the model in different subsamples. The subsample of low (high) acquirer entrenchment index is comprised of M&A contests in which the acquirer's E-index value is below (above) the median. The subsample of low (high) acquirer blockholder ownership contains M&A contests in which the fraction of the acquirer's shares held by a blockholder, defined as a shareholder with at least a 5% block, is below (above) the median. The subsample of horizontal (diversifying) mergers is comprised of M&A contests in which the acquirer and target belong to the same (unrelated) industry. We define a horizontal merger as one in which the target and acquirer belong to the same four-digit SIC industry, and a diversifying merger as one that is neither horizontal nor vertical. Following Fan and Goyal (2006), we define a vertical merger as one in which the acquirer and target industries are different and yet connected, as measured by the BEA input-output tables. The subsamples based on acquirer CEO overconfidence use the Malmendier and Tate (2005) option-based measure, closely following the implementation by Humphery-Jenner et al. (2016). Subsample 6 excludes from the full sample all deals in which the acquirer is involved in another M&A or had equity issuance in the window of $[-12, 12]$ months around the deal announcement. Subsample 7 excludes from the full sample all deals in which the target's asset intangibility measure ranks in the top quintile. We measure intangibility as in Section 4.4. Subsample 8 excludes 280 contests that do not result in the purchase of the target firm.

	E$[s]$	SD$[s]$	E$[\varepsilon]$	Stdev$[\varepsilon]$	E$[k]$	Stdev$[k]$	r_{sM}	r_{kM}
1. Full sample	0.676	0.444	0.058	0.070	0.869	1.034	0.386	0.441
2. Entrenchment								
Low	0.622	0.395	0.055	0.081	0.690	0.749	0.369	0.464
High	0.590	0.356	0.049	0.070	0.706	0.650	0.450	0.466
3. Acquirer blockholder ownership								
Low	0.702	0.457	0.049	0.089	0.893	1.037	0.393	0.388
High	0.691	0.443	0.053	0.079	0.877	1.035	0.411	0.481
4. Merger types								
Horizontal	0.663	0.421	0.048	0.072	0.794	0.906	0.465	0.464
Diversification	0.716	0.452	0.056	0.081	0.864	0.940	0.426	0.469
5. Acquirer CEO Overconfidence								
Yes	0.612	0.392	0.060	0.072	0.691	0.749	0.387	0.461
No	0.572	0.350	0.057	0.071	0.759	0.763	0.308	0.482
6. No M&A or SEO surrounding deal	0.637	0.393	0.055	0.062	0.622	0.693	0.439	0.372
7. Excld. high-intangibility targets	0.644	0.418	0.055	0.063	0.698	0.814	0.437	0.381
8. Excluding failed bids	0.694	0.453	0.051	0.080	1.083	1.208	0.394	0.489

Table A.3: Sensitivity of Moments to Parameters in Overidentified SMM

This table shows the sensitivity of model-implied moments (in columns) with respect to model parameters (in rows). To make the sensitivities comparable across parameters and moments, we scale the sensitivities by a ratio of standard errors. The table contains the values of $\frac{dm}{dp}\frac{Stderr(p)}{Stderr(m)}$, where $\frac{dm}{dp}$ is the derivative of simulated moment m with respect to parameter p (evaluated at estimated parameter values), $Stderr(p)$ is the estimated standard error for parameter p, and $Stderr(m)$ is the estimated standard error for the empirical moment m (from Table A.4). The first moment is $E[OfferPrem_i]$, the average offer premium. The second moment is $Var(u_i)$, the conditional variance of offer premia, measured using regression (5). The third moment is a_1, the slope coefficient of offer premium on the logarithm of relative firm size, also from regression (5). The fourth moment is $E[AcqAR_i]$, the average acquirer announcement return. The fifth moment is b_1, the slope coefficient of acquirer announcement return on the fraction of cash used in the bid, from regression (6). The sixth moment is $E[CashFrac_i]$, the average fraction of cash in bids. The seventh moment is $Var(w_i)$, the conditional variance of $CashFrac$, measured using regression (7). The eighth moment is c_1, the slope coefficient of cash usage on the logarithm of relative firm size, from regression (7). The ninth moment is $E[OfferPrem_i|All\ Cash]$, the average offer premium of the all-cash bids. The tenth moment is $Var[u_i|All\ Cash]$, the conditional variance of offer premium within the all-cash bids. The last moment is $E[AcqRet_i|All\ Cash]$, the average acquirer announcement return among the all-cash bids. Parameter definitions are as follows. Synergy s is assumed to follow a normal distribution $\mathcal{N}(\mu_s, \sigma_s^2)$ that is left-truncated at zero. The misvaluation factor ε is assumed to follow a normal distribution $\mathcal{N}(\mu_\varepsilon, \sigma_\varepsilon^2)$. Cash capacity is assumed to follow a normal distribution $\mathcal{N}(\mu_k, \sigma_k^2)$ that is left-censored at zero. Parameter ρ_{sM} is the Spearman's rank correlation between synergy and acquirer relative size. Parameter ρ_{kM} is the Spearman's rank correlation between cash capacity and acquirer relative size.

	Offer Premium			Acquirer Ann. Return		Fraction of Bid in Cash			All-Cash Subsample		
Parameter	Mean	Cond. Var.	Slope on $\log(M)$	Mean	Slope on Cash Frac	Mean	Cond. Var.	Slope on $\log(M)$	Mean of Prem.	Cond. Var. of Prem.	Mean of AcqRet
μ_s	0.658	0.422	0.065	0.225	−0.029	−0.033	0.247	−0.252	0.341	0.529	0.411
σ_s	0.419	0.748	0.104	0.284	−0.355	0.019	−0.322	0.050	0.093	0.858	0.172
ρ_{sM}	−0.121	−0.204	0.980	−0.416	0.102	−0.162	−0.342	−0.199	−0.053	−0.030	−0.219
μ_ε	−0.008	0.041	−0.108	−0.744	−0.005	−0.034	0.055	0.099	−0.135	0.253	−0.458
σ_ε	0.014	−0.048	0.131	−0.193	0.627	−0.181	−0.465	−0.105	0.669	−0.180	0.485
μ_k	0.158	0.051	−0.102	0.279	0.115	0.657	0.372	−0.170	0.435	0.190	0.250
σ_k	0.026	−0.061	0.021	−0.101	0.402	−0.033	0.593	−0.144	0.876	−0.373	−0.009
ρ_{kM}	−0.269	−0.219	0.290	−0.098	−0.660	−0.186	−0.417	0.600	−0.312	0.044	−0.638

Table A.4: Results from Overidentified SMM

This table reports the results of SMM estimation with three additional moments. Panel A shows how well the model fits the eleven moments targeted in SMM estimation. The first moment is $E[OfferPrem_i]$, the average offer premium. The second moment is $Var(u_i)$, the conditional variance of offer premia, measured using regression (5). The third moment is a_1, the slope coefficient of offer premium on the logarithm of relative firm size, also from regression (5). The fourth moment is $E[AcqAR_i]$, the average acquirer announcement return. The fifth moment is b_1, the slope coefficient of acquirer announcement return on the fraction of cash used in the bid, from regression (6). The sixth moment is $E[CashFrac_i]$, the average fraction of cash in bids. The seventh moment is $Var(w_i)$, the conditional variance of $CashFrac$, measured using regression (7). The eighth moment is c_1, the slope coefficient of cash usage on the logarithm of relative firm size, from regression (7). The ninth moment is $E[OfferPrem_i|All\ Cash]$, the average offer premium of the all-cash bids. The tenth moment is $Var[u_i|All\ Cash]$, the conditional variance of offer premium within the all-cash bids. The last moment is $E[AcqRet_i|All\ Cash]$, the average acquirer announcement return among the all-cash bids. Standard errors for the data moments are in parentheses. Panel B reports the quantities implied by the parameter estimates from SMM. E[s], E[ε], and E[k] are the implied means of synergy, misvaluation, and cash capacity, respectively. Stdev[s], Stdev[ε], and Stdev[k] are the implied standard deviations of synergy, misvaluation, and cash capacity, respectively. r_{sM} and r_{kM} are the implied Pearson's linear correlations between the subscripted variables. Panel C reports the model implications. Percent of deals inefficient is the percent of simulated deals in which the low-synergy bidder wins; Avg. loss in inefficient deals is the average synergy loss across all inefficient deals; and Avg. loss in all deals is the average synergy loss across all deals. Both average losses are measured as a percent of the target's pre-acquisition market value.

	Panel A: Model Fit										
	Offer Premium			Acquirer Ann. Return		Fraction of Bid in Cash			All-Cash Subsample		
Parameter	Mean	Cond. Var.	Slope on log(M)	Mean	Slope on Cash Frac	Mean	Cond. Var.	Slope on log(M)	Mean of Prem.	Cond. Var. of Prem.	Mean of AcqRet
Data	0.437	0.085	0.033	−0.023	0.031	0.306	0.119	0.050	0.479	0.079	0.004
Standard error	(0.016)	(0.006)	(0.004)	(0.004)	(0.005)	(0.028)	(0.007)	(0.009)	(0.019)	(0.011)	(0.004)
Model	0.432	0.085	0.031	−0.023	0.024	0.284	0.117	0.040	0.503	0.081	0.006
Difference	−0.005	0.000	−0.002	0.001	−0.007	−0.022	−0.002	−0.010	0.024	0.002	0.002
t-stat	−0.307	0.057	−0.523	0.174	−1.354	−0.799	−0.312	−1.130	1.254	0.184	0.525
Overidentification test	χ^2	10.34		p-value	0.02						
	Panel B: Quantities Implied by Parameter Estimates										
	E[s]	Stdev[s]	E[ε]	Stdev[ε]	E[k]	Stdev[k]	r_{sM}	r_{kM}			
Estimate	0.678	0.445	0.054	0.065	0.893	1.040	0.403	0.457			
Standard error	(0.017)	(0.013)	(0.003)	(0.005)	(0.070)	(0.070)	(0.032)	(0.037)			
	Panel C: Model Implications										
Percent of deals inefficient	6.25										
Avg. loss in inefficient deals (%)	8.31										
Avg. loss in all deals (%)	0.52										

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