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 8% of transactions, resulting in an average synergy loss equal to 12% of the target's value in these inefficient deals. The implied average loss across all deals is 1%. Although the inefficiency is small on average, it is large for certain deals and 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 knows 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 itself 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 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

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[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 focused on the effect of stock-market misvaluation on the method of payment and the acquisition performance, painting a picture of value transfer between targets and opportunistic acquirers (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' synergy 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 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. Bidders, however, are subject to cash constraints, for example, due to limited debt capacity. Thus, high-synergy bidders are often forced to finance at least part of the deal using shares. Cash constraints are not perfectly observable, however, which limits less-overvalued acquirers' ability to separate themselves from the more-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 2,771 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 7.9% 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 7.9% of deals that are inefficient, the winner's synergy is on average 23.3% below the loser's synergy, which amounts to an average synergy loss equal to 11.8% of the target's pre-announcement market value. Averaging across all deals (efficient and inefficient), the aggregate efficiency loss is 0.9% of the target's pre-announcement value, with a standard error of 0.4%. The main reason we find this small efficiency loss is that the estimated dispersion in synergies is almost an order of magnitude larger than the dispersion in misvaluation. As a result, high-synergy acquirers out-bid overvalued acquirers about 92% of the time, producing efficient deals.

While the unconditional average loss we find is low in percentage terms, it translates to a nontrivial $6.5 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 58.6% below the loser's synergy, amounting to a synergy loss equal to 27.4% of the target's pre-announcement

[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] $6.5 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 0.93% average efficiency loss.

market value. Using high Sentiment (Baker and Wurgler, 2006, 2007) and high stock-market volatility to proxy for high misvaluatoin risk, we find that the efficiency loss is more than 60% higher in times when misvaluation is more likely, compared to the full sample.

Next, we measure how misvaluation affects the distribution of merger gains across acquirers. We define the merger gain as the acquirer's 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. Misvaluation helps overvalued acquirers by allowing them to use their shares as a cheap currency. Misvaluation hurts underval-ued 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 un-dervalued to overvalued acquirers is 7.1% of the target's pre-acquisition value, which translates to roughly $50 billion of wealth redistributed per year among U.S. public acquirers.[6] Underval-ued bidders can avoid this negative externality by using cash, as long as their cash capacity is high enough.

Finally, we use the estimated model to measure the value of extra cash capacity. Intuitively, extra cash capacity is valuable because it allows a bidder to signal that it is undervalued by pay-ing cash. On average across all deals, we find that one extra dollar of cash capacity increases a bidder's merger gain by 2.7 cents. This marginal value of cash capacity is about 60% larger in high-misvaluation periods relative to low-misvaluation periods. 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 capac-ity, an additional dollar of cash capacity can increase its merger gain by 12 cents when the deal synergy is high. Overall, these results highlight one way that financial constraints harm firms: Financial 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.

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

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[6] $50 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 7.1%.

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 performances 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 also 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 using a hand-collected dataset of pre-announcement bids, 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 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 concludes.

2 Model

We extend the model of Rhodes-Kropf and Viswanathan (2004) by allowing acquirers to use both cash and equity as the means of payment. We start by setting up the model and discussing its assumptions. Next, we explain how the model works, and we describe the predictions that are important for our empirical strategy.

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, before the acquisition, the market value of acquirer i as an independent entity 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

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[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.

for M&A, since an overvalued firm has an incentive to buy other companies using its equity as currency (Rhodes-Kropf, Robinson, and Viswanathan, 2005; Rhodes-Kropf and Viswanathan, 2004; Shleifer and Vishny, 2003). Lastly, the acquirers are subject to a cash capacity constraint. That is, 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 itself. 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. 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 premiums (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 a larger acquirer is more likely to have enough cash capacity to buy a given 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 acquirer's cash capacity. In sum, the

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[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.

acquirer characteristics $(s_i, \varepsilon_i, k_i, M_i)$ are an independent realization from the joint distribution $\mathcal{F}(\mathcal{N}_s(\mu_s, \sigma_s^2), \mathcal{N}_\varepsilon(\mu_\varepsilon, \sigma_\varepsilon^2), \mathcal{N}_k(\mu_k, \sigma_k^2), \mathcal{M}(\cdot); \rho_{sM}, \rho_{kM}), i = 1, 2.$

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, $b_i = (C_i, \alpha_i)$, 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]

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\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. \quad (1)
\end{aligned}
$$

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 value 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.

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[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 $\mathcal{F}(\cdot)$.

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 expected profit, given the target's scoring rule; and the target evaluates the bids conditional on its available information and the acquirers' bidding strategy. Formally, the definition of such an equilibrium is given 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*

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

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 that equals one if the conditions specified in the subscript is true and zero otherwise.

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.

Though we allow misvaluation in the model, we do not require it for the model to function. The model works fine if all acquirers are fairly valued ($\mu_\varepsilon = \sigma_\varepsilon = 0$). We therefore do not take a stance on whether misvaluation exists or whether it is an important motive for acquisitions. By estimating this flexible model, we let the data tell us whether and how misvaluation matters.

We focus on the opportunistic bidding of overvalued acquirers, but we do not explicitly model targets' misvaluation. Of course, target firms may also be misvalued and behave opportunistically. However, 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. Moreover, we normalize all values in the model and in the estimation using the pre-acquisition market values of the targets. Therefore, we treat acquirer misvaluation on a relative basis. That is, the misvaluation factor ε_i captures how much more overvalued the acquirer is compared with the target.

We take the targets and acquirers as given, and we do not model the choice of becoming a target or acquirer. Therefore, the distribution of acquirer characteristics describes the pool of firms who have selected to become acquirers. This is consistent with our estimation, because our sample is also based on the selected sample of observed acquirers.

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 acquirers before any bid is publicly announced.[11] 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 competing 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, we extend our baseline model estimation to include more than two bidders. We simulate contests with more than two bidders while keeping the equilibrium bidding strategy and scoring rule unchanged. We find that our main results are quite similar as long as the number of competing bidders is

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[11] 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.

kept within a reasonable range (e.g., less than five). Therefore, we do not expect the two-bidder assumption to materially affect our conclusions.

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.[12] 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;[13] 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.

Lastly, the assumption of a partially unobservable cash capacity constraint (k_i) is important. Intuitively, if acquirers have unlimited cash capacity, relatively undervalued acquirers in our model can separate by bidding only with cash, thereby avoiding being taken advantage of by more overvalued rivals. The target then imposes even more severe penalties on the use of equity, which eventually deters the use of equity by overvalued acquirers. In such an equilibrium, the target will not accept any equity as payment, so misvaluation will have no effect on the M&A market. 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 constraint. Given researchers' difficulties in measuring financing constraints, it is plausible that targets can only partially observe these constraints.

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[12] In fact, under the private value paradigm and the assumptions we make in the previous subsection, they are also equivalent to the first-price auction from the ex-ante perspective according to the Revenue Equivalence Theorem of Myerson (1981) and Riley and Samuelson (1981). The theorem states that two selling mechanisms generate the same expected revenue to the seller if (i) they result in the same allocation of the item for sale; and (ii) the expected surplus of the bidder with the lowest value is the same between two selling mechanisms. These two conditions are satisfied in our setting.

[13] 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.

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. $\square$

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. Acquirers with different characteristics (i.e., synergy, misvaluation, and cash capacity) 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.[14] 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

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

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.[15] 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.

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. Undervalued acquirers with severe cash capacity constraint suffer the most by paying with their undervalued equity, which provides camouflage for overvalued acquirers in the pooling equilibrium.[16]

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

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[15] 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.

[16] Even though these undervalued acquirers with severe cash capacity constraint suffer by paying equity, they may still have positive gains from the mergers if the synergy is large enough.

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.[17] 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.

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 $2,771$ acquisition deals (same size as our sample) based on the numerical solution of the 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 dispersion, i.e., when σ_ε is larger. This prediction is crucial to our identifi-

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[17] The method of numerically solving the model is presented in Appendix C.

cation 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 dispersion 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. 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;[18]

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.

Following Betton, Eckbo, and Thorburn (2008), we group bids into control contests. A control contest begins with the first 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. For each control contest, we identify the initial bid in the contest and construct the moments of interest (e.g., offer premium, announcement returns, method of payment, etc.) based on this initial bid.

We measure a bid's offer premium 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 measure the bidder and target's 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.

Our final sample includes 2,771 bids. Table 1 provides summary statistics. The average transaction value is 1,482 million in 2009 dollars, significantly skewed to the right. Offer premium, measured as the offer price deflated by the target stock price 4 weeks before the bid announcements less one, averages 44% with a standard deviation of 32%. Bidders pay on average 30% 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 acquirer to target market value ratio averages 2.19. The mean acquirer announcement return is slightly negative, −2.2%. The target's announcement return is significantly positive with an average of 21.5%. Also consistent with previous findings, the combined firm announcement return is positive and around

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[18] 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.

one percent. 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. The Appendix E contains additional details on the SMM estimator.

3.3 Identification and Choice of Moments

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. To explain how the identification works, this subsection explains how our moments vary with the 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.[19]

The first two moments are the mean and variance across deals' observed offer premia. The

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[19] 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).

mean and variance of offer premia are most informative about the mean and variance of synergies (μ_s and σ_s), respectively. 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 mean and variance. Table 2 confirms that these two moments are most sensitive to μ_s and σ_s.

The third moment is the average acquirer announcement return. Table 2 shows that this moment is most senstive to μ_ε, which controls the average level of misvaluation. 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. 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 fourth moment is the slope from a regression of bidder announcement return on the fraction of the bid made in cash. This slope is positive in both the data and the model. Table 2 shows that this moment is most sensitive to σ_ε, which controls the dispersion in bidders' misvaluation. 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 fifth and sixth moments are the fraction of bids made in all cash or all equity, respectively. In the data, 19.5% of bids are all cash, 52.9% are all equity (Table 3). These moments mainly identify μ_k and σ_k. The larger the average cash capacity μ_k, the more all-cash deals and the fewer all-equity deals we should observe, holding other parameters constant. We see exactly this pattern in Table 2. The larger the dispersion σ_k across bidders' cash capacity, the more deals should fall into the extreme all-cash and all-equity bins. This intuition manifests as a strong positive relation between σ_k and both of these moments.

The seventh moment is the slope from a regression of offer premia on $\ln(M)$, the acquirers' relative size. Table 2 shows that this moment is highly informative about ρ_{sM}, the correlation

between the synergy and $\ln(M)$. The reason is that the offer premium is closely linked to the deal's synergy, as explained above.

The eighth moment is the slope from a regression of cash fraction used on $\ln(M)$. Table 2 shows that once we pin down the previous seven parameters, this moment helps identify ρ_{kM}, the correlation between cash capacity and $\ln(M)$. The reason is that a firm's cash capacity k is strongly related to amount of cash it ends up using in its bid.

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, the marginal value of cash capacity, and additional counterfactuals. Finally, we compare our results across subsamples.

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 of 43.2%. The offer premium varies significantly across deals with a standard deviation of 32.4% (or a variance of 10.5%). 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 rev-

elation 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 correlated with 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. Because announcement returns are abnormal returns estimated using asset-pricing models around the event window, they contain measurement errors that add to the variances. More importantly, announcement returns in the data are affected by factors outside of the model. These factors need not bias the average announcement returns, they add to the variance of announcement returns. That means the estimated model is expected to explain only a fraction, rather than all, of the announcement return variance in the data.

Among other untargeted moments, the model successfully matches the average announcement return of the combined firm and the correlation between acquirer and target announcement returns.[20] 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 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 38.7% in the model and 28.2% 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

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[20] Consistent with the literature, we measure the target's announcement return using a longer window that begins 30 days before the announcement. This longer window is required to capture the well-documented information leakage.

to average roughly -10% in data to explain the difference, which seems implausible.

The target announcement return 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 target announcement return 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, the target's announcement return may be confounded by revelation about the target, which is outside our model.

Finally, Figure 3 shows how the model fits the full distributions of offer premia, cash usage, and acquirer announcement returns. The model fits not just the mean and variance of these distributions, but also their shape, mainly because of our chosen distributions for s, k, and ε. In both the model and data, offer premia are right-skewed, and cash usage 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 equal the variables' means and variances. To help interpret the parameters, the table's bottom panel reports the mean and standard deviation implied by the parameter estimates.

The merger synergy s, expressed as a fraction of the target firm's pre-announcement market value, is assumed to follow a normal distribution $\mathcal{N}(\mu_s, \sigma_s^2)$ left-truncated at zero in our model. Parameter μ_s is estimated as 0.15 and σ_s is 0.77. Based on these estimates, the model implied average synergy is 0.67 with a standard deviation of 0.49. Hence the estimates suggest that a typical merger creates value that averages 67% of the target's market value. The synergy varies significantly across merger deals.

Because misvaluation is assumed to follow a normal distribution truncated at a high upper bound, the mean and standard deviation of misvaluation are equal to μ_ε and σ_ε. Parameter μ_ε is estimated as 0.055, meaning the market believes the average bidder is overvalued by 5.5%. The

market therefore adjusts its assessment of acquirers' stand-alone value downwards by 5.5% 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).

The standard deviation of acquirer misvaluation is estimated as 0.062. This result implies that 90% of acquiring firms are misvalued less than +10% relative to their targets.

Cash capacity is assumed to follow a normal distribution $\mathcal{N}(\mu_k, \sigma_k^2)$ left-censored at zero. Parameter μ_k is estimated as 0.67 and σ_k as 3.30. The estimates translate into an average cash capacity of 1.67 and a standard deviation of 2.15. Because we normalize the target pre-acquisition market value to be 1, the estimates imply that an average acquirer has enough cash capacity to buy the target entirely with cash. Acquirers' cash 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 with limited access to cash, 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 0.43 linear (i.e. Pearson's) correlation between the synergy and acquirer 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 0.32 linear correlation between cash capacity and acquirer 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 likely face lower financing constraints, giving them more access to cash.

4.3 Aggregate Efficiency Loss: The Crowd-Out Effect

Equipped with the estimated model, we now explore its main implications for 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 with perfect information.

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. The latter deals are inefficient in the sense that the low-synergy bidder would never win in an ideal, counterfactual economy with perfect information. 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 the ideal, counterfactual economy with perfect information.

Table 5 presents the results. We find that 7.9% of deals are inefficient, meaning the overvalued acquirer crowds out the synergistic acquirer. In these inefficient deals, the synergy loss averages 11.8% of the target's pre-acquisition market value. Put differently, the winner's synergy is 23.3% lower than the loser's synergy in the average inefficient deal. Averaging across all deals (efficient, inefficient, and failed), the average efficiency loss is 0.93% (roughly 7.9% times 11.8%) of

targets' pre-acquisition market value. The average efficiency loss is low mainly because the estimated dispersion in synergies (49%) is almost an order of magnitude larger than the estimated dispersion of misvaluation (6%). When two bidders compete, the difference in their synergies is usually much larger than the difference in their misvaluations, so it is almost always synergies and not misvaluation that determines the winner. Crowding out therefore occurs in only a small fraction of deals. The low estimated average efficiency loss suggests that the M&A market overall reallocates assets efficiently.

Though the average efficiency loss is small, the efficiency loss varies significantly across deals and is quite large in certain transactions. For example, the efficiency loss in the top 10% of crowd-out deals amounts to more than 27.35% of the target pre-acquisition market value, or almost 60% of the first-best deal 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.[21] Our estimates are quite precise. For example, the estimated 0.93% average loss in all deals has a standard error of 0.39%, 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 0.9% higher if we could somehow eliminate misvaluation. The problem is that firms would reoptimize if misvaluation disappeared, and our model would capture some but not all 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 become 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.

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[21] 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 estimate the standard error as the standard deviation across simulations.

4.4 The Redistribution Effect

Misvaluation and opportunistic bidding lead to not only an aggregate inefficiency, but also a redistribution of merger gains across bidders. 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 opportunistic bids. In this section, we quantify this wealth redistribution across different types of bidders.

Because the winning bidder pays the price offered by the losing bidder, in an economy with perfect information, the expected merger gain of bidder i in contest n with state variable $(s_{i,n}, \varepsilon_{i,}, k_{i,n}, M_{i,n})$ is

$$u_{i,n}^{PI} = E[\max\{s_{i,n} - \tilde{s}_{i,n}, 0\}].$$

This expectation is taken with respect to the opponent's synergy $\tilde{s}_{i,n}$, and it takes into account bidder i's probability of winning the deal. It follows that, in the economy with perfect information, a bidder's expected merger gain only depends on its own synergy. In our estimated economy with asymmetric information, the expected merger gain for the same bidder, $u_{i,n}^{AI}$, depends on all its state variables and is derived in Equation (2). In general, $u_{i,n}^{AI}$ is not equal to $u_{i,n}^{PI}$, suggesting that some bidders gain more than they would in the perfect-information economy, while others gain less. We define wealth redistribution for bidder i as

$$\Delta_{i,n} = u_{i,n}^{AI} - u_{i,n}^{PI}. \tag{5}$$

Figure 4 illustrates the wealth redistribution 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 entirely in cash.

Each curve describes how the wealth redistribution, $\Delta_{i,n}$, 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,

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when synergy is high ($s = 0.8$) in the right panel, a bidder with top 5% misvaluation (i.e., overvalued by $1.65 \times 6.2\%$ above the mean) gains more than it does in the perfect information economy by 10% of the target 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 becomes zero if the bidder is able to pay all in cash. Cash capacity has a much smaller effect on overvalued bidders, because most overvalued bidders bid with little or even no cash.

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 measure the average wealth redistribution across bidders by averaging the absolute value of individual bidders' redistribution:

$$\chi = \frac{1}{2N} \sum_{n=1}^{N} \sum_{i=1}^{2} |\Delta_{i,n}|. \tag{6}$$

When χ is large, bidders' expected gains in our model economy deviate more from their benchmarks in the perfect-information economy, indicating that the opportunistic bidding causes more wealth redistribution across bidders. We estimate χ as 0.071 in our baseline model, so the average absolute wealth redistribution across bidders is 7.1% of the target's pre-acquisition market value.

4.5 Marginal Value of Cash Capacity

Extra cash capacity is valuable to acquirers, because a bidder can signal that it is undervalued by bidding cash rather than equity. In this section, we explore the marginal value of cash capacity for different types of bidders. We measure the marginal value of cash capacity for a given bidder in our model economy by numerically computing the partial derivative of its expected merger

gain with respect to its cash capacity:[22]

$$\lambda_{i,n}^{AI} = \frac{\partial u_{i,n}^{AI}}{\partial k_{i,n}}. \tag{7}$$

Because both $u_{i,n}^{AI}$ and $k_{i,n}$ are measured relative to the target pre-acquisition market value, $\lambda_{i,n}^{AI}$ simply 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, $\lambda_{i,n}^{AI}$, 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 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 constrained in cash. 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 shrinks to 0 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^{AI} across all bidders:

$$\bar{\lambda} = \frac{1}{2N} \sum_{n=1}^{N} \sum_{i=1}^{2} \lambda_{i,n}^{AI}. \tag{8}$$

[22] In the perfect information economy, u_i^{PI} does not depend on k_i, so $\lambda_i^{PI} = 0$ and the marginal value of cash capacity is always zero.

We estimate $\bar{\lambda}$ as 0.027 in our baseline model. Therefore, one additional dollar in cash capacity increases the bidder's merger gain by 2.7 cents on average.

4.6   What is Driving These Results?

Which elements of the model are most important for generating the results above? To answer this question, we use the estimated model as a benchmark, then we create counterfactual scenarios in which we change one parameter's value while keeping other parameters at their estimated value (i.e., comparative statics). We solve the model in these counterfactual scenarios and recompute the model's main implications. Results are in Table 6.

In the first counterfactual analysis, we shock the average amount of overvaluation by doubling μ_ε. The probability of crowd-out, average inefficiency, average wealth redistribution, and the average marginal value of cash capacity increase only slightly. This small effect is not surprising, because if the market rationally expects that acquirers are more overvalued on average, it simply makes a larger negative adjustment to all acquirers' stand-alone values upon bid announcements, which reduces all acquirers' announcement returns. The increase in average overvaluation, however, does not significantly increase the market's confusion and hence only marginally helps opportunistic bidders to camouflage.

In the second analysis, we double the parameter σ_ε. This experiment represents an increase in the dispersion of overpricing across acquirers, or, more simply, an increase in the amount of unanticipated misvaluation. This change has large effects: The probability of crowd-out and the efficiency loss in crowd-out deals increase by almost 70% and 50%, respectively. The average efficiency loss in all deals more than doubles. Average wealth redistribution is also significantly larger, and the marginal value of cash rises. To summarize, we find that changing the *level* of overvaluation has a small effect, whereas changing the *dispersion* in overvaluation has a very large effect. The reason is that a higher dispersion increases the target's confusion, allowing overvalued, opportunistic acquirers to more easily camouflage and crowd out synergistic acquirers.

We then examine the effects of cash capacity. Because the distribution of cash capacity is assumed to follow a censored normal distribution, the average and dispersion of cash capacity depend on both μ_k and σ_k. To isolate the effect of average cash capacity from that of the dispersion

of cash capacity, we make sure that we preserve one when we set the other to the targeted value. We do so by changing μ_k and σ_k simultaneously.

In the third counterfactual scenario, we reduce the average cash capacity by half (i.e., reduce $E[k]$ from 1.67 to 0.835). Reducing the average cash capacity increases the probability of crowd-out and the average efficiency loss. When cash capacity becomes tighter, undervalued bidders are forced to use more equity in their bids, which makes the target more confused and provides better camouflage for opportunistic bidders. The average wealth redistribution and the marginal value of cash rise accordingly. The magnitude of changes in this counterfactual, however, is small, because the average bidder still affords to pay 50% of the deal value in cash.

In the last counterfactual analysis, we double the dispersion of cash capacity (i.e., increase $Stdev(k)$ from 2.15 to 4.30). When the cross-sectional variation in cash capacity increases, the target becomes more uncertain of a bidder's unobservable capacity of cash, which allows opportunistic bidders to more easily pool with cash-constrained synergistic bidders. Consistent with our conjecture above, doubling the dispersion of cash capacity dramatically increases the probability of crowd-out and the average efficiency loss. Not surprisingly, the average wealth redistribution rises as well. The marginal value of cash capacity increases slightly. In sum, changing the *level* of financing constraints has a modest effect on the inefficiency and redistribution we study. Changing the *dispersion* in financing constraints has a much larger effect, because it increases targets' confusion and thereby allows opportunistic acquirers to more easily camouflage.

4.7   Subsample Analysis

We assume the model parameters are constant in the baseline estimation. Previous studies (Ang and Cheng, 2006; Bouwman, Fuller, and Nain, 2009; Rhodes-Kropf, Robinson, and Viswanathan, 2005) document that misvaluation risk varies over time. 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).[23] Specifically, we classify a calendar month as a high (low) market senti-

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[23] The investor-sentiment index of Baker and Wurgler (2006, 2007) is a composite index constructed using six indices–

ment period if the investor-sentiment index in that month is within the top (bottom) quintile of the whole time series. When the sentiment index 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 also shifts up the level of overvaluation, then high sentiment also corresponds to high μ_ε in our model.

The subsample with high sentiment has three important features. First, the average acquirer announcement return is lower in this subsample (-4.3%) than that in the full sample (-2.2%). A lower average announcement return is consistent with more overvaluation on average (i.e. higher μ_ε) in high-sentiment months. Second, the acquirer announcement return is also more sensitive to the method of payment. Regressing acquirer announcement returns on cash fraction in the bid, we get a coefficient of 0.071 in this subsample and 0.033 in the full sample. This second feature is consistent with more misvaluation (i.e. higher σ_ε) in high-sentiment months. Third, the offer premium is higher on average and much more dispersed. Specifically, the average offer premium is 50.6% in this subsample, compared with 43.9% in the full sample. The standard deviation of offer premium reaches 37.4% in this subsample and it is only 32.1% in the full sample.

Panel A of Table 7 presents the parameter estimates. To facilitate our analysis, we report the mean and standard deviation of variables rather than raw parameters. $E[s]$ and $Stdev[s]$, which are mainly identified off the offer premium, are both higher in the high-sentiment subsample. The estimate of $E[\varepsilon]$ increases from 0.055 in the full sample estimation to 0.076 in the high-sentiment subsample, mainly due to the lower average acquirer announcement return. $Stdev[\varepsilon]$ is estimated as 0.101 in the high-sentiment subsample, much higher than its full-sample estimate of 0.062. The main reason is that announcement returns are more sensitive to cash usage in high-sentiment months. These results confirm that high sentiment is associated with both more overvaluation (higher μ_ε) and more misvaluation (higher σ_ε). Our parameter estimates also indicate a higher level and more dispersion in synergies during high-sentiment months. We obtain this result because offer premia are both higher and more dispersed in high-sentiment months.

closed-end fund discount, NYSE share 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.

Panel B of Table 7 summarizes the main model implications for different subsamples. Due to greater misvaluation in high-sentiment months, the probability of crowd-out rises to 10.13%, increasing by almost 30% from the estimate of 7.86% in the full sample. The synergy loss in inefficient deals also increases to 15.79% of the target pre-acquisition value or 24.28% of the first-best deal synergy. In the top 10% of these crowd-out deals, the efficiency loss amounts to more than 35.74% of the target pre-acquisition value or 55.15% of the first-best deal synergy. The reason we find greater inefficiencies in high-sentiment periods is that there is more misvaluation 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 crowd-out effect.

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.

We find the opposite results in the low-sentiment subsample. Though the mean and dispersion of synergies are estimated to be similar to those in the full sample, the estimated $E[\varepsilon]$ and $Stdev[\varepsilon]$ are both lower than those in the full sample, implying a lower misvaluation risk. The probability of crowd-out, inefficiencies, average wealth redistribution, and the marginal value of cash capacity are all reduced from their estimates in the full sample, consistent with the notion that this subsample represents periods with low misvaluation risks and thus less opportunistic bidding.

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.[24] We classify a calendar month as a high- (low-) misvaluation period if the stock-market volatility is in the top (bottom) quintile of the whole time series. We expect that the inefficiency is greater during the periods with high stock market volatility.

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[24] Pástor, Stambaugh, and Taylor (2015) follow this same rationale in using return volatility to proxy for misvaluation.

Our results with stock-market volatility resemble our results with sentiment. Specifically, bids announced during periods with high market volatility are estimated to face a high 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 of high market volatility.

5   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. This paper's main contribution is to quantify this inefficiency. We find that the inefficiency is relatively low on average but high in certain deals and 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.

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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 $z(C_i, \tilde{\alpha}_i, M_i) = \max\{1, z(C_j, \alpha_j, M_j)\}$. $\qquad\square$.

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

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

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:

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

$\square$

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.[25] 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

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

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[25] 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:

$$C_t(s, \varepsilon, k, M) = \underset{C}{\text{argmax}} \int_{\Phi'} [M(1-\varepsilon) + (1+s) - \tilde{C}_{t-1}] \times (\alpha - \tilde{\alpha}_{t-1})$$
$$\times I_{t-1}(C, \alpha, M, \Phi') d\mathcal{F}(\Phi'),$$

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 $I_{t-1}(\cdot)$ is defined as

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

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

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

And finally, the conditional combined abnormal announcement return is

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

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.

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

The conditional abnormal announcement return to the target is

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

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

$$AR_{in,3}^c = \frac{M_{in}(1 + AR_{in,3}^a) + 1 + AR_{in,3}^n}{1 + M_{in}} - 1.$$

In the end, we can compute the ex-ante abnormal announcement returns as follows.

$$
\begin{aligned}
AR_{in}^a &= E_j\left[I_1 \cdot AR_{in,1}^a + I_2 \cdot AR_{in,2}^a + I_3 \cdot AR_{in,3}^a | M_{in}, b_{in}\right] \\
AR_{in}^t &= E_j\left[I_1 \cdot AR_{in,1}^t + I_2 \cdot AR_{in,2}^t + I_3 \cdot AR_{in,3}^t | M_{in}, b_{in}\right] \\
AR_{in}^c &= E_j\left[I_1 \cdot AR_{in,1}^c + I_2 \cdot AR_{in,2}^c + I_3 \cdot AR_{in,3}^c | M_{in}, b_{in}\right]
\end{aligned}
$$

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,

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

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$$+ h(\Phi_j|b_i, M_i, J_i, Z_i < Z_j) \Pr(Z_i < Z_j|b_i, M_i, J_i)$$
$$= h(\Phi_j|b_i, M_i, Z_i > Z_j) \times 0.87 + h(\Phi_j|b_i, M_i, Z_i < Z_j) \times 0.13 \qquad (D.1)$$

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

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

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

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:

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

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.
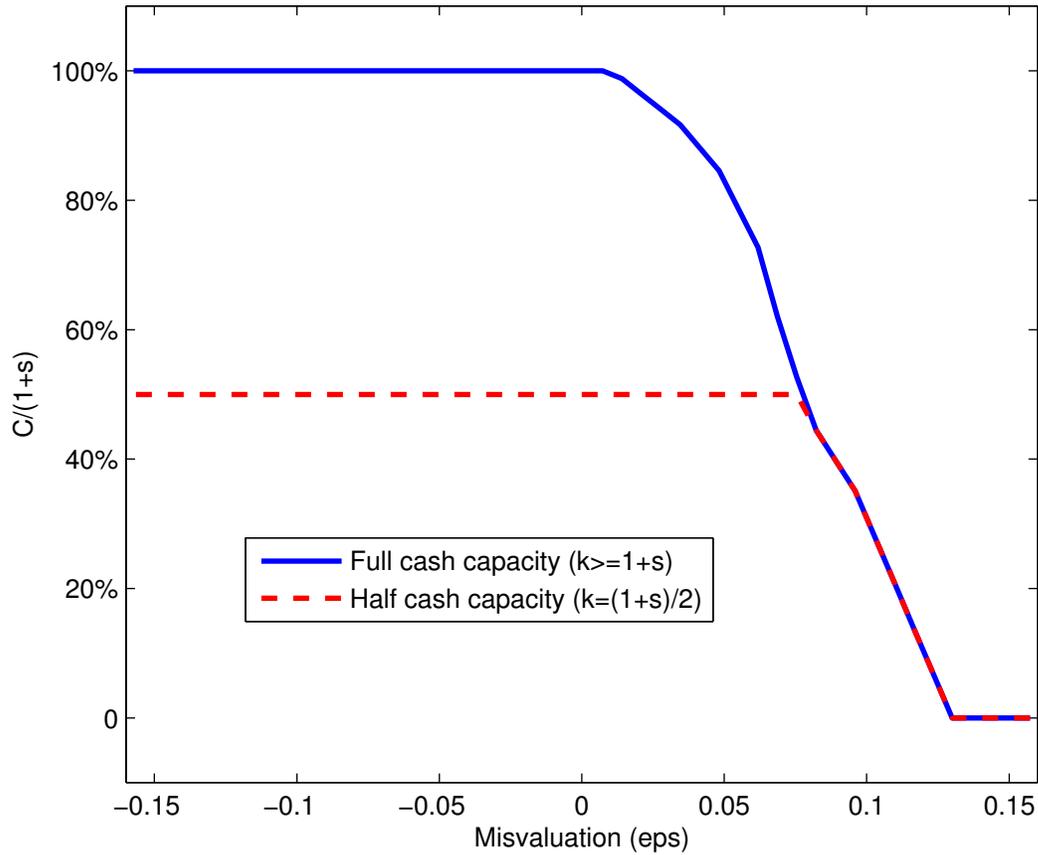
Figure 1: Cash Fraction in the Optimal Bid

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.
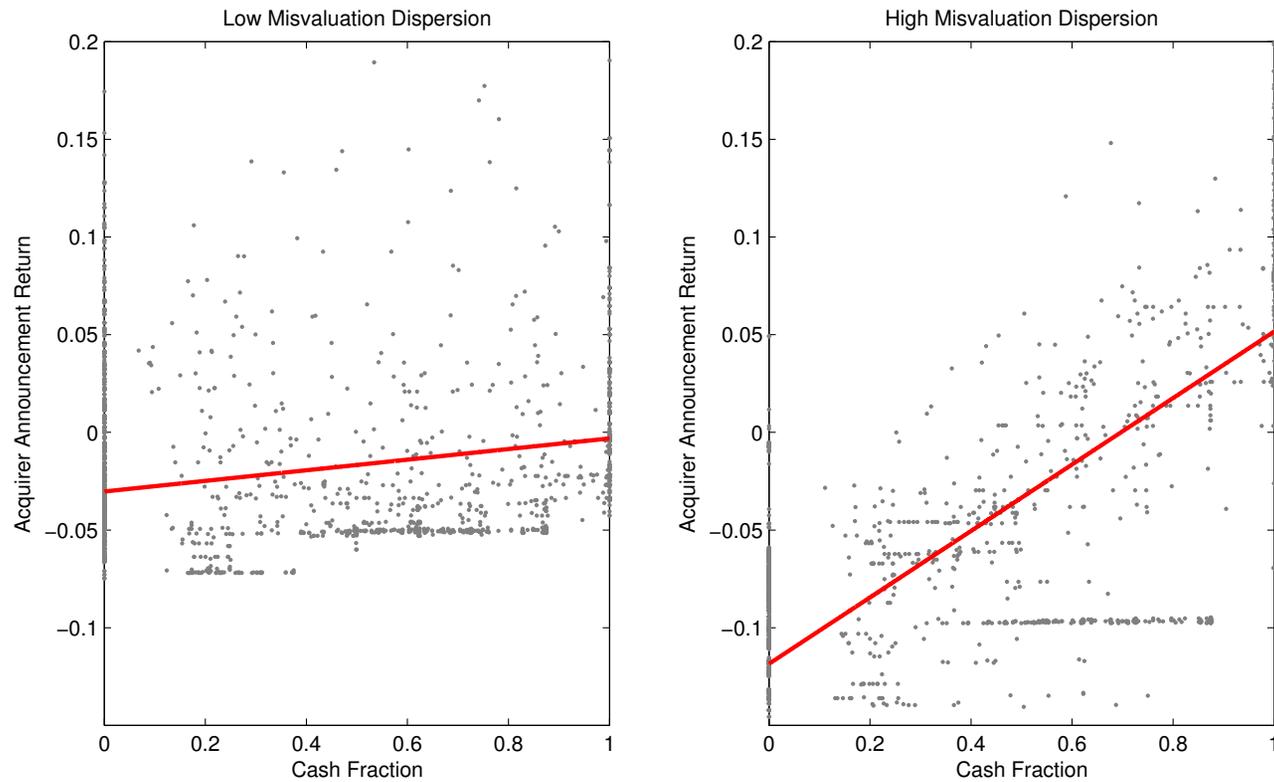
Figure 2: Revelation Effect of Cash

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

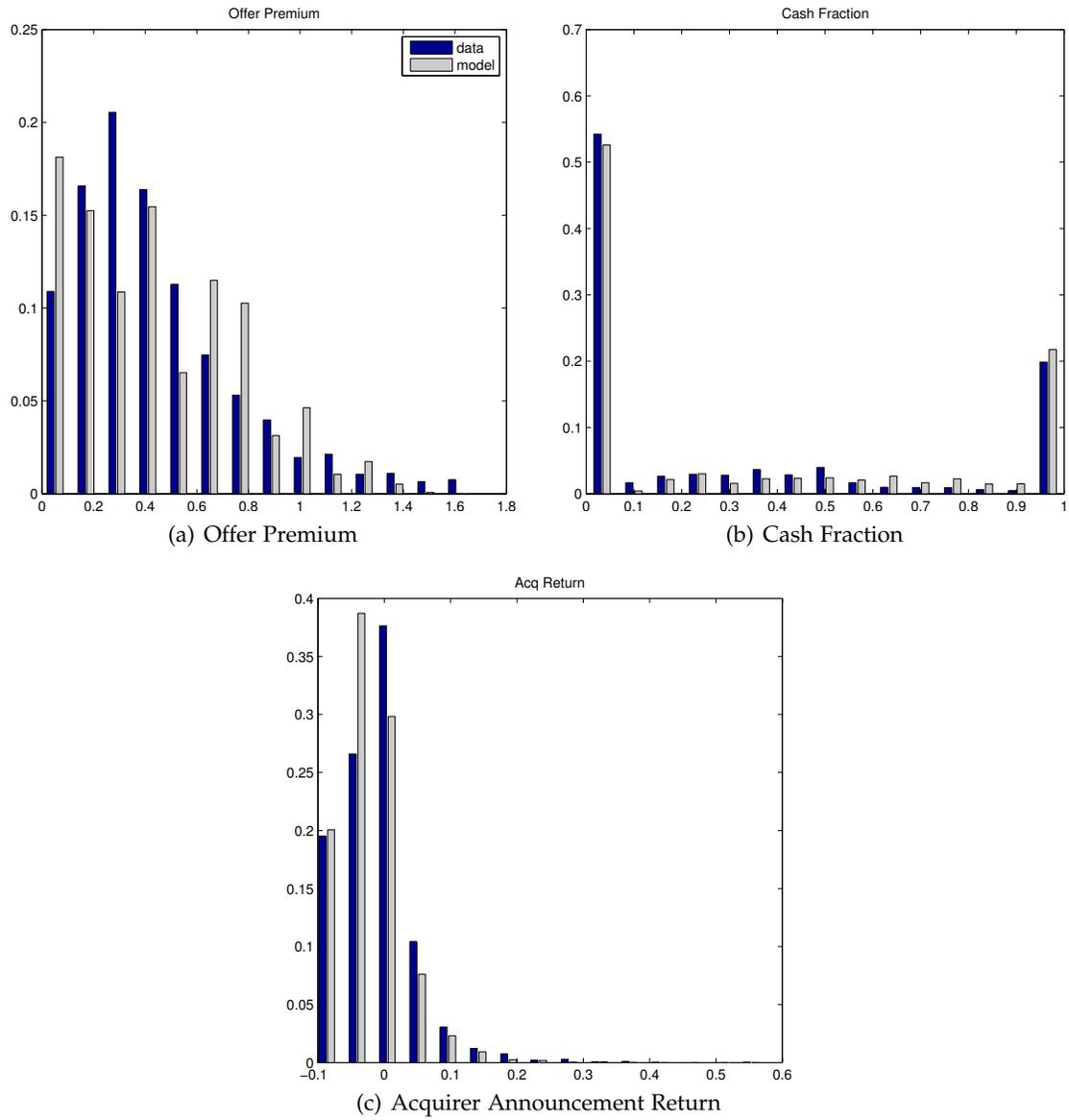This figure compares the distributions of offer premium, cash usage, and acquirer announcement return in the data and in the model. The model is solved under the parameters presented in Table 4 using the method described in Appendix C, and the variables of interest are computed using the method described in Appendix D.
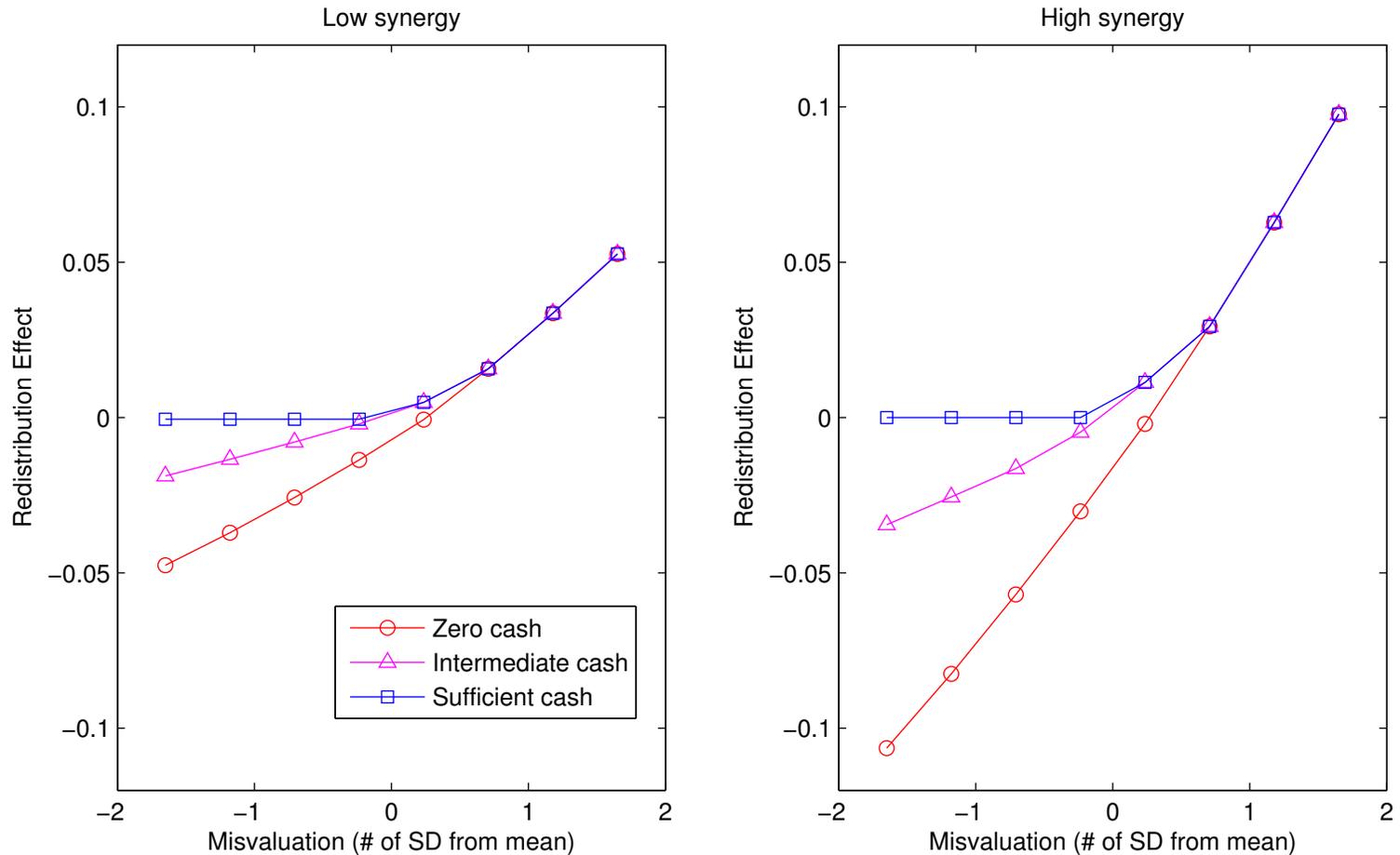
Figure 4: Redistribution Effect

This figure presents the redistribution effect for different types of bidders. The redistribution effect, which is measured by equation 5, 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.
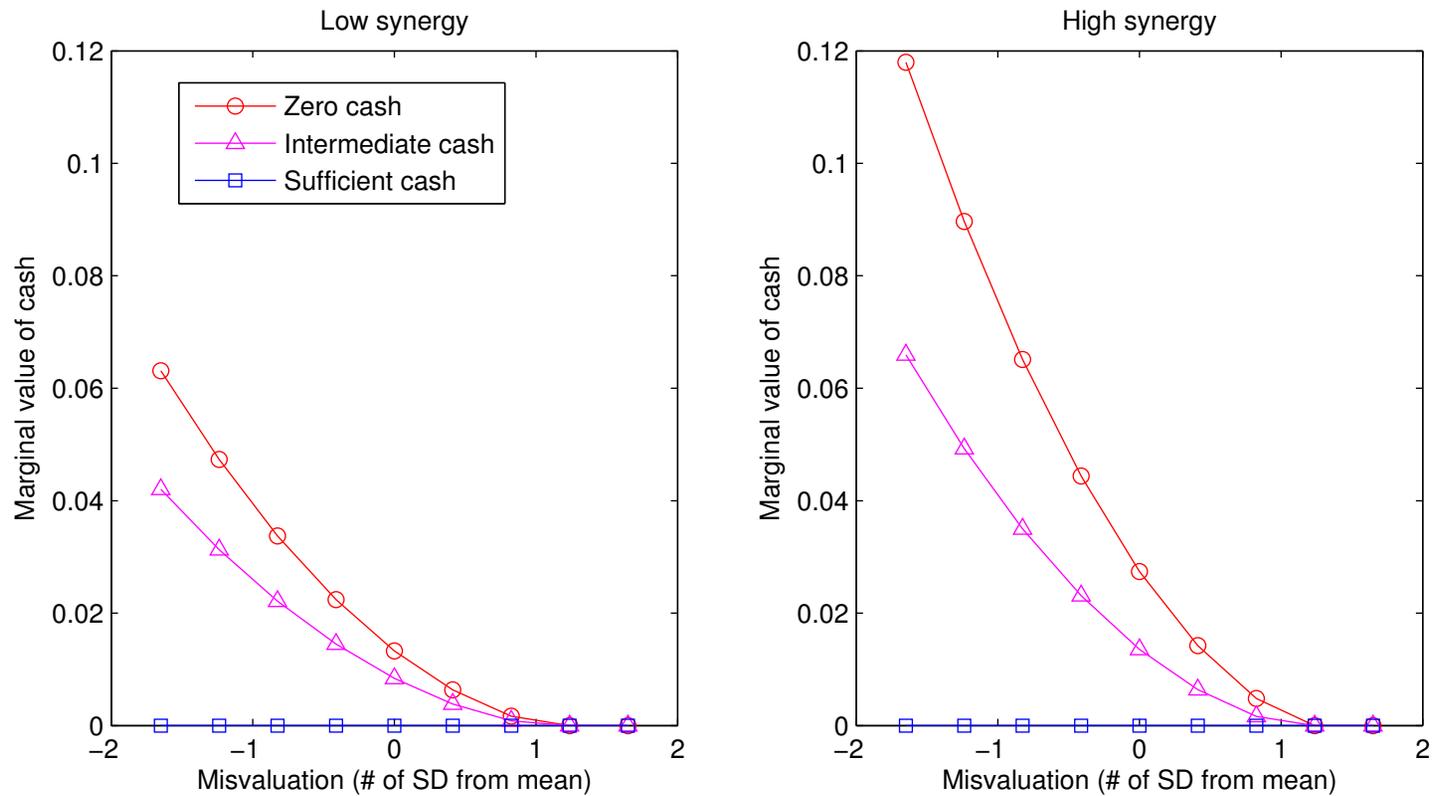
Figure 5: Marginal Value of Cash

This figure presents the marginal value of cash for different types of bidders. The marginal value of cash, which is measured by equation 7, 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. Deal size is the transaction value expressed in 2009 dollars (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. All cash (equity) bid is a dummy variable which equals one if the bid is paid with all cash (equity) and zero otherwise. Acq relative size is the logarithm of the ratio of acquirer market value to target market value, measured 4 weeks before the bid announcement. Acq ann return $(-1,1)$ is the acquirer cumulative abnormal return in a 3-day event window around the bid announcement, computed based on the market model; Tar ann return and CombFirm ann return follow a similar definition but for the target or combined firm cumulative abnormal returns. 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)	1,482	6,314	38	249	2,782	484	1,532	1,666
Offer premium	0.440	0.320	0.100	0.360	0.880	0.460	0.450	0.410
Cash fraction	0.300	0.400	0.000	0.000	1.000	0.340	0.190	0.470
All cash bids	0.200	0.400	0.000	0.000	1.000	0.250	0.100	0.320
All equity bids	0.530	0.500	0.000	1.000	1.000	0.510	0.670	0.310
Acq relative size	2.190	1.620	0.330	1.930	4.420	2.120	2.130	2.300
Acq ann return $(-1,1)$	−0.022	0.079	−0.101	−0.014	0.045	−0.014	−0.027	−0.017
Tar ann return $(-1,1)$	0.215	0.223	−0.007	0.177	0.492	0.195	0.190	0.265
CombFirm ann return $(-1,1)$	0.010	0.075	−0.058	0.008	0.087	0.015	0.004	0.017
Number of obs	2,771	2,771	2,771	2,771	2,771	256	1,539	976

Table 2: Sensitivity of Moments to Parameters

This table reports the sensitivity of model implied moments with respect to model parameters. E[offerprem] is the average offer premium. Var[offerprem] is the variance of offer premium. E[AcqRet] is the average acquirer announcement return. β(AcqRet, CshFrac) is the coefficient from regressing acquirer announcement return on the fraction of cash used in the bid. All Cash is the fraction of bids made with all cash. All Equity is the fraction of bids made with all equity. β(OfferPrem, M) is the coefficient from regressing offer premium on acquirers' relative size (i.e., the logarithm of acquirer market value divided by target market value). β(CshFrac, M) is the coefficient from regressing the fraction of cash used in the bid on acquirers' relative size. 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 $\mathcal{N}(\mu_\varepsilon, \sigma_\varepsilon^2)$ that is right truncated at one. 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.

	E[offerprem]	Var[offerperm]	E[AcqRet]	β(AcqRet, CshFrac)	All Cash	All Equity	β(Offerprem, M)	β(CshFrac, M)
μ_s	1.525	1.444	0.127	0.564	0.777	-1.450	2.084	-0.450
σ_s	0.846	1.117	0.216	-0.089	-0.243	0.023	0.354	-0.338
μ_ε	-0.001	-0.013	-1.735	-0.058	-0.006	-0.485	-0.009	0.317
σ_ε	0.181	0.394	-0.516	1.691	-0.251	-0.556	1.120	1.108
μ_k	0.284	1.044	-1.261	0.583	0.567	-3.285	1.073	-0.175
σ_k	0.455	0.298	0.652	0.942	0.539	0.856	0.308	1.481
ρ_{sM}	0.020	-0.205	-0.561	0.208	-0.007	0.302	1.692	0.175
ρ_{kM}	-0.381	-0.338	-0.002	-0.381	-0.203	-0.336	-0.384	0.867

Table 3: Model Fit

Panel A reports the results for moments that are targeted in SMM, and Panel B reports the results for untargeted moments. E[offerprem] is the average offer premium. Var[offerprem] is the variance of offer premium. E[AcqRet] is the average acquirer announcement return. β(AcqRet, CshFrac) is the coefficient from regressing acquirer announcement return on the fraction of cash used in the bid. All Cash is the fraction of bids made with all cash. All Equity is the fraction of bids made with all equity. β(Offerprem, M) is the coefficient from regressing offer premium on acquirers' relative size (i.e., the logarithm of acquirer market value divided by target market value). β(CshFrac, M) is the coefficient from regressing the fraction of cash used in the bid on acquirers' relative size. E[CombRet] and E[TarRet] are the average combined firm and target announcement return including 4-week runup. Var[AcqRet], Var[CombRet], and Var[TarRet] are the variance of acquirer, the combined firm, and target announcement return. Corr(AcqRet, TarRet) is the Peason's correlation between acquirer announcement return and target announcement return. S.E. stands for standard error and Diff stands for the difference between the model-implied moments and those from the data.

| | Panel A: Targeted Moments | | | | | | | |
	E[offerprem]	Var[offerperm]	E[AcqRet]	β(AcqRet, CshFrac)	All Cash	All Equity	β(OfferPrem, M)	β(CshFrac, M)
Data	0.439	0.103	−0.022	0.033	0.195	0.529	0.044	0.048
S.E.	0.015	0.008	0.003	0.006	0.021	0.038	0.005	0.009
Model	0.432	0.105	−0.022	0.037	0.206	0.526	0.044	0.049
Diff	−0.006	0.002	0.000	0.004	0.011	−0.004	0.000	0.001
t-stat	−0.417	0.248	0.149	0.593	0.527	−0.102	0.064	0.090

| | Panel B: Untargeted Moments | | | | | |
	Var[AcqRet]	E[CombRet]	Var[CombRet]	E[TarRet]	Var[TarRet]	Corr[AcqRet,TarRet]
Data	0.006	0.015	0.018	0.282	0.063	0.109
S.E.	0.001	0.002	0.001	0.005	0.002	0.002
Model	0.002	0.012	0.007	0.387	0.037	0.083

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 $\mathcal{N}(\mu_\varepsilon, \sigma_\varepsilon^2)$ that is right truncated at one; cash capacity is assumed to follow a normal distribution $\mathcal{N}(\mu_k, \sigma_k^2)$ that is left censored at zero; ρ_{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 truncated 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	0.150	0.770	0.055	0.062	0.670	3.300	0.550	0.430
Standard Error	0.041	0.023	0.006	0.012	0.248	1.007	0.064	0.034
	E[s]	Stdev[s]	E[ε]	Stdev[ε]	E[k]	Stdev[k]	r_{sM}	r_{kM}
Estimate	0.670	0.490	0.055	0.062	1.674	2.151	0.433	0.315
Standard Error	0.016	0.011	0.006	0.012	0.523	0.665	0.054	0.029

Table 5: Estimated Efficiency Losses

This table reports the estimated efficiency losses in the baseline model. P(crowd-out) is the probability of crowd-out. Avg. loss in crowd-out is the average efficiency loss in the crowd-out deals. % of target size expresses the efficiency loss as a fraction of target pre-announcement market value, and % of synergy expresses the efficiency loss as a fraction of total synergy that can be achieved in a perfect information economy. Avg. loss in all deals is the average efficiency loss in all deals. S.E. stands for standard error.

		Panel A: Probability of Crowd-Out					
P(crowd-out)	Estimate	7.88%					
	Standard Error	1.04%					

		Panel B: Average Loss Conditional on Crowd-Out					
					Percentile		
		Mean	0.10	0.25	0.50	0.75	0.90
% of target size	Estimate	11.83	1.16	3.21	7.65	15.69	27.35
	Standard Error	3.11					
% of synergy	Estimate	23.30	2.32	6.30	15.49	32.79	58.61
	Standard Error	3.83					

		Panel C: Average Loss in All Deals					
					Percentile		
		Mean	0.10	0.25	0.50	0.75	0.90
% of target size	Estimate	0.93	0.09	0.25	0.60	1.23	2.15
	Standard Error	0.39					
% of synergy	Estimate	1.83	0.18	0.50	1.22	2.58	4.61
	Standard Error	0.55					

Table 6: Additional Counterfactual Analyses

This table reports results of counterfactual analyses in which we change one or more parameter values while keeping others at their estimated values. High Overvaluation represents the case in which parameters are set to such values that the average overvaluation (ε) is doubled from the baseline model. High Misvaluation represents the case in which the standard deviation of ε is doubled. Low Average Cash Capacity represents the case in which the average cash capacity is reduced by half. High Cash Cap. Dispersion represents the case in which the standard deviation of cash capacity is doubled. P(crowd-out) is the probability of crowd-out. Avg. loss in crowd-out is the average efficiency loss for the crowd-out deals. Stdev. of loss in crowd-out is the standard deviation of efficiency loss in crowd-out deals. % of target size expresses the efficiency loss as a fraction of target pre-announcement market value and % of synergy expresses the efficiency loss as a fraction of total synergy that can be achieved in a perfect information economy. Avg. loss in all deals is the average efficiency loss in all deals. Avg. wealth redistribution (χ) is defined in Equation (6). Avg. marginal value of cash ($\bar{\lambda}$) is defined in Equation (8).

		Using Estimated Parameter Values	Using Counterfactual Parameters			
			High Overvaluation	High Misvaluation	Low Average Cash Capacity	High Cash Cap. Dispersion
P(crowd-out)		7.86%	8.39%	13.24%	8.35%	11.34%
Avg. loss in crowd-out	% of target size	11.83	13.21	17.56	13.01	22.50
	% of synergy	23.30	24.78	30.40	24.10	32.74
Stdev. of loss in crowd-out	% of target size	13.26	14.87	16.16	16.13	26.37
	% of synergy	22.81	23.06	24.56	23.41	27.56
Avg. loss in all deals	% of target size	0.93	1.11	2.32	1.10	2.55
	% of synergy	1.83	2.08	4.02	2.01	3.71
Avg. wealth redistribution		0.071	0.073	0.102	0.075	0.161
Avg. marginal value of cash		0.027	0.028	0.037	0.030	0.029

Table 7: Estimation in Subsamples

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. P(crowd-out) is the probability of crowd-out; Avg. loss in crowd-out is the average efficiency loss for the crowd-out deals; Stdev. of loss in crowd-out is the standard deviation of efficiency loss in crowd-out deals; % of target size expresses the efficiency loss as a fraction of target pre-announcement market value and % of synergy expresses the efficiency loss as a fraction of total synergy that can be achieved in a perfect information economy; Avg. loss in all deals is the average efficiency loss in all deals; Avg. wealth transfer (χ) is defined in Equation (6); and Avg. marginal value of cash ($\bar{\lambda}$) is defined in Equation (8).

	Panel A: Moments Implied by Parameter Estimates				
		Sentiment		Market Volatility	
	Full Sample	High	Low	High	Low
$E[s]$	0.670	0.763	0.683	0.761	0.571
$Stdev[s]$	0.490	0.544	0.487	0.505	0.457
$E[\varepsilon]$	0.055	0.076	0.050	0.071	0.039
$Stdev[\varepsilon]$	0.062	0.101	0.048	0.076	0.053
$E[k]$	1.674	1.383	1.404	1.192	2.771
$Stdev[k]$	2.151	1.803	1.958	1.685	2.300
r_{sM}	0.433	0.391	0.468	0.474	0.454
r_{kM}	0.315	0.259	0.327	0.268	0.380

		Panel B: Model Implications				
			Sentiment		Market Volatility	
		Full Sample	High	Low	High	Low
P(crowd-out)		7.86%	10.13%	5.96%	8.81%	6.89%
Avg. loss in crowd-out	% of target size	11.83	15.79	9.44	12.11	10.12
	% of synergy	23.30	24.28	19.21	19.59	24.07
Stdev. of loss in crowd-out	% of target size	13.26	15.28	11.44	12.08	12.19
	% of synergy	22.80	21.40	20.92	18.11	23.26
Avg. loss in all deals	% of target size	0.93	1.60	0.56	1.07	0.70
	% of synergy	1.83	2.46	1.14	1.73	1.66
Avg. wealth redistribution		0.071	0.081	0.055	0.073	0.062
Avg. marginal value of cash		0.027	0.038	0.024	0.032	0.014