

# Inefficiencies and Externalities from Opportunistic Acquirers \*

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## Abstract

If opportunistic acquirers can buy targets using overvalued shares, then there is an inefficiency in the merger and acquisition (M&A) market: The most overvalued rather than the highest-synergy bidder may buy the target. We quantify this inefficiency using a structural estimation approach. We find that the M&A market allocates resources efficiently on average. Opportunistic bidders crowd out high-synergy bidders in only 7% of transactions, resulting in an average synergy loss equal to 9% of the target's value in these inefficient deals. The implied average loss across all deals is 0.63%. Although the inefficiency is small on average, it is large for certain deals, and it is larger 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” (McGrath, 2015). 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, because AOL potentially crowded out an alternative acquirer that had a higher real synergy with Time Warner.

In general, if a firm believes its shares are overvalued, it has an incentive to opportunistically acquire other firms using its shares as currency (Rhodes-Kropf and Viswanathan, 2004; Shleifer and Vishny, 2003). This behavior creates an inefficiency. If opportunistic, overvalued acquirers crowd out acquirers with higher real synergies, then target firms may not get matched with the highest-synergy acquirers. This inefficiency results in a loss of value, not just a transfer of value, making the inefficiency potentially important for social welfare.

Researchers have raised concerns about the inefficiency from opportunistic acquirers. For example, Eckbo, Makaew, and Thorburn (2017) write, “The empirical relevance of such bidder opportunism in M&A activity is central to the debate over the efficiency of the market for corporate control. The larger concern is that the most overvalued rather than the most efficient bidder may be winning the target—potentially distorting the disciplinary role of the takeover market.” There is debate, however, over whether the inefficiency is large, small, or even absent. On one side of the debate, there is extensive support for the inefficiency’s mechanism. The underlying idea that managers have private information about their firms, which can lead to stock misvaluation, is a central concept in corporate finance. Several papers show empirically that misvaluation is an important motive for acquisitions, for example, by relating misvaluation to the decision to become an acquirer or target, the chosen method of payment, acquisition performance, and merger waves.<sup>1</sup> On the other side of the debate, there are several reasons why the inefficiency may be small or even absent. In contrast to earlier research, Eckbo, Makaew, and Thorburn (2017) find evidence inconsistent with bidders’ opportunistic use of stock, which undermines the inefficiency’s mechanism. Bidder opportunism may also be limited because targets and their financial advisors perform due diligence on the acquirer’s stock value, and merger contracts can be designed to protect against bidder misvaluation. Given the huge size of the M&A market (roughly \$1 trillion in deals by U.S. public acquirers in 2016), it is important to resolve this debate and

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<sup>1</sup> See Ang and Cheng (2006); Ben-David et al. (2015); Bouwman, Fuller, and Nain (2009); Dong et al. (2006); Fu, Lin, and Officer (2013); Malmendier, Opp, and Saidi (2016); Rhodes-Kropf, Robinson, and Viswanathan (2005); Savor and Lu (2009); Vermaelen and Xu (2014).

determine whether the market is allocating targets to their most efficient buyers.

Our main contribution is to show that the aggregate inefficiency from opportunistic acquirers is quite modest, meaning the M&A market usually allocates targets efficiently. We do find, however, that the inefficiency is large for certain deals, and it is larger in deals where misvaluation is more likely. These results shed light on the fundamental economic question of whether capital market imperfections matter for resource allocation. We also show that misvaluation results in a large externality that redistributes merger gains across acquirers.

Quantifying these effects is difficult. Stock misvaluation and synergies are not directly observable. More important, 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 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. Overall, it is unclear how to quantify the inefficiency without a model.

We overcome these challenges by structurally estimating a model of M&A contests. Bidders in the model compete in an auction to buy a target firm. A bidder's shares can be misvalued, for example, because of managers' private information or investors' mistakes. The bidders and target maximize expected profits and are fully rational, but the target cannot perfectly observe bidders' synergies or the misvaluation of bidders' shares. Since targets have limited information, bids made by overvalued acquirers can 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 allow bidders to optimally use both cash and shares as a method of payment. Cash is especially valuable to undervalued bidders, because they can signal their undervaluation by offering cash instead of shares. Financing constraints limit bidders' access to cash, however, forcing some bidders to finance at least part of the deal using shares. Cash constraints are not perfectly observable, which limits undervalued acquirers' ability to separate themselves from overvalued acquirers. This limitation aggravates the target's confusion and makes the crowd-out problem more severe.

The model imposes no priors on whether M&A deals are driven primarily by synergies or misvaluation. The inefficiency in the model could be large, small, or even zero depending on

parameter values. We let the data tell us how large the inefficiency is. We do so by estimating the model's parameters using the simulated method of moments (SMM). Our dataset includes 2,503 U.S. M&A contests involving public acquirers and targets from 1980 to 2013. The key parameters to estimate are the dispersion across bidders' synergies, cash capacities, and misvaluations. The dispersion across deals' observed offer premiums 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 (e.g., [Betton, Eckbo, and Thorburn, 2008](#)). 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 premiums 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 inefficiency from opportunistic acquirers. By simulating data off the model, we find that an overvalued bidder crowds out a bidder with a higher synergy in 7.0% of deals. These deals are inefficient in the sense that the high-synergy bidder would always win in an ideal, counterfactual world with no misvaluation. In the 7.0% of deals that are inefficient, the winner's synergy is on average 15.8% below the loser's synergy, which amounts to an average synergy loss equal to 9.0% of the target's pre-announcement market value. Averaging across all deals (efficient and inefficient), the aggregate efficiency loss is 0.63% ( $= 7\% \times 9\%$ ) of the target's pre-announcement value, with a standard error of 0.19%.

The estimated inefficiency is small mainly because we find that differences in synergies across acquirers are much larger than differences in misvaluation. As a result, high-synergy acquirers out-bid their (potentially overvalued) competitors 93% of the time, producing efficient deals. More simply, synergies swamp misvaluation. Our relatively low estimate of misvaluation dispersion is plausible given the significant due diligence, negotiation, and contracting that targets and their financial advisors perform to guard against bidder opportunism.

While the estimated average synergy loss is low in percentage terms, it translates to a non-trivial \$4.5 billion in lost synergies per year in deals made by U.S. public acquirers.<sup>2</sup> Also, the loss is quite high for certain deals. For example, at the 90th percentile among inefficient deals, the winner's synergy is 36% below the loser's synergy, amounting to a synergy loss equal to 20%

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<sup>2</sup> \$4.5 billion equals \$709 billion (i.e., the total pre-acquisition market value of targets acquired by U.S. public acquirers in 2016) times the estimated 0.63% average efficiency loss.

of the target's pre-announcement market value. We show that the inefficiency is larger when acquirer misvaluation is more likely: in all-equity deals, when the acquirer's assets are more intangible, with smaller targets, in months with higher investor sentiment, and in months when the stock market is more volatile.

Next, we measure how misvaluation affects the distribution of merger gains across acquirers, which is new to the literature. We define a bidder's merger gain as its expected synergy minus what it pays for that synergy. We then define the redistribution effect as the difference in a bidder's merger gain between the estimated economy and a counterfactual economy with no misvaluation uncertainty. Misvaluation benefits overvalued acquirers by helping them to win contests and to use their shares as a cheap currency. Misvaluation hurts undervalued acquirers, because it reduces their chances of winning a contest, and even when they do manage to win, 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 redistribution effect is quite large: 5.1% of the target's pre-acquisition value, which translates to roughly \$36 billion ( $= 5.1\% \times \$709$  billion) of gains redistributed from undervalued to overvalued acquirers per year in the U.S. The redistribution effect is even larger for bidders that are severely misvalued, cash-constrained, and have a large synergy.

Structural estimation lets us answer important questions that are hard to answer otherwise. However, "structural estimation does not magically solve all endogeneity problems" (Strebulaev and Whited, 2012). Any model omits certain features of reality, and an important question is whether those omissions bias our results. For example, our model omits overpayment and governance failures within acquirers. We find very similar results across acquirers with strong and weak governance, however, suggesting that these omissions are not an important source of bias. We also show that our conclusions are robust to allowing more than two bidders, negative synergies, correlated synergies, variation in targets' reservation prices, price pressure from merger arbitrage, and several other factors we omit from our baseline model.

Our paper contributes to three strands of literature. First, several papers focus on the relation between stock misvaluation, method of payment, and merger performance of acquirers and targets. Ang and Cheng (2006), Rhodes-Kropf, Robinson, and Viswanathan (2005), Shleifer and Vishny (2003), and Savor and Lu (2009) find 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. More recently, Eckbo, Makaew, and Thorburn (2017) show that bidders use more stock when targets know more about the bidder, implying that adverse selection on the

target's side is more important than opportunism on the acquirer's side. We add to this literature by examining another important question that deserves more attention: How does misvaluation reduce the allocational efficiency of the M&A market? Our paper therefore highlights the effects of capital market imperfections and corporate finance on real economic efficiency.

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

Finally, this paper is among the few studies that structurally investigate the effects of misvaluation on corporate decisions. [Warusawitharana and Whited \(2016\)](#) estimate a dynamic model to show 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.

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, and externalities. Section 5 discusses robustness, and Section 6 concludes.

## 2 Model

The model we estimate is most closely related to [Rhodes-Kropf and Viswanathan \(2004\)](#). We extend their model by allowing acquirers to use both equity and cash as the means of payment.

### 2.1 Setup

Our model features a takeover contest in which two acquiring firms, or bidders, compete to buy a target firm. All firms are risk neutral. The market value of the target as an independent entity is normalized to one. Therefore, all values hereafter should be interpreted as dollar values scaled by 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 true value is  $V_i = 1 + s_i$ , where  $s_i$  is the synergy between the target and acquirer  $i$ . The second characteristic,  $M_i$ , is the ratio of acquirer  $i$ 's market value to the target's market value, both measured as independent entities before the acquisition. Third, an acquirer can be misvalued, in the sense that the acquirer's true value  $X_i$  can differ from its market value  $M_i$ . Specifically, we assume  $X_i = M_i(1 - \varepsilon_i)$ , where  $\varepsilon_i$  is the misvaluation factor. Acquirers can be fairly valued ( $\varepsilon = 0$ ), overvalued ( $\varepsilon > 0$ ), or undervalued ( $\varepsilon < 0$ ). Unlike the other acquirer characteristics,  $\varepsilon$  is unitless. Fourth, the acquirers are subject to a cash capacity constraint. The amount of cash that acquirer  $i$  can use in the acquisition cannot exceed  $k_i$ . The constraint  $k_i$  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 M&A contest. To summarize, an acquirer is identified by a vector of four characteristics  $\Phi_i = (s_i, \varepsilon_i, k_i, M_i)$ .

Among acquirer characteristics, the market value  $M_i$  is publicly observable, and the other characteristics (synergy, misvaluation, and cash capacity) are fully observed by the acquirer but imperfectly observed by the target and market. Everyone understands, however, 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  $\varepsilon_i$  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 acquirer market values relative to the target,  $M$ , is denoted  $\mathcal{M}(M)$  and is taken directly from the data.

Empirically, acquirers' relative size  $M$  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  $\rho_{sM}$ . Second, larger firms tend to be less financially constrained (e.g., Hadlock and Pierce, 2010; Whited and Wu, 2006), and an acquirer can more easily pay cash to buy a small target than a large target. We therefore allow  $M_i$  and  $k_i$  to have a non-zero Spearman rank correlation, denoted  $\rho_{kM}$ . These correlations let the acquirer's relative size  $M_i$  serve as a signal to the target about the deal's synergy and the acquirer's cash capacity. In sum, acquirer  $i$ 's characteristics  $(s_i, \varepsilon_i, k_i, M_i)$  are an independent realization from the joint distribution  $\mathcal{F}(\mathcal{N}_s(\mu_s, \sigma_s^2), \mathcal{N}_\varepsilon(\mu_\varepsilon, \sigma_\varepsilon^2), \mathcal{N}_k(\mu_k, \sigma_k^2), \mathcal{M}(\cdot); \rho_{sM}, \rho_{kM})$ .

We model the takeover contest as a modified sealed second-price auction. The two acquirers

privately submit their bids as combinations of cash and equity to the target. We denote acquirer  $i$ 's bid as  $b_i = (C_i, \alpha_i)$ , where  $C_i$  is the amount of cash and  $\alpha_i$  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:

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

Variables  $Z_i$ ,  $C_i$ ,  $X_i$ , and  $V_i$  are all fundamental values scaled by the target's pre-acquisition market value. The target computes the combined firm's expected value by making a rational forecast of the bidder's misvaluation ( $\varepsilon_i$ ) and synergy ( $s_i$ ) based on what it can observe:  $C_i$ ,  $\alpha_i$ , and  $M_i$ . The target uses  $z(\cdot)$  as a scoring rule to rank bids. If the target believes that both bids have a valuation lower than its reservation value (i.e., 1, the target's pre-acquisition market value), the contest fails. Otherwise, the bid with the highest score wins, and the acquisition is settled as follows. For convenience, let  $i$  be the winner and  $j$  the loser. If  $C_i \geq \max\{1, z(C_j, \alpha_j, M_j)\}$ , 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 stock such that  $z(C_i, \tilde{\alpha}_i, M_i) = \max\{1, z(C_j, \alpha_j, M_j)\}$ . Intuitively,  $\tilde{\alpha}_i$  is set such that the winner pays the value offered by the loser, evaluated from the target's perspective. As we explain in Online Appendix A.1, there may be other feasible settlement rules, but they would deliver the same expected ultimate payment, and the specific rule we have chosen better matches reality.

We consider a Nash equilibrium in which acquirers strategically choose their bids as a combination of cash and equity to maximize their current shareholders' expected profit from the M&A contest given the target's scoring rule; and the target rationally evaluates the bids conditional on its available information and the acquirers' equilibrium 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 the scoring rule  $z(C, \alpha, M)$  and expecting that the rival (bidder  $j$ ) adopts the equilibrium bidding strategy,  $b_j^* = b^*(\Phi_j)$ , the bidding strategy of bidder  $i$  ( $i \neq j$ ),  $b_i^* = b^*(\Phi_i)$  satisfies*

$$b_i^* = \operatorname{argmax}_{b=(C,\alpha)} E \left\{ [V_i - \tilde{\alpha}^*(X_i + V_i - \tilde{C}) - \tilde{C}] \cdot \mathbf{1}_{\{\max\{1, z(b^*(\Phi_j), M_j)\} \leq z(b, M_i)\}} \mid \Phi_i \right\}, \quad (2)$$

subject to  $C \leq k_i$ , where  $\tilde{C} = \min\{C, \max\{1, z(b^*(\Phi_j), M_j)\}\}$ ;  $\tilde{\alpha}^* = 0$  if  $C \geq \max\{1, z(b^*(\Phi_j), M_j)\}$  and otherwise it satisfies  $z(C, \tilde{\alpha}^*, M_i) = \max\{1, z(b^*(\Phi_j), M_j)\}$ ; and  $1_{\{\cdot\}}$  is an indicator function.

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

## 2.2 Discussion

Before describing the model's predictions, we explain some of its elements, and we address potential concerns about the setup and omitted factors.

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—"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 the target cannot.

The model assumes bidder  $i$  faces a cash capacity constraint ( $k_i$ ) that is partially unobservable. Intuitively, if acquirers have unlimited cash capacity, relatively undervalued acquirers can separate by bidding only with cash, so there is no scope for opportunistic behavior. Given the large body of evidence on financing constraints, it is plausible to assume a cash capacity constraint. The parameter  $\rho_{kM}$  allows cash capacity and relative firm size to be correlated, so targets rationally use the acquirer's size as a noisy signal about its cash capacity. It is reasonable to assume that cash capacity is only partially observed, because it is difficult to observe financing constraints and whether the acquirer has earmarked cash for other projects.

The equilibrium concept in Equation (2) implies that a bidder maximizes the long-run value going to existing shareholders. This assumption allows bidders to take actions that benefit shareholders in the long run and yet depress the stock price in the short run. For example, overvalued bidders in our model will bid with equity in order to transfer value from new to existing shareholders, even though this action depresses the stock price in the short term. This assumption is plausible, for example, if the existing shareholders include the acquirer's management team, and they expect any misvaluation to get corrected before they sell their shares.

We take the targets and acquirers as given, and we do not model the choice to participate as a target or acquirer. Therefore, the model's parameters describe the pool of firms that have already endogenously selected to be acquirers and targets. For example,  $\varepsilon$  reflects the misvaluation of firms that choose to become acquirers. Similarly, cash capacity  $k$  can reflect endogenous actions, such as cash hoarding, taken in preparation for the acquisition. The model is consistent with our

estimation, because our sample is also based on the selected sample of observed acquirers and targets. The model is also consistent with our goal, which is to quantify the inefficiency among the deals we observe, which of course are endogenous.

The model assumes bidders have independent private values of the target. [Gorbenko and Malenko \(2014\)](#) find that this assumption is more valid when bidders are strategic rather than financial. Fortunately, 97% of the bidders in our data sample are strategic (Section 3.1).

We model the M&A process as a sealed second-price (SP) auction, as do [Rhodes-Kropf and Viswanathan \(2004\)](#). In the literature, the M&A process is also sometimes modeled as an English ascending (EA) auction (e.g., [Dimopoulos and Sacchetto, 2014](#); [Fishman, 1989](#); [Gorbenko and Malenko, 2014, 2016](#)). As we explain in Online Appendix A.1, within the model's private-value paradigm, the EA auction has an equilibrium equivalent to the one in this paper. Therefore, one can think of our auction as one in which the two bidders make repeated offers with ascending values until one bidder drops out, then the remaining bidder pays the last value offered, evaluated at the expectation of the target. We choose to follow the SP format because it gives rise to a simple and unambiguous analytic relation between the bid's two components (cash and equity), which substantially simplifies the optimization problem of the acquirer in Equation (2).

We assume two bidders compete in the auction. In most observed M&A contests there is only one publicly announced bidder. However, these contests 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.<sup>3</sup> 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 common in the literature (e.g. [Dimopoulos and Sacchetto, 2014](#); [Fishman, 1988, 1989](#); [Gorbenko and Malenko, 2016](#)). For robustness, Section 5 shows that we reach similar conclusions if we allow three, four, five, or a random number of competing bidders.

Target misvaluation does not explicitly appear in our model. The model, however, does allow target misvaluation, because we do not require the target's market value to equal its true, fundamental value. To improve tractability, we assume in the baseline model that the target's mis-

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<sup>3</sup> 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 sign the confidentiality agreement as the indication of serious interest. Using more restrictive criterion, there are on average 1.29 bidders who submit private written offers and 1.13 bidders who make publicly announced bids.

valuation has no effect on its reservation price, which we set equal to the target's pre-acquisition market value. Therefore, the model's solution does not depend on target misvaluation. Our assumption about reservation prices is plausible if the target, focusing on the short term, considers its outside option to be remaining a stand-alone firm at the pre-acquisition market value. Our assumption is less plausible, though, if undervalued targets demand a higher reservation price. In Section 5.1 we extend the model to explore how target misvaluation affects reservation prices.

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

Another way to profit from overvaluation is to sell shares in a seasoned equity offering (SEO). Our paper is silent on a firm's choice between M&A and SEO, and in fact the two are not mutually exclusive. [Shleifer and Vishny \(2003\)](#) analyze the choice between M&A and SEO. Intuitively, an overvalued firm may prefer M&A if it has a real synergy, whereas it may prefer an SEO if it has real internal investment opportunities.

Targets can reduce the risk of acquirer misvaluation by performing due diligence and including provisions such as collars, floating exchange ratios, walk-away provisions, and top-up rights in the merger contract. These contract provisions are not common. For example, [Officer \(2004\)](#) reports that only 15% of merger bids in the 1990s include collars. Nevertheless, our model accommodates these provisions, because we interpret and estimate  $\varepsilon$  as the misvaluation that remains after implementing these contractual provisions, and also after the target's due diligence. It is precisely this remaining misvaluation that matters for the inefficiency we study. It is possible that some misvaluation remains even after this due diligence and contracting, because the target's due diligence may not reveal all private information held by the bidder, and the contract provisions protect the target only up to the deal completion date.

Our model abstracts away from the sequential nature of M&A contests. In our data, less than 2% of contests have multiple public bids. Any sequential competition therefore takes place mainly in private, with bidders typically unable to observe each other's move. For this reason, it is not clear that a model of sequential bidding describes the data better than our model with simultaneous bidding. [Dimopoulos and Sacchetto \(2014\)](#) model sequential M&A contests with a strategic preemptive motive. They find that preemption contributes little to offer premiums, which suggests that building preemption into our model is not of first-order importance.

Section 5 analyzes several of these issues in depth. We also show that our conclusions are robust to allowing governance problems, overpayment, additional signals about the bidders' type,

negative synergies, correlations between cash capacity and misvaluation, and merger arbitrage.

### 2.3 Model Solution

We start by showing that, in equilibrium, acquirers bid their true valuation of the target.

**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  $(C_i^*, \alpha_i^*)$  such that*

$$\alpha_i^*(X_i + V_i - C_i^*) + C_i^* = V_i. \quad (3)$$

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

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

See Online Appendix A.2 for proof and discussion of uniqueness.

Although a bidder optimally bids its true valuation of the target, the target and market remain confused about the bidder's type. The reason is that bidders have three dimensions of private information (synergy, misvaluation, and cash capacity), but their bids have only two dimensions (cash and equity), so bids are not fully revealing. Confusion occurs because bidders with different characteristics may end up submitting exactly the same bid. Consider a simple example in which two equally sized bidders have zero cash capacity and therefore bid with all equity, so Equation (3) simplifies to  $\alpha_i^* = 1/(1 + X_i/V_i)$ . If both acquirers have the same ratio of  $X/V$ , then an overvalued acquirer (low  $X$ ) with low synergy (low  $V$ ) will submit the same bid as an undervalued acquirer (high  $X$ ) with high synergy (high  $V$ ). Confusion is more severe than in this simple example, because acquirers can bid with cash, and their cash capacity is unobservable. For example, when an all-stock bid arrives, the target cannot tell whether the bidder is severely cash-constrained or opportunistically dumping overpriced stock. Therefore, the model solution features a pooling equilibrium in which the target and market cannot perfectly learn a bidder's synergy, misvaluation, and cash capacity based on its bid. The target and market can only infer the average of these three characteristics across all pooling acquirers who submit the same bid.

A direct implication is that the method of payment affects the target's assessment of a bid's value. Bids that have the same true, unobservable value but differ in their payment methods will appear different to the target. For example, equity bids made by highly overvalued acquirers appear more valuable than they truly are. We illustrate this result, along with other features of targets' scoring rule, in Online Appendix A.3. More generally, the target and market only adjust for the *average* misvaluation in the group of bidders who make the same type of bids. Therefore,

a bid made by an acquirer with above-average overvaluation relative to its group is still inflated after the target's (and market's) adjustment. In other words, its equity bid looks more attractive than it really is, which allows the bidder to profit from paying with overvalued equity.

Bidders face a trade-off when choosing their payment method. Bidding with cash signals undervaluation, making the bid's equity component appear more attractive to the target. But bidding with cash prevents acquirers from dumping overvalued shares. In equilibrium, acquirers choose the payment method so that the marginal benefit is offset by the marginal cost. More overvalued acquirers prefer using more equity. To avoid costly equity payment, undervalued acquirers prefer using as much cash as possible, subject to their cash capacity constraint. These predictions are consistent with the evidence in [Dong et al. \(2006\)](#), [Rhodes-Kropf, Robinson, and Viswanathan \(2005\)](#), [Williamson and Yang \(2016\)](#), and several others. We illustrate these predictions by numerically solving the model (details in Online Appendix [A.3.1](#)). Figure 1 then plots the relation between the bid's optimal cash component and bidder's misvaluation. The 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 ( $k \geq 1 + s$ ). Undervalued and fairly-valued acquirers ( $\varepsilon \leq 0$ ) 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 bid with all equity. The dashed line in Figure 1 plots the cash usage by acquirers whose cash capacity equals half of the bid's value ( $k = \frac{1+s}{2}$ ). Many of these acquirers would like to include more cash in their bid, but their limited cash capacity forces them to include equity in their bid. These constrained bidders provide camouflage to overvalued bidders who opportunistically bid with equity.

Targets do not take bids at their face value. Instead, they rationally account for acquirers' bidding strategy and use equity payment as a signal. If a bid contains more equity, the target infers that the acquirer is more likely to be overvalued. The equilibrium scoring rule (4) implies that one more dollar offered in equity increases the target's valuation of the bid by less than one dollar, because it reduces the valuation of the bid's equity component. This equilibrium scoring rule explains why some overvalued acquirers choose to include some cash in their bids.

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 influences the acquirer's announcement return. For example, when the market observes a bid that only includes cash, the market infers that the acquirer is probably not overvalued, resulting in a higher acquirer announcement return. To demonstrate this revelation effect, we simulate bids from our estimated model, compute the bidders' announcement returns,

and plot the announcement returns against the bids' cash usage in Figure 2. As expected, there is a positive relation between the acquirer announcement returns and the use of cash.

This positive relation is stronger when there is more misvaluation uncertainty, i.e., when  $\sigma_\varepsilon$  is larger. This prediction is crucial to our empirical identification of  $\sigma_\varepsilon$ . The prediction manifests as a steeper slope in Figure 2 when  $\sigma_\varepsilon = 0.20$  (right panel) compared to  $\sigma_\varepsilon = 0.05$  (left panel). 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, and hence stock prices do not respond to cash usage. When misvaluation uncertainty increases, the target and market become more confused and thus rely more on cash as a signal. In such a case, the revelation effect of cash becomes more pronounced, producing the steeper slope in Figure 2's right panel.

The pooling equilibrium gives rise to two adverse effects. First, the crowd-out effect: an overvalued bidder may defeat ("crowd out") a rival bidder who has a higher synergy, creating an inefficiency. Second, the redistribution effect: misvaluation shifts merger gains from undervalued to overvalued acquirers. We use structural estimation to quantify both effects.

### 3 Estimation

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

#### 3.1 Data

Data on M&A 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 publicly traded U.S. 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. Following the classification of [Betton, Eckbo, and Thorburn \(2008\)](#), the deal is a merger, not a tender offer or a block trade;
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 announcement returns.

Our final sample includes 2,503 bids. By including only public acquirers, we exclude almost all buyout firms and other financial bidders, which together make up just 3% of the final sample.

We use data on the first publicly announced bid in each control contest. Following [Betton, Eckbo, and Thorburn \(2008\)](#), we say that a control contest begins with the first public bid for a given target and continues until 126 trading days have passed without any additional offer. Each time an additional offer for the target is identified, the 126 trading-day search window rolls forward. We do not use data on earlier, pre-public bids, because key variables like the offer premium are not observable. Finding even the identity and number of pre-public bidders is impossible for the majority of our contests. We also exclude subsequent public bids, for two reasons. First, they are extremely rare. Less than 2% of our sample contests have multiple publicly announced bids. Second, our model is not designed to explain subsequent bids, which would condition on the initial public bid in ways that our simultaneous-bidding model cannot capture. Extending our model to accommodate these few extra observations would significantly complicate our analysis.

Next, we define our main variables. We measure bid  $i$ 's offer premium, denoted  $OfferPrem_i$ , as the offer price per share divided by the target stock price four weeks before the bid announcement, minus one. The offer premium data provided by SDC include some large outliers. Following [Officer \(2003\)](#) and [Bates and Lemmon \(2003\)](#), we drop observations with offer premium lower than zero or larger than two. We denote acquirer  $i$ 's announcement return as  $AcqAR_i$ , and we measure it using the market model with a three-day window around the bid's announcement, which is standard in the literature (e.g., [Betton, Eckbo, and Thorburn, 2008](#)). We obtain very similar results if we measure acquirer announcement returns using a window of  $[-22, +1]$  trading days. Online Appendix [A.3.3](#) explains how we compute the announcement return within the model.  $CashFrac_i$  is the fraction of bid  $i$  made up of cash. We measure  $M_i$  as the ratio of acquirer to target market capitalization four weeks before bid  $i$ .

Table 1 provides summary statistics. The average transaction value is \$1.59 billion in 2009 dollars, significantly skewed to the right. The offer premium averages 44% with a standard deviation of 32%. Bidders pay on average 31% of deal value in cash, with 20% of bidders making

all-cash bids and 53% of bidders making all-equity bids. Acquirers are typically much larger than targets: the logarithm of  $M$  averages 2.17. The mean acquirer announcement return is slightly negative,  $-2.3\%$ . 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  $\mu_s$  and  $\sigma_s$ , which control the mean and variance of bidders' synergies;  $\mu_\varepsilon$  and  $\sigma_\varepsilon$ , which control the mean and variance of bidders' misvaluation;  $\mu_k$  and  $\sigma_k$ , which control the mean and variance of bidders' cash capacity; and  $\rho_{sM}$  and  $\rho_{kM}$ , the Spearman rank correlations between the logarithm of relative firm size ( $\log(M)$ ) and the synergy and cash capacity, respectively. Since  $M$  is directly observed in the data, we feed the empirical distribution of  $M$  directly into the model and SMM estimator. The appendix contains additional details on the SMM estimator.

### 3.3 Identification, Selection of Moments, and Heterogeneity

Since we conduct a structural estimation, identification requires choosing moments whose predicted values move in different ways with the model's parameters, and choosing enough moments so there is a unique parameter vector that makes the model fit the data as closely as possible. It is important to exclude moments contaminated by forces outside the model. We use eight moments to identify our eight parameters. Following the advice of [Bazdresch, Kahn, and Whited \(2016\)](#), we include moments that describe acquirers' policy functions, meaning their choices of offer premium and method of payment.

Before defining our moments, we address the issue of heterogeneity. Our parameters  $\sigma_s$ ,  $\sigma_\varepsilon$ , and  $\sigma_k$  describe variation across bidders within a single contest. The data, however, reflect heterogeneity not just within but also across contests. To isolate within-contest variation, we use moments that purge cross-contest heterogeneity driven by unobserved time effects, unobserved target-industry effects, and observable target characteristics.<sup>4</sup> Specifically, when measuring sev-

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<sup>4</sup>In our main analysis, we do not purge variation coming from acquirer characteristics, because our goal is to estimate variation in acquirer characteristics. We control for acquirer characteristics later, for robustness. Like us, [Gorbenko and Malenko \(2014\)](#) and [Dimopoulos and Sacchetto \(2014\)](#) exclude acquirer characteristics from their sets of observables.

eral moments in the data, we control for relative firm size ( $M_i$ ) and a vector  $Controls_i$  that includes year indicators, targets' Fama-French 48 industry indicators, and five target characteristics that are outside our model: logarithm of market capitalization, market leverage, market-to-book ratio of equity, return on assets, and cash-to-assets ratio. Structural estimation papers have dealt with heterogeneity in a variety of ways. Our approach offers several advantages.<sup>5</sup> We reach very similar conclusions if we do not include  $Controls$  when measuring our moments.

Next, we define our moments and, to explain how the identification works, we show how the predicted moments vary with our parameters. Each moment depends on all model parameters, but we explain below which moments are most important for identifying each parameter. To illustrate, Table 2 shows the sensitivity of our eight simulated moments with respect to the eight parameters.

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

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

In this and the next two regressions, we set  $Controls$  to zero in simulated data, because  $Controls$  includes variables that are outside our model. The mean and conditional variance of offer premiums are most informative about the mean and variance of synergies, which depend on parameters  $\mu_s$  and  $\sigma_s$ . The intuition is that competition between bidders makes a large fraction of a deal's synergy accrue to the target firm in the form of an offer premium. Since the offer premium is informative about the synergy, there is a close link between their means and variances. Table 2 confirms that these two moments are most sensitive to  $\mu_s$  and  $\sigma_s$ .

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

The fourth moment is the average acquirer announcement return. Table 2 shows that this moment is most sensitive to  $\mu_\varepsilon$ , the average level of misvaluation. The intuition is that the market

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<sup>5</sup> A chief advantage is that our approach is computationally feasible. Building heterogeneity directly into our model would be infeasible, as it would require numerically solving the model not just for every trial parameter vector, but also for every data point. [Gorbenko and Malenko \(2014\)](#) and [Dimopoulos and Sacchetto \(2014\)](#) avoid this problem by having a closed-form solution. Similar to us, [Hennessy and Whited \(2007\)](#) remove the effects of heterogeneity by including firm and time fixed effects when measuring certain moments. Another advantage is that we can easily include many variables in  $Controls$  (e.g. industry and year indicators), whereas building many such variables into the model and estimating their coefficients via SMM would be computationally prohibitive. Yet another advantage is that we can easily purge heterogeneity from multiple variables (offer premium, method of payment, and acquirer announcement return).

rationally updates its beliefs about a bidder's stock price when it sees that the firm has chosen to become a bidder, regardless of the chosen method of payment. If the market understands that  $\mu_\varepsilon$  is higher, meaning the average bidder is more overvalued, then the average announcement return around the bid is lower, reflecting a more negative revelation effect.

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

$$AcqAR_i = b_0 + b_1 CashFrac_i + b_2 \log(M_i) + b_3' Controls_i + v_i. \quad (6)$$

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

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

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

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

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

Since we have eight moments and eight parameters, we have an exactly identified model. We check in Section 4 whether the estimated model is able to match six additional, untargeted moments, and we show in Section 5 that our conclusions are robust to using an overidentified model. Although adding moments would provide a test of overidentifying restrictions and potentially smaller standard errors, we prefer an exactly identified model for three reasons: our standard errors are sufficiently small, the intuition behind identification is more transparent,

and—most important—the model is simply not designed to match certain additional moments, as we explain in the next section.

## 4 Empirical Results

We begin by assessing how the model fits the data. We then discuss our parameter estimates. Next, we use the estimated model to quantify the inefficiency from opportunistic acquirers, and we explore where the inefficiency is largest. Finally, we use the model to quantify the redistribution effect.

### 4.1 Model Fit

Table 3 compares empirical and model-implied moments. Panel A presents the moments we try to match in SMM estimation. The model fits these moments very closely. The estimated model predicts a high average offer premium equal to 44.2% of the target’s size. The offer premium varies significantly, with a conditional standard deviation of  $30\% = \sqrt{0.088}$  of the target’s size. The model-implied acquirer announcement returns are on average negative even though acquirers gain from mergers in the long run. The negative announcement return is caused by the negative revelation effect. The mean fraction of the bid in cash is 31%, but there is considerable variation across contests. Acquirers’ relative size  $M$  has a strong, positive relation to both the offer premium and fraction of cash used in bids.

Panel B illustrates how the model matches six additional moments that were not targeted during estimation. We examine the announcement return not just for the acquirer, but also for the target (*TarAR*) and combined firm (*CombAR*). Consistent with the literature, we measure *TarAR* and *CombAR* using a longer window that begins four weeks before the announcement. This longer window is required to capture the well-documented information leakage in target announcement returns.

The model comes close to matching the average announcement return of the combined firm and the correlation between acquirer and target announcement returns. 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 synergies usually produce both high acquirer and target returns. The second effect dominates in both the model and the data.

The model-implied variances of all three announcement returns are much lower than their

empirical counterparts. This result is expected and reassuring. Unlike announcement returns in our model, announcement returns in the data are contaminated by unrelated events that occur during the measurement window, and by other measurement errors. Those factors outside our model do not contribute to the mean announcement return, but they increase the variance of announcement returns. The estimated model is therefore expected to explain only a fraction of the announcement return variance in the data.

The model fails to match the average target announcement return ( $TarAR$ ), which equals 43.8% in the model and 28.3% in the data. The target announcement return and offer premium contain similar information for model identification; both are informative about the acquirer's valuation of the target. The model struggles to match both moments simultaneously. We use the offer premium rather than the  $TarAR$  in our main analysis, because the offer premium measures acquirers' valuation of the target with less error, for two reasons. First, the offer premium can be directly observed in data without auxiliary assumptions about announcement windows and market models. More important, unlike the offer premium, the  $TarAR$  is confounded by elements outside our model, including noise trading, information revelation about the target, and antitrust issues. For robustness, in Section 5 we estimate the model using target announcement returns in place of the offer premium, and we reach very similar conclusions.

Finally, Figure 3 shows how the model fits the full distributions of offer premiums, cash usage, and acquirer announcement returns. Since our estimation only targets means, regression slopes, and conditional variances, we do not necessarily expect the model to fit the full, unconditional distributions. The model fits surprisingly well, though. In both the model and data,  $OfferPrem$  is right-skewed, and  $CashFrac$  has a multi-modal distribution. A significant fraction of acquirers pay by either all cash or all equity, and there is some spread between.

## 4.2 Parameter Estimates

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

The most important result in Table 4 is that the dispersion in synergies across bidders is much larger than the dispersion in their misvaluations. The estimated standard deviation of synergy ( $s$ ) is 44% of the target's size. The estimated standard deviation of misvaluation ( $\epsilon$ ) is much smaller, 7%. This difference drives our paper's main result. Since  $Stdev(s) \gg Stdev(\epsilon)$ , the high-synergy bidder almost always wins the M&A contest, which is efficient. The reason is that when two

bidders compete, the gap between their synergies is usually much larger than the gap between their misvaluations, so it is almost always synergies and not misvaluations that determine the winner.<sup>6</sup> The main reason we find  $Stdev(s) \gg Stdev(\varepsilon)$  is that the conditional standard deviation of offer premiums in the data is very high, 30% (Table 3). Dispersion in misvaluation can explain only a small fraction of the dispersion in offer premiums, so the model needs a very high  $Stdev(s)$  to explain the rest. A large estimate of  $Stdev(s)$  is plausible, because the target's and acquirer's assets are likely complements, and different acquirers may use the target's assets very differently. A relatively low estimate of  $Stdev(\varepsilon)$  is also plausible, because the stock market is quite efficient, targets and their financial advisors perform significant due diligence on the acquirer's stock value, and merger contracts sometimes include collars and other provisions designed to reduce misvaluation risk.

The estimated mean synergy is 0.68, implying the average merger creates value that amounts to 68% of the *target's* market value. The estimated mean synergy appears much lower, 8%, if we instead report it as a percent of the *combined* firm's market value. For comparison, using a different sample and method, [Devos, Kadapakkam, and Krishnamurthy \(2009\)](#) estimate the average synergy gain to be 10% of the combined firm's value, which is close to our 8% estimate.

Comparing the 68% mean synergy to the 44% mean offer premium, we find that the average target captures 65% ( $= 44\%/68\%$ ) of the synergy, and the acquirer captures 35%. Competition between acquirers makes it reasonable that they would capture less than half of the synergy. For comparison, [Ray and Warusawitharana \(2009\)](#) find that acquirers capture 40% of the total abnormal returns generated by acquisitions, on average. Their 40% estimate is quite close to our 35% estimate, if we interpret the total abnormal return as a proxy for the synergy.

Parameter  $\mu_\varepsilon$  is estimated as 0.058, meaning the market believes the average bidder is overvalued by 5.8%. The market therefore adjusts the average bidder's stand-alone value downwards upon bid announcements. This reevaluation can be caused by different reasons. For example, related to the opportunistic bidding 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' stand-alone value (see e.g., [Wang, 2017](#)). Even though the average acquisition reveals this negative information, it benefits long-term shareholders by providing a positive synergy.

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<sup>6</sup> To be more precise, what matters is whether variation in  $\varepsilon$  or  $s$  drives more of the variation in bid scores  $Z$  assigned by targets. Variables  $\varepsilon$  and  $s$  affect  $Z$  slightly differently, in part because they are measured in different units. In Online Appendix A.4, we adjust for this difference and show that finding  $Stdev(s) \gg Stdev(\varepsilon)$  is sufficient to explain why the high-synergy bidder almost always wins.

We estimate an average cash capacity of 0.869 with a standard deviation of 1.034. Because we normalize the target’s pre-acquisition market value to be 1, the estimates imply that the average acquirer only has enough cash capacity to pay 87% of the target’s pre-acquisition market value with cash. Acquirers’ cash capacity, however, exhibits high cross-sectional variation and skews to the right. This evidence is consistent with the stylized facts that some firms are financially constrained, while other firms have large cash holdings or reserve credit lines that can be used to finance acquisitions. Our parameter estimates, together with the assumed censored distribution for  $k$ , imply that 38% of firms have zero cash capacity. The model needs this feature to match the fact that 53% of bids in the data include zero cash (Figure 3 Panel B).<sup>7</sup>

The estimate of  $\rho_{sM}$  implies a 0.39 linear correlation between the synergy and the acquirer’s relative size. This large correlation is not surprising, because 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—measured as a fraction of target size—is larger when the acquirer is larger.

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

### 4.3 Aggregate Efficiency Loss: The Crowd-Out Effect

Now that we have estimated the model, we can use it to quantify the inefficiency from opportunistic acquirers. 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 what could have been achieved in

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<sup>7</sup>One interpretation is that, while almost all firms hold some cash and can access external finance, that cash may be needed for other projects within the firm, leaving some firms with effectively zero cash capacity for the acquisition in question. One limitation of our study is that we model cash constraints in a simple way. There may be more sophisticated ways to create a model that generates 53% of bids with zero cash. Those models will be more complicated than ours, but they will share the key feature that opportunistic bidders can camouflage themselves with cash-constrained bidders.

an economy without misvaluation.

To quantify the inefficiency from opportunistic acquirers, we simulate a large number of M&A contests from our estimated model. In each contest, we independently draw two bidders from the estimated joint distribution of state variables,  $\mathcal{F}(\mathcal{N}_s(\mu_s, \sigma_s^2), \mathcal{N}_\varepsilon(\mu_\varepsilon, \sigma_\varepsilon^2), \mathcal{N}_k(\mu_k, \sigma_k^2), \mathcal{M}(\cdot); \rho_{sM}, \rho_{kM})$ . The bidders submit their optimal bids, and the target optimally scores each bid and then either rejects both bids or chooses a winner. We classify a simulated contest as inefficient if the bidder with the lower synergy wins. Within the inefficient contests, we compute the efficiency loss as the loser’s higher synergy minus the winner’s lower synergy. In other words, the efficiency loss is the amount of synergy lost in the estimated economy relative to an ideal, counterfactual economy in which the high-synergy bidder always wins. An example of that counterfactual economy is one with no misvaluation uncertainty. If  $\sigma_\varepsilon = 0$ , then bidders’ types would be perfectly revealed in equilibrium, and the high-synergy bidder would always win. Other examples include a counterfactual economy without asymmetric information, or a counterfactual constrained-efficient economy in which optimal contracts induce bidders to reveal their types in equilibrium.

Table 5 presents the results. We find that 7.01% of deals are inefficient, meaning the overvalued acquirer crowds out the high-synergy acquirer. In these inefficient contests, the synergy loss averages 9.02% of the target’s pre-acquisition market value. Stated in different units, the winner’s synergy is 15.8% lower than the loser’s synergy in the average inefficient deal. Across all deals, the average efficiency loss is 0.63% ( $= 7.01\% \times 9.02\%$ ) of the target’s size. The low estimated average efficiency loss implies that the M&A market reallocates assets quite efficiently on average.

The main reason we find a low average efficiency loss is that the estimated dispersion in synergies ( $Stdev(s) = 44\%$ ) is much larger than the estimated dispersion of misvaluation ( $Stdev(\varepsilon) = 7\%$ ). As explained in Section 4.2, since  $Stdev(s) \gg Stdev(\varepsilon)$ , it is almost always synergies and not misvaluations that determine the auction’s winner. Crowding out therefore occurs in only a small fraction of deals.

A second reason for the low inefficiency is that we assume targets are sophisticated and use Bayes’ Rule to update their beliefs about bidder misvaluation upon seeing the bidder’s method of payment. If targets were instead naïve and made no inference about misvaluation from the method of payment, then inflated, opportunistic equity bids would appear even more attractive to the target. As a result, these bids would crowd out high-synergy bids more often, leading to a larger inefficiency. To quantify this channel, we measure how the estimated inefficiency would change if targets did no Bayesian updating and instead believed all bidders were fairly valued.

Details are in Online Appendix [A.5](#). We keep parameters at their estimated values but solve for the target’s new (suboptimal) scoring rule and the acquirer’s optimal bidding rule. We find that the average synergy loss increases from 0.63% to 1.38%. Although the inefficiency roughly doubles, it remains small in magnitude. The reason is that  $Stdev(s) \gg Stdev(\varepsilon)$ , so high-synergy bidders would still outbid opportunistic bidders in roughly 90% of contests even if targets were naïve and failed to discount equity payment.

We estimate the average synergy loss from opportunistic acquirers with error, because our model’s parameters are estimated with error. Table 5 contains the inefficiencies’ standard errors, which we compute by Monte Carlo using the parameters’ estimated covariance matrix from SMM. Our estimates are quite precise. For example, the estimated 0.63% average synergy loss across all contests has a standard error of 0.19%, meaning that the average loss is a precisely estimated small number.

#### 4.4 Where Is the Inefficiency Largest?

The results above describe the average M&A deal. The inefficiency, however, varies significantly across deals. As explained above, the inefficiency is zero in 93% of deals, and it averages 9% of target size in the remaining 7% of deals. There is significant variation within these inefficient deals. For example, the synergy loss in the top 10% of inefficient deals is more than 20% of the target’s size, or 36% of the first-best synergy (Table 5). Therefore, while we find that the inefficiency is small on average, it is very large in certain deals. Next, we explore where the inefficiency is largest.

We start by exploring variation within the model. We simulate contests from the estimated model, split the contests into groups based on the winning bid’s observable characteristics, and then compute the average synergy loss within each group. Results are in Table 6.

First, we compare deals by their method of payment. The average synergy loss is significantly larger (0.71% versus 0.49% of target size) when the winner pays with all equity rather than all cash. To help explain why, Panel B reports the winning bidder’s average characteristics. All-equity bidders are more likely to be overvalued ( $\bar{\varepsilon} = +8.5\%$ ), whereas all-cash bidders are more likely to be undervalued ( $\bar{\varepsilon} = -3.9\%$ ). The existence of more overvalued, opportunistic bidders in all-equity deals creates a larger crowd-out effect. Despite being smaller, the inefficiency remains positive (0.49%) in the all-cash group. The reason is that a winning cash bidder sometimes inefficiently crowds out an undervalued, cash-constrained bidder whose synergy is higher, but whose equity bid gets discounted by the target.

Second, we find that the inefficiency is almost twice as large (0.82% versus 0.43%) in deals

with lower offer premiums. Panel B shows that winners with lower offer premiums have lower average synergies (57% versus 117%). If the winner has a low synergy, the loser typically has an even lower synergy. Deals with low offer premiums therefore feature competing bidders with synergies that are low and, therefore, compressed together. It is then more likely that differences in bidders' misvaluations rather than synergies determine the winner. The result is a higher percent of deals that are inefficient (11.0% versus 4.0%), yet a smaller average synergy loss across inefficient deals (7.4% versus 10.7%). The former effect dominates, leading to a larger average inefficiency in low-premium deals.

Next, to explore variation outside our model, we estimate the model in subsamples formed using four proxies for acquirer misvaluation. We expect to find a larger inefficiency in subsamples with more dispersion in misvaluation across acquirers. Results are in Table 7.

Our first misvaluation proxy is the acquirer's asset intangibility, measured as the acquirer's intangible capital divided by its total capital. The logic is that intangible assets are harder to value, so the acquirer is more likely to have private information about their value. We measure intangible capital as in Peters and Taylor (2017), and total capital as the sum of all balance sheet assets and off-balance-sheet intangible assets. We independently estimate the model using deals in the bottom and top intangibility quintiles, then we compute implications from the two estimated models. We find that the inefficiency is 2.28% of target size in the high-intangibility subsample, and just 0.08% in the low-intangibility subsample. The main reason for this difference is that we find more misvaluation dispersion among high-intangibility acquirers: the estimated  $Stdev(\varepsilon)$  is 16.1% versus 2.4% in the low-intangibility subsample. With more misvaluation dispersion, it is more likely that misvaluations rather than synergies determine a contest's winner. We find the stark difference in  $Stdev(\varepsilon)$  mainly because the regression slope of  $AcqAR$  on  $CashFrac$  is more than three times larger (0.07 versus 0.02) in the high-intangibility subsample.

The second misvaluation proxy is based on the target's absolute size. On one hand, smaller targets arguably perform less due diligence about the acquirer's valuation, because they typically have fewer resources and are granted less access to information about the acquirer. By this logic, smaller targets face more misvaluation risk. On the other hand, acquirers may choose not to act opportunistically with a small target, preferring to keep their powder dry for a large target. To determine which force dominates, we independently estimate the model using the highest and lowest quintiles of target size, measured as market capitalization in 2009 dollars. We find that  $Stdev(\varepsilon)$  is much higher among the smaller targets (10.3% versus 6.5%), consistent with smaller targets performing less due diligence. As a result, the average synergy loss is significantly higher for smaller targets (1.14% versus 0.52%). This result implies that, fortunately, the inefficiency

from opportunistic acquirers is concentrated in the smallest, least important deals.

Our third misvaluation proxy uses the aggregate investor sentiment index of Baker and Wurgler (2006, 2007). We separately estimate the model in the highest and lowest quintiles of months according to the sentiment measure. When sentiment is high, sentiment-driven noise traders play a larger role, leading to more mispricing. In other words, high-sentiment periods correspond to high  $Stdev(\varepsilon)$  in our model. If sentiment also makes stocks more overpriced on average, then high sentiment corresponds to high  $E[\varepsilon]$  in our model. Consistent with this logic, we find higher values of both  $Stdev(\varepsilon)$  (10.8% versus 6.1%) and  $E[\varepsilon]$  (8.1% versus 4.9%) in the high-sentiment subsample. The estimated inefficiency is almost three times larger (1.30% versus 0.49%) in the high-sentiment subsample, mainly because there is more misvaluation dispersion and hence more scope for opportunistic bidding.

We use aggregate stock market volatility as the last misvaluation proxy. Higher volatility coincides with more uncertainty about future values and hence more potential for private information and investor mistakes regarding those values. We measure volatility in calendar month  $t$  as the cross-sectional standard deviation of individual stock returns in month  $t$ . We separately estimate the model in the highest and lowest quintiles of months according to the volatility measure. Consistent with our logic, we find slightly more misvaluation dispersion in high-volatility months ( $Stdev(\varepsilon)$  of 8.1% versus 7.2%). This higher misvaluation dispersion contributes to a larger estimated inefficiency in high-volatility months (0.90% versus 0.41%).<sup>8</sup>

To summarize, the inefficiency from opportunistic acquirers varies considerably across deals, and the inefficiency is larger when overvaluation or misvaluation uncertainty is higher: in all-equity deals, when the acquirer's assets are highly intangible, when the target is small, in high-sentiment months, and in high-volatility months. Besides being interesting in themselves, these results provide a reassuring consistency check. While we find some variation across subsamples, the average inefficiency remains below 2.5% of target size in every subsample we consider. This result reinforces our main conclusion that the inefficiency is small overall.

#### 4.5 The Redistribution Effect

Misvaluation and opportunistic bidding lead not only to an inefficiency, but also to a redistribution of merger gains across acquirers. Misvaluation benefits overvalued acquirers by helping them to win contests and to use their shares as a cheap currency. Misvaluation hurts underval-

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<sup>8</sup> Part of the increased inefficiency is also due to higher estimated dispersion in cash capacity in high-volatility months ( $Stdev(k)$  of 82% versus 64%). Greater uncertainty about cash capacity makes sense if high volatility coincides with high uncertainty about firms' access to external finance or greater uncertainty about acquirers' other cash needs.

ued acquirers, because it reduces their chances of winning a contest, and even when they do manage to win, they often end up paying a higher price due to competing, inflated bids. In this section, we quantify this wealth redistribution across different types of bidders.

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

$$g_i^{Bench} = E[\max\{s_i - \tilde{s}_i, 0\}]. \quad (8)$$

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

$$\Delta_i = g_i^{Est} - g_i^{Bench}. \quad (9)$$

We can interpret  $\Delta_i$  as the change in merger gains caused by misvaluation uncertainty, because the only difference between the estimated and benchmark economies is the value of  $\sigma_\varepsilon$ .

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

Each curve describes how the wealth redistribution,  $\Delta_i$ , varies with a bidder's misvaluation, *ceteris paribus*. A bidder's misvaluation, plotted on x-axis of the figure, is measured as the number of standard deviations from the sample mean. In general, the wealth redistribution is increasing in a bidder's misvaluation, with highly overvalued acquirers gaining ( $\Delta > 0$ ) and certain undervalued acquirers losing ( $\Delta < 0$ ). The magnitudes are economically large. For example, when the synergy is high ( $s = 0.8$ , right panel), a bidder at the 95th percentile of misvaluation (i.e., overvalued by  $1.65 \times 7.0\%$  above the mean) gains more than it does in the benchmark economy by 10% of the target's pre-acquisition market value.

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

Comparing the two panels of Figure 4, we find that the wealth redistribution is more pronounced when the deal synergy is high, holding other bidder characteristics constant. Intuitively, when the synergy is larger, there is more to gain or lose.

We then compute the average of  $|\Delta_i|$  across all simulated bidders. We find an average of 0.051, meaning misvaluation causes an average absolute wealth distribution across bidders equal to 5.1% of the target’s size. Even though misvaluation causes a rather small aggregate inefficiency, it causes a very large redistribution of merger gains from undervalued to overvalued acquirers.

## 5 Robustness

This section describes how results change when we use different assumptions in the model or empirical implementation (Table 8). It also explores the robustness of our results across additional subsamples (Table 9).

### 5.1 Target Misvaluation and Reservation Prices

Our main model sets the target’s reservation price equal to its current market value, which we normalize to 1. A potential concern is that a target’s misvaluation could make its reservation price deviate from the market value. For example, if a target believes its fundamental value is 10% above its market value, then the target may only accept bids that are at least 10% above the market value. We now extend the model to incorporate this feature, and we show that our main conclusions are robust.

We add the following assumptions. A target’s fundamental value equals its market value times  $1 - \delta$ . The target’s misvaluation factor  $\delta$  is a new state variable. The bidders observe  $\delta$ , for example, through the due diligence process, but the market does not observe  $\delta$ . Everyone understands, though, that  $\delta$  follows a normal distribution  $\mathcal{N}_\delta(\mu_\delta, \sigma_\delta^2)$ . For the target to accept a bid, the bid must exceed both the target’s market value and its fundamental value. Therefore, the target’s reservation price equals its market value times  $\max\{1, 1 - \delta\}$ . The reservation price

still equals the market value for overvalued targets ( $\delta > 0$ ), and it exceeds the market value for undervalued targets ( $\delta < 0$ ). The target basically now acts like a third competing bidder, as the winning bidder must pay the greater of the second highest bid and the target's reservation price. Variation in target misvaluation now generates variation in reservation prices, which can contribute to variation in offer premiums.<sup>9</sup>

We re-estimate our model using a range of assumed values for the new parameters  $\mu_\delta$  and  $\sigma_\delta$ . Results are in Table 8. We start by assuming the average target is fairly valued ( $\mu_\delta = 0$ ), and  $\sigma_\delta = 10\%$ . We consider  $\sigma_\delta = 10\%$  a plausible value, because it is comparable to our estimated standard deviation of acquirer misvaluation ( $\hat{\sigma}_\varepsilon = 7.0\%$ ). We re-estimate the model's other parameters, compute model implications, and find that the estimated average synergy loss is 0.70%, compared to 0.63% in our baseline model. The change is small for two reasons. First, in the 50% of contests with overvalued targets, the reservation price is the market value, so we are back to our baseline model. Second, even when the target is undervalued, its reservation price rarely affects the offer premium. To affect the offer premium, the target's reservation price has to be above the lower bid but below the higher bid. This rarely occurs, because the estimated level of bidder synergies is very high ( $\hat{E}[s] = 67\%$  of target size) compared to the typical levels of undervaluation ( $\mu_\delta = 0$  and  $\sigma_\delta = 10\%$  of target size in this exercise).

Next, to place an upper bound on the effects of target misvaluation, we re-estimate the model assuming  $\mu_\delta = -20\%$  and  $\sigma_\delta = 40\%$ . These parameter values are extreme, for example, because they produce more failed contests than we see in the data.<sup>10</sup> Even with these extreme parameter values, the average synergy loss changes only slightly, to 0.50%.

To summarize, even if we allow an extreme degree of target misvaluation, we still find a small inefficiency from opportunistic acquirers. While we have not estimated the distribution of target misvaluation, our results imply that an implausibly large degree of target undervaluation would be needed to have any meaningful impact on our conclusions.

In both this extension and our main model, targets do not have private information about their own misvaluation. In reality, a target may privately know it is overvalued, so it may try to opportunistically sell its shares for cash. We focus on acquirers' opportunistic behavior for two reasons.

<sup>9</sup> In theory, targets' reservation prices can exceed the current market value not only due to target misvaluation, but also due to anti-takeover provisions, managerial resistance, and board reputation. One can interpret  $\delta$  as summarizing all these determinants of the reservation price.

<sup>10</sup> Contests can fail in extended model if the target is so undervalued that it rejects both bids. After re-estimating the model with  $\mu_\delta = -20\%$  and  $\sigma_\delta = 40\%$ , we find that 12% of simulated contests fail, compared to 11% in the data. The 11% value in the data is biased upwards in the sense that it includes contests that fail for regulatory and other reasons that are exogenous to our model. This comparison implies that the values  $\mu_\delta = -20\%$  and  $\sigma_\delta = 40\%$  produce more target misvaluation than we see in the data.

First, as [Shleifer and Vishny \(2003\)](#) argue, overvalued firms are more likely to become acquirers, and the relatively undervalued firms are more likely to become targets. Therefore, opportunistic behavior is arguably more common on the acquirer side. Second, the due diligence process usually gives acquirers privileged access to information about the target, mitigating concerns about targets' private information. To address any remaining concerns, we argue that targets' private information is most severe when targets' assets are highly intangible and therefore hard to value. To omit the deals that least conform to our model, we drop the 20% of contests with the highest degree of target intangibility, and we re-estimate the model. The estimated average inefficiency is 0.49%, slightly lower than the full-sample estimate of 0.63% (Table 9). The results' similarity suggests that omitting targets' private information about misvaluation from our model is not an important source of bias.

## 5.2 Overpayment and Governance

A few recent studies conclude that overvalued acquirers destroy shareholder value by overpaying their targets ([Akbulut, 2013](#); [Fu, Lin, and Officer, 2013](#); [Gu and Lev, 2011](#)). Our main model does not allow this possibility, because we assume acquirers rationally maximize expected profits, so they never bid more than their true valuation of the target. In reality, acquirers may overpay if their managers are allowed to build empires rather than maximize firm value. Overpayment would clearly transfer wealth from the acquirer to the target. It is less clear whether overpayment has any effect on the inefficiency we study. For example, if all bidders overpay to the same degree, then overpayment obviously has no effect on which bidder wins the contest. Furthermore, the evidence on overpayment is not unanimous. [Savor and Lu \(2009\)](#) find that overvalued firms create value by paying with shares. By comparing acquisitions and SEOs, [Golubov, Petmezas, and Travlos \(2016\)](#) find that stock-financed acquisitions do not destroy value. Also, shareholder approval is required when an acquirer issues more than 20% new shares to finance a deal, reducing concerns about overpayment in these large equity deals.

To explore whether omitting overpayment from our model is biasing our results, we estimate the model in subsamples with different propensities for overpayment. Since we are essentially sorting firms on the degree of potential bias, our results should look different across these subsamples if the bias indeed exists. We find instead that our results are quite similar across these subsamples, which suggests that ignoring overpayment is not an important source of bias. Subsample estimation results are in Table 9.

The first subsamples we examine are related to governance. [Fu, Lin, and Officer \(2013\)](#) find that overpayment is concentrated among acquirers with the weakest governance. Their

result is strongest when they proxy for weak governance using the entrenchment index ( $E$ ) of [Bebchuk, Cohen, and Ferrell \(2009\)](#). We therefore follow [Fu, Lin, and Officer \(2013\)](#) in using the  $E$ -index.<sup>11</sup> We split our full sample into two roughly equally sized subsamples based on the acquirer's  $E$ . One complication is that relative firm size  $M$  is significantly different across the two subsamples, which by itself can cause the estimated inefficiency to differ. To isolate variation coming from governance rather than firm size, we measure our data moments using a weighting scheme that controls for differences in  $M$  across subsamples.<sup>12</sup> When we estimate the model in the low- and high-entrenchment subsamples, we find that the difference in estimated average synergy losses across subsamples is economically small (0.82% versus 0.60%) and statistically insignificant. We also find the difference to be small and statistically insignificant if we repeat the exercise while replacing the  $E$ -index with two alternative governance proxies. The first alternative is the fraction of acquirer shares held by blockholders. The second compares horizontal and diversifying mergers, using the argument that diversifying mergers are more likely to result from empire-building motives.

Next, we estimate the model in subsamples with high and low acquirer CEO overconfidence, using the [Malmendier and Tate \(2005\)](#) option-based measure. We expect any overpayment to be more severe when the acquirer is overconfident. Our estimated inefficiencies are almost identical (0.66% and 0.65%) in the two overconfidence subsamples, again suggesting that ignoring overpayment is not biasing our results.

Finally, we consider an alternative approach to concerns about omitting governance failures. The approach involves purging governance-related variation from the data when measuring our empirical moments. Specifically, we expand the vector of *Controls* in regressions (5)-(7) to include two acquirer governance proxies: the acquirer's  $E$ -index and fraction of shares held by blockholders. To additionally control for agency problems and resistance within the target, we add controls for the target's  $E$ -index, whether the target's CEO is the founder,<sup>13</sup> and whether the bid is hostile. We exclude these extra controls from our main analysis because they are often

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<sup>11</sup> A limitation of this exercise is that, while the  $E$ -index is clearly useful for thinking about governance failures within targets, it is not clearly useful for thinking about governance failures within acquirers. Some components of the  $E$ -index, such as the presence of a poison pill, measure the extent to which a firm avoids becoming a *target* in an acquisition. Such components do not directly relate to a firm's likelihood of becoming an *acquirer* that overpays. Poison pills could, however, be correlated with weak governance overall, which in turn could lead firms to become acquirers that overpay. Other components of the  $E$ -index, such as the presence of a staggered board, are more plausibly related to becoming an acquirer that overpays, for example, out of an empire-building motive.

<sup>12</sup> This scheme assigns weights to observations so that the weighted distribution of  $M$  in both subsamples matches the full-sample distribution. The scheme assigns a larger weight to observations whose  $M$  value is underrepresented in the subsample compared to the full sample. Additional details are in [Wooldridge \(2002\)](#), page 592. We also apply this scheme to the other subsamples discussed in this section.

<sup>13</sup> We thank Rudi Fahlenbrach for the founder-CEO data.

missing. For example, the *E*-index is available for both the target and acquirer in only 18% of contests. We find that adding these extra controls has a negligible effect on the moments used in estimation, and hence on the estimated parameters and inefficiency (Table A.1 of the Online Appendix). These results again imply that omitting acquirer and target governance failures is not an important source of bias.

### 5.3 Bidder Characteristics and Other Controls

Our main analysis excludes bidder characteristics from *Controls*, because we wish to estimate dispersion across bidders within an M&A contest. One could argue, however, that there are additional public signals about bidders' characteristics, and only the unobservable, residual variation across bidders contributes to the crowd-out inefficiency. In this case, we should purge variation related to observable bidder characteristics from the data before computing our moments. We now do so and show that our conclusions strengthen slightly. Specifically, we supplement our vector *Controls* with 13 variables used by Eckbo, Makaew, and Thorburn (2017). These variables include eight bidder characteristics: pre-acquisition size, leverage, cash holdings, market-to-book ratio, dividend-payer indicator, R&D, asset tangibility, and return on assets. We include two proxies for the external pressure to pay cash: the fraction of all merger bids within the target's industry and year in which the bidder is private, and the Herfindahl index for the bidder's industry. We also include three proxies for the target's information regarding the bidder's valuation: an indicator for whether the target and the bidder are located nearby, an indicator for whether the bidder has SEOs or other acquisitions 24 months around the bid announcement, and an indicator for whether the target and the bidder are in the same industry. We can interpret these additional controls as public signals about the bidder's synergy, misvaluation, and cash capacity. Adding these variables to *Controls* slightly changes the data moments used in SMM estimation. For example, the estimated sensitivity of *AcqAR* to *CashFrac* is slightly lower, indicating that some of the extra control variables are informative about acquirers' misvaluation. Using these updated moments, we re-estimate the model and find that the inefficiency decreases slightly, from 0.63% to 0.51% (Table 8). The change is small, in part because the original *Controls* already include several first-order variables: relative firm size (*M*), multiple target characteristics, and target-industry and year fixed effects.<sup>14</sup>

<sup>14</sup> One limitation of this exercise is that we cannot control for characteristics of the second, unobserved bidder. Our conditional variance moments may therefore be too high, a concern we address in Section 5.7. Another potential concern is that the regression slope coefficients we target in SMM, i.e., the slopes on *M* and *CashFrac* in regressions (5)–(7), are biased because *Controls* omits the characteristics of the second, unobserved bidder. We make the implicit assumption that the second bidder's characteristics are uncorrelated with the first bidder's *M*, *CashFrac*, and other characteristics. In this case, omitting the second bidders' characteristics from *Controls* has no effect on the slope

## 5.4 Number of Bidders

Our main model assumes  $N = 2$  bidders compete in each M&A contest. We now explore how our conclusions change if we relax this assumption.

First, we consider fixed values of  $N$  besides two. If there were just one bidder in each contest, then there would be no possibility of crowding out a second bidder, so the inefficiency would be zero. The more interesting case involves  $N > 2$  bidders. We perform a simple exercise to show that the inefficiency increases, but remains fairly small, if there are more than two bidders. Specifically, we assume targets and acquirers behave as in our main estimated model, but instead of simulating  $N = 2$  bidders per contest, we now simulate  $N = 3, 4,$  or  $5$  bidders. We view  $N = 5$  as an upper bound, because [Boone and Mulherin \(2007\)](#) find on average that only 1.13 bidders make a publicly announced bid, and only 3.75 potential bidders express interest in purchasing the target during the pre-announcement stage. Similar to before, we say the deal is inefficient if the highest-synergy bidder does not win the contest, and we define the synergy loss in such deals as the gap between the winner's synergy and highest synergy. [Table 8](#) shows how our model's main implications change. As the number of competing bidders increases from two to five, we see an increase in the percent of deals that are inefficient (from 7% to 14%), the average loss in inefficient deals (from 9% to 11%), and the unconditional loss (from 0.63% to 1.59%). The inefficiency increases because a larger number of bidders increases the chance of at least one bidder being highly overvalued and crowding out the others. The effect is modest in size, though, because a larger number of bidders also increases the chance of at least one bidder having a very high synergy, placing a high bid, and efficiently winning the contest.

Next, we allow the number of bidders to be random. In reality, the number of bidders varies across M&A contests, and this variation can contribute to variation in takeover premiums. To capture this variation, we simulate contests from our model while drawing  $N$  from a random distribution. We choose the distribution of  $N$  to match its empirical counterpart as closely as possible. [Liu and Mulherin \(2017\)](#) report several statistics about the distribution of  $N$  in a sample of M&A contests with public targets. If we interpret a bidder as a company that makes an indication of interest, then [Liu and Mulherin \(2017\)](#) find that  $N$  has 25th percentile = 1, median = 1, 75th percentile = 2, and mean = 2. To match these four empirical statistics, we set  $\Pr\{N = 1\} = 0.5$ ,  $\Pr\{N = 2\} = 0.25$ , and  $\Pr\{N = 4\} = 0.25$ . If we use our main estimated parameters and simulate the model with random  $N$ , the model-implied standard deviation of offer premiums is much higher than in the data. The reason is that dispersion in  $N$  contributes to dispersion in

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coefficients on  $M$  and  $CashFrac$ .

offer premiums. Low competition in contests with few competing bidders generates low offer premiums, while high competition in contests with many competing bidders generates high offer premiums. To make the model with random  $N$  fit the data again, we re-estimate the model parameters. Model implications from the re-estimated model are in Table 8. The average synergy loss is 0.53%, slightly smaller than the 0.63% loss in our main model. The contests with  $N = 4$  bidders produce large inefficiencies, but there is a stronger force acting in the opposite direction: Many contests have  $N = 1$  bidder, producing an inefficiency of zero. To summarize, when we allow empirically plausible variation in the number of bidders, we still conclude that the inefficiency from opportunistic acquirers is small.

## 5.5 Negative Synergies

We do not allow negative synergies in our main model. In reality, bidders with negative synergies could win M&A contests if they are highly overvalued. Allowing negative synergies would introduce an additional type of inefficiency. For example, if the winning bidder's synergy is  $-5\%$  and the loser's synergy is  $-8\%$ , we could define the efficiency loss to be  $5\%$  even though the high-synergy bidder won the contest. We perform a simple exercise to check whether negative synergies and this broader notion of inefficiency would change our conclusions. We continue using our estimated model, but we move the synergy's left-truncation point from zero to  $-20\%$  of the target's size.<sup>15</sup> Now,  $10\%$  of bidders have negative synergies. We simulate this alternative model and consider two types of inefficiency. First, as in our baseline model, if the winner's synergy is non-negative and yet lower than the loser's synergy, we define the inefficiency as the gap between their synergies. Second, if the winner has a negative synergy, we define the inefficiency as the gap between its negative synergy and the max of zero and the loser's synergy.

Results are in Table 8. With negative synergies,  $5.98\%$  of contests are inefficient. This number is the sum of  $5.36\%$  of contests having the first type inefficiency and  $0.62\%$  having the new, second type. The average synergy loss is  $0.54\%$  with negative synergies, even smaller than the  $0.63\%$  loss in our baseline model. In other words, incorporating negative synergies into the model slightly strengthens our conclusion that the inefficiency is small on average. The reason for this result is that negative synergies introduce two opposing forces. On one hand, negative synergies introduce the extra type of inefficiency. On the other hand, negative-synergy bidders place very low bids, which are more easily defeated by the high-synergy, efficient bidder. We find that this

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<sup>15</sup> The choice of  $-20\%$  is arbitrary, but it has the virtue of allowing a non-trivial fraction of acquirers to have negative synergies. A more involved exercise would involve re-estimating our parameters with this new truncation point, but the parameter estimates would likely not change much. The reason is that our model continues to fit the data very well even after moving the truncation point, suggesting any new parameter estimates would be similar.

second effect dominates, reducing the overall inefficiency.

We also find that introducing negative synergies improves the model’s fit in one dimension. Empirically, 89% of contests are successful, meaning the target is acquired by one of the bidders. In contrast, virtually all contests are successful in our baseline model. Allowing negative synergies reduces the success rate to roughly 95%, closer to the data. The remaining gap between 89% and 95% may be due to regulatory or other factors that are exogenous to our model.

## 5.6 Correlated Synergies

Our main model assumes the contest’s two competing bidders have uncorrelated synergies. In reality, their synergies may be correlated. We mitigate concerns about a positive correlation by controlling for the vector  $Controls_i$  in regression (5). Suppose synergies are positively correlated only because both acquirers share the same expected synergy, and this expected synergy varies as a function of  $Controls_i$  across contests. By including  $Controls_i$  in the regression, we remove the shared variation in expected offer premiums across contests, making it more plausible that any remaining variation is uncorrelated across acquirers.

To address any remaining concerns, we perform a simple exercise to argue that allowing correlated synergies would not significantly change our conclusions. We assume the target and acquirers behave as in our estimated model, but we simulate M&A contests from the model assuming the two bidders’ synergies have an extremely large +50% correlation.<sup>16</sup> Model implications are in Table 8. Moving from a zero to a +50% correlation changes the average synergy loss across all deals from 0.63% to 0.88%. The change is fairly small, because allowing a positive correlation has two opposing effects. First, the positive correlation increases the probability of crowd-out, because it reduces the difference between the competing bidders’ synergies, thereby allowing the difference in misvaluations to play a larger role. Second, the positive correlation decreases the average loss in inefficient deals, because it reduces the gap between the winner and loser’s synergy. Analogously, Table 8 shows that an extreme –50% correlation between bidders’ synergies reduces the unconditional average loss from 0.63% to 0.48%. To summarize, even if bidders’ synergies are highly correlated (either positively or negatively), we reach the same main conclusion: the inefficiency from opportunistic acquirers is small on average.

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<sup>16</sup> Facing correlated synergies, a target could better infer a given bid’s true value by using information from the competing bid. We do not allow targets to use this information from competing bids, which is a limitation of our robustness exercise. Incorporating this feature into the model would significantly complicate the model’s solution. Given how little our conclusions change when we introduce correlations within our estimated model, we doubt the results would change considerably if we fully re-solved the model with correlated synergies.

## 5.7 Other Potential Issues

Our model assumes no correlation between misvaluation ( $\varepsilon$ ) and cash capacity ( $k$ ). A positive correlation could arise, however, if overvalued firms can more easily raise cash by issuing equity or debt before the M&A transaction (Gao and Lou, 2013). The correlation is less relevant, however, if such an issuance reveals the firm's type, causing a price correction before the M&A deal. Nevertheless, to explore the potential bias from omitting this correlation, we perform a simple exercise. We set  $Corr(\varepsilon, k) = +20\%$ , which we view as a very high value, and then we re-estimate the model. The estimated inefficiency increases slightly, from 0.63% to 0.78% (Table 8). The inefficiency increases because the positive correlation makes undervalued bidders, which want to use cash, more cash constrained. It is then easier for overvalued acquirers to mimic undervalued acquirers by paying equity. We then repeat the exercise with a  $-20\%$  correlation and find an estimated inefficiency of 0.59%. In sum, even if misvaluation and cash capacity were highly correlated, we would still conclude that the inefficiency is quite small.

By focusing on a single M&A contest, our model omits potentially important dynamic effects. For example, an acquirer may optimally conceal its overvaluation in a small M&A deal if it plans to do a large M&A deal or SEO one month later. To check whether this omission is biasing our results, we drop contests in which the bidder does another M&A deal or issues equity in a window of  $[-12, 12]$  months around the contest, and then we re-estimate the model. The estimated average inefficiency is 0.52%, compared to 0.63% in our full sample (Table 9). Given how similar the results are, omitting these dynamic effects does not seem to be an important source of bias.

M&A contests in reality can fail for regulatory and other factors that are outside of our model. To check whether those omitted factors are biasing our main results, we re-estimate the model using the 89% of bids that result in completed acquisitions. The estimated average inefficiency is 0.73%, which is very similar to the full-sample estimate of 0.63% (Table 9). Given how similar the results are, and given that it is unknown at the time of the bid whether a contest will ultimately fail, we rely on the full sample of bids in our main analysis.

Our model also omits merger arbitrage trading by hedge funds. These funds short acquirers' shares when equity bids occur, pushing down acquirers' stock prices and thereby pushing up the regression slope of acquirer announcement returns on *CashFrac* (Mitchell, Pulvino, and Stafford, 2004). If we were to adjust this slope downward to remove the effects of merger arbitrage, we would find a smaller estimate of  $Stdev(\varepsilon)$  and hence a smaller estimated inefficiency. We find this bias to be small, though. We adapt regression (6) to control for the predicted amount of

merger-arbitrage trades, and then we re-estimate the model.<sup>17</sup> We find that the inefficiency only decreases from 0.63% to 0.49% (Table 8).

Section 4.1 explains that the offer premium and target announcement return contain similar information for identification, yet the model cannot match both simultaneously. Our main estimation results rely on the offer premium. For robustness, we replace the offer premium with the target announcement return, recompute the relevant moments in both the data and the model, and re-estimate the model. The estimated average synergy becomes significantly lower. In contrast, the estimated inefficiency increases only slightly, from 0.63% to 0.78% (Table 8), because the synergy's average—as opposed to its dispersion—is not a main determinant of the inefficiency.

Our main SMM procedure estimates eight parameters using eight moments. Next, we show that our conclusions are robust to using an overidentified model with three extra moments: the mean offer premium, conditional variance of offer premium, and average acquirer announcement return, all computed within the subsample of all-cash bids. All-cash bids are useful because their value does not depend on stock misvaluation, hence they are especially informative about the distribution of synergies. Also, the all-cash subsample represents the outcome of a selection effect in our model: Bidders optimally choose their method of payment and bids based on their misvaluation, cash capacity, and synergy. The all-cash subsample is therefore informative about these variables' distributions. Re-estimating the model using this expanded set of moments, we find that the estimated inefficiency decreases slightly, from 0.63% to 0.52% (Table 8). Detailed results are in Online Appendix Section A.6.

Officer (2003) reports that SDC's data are sometimes missing or noisy. For robustness, we use the method of Officer (2003) to compute alternative *OfferPrem* and *CashFrac* measures based on each bid's components. We then recompute the data moments and re-estimate the model. The estimated inefficiency decreases slightly, from 0.63% to 0.56% (Table 8). The inefficiency decreases because the alternative *OfferPrem* measure is more dispersed, consistent with Officer (2003), which results in more synergy dispersion and hence a weaker crowd-out effect.

We include *Controls* in regressions (5)-(7) to purge cross-deal variation coming from factors omitted from the model. As explained above, our results do not change significantly if we expand *Controls* to include governance-related variables, bidder characteristics, and other deal characteristics. Of course, it is possible that *Controls* still omits important factors, such as characteristics of the second, unobserved bidder. Of particular concern, omitting important controls could pro-

<sup>17</sup> We follow Mitchell, Pulvino, and Stafford (2004) in constructing a predicted amount of merger arbitrage trading, and we add this predicted amount to the vector *Controls*. We also reduce the average acquirer announcement return by half, based on the finding in Mitchell, Pulvino, and Stafford (2004) that price pressure from merger arbitrage accounts for roughly half of the average acquirer announcement return.

duce an upward-biased estimate of  $Var(u)$ , the conditional variance of offer premiums. Since we rely on the moment  $Var(u)$  to identify the within-contest variance of synergies, it is possible that our estimated variance in synergies is too high, leading us to find an inefficiency that is too low. As a simple check, we cut the value of  $Var(u)$  in half and re-estimate the model. Cutting  $Var(u)$  in half is extreme, implying that omitted cross-contest variables can explain half the remaining unexplained variance of offer premiums, even though *Controls* already includes industry and time fixed effects as well as several first-order target characteristics. Despite this extreme change, we find that the average inefficiency only increases from 0.63% to 0.99% (Table 8). The inefficiency remains small because the offer premium's variance, even after being cut in half, is still large enough to imply  $Var(s) \gg Var(\varepsilon)$ . This result suggests that our main conclusion would still hold even if  $Var(u)$  is too large due to omitted variables from *Controls*.

## 6 Conclusion

There has been considerable research on overvaluation as a motive for acquisitions. If opportunistic, overvalued acquirers crowd out high-synergy acquirers, then there is an inefficiency in the M&A market. Our main contribution is to quantify this inefficiency. We find that the inefficiency is relatively small on average, but it is large in certain deals, and it is larger in deals where misvaluation is more likely. These results shed light on the fundamental question of whether capital market imperfections matter for resource allocation. We also document a large negative externality that overvalued bidders impose on synergistic bidders: Overvalued bidders not only crowd out synergistic bidders, but also drive up acquisition prices.

Our study could be extended in several directions. We have analyzed how misvaluation redistributes gains across acquirers, but our framework could also be used to analyze wealth redistribution between acquirers and targets. It would also be interesting to explore whether undervalued firms avoid becoming acquirers, which would be another inefficiency from misvaluation. Yet another promising direction is to quantify the inefficiencies from search frictions and agency conflicts within the target or acquirer. We leave these challenges for future work.

## Appendix: Details on SMM Estimation

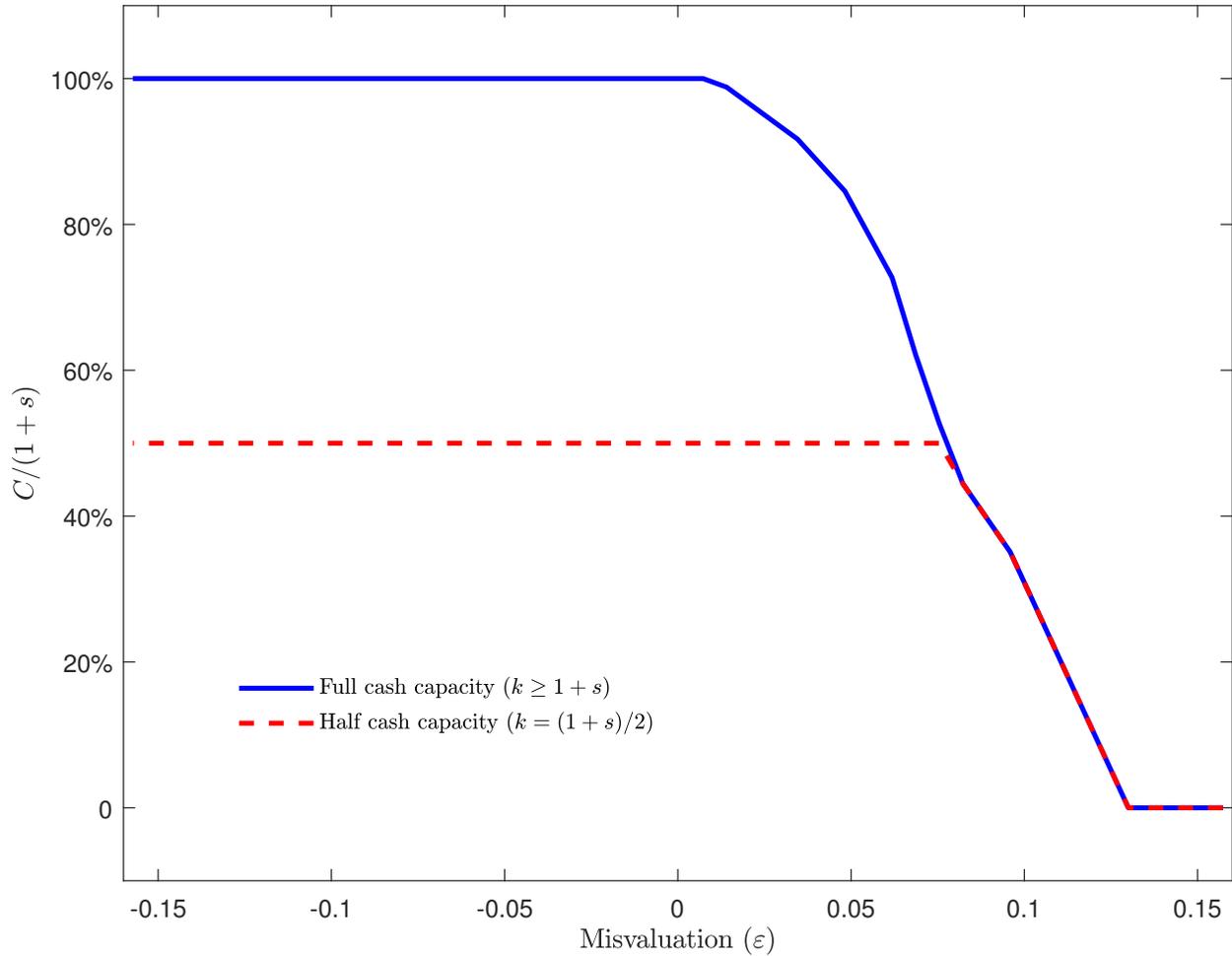
For each given set of parameters,  $\Theta$ , we solve the model numerically and obtain the optimal bidding rule,  $b^*(\Phi_i) = (C^*(\Phi_i), \alpha^*(\Phi_i))$  and target scoring rule,  $z(C, \alpha, M)$ . We then simulate a large number of takeover contests, in each of which we draw two competing 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. 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 is below 0.87 and the losing bidder is assigned as the initial bidder if otherwise.

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 Online Appendix A.3.3. The SMM estimator  $\hat{\Theta}$  searches for the parameter values that minimize the distance between the data moments and the model-implied moments:

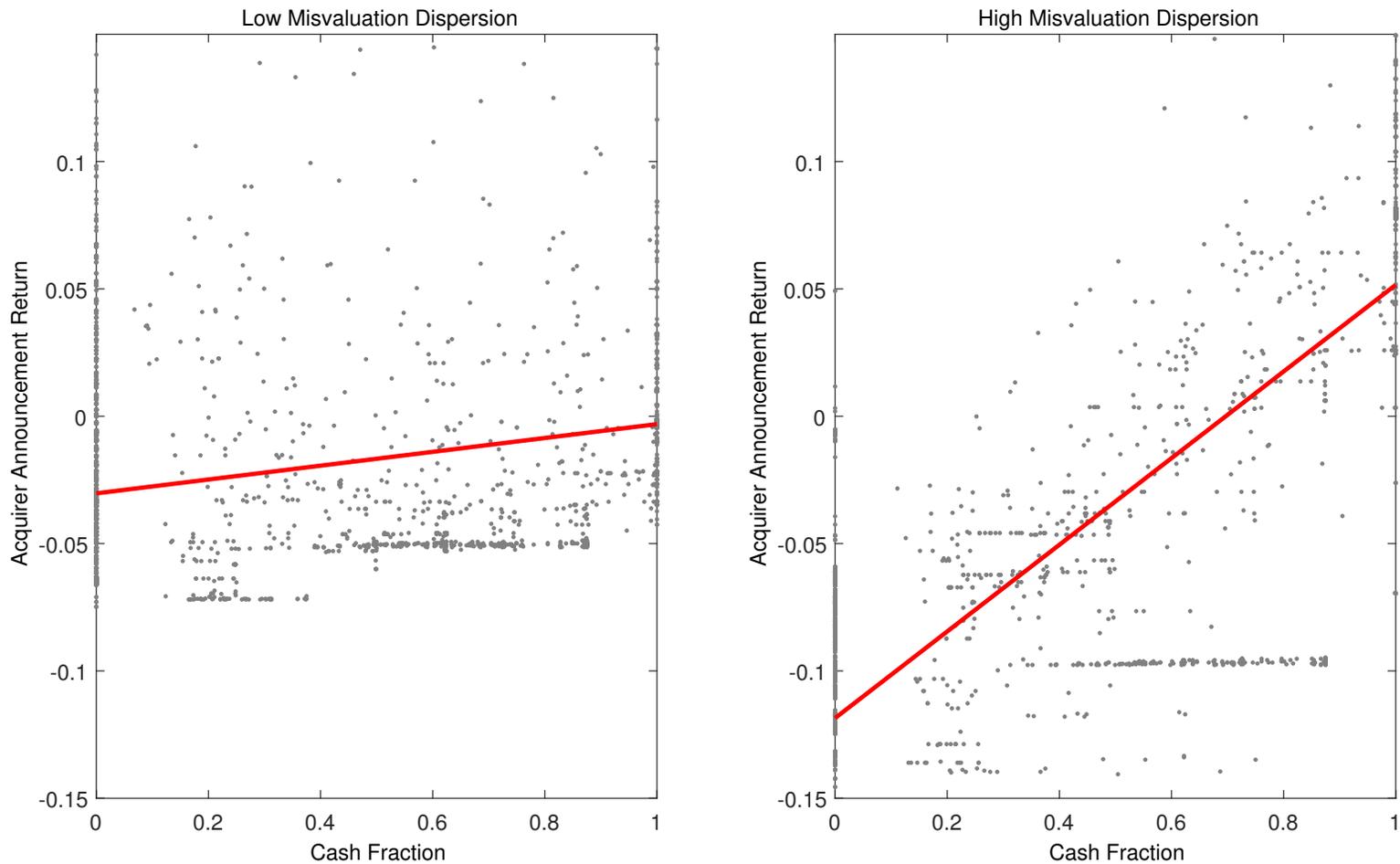
$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} \left( \hat{m} - \frac{1}{L} \sum_{l=1}^L \hat{m}^l(\Theta) \right)' W \left( \hat{m} - \frac{1}{L} \sum_{l=1}^L \hat{m}^l(\Theta) \right).$$

Vector  $\hat{m}$  contains the moments estimated from data, and  $\hat{m}^l(\Theta)$  is the corresponding vector of moments estimated from the  $l$ th sample simulated using parameter  $\Theta$ .  $W$  is 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. [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.



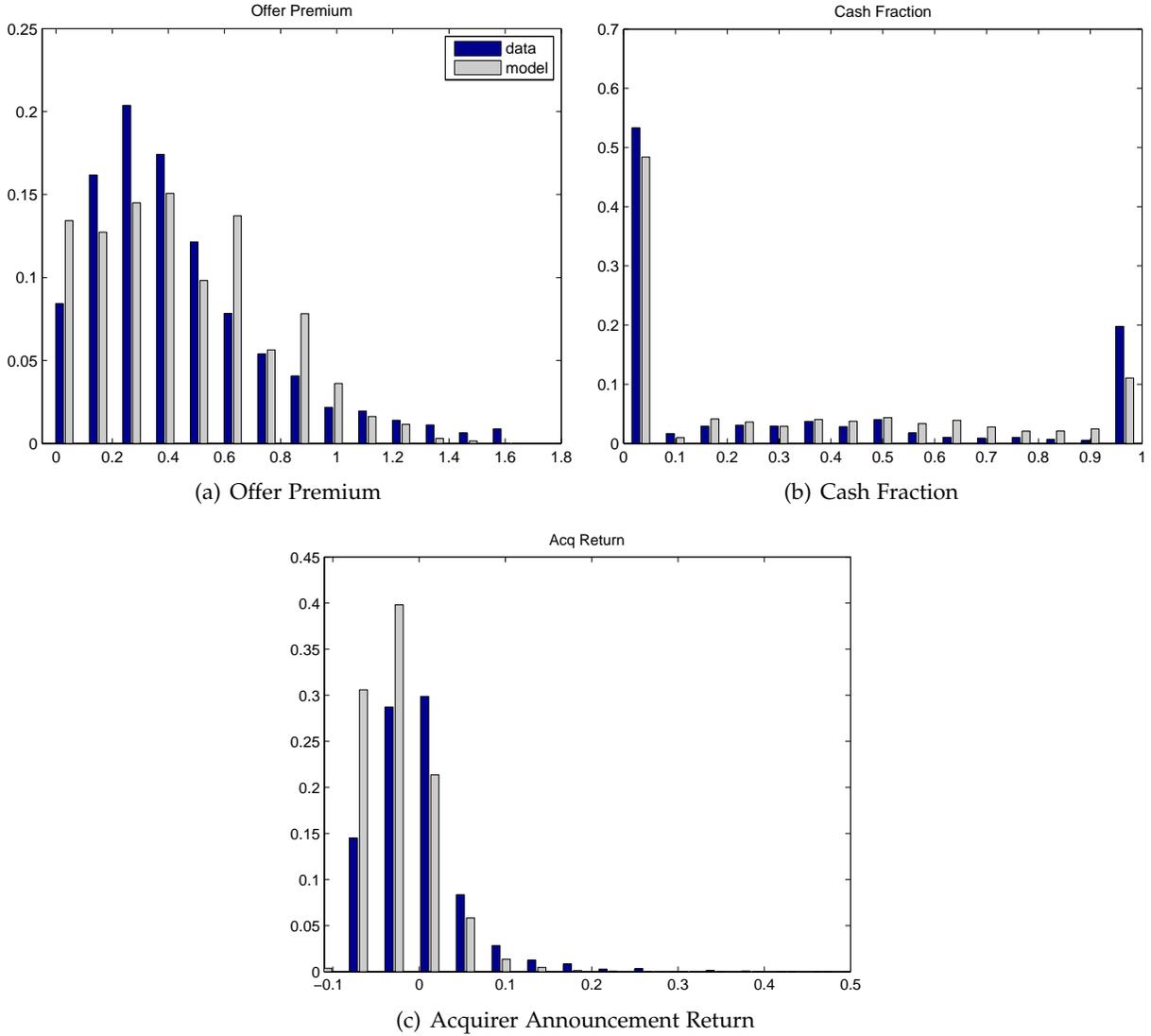
**Figure 1: Cash Fraction in the Optimal Bid**

This figure presents the cash fraction in optimal bids from acquirers with different degrees of misvaluation. The vertical axis denotes the ratio of the bid's cash to the acquirer's true valuation of the target. The optimal bidding rule is solved numerically using the method described in Online Appendix A.3.1 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.



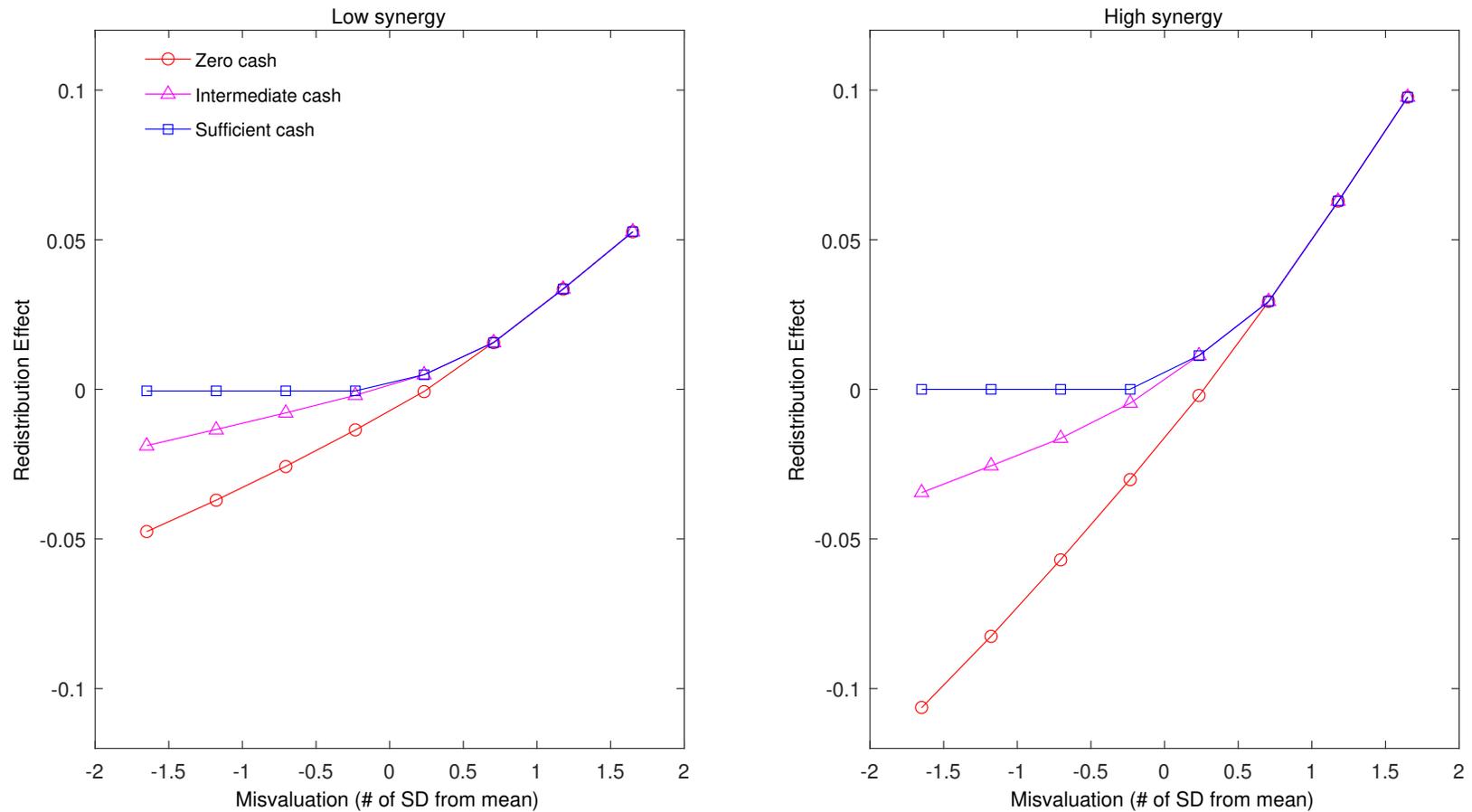
**Figure 2: Revelation Effect of Cash**

This figure presents the revelation effect of cash in acquirer announcement returns. We simulate acquisition bids based on the numerical solution of the model. The model is solved under the parameters presented in Table 4 using the method described in Online Appendix A.3.1. For each deal the acquirer announcement return is computed using the method described in Online Appendix A.3.3. 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 dispersion ( $\sigma_\varepsilon = 0.05$ ), and the right panel presents that in the case of high misvaluation dispersion ( $\sigma_\varepsilon = 0.20$ ).



**Figure 3: Comparing Simulated and Empirical Distributions**

This figure compares the distributions of offer premium, cash fraction in the bid, and acquirer announcement return in the data and in the model. The model is solved using the parameter values in Table 4 and the method described in Online Appendix A.3.1, and the variables of interest are computed using the method described in Online Appendix A.3.3.



**Figure 4: Redistribution Effect**

This figure presents the redistribution effect for different types of bidders. The redistribution effect, which is measured by Equation (9), is the bidder's merger gain in the estimated economy minus its merger gain in a counterfactual benchmark economy without misvaluation. More simply, the redistribution effect equals the effect of misvaluation on a bidder's merger gains. 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,  $\Delta_i$ , varies with a bidder  $i$ 's misvaluation, ceteris paribus. A bidder's misvaluation, denoted  $\varepsilon_i$  in the model, is measured as the number of standard deviations from the sample mean.

**Table 1: Summary Statistics**

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

	1980–2013					1980–1990	1991–2000	2001–2013
	Mean	Std. Dev.	10%	Median	90%	Mean	Mean	Mean
Deal size (\$M)	1,590	6,618	40	280	2,979	636	1,333	1,673
Offer premium	0.44	0.32	0.10	0.36	0.88	0.45	0.45	0.41
Cash fraction	0.31	0.40	0.00	0.00	1.00	0.31	0.18	0.48
Acquirer relative size	2.17	1.64	0.32	1.90	4.45	2.08	2.07	2.30
Acquirer AR	-0.02	0.08	-0.11	-0.02	0.05	-0.02	-0.02	-0.02
Target size	5.30	1.71	3.21	5.20	7.57	4.76	5.24	5.48
Target leverage	0.28	0.26	0.00	0.23	0.66	0.30	0.27	0.29
Target ME/BE	2.47	3.20	0.71	1.67	4.88	1.88	2.56	2.27
Target ROA	-0.02	0.20	-0.17	0.01	0.10	0.02	-0.01	-0.04
Target cash	0.18	0.22	0.01	0.07	0.54	0.17	0.15	0.20
Number of obs.	2,503	2,503	2,503	2,503	2,503	172	1,379	952

**Table 2: Sensitivity of Moments to Parameters**

This table shows the sensitivity of model-implied moments (in columns) with respect to model parameters (in rows). To make the sensitivities comparable across parameters and moments, we scale the sensitivities by a ratio of standard errors. The table contains the values of  $\frac{dm}{dp} \frac{Stderr(p)}{Stderr(m)}$ , where  $\frac{dm}{dp}$  is the derivative of simulated moment  $m$  with respect to parameter  $p$  (evaluated at estimated parameter values from Table 4),  $Stderr(p)$  is the estimated standard error for parameter  $p$  (from Table 4), and  $Stderr(m)$  is the estimated standard error for the empirical moment  $m$  (from Table 3). The first moment is  $E[OfferPrem_i]$ , the average offer premium. The second moment is  $Var(u_i)$ , the conditional variance of offer premia, measured using regression (5). The third moment is  $a_1$ , the slope coefficient of offer premium on the logarithm of relative firm size, also from regression (5). The fourth moment is  $E[AcqAR_i]$ , the average acquirer announcement return. The fifth moment is  $b_1$ , the slope coefficient of acquirer announcement return on the fraction of cash used in the bid, from regression (6). The sixth moment is  $E[CashFrac_i]$ , the average fraction of cash in bids. The seventh moment is  $Var(w_i)$ , the conditional variance of  $CashFrac$ , measured using regression (7). The eighth moment is  $c_1$ , the slope coefficient of cash usage on the logarithm of relative firm size, from regression (7). Parameter definitions are as follows. Synergy  $s$  is assumed to follow a normal distribution  $\mathcal{N}(\mu_s, \sigma_s^2)$  that is left-truncated at zero. The misvaluation factor  $\varepsilon$  is assumed to follow a normal distribution  $\mathcal{N}(\mu_\varepsilon, \sigma_\varepsilon^2)$ . Cash capacity is assumed to follow a normal distribution  $\mathcal{N}(\mu_k, \sigma_k^2)$  that is left-censored at zero. Parameter  $\rho_{sM}$  is the Spearman's rank correlation between synergy and acquirer relative size. Parameter  $\rho_{kM}$  is the Spearman's rank correlation between cash capacity and acquirer relative size.

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Parameter	Offer Premium			Acquirer Announcement Return		Fraction of Bid in Cash		
	Mean	Cond. Var.	Slope on $\log(M)$	Mean	Slope on Cash Frac	Mean	Cond. Var.	Slope on $\log(M)$
$\mu_s$	0.825	0.510	0.444	0.200	-0.455	0.121	-0.111	0.269
$\sigma_s$	0.899	1.675	0.181	0.435	-1.288	0.008	-0.337	0.137
$\rho_{sM}$	-0.094	-0.243	1.315	-0.485	0.250	-0.075	0.034	0.100
$\mu_\varepsilon$	0.001	0.005	-0.009	-0.901	-0.079	0.045	-0.046	-0.005
$\sigma_\varepsilon$	0.440	-0.521	0.520	-0.773	1.844	0.266	0.538	0.735
$\mu_k$	0.146	0.258	-0.311	0.514	-0.795	1.181	0.617	0.876
$\sigma_k$	0.104	-0.079	0.235	0.124	0.119	0.070	1.183	0.118
$\rho_{kM}$	-0.110	-0.270	0.209	-0.126	-0.313	0.251	0.791	1.092

**Table 3: Model Fit**

The top panel shows how well the model fits the eight moments targeted in SMM estimation. The first moment is  $E[\text{OfferPrem}_i]$ , the average offer premium. The second moment is  $\text{Var}(u_i)$ , the conditional variance of offer premia, measured using regression (5). The third moment is  $a_1$ , the slope coefficient of offer premium on the logarithm of relative firm size, also from regression (5). The fourth moment is  $E[\text{AcqAR}_i]$ , the average acquirer announcement return. The fifth moment is  $b_1$ , the slope coefficient of acquirer announcement return on the fraction of cash used in the bid, from regression (6). The sixth moment is  $E[\text{CashFrac}_i]$ , the average fraction of cash in bids. The seventh moment is  $\text{Var}(w_i)$ , the conditional variance of  $\text{CashFrac}$ , measured using regression (7). The eighth moment is  $c_1$ , the slope coefficient of cash usage on the logarithm of relative firm size, from regression (7). Standard errors for the data moments are in parentheses. The lower panel reports results for untargeted moments.  $E[\text{CombAR}]$  and  $E[\text{TarAR}]$  are the average combined-firm and target announcement returns, including the 4-week runup.  $\text{Var}[\text{AcqAR}]$ ,  $\text{Var}[\text{CombAR}]$ , and  $\text{Var}[\text{TarAR}]$  are the variances of the acquirer, combined firm, and target announcement returns.  $\text{Corr}[\text{AcqAR}, \text{TarAR}]$  is the Pearson's correlation between the acquirer announcement return and target announcement return.

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

**Table 4: Parameter Estimates**

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

	$\mu_s$	$\sigma_s$	$\mu_\varepsilon$	$\sigma_\varepsilon$	$\mu_k$	$\sigma_k$	$\rho_{sM}$	$\rho_{kM}$
Estimate	0.439	0.603	0.058	0.070	0.480	1.518	0.496	0.566
Standard Error	0.021	0.041	0.004	0.013	0.111	0.117	0.045	0.024
	$E[s]$	$\text{Stdev}[s]$	$E[\varepsilon]$	$\text{Stdev}[\varepsilon]$	$E[k]$	$\text{Stdev}[k]$	$r_{sM}$	$r_{kM}$
Estimate	0.676	0.444	0.058	0.070	0.869	1.034	0.386	0.441
Standard Error	0.024	0.022	0.004	0.013	0.086	0.084	0.020	0.036

**Table 5: Estimated Efficiency Losses**

This table reports the estimated efficiency losses in the baseline model. Panel A shows the percent of deals that are inefficient, which equals the percent of simulated deals in which the low-synergy bidder wins. Panel B shows the average synergy loss in inefficient deals, which equals the gap between the loser’s higher synergy and winner’s lower synergy in inefficient deals. % of target size expresses the synergy loss as a percent of the target’s pre-announcement market value, and % of synergy expresses the synergy loss as a percent of the higher synergy, which is the winner’s synergy in efficient deals and the loser’s synergy in inefficient deals. Panel C shows the average efficiency loss across all deals (efficient and inefficient). Standard errors are computed by Monte Carlo. 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.

		Panel A: Percent of Deals That Are Inefficient					
	Estimate	7.01%					
	Standard Error	1.03%					
		Panel B: Average Synergy Loss in Inefficient Deals					
			Percentile				
		Mean	0.10	0.25	0.50	0.75	0.90
% of target size	Estimate	9.02	1.09	2.99	6.78	12.9	20.01
	Standard Error	0.63					
% of synergy	Estimate	15.79	1.93	5.29	11.95	22.05	36.37
	Standard Error	1.08					
		Panel C: Average Synergy Loss in All Deals					
			Percentile				
		Mean	0.10	0.25	0.50	0.75	0.90
% of target size	Estimate	0.63	0.08	0.21	0.47	0.90	1.40
	Standard Error	0.19					
% of synergy	Estimate	1.14	0.14	0.37	0.84	1.54	2.55
	Standard Error	0.31					

**Table 6: Who Creates the Largest Inefficiency? Variation Across Deals**

This table reports the model implications for M&A contests with different characteristics. We simulate our model using the baseline parameter estimates in Table 4, and we split the simulated contests into subsamples based on the winning bid's observable characteristics. Columns 2-3 report the estimates for deals with different methods of payment (All Equity v.s. All Cash), and Columns 4-5 report the estimates for deals with offer premiums in the bottom tercile (Low) or top tercile (High). Panel A reports the model implications in the corresponding subsamples, and Panel B reports the average characteristics of the winning bidder. Percent of deals inefficient is the percent of simulated deals in which the low-synergy bidder wins; Avg. loss in inefficient deals is the average synergy loss across all inefficient deals; and Avg. loss in all deals is the average synergy loss across all deals. Both average losses are measured in percent of the target's pre-acquisition market value.

	Method of Payment		Offer Premium	
	All Equity	All Cash	Low	High
Panel A: Model Implications				
Percent of deals inefficient	7.40	6.44	11.02	4.00
Avg. loss in inefficient deals (%)	9.54	7.67	7.43	10.67
Avg. loss in all deals (%)	0.71	0.49	0.82	0.43
Panel B: Average Characteristics of the Winning Bidder				
Synergy ( $s$ )	0.897	0.911	0.565	1.168
Misvaluation ( $\varepsilon$ )	0.085	-0.039	0.061	0.056
Cash capacity ( $k$ )	0.210	2.538	0.746	1.167
Acquirer / target size ( $M$ )	34.00	130.40	54.20	79.10

**Table 7: Where Is the Inefficiency Largest? Variation Across Misvaluation Subsamples**

This table contains results from estimating the model in different subsamples. Panel A reports the quantities 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) acquirer intangibility is comprised of M&A deals in which the acquirer’s measure of asset intangibility ranks in the top (bottom) quintile. The subsample with small (large) target size contains targets whose market capitalization, measured in 2009 dollars, is in the bottom (top) quintile. The subsample with high (low) sentiment is comprised of M&A deals announced during months in the top (bottom) quintile of the market sentiment measure; we use the version of the sentiment index from Jeffrey Wurgler’s website that is orthogonalized to the business cycle. The subsample with high (low) market volatility is comprised of M&A deals announced during months in the top (bottom) quintile of aggregate stock market volatility, measured as the cross-sectional standard deviation of individual stock returns within the month. Percent of deals inefficient is the percent of simulated deals in which the low-synergy bidder wins; Avg. loss in inefficient deals is the average synergy loss across all inefficient deals; and Avg. loss in all deals is the average synergy loss across all deals. Both average losses are measured as a percent of the target’s pre-acquisition market value.

	Full Sample	Acquirer Intangibility		Target Size		Sentiment		Market Volatility	
		High	Low	Small	Large	High	Low	High	Low
Panel A: Quantities Implied by Parameter Estimates									
E[s]	0.676	0.742	0.584	0.882	0.504	0.753	0.639	0.744	0.533
SD[s]	0.444	0.494	0.379	0.528	0.283	0.470	0.388	0.465	0.346
E[ε]	0.058	0.041	0.055	0.040	0.052	0.081	0.049	0.071	0.042
Stdev[ε]	0.070	0.161	0.024	0.103	0.065	0.108	0.061	0.081	0.072
E[k]	0.869	1.001	0.529	1.057	0.589	0.736	0.703	0.669	0.928
Stdev[k]	1.034	0.888	0.580	1.158	0.457	0.855	0.828	0.821	0.641
$r_{sM}$	0.386	0.377	0.577	0.474	0.322	0.312	0.470	0.424	0.336
$r_{kM}$	0.441	0.482	0.152	0.401	0.454	0.378	0.552	0.335	0.536
Panel B: Model Implications									
Percent of deals inefficient	7.01	12.42	2.64	8.34	7.77	9.62	6.49	8.06	6.12
Avg. loss in inefficient deals (%)	9.02	18.37	2.97	13.68	6.72	13.54	7.60	11.19	6.72
Avg. loss in all deals (%)	0.63	2.28	0.08	1.14	0.52	1.30	0.49	0.90	0.41

**Table 8: Robustness – Alternative Assumptions**

This table reports the model implications when we make alternative assumptions in the model or empirical implementation. Detailed descriptions of these exercises are in Online Appendix A.7. Spec. 1 is the baseline model; results match those in Table 5. Spec. 2 assumes the target is overvalued by a fraction  $\delta$ , with  $\delta \sim \mathcal{N}_\delta(\mu_\delta, \sigma_\delta)$ . Spec. 3 supplements *Controls* with 13 additional variables including bidder characteristics, proxies for the target’s information about the bidder’s value, and proxies for external pressure to pay cash. Spec. 4 simulates the estimated baseline model allowing  $N > 2$  bidders. Spec. 5 simulates the model with random  $N$ . Spec. 6 allows negative synergies by moving the estimated model’s lower bound of synergies ( $s$ ) from 0 to  $-0.2$ . Spec. 7 assumes that the synergy of competing bidders are correlated. Spec. 8 assumes a bidder’s misvaluation and cash capacity are correlated. Spec. 9 controls for the negative price pressure induced by M&A arbitrageurs on acquirers’ announcement returns in equity or mixed deals. Spec. 10 estimates the model using moments that replace the offer premium with the target’s announcement return. Spec. 11 supplements the SMM estimation with three extra moments: the mean and conditional variance of *OfferPrem* and the mean *AcqAR*, all computed in the subsample of all-cash bids. Spec. 12 replaces the offer premium reported by SDC with an alternative measure computed following Officer (2003). Spec. 13 re-estimates the model after reducing the conditional variance of offer premium measured in the data by half. Percent of Deals Inefficient is the percent of simulated deals in which the low-synergy bidder wins, except in Specification 6 where we use a broader definition. Average Synergy Loss is measured as a percent of the target’s pre-acquisition market value.

Specification	Percent of Deals Inefficient	Average Synergy Loss (%)	
		Inefficient Deals	All Deals
1. Baseline	7.01	9.02	0.63
2. Target misvaluation and reservation prices			
$\mu_\delta = 0\%, \sigma_\delta = 10\%$	7.16	9.80	0.70
$\mu_\delta = -20\%, \sigma_\delta = 40\%$	5.21	9.55	0.50
3. Bidder characteristics and other controls	5.82	8.79	0.51
4. $N > 2$ bidders			
$N = 3$	10.08	10.29	1.04
$N = 4$	12.39	10.73	1.33
$N = 5$	14.04	11.31	1.59
5. Random number of bidders	6.48	8.18	0.53
6. Negative synergies	5.98	9.00	0.54
7. Correlated bidder synergies			
$Corr = +0.5$	10.13	8.68	0.88
$Corr = -0.5$	5.33	9.02	0.48
8. $Corr(\text{Misvaluation, Cash Capacity})$			
$Corr = +0.2$	7.57	10.30	0.78
$Corr = -0.2$	6.92	8.59	0.59
9. Price pressure from merger arbitrage	6.17	8.02	0.49
10. Replace <i>OfferPrem</i> with <i>TarAR</i>	7.21	10.85	0.78
11. Overidentified model	6.25	8.31	0.52
12. Alternative <i>OfferPrem</i> measure	6.38	8.82	0.56
13. Half $Var(\text{OfferPrem})$	9.29	10.76	0.99

**Table 9: Robustness – Additional Subsample Results**

This table contains results from estimating the model in different subsamples. The subsample of low (high) acquirer entrenchment index is comprised of M&A contests in which the acquirer’s *E*-index value is below (above) the median. The subsample of low (high) acquirer blockholder ownership contains M&A contests in which the fraction of the acquirer’s shares held by blockholders, defined as a shareholder with at least a 5% block, is below (above) the median. The subsample of horizontal (diversifying) mergers is comprised of M&A contests in which the acquirer and target belong to the same (unrelated) industry. We define a horizontal merger as one in which the target and acquirer belong to the same four-digit SIC industry, and a diversifying merger as one that is neither horizontal nor vertical. Following Fan and Goyal (2006), we define a vertical merger as one in which the acquirer and target industries are different and yet connected, as measured by the BEA input-output tables. The subsamples based on acquirer CEO overconfidence use the [Malmendier and Tate \(2005\)](#) option-based measure, closely following the implementation by [Humphery-Jenner et al. \(2016\)](#). Subsample 6 excludes from the full sample all deals in which the acquirer is involved in another M&A or had equity issuance in the window of  $[-12, 12]$  months around the deal announcement. Subsample 7 excludes from the full sample all deals in which the target’s asset intangibility measure ranks in the top quintile. We measure intangibility as in Section 4.4. Subsample 8 excludes 280 contests that do not result in the purchase of the target firm. The model parameters are estimated for each subsample. The subsamples’ estimated bidder characteristics can be found in Table A.2 of the Online Appendix. Percent of Deals Inefficient is the percent of simulated deals in which the low-synergy bidder wins. Average Synergy Loss is measured as a percent of the target’s pre-acquisition market value.

Subsample	Percent of Deals Inefficient	Average Synergy Loss (%)	
		Inefficient Deals	All Deals
1. Full sample	7.01	9.02	0.63
2. Acquirer entrenchment index			
Low	8.30	9.82	0.82
High	7.52	8.00	0.60
3. Acquirer blockholder ownership			
Low	8.25	11.20	0.92
High	7.47	9.98	0.75
4. Merger type			
Horizontal	7.01	8.66	0.61
Diversifying	7.32	9.82	0.72
5. Overconfident acquirer CEO			
Yes	7.62	8.70	0.66
No	7.81	8.29	0.65
6. No M&A or SEO surrounding deal	6.67	7.75	0.52
7. Excluding high-intangibility targets	6.35	7.71	0.49
8. Excluding failed bids	7.23	10.10	0.73

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