Inefficiencies and Externalities from Opportunistic Acquirers *

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Abstract

If opportunistic acquirers can buy targets using overvalued shares, then there is an inefficiency in the merger and acquisition (M&A) market: The most overvalued rather than the highest-synergy bidder may buy the target. We quantify this inefficiency using a structural estimation approach. We find that the M&A market allocates resources efficiently on average: Opportunistic bidders crowd out high-synergy bidders in only 7% of transactions, resulting in an average synergy loss equal to 9% of the target's value in these inefficient deals. The implied average loss across all deals is 0.6%. Although the inefficiency is small on average, it is large for certain deals, and it is larger in times when misvaluation is more likely. Even when opportunistic bidders lose the contest, they drive up prices, imposing a large negative externality on the winning synergistic bidders.

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1 Introduction

In 2000, AOL acquired Time Warner in a deal "usually described as the worst merger of all time."[1] AOL paid with shares whose value dropped by almost 90% in the subsequent two years, raising the possibility that AOL's managers did the deal precisely because they knew they could pay using overvalued shares. The merger clearly transferred value from Time Warner to AOL shareholders ex post. The merger may have also destroyed value overall: AOL potentially crowded out an alternate acquirer that had a higher real synergy with Time Warner.

In general, if a firm believes its shares are overvalued, it has an incentive to opportunistically acquire other firms using its shares as currency (Rhodes-Kropf and Viswanathan, 2004; Shleifer and Vishny, 2003). This behavior creates an inefficiency: If opportunistic, overvalued acquirers crowd out acquirers with higher real synergies, then target firms may not get matched with the highest-synergy acquirers. The literature has raised concerns about this inefficiency, but it remains unclear whether the inefficiency is large or small.[2] It could be large, because researchers have already provided evidence that misvaluation is an important motive for acquisitions,[3] and because the M&A market is very large ($1.04 trillion in deal volume for U.S. public acquirers in 2014). Our main contribution is to show that the aggregate inefficiency from opportunistic acquirers is actually quite modest, meaning the M&A market usually allocates resources efficiently. We do find, however, that the inefficiency is large for certain deals, and it is larger in times when misvaluation is more likely. We also show that misvaluation results in a large redistribution of merger gains across acquirers, and it makes cash valuable to synergistic acquirers.

Quantifying these effects is difficult. Stock misvaluation and synergies are not directly observable. More importantly, the M&A transactions observed in the data are outcomes of an equilibrium in which acquirers and targets act strategically. To assess the inefficiency from opportunistic acquirers, we need to observe what would have happened in a parallel, counterfactual

[1] http://fortune.com/2015/01/10/15-years-later-lessons-from-the-failed-aol-time-warner-merger/

[2] For example, Eckbo, Makaew, and Thorburn (2015) write, "Understanding the likelihood that bidders get away with selling overpriced shares is important not only for the parties to mergers negotiations, but more generally for the debate over the efficiency of the market for corporate control.... The extant takeover literature is split on this issue...."

[3] Several studies provide empirical evidence consistent with misvaluation-driven merger waves (Ang and Cheng, 2006; Bouwman, Fuller, and Nain, 2009; Rhodes-Kropf, Robinson, and Viswanathan, 2005). Other studies have linked proxies for misvaluation with the decision to become an acquirer or target, the chosen method of payment, and acquisition performance (Ben-David et al., 2015; Bouwman, Fuller, and Nain, 2009; Dong et al., 2006; Fu, Lin, and Officer, 2013; Savor and Lu, 2009; Vermaelen and Xu, 2014).

world in which acquirers were not opportunistic. Measuring this counterfactual is difficult, because it is hard to find exogenous shocks that prevent acquirers from acting opportunistically. Even if there were such a shock, it is likely to be limited in scope, raising concerns about external validity.

We overcome these challenges by estimating a structural model of M&A contests. Our model is related to that of Rhodes-Kropf and Viswanathan (2004). Potential acquirers in the model compete in a second-price auction to buy a target firm. A bidder's shares can be misvalued, for example, because of managers' private information or a stock-market inefficiency. The bidders and target maximize expected profits and are fully rational, but the target cannot observe bidders' synergies or the misvaluation of the bidders' shares. Since targets have limited information, bids made by overvalued acquirers often appear more attractive to the target than they really are. An overvalued acquirer with a low synergy may therefore win the auction, inefficiently crowding out a high-synergy acquirer.

This crowd-out problem stems from the target's confusion when evaluating equity bids from acquirers with different unobservable synergies and misvaluations. Paying with cash can mitigate these problems, because cash's value is unambiguous. We therefore extend the model of Rhodes-Kropf and Viswanathan (2004) so that bidders can optimally use both cash and shares as a method of payment. Cash is especially valuable to undervalued bidders, because they can signal their undervaluation by offering cash instead of shares. Financing constraints limit bidders' access to cash, forcing some bidders to finance at least part of the deal using shares. Cash constraints are not perfectly observable, however, which limits undervalued acquirers' ability to separate themselves from overvalued acquirers. This limitation aggravates the target's confusion and makes the crowd-out inefficiency more severe.

The model imposes no priors on whether M&A deals are driven primarily by synergies or misvaluation. The inefficiency in the model could be large, small, or even zero depending on parameter values. We let the data tell us how large the inefficiency is. We do so by estimating the model's parameters using the simulated method of moments (SMM). Our dataset includes 2,503 U.S. M&A contests involving public acquirers and targets from 1980 to 2013. The key parameters to estimate are the dispersion across bidders' synergies, cash capacities, and misvaluations. The dispersion across deals' observed offer premia helps identify the dispersion in synergies, while the dispersion in observed cash usage helps identify the dispersion in cash capacity. The dispersion in misvaluation is mainly identified off the well-documented positive relation between an acquirer's announcement return and its use of cash in the bid.[4] This positive relation emerges from our model, because the market infers from a cash bid that the bidder's equity is not likely to be overvalued, causing the bidder's share price to increase. The predicted relation is especially positive when there is more dispersion in misvaluation, which helps identify this key parameter. Overall, the model can closely fit the distribution of offer premia and cash usage, as well as their relation to deal size. The model also closely fits the relation between bidders' announcement returns and method of payment.

We use the estimated model to quantify the inefficiencies from opportunistic acquirers. By simulating data off the model, we find that an overvalued bidder crowds out a bidder with a higher synergy in 7.0% of simulated deals. These deals are inefficient in the sense that the high-synergy bidder would always win in an ideal, counterfactual world with no misvaluation. In the 7.0% of deals that are inefficient, the winner's synergy is on average 15.8% below the loser's synergy, which amounts to an average synergy loss equal to 9.0% of the target's pre-announcement market value. Averaging across all deals (efficient and inefficient), the aggregate efficiency loss is 0.63% of the target's pre-announcement value, with a standard error of 0.19%. The main reason we find a small efficiency loss is that the estimated dispersion in synergies is many times larger than the dispersion in misvaluation. As a result, high-synergy acquirers outbid their (potentially overvalued) competitors about 93% of the time, producing efficient deals.

While the unconditional average loss we find is low in percentage terms, it translates to a nontrivial $4.4 billion in lost synergies per year in deals made by U.S. public acquirers.[5] Also, the loss is quite high for certain deals and for subperiods with high misvaluation risk. For example, at the 90th percentile among inefficient deals, the winner's synergy is 36% below the loser's synergy, amounting to a synergy loss equal to 20% of the target's pre-announcement market

[4] Examples inlcude (though are not limited to) Asquith, Bruner, and Mullins Jr. (1983); Eckbo, Giammarino, and Heinkel (1990); Eckbo and Thorburn (2000); Schlingemann (2004); Servaes (1991); Smith and Kim (1994); Travlos (1987) and many others.

[5] $4.4 billion equals $700 billion (i.e., the total pre-acquisition market value of targets acquired by U.S. public acquirers in 2014) times the estimated 0.63% average efficiency loss.

value. Using high Sentiment (Baker and Wurgler, 2006, 2007) and high stock-market volatility to proxy for high misvaluation risk, we find that the efficiency loss is more than 40% higher in times when misvaluation is more likely, compared to the full sample. The efficiency loss is similar for acquirers with strong and weak governance, and for horizontal and non-horizontal mergers.

Next, we measure how misvaluation affects the distribution of merger gains across acquirers. We define the merger gain as the acquirer's expected synergy minus what it pays for that synergy. We then define the redistribution effect as the difference in bidders' merger gains between the estimated economy and a counterfactual economy with no misvaluation uncertainty. Misvaluation uncertainty helps overvalued acquirers by allowing them to use their shares as a cheap currency. Misvaluation uncertainty hurts undervalued acquirers, because even when they do manage to win the auction, they often end up paying a higher price due to competing, inflated bids. In other words, overvalued acquirers impose a negative externality on other acquirers. We find that the average wealth redistributed from undervalued to overvalued acquirers is quite large: 5.1% of the target's pre-acquisition value, which translates to roughly $36 billion of wealth redistributed per year among U.S. public acquirers.[6]

Finally, we use the estimated model to measure the value of extra cash capacity. Intuitively, extra cash capacity is valuable because it lets undervalued acquirers avoid using expensive equity, and because it allows any acquirer to signal undervaluation by paying cash. On average across all deals, we find that one extra dollar of cash capacity increases a bidder's merger gain by 3.3 cents. The marginal value is especially large for undervalued bidders, since they have no desire to pay using shares, and also for bidders with little cash capacity. For a severely undervalued bidder (5th percentile) with zero cash capacity, an additional dollar of cash capacity can increase its merger gain by 12 cents when the deal synergy is high. A high marginal value of cash capacity implies a high marginal cost of obtaining cash via external finance. Our results therefore imply that external financing costs may be modest for the average acquirer but are very high for certain acquirers. The results also highlight one way that financing constraints harm firms: Financing constraints force undervalued firms to make acquisitions using shares rather than cash, which makes them pay more and increases their chances of being crowded out.

[6] $36 billion equals $700 billion (i.e., the total pre-acquisition market value of targets acquired by U.S. public acquirers in 2014) times the estimated average redistribution effect of 5.11%.

The idea that opportunistic, overvalued acquirers create inefficiencies in the M&A market comes from the theoretical work of Rhodes-Kropf and Viswanathan (2004, 2005). They show that the target may be sold to the acquirer with lower synergies when the financing of acquisition bids is subject to frictions like default or misvaluation. Our paper is the first to quantify this inefficiency. In addition, we study the redistribution of merger gains between overvalued and undervalued bidders, which is new to the literature.

More broadly, our paper contributes to three strands of literature. First, recent literature has focused on the effect of stock misvaluation on the method of payment and merger performance of acquirers and targets. Ang and Cheng (2006); Rhodes-Kropf, Robinson, and Viswanathan (2005); Shleifer and Vishny (2003); and Savor and Lu (2009) demonstrate that overvalued acquirers create value for their shareholders by cashing out their overvalued equity. In contrast, Akbulut (2013); Fu, Lin, and Officer (2013); and Gu and Lev (2011) find that overvalued acquirers destroy shareholder value by overpaying their targets. We add to this literature by examining another important question that deserves more attention in the literature. Specifically, we measure how misvaluation can reduce the overall economic efficiency of the M&A market. Our paper therefore highlights the effect of corporate financing on real economic efficiency.

Second, our study adds to the emerging literature that calibrates or estimates structural M&A models. For example, Gorbenko and Malenko (2014b) estimate valuations of strategic and financial bidders, and they find that different targets appeal to different types of bidders. Albuquerque and Schroth (2014) estimate a search model of block trades in order to quantify the value of control and the costs of illiquidity. Dimopoulos and Sacchetto (2014) estimate an auction model to evaluate two sources of large takeover premia, and they find that target resistance plays the dominant role in driving up premia. Warusawitharana (2008) links asset purchases and sales to firm fundamentals, and Yang (2008) estimates a structural model that predicts firms with rising productivity acquire firms with declining productivity. Our paper also takes a structural approach, but it addresses different questions than the previous studies.

Finally, this paper is among the few studies that structurally investigate the effects of misvaluation on corporate decisions. For example, Warusawitharana and Whited (2015) estimate a dynamic model to demonstrate how equity misvaluation affects firms' investment, financing, and payout policies. Our focus on M&A is quite different. Both papers, however, estimate the distribution of misvaluation and quantify its effect on corporate finance decisions.[7]

The remainder of the paper is organized as follows. Section 2 presents our model of M&A contests, and Section 3 describes our data and estimation method. Section 4 presents our empirical results on model fit, parameter estimates, inefficiencies, effects on merger gains, and the marginal value of cash capacity. Section 5 discusses robustness, and Section 6 concludes.

2 Model

2.1 Setup

2.1.1 M&A Participants

Consider a takeover contest in which a risk-neutral target is up for sale and two risk-neutral acquirers (or bidders) compete for the target. The market value of the target as an independent entity is normalized as one.[8] Therefore, all values hereafter should be interpreted as the values relative to the target's pre-acquisition market value.

Four acquirer characteristics are critical for the takeover contest. First, under the management of acquirer i, the target's value is $V_i = 1 + s_i$, where s_i is the synergy between the target and acquirer. Synergies are the most frequently declared motive for M&As. Second, the ratio of acquirer i's market value to the target's market value, both measured as independent entities before the acquisition, is M_i. Third, an acquirer can be misvalued, in the sense that its true value X_i can differ from its market value M_i. Specifically, we assume $X_i = M_i(1 - \varepsilon_i)$, where ε_i is the misvaluation factor. Acquirers can be fairly valued ($\varepsilon = 0$), overvalued ($\varepsilon > 0$), or undervalued ($\varepsilon < 0$). Overvaluation becomes a second motive for M&A, since an overvalued firm has an incentive to buy other companies using its equity as currency (Rhodes-Kropf and Viswanathan, 2004; Shleifer and Vishny, 2003). Lastly, the acquirers are subject to a cash capacity constraint:

[7] There are two differences between the estimates in Warusawitharana and Whited (2015) and those in our paper. First, our paper estimates the misvaluation of acquirers relative to the targets, while Warusawitharana and Whited (2015) estimate the firms' own misvaluation. Second, the distribution of misvaluation in our paper is estimated specifically for the sample of acquirers, while their estimates apply to the universe of COMPUSTAT firms.

[8] We assume that the acquisition is fully unanticipated and therefore the target's pre-announcement market value does not contain any expected gains from the acquisition.

The amount of cash that acquirer i can use in the acquisition cannot exceed $k_i \geqslant 0$. This constraint summarizes the acquirer's cash holdings, its external financing constraints, and the resources it is willing to allocate to this specific takeover contest. For example, an acquirer may hold more than k_i in cash, but it may need some of that cash for other projects in the firm, making the firm cash-constrained for this specific contest. To summarize, an acquirer is identified by a vector of four characteristics $\Phi_i = (s_i, \varepsilon_i, k_i, M_i)$, $i = 1, 2$.

Among acquirer characteristics, the market value M_i is publicly observable, and the other characteristics (synergy, misvaluation, and cash capacity) are observed only by the acquirer's managers. Other participants in the M&A market, though they cannot observe these characteristics, understand that the synergy s_i follows a normal distribution $\mathcal{N}_s(\mu_s, \sigma_s^2)$ that is left-truncated at zero; the misvaluation factor ε_i follows a normal distribution $\mathcal{N}_\varepsilon(\mu_\varepsilon, \sigma_\varepsilon^2)$; and the cash capacity k_i follows a normal distribution $\mathcal{N}_k(\mu_k, \sigma_k^2)$ that is left-censored at zero. Left-censoring creates a large mass in the distribution at $k = 0$. We choose these specific distributions because they allow the model to fit the data well, as we show in Section 4. The distribution of the observed acquirer market values relative to the target, M, is denoted $\mathcal{M}(M)$.[9] Empirically, acquirers' size is correlated with two other characteristics. First, larger acquirers often pay higher premia (Alexandridis et al., 2013, for instance), suggesting a possible correlation between the acquirer's size and deal synergies. A positive correlation is plausible if the target's and acquirer's assets are complements. We therefore allow M_i and s_i to have a non-zero Spearman's rank correlation, denoted ρ_{sM}. Second, larger firms tend to be less financially constrained (e.g., Almeida, Campello, and Weisbach, 2004; Gilchrist and Himmelberg, 1995; Hadlock and Pierce, 2010; Whited and Wu, 2006), and an acquirer can more easily pay cash to buy a small target than a large target. We therefore allow M_i and k_i to have a non-zero Spearman rank correlation, denoted ρ_{kM}. These correlations let the acquirer's relative size M_i serve as a signal to the target about the deal's synergy and the acquirer's cash capacity. In sum, the acquirer characteristics $(s_i, \varepsilon_i, k_i, M_i)$ are an independent realization from the joint distribution $\mathcal{F}(\mathcal{N}_s(\mu_s, \sigma_s^2), \mathcal{N}_\varepsilon(\mu_\varepsilon, \sigma_\varepsilon^2), \mathcal{N}_k(\mu_k, \sigma_k^2), \mathcal{M}(\cdot); \rho_{sM}, \rho_{kM})$, $i = 1, 2$.

[9] Though the market values are publicly observable, the identity of the rivals may not be disclosed during the acquisition process. That is, the target knows who the acquirers are, but the acquirers may not know whom they are competing with. Therefore, they make their decisions taking into account the distribution of acquirers' size.

2.1.2 Takeover Contest

We model the takeover contest as a modified sealed second-price auction. Specifically, the two acquirers privately submit their bids as combinations of cash and equity to the target. We denote acquirer i's bid as $b_i = (C_i, \alpha_i)$, where C_i is the amount of cash and α_i is the target's share in the combined firm after the acquisition. The target values the bid as Z_i, the bid's cash plus the expected value of the target's share in the combined firm:[10]

$$\begin{aligned} Z_i \equiv z(C_i, \alpha_i, M_i) &= C_i + E[\alpha_i(X_i + V_i - C_i)|C_i, \alpha_i, M_i] \\ &= \alpha_i\{M_i(1 - E[\varepsilon_i|C_i, \alpha_i, M_i]) + 1 + E[s_i|C_i, \alpha_i.M_i]\} + (1 - \alpha_i)C_i. \end{aligned} \tag{1}$$

The target computes the combined firm's expected value by making a rational forecast of the bidder's misvaluation (ε_i) and synergy (s_i) based on what it can observe: C_i, α_i, and M_i. The target uses z as a scoring rule to rank bids. If the target believes that both bids have a valuation lower than its reservation value (i.e., the target's pre-acquisition market value which is normalized as one), the acquisition fails. Otherwise, the bid with the highest score Z wins, and the acquisition is settled as follows. For convenience, let i be the winner and j the loser. If $C_i \geqslant \max\{1, z(C_j, \alpha_j, M_j)\}$, the winner pays cash in the amount of $\max\{1, z(C_j, \alpha_j, M_j)\}$; otherwise, the winner pays a cash amount of C_i and a fraction $\tilde{\alpha}_i$ of the combined firm's stocks such that $z(C_i, \tilde{\alpha}_i, M_i) = \max\{1, z(C_j, \alpha_j, M_j)\}$. Intuitively, the actual fraction of the combined firm received by the target is determined in accordance with the *second-price* auction rule. In Appendix A, we show that such an settlement exists and is unique.

2.1.3 Equilibrium Concept

We consider an equilibrium in which acquirers strategically choose their bids as a combination of cash and equity to maximize their current shareholders' expected profit, given the target's scoring rule; and the target rationally evaluates the bids conditional on its available information and the acquirers' bidding strategy. Formally, the definition of such an equilibrium is given

[10] Here, the target evaluates a bid only based on the bid's own characteristics, even though it also observes the characteristics of the competing bid. This is because the two bidders are independent realizations of the joint distribution $\mathcal{F}(\cdot)$.

below.

Definition 1. *Given the second-price auction setting, the equilibrium is characterized by the optimal bidding rule* $b^*(\Phi_i) = (C^*(\Phi_i), \alpha^*(\Phi_i))$, *where* $\Phi_i = \{s_i, \varepsilon_i, k_i, M_i\}$ *is a set of acquirer characteristics* ($i = 1, 2$)*, and the scoring rule adopted by the target* $z(C, \alpha, M)$ *such that*

1. *Given* $b_j^* = b^*(\Phi_j)$, $j \neq i$, *and the scoring rule* $z(C, \alpha, M)$, $b_i^* = b^*(\Phi_i)$ *satisfies*

$$b_i^* = \underset{b=(C,\alpha)}{\text{argmax}}\ E\left\{ [V_i - \tilde{\alpha}^*(X_i + V_i - \tilde{C}) - \tilde{C}] \cdot 1_{\{\max\{1, z(b^*(\Phi_j), M_j)\} \leqslant z(b, M_i)\}} \middle| \Phi_i \right\}, \qquad (2)$$

   subject to $C \leqslant k_i$, *where* $\tilde{C} = \min\{C, \max\{1, z(b^*(\Phi_j), M_j)\}\}$, $\tilde{\alpha}^*$ *is the equity share settlement specified in Subsection 2.1.2, and* $1_{\{\cdot\}}$ *is an indicator function.*

2. *The scoring rule adopted by the target is defined in Equation (1), in which the equilibrium bidding rule* $b^*(\cdot)$ *is incorporated in the valuation of the bids.*

2.2 Discussion

First, where does misvaluation come from? One source is the acquirer's private information about its value. Other sources include mistakes made by behavioral investors, i.e., "mispricing" in the asset-pricing sense. The private-information channel is more relevant in this paper, because we assume acquirer i can observe its true value X_i, yet targets cannot observe X_i.

Our model allows targets to be misvalued, because all variables in the model are scaled by the target's value. Variable ε captures the acquirer's misvaluation relative to the target's misvaluation. Since we assume ε is privately observed by the acquirer, we do not allow the target to have private information about its own misvaluation. In reality, a target may privately know it is overvalued, so it may try to opportunistically sell its shares for cash. We focus on acquirers' opportunistic behavior for two reasons. First, as Shleifer and Vishny (2003) argue, overvalued firms are more likely to become acquirers, and the relatively undervalued firms are more likely to become targets. Therefore, the effects of opportunistic behavior are more important on the acquirer side. Second, the due-diligence process usually gives acquirers privileged access to information about the target, making it less likely that the target has private information.

We take the targets and acquirers as given, and we do not model the choice to participate as a target or acquirer. Therefore, the model's parameters describe the pool of firms that have already endogenously selected to be acquirers and targets. The model is consistent with our estimation, because our sample is also based on the selected sample of observed acquirers and targets.

Another way to profit from overvaluation is to sell shares in a seasoned equity offering (SEO). Our paper is silent on a firm's choice between M&A and SEO, and in fact the two are not necessarily mutually exclusive. An overvalued firm may prefer M&A if it has a real synergy, whereas it may prefer an SEO if it has real internal investment opportunities.[11]

By assuming the synergy's distribution is left-truncated at zero, we assume no bidders have negative synergies. We could extend the model to allow negative synergies, but we have chosen not to for two reasons. First, we suspect our main results would not change much if we allowed negative synergies. Firms with very negative synergies would choose not to participate, because they may prefer to do an SEO instead, and because their bids would be so low that the target would always reject them in favor of remaining a stand-alone company. In other words, if we extended the model to allow endogenous participation, the endogenous participation cutoff for synergies would probably be close to our assumed cutoff of zero. In theory, a highly overvalued firm with a slightly negative synergy may still choose to participate and could even win the contest. Our parameter estimates, however, indicate that such firms would be extremely rare and hence not have much influence on our inefficiency estimates.[12] Second, allowing negative synergies would present us with two undesirable modeling options: We either model firms' participation decision, which greatly increases the model's complexity, or we treat the synergy's truncation point as an extra parameter to estimate. For the latter approach, the truncation point would likely be identified off the distribution of offer premia, and our current model already fits that distribution well with the assumed truncation point of zero (Section 4.1).

We model the acquisition as an auction with two competing bidders. In most observed M&A deals there is only one publicly announced bidder. However, these deals do not indicate a lack of competition. Boone and Mulherin (2007) show a high degree of competition between potential

[11] Shleifer and Vishny (2003) analyze the choice between M&A and SEO. They show that an overvalued firm may prefer M&A if the cost of acquiring the target is lower than the cost of replicating the target's assets using the SEO's proceeds.

[12] The reason is that the estimated dispersion in synergies is many times larger than the dispersion in overvaluation.

acquirers before any bid is publicly announced.[13] Even without this pre-announcement competition, a single bidder may behave as if it is competing with other bidders in order to deter those bidders from entering (Fishman, 1988, 1989). Also, a single bidder may submit a competitive bid to prevent target resistance (Burkart, Gromb, and Panunzi, 2000; Dimopoulos and Sacchetto, 2014). For these reasons, it is reasonable to model the acquisition as a competitive auction with multiple bidders. Although takeover contests sometimes involve more than two competiting bidders, our two-bidder assumption is not uncommon in the literature (e.g. Dimopoulos and Sacchetto, 2014; Fishman, 1988, 1989; Gorbenko and Malenko, 2014a). For robustness, Section 5 shows that we reach similar conclusions if we allow three, four, or five competing bidders.

The M&A process in practice is very complex. In the literature, it is often modeled as an English ascending (EA) auction (e.g., Dimopoulos and Sacchetto, 2014; Fishman, 1989; Gorbenko and Malenko, 2014a,b) or a sealed second-price (SP) auction (e.g., Rhodes-Kropf and Viswanathan, 2004). Under our model's independent private value paradigm, these two auction formats are equivalent. We choose to follow the SP format because (a) it gives rise to a simple and unambiguous analytic relation between the bid's two components (cash and equity), with which the optimization problem of the acquirer in (2) may be substantially simplified;[14] and, more importantly, (b) it establishes an intuitive structure on which the optimal cash offer in the equilibrium bid can be determined. The EA format can provide (a) but not (b), and the sealed first-price (FP) auction format can provide (b) but does not imply a straightforward analytic relation between the cash and equity components in a bid.

Our model abstracts away from the sequential nature of M&A contests. In our data, less than 2% of contests have multiple public bids. Any sequential competition therefore takes place mainly in private, with bidders typically unable to observe each other's move. For this reason, it is not clear that a model of sequential bidding describes the data better than our model with simultaneous bidding. Dimopoulos and Sacchetto (2014) model sequential M&A contests with a

[13] During this pre-announcement stage, an average of 3.75 potential bidders express interest in purchasing the target. This figure is based on the number of potential buyers who signed the confidentiality agreement as the indication of serious interest. Using more restrictive criterion, there are on average 1.29 bidders who submitted private written offers and 1.13 bidders who made publicly announced bids. Boone and Mulherin (2007) obtain this evidence from target firms' SEC filings.

[14] That is, with the equilibrium relation between the cash and equity components, the optimization can be operated just over the choice of cash instead of both components.

strategic preemptive motive. They find that preemption contributes little to offer premia, which suggests that building preemption into our model is not of first-order importance.

In reality, target shareholders must pay capital gains taxes immediately in an all-cash deal, but they can defer taxes in equity deals. We omit this detail from our model, because the tax difference is quite minor: The tax benefit of paying equity comes only from the time value of money, and the majority of shareholders are tax-exempt entities like pension funds.

Lastly, the assumption of a partially unobservable cash capacity constraint (k_i) is important. Intuitively, if acquirers have unlimited cash capacity, relatively undervalued acquirers can separate by bidding only with cash, so there is no scope for opportunistic behavior. Given the large body of evidence on financing constraints, it is plausible to assume a cash capacity constraint. Our parameter ρ_{kM} allows a relation between cash capacity and relative firm size, consistent with the evidence in Hadlock and Pierce (2010) and others that firm size is a strong predictor of financial constraints. Target firms in our model rationally use the acquirer's size as a noisy signal about its cash capacity. It is plausible that cash capacity is only partially observed, because it is difficult to observe financing constraints and whether the acquirer has earmarked cash for other projects.

2.3 Model Solution

Next, we show that in the equilibrium, acquirers bid their true valuation of the target, which imposes a simple and unambiguous relation between the two bid components.

Proposition 1. *Bidding the true valuation is an equilibrium that satisfies the conditions given in Definition 1. That is, in the equilibrium it is a weakly dominant strategy for the acquirers to submit the bid* (C_i^*, α_i^*) *such that* $\alpha_i^*(X_i + V_i - C_i^*) + C_i^* = V_i$*. As a result, in the equilibrium the optimal bids* (C_i^*, α_i^*) *satisfy the following relation:*

$$\alpha_i^* = \frac{V_i - C_i^*}{X_i + V_i - C_i^*},\ i = 1, 2. \tag{3}$$

Being aware of this equilibrium relation, the target sets the scoring rule as

$$z(C, \alpha, M) = \frac{\alpha M}{1-\alpha}\left(1 - E[\varepsilon | C, \alpha, M; b^*(\cdot)]\right) + C. \tag{4}$$

Proof. See Appendix B. □

Based on the equilibrium results in Proposition 1, we can derive several implications. First, though the bidders truthfully bid their valuation (V_i), the target still cannot perfectly tell apart the acquirers. The reason is that there are three dimensions of asymmetric information (synergy, misvaluation, and cash capacity), but bids have only two dimensions (cash and equity). Acquirers with different characteristics may end up submitting the same bid. Consider a simple example in which both acquirers have zero cash capacity and therefore bid with all equity. An overvalued acquirer (low X) with low synergy (low V) may submit the same bid as an undervalued acquirer (high X) with high synergy (high V) if both acquirers have the same ratio of X/V.[15] The target in our model is more confused than it is in this simple example, because acquirers can bid with cash, and their cash capacity is unobservable. The model solution therefore features a pooling equilibrium in which the target cannot perfectly learn a bidder's synergy, misvaluation, and cash capacity based on its bid. The target can only infer the average of these three characteristics across all pooling acquirers who submit the same type of bids.

A direct implication of the pooling equilibrium is that the method of payment affects the target's assessment of bid value. Bids that have the same true value but differ in their payment methods will appear different to the target. For example, equity bids made by highly overvalued acquirers often appear to be worth more than they truly are, from the target's point of view.[16] More generally, as we discussed above, the target only adjusts for the *average* misvaluation in the group of bidders who make the same type of bids. Therefore, an acquirer with above-average overvaluation relative to its group is still inflated after the target's adjustment, making its equity bid look more attractive to the target than it really is. Analogously, an equity bid made by an undervalued acquirer appears less valuable than it really is.

[15] When $C^* = 0$, equation (3) becomes $\alpha_i^* = \frac{1}{X_i/V_i+1}$, $i = 1, 2$. Therefore, $\alpha_i^* = \alpha_j^*$ if $\frac{X_i}{V_i} = \frac{X_j}{V_j}$.

[16] Consider one example in which two bidders are drawn from the model distribution, $\mathcal{F}(\cdot)$, such that: 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 ($k_1 = k_2 = 0$); bidder one is overvalued and its true stand-alone value is 0.5, while 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.

Acquirers therefore strategically choose the payment methods in their bids. More-overvalued acquirers prefer using more equity, while undervalued acquirers prefer using as much cash as possible (subject to their cash capacity constraint) to avoid costly equity payment. These predictions are consistent with the evidence in Dong et al. (2006); Rhodes-Kropf, Robinson, and Viswanathan (2005); Williamson and Yang (2016); and several others. Undervalued acquirers with low cash capacity suffer the most by paying with their undervalued equity, which provides camouflage for overvalued acquirers in the pooling equilibrium.[17]

The target takes into account acquirers' bidding strategy and considers cash payment as a signal in evaluating the bids. If a bid contains more cash, the target infers that the acquirer is less likely to be overvalued. The equilibrium scoring rule (4) indicates that one more dollar offered in cash increases the target's valuation of the bid by more than one dollar, because it lifts the valuation of the bid's equity component. Similarly, one more dollar offered in equity lifts the total bid valuation by less than one dollar, because it simultaneously reduces the target's valuation of the acquirer's equity. This equilibrium scoring rule explains why some overvalued acquirers may also choose to include some cash in their bids. The benefits of using cash for overvalued acquirers include less discount imposed by the target on their equity payment, and less adverse impacts imposed by rival acquirers that are even more overvalued. The cost is the missed opportunity to use overvalued equity as currency in the transaction. This tradeoff implies that cash is used less as a bidder's overvaluation increases.

To demonstrate the implications, we numerically solve the model using the estimated parameters presented in Table 4, then we plot the relation between the optimal cash component and misvaluation in Figure 1.[18] Cash component is presented as a ratio of the cash payment to the acquirer's true valuation of the target. The solid line depicts the cash component of optimal bids made by acquirers that have sufficient cash capacity ($k \geqslant 1 + s$). As expected, undervalued and fairly-valued acquirers ($\varepsilon \leqslant 0$) choose to bid with all cash because equity is more expensive for them. Cash usage gradually drops as acquirers become more overvalued. Highly overvalued acquirers find it desirable to bid with all equity.

[17] Even though these undervalued acquirers with low cash capacity suffer by paying equity, they may still have positive gains from the merger if the synergy is large enough.
[18] The method of numerically solving the model is presented in Appendix C.

Cash capacity also plays an important role in determining the payment method. The dashed line in Figure 1 plots the cash usage by acquirers with a cash capacity equal to half of the bid value ($k = \frac{1+s}{2}$). In general, cash usage still decreases (weakly) in overvaluation. However, many acquirers that prefer bidding with more cash are now constrained by their cash capacity and are forced to use more equity. This effect is important because it restricts acquirers' ability to signal their types with cash, which in turn aggravates the target's confusion in equilibrium. As a result, the adverse effect from opportunistic bidding becomes more severe.

The pooling equilibrium also determines the market reaction to bid announcements. Once the market observes a bid, it rationally reassesses the acquirer's stand-alone value, resulting in a revelation effect that is an important component of the acquirer's announcement return. For example, when the market observes a bid that includes little or no cash, the market infers that the acquirer is overvalued (in expectation), resulting in a negative revelation effect and hence a lower announcement return. To demonstrate this effect, we simulate $2,503$ acquisition deals (same size as our sample) from our estimated model. We construct the acquirer announcement returns for the simulated acquisitions using the method described in Appendix D, and we plot the announcement returns against the bids' cash usage in Figure 2. As expected, the simulated acquirer announcement returns increase in the use of cash.

The positive relation between announcement returns and cash usage is stronger when there is more misvaluation uncertainty, i.e., when σ_ε is larger. This prediction is crucial to our identification of σ_ε. This prediction manifests as a steeper slope in Figure 2 when $\sigma_\varepsilon = 0.20$ compared to 0.05. To see the intuition, consider the extreme case where $\sigma_\varepsilon = 0$. The target and market know exactly how misvalued the bidder is ($\varepsilon_i = \mu_\varepsilon$), so cash usage provides no additional information, hence stock prices do not respond to cash usage. When misvaluation uncertainty increases, the target becomes more confused and thus relies more on the signal from cash usage. In such a case, the revelation effect of cash becomes more pronounced, producing the steeper slope in Figure 2's right panel.

Overall, the pooling equilibrium gives rise to two adverse effects. First, the crowd-out effect: An overvalued acquirer may defeat ("crowd out") a rival bidder who has a higher synergy, resulting in inefficiencies. Second, the redistribution effect: Overvalued acquirers gain more, and undervalued acquirers gain less, than they would in an economy with no misvaluation uncertainty. We use structural estimation to quantify these effects in the M&A market.

3 Estimation

This section describes the data, SMM estimator, and intuition behind the estimation method.

3.1 Data

Data on merger and acquisition characteristics come from Thomson Reuters SDC Platinum. We examine bids announced between 1980 and 2013. To be included in the final sample, a bid has to satisfy the following criteria:

1. The announcement date falls between 1980 and 2013;
2. Both the acquirer and target are U.S. publicly traded firms;
3. The deal can be clearly classified as successfully completed or a failure, and the date of bid completion or bid withdrawal is available;
4. The acquirer seeks to acquire more than 50 percent of target shares in order to gain control of the firm and holds less than 50 percent of target shares beforehand;
5. The deal value exceeds one million dollars;
6. The deal is classified as a merger, not a tender offer or a block trade;[19]
7. The payment method and offer premium are available, and the acquirer and target have sufficient valuation data covered by CRSP for computing their market values and abnormal announcement returns.

In our main estimation, we only use data on the first publicly announced bid in each control contest. Following Betton, Eckbo, and Thorburn (2008), we say that a control contest begins with

[19] We follow Betton, Eckbo, and Thorburn (2008) in classifying the deal type: If the tender flag is "no" and the deal form is a merger, then the deal is a merger. If the tender flag is "no" and the deal form is "acquisition of majority interest" and the effective date of the deal equals the announcement date, then the deal is classified as a control-block trade. If the tender flag is "yes", or if the tender flag is "no" and it is not a block trade, then the deal is a tender offer.

the first public bid for a given target and continues until 126 trading days have passed without any additional offer. Each time an additional offer for the target is identified, the 126 trading day search window rolls forward. We do not use data on earlier, pre-public bids for two reasons. Most importantly, key variables like the offer premium are not observable for those bids. Also, finding even the identity and number of pre-public bidders is impossible for the majority of our contests.[20] Our main estimation also excludes subsequent public bids, for two reasons. First, they are extremely rare; less than 2% of our sample contests have multiple publicly announced bids. Second, our model is not designed to explain subsequent bids, which would condition on the initial public bid in ways that our simultaneous-bidding model cannot capture. Extending our model to accommodate these few extra observations would significantly complicate our analysis.

Next, we define our main variables. We measure bid i's offer premium, denoted $OfferPrem_i$, as the offer price per share divided by the target stock price four weeks before the bid announcement, minus one. The offer premia data provided by SDC include some large outliers. Following Officer (2003) and Bates and Lemmon (2003), we drop observations with offer premium lower than zero or larger than two. We denote the acquirer and target's announcement returns around bid i as $AcqAR_i$ and $TarAR_i$, respectively. We measure these announcement returns using the market model with a three-day window around the bid's announcement. Appendix D explains how we compute the announcement return within the model. $CashFrac_i$ is the fraction of bid i made up of cash. We measure M_i as the ratio of acquirer to target market capitalization four weeks before bid i.

Our final sample includes 2,503 bids. Table 1 provides summary statistics. The average transaction value is 1,590 million in 2009 dollars, significantly skewed to the right. The offer premium averages 44% with a standard deviation of 32%. Bidders pay on average 31% of deal value in cash, with 20% of bidders making all-cash bids and 53% of bidders making all-equity bids. Acquirers are much larger than targets: the logarithm of M averages 2.17. The mean acquirer announcement return is slightly negative, -2.3%. The target's announcement return is significantly positive with an average of 21.5%. Also consistent with previous findings, the

[20] For example, Jurich and Walker (2015) hand-collect data and find that only 44% of the mergers in their sample have SEC filings that describe the merger's background information. Even in the 44% of cases with an SEC filing, information on the number and identity of bidders is often missing or imprecise.

combined firm announcement return is positive and around 1%. We also break the whole sample period into three subperiods: 1980-1990, 1991-2000, and 2001-2013. The summary statistics are quite comparable across these subperiods, with some variation in the payment method.

3.2 Estimator

We estimate the model using the simulated method of moments (SMM), which chooses parameter estimates that minimize the distance between moments generated by the model and their sample analogs. The following subsection defines our moments and explains how they identify our parameters. The eight parameters we estimate are μ_s and σ_s, which control the mean and variance of bidders' synergies; μ_ε and σ_ε, which control the mean and variance of bidders' misvaluation; μ_k and σ_k, which control the mean and variance of bidders' cash capacity; and ρ_{sM} and ρ_{kM}, the Spearman rank correlations between the logarithm of relative firm size ($\ln(M)$) and the synergy and cash capacity, respectively. Since M is directly observed in the data, we do not need to estimate it. The empirical distribution of M is an input to the SMM estimator. Appendix E contains additional details on the SMM estimator.

3.3 Identification, Selection of Moments, and Heterogeneity

Since we conduct a structural estimation, identification requires choosing moments whose predicted values move in different ways with the model's parameters, and choosing enough moments so there is a unique parameter vector that makes the model fit the data as closely as possible. We use eight moments to identify our eight parameters. Following the advice of Bazdresch, Kahn, and Whited (2014), we include moments that describe acquirers' policy functions, i.e., their choices of offer premium and method of payment.

Before defining our moments, we address the issue of heterogeneity. Our parameters σ_s, σ_ε, and σ_k describe variation across acquirers within a single contest. The data, however, reflect heterogeneity not just within but also across contests. To isolate within-contest variation, we use moments that purge cross-contest heterogeneity driven by unobserved time effects, unobserved target industry effects, and observable target characteristics.[21] Specifically, when measuring sev-

[21] Purging variation that comes from acquirer characteristics would be inappropriate, since our goal is to estimate

eral moments below, we control for M_i and a vector $Controls_i$ that includes year dummies, targets' Fama-French 48 industry dummies, and several target characteristics that are outside our model: logarithm of market capitalization, market leverage, market-to-book ratio of equity, return on assets, and cash-to-assets ratio. Structural estimation papers have taken a variety of approaches to heterogeneity.[22] Our approach offers several advantages, although it is not perfect.[23] We reach very similar conclusions if we do not include $Controls$ when measuring our moments.

Next, we define our moments and, to explain how the identification works, we show how the moments vary with our parameters. Each moment depends on all model parameters, but we explain below which moments are most important for identifying each parameter. To illustrate, Table 2 presents the Jacobian matrix containing the derivatives of our eight predicted moments with respect to our eight parameters.[24]

The first two moments are the mean and conditional variance of offer premia. The mean is measured using the full sample, and the conditional variance is $Var(u_i)$ from the regression

$$OfferPrem_i = a_0 + a_1 log(M_i) + a_2' \, Controls_i + u_i. \quad (5)$$

In this and the next two regressions, we set $Controls$ to zero in simulated data, since $Controls$

variation in acquirer characteristics. Like us, Gorbenko and Malenko (2014b) and Dimopoulos and Sacchetto (2014) exclude acquirer characteristics from their sets of observables.

[22] Similar to us, Hennessy and Whited (2007) remove the effects of heterogeneity by including firm and time fixed effects when measuring certain moments. In the M&A literature, Gorbenko and Malenko (2014b) and Dimopoulos and Sacchetto (2014) build heterogeneity directly into their structural models. They model bidders' valuations as having an observable component, which they model and estimate as a function of target characteristics and macroeconomic variables. Dimopoulos and Sacchetto (2016) propose an importance-sampling procedure to allow parameter heterogeneity in SMM estimation. Another approach is to estimate in subsamples, as we do later in this paper.

[23] The main advantage is that our approach is computationally feasible. Building heterogeneity directly into the structural model would be infeasible, as it would require numerically solving the model not just for every trial parameter vector, but also for every data point. Gorbenko and Malenko (2014b) and Dimopoulos and Sacchetto (2014) avoid this problem by having a closed-form solution. Another advantage is that we can easily include many variables in $Controls$ (e.g. industry and year dummies), whereas building many such variables into the structural model and estimating their coefficients via SMM would be computationally prohibitive. Building heteroegneity directly into the structural model is conceptually cleaner, but since understanding cross-contest heterogeneity is not our goal, we take the simpler approach. We suspect our conclusions would not change if we directly modeled and estimated heterogeneity in our unobservables' means, since we find that the inefficiency we study to be quite insensitive to these means.

[24] We present the Jacobian evaluated at estimated parameter values. To make the sensitivities comparable across parameters and moments, we scale the sensitivity by a ratio of standard errors. Specifically, for moment m and parameter p, the table presents the value 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, $Stderr(p)$ is the estimated standard error for parameter p (from Table 4) and $Stderr(m)$ is the estimated standard error for the empirical moment m (from Table 3).

includes variables that are outside our model. The mean and conditional variance of offer premia are most informative about the mean and variance of synergies, which depend on parameters μ_s and σ_s. The intuition is that competition between bidders makes a large fraction of a deal's synergy accrue to the target firm in the form of an offer premium. Since the offer premium is a proxy for the synergy, there is a close link between their means and variances. Table 2 confirms that these two moments are most sensitive to μ_s and σ_s.

The third moment is a_1, the slope of offer premium on $log(M)$ from regression (5). Table 2 shows that this moment is highly informative about ρ_{sM}, the rank correlation between the synergy and M. The reason is that the offer premium is a rough proxy for the deal's synergy, as explained above.

The fourth moment is the average acquirer announcement return. Table 2 shows that this moment is most senstive to μ_ε, the average level of overvaluation. The intuition is that the market rationally updates its beliefs about a bidder's stock price when it sees that the firm has chosen to become a bidder, regardless of the chosen method of payment. If the market understands that μ_ε is higher, meaning the average bidder is more overvalued, then the average announcement return around the bid is lower, reflecting a more negative revelation effect.

The fifth moment is b_1, the slope coefficient of acquirer announcement return on the fraction of the bid made in cash, from the regression

$$AcqAR_i = b_0 + b_1 CashFrac_i + b_2 log(M_i) + b_3' \, Controls_i + v_i. \tag{6}$$

The slope b_1 is positive in both the data and the model. Table 2 shows that this moment is most sensitive to σ_ε, the degree of misvaluation uncertainty. To recap the model's intuition from Section 2.3, a bid containing more cash partially reveals that the bidder is more undervalued (recall Figure 2), so the market rationally adjusts the bidder's stock price upwards. The revision in stock price is especially large when there is a bigger difference between an undervalued and overvalued bidder, so the slope is more positive when σ_ε is larger. Conversely, in the extreme where $\sigma_\varepsilon = 0$, there is no valuation information revealed by a bidder's use of cash, so the announcement return is unrelated to the use of cash.

The sixth and seventh moments are the mean and conditional variance of $CashFrac_i$, the fraction of bid i made up of cash. The mean is measured using the full sample, and the conditional variance is $Var(w_i)$ from the regression

$$CashFrac_i = c_0 + c_1 log(M_i) + c_2' \ Controls_i + w_i. \tag{7}$$

These moments mainly identify μ_k and σ_k. Intuitively, the larger is the average cash capacity μ_k, the more cash usage we should see on average. The larger is the dispersion σ_k across bidders' cash capacity, the higher should be the conditional variance of cash usage. As expected, in Table 2 we see that $E[CashFrac_i]$ is most sensitive to μ_k, and $Var(w_i)$ is most sensitive to σ_k.

The eighth moment is c_1, the slope of $CashFrac$ on $log(M)$ from regression (7). Table 2 shows that this moment mainly helps identify ρ_{kM}, the rank correlation between cash capacity and M. The reason is that a bidder's cash capacity k is strongly related to its chosen cash usage.

Since we have eight moments and eight parameters, we have an exactly identified model. We check in Section 4 whether the estimated model is able to match six additional, untargeted moments. Although using extra moments in the estimation would provide a test of overidentifying restrictions and potentially smaller standard errors, we prefer an exactly identified model for three reasons. First, our standard errors are sufficiently small. Second, the intuition behind identification is more transparent. Most importantly, the model is simply not designed to match some of these additional moments, as we explain in Section 4.

4 Empirical Results

We begin by assessing how the model fits the data, then we present the parameters' estimates. Next, we use the estimated model to quantify the inefficiencies from opportunistic acquirers, the redistribution of merger gains, and the marginal value of cash capacity. Finally, we compare our results across periods with low and high aggregate misvaluation.

4.1 Model Fit

Table 3 compares empirical and model-implied moments. Panel A presents the moments we target to match in SMM estimation. The model fits these moments very closely. The differences between the empirical and model-implied moments are statistically insignificant and economically negligible. The estimated model predicts a high average offer premium equal to 44.2% of the target's size. The offer premium varies significantly, with a conditional standard deviation of 30%=$\sqrt{0.088}$ of the target's size. The model-implied acquirer announcement returns are on average negative even though acquirers gain from mergers. The negative announcement return is caused by the negative revelation effect. Method of payment follows a bimodal distribution with a significant fraction of acquirers paying by either all cash or all equity. Acquirers' relative size (i.e., the logarithm of acquirers' pre-acquisition market value divided by the target's pre-acquisition market value) is positively related to both the offer premium and fraction of cash used in bids.

Panel B shows how well the model matches additional moments that were not targeted during estimation. The model-implied variances of announcement returns are overall much lower than their empirical counterparts. This result is expected, and we consider it a success of the model. Unlike announcement returns in our model, announcement returns in the data are contaminated by unrelated events that occur during the measurement window, and by other measurement errors. Those factors outside our model do not contribute to the mean announcement return, but they increase the variance of announcement returns. The estimated model is therefore expected to explain only a fraction, rather than all, of the announcement return variance in the data.

Among other untargeted moments, the model comes close to matching the average announcement return of the combined firm and the correlation between acquirer and target announcement returns.[25] The correlation between acquirer and target announcement returns is driven by two competing effects. On the one hand, acquirer and target announcement returns are negatively correlated within a deal, because the two firms split a fixed synergy. On the other hand, they are positively correlated across deals, because deals with high synergy usually produce both high

[25] Consistent with the literature, we measure the target's announcement return using a longer window that begins 4 weeks before the announcement. This longer window is required to capture the well-documented information leakage.

acquirer and target returns. The second effect dominates in both the model and the data.

The model fails to match the average target announcement return, which equals 43.8% in the model and 28.3% in the data. The target's announcement return reflects the offer premium and probability of deal completion. One potential explanation for the model's failure is that deal completion is negatively correlated with the offer premium, and the model cannot capture this correlation. Empirically, this correlation is close to zero, which rules out this explanation. A second possible explanation is that takeover announcements may reveal new information about the target, confounding the target announcement returns. This revelation effect, however, needs to average roughly -10% in data to explain the difference, which seems implausible.

The target announcement return ($TarAR$) and offer premium contain similar information for model identification. The model is apparently unable to match both moments simultaneously. We use the offer premium rather than the $TarAR$ in our estimation for two reasons. First, the offer premium measures acquirers' valuation of the target with less error: The offer premium can be directly observed in data without auxiliary assumptions about announcement windows, market models, etc., and the offer premium is not influenced by noise trading. Second, $TarAR$ may be confounded by revelation about the target, which is outside our model. To include any potential revelation about the target, we include the four-week run-up period when measuring $TarAR$. One cost of using such a long window is that $TarAR$ contains considerable noise, which may help explain why $Var(TarAR)$ is much higher in the data than the model.

Finally, Figure 3 shows how the model fits the full distributions of offer premia, cash usage, and acquirer announcement returns. Since our estimation only targets means, regression slopes, and conditional variances, we do not necessarily expect the model to fit the full, unconditional distributions. The model fits surprisingly well, though. In both the model and data, $OfferPrem$ is right-skewed, and $CashFrac$ has large spikes at zero and one, with some spread between.

4.2 Parameter Estimates

Table 4 contains parameter estimates from SMM. Since the model uses truncated and censored distributions, the μ and σ parameters do not always equal the variables' means and variances. To help interpret the parameters, Table 4's bottom panel reports the mean and standard deviation implied by the parameter estimates.

The most important result in Table 4 is that the dispersion in synergies is much larger than the dispersion in misvaluation. The estimated standard deviation of synergy (s) is 44% of the target's size. The estimated standard deviation of misvaluation (ε) is much smaller, 7%. This difference drives our paper's main result. Since $Stdev(s) \gg Stdev(\varepsilon)$, the high-synergy bidder almost always wins the M&A contest. The reason is that when two bidders compete, the gap between their synergies is usually much larger than the gap between their misvaluations, so it is almost always synergies and not misvaluations that determine the winner. The main reason we find $Stdev(s) \gg Stdev(\varepsilon)$ is that the conditional standard deviation of offer premia is very high, 30% (Table 3). Dispersion in misvaluation can explain only a small fraction of the dispersion in offer premia, so the model needs a very high $Stdev(s)$ to explain the rest.

The estimated mean synergy is 0.68, implying that the average merger creates value that amounts to 68% of the *target's* market value. The estimated mean synergy appears much lower (8%) if we instead report it as a percent of the *combined* firm's market value. Comparing the 68% mean synergy to the 44% mean offer premium, we are finding that the target captures roughly 2/3 ($\approx 44\%/68\%$) of the synergy, and the acquirer captures roughly 1/3 on average. Competition between acquirers makes it reasonable that acquirers would capture less than half of the synergy.

Parameter μ_ε is estimated as 0.055, meaning the market believes the average bidder is overvalued by 5.5%, relative to the target.[26] The market therefore adjusts its assessment of acquirers' stand-alone value downwards on bid announcements. This reevaluation can be caused by different reasons. For example, related to the opportunistic bidding activities we study in this paper, acquirers that bid with equity may raise concerns about overvaluation, inducing the market to adjust their valuations downwards (see e.g., Savor and Lu, 2009). The negative reevaluation can also arise because takeover announcements simply reveal negative information regarding the acquirers' fundamental performance that affects their stand-alone value (see e.g., Wang, 2015).

We estimate an average cash capacity of 0.869 with a standard deviation of 1.034. Because we normalize the target pre-acquisition market value to be 1, the estimates imply that the average acquirer only has enough cash capacity to buy 87% of the target with cash. Acquirers' cash

[26] Recall that all variables in the model are scaled by the target's market value, so the misvaluation factor ε_i measures acquirer i's misvaluation relative to the target's misvaluation.

capacity, however, exhibits a large cross-sectional variation and skews to the right. This evidence is consistent with the stylized facts that some firms are financially constrained, while other firms have large cash holdings or reserve credit lines that can be used to finance acquisitions.

The estimate of ρ_{sM} implies a 0.39 linear (i.e. Pearson's) correlation between the synergy and the acquirer's relative size. This large correlation is not surprising, since target and acquirer assets are plausibly complements. For example, the target may own a technology that improves all the acquirer's assets, so the synergy is larger when the acquirer is larger.

The estimate of ρ_{kM} implies a 0.44 linear correlation between cash capacity and the acquirer's relative size. This result also makes sense. Recall that M equals acquirer size divided by target size. If the acquirer is many times larger than the target, the acquirer likely holds enough cash to pay fully in cash. Also, larger acquirers face lower financing constraints, giving them more access to cash (Hadlock and Pierce, 2010).

4.3 Aggregate Efficiency Loss: The Crowd-Out Effect

Now that we have estimated the model, we can use it to quantify the takeover market's efficiency. Because of misvaluation and the implied opportunistic bidding, the winning bidder in our model does not necessarily have the highest synergy. When the bidder with a lower synergy wins the auction, we say that the opportunistic acquirer crowds out the synergistic acquirer. How can this crowding out occur, especially given that acquirers bid their true, privately known valuations? The reason is that the target cannot separately infer the acquirer's true synergy, misvaluation, and cash capacity from its bid. An overvalued bidder knows that its equity bid is inflated, yet that equity bid may appear more attractive to the target than a bid made by an undervalued bidder, even if the inflated bid's true value is lower. There is an inefficiency when crowd-out occurs, because the realized synergy is lower than could have been achieved in an economy without misvaluation.

To quantify the inefficiency from opportunistic acquirers, we simulate a large number of M&A contests from our estimated model. In each contest, we independently draw two bidders from the estimated joint distribution of state variables, $\mathcal{F}(\mathcal{N}_s(\mu_s, \sigma_s^2), \mathcal{N}_\varepsilon(\mu_\varepsilon, \sigma_\varepsilon^2), \mathcal{N}_k(\mu_k, \sigma_k^2), \mathcal{M}(\cdot); \rho_{sM}, \rho_{kM})$. The bidders submit their optimal bids, and the target optimally scores each bid and then either rejects both bids or chooses a winner. Next, we classify each simulated contest outcome as either efficient, inefficient, or failed (both bids rejected). We say that a contest is efficient if the bidder with the higher synergy wins, and is inefficient if the bidder with the lower synergy wins. Within the inefficient deals, we then compute the efficiency loss as the loser's higher synergy minus the winner's lower synergy. In other words, the efficiency loss is the amount of synergy lost in the estimated economy relative to an ideal, counterfactual economy in which the high-synergy bidder always wins. An example of that counterfactual economy is one with no misvaluation uncertainty: If σ_ε=0, then bidders' types would be perfectly revealed in equilibrium, and the high-synergy bidder would always win.[27]

Table 5 presents the results. We find that 7.01% of deals are inefficient, meaning the overvalued acquirer crowds out the synergistic acquirer. In these inefficient deals, the synergy loss averages 9.02% of the target's pre-acquisition market value. Stated in different units, the winner's synergy is 15.8% lower than the loser's synergy in the average inefficient deal. Averaging across all deals (efficient, inefficient, and failed), the average efficiency loss is 0.63% (= 7.01% $\times$ 9.02%) of the target's size. The average efficiency loss is low mainly because the estimated dispersion in synergies ($Stdev(s)$=44%) is much larger than the estimated dispersion of misvaluation ($Stdev(\varepsilon)$=7%). As explained in Section 4.2, since $Stdev(s) \gg Stdev(\varepsilon)$, it is almost always synergies and not misvaluations that determine the auction's winner. Crowding out therefore occurs in only a small fraction of deals. The low estimated average efficiency loss implies that the M&A market reallocates assets quite efficiently on average.

Though the average efficiency loss is small, the efficiency loss varies significantly and is quite large in certain deals. For example, the synergy loss in the top 10% of inefficient deals amounts to roughly 20% of the target's size, or 36% of the first-best synergy.

We estimate these inefficiencies with error, since our model's parameters are estimated with error. Table 5 contains standard errors for the inefficiencies. We compute these standard errors by Monte Carlo using the parameters' estimated covariance matrix from SMM.[28] Our estimates

[27] Another example is a counterfactual economy with perfect information. Yet another example is a constrained-efficient economy in which all three dimensions of asymmetric information still exist, yet an optimal contract induces bidders to reveal their types in equilibrium.

[28] Specifically, we draw a large number of model parameters from a jointly normal distribution with a mean equal to the SMM parameter estimates, and with a covariance matrix equal to its SMM estimate. For each draw of model parameters, we solve the model, then compute the model-implied probability of crowd-out and efficiency loss. We

are quite precise. For example, the estimated 0.63% average loss in all deals has a standard error of 0.19%, meaning that the average loss is a precisely estimated small number.

Like most counterfactual analyses, all the counterfactual analyses in this paper are subject to a Lucas-type critique. For example, we cannot claim that synergies would be 0.63% higher if we could somehow eliminate misvaluation uncertainty. The problem is that firms would reoptimize if misvaluation uncertainty disappeared, and our model would capture only part of this reoptimization. Specifically, our model would capture optimal changes in bidding and scoring behavior, but it would not capture changes in firms' decisions to participate as acquirers or targets in the first place. A comprehensive policy analysis would need to incorporate all reactions to any policy interventions. The Lucas critique is less severe in our paper than in many structural papers, because we do not interpret our counterfactual analyses as actual policy interventions. Instead, we simply measure synergy losses relative to a counterfactual in which the highest-synergy bidder wins, which is the natural benchmark.

4.4 The Redistribution Effect

Misvaluation and opportunistic bidding lead to not only an aggregate inefficiency, but also a redistribution of merger gains across acquirers. Misvaluation makes overvalued acquirers gain more, because they are able to pay using overvalued equity. Undervalued acquirers gain less, because they end up paying a higher price due to the externality from competing bidders. In this section, we quantify this wealth redistribution across different types of bidders.

We define a bidder's merger gain, denoted u, as its expected synergy minus what it pays for that synergy. We compare u between our estimated economy ("*Est*") and a counterfactual benchmark economy ("*Bench*") that is equivalent, except it has no misvaluation uncertainty, meaning $\sigma_\varepsilon = 0$. In the benchmark, bidders' types are perfectly revealed in equilibrium, so the high-synergy bidder always wins. Because the winning bidder pays the price offered by the losing bidder, bidder i's expected merger gain in the benchmark economy is

$$u_i^{Bench} = E[\max\{s_i - \tilde{s}_i, 0\}].$$

estimate the standard error as the standard deviation across simulations.

This expectation is taken with respect to the opponent's synergy $\tilde{s}_i$, and it takes into account bidder i's probability of winning the contest. It follows that, in the benchmark economy, a bidder's expected merger gain only depends on its own synergy. In our estimated economy, the expected merger gain for the same bidder, u_i^{Est}, depends on all its state variables; its value is the maximum in equation (2). We define the wealth redistribution for bidder i as

$$\Delta_i = u_i^{Est} - u_i^{Bench}. \tag{8}$$

We can interpret Δ_i as the change in merger gains caused by misvaluation uncertainty, because the only difference between the estimated and benchmark economies is the value of σ_ε.

Figure 4 plots Δ_i for different types of bidders. The left and right panels shows results for bidders with low and high synergies, respectively. Each panel shows three curves representing bidders with zero, intermediate, and sufficient cash capacity. Bidders with intermediate cash capacity are able to (but not obligated to) buy the target with 50% cash, and bidders with sufficient cash capacity can pay entirely in cash.

Each curve describes how the wealth redistribution, Δ_i, varies with a bidder's misvaluation, ceteris paribus. A bidder's misvaluation, plotted on x-axis of the figure, is measured in the number of standard deviation from the sample mean. In general, the wealth redistribution is increasing in a bidder's overvaluation, and the magnitude is economically large. For example, when synergy is high ($s = 0.8$) in the right panel, a bidder with top 5% misvaluation (i.e., overvalued by $1.65 \times 7.0\%$ above the mean) gains more than it does in the perfect-information economy by 10% of the target's pre-acquisition market value.

Cash capacity helps undervalued and fairly-valued bidders avoid the adverse effects of opportunistic bidders. For example, when the synergy is high, a bidder with bottom 5% misvaluation and zero cash capacity gains less than it does in the perfect-information economy by about 10% of the target's market value. The wealth redistribution shrinks in magnitude to 4% if the bidder can pay half of the deal in cash, and it becomes zero if the bidder is able to pay all in cash. Cash capacity has a much smaller effect on overvalued bidders, who prefer to bid with equity.

Comparing the two panels of Figure 4 in which the deal synergy differs, we find that the wealth redistribution is more pronounced when deal synergy is high, holding other bidder characteristics constant.

We then compute the average of $|\Delta_i|$ across all bidders i. We find an average of 0.051, which means that misvaluation uncertainty causes an average absolute wealth distribution across bidders equal to 5.1% of the target's size. Misvaluation causes a large redistribution of wealth, even though it causes a rather small aggregate inefficiency.

4.5 Marginal Value of Cash Capacity

Extra cash capacity is valuable to acquirers for two reasons. It is valuable to undervalued acquirers, because it lets them avoid paying with expensive equity. Second, any bidder can signal that it is undervalued by bidding cash rather than equity. In this section, we quantify the marginal value of cash capacity for different types of bidders. To measure this marginal value, we use our estimated model and numerically compute the partial derivative of a bidder's expected merger gain with respect to its cash capacity:[29]

$$\lambda_i^{Est} = \frac{\partial u_i^{Est}}{\partial k_i}. \tag{9}$$

Because both u_i^{Est} and k_i are measured relative to the target's pre-acquisition market value, λ_i^{Est} measures how much more a bidder can gain, in dollar terms, from the merger if its cash capacity increases by one dollar.

Figure 5 presents the results. The left and right panels show the results for bidders with low and high synergies, respectively. Each panel presents three curves representing bidders with zero, intermediate, and sufficient cash capacity. Each curve describes how the marginal value of cash capacity, λ_i^{Est}, varies with a bidder's misvaluation, ceteris paribus. In general, the marginal value of cash is decreasing in bidders' overvaluation, so cash capacity is more valuable for undervalued bidders. The marginal value of cash capacity is zero for bidders that are significantly overvalued, because they do not bid with cash no matter how much cash they can afford to use. Comparing the results across the three curves in each panel, we find that the

[29] In the benchmark economy without misvaluation uncertainty, u_i^{Bench} does not depend on k_i, so $\lambda_i^{Bench} = 0$, meaning the marginal value of cash capacity is always zero.

marginal value of cash capacity is decreasing in a bidder's cash capacity level. Therefore, cash capacity is more valuable for bidders that are more cash-constrained. For example, for a bidder with the bottom 5% misvaluation and zero cash capacity, one additional dollar in cash capacity increases the bidder's merger gain by 12 cents when the deal synergy is high. The marginal value of cash capacity drops to 6.5 cents if the bidder is able to pay 50% of the deal value in cash, and it shrinks to zero if the bidder already has enough cash to pay for the entire deal. Comparing the two panels of Figure 5, we find that the marginal value of cash capacity is larger when the deal synergy is higher, holding other bidder characteristics constant.

We measure the overall average marginal value of cash by averaging λ_i^{Est} across all bidders. We find an average of 0.033, implying that one additional dollar in cash capacity increases a bidder's merger gain by 3.3 cents on average.

These estimates shed new light on acquirers' financing constraints. The estimated marginal value of cash capacity can be interpreted as a lower bound on firms' marginal costs of external finance. For example, we find that some acquirers' marginal value of cash is 12 cents per dollar. If cash is so valuable, why don't these acquirers raise more cash by issuing new debt or equity? The marginal cost of raising that extra cash must be greater than 12 cents per dollar. According to this interpretation, we find that acquirers' financing constraints may be modest on average (possibly as low as 3 cents per dollar), but can be very high (at least 12 cents per dollar) for certain acquirers.

4.6 Comparing Low- and High-Misvaluation Periods

We assume the model parameters are constant in the baseline estimation. Previous studies document that misvaluation risk varies over time.[30] In this section, we estimate our model in subsamples with different empirical proxies of misvaluation, then we investigate the main model implications in these subsamples.

We construct the first two subsamples based on the investor sentiment index of Baker and Wurgler (2006, 2007).[31] We separately estimate the model in the highest and lowest quintiles

[30] For example, see Ang and Cheng (2006); Bouwman, Fuller, and Nain (2009); Rhodes-Kropf, Robinson, and Viswanathan (2005).

[31] The sentiment measure is a composite index constructed using six indices–closed-end fund discount, NYSE share

of months according to the sentiment index. When sentiment is high, sentiment-driven noise traders play a larger role, leading to more mispricing. In other words, high-sentiment periods correspond to high σ_ε in our model. If sentiment makes stocks more overpriced on average, the high sentiment also corresponds to high μ_ε in our model.

Panel A of Table 6 contains parameter estimates from the sentiment subsamples. We find that $E[s]$ and $Stdev[s]$ are both higher in the high-sentiment subsample. We find this result mainly because high-sentiment months have offer premia that are higher (51% vs. 44% in the full sample) and more dispersed (conditional standard deviation of 32% vs. 30% in the full sample). The estimate of $E[\varepsilon]$ increases from 0.058 in the full sample estimation to 0.081 in the high-sentiment subsample, mainly because high-sentiment months have a lower average acquirer announcement return (-4.3% vs. -2.2% in the full sample). $Stdev[\varepsilon]$ is estimated as 0.108 in the high-sentiment subsample, considerably higher than its full-sample estimate of 0.070. The main reason is that announcement returns are more sensitive to cash usage in high-sentiment months: The slope of $AcqAR$ on $CashFrac$ (b_1 from regression (6)) is 0.047 in high-sentiment months, compared to 0.031 in the full sample. These results confirm that high sentiment is associated with both more overvaluation on average (higher μ_ε) and more misvaluation dispersion (higher σ_ε).

Panel B of Table 6 summarizes the main model implications for different subsamples. We find that 9.62% of deals are inefficient in high-sentiment months, an increase of 37% from the full-sample estimate of 7.01%. The synergy loss in inefficient deals also increases to 13.54% of the target's size, a 50% increase over the full-sample estimate. The dispersion of synergy losses in inefficient deals is also higher in high-sentiment months, meaning the inefficiency is especially large in certain deals. The average synergy loss across all deals is 1.30% of the target's size in high-sentiment months, compared to 0.63% in the full sample. Although the inefficiency estimate has roughly doubled, it still remains quite modest in size. The main reason we find greater inefficiencies in high-sentiment periods is that there is more misvaluation uncertainty (higher estimated σ_ε) and hence more scope for opportunistic bidding. This result is slightly offset by the greater dispersion in synergies in high-sentiment periods, which tends to reduce the

turnover, the number of IPOs, the average first-day returns on IPOs, the equity share in new issues, and the dividend premium. We use the version of the investor-sentiment index that is orthogonalized to the business cycle. The reason is that M&A activities are in general procyclical. As documented by Harford (2005), many business cycle indicators such as liquidity and technological progress are also the drivers of merger waves.

crowd-out effect. We find the opposite results in the low-sentiment subsample.

We also find that the average wealth redistribution and marginal value of cash are higher in the high-sentiment subsample. Because misvaluation is higher and opportunistic bidding is more prevalent in high-sentiment periods, average wealth redistribution increases. Synergistic bidders value cash more highly during these periods, because they wish to avoid the negative effects from opportunistic bidders.

Next, we use stock-market volatility as a second proxy for misvaluation. Specifically, we measure volatility as the cross-sectional standard deviation of individual stock returns in a calendar month. The rationale is that higher volatility coincides with more uncertainty about future values and hence more potential for investors to err in assessing those values.[32] We separately estimate the model in the highest and lowest quintiles of months according to the volatility measure. We expect that the inefficiency is greater during the periods with high stock-market volatility.

Our results with stock-market volatility resemble our results with sentiment. Bids announced during periods with higher volatility are estimated to face a higher risk of misvaluation and opportunistic bidding. The probability of crowd-out, inefficiencies, average wealth redistribution, and the marginal value of cash capacity are all estimated to be higher in the subsample with high market volatility.

5 Robustness

This section describes how results change when we use different assumptions. It also explores our results' robustness across additional subsamples.

5.1 Correlated Synergies

Our main model assumes the contest's two competing bidders have uncorrelated synergies. In reality, their synergies may be correlated. For example, the target firm may own a technology that is similarly useful to the two acquirers, leading to positively correlated synergies. Negatively correlated synergies would imply that contests often include one strong and one weak bidder,

[32] Pástor, Stambaugh, and Taylor (2015) use this same rationale.

which could explain why we often observe only one publicly announcing bidder in the data.

We mitigate concerns about a positive correlation by controlling for the vector $Controls_i$ in regression (5). Suppose synergies are positively correlated only because both acquirers share the same expected synergy, and this expected synergy varies as a function of $Controls_i$ across contests. By including $Controls_i$ in the regression, we remove the shared variation in expected offer premia across contests, making it more plausible that any remaining variation is uncorrelated across acquirers.

To address any remaining concerns, we perform a simple exercise to argue that allowing correlated synergies would not significantly change our conclusions. We start with our estimated model, keeping the target's optimal scoring rule and acquirers' optimal bidding rule unchanged.[33] We then simulate M&A contests from the model assuming the two bidders' synergies have a +50% correlation and compute the model's main implications. Results are in Table 7. Moving from a zero to a +50% correlation changes the average loss across all deals from 0.63% to 0.88%. The change is small, because allowing a positive correlation has two opposing effects. First, the positive correlation increases the probability of crowd-out, because it reduces the difference between the bidder's synergies, thereby allowing the difference in their misvaluations to dominate the difference in their synergies. Second, the positive correlation decreases the average loss in inefficient deals, because the gap between the winner and loser's synergy is smaller when the synergies are positively correlated. Analogously, Table 7 shows that a −50% correlation between bidders' synergies reduces the unconditional average loss from 0.63% to 0.48%. To summarize, even if bidders' synergies are highly correlated (either positive or negative), we reach the same main conclusion: The inefficiency from opportunistic acquirers is small on average.

[33] One shortcoming of this exercise is that the target's and acquirers' optimal decisions are likely to change if they know that bidders' synergies are correlated. For instance, if synergies are positively correlated, the target ought to evaluate a bid taking into account the other bid, since a high-value competing bid often indicates that the bid under consideration is likely to have a high synergy as well. We perform the simple exercise above because solving for target's and bidders' optimal choices with correlated synergies increases the model's complexity and solution time considerably. However, we expect that the results based on the model with correlated synergies are both qualitatively and quantitatively similar because the two opposing forces we described below are still present.

5.2 Additional Bidders

Our main model assumes two bidders compete in each M&A contest. Section 2.2 defends this assumption. In this subsection we explore how our conclusions would change if we relaxed the assumption. If all parties understood there was just one bidder in each contest, then there would be no possibility of crowding out a second bidder. The more interesting case involves $N > 2$ bidders. We perform a simple exercise to show that the inefficiency increases, but remains fairly small, if there are more than two bidders. Specifically, we assume targets and acquirers behave as in our main estimated model, but instead of simulating $N = 2$ bidders per contest, we now simulate N= 3, 4, or 5 bidders.[34] We view $N = 5$ as an upper bound, since Boone and Mulherin (2007) find that only 1.13 bidders on average make a publicly announced bid, and only 3.75 potential bidders express interest in purchasing the target during the pre-announcement stage. Similar to before, we say that inefficient crowd-out occurs if the highest-synergy bidder does not win the contest, and we define the loss given crowd-out as the gap between the winner's synergy and highest synergy. Table 7 shows how our main model implications change. As the number of competing bidders increases from two to five, we see an increase in the percent of deals that are inefficient (from 7% to 14%), the average loss in inefficient deals (from 9% to 11%), and the unconditional loss (from 0.63% to 1.59%). The inefficiency increases because a larger number of bidders increases the chance of at least one bidder being highly overvalued and crowding out the others. The effect is modest in size, though, because a larger number of bidders also increases the chance of at least one bidder having a very high synergy, placing a high bid, and efficiently winning the contest.

[34] A more complete exercise would take into account that the optimal bidding decision might change if all parties understand that there are more than two bidders. The optimal bidding rule may be different since the bidder is now effeectively competing with the bidder with the highest score among the other bidders, whose distribution is different from a random competitor. We focus on the simple exercise above mainly because solving the full model with multiple bidders significantly increases the solution time. Nevertheless, we expect the more complete exercise would produce similar results, since the same intuition about the effects of multiple bidders would still go through.

5.3 Overpayment and Governance

A few recent studies find that overvalued acquirers destroy shareholder value by overpaying their targets.[35] Our main model does not allow this possibility, because we assume acquirers rationally maximize expected profits and therefore bid a fair price for the target. In reality, acquirers may overpay if managers are allowed to empire-build rather than maximize firm value. Overpayment would clearly transfer wealth from the acquirer to the target. It is less clear whether overpayment would have any effect on the inefficiency we study. For example, if all bidders overpay to the same degree, then overpayment obviously has no effect on which bidder wins the contest.

To explore whether omitting overpayment from our model is biasing our results, we estimate the model in subsamples with different propensities for overpayment. Since we are essentially sorting firms on the degree of potential bias, our results should look different across these subsamples if the bias indeed exists. We find instead that our results are quite similar across these subsamples, which suggests that ignoring overpayment is not biasing our results. Subsamples' parameter estimates and model implications are in Table 8.

The first subsamples we examine are related to governance. Fu, Lin, and Officer (2013) find that overpayment is concentrated among acquirers with the weakest governance. Using the entrenchment index (E) of Bebchuk, Cohen, and Ferrell (2009) as a proxy for governance strength, we split our full sample into two roughly equally sized subsamples based on the acquirer's E. One complication is that relative firm size M is significantly different across the two subsamples, which by itself can cause the estimated inefficiency to differ. To isolate variation coming from governance rather than firm size, we measure our data moments using a weighting scheme that controls for differences in M across subsamples.[36] When we estimate the model in the low- and high-entrenchment subsamples, we find that the difference in estimated average synergy loss is economically small (0.82% vs. 0.60%) and statistically insignificant.

[35] See Akbulut (2013); Fu, Lin, and Officer (2013); and Gu and Lev (2011). Other papers reach a different conclusion. For example, Savor and Lu (2009) find that overvalued firms create value by paying with shares. By comparing acquisitions and SEOs, Golubov, Petmezas, and Travlos (2016) find that stock-financed acquisitions do not destroy value.

[36] This scheme assigns weights to observations so that the weighted distribution of M in both subsamples matches the full-sample distribution. The scheme assigns a larger weight to observations whose M value is underrepresented in the subsample compared to the full sample. Additional details are in Wooldridge (2002), page 592. We also apply this scheme to the subsamples of horizontal and non-horizontal mergers.

Next, we compare horizontal and non-horizontal mergers. We define a horizontal merger as one in which the target and acquirer belong to the same Fama-French 48 industry. In our sample, 1,979 mergers are horizontal, 793 are not. We suspect that overpayment is more severe in non-horizontal mergers, since these are diversifying mergers that may result from an empire-building motive. Of course, there may be other differences between these merger types, so the comparison is not perfect. We find that the average synergy loss is 0.66% in horizontal mergers, 0.59% in non-horizontal mergers. This difference is small in magnitude and not statistically significant.

6 Conclusion

There has been considerable research on overvaluation as a motive for acquiring another firm. If opportunistic, overvalued bidders crowd out high-synergy bidders, then there is an inefficiency in the M&A market. Our main contribution is to quantify this inefficiency. We find that the inefficiency is relatively small on average, but it is large in certain deals, and is larger during times when misvaluation is more likely. We also measure an externality that overvalued bidders impose on synergistic bidders: By pushing up acquisition prices, overvalued bidders reduce undervalued bidders' merger gains. Undervalued bidders can avoid these externalities by paying in cash rather than shares, which makes access to cash more valuable. Overall, our paper shows that corporate financing has important effects on real economic efficiency.

Our study could be extended in several directions. It could be interesting to quantify an additional inefficiency created by misvaluation: Undervalued firms may choose not to become acquirers despite having positive synergies. Another promising direction is to quantify the inefficiencies from agency conflicts within the target or acquirer. It would also be interesting to find the theoretically optimal M&A mechanism that reveals all bidders' types, thereby ensuring that the high-synergy bidder always wins. We leave these challenges for future work.

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Appendix

A Existence and Uniqueness of Equity Settlement

To make sense of the scoring rule used by the target, we make the following assumption:

Assumption 1. *The scoring rule $z(\cdot)$ defined in Equation (1) is continuous and differentiable with respect to its arguments. Moreover, it is increasing in the bid components, i.e., $\partial z(C_i, \alpha_i, M_i)/\partial C_i > 0$, and $\partial z(C_i, \alpha_i, M_i)/\partial \alpha_i > 0$.*

The intuition of this assumption is that a sweetened bid (either by increasing the cash offer of by increasing the share in the combined firm) should not reduce its own valuation by the target. This assumption however does not imply that the target does not penalize the use of the potentially overvalued equity. The penalty is reflected in the fact that the additional value attached to the incremental equity share is decreasing. This latter relation is not assumed and we shall derive it from the solution of the model.

Based on Assumption 1, we can show that there exists a unique $\tilde{\alpha}$ such that $z(C_i, \tilde{\alpha}_i, M_i) = \max\{1, z(C_j, \alpha_j, M_j)\}$ in the case that $C_i < \max\{1, z(C_j, \alpha_j, M_j)\}$, where bidder i is the winner of the acquisition auction and j is the loser. It follows $z(C_i, 0, M_i) = C_i < \max\{1, z(C_j, \alpha_j, M_j)\}$ and the fact $z(C_i, \alpha_i, M_i) \geqslant \max\{1, z(C_j, \alpha_j, M_j)\}$ since bidder i is the winner of the acquisition auction. Therefore, by the continuity and monotonicity of the scoring function, there must be a unique $\tilde{\alpha}_i$ in $(0, \alpha_i)$ such that $z(C_i, \tilde{\alpha}_i, M_i) = \max\{1, z(C_j, \alpha_j, M_j)\}$. $\square$.

B 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 (Assumption 1).

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 (3).

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 for the target should the bid be executed is $\alpha_i^*(X_i + V_i - C_i^*) + C_i^* = V_i$, 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:

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

□

C Numerical Solution of the Model

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, the optimal α and C satisfy the relation (3). 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.[37] 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

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

[37] 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.

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

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

where all variables with an apostrophe subscript 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 (3), i.e., $\alpha = [(1+s) - C]/[M(1-\varepsilon) + (1+s) - C]$; $\tilde{\alpha}_{t-1} = 0$ 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 $\mathtt{I}_{t-1}(\cdot)$ is defined as

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

We repeat this procedure until $\|C_t(\cdot) - C_{t-1}(\cdot)\| < \delta$, where δ is the criterion of convergence that is a small number. 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.

D Announcement Returns

In most acquisitions, only one bidder is publicly announced. To map our model to the data, of the two bidders i and j, we assume that the target chooses to announce bidder i's bid (as the initial 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 announcement 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 conditional announcement return only reflects the revision of the market value of the bidder given the announced bid. Since no bidder wins, the conditional announcement return to the target is zero. That is, $AR^t_{in,1} = 0$. And finally, the combined conditional announcement 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 conditional abnormal announcement 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 Subsection 2.1.2. The conditional abnormal announcement 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 conditional combined abnormal announcement 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 announcement 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 conditional abnormal announcement return to the target is

$$AR^t_{in,3} = \tilde{C}_{jn} + \tilde{\alpha}_{jn}\left\{M_{jn}E[(1-\varepsilon_{jn})|M_{jn}, b_{jn}, I_3 = 1] + E[(1+s_{jn})|M_{jn}, b_{jn}, I_3 = 1] - \tilde{C}_{jn}\right\} - 1,$$

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 Subsection 2.1.2. And the combined announcement return in this case is

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

In the end, 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 87%. 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 ($\Phi_j = \{s_j, \varepsilon_j, k_j, M_j, w_j\}$) conditional on the observation of the bid by bidder i and the fact that i is announced (J_i is the indicator), where w represents the observed signal variables. Then,

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

$$
\begin{aligned}
&+ h(\Phi_j|b_i, M_i, J_i, Z_i < Z_j)\Pr(Z_i < Z_j|b_i, M_i, J_i) \\
= \;& h(\Phi_j|b_i, M_i, Z_i > Z_j) \times 0.87 + h(\Phi_j|b_i, M_i, Z_i < Z_j) \times 0.13 \qquad \text{(D.1)}
\end{aligned}
$$

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

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

E SMM Estimator

For each given set of parameters, Θ, we solve the model numerically and obtain the joint distribution of acquirer characteristics, $\mathcal{F}(\mathcal{N}_s(\mu_s, \sigma_s^2), \mathcal{N}_\varepsilon(\mu_\varepsilon, \sigma_\varepsilon^2), \mathcal{N}_k(\mu_k, \sigma_k^2), \mathcal{M}(\cdot); \rho_{sM}, \rho_{kM})$, optimal bidding rule, $b^*(\Phi_i) = (C^*(\Phi_i), \alpha^*(\Phi_i))$, and target scoring rule, $z(C, \alpha, M)$. We then simulate a large number of takeover contests, in each of which we draw two competing bidders independently from the joint distribution. In each takeover contest, we compute each bidder's optimal bid based on the optimal bidding rule. We then compute the score each bid receives from the target, which identifies the winner, if there is one.

The model does not specify which bidder in a takeover contest eventually becomes the initial bidder, because they submit their bids simultaneously in the auction process. Since we match our model-implied moments to the data moments constructed from initial bidders only, it is necessary to determine in our simulation which bidder in each takeover contest is selected to be the initial bidder. We adopt a reduced-form approach to solve this problem. In our sample, 87% of initial bidders successfully acquired their targets, so we assume that in our simulation the winning bidder becomes the initial bidder with a probability of 87% and the losing bidder becomes the initial bidder with a probability of 13%. Specifically, for each takeover contest, after determining the winner, we draw a random variable from a uniform distribution between 0 and 1. The winner is assigned as the initial bidder if the realization of this random variable is below 0.87 and the losing bidder is assigned as the initial bidder is the realization is above 0.87.

We then construct the model-implied moments, including the announcement returns for acquirer, target and the combined firm, the offer premium, and the cash usage for the initial bidder in each contest based on equations provided in Appendix D. The SMM estimator $\hat{\Theta}$ searches for the parameter values that minimize the distance between the data moments and the model-implied moments:

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} \left(\hat{M} - \frac{1}{L} \sum_{l=1}^{L} \hat{m}^l(\Theta) \right)' W \left(\hat{M} - \frac{1}{L} \sum_{l=1}^{L} \hat{m}^l(\Theta) \right)$$

where W is chosen to be the efficient weighting matrix, equal to the inverse of the estimated covariance of moments M. The efficient weighting matrix W is constructed using the seemingly unrelated regression (SUR) procedure in which each data moment is estimated as a coefficient from a regression equation. We cluster the errors in deals that happen in the same or consecutive years and involve acquirers or targets in the same Fama-French 48 industry. $\hat{M}$ is the vector of moments estimated from data, and $\hat{m}^l(\Theta)$ is the corresponding vector of moments estimated from the lth sample simulated using parameter Θ. Michaelides and Ng (2000) find that using a simulated sample 10 times as large as the empirical sample generates good small-sample performance. We choose $L = 20$ simulated samples to be conservative.

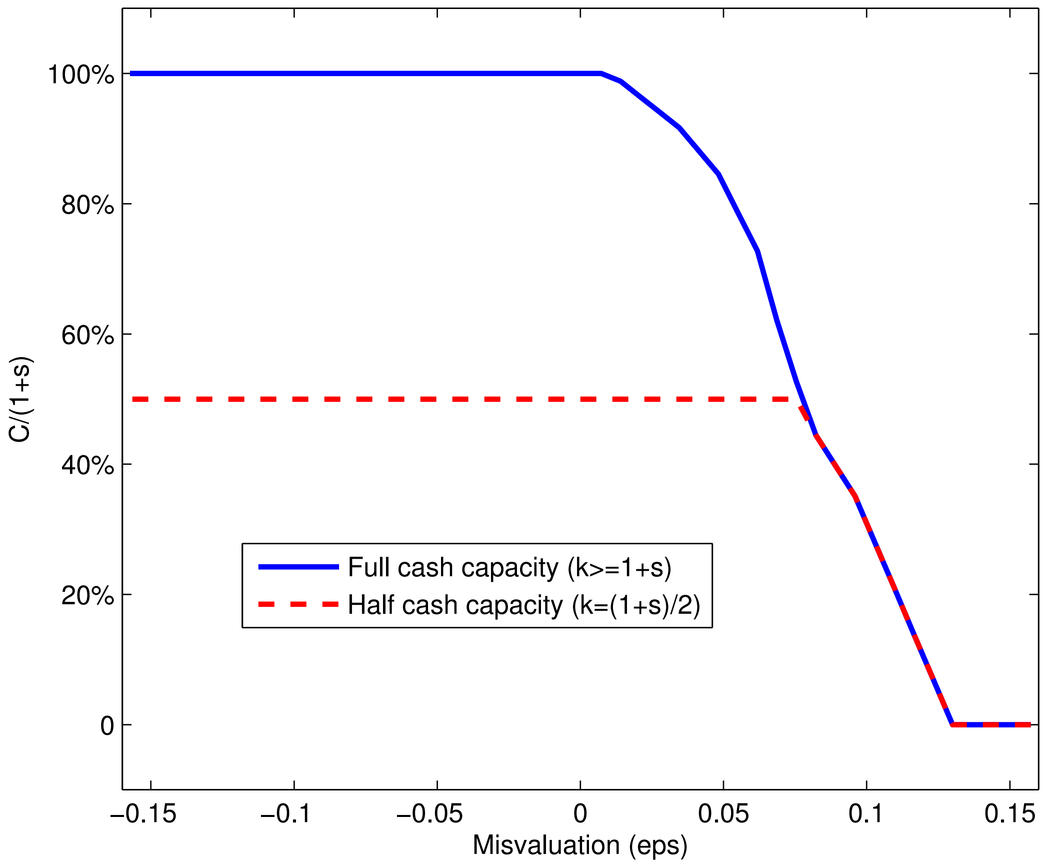


Figure 1: Cash Fraction in the Optimal Bid

This figure presents the cash fraction of optimal bids from acquirers with different misvaluation. The cash fraction is presented as the ratio of cash component to the acquirer's true valuation of the target. The optimal bidding rule is solved numerically using the method described in Appendix C with the estimated parameters presented in Table 4. The solid line depicts the cash fraction in the optimal bids of acquirers with sufficient cash capacity, and the dashed line depicts the cash fraction in the optimal bids of acquirers with a cash capacity that is only half of the true valuation by the acquirers.

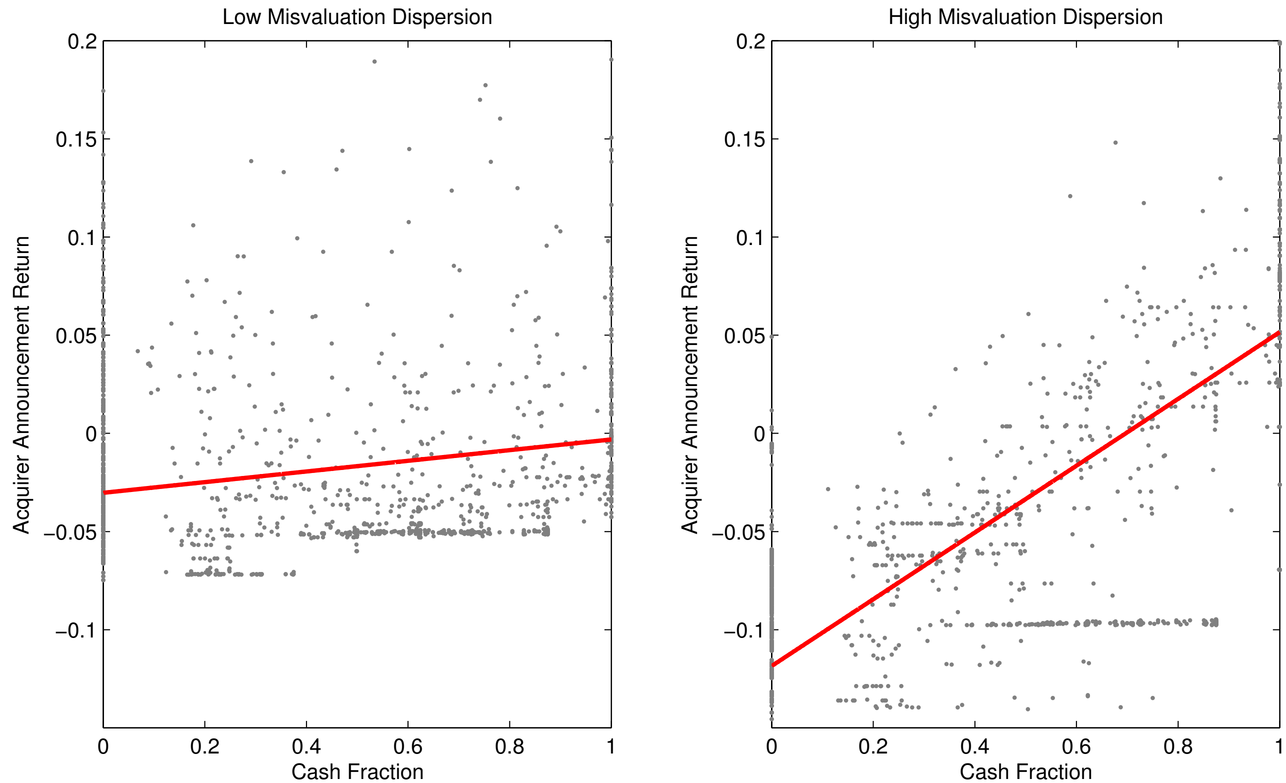
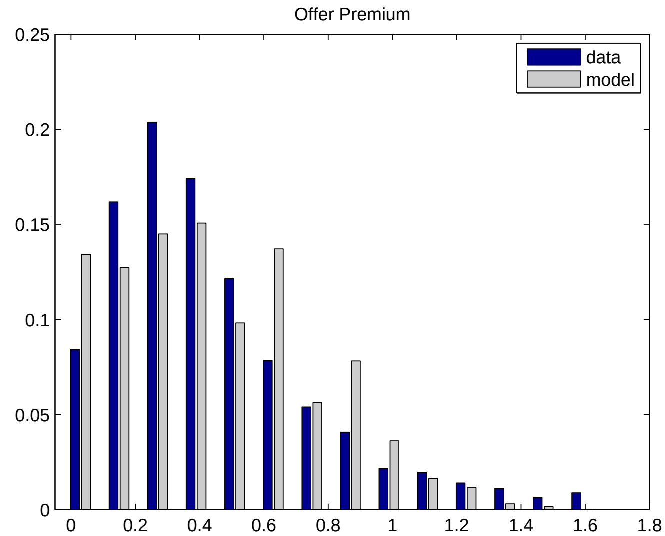
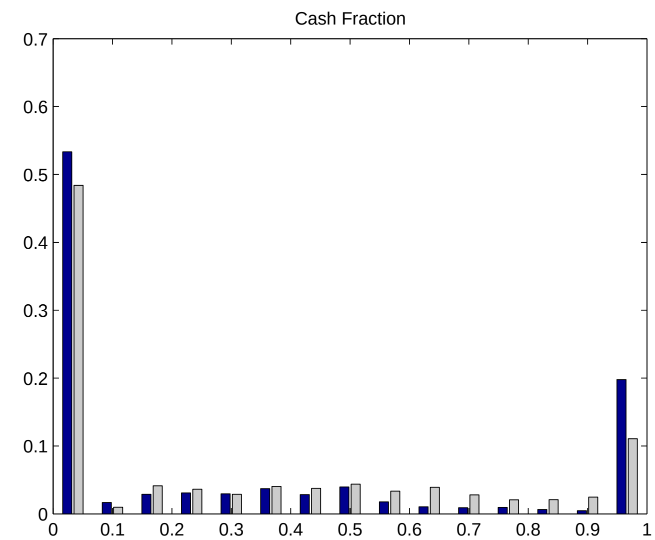


Figure 2: Revelation Effect of Cash

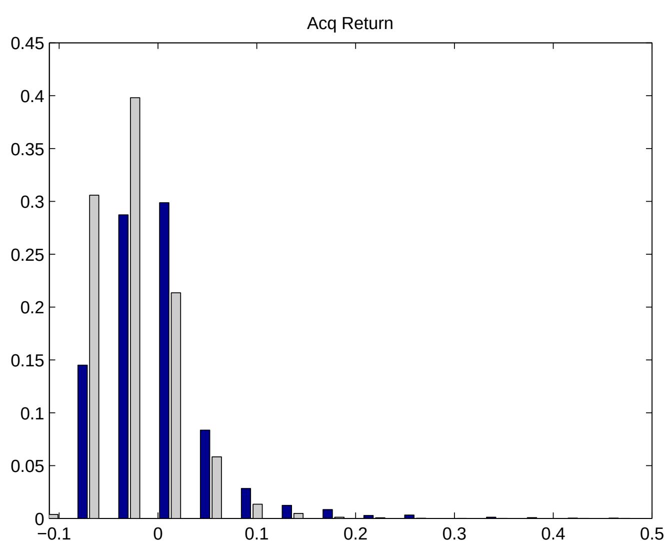
This figure presents the revelation effect of cash in acquirer announcement returns. We simulate acquisition deals based on the numerical solution of the model. The model is solved under the parameters presented in Table 4 using the method described in Appendix C. For each deal the acquirer announcement return is computed using the method described in Appendix D. This figure plots the simulated acquirer announcement returns against the cash fraction in the bids. The left panel presents the relation in the case of low misvaluation ($\sigma_\varepsilon = 0.05$) and the right panel presents that in the case of high misvaluation ($\sigma_\varepsilon = 0.20$).



(a) Offer Premium



(b) Cash Fraction



(c) Acquirer Announcement Return

Figure 3: Comparing Simulated and Empirical Distributions

This figure compares the distributions of offer premium, cash usage, and acquirer announcement

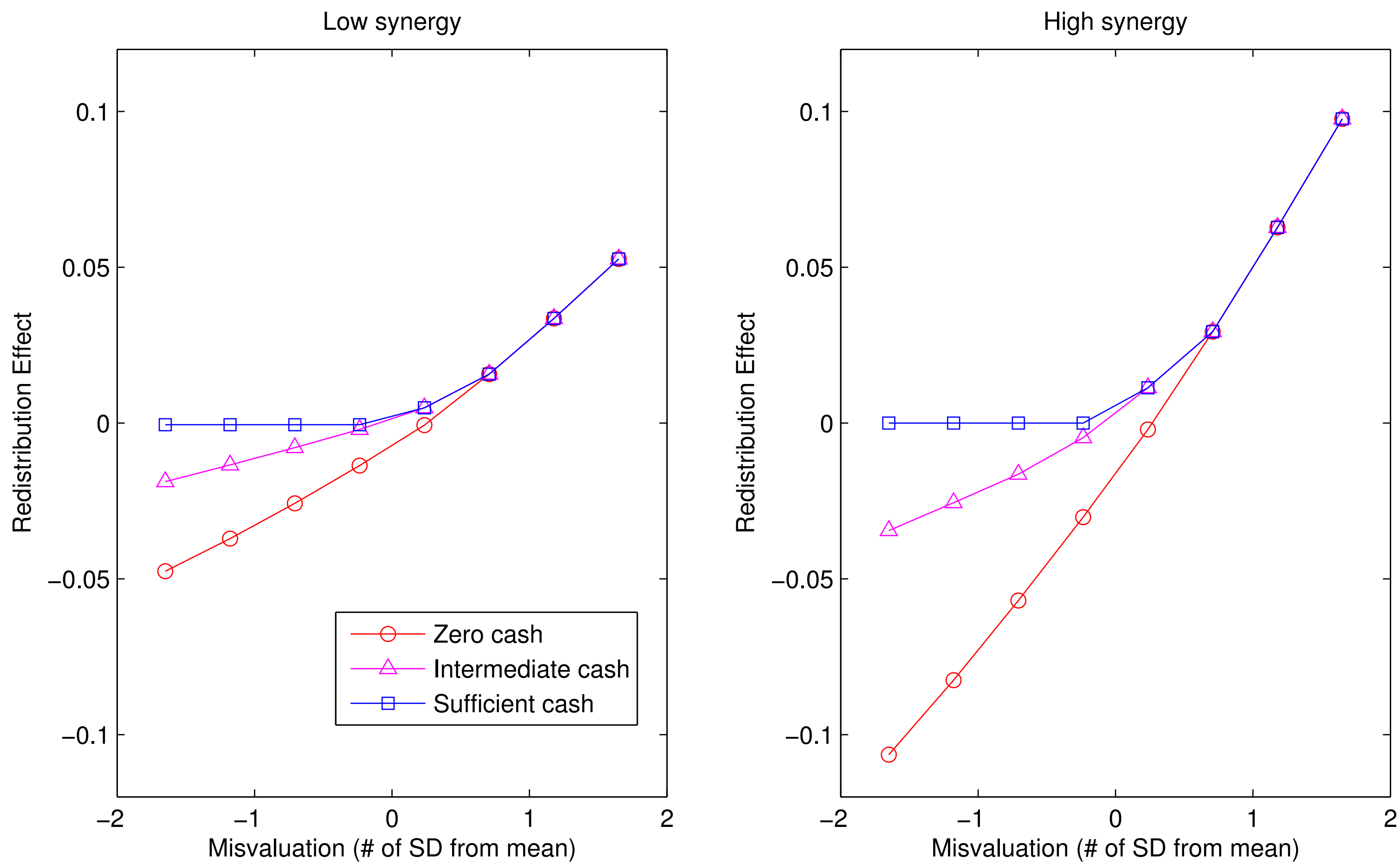


Figure 4: Redistribution Effect

This figure presents the redistribution effect for different types of bidders. The redistribution effect, which is measured by equation 8, is the bidder's merger gain in the estimated economy minus its merger gain in a counterfactual benchmark economy without misvaluation. The model is solved using the parameters in Table 4. The left panel shows the results for bidders with low synergy ($s = 0.4$) while the right panel for bidders with high synergy ($s = 0.8$). Each panel presents three curves representing bidders with zero, intermediate, and sufficient cash capacity, respectively. Bidders with intermediate cash capacity are able to pay the deal with 50% of cash, and bidders with sufficient cash capacity can pay the deal with all cash. Each curve describes how the redistribution effect, $\Delta_{i,n}$, varies with a bidder's misvaluation, ceteris paribus. A bidder's misvaluation, denoted ε in the model, is measured in the number of standard deviation from the sample mean.

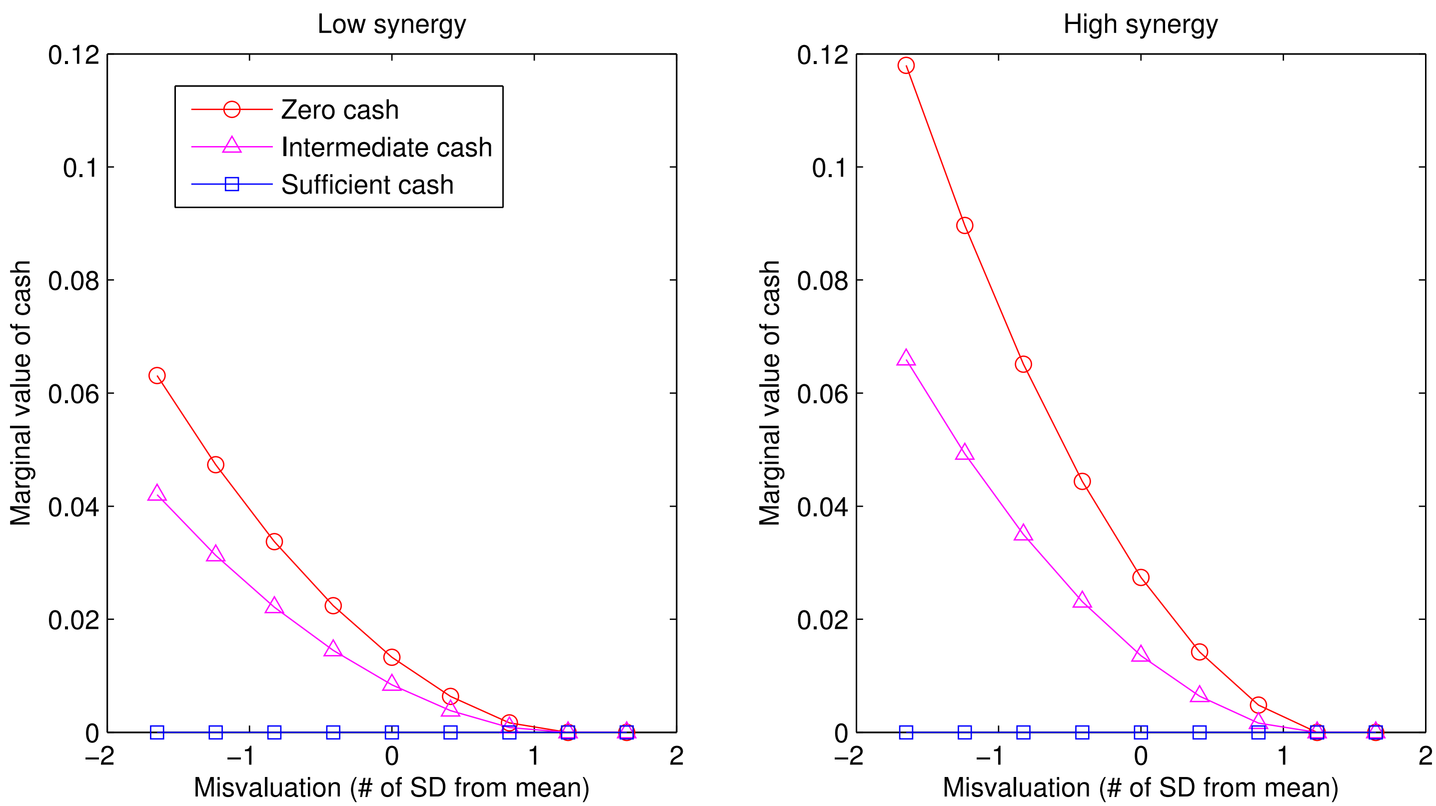


Figure 5: Marginal Value of Cash

This figure presents the marginal value of cash for different types of bidders. The marginal value of cash, which is measured by equation 9, is the partial derivative of a bidder's merger gain with respect to its cash capacity. The model is solved under the parameters in Table 4. The left panel shows the results for bidders with low synergy ($s = 0.4$) while the right panel for bidders with high synergy ($s = 0.8$). Each panel presents three curves representing bidders with zero, intermediate, and sufficient cash capacity, respectively. Bidders with intermediate cash capacity are able to pay the deal with 50% of cash, and bidders with sufficient cash capacity can pay the deal with all cash. Each curve describes how the marginal value of cash, $\lambda_{i,n}^{ME}$, varies with a bidder's misvaluation, denoted ε in the model, is measured in the number of standard deviation from the sample mean.

Table 1: Summary Statistics

This table reports the summary statistics for our sample of mergers and acquisitions. All values are expressed in 2009 dollars. Deal size is the transaction value (in million). Offer premium equals the offer price per share divided by the target stock price 4 weeks before the bid announcement minus one. Cash fraction is the percentage of cash payment in the bid. Acq relative size is the market value of the acquirer divided by the market value of the target 4 weeks before the bid announcement. Acquirer AR, Combined-firm AR, and Target AR are the cumulative abnormal return in a 3-day event window around the bid announcement of the acquirer, the combined firm, and the target, respectively, computed based on the market model. Target size is the logarithm of the target market value (in million) 4 weeks prior to the bid announcement. Target leverage is the ratio of debt and assets of the target. Target ME/BE is the market-to-book ratio of target equity.Target ROA is return on assets of the target. Target cash is the ratio of cash and book assets of the target. Number of obs. is the total number of observation for computing the statistics.

	1980–2013					1980–1990	1991–2000	2001-2013
	Mean	Std. Dev.	10%	Median	90%	Mean	Mean	Mean
Deal size ($M)	1,590.00	6,618.00	39.57	280.00	2,979.00	636.00	1,333.00	1,673.00
Offer premium	0.44	0.32	0.10	0.36	0.88	0.45	0.45	0.41
Cash fraction	0.31	0.40	0.00	0.00	1.00	0.31	0.18	0.48
Acq relative size	2.17	1.64	0.32	1.90	4.45	2.08	2.07	2.30
Acq AR	−0.02	0.08	−0.11	−0.02	0.05	−0.02	−0.02	−0.02
Target AR	0.22	0.23	0.00	0.18	0.50	0.20	0.18	0.27
Combined-firm AR	0.01	0.08	−0.06	0.01	0.09	0.01	0.01	0.02
Target size	5.30	1.71	3.21	5.20	7.57	4.76	5.24	5.48
Target leverage	0.28	0.26	0.00	0.23	0.66	0.30	0.27	0.29
Target ME/BE	2.47	3.20	0.71	1.67	4.88	1.88	2.56	2.27
Target ROA	−0.02	0.20	−0.17	0.01	0.10	0.02	−0.01	−0.04
Target cash	0.18	0.22	0.01	0.07	0.54	0.17	0.15	0.20
Number of obs.	2,503	2,503	2,503	2,503	2,503	172	1,379	952

Table 2: Sensitivity of Moments to Parameters

This table shows the sensitivity of model-implied moments (in columns) with respect to model parameters (in rows). 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, $Stderr(p)$ is the estimated standard error for parameter p (from Table 4) and $Stderr(m)$ is the estimated standard error for the empirical moment m (from Table 3). 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 log 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 eigth moment is c_1, the slope coefficient of cash usage on the log of relative firm size, from regression (7). 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 Announcement Return		Fraction of Bid in Cash		
Parameter	Mean	Cond. Var.	Slope on log(M)	Mean	Slope on Cash Frac	Mean	Cond. Var.	Slope on log(M)
μ_s	0.825	0.510	0.444	0.200	−0.455	0.121	−0.111	0.269
σ_s	0.899	1.675	0.181	0.435	−1.288	0.008	−0.337	0.137
ρ_{sM}	−0.094	−0.243	1.315	−0.485	0.250	−0.075	0.034	0.100
μ_ε	0.001	0.005	−0.009	−0.901	−0.079	0.045	−0.046	−0.005
σ_ε	0.440	−0.521	0.520	−0.773	1.844	0.266	0.538	0.735
μ_k	0.146	0.258	−0.311	0.514	−0.795	1.181	0.617	0.876
σ_k	0.104	−0.079	0.235	0.124	0.119	0.070	1.183	0.118
ρ_{kM}	−0.110	−0.270	0.209	−0.126	−0.313	0.251	0.791	1.092

Table 3: Model Fit

This table assesses model fit. The top panel shows how well the model fits the eight targeted moments, shown in the columns. The first moment is $E[\text{OfferPrem}_i]$, the average offer premium. The second moment is $\text{Var}(u_i)$, 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 $\text{Var}(w_i)$, 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 lower panel reports the results for untargeted moments. E[CombAR] and E[TarAR] are the average combined-firm and target announcement return, including the 4-week runup. Var[AcqAR], Var[CombAR], and Var[TarAR] are the variance of acquirer, the combined firm, and target announcement return. Corr(AcqAR, TarAR) is the Peason's correlation between acquirer announcement return and target announcement return.

	Panel A: Targeted Moments							
	Offer Premium			Acquirer Announcement Return		Fraction of Bid in Cash		
	Mean	Cond. Var.	Slope on log(M)	Mean	Slope on Cash Frac	Mean	Cond. Var.	Slope on log(M)
Data	0.437	0.085	0.033	−0.023	0.031	0.306	0.119	0.050
Standard error	0.016	0.006	0.004	0.004	0.005	0.028	0.007	0.009
Model	0.442	0.088	0.033	−0.024	0.032	0.308	0.120	0.052
Difference	0.006	0.004	0.000	−0.001	0.001	0.002	0.001	0.001
t-stat	0.351	0.594	−0.041	−0.334	0.228	0.081	0.179	0.149
	Panel B: Untargeted Moments							
	V[AcqAR]	E[CombAR]	V[CombAR]	E[TarAR]	V[TarAR]	Corr[AcqAR,TarAR]		
Data	0.006	0.014	0.017	0.283	0.057	0.115		
Standard error	0.001	0.003	0.001	0.005	0.002	0.020		
Model	0.002	0.020	0.008	0.438	0.038	0.087		

Table 4: Parameter Estimates

This table reports parameter estimates of the baseline model using the simulated method of moment (SMM). The top panel shows estimated parameters, and the bottom panel shows the moments implied by those estimates. Synergy s is assumed to follow a normal distribution $\mathcal{N}(\mu_s, \sigma_s^2)$ that is left truncated at zero; 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; $\rho_{sM}$is the Spearman's rank correlation between synergy and acquirer relative size; ρ_{kM} is the Spearman's rank correlation between cash capacity and acquirer relative size. E[s] and Stdev[s] are the average and standard deviation of synergy computed from the truncated normal distribution $\mathcal{TN}(\mu_s, \sigma_s^2; 0)$; E[$\varepsilon$] and Stdev[$\varepsilon$] are the average and standard deviation of misvaluation computed from the normal distribution $\mathcal{TN}(\mu_\varepsilon, \sigma_\varepsilon^2; 1)$; E[$k$] and Stdev[$k$] are the average and standard deviation of cash capacity computed from the censored normal distribution $\mathcal{CN}(\mu_k, \sigma_k^2; 0)$; r_{sM} and r_{kM} are the Pearson's linear correlation.

	μ_s	σ_s	μ_ε	σ_ε	μ_k	σ_k	ρ_{sM}	ρ_{kM}
Estimate	0.439	0.603	0.058	0.070	0.480	1.518	0.496	0.566
Standard Error	0.021	0.041	0.004	0.013	0.111	0.117	0.045	0.024
	E[s]	Stdev[s]	E[ε]	Stdev[ε]	E[k]	Stdev[k]	r_{sM}	r_{kM}
Estimate	0.676	0.444	0.058	0.070	0.869	1.034	0.386	0.441
Standard Error	0.024	0.022	0.004	0.013	0.086	0.084	0.020	0.036

Table 5: Estimated Efficiency Losses

This table reports the estimated efficiency losses in the baseline model. Percent of deals that are inefficient is the percent of simulated deals in which the low-synergy bidder wins. The average synergy loss in inefficient deals equals the gap between the loser's higher synergy and winner's lower synergy in inefficient deals. % of target size expresses the synergy loss as a percent of the target's pre-announcement market value, and % of synergy expresses the synergy loss as a percent of the higher synergy, which is the winner's synergy in efficient deals and the loser's synergy in inefficient deals. Average loss in all deals is the average efficiency loss acrpss all deals.

Panel A: Percent of Deals That Are Inefficient

	Estimate	7.01%
	Standard Error	1.03%

Panel B: Average Synergy Loss in Inefficient Deals

			Percentile				
		Mean	0.10	0.25	0.50	0.75	0.90
% of target size	Estimate	9.02	1.09	2.99	6.78	12.9	20.01
	Standard Error	0.63					
% of synergy	Estimate	15.79	1.93	5.29	11.95	22.05	36.37
	Standard Error	1.08					

Panel C: Average Synergy Loss in All Deals

			Percentile				
		Mean	0.10	0.25	0.50	0.75	0.90
% of target size	Estimate	0.63	0.08	0.21	0.47	0.90	1.40
	Standard Error	0.19					
% of synergy	Estimate	1.14	0.14	0.37	0.84	1.54	2.55
	Standard Error	0.31					

Table 6: Comparing High- and Low-Misvaluation Periods

This table reports the estimates for different subsamples. Panel A reports the moments implied by the parameter estimates and Panel B reports the model implications. Full sample is the sample used for our baseline estimation; the subsample with high (low) sentiment is comprised of M&A deals announced in periods with the top (bottom) quintile of market sentiment measure; the subsample with high (low) market volatility is comprised of M&A deals announced in period with the top (bottom) quintile of stock-market volatility. Definition of moments is the same as in Table 4. 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 across inefficient deals of the synergy loss, measured as a percent of the target's pre-acquisition market value; Stdev. of loss in inefficient deals is the standard deviation of the synergy loss across inefficient deals; Avg. loss in all deals is the average synergy loss across all deals; Avg. wealth redistribution is defined as the average of $|\Delta_i|$ in Equation (8); and Avg. marginal value of cash is defined as the average of λ_i^{Est} in Equation (9).

		Sentiment		Market Volatility	
	Full Sample	High	Low	High	Low
	Panel A: Moments Implied by Parameter Estimates				
E[s]	0.676	0.753	0.639	0.744	0.533
Stdev[s]	0.444	0.470	0.388	0.465	0.346
E[ε]	0.058	0.081	0.049	0.071	0.042
Stdev[ε]	0.070	0.108	0.061	0.081	0.072
E[k]	0.869	0.736	0.703	0.669	0.928
Stdev[k]	1.034	0.855	0.828	0.821	0.641
r_{sM}	0.386	0.312	0.470	0.424	0.336
r_{kM}	0.441	0.378	0.552	0.335	0.536
	Panel B: Model Implications				
Percent of deals inefficient	7.01	9.62	6.49	8.06	6.12
Avg. loss in inefficient deals (%)	9.02	13.54	7.60	11.19	6.72
Stdev. of loss in inefficient deals (%)	8.31	12.38	6.90	10.21	6.47
Avg. loss in all deals (%)	0.63	1.30	0.49	0.90	0.41
Avg. wealth redistribution	5.11	6.22	4.19	5.37	3.32
Avg. marginal value of cash	3.32	4.59	3.15	3.95	3.34

Table 7: Additional Robustness Tests

This table presents robustness tests regarding the correlation between acquirers' synergies and the number of bidders. The first column shows results from our baseline estimation described in Tables 3–5. The next columns show results for the correlated-bidder test, in which we use the optimal scoring rule and bidding rule in our baseline estimation, then simulate contests with correlated bidder synergies. We then compute the model implications based on the simulated contests. The last columns show results for the multiple-bidder test, in which we use the optimal scoring rule and bidding rule in our baseline estimation, then simulate contests containing more than two competing bidders. For each simulated contest, the bidder with the highest score Z wins the contest. The efficiency loss is defined as the difference between the highest synergy and the winner's synergy.

		Correlated Bidder Synergies		$N > 2$ Bidders		
	Baseline	Corr $= +0.5$	Corr $= -0.5$	$N = 3$	$N = 4$	$N = 5$
Percent of deals inefficient	7.01	10.13	5.33	10.08	12.39	14.04
Avg. loss in inefficient deals (%)	9.02	8.68	9.02	10.29	10.73	11.31
Stdev. of loss in inefficient deals (%)	8.31	8.14	8.10	9.22	9.53	9.99
Avg. loss in all deals (%)	0.63	0.88	0.48	1.04	1.33	1.59

Table 8: Additional Subsample Results

This table contains the results from estimating our model in different subsamples. Panel A reports the moments implied by the parameter estimates and Panel B reports the model implications. Data on acquirer's Entrenchment (E) Index are from Lucian Bebchuk's website. E-Index data are available only after 1996 and are coded as a number ranging from 0 to 6, with a lower number representing stronger governance (i.e., lower manager entrenchment). Among 2,772 observations in our full sample, 1,595 observations have E-Index data available for acquirer firms. E-Index is more likely missing for small acquirers, so excluding observations without E-Index data tilts our sample towards large acquirers. Among all observations with E-Index data, the average E-Index is 2.27 and the median is 2. We split the sample based on whether the E-Index is above 2 or less than or equal to 2. Next, we split the sample into horizontal and non-horizontal mergers. We define a horizontal merger as one in which the acquirer and target belong to the same Fama-French 48 industry. Definitions of Panel A's moments are the same as in Table 4. 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 across inefficient deals of the synergy loss, measured as a percent of the target's pre-acquisition market value; Stdev. of loss in inefficient deals is the standard deviation of the synergy loss across inefficient deals; Avg. loss in all deals is the average synergy loss across all deals; Avg. wealth redistribution is defined as the average of $|\Delta_i|$ in Equation (8); and Avg. marginal value of cash is defined as the average of λ_i^{Est} in Equation (9).

		Entrenchment Index		Horizontal Merger?	
	Full Sample	Low	High	Yes	No
	Panel A: Moments Implied by Parameter Estimates				
$E[s]$	0.676	0.622	0.590	0.676	0.658
$Stdev[s]$	0.444	0.395	0.356	0.431	0.426
$E[\varepsilon]$	0.058	0.055	0.049	0.057	0.055
$Stdev[\varepsilon]$	0.070	0.081	0.070	0.072	0.071
$E[k]$	0.869	0.690	0.706	0.667	0.864
$Stdev[k]$	1.034	0.749	0.650	0.768	0.940
r_{sM}	0.386	0.369	0.450	0.434	0.369
r_{kM}	0.441	0.464	0.466	0.409	0.442
	Panel B: Model Implications				
Percent of deals inefficient	7.01	8.30	7.52	7.30	6.74
Avg. loss in inefficient deals (%)	9.02	9.82	8.00	9.08	8.77
Stdev. of loss in inefficient deals (%)	8.31	8.88	7.15	8.33	8.28
Avg. loss in all deals (%)	0.63	0.82	0.60	0.66	0.59
Avg. wealth redistribution	5.11	4.73	3.69	4.77	4.89
Avg. marginal value of cash	3.32	3.78	3.25	3.55	3.38