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."[1] AOL paid with shares whose value dropped by almost 90% in the subsequent two years, raising the possibility that AOL's managers did the deal precisely because they knew they could pay using overvalued shares. The merger clearly transferred value from Time Warner to AOL shareholders ex post. The merger may have also destroyed value overall: AOL potentially crowded out an 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. The literature has raised concerns about this inefficiency,[2] but it remains unclear whether the inefficiency is large or small. It could be large, because researchers have already provided evidence that misvaluation is an important motive for acquisitions,[3] and because the M&A market is very large ($1.04 trillion in deals for U.S. public acquirers in 2014).

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

Quantifying these effects is difficult. Stock misvaluation and synergies are not directly observable. More 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

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

[2] For example, Eckbo, Makaew, and Thorburn (2016) 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."

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

hard to find exogenous shocks that prevent acquirers from acting opportunistically. Even if there were such a shock, it is likely to be limited in scope, raising concerns about external validity.

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

This crowd-out problem stems from the target's confusion when evaluating equity bids from acquirers with different unobservable synergies and misvaluations. Paying with cash can mitigate these problems, because cash's value is unambiguous. We therefore 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 premia helps identify the dispersion in synergies, while the dispersion in observed cash usage helps identify the dispersion in cash capacity. The dispersion in misvaluation is mainly identified off the well-documented positive relation between an acquirer's announcement return and its use of cash in the bid.[4] This positive relation emerges from our model because the market infers from a cash bid that the bidder's equity is not likely to be overvalued, causing the bidder's share price to increase. The predicted relation is especially

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

positive when there is more dispersion in misvaluation, which helps identify this key parameter. Overall, the model can closely fit the distribution of offer premia and cash usage, as well as their relation to deal size. The model also closely fits the relation between bidders' announcement returns and method of payment.

We use the estimated model to quantify the inefficiencies from opportunistic acquirers. By simulating data off the model, we find that an overvalued bidder crowds out a bidder with a higher synergy in 7.0% of 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 main reason we find a small efficiency loss is that the estimated dispersion in synergies is many times larger than the dispersion in misvaluation. As a result, high-synergy acquirers out-bid their (potentially overvalued) competitors 93% of the time, producing efficient deals.

While the estimated average synergy loss is low in percentage terms, it translates to a non-trivial \$4.4 billion in lost synergies per year in deals made by U.S. public acquirers.[5] Also, the loss is quite high for certain deals. For example, at the 90th percentile among inefficient deals, the winner's synergy is 36% below the loser's synergy, amounting to a synergy loss equal to 20% of the target's pre-announcement market value. We show that the inefficiency is larger when misvaluation is more likely, for example, in all-equity deals, when the acquirer's assets are more intangible, in months with higher investor sentiment (Baker and Wurgler, 2006, 2007), and in months when markets are more volatile.

Next, we measure how misvaluation affects the distribution of merger gains across acquirers. We define the merger gain as the acquirer's expected synergy minus what it pays for that synergy. We then define the redistribution effect as the difference in a bidder's merger gains between the estimated economy and a counterfactual economy with no misvaluation uncertainty. Misvaluation uncertainty helps overvalued acquirers by allowing them to win contests and use their shares as a cheap currency. Misvaluation uncertainty 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 misvaluation causes a

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

redistribution of wealth from undervalued to overvalued acquirers that is quite large on average: 5.1% of the target's pre-acquisition value, which translates to roughly $36 billion of wealth redistributed per year in the U.S.[6]

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

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 concern 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 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, and several other factors we omit from our baseline model.

The idea that opportunistic, overvalued acquirers create inefficiencies in the M&A market comes from the theoretical work of Rhodes-Kropf and Viswanathan (2004, 2005). They show that the target may be sold to the acquirer with lower synergies when the financing of acquisition bids is subject to frictions like misvaluation or default. The model we estimate is most closely related to that of Rhodes-Kropf and Viswanathan (2004). Our paper is the first to quantify the inefficiencies from opportunistic acquirers. In addition, we study the negative externality that overvalued acquires impose on undervalued acquirers, which is new to the literature.

More broadly, our paper contributes to three strands of literature. First, several papers focus

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

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 (2016) 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 in the literature. Specifically, we measure how misvaluation can reduce the overall 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 premia, and they find that target resistance plays the dominant role in driving up premia. Warusawitharana (2008) links asset purchases and sales to firm fundamentals, and Yang (2008) estimates a model that predicts firms with rising productivity acquire firms with declining productivity. Our paper also takes a structural approach, but it addresses different questions. Like us, Matvos and Seru (2014) use structural estimation to study whether resources are allocated efficiently, but their paper is neither about M&A nor misvaluation.

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, externalities, and the marginal value of cash capacity. Section 5 discusses robustness, and Section 6 concludes.

2 Model

2.1 Setup

2.1.1 M&A Participants

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

Four acquirer characteristics are critical for the takeover contest. First, under the management of acquirer i, the target's value is $V_i = 1 + s_i$, where s_i is the synergy between the target and acquirer i. Synergies are the most frequently declared motive for M&As. Second, M_i denotes the acquirer's size relative to the target. Specifically, 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 relative value X_i can differ from the relative market value M_i. Specifically, we assume $X_i = M_i(1 - \varepsilon_i)$, where ε_i is the misvaluation factor.[7] Acquirers can be fairly valued ($\varepsilon = 0$), overvalued ($\varepsilon > 0$), or undervalued ($\varepsilon < 0$) relative to the target. Overvaluation becomes a second motive for M&A, since an overvalued firm has an incentive to buy other companies using its equity as currency (Rhodes-Kropf and Viswanathan, 2004; Shleifer and Vishny, 2003). Fourth, the acquirers are subject to a cash capacity constraint. The amount of cash that acquirer i can use in the acquisition cannot exceed $k_i \geqslant 0$. 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 $\Phi_i = (s_i, \varepsilon_i, k_i, M_i)$, $i = 1, 2$.

Among acquirer characteristics, the market value M_i is publicly observable, and the other characteristics (synergy, misvaluation, and cash capacity) are observed only by the acquirer's managers. Other participants in the M&A market, though they cannot observe these characteristics, understand that the synergy s_i follows a normal distribution $\mathcal{N}_s(\mu_s, \sigma_s^2)$ that is left-truncated at zero; the misvaluation factor ε_i follows a normal distribution $\mathcal{N}_\varepsilon(\mu_\varepsilon, \sigma_\varepsilon^2)$; and the cash capacity k_i follows a normal distribution $\mathcal{N}_k(\mu_k, \sigma_k^2)$ that is left-censored at zero. Left-censoring creates a large mass in the distribution at $k = 0$. We choose these specific distributions because they allow

[7] Because ε multiplies M, ε is unitless. In particular, ε is not in units of fraction of target size. For example, if the acquirer's shares are overvalued by 7% and the target's shares are overvalued by 3%, then $\varepsilon = 4.12\% \approx 7\% - 3\%$.

the model to fit the data well, as we show in Section 4. The distribution of the observed acquirer market values relative to the target, M, is denoted $\mathcal{M}(M)$.[8]

Empirically, acquirers' relative size is correlated with two other characteristics. First, larger acquirers often pay higher premia (Alexandridis et al., 2013, for instance), suggesting a possible correlation between the acquirer's size and deal synergies. A positive correlation is plausible if the target's and acquirer's assets are complements. We therefore allow M_i and s_i to have a non-zero Spearman's rank correlation, denoted ρ_{sM}. Second, larger firms tend to be less financially constrained (e.g., Almeida, Campello, and Weisbach, 2004; Gilchrist and Himmelberg, 1995; Hadlock and Pierce, 2010; Whited and Wu, 2006), and an acquirer can more easily pay cash to buy a small target than a large target. We therefore allow M_i and k_i to have a non-zero Spearman rank correlation, denoted ρ_{kM}. These correlations let the acquirer's relative size M_i serve as a signal to the target about the deal's synergy and the acquirer's cash capacity. In sum, the acquirer characteristics $(s_i, \varepsilon_i, k_i, M_i)$ are an independent realization from the joint distribution $\mathcal{F}(\mathcal{N}_s(\mu_s, \sigma_s^2), \mathcal{N}_\varepsilon(\mu_\varepsilon, \sigma_\varepsilon^2), \mathcal{N}_k(\mu_k, \sigma_k^2), \mathcal{M}(\cdot); \rho_{sM}, \rho_{kM})$, $i = 1, 2$.

2.1.2 Takeover Contest

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 α_i is the target's share in the combined firm after the acquisition. The target values the bid as Z_i, the bid's cash plus the expected value of the target's share in the combined firm:[9]

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

The target computes the combined firm's expected value by making a rational forecast of the bidder's misvaluation (ε_i) and synergy (s_i) based on what it can observe: C_i, α_i, and M_i. The target uses z as a scoring rule to rank bids. If the target believes that both bids have a valuation lower than its reservation value (i.e., the target's pre-acquisition market value which is normalized to one), the acquisition fails. Otherwise, the bid with the highest score Z wins, and the acquisition is settled as follows. For convenience, let i be the winner and j the loser. If

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

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

$C_i \geqslant \max\{1, z(C_j, \alpha_j, M_j)\}$, the winner pays cash in the amount of $\max\{1, z(C_j, \alpha_j, M_j)\}$; otherwise, the winner pays a cash amount of C_i and a fraction $\tilde{\alpha}_i$ of the combined firm's stocks such that $z(C_i, \tilde{\alpha}_i, M_i) = \max\{1, z(C_j, \alpha_j, M_j)\}$. Intuitively, the actual fraction of the combined firm received by the target is determined in accordance with the second-price auction rule. In Online Appendix A.1.1, we show that such an settlement exists and is unique.

2.1.3 Equilibrium Concept

We consider an equilibrium in which acquirers strategically choose their bids as a combination of cash and equity to maximize their current shareholders' expected profit 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' bidding strategy. Formally, the definition of such an equilibrium is given below.

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

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

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

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

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

2.2 Discussion

First, where does misvaluation come from? One source is the acquirer's private information about its value. Other sources include mistakes made by behavioral investors— "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 relative value X_i, yet the target cannot.

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

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

Another way to profit from overvaluation is to sell shares in a seasoned equity offering (SEO). Our paper is silent on a firm's choice between M&A and SEO, and in fact the two are not necessarily mutually exclusive. An overvalued firm may prefer M&A if it has a real synergy, whereas it may prefer an SEO if it has real internal investment opportunities.[10]

By assuming the synergy's distribution is left-truncated at zero, we assume no bidders have negative synergies. For robustness, in Section 5 we allow negative synergies and show that it has little effect on our conclusions.

We model the acquisition as an auction with two competing bidders. In most observed M&A deals there is only one publicly announced bidder. However, these deals do not indicate a lack of competition. Boone and Mulherin (2007) show a high degree of competition between potential acquirers before any bid is publicly announced.[11] Even without this pre-announcement competition, a single bidder may behave as if it is competing with other bidders in order to deter those bidders from entering (Fishman, 1988, 1989). Also, a single bidder may submit a competitive bid to prevent target resistance (Burkart, Gromb, and Panunzi, 2000; Dimopoulos and Sacchetto, 2014). For these reasons, it is reasonable to model the acquisition as a competitive auction with multiple bidders. Although takeover contests sometimes involve more than two competiting bidders, our two-bidder assumption is not uncommon in the literature (e.g. Dimopoulos and Sacchetto, 2014; Fishman, 1988, 1989; Gorbenko and Malenko, 2016). For robustness, Section 5

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

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

shows that we reach similar conclusions if we allow three, four, or five competing bidders.

The M&A process in practice is very complex. In the literature, it is often modeled as an English ascending (EA) auction (e.g., Dimopoulos and Sacchetto, 2014; Fishman, 1989; Gorbenko and Malenko, 2014, 2016) or a sealed second-price (SP) auction (e.g., Rhodes-Kropf and Viswanathan, 2004). Under our model's independent private value paradigm, these two auction formats are equivalent. We choose to follow the SP format because (a) it gives rise to a simple and unambiguous analytic relation between the bid's two components (cash and equity), with which the optimization problem of the acquirer in (2) may be substantially simplified;[12] and, more important, (b) it establishes an intuitive structure on which the optimal cash offer in the equilibrium bid can be determined. The EA format can provide (a) but not (b), and the sealed first-price (FP) auction format can provide (b) but does not imply a straightforward analytic relation between the cash and equity components in a bid.

Our model abstracts away from the sequential nature of an M&A contest. 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 premia, which suggests that building preemption into our model is not of first-order importance.

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

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

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

2.3 Model Solution

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^*, α_i^*) *such that* $\alpha_i^*(X_i + V_i - C_i^*) + C_i^* = V_i$. *As a result, in the equilibrium the optimal bids* (C_i^*, α_i^*) *satisfy the following relation:*

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

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

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

Proof. See Online Appendix A.1.2. □

Although a bidder optimally bids its true valuation of the target, the target remains confused about the bidder's type. The reason is that bidders have three dimensions of private information (their synergy, misvaluation, and cash capacity), but their bids have only two dimensions (cash and equity). Bidders with different characteristics may end up submitting exactly the same bid. Consider a simple example in which both acquirers have zero cash capacity and therefore bid with all equity. An overvalued acquirer (low X) with low synergy (low V) will submit the same bid as an undervalued acquirer (high X) with high synergy (high V) if both acquirers have the same ratio of X/V.[13] The target in our model is more confused 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. The model solution features a pooling equilibrium in which the target cannot perfectly learn a bidder's synergy, misvaluation, and cash capacity based on its bid. The target can only infer the average of these three characteristics across all pooling acquirers who submit the same 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 value but differ in their payment methods will appear different to the target. For example, equity bids made by highly overvalued acquirers often appear to be worth more than they truly are, from the target's point of view.[14] More generally,

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

[14] Consider one example in which two bidders are drawn from the model distribution, $\mathcal{F}(\cdot)$, such that: They have the same relative size of one ($M_1 = M_2 = 1$), the same synergy of one ($s_1 = s_2 = 1$), and the same zero cash capacity ($k_1 = k_2 = 0$); bidder one is overvalued and its true stand-alone value is 0.5, while bidder two is undervalued and

the target only adjusts for the *average* misvaluation in the group of bidders who make the same type of bids. Therefore, an acquirer with above-average overvaluation relative to its group is still inflated after the target's adjustment, making its equity bid look more attractive to the target than it really is.

Acquirers strategically choose the payment method in their bids. 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. To illustrate this prediction, we numerically solve the model using the estimated parameters presented in Table 4, then Figure 1 plots the relation between the bid's optimal cash component and bidder's misvaluation.[15] Cash component is presented as a ratio of the cash payment to the acquirer's true valuation of the target. The solid line depicts the cash component of optimal bids made by acquirers that have sufficient cash capacity ($k \geqslant 1+s$). Undervalued and fairly-valued acquirers ($\varepsilon \leqslant 0$) choose to bid with all cash, because equity is more expensive for them. Cash usage gradually drops as acquirers become more overvalued. Highly overvalued acquirers 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.

When evaluating bids, the target takes into account acquirers' bidding strategy and considers cash payment as a signal. If a bid contains more cash, the target infers that the acquirer is less likely to be overvalued. The equilibrium scoring rule (4) indicates that one more dollar offered in cash increases the target's valuation of the bid by more than one dollar, because it lifts the valuation of the bid's equity component. 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

its true stand-alone value is 1.5. This precise information is private and not available to the target or the rival bidder. In the equilibrium, they both bid the true valuation and hence bidder one offers $\alpha_1 = 2/(0.5+2) = 4/5$ and bidder two offers $\alpha_2 = 2/(1.5+2) = 4/7$. Apparently, though they have the same synergy and their bids have the same true value, the bid made by the overvalued bidder (bidder one) appears more attractive to the target, because all else equal, a sweetened bid (higher equity offer given the same cash component) appears more valuable in the eyes of the target in the equilibrium.

[15] The method of numerically solving the model is presented in Online Appendix A.2.1.

market observes a bid that includes little or no cash, the market infers that the acquirer is overvalued in expectation, resulting in a negative revelation effect and hence a lower announcement return. To demonstrate this effect, we simulate bids from our estimated model, we compute the bidders' announcement returns, and we 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 σ_ε is larger. This prediction is crucial to our empirical identification of σ_ε. 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 becomes more confused and thus relies 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.

Overall, 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: overvalued acquirers gain more and undervalued acquirers gain less than they would in an economy with no misvaluation uncertainty. We use structural estimation to quantify these effects.

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. The deal is classified as a merger, not a tender offer or a block trade;[16]

7. The payment method and offer premium are available, and the acquirer and target have sufficient valuation data covered by CRSP for computing their market values and abnormal announcement returns.

We only use data on the first publicly announced bid in each control contest. Following Betton, Eckbo, and Thorburn (2008), we say that a control contest begins with the first public bid for a given target and continues until 126 trading days have passed without any additional offer. Each time an additional offer for the target is identified, the 126 trading day search window rolls forward. We do not use data on earlier, pre-public bids for two reasons. Most important, key variables like the offer premium are not observable for those bids. Also, finding even the identity and number of pre-public bidders is impossible for the majority of our contests.[17] Our main estimation also excludes subsequent public bids, for two reasons. First, they are extremely rare; less than 2% of our sample contests have multiple publicly announced bids. Second, our model is not designed to explain subsequent bids, which would condition on the initial public bid in ways that our simultaneous-bidding model cannot capture. Extending our model to accommodate these few extra observations would significantly complicate our analysis.

Next, we define our main variables. We measure bid i's offer premium, denoted $OfferPrem_i$, as the offer price per share divided by the target stock price four weeks before the bid announcement, minus one. The offer premia data provided by SDC include some large outliers. Following Officer (2003) and Bates and Lemmon (2003), we drop observations with offer premium lower than zero or larger than two. We denote the acquirer and target's announcement returns around bid i as $AcqAR_i$ and $TarAR_i$, respectively. We measure these announcement returns using the market model with a three-day window around the bid's announcement. Online Appendix A.2.2 explains how we compute the announcement return within the model. $CashFrac_i$ is the fraction

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

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

of bid i made up of cash. We measure M_i as the ratio of acquirer to target market capitalization four weeks before bid i.

Our final sample includes 2,503 bids. Table 1 provides summary statistics. The average transaction value is 1,590 million in 2009 dollars, significantly skewed to the right. The offer premium averages 44% with a standard deviation of 32%. Bidders pay on average 31% of deal value in cash, with 20% of bidders making all-cash bids and 53% of bidders making all-equity bids. Acquirers are much larger than targets: the logarithm of M averages 2.17. The mean acquirer announcement return is slightly negative, -2.3%. The target's announcement return is significantly positive with an average of 21.5%. Also consistent with previous findings, the combined firm announcement return is positive and around 1%. We also break the whole sample period into three subperiods: 1980-1990, 1991-2000, and 2001-2013. The summary statistics are quite comparable across these subperiods, with some variation in the payment method.

3.2 Estimator

We estimate the model using the simulated method of moments (SMM), which chooses parameter estimates that minimize the distance between moments generated by the model and their sample analogs. The following subsection defines our moments and explains how they identify our parameters. The eight parameters we estimate are μ_s and σ_s, which control the mean and variance of bidders' synergies; μ_ε and σ_ε, which control the mean and variance of bidders' misvaluation; μ_k and σ_k, which control the mean and variance of bidders' cash capacity; and ρ_{sM} and ρ_{kM}, the Spearman rank correlations between the logarithm of relative firm size ($\ln(M)$) and the synergy and cash capacity, respectively. Since M is directly observed in the data, we input the empirical distribution of M into the 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. 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 σ_s, σ_ε, and σ_k describe variation across acquirers within a single contest. The data, however, reflect heterogeneity not just within but also across contests. To isolate within-contest variation, we use moments that purge cross-contest heterogeneity driven by unobserved time effects, unobserved target-industry effects, and observable target characteristics.[18] Specifically, when measuring several moments below, we control for M_i and a vector $Controls_i$ that includes year dummies, targets' Fama-French 48 industry dummies, 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 taken a variety of approaches to heterogeneity.[19] Our approach offers several advantages, although it is not perfect.[20] We reach very similar conclusions if we do not include *Controls* when measuring our moments.

Next, we define our moments and, to explain how the identification works, we show how the moments vary with our parameters. Each moment depends on all model parameters, but we explain below which moments are most important for identifying each parameter. To illustrate, Table 2 presents the Jacobian matrix containing the derivatives of our eight predicted moments with respect to our eight parameters.[21]

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

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

[18] Purging variation that comes from acquirer characteristics would be inappropriate, since our goal is to estimate variation in acquirer characteristics. Like us, Gorbenko and Malenko (2014) and Dimopoulos and Sacchetto (2014) exclude acquirer characteristics from their sets of observables.

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

[20] One large advantage is that our approach is computationally feasible. Building heterogeneity directly into the structural model would be infeasible, as it would require numerically solving the model not just for every trial parameter vector, but also for every data point. Gorbenko and Malenko (2014) and Dimopoulos and Sacchetto (2014) avoid this problem by having a closed-form solution. Another advantage is that we can easily include many variables in *Controls* (e.g. industry and year dummies), whereas building many such variables into the structural model and estimating their coefficients via SMM would be computationally prohibitive. Yet another advantage is that our approach allows us to easily address heterogeneity not just in average synergies but also in cash capacity and misvaluation. For example, the time fixed effects in *Controls* absorb time variation in the external pressures to pay cash, which Eckbo, Makaew, and Thorburn (2016) show to be an important determinant of the method of payment. Building heteroegneity directly into the structural model is conceptually cleaner, but since understanding cross-contest heterogeneity is not our goal, we take the simpler approach.

[21] We present the Jacobian evaluated at estimated parameter values. To make the sensitivities comparable across parameters and moments, we scale the sensitivity by a ratio of standard errors. Specifically, for moment m and parameter p, the table presents the value of $\frac{dm}{dp}\frac{Stderr(p)}{Stderr(m)}$, where $\frac{dm}{dp}$ is the derivative of simulated moment m with respect to parameter p, $Stderr(p)$ is the estimated standard error for parameter p (from Table 4) and $Stderr(m)$ is the estimated standard error for the empirical moment m (from Table 3).

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

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

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

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

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

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

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

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

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

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

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

4 Empirical Results

We begin by assessing how the model fits the data. We then discuss our parameter estimates. Next, we use the estimated model to quantify the inefficiencies from opportunistic acquirers, and we explore where the inefficiency is largest. Finally, we use the model to quantify the redistribution of merger gains and the marginal value of cash capacity.

4.1 Model Fit

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

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

Among other untargeted moments, the model comes close to matching the average announcement return of the combined firm and the correlation between acquirer and target announcement returns.[22] The correlation between acquirer and target announcement returns is driven by two competing effects. On the one hand, acquirer and target announcement returns are negatively correlated within a deal, because the two firms split a fixed synergy. On the other hand, they are positively correlated across deals, because deals with high synergy usually produce both high acquirer and target returns. The second effect dominates in both the model and the data.

The model fails to match the average target announcement return ($TarAR$), which equals 43.8% in the model and 28.3% in the data. The target's announcement return depends mainly on the offer premium, which our model fits very closely, and on the probability of deal completion. Our model overshoots the probability of deal completion, which helps explain why the model's average target announcement return is too high. One reason the model overshoots the deal-completion rate is that deals in reality can fail for antitrust and other reasons that are orthogonal to our model. We discuss this issue and partially remedy it in Section 5.

The target announcement return and offer premium contain similar information for model identification. The model is apparently unable to match both moments simultaneously. We use the offer premium rather than the $TarAR$ in our estimation, 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: noise trading, information revelation about the target, and the antitrust issues discussed above.

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

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

4.2 Parameter Estimates

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

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

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

Parameter μ_ε is estimated as 0.055, meaning the market believes the average bidder is overvalued by 5.5%, relative to the target. 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 activities we study in this paper, acquirers that bid with equity may raise concerns about overvaluation, inducing the market to adjust their valuations downwards (see e.g., Savor and Lu, 2009). The negative reevaluation can also arise because takeover announcements simply reveal negative information regarding the acquirers' fundamental performance that affects their stand-alone value (see e.g., Wang, 2015).

We estimate an average cash capacity of 0.869 with a standard deviation of 1.034. Because we normalize the target pre-acquisition market value to be 1, the estimates imply that the average acquirer only has enough cash capacity to buy 87% of the target with cash. Acquirers' cash capacity, however, exhibits a large cross-sectional variation and skews to the right. This evidence is consistent with the stylized facts that some firms are financially constrained, while other firms have large cash holdings or reserve credit lines that can be used to finance acquisitions.

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

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

4.3 Aggregate Efficiency Loss: The Crowd-Out Effect

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

To quantify the inefficiency from opportunistic acquirers, we simulate a large number of M&A contests from our estimated model. In each contest, we independently draw two bidders from the estimated joint distribution of state variables, $\mathcal{F}(\mathcal{N}_s(\mu_s, \sigma_s^2), \mathcal{N}_\varepsilon(\mu_\varepsilon, \sigma_\varepsilon^2), \mathcal{N}_k(\mu_k, \sigma_k^2), \mathcal{M}(\cdot); \rho_{sM}, \rho_{kM})$. The bidders submit their optimal bids, and the target optimally scores each bid and then either rejects both bids or chooses a winner. Next, we classify each simulated contest outcome as either efficient, inefficient, or failed (both bids rejected). We say that a contest is efficient if the bidder with the higher synergy wins, and is inefficient if the bidder with the lower synergy wins. Within the inefficient deals, we then compute the efficiency loss as the loser's higher synergy minus the winner's lower synergy. In other words, the efficiency loss is the amount of synergy lost in the estimated economy relative to an ideal, counterfactual economy in which the high-synergy bidder always wins. An example of that counterfactual economy is one with no misvaluation uncertainty: If $\sigma_\varepsilon = 0$, then bidders' types would be perfectly revealed in equilibrium, and the high-synergy bidder would always win.[23]

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

We estimate these inefficiencies with error, because our model's parameters are estimated with error. Table 5 contains standard errors for the inefficiencies. We compute these standard errors by Monte Carlo using the parameters' estimated covariance matrix from SMM.[24] Our estimates are quite precise. For example, the estimated 0.63% average loss in all deals has a standard error of 0.19%, meaning that the average loss is a precisely estimated small number.

Like most counterfactual analyses, all the counterfactual analyses in this paper are subject to a Lucas-type critique. For example, we cannot claim that synergies would be 0.63% higher if we could somehow eliminate misvaluation uncertainty. The problem is that firms would reoptimize if misvaluation uncertainty disappeared, and our model would capture only part of this reoptimization. Specifically, our model would capture optimal changes in bidding and scor-

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

[24] 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.

ing behavior, but it would not capture changes in firms' decisions to participate as acquirers or targets in the first place. A comprehensive policy analysis would need to incorporate all reactions to any policy interventions. The Lucas critique is less severe in our paper than in many structural papers, because we do not interpret our counterfactual analyses as actual policy interventions. Instead, we simply measure synergy losses relative to a counterfactual in which the highest-synergy bidder wins, which is the natural benchmark.

4.4 Where Is the Inefficiency Largest?

The results above describe the average M&A deal. The inefficiency varies significantly across deals, however. 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. So 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, we split the contests into subsamples based on the announcing bidder's observable characteristics, and then we compute the average synergy loss within each subsample. Results are in Table 6.

First, we compare bids by their method of payment. In the all-equity subsample, the average synergy loss is 0.80% of target size, more than twice as large as the 0.32% average loss in the all-cash subsample. The estimated bidder characteristics reported in Panel A explain why. All-equity bidders feature significantly more misvaluation ($Stdev(\varepsilon)$ of 7.6% versus 4.5%), because overvalued bidders are opportunistically pooling with undervalued, cash-constrained bidders. With more misvaluation, the crowd-out effect is larger. The inefficiency remains positive (0.32%) in the all-cash subsample for two reasons. The first reason is that an all-cash bidder can crowd out an undervalued bidder whose synergy is higher, but whose bid includes equity (due to cash constraints) and therefore gets discounted by the target. Another reason is that some all-cash bids get crowded out by higher, inefficient bids that contains some equity.

The average synergy losses are significantly higher (0.82% versus 0.49%) when the offer premium is lower. The main reason is that a weak, low bid is easily crowded out by an opportunistic acquirer.

The inefficiency is also higher (0.76% versus 0.48%) when the target is relatively larger (i.e, M is lower). The reason is that a larger target makes bidders' ability to pay cash lower ($E[k]$ equal to 35% versus 154%) and more uncertain ($Stdev(k)$ equal to 62% versus 116%), thereby making it easier for overvalued bidders to camouflage when they bid in equity. This result indicates that, unfortunately, the inefficiency is larger in the deals that are more important, as indicated by a larger target.

To explore variation outside our model, we estimate the model in subsamples. Our model predicts the inefficiency to be larger when there is more misvaluation. To test this prediction, we create subsamples using three proxies for acquirer misvaluation. Subsample estimation results are in Table 7.

Our first 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 (2016), and total capital is 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 is just 0.08% in the low-intangibility subsample. There are two main reasons for this difference. First, consistent with the logic above, we find more misvaluation uncertainty among high-intangibility acquirers: the estimated $Stdev(\varepsilon)$ is 16.1% versus 2.4% in the low-intangibility subsample. We find this stark difference because the regression slope of acquirer announcement return on $CashFrac$ is 0.07 in the high-intangibility subsample but only 0.02 in the low-intangibility subsample. Second, there is more uncertainty about cash capacity when intangibility is high: $Stdev(k)$ is 89% versus 58%. This higher uncertainty makes it easier for overvalued acquirers to camouflage themselves when they bid with shares.

Our second misvaluation proxy is based on the aggregate investor sentiment index of Baker and Wurgler (2006, 2007).[25] 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 makes stocks more overpriced on average, then high sentiment also 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 (Table 7 Panel A). The estimated inefficiency is almost three times larger (1.30% versus 0.49%) in the high-sentiment subsample, mainly because there is more misvaluation uncertainty

[25] The sentiment measure is a composite index constructed using six indices–closed-end fund discount, NYSE share turnover, the number of IPOs, the average first-day returns on IPOs, the equity share in new issues, and the dividend premium. We use the version of the investor-sentiment index that is orthogonalized to the business cycle. The reason is that M&A activities are in general procyclical. As documented by Harford (2005), many business cycle indicators such as liquidity and technological progress are also the drivers of merger waves.

and hence more scope for opportunistic bidding.

We use aggregate stock market volatility as a third proxy for misvaluation. 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, Panel A of Table 7 shows slightly more misvaluation uncertainty in high-volatility months ($Stdev(\varepsilon)$ of 8.1% versus 7.2%). This higher misvaluation uncertainty results in a larger estimated inefficiency in high-volatility months (0.90% versus 0.41%). 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.

To summarize, the inefficiency from opportunistic acquirers varies considerably across deals, and the inefficiency is larger when misvaluation is more likely: in all-equity deals, when the acquirer's assets are highly intangible, in high-sentiment months, and in high-volatility months. The inefficiency is also larger when there is more uncertainty about acquirers' cash capacity, for example, when the target is larger. Besides being interesting in themselves, these results provide a useful 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 makes overvalued acquirers gain more, because they are able to pay using overvalued equity. It makes undervalued acquirers gain less, because they end up paying a higher price due to the externality from competing bidders. In this section, we quantify this wealth redistribution across different types of bidders.

We define bidder i's merger gain, denoted u_i, as its expected synergy minus what it pays for that synergy. We compare u_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 expected merger gain in the benchmark economy is

$$u_i^{Bench} = E[\max\{s_i - \tilde{s}_i, 0\}]. \tag{8}$$

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, u_i^{Est}, depends on all its state variables; its value is the maximum in equation (2). We define the wealth redistribution for bidder i as

$$\Delta_i = u_i^{Est} - u_i^{Bench}. \tag{9}$$

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

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

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

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

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

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

4.6 Marginal Value of Cash Capacity

Misvaluation makes cash capacity valuable to acquirers for two reasons. It is valuable to undervalued acquirers, because it lets them avoid paying with expensive equity. Second, any bidder can signal that it is undervalued by bidding cash rather than equity. In contrast, cash capacity would have no effect on merger gains in a counterfactual world with no misvaluation.[26] In this section, we quantify the marginal value of cash capacity for different types of bidders. To measure this marginal value, we use our estimated model and numerically compute the partial derivative of a bidder's expected merger gain with respect to its cash capacity:

$$\lambda_i^{Est} = \frac{\partial u_i^{Est}}{\partial k_i}. \tag{10}$$

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

Figure 5 presents the results. The left and right panels show the results for bidders with low and high synergies, respectively. Each panel presents three curves representing bidders with zero, intermediate, and sufficient cash capacity. Each curve describes how the marginal value of cash capacity, λ_i^{Est}, varies with a bidder's misvaluation, ceteris paribus. In general, the marginal value of cash is decreasing in bidders' overvaluation, so cash capacity is more valuable for undervalued bidders. The marginal value of cash capacity is zero for bidders that are significantly overvalued, because they do not bid with cash no matter how much cash they are able to use. Comparing the results across the three curves in each panel, we find that the marginal value of cash capacity is decreasing in a bidder's cash capacity level. Therefore, cash capacity is more valuable for bidders that are more cash-constrained. For example, for a bidder with misvaluation at the 5th percentile and zero cash capacity, one additional dollar in cash capacity increases the bidder's merger gain by 12 cents when the deal synergy is high. The marginal value of cash capacity drops to 6.5 cents if the bidder is able to pay 50% of the deal value in cash, and it shrinks to zero if the bidder already has enough cash to pay for the entire

[26] Equation (8) shows that merger gains u_i^{Bench} do not depend on k in a the benchmark economy with $\sigma_\varepsilon = 0$.

deal. Comparing the two panels of Figure 5, we find that the marginal value of cash capacity is larger when the deal synergy is higher, holding other bidder characteristics constant.

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

These estimates shed new light on acquirers' financing constraints. The estimated marginal value of cash capacity can be interpreted as a lower bound on firms' marginal cost of external finance. For example, we find that some acquirers' marginal value of cash is 12 cents per dollar. If cash is so valuable, why don't these acquirers raise more cash by issuing new debt or equity? It must be that the marginal cost of raising that extra cash is greater than 12 cents per dollar. According to this interpretation, we find that acquirers' financing constraints may be modest on average (possibly as low as 3.3 cents per dollar), but can be very high (at least 12 cents per dollar) for certain acquirers.

5 Robustness

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

5.1 Overpayment and Governance

A few recent studies conclude that overvalued acquirers destroy shareholder value by overpaying their targets.[27] 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 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.

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 sub-

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

samples 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. Subsamples' parameter estimates and model implications are in Table 8.

The first subsamples we examine are related to governance. Fu, Lin, and Officer (2013) find that overpayment is concentrated among acquirers with the weakest governance. Using the entrenchment index (E) of Bebchuk, Cohen, and Ferrell (2009) as a proxy for governance strength, we split our full sample into two roughly equally sized subsamples based on the acquirer's E. One complication is that relative firm size M is significantly different across the two subsamples, which by itself can cause the estimated inefficiency to differ. To isolate variation coming from governance rather than firm size, we measure our data moments using a weighting scheme that controls for differences in M across subsamples.[28] When we estimate the model in the low- and high-entrenchment subsamples, we find that the difference in estimated average synergy loss is economically small (0.82% versus 0.60%) and statistically insignificant.

Next, we compare horizontal and diversifying mergers.[29] We expect any overpayment to be more severe in diversifying mergers, because these are more likely to result from an empire-building motive. We find that the average synergy loss is 0.61% in horizontal mergers and 0.72% in diversifying mergers. This difference is small in magnitude and not statistically significant.

Third, we estimate the model in subsamples with high and low acquirer CEO overconfidence, using the Malmendier and Tate (2005) option-based measure.[30] 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 key 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 total blockholdings.[31] To

[28] 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.

[29] 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.

[30] Specifically, we define a CEO to be overconfident the first time his or her average value per vested option is at least 67% of the average strike price. Intuitively, an overconfident CEO is one who continues holding options that are deep in the money. Our measure closely follows that of Humphery-Jenner et al. (2015).

[31] A blockholder is either an institutional investor or a corporate insider who holds at least 5% of the company's

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,[32] and whether the bid is hostile. Because these extra control variables are often missing,[33] we exclude them from our main analysis. We find that adding these extra controls has a negligible effect on the moments we use in estimation, and hence on our estimated parameters and inefficiencies.[34] These results again imply that omitting acquirer and target governance is not an important source of bias.

5.2 Additional Bidders

Our main model assumes two bidders compete in each M&A contest. Section 2.2 defends this assumption. In this subsection we explore how our conclusions would change if we relaxed the assumption. If all parties understood there was just one bidder in each contest, then there would be no possibility of crowding out a second bidder, 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.[35] We view $N = 5$ as an upper bound, since Boone and Mulherin (2007) find that only 1.13 bidders on average make a publicly announced bid, and only 3.75 potential bidders express interest in purchasing the target during the pre-announcement stage. Similar to before, we say that inefficient crowd-out occurs if the highest-synergy bidder does not win the contest, and we define the loss given crowd-out as the gap between the winner's synergy and highest synergy. Table 9 shows how our main model implications change. As the number of competing bidders increases from two to five, we see an increase in the percent of deals that are inefficient (from 7% to 14%), the average loss in inefficient deals (from 9% to 11%), and the unconditional loss (from 0.63% to 1.59%). The inefficiency increases because a larger number of bidders increases the chance of at least one bidder being highly overvalued and crowding out the others. The effect is modest in size, though, because a larger number of bidders also increases the chance of at least one bidder having a very

shares. Our measure equals the total fraction of the company's equity held by blockholders.

[32] We thank Rudi Fahlenbrach for the founder-CEO data.

[33] For example, the *E*-index is available for both the target and acquirer in only 18% of contests.

[34] See Table A.1 of the Online Appendix.

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

high synergy, placing a high bid, and efficiently winning the contest.

5.3 Negative Synergies

We do not allow negative synergies in our main model. 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.[36] 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 zero.

Results are in Table 9. With negative synergies, 5.36% of contests have the first type of inefficiency and 0.62% have the second type, so a total of 5.98% of contests are inefficient. 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 an 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 second effect dominates, reducing the overall inefficiency. This result hinges on our assumption that bidders maximize expected profits. In an alternative model allowing overpayment, negative-synergy bidders could win more often. We discuss overpayment above.

We also find that introducing negative synergies improves the model's fit in one dimension. Empirically, 90% 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 90% and 95% may be due regulatory or other factors that are exogenous to our model.

[36] 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.

5.4 Correlated Synergies

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

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

To address any remaining concerns, we perform a simple exercise to argue that allowing correlated synergies would not significantly change our conclusions. We start with our estimated model, keeping the target's optimal scoring rule and acquirers' optimal bidding rule unchanged.[37] We then simulate M&A contests from the model assuming the two bidders' synergies have an extremely large +50% correlation. Model implications are in Table 9. Moving from a zero to a +50% correlation changes the average loss across all deals from 0.63% to 0.88%. The change is small, because allowing a positive correlation has two opposing effects. First, the positive correlation increases the probability of crowd-out, because it reduces the difference between the bidder's synergies, thereby allowing the difference in their misvaluations to dominate the difference in their synergies. Second, the positive correlation decreases the average loss in inefficient deals, because it reduces the gap between the winner and loser's synergy. Analogously, Table 9 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 positive or negative), we reach the same main conclusion: The inefficiency from opportunistic acquirers is small on average.

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

5.5 Correlation Between Misvaluation and Cash Capacity

Our model assumes no correlation between misvaluation (ε) and cash capacity (k). A positive correlation could arise, however, if overvalued firms raise cash by issuing equity or debt before the M&A transaction (Gao and Lou, 2013). The correlation is less relevant, however, if the 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 an extremely high value, and then we re-estimate the model. The estimated inefficiency increases slightly, from 0.63% to 0.78% (Table 9). 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.

5.6 Other Omitted Factors

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 we re-estimate the model. The estimated average inefficiency is 0.52%, compared to 0.63% in our full sample (Table 8). Given how similar the results are, omitting these dynamic effects does not seem to be an important source of bias.

Our main model does not allow the target to have private information about its own misvaluation, an assumption we defend in Section 2.2. This private information is arguably most severe when the target's 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.[38] The estimated average inefficiency is 0.49%, slightly lower than the full-sample estimate of 0.63% (Table 8). Again, the similarity of results suggests this omission is not a serious source of bias.

Our model also omits merger-arbitrage trading by hedge funds. These funds short acquirers' shares when an equity bid occurs, pushing down acquirer 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 $Var(\varepsilon)$ and hence a smaller estimated inefficiency. We

[38] We measure asset intangibility as in Section 4.4. The correlation between acquirer and target intangibility is close to zero (-0.07), so dropping high-intangibility targets has little effect on acquirer intangibility.

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.[39] We find that the inefficiency only decreases from 0.63% to 0.49% (Table 9).

We include *Controls* in regressions (5)-(7) in order 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. Of course, it is possible that we have failed to include all important omitted factors in *Controls*. Of particular concern, omitting important controls could produce an upward-biased estimate of $Var(u)$, the conditional variance of offer premia. Since we rely on the moment $Var(u)$ to identify the variance of synergies within contests, 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 premia, 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 9). Even if there remain important omitted variables, we still find a relatively small inefficiency.

6 Conclusion

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

Our study could be extended in several directions. We have analyzed how misvaluation

[39] 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.

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

Appendix: Details on SMM Estimation

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

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

We then construct the model-implied moments, including the announcement returns for acquirer, target and the combined firm, the offer premium, and the cash usage for the initial bidder in each contest based on equations provided in Online Appendix A.2.2. The SMM estimator $\hat{\Theta}$ searches for the parameter values that minimize the distance between the data moments and the model-implied moments:

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

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

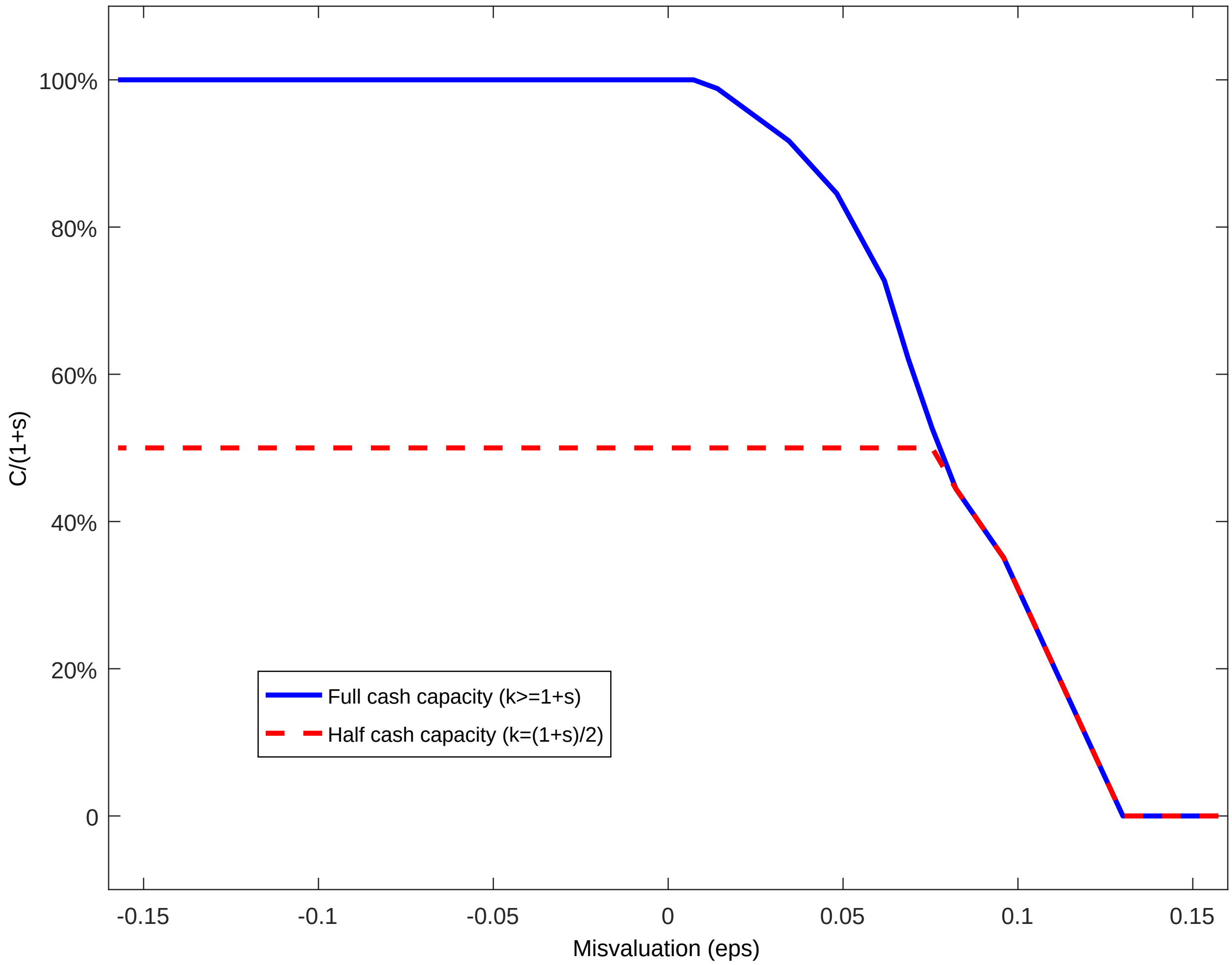


Figure 1: Cash Fraction in the Optimal Bid

This figure presents the cash fraction in optimal bids from acquirers with different 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.2.1 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.

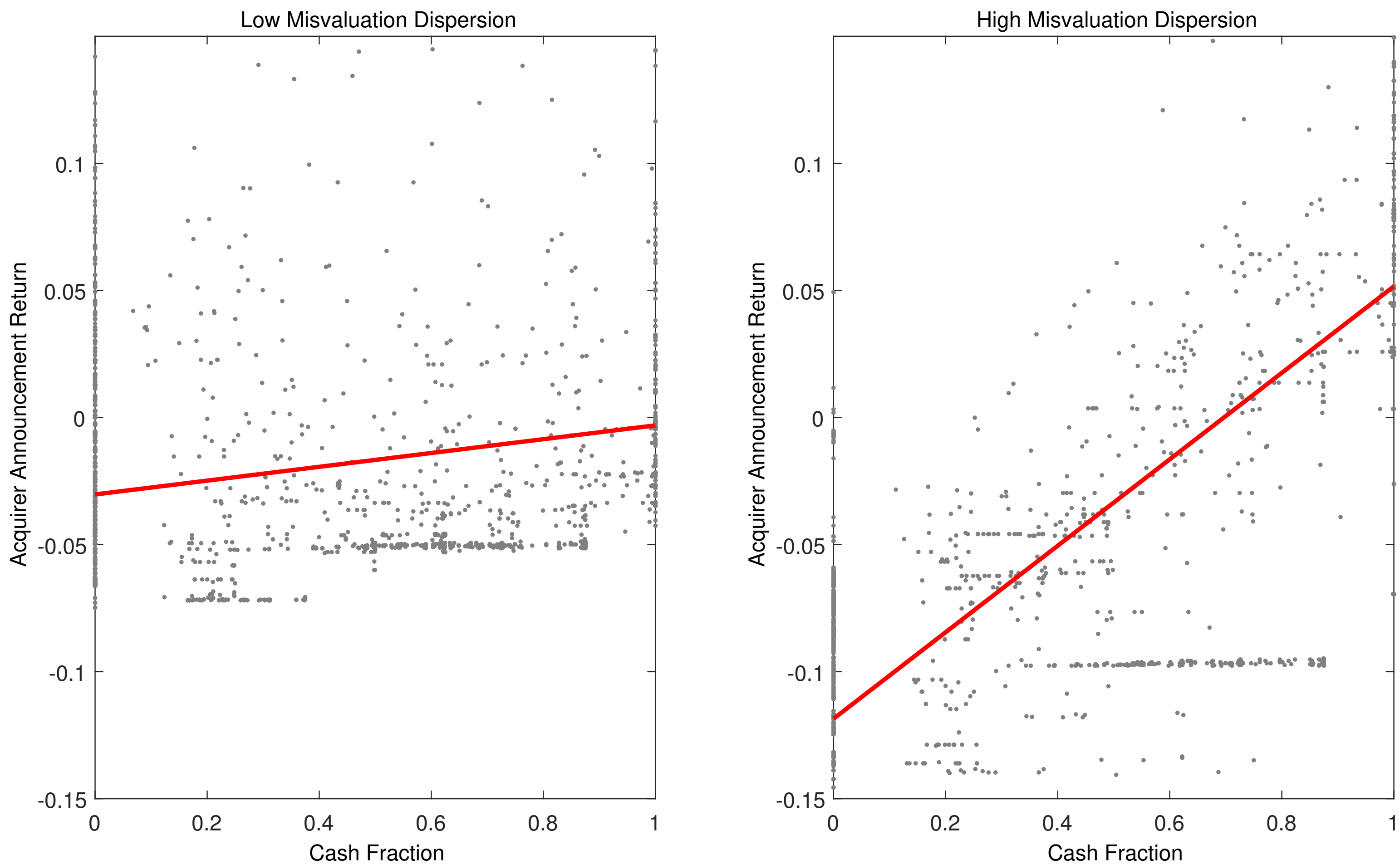
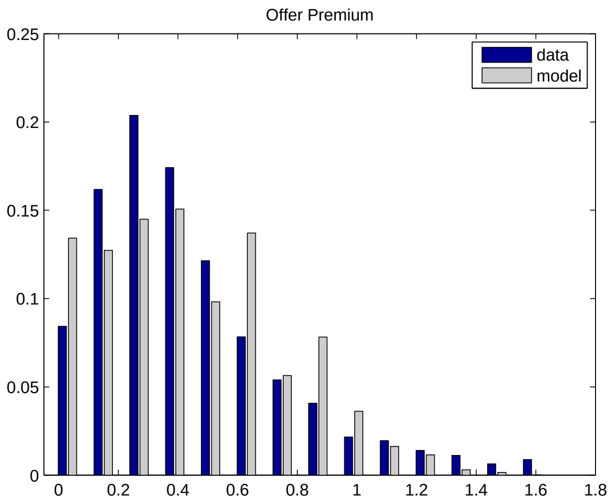
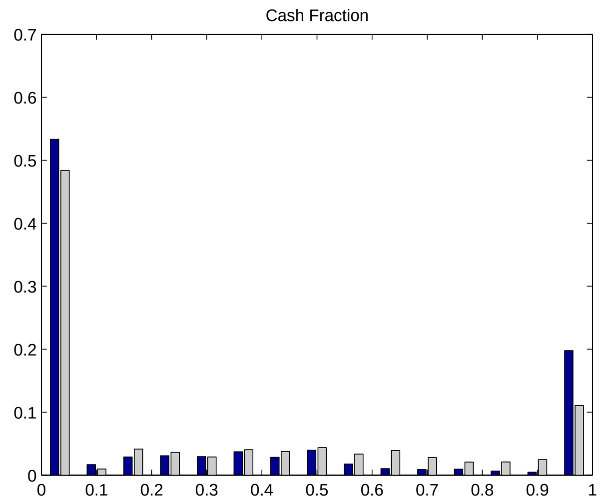


Figure 2: Revelation Effect of Cash

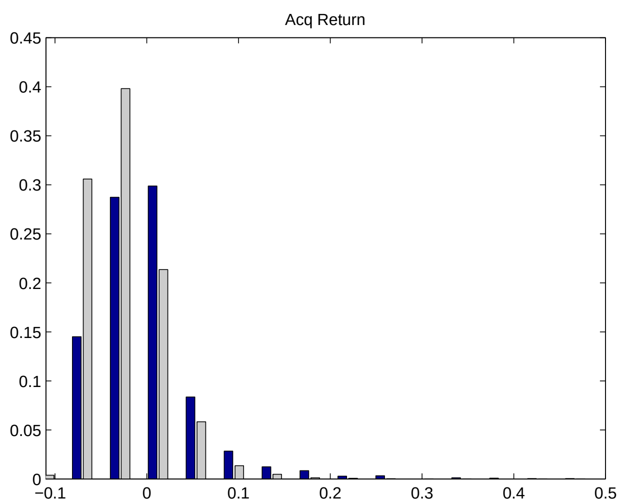
This figure presents the revelation effect of cash in acquirer announcement returns. We simulate acquisition bids based on the numerical solution of the model. The model is solved under the parameters presented in Table 4 using the method described in Online Appendix A.2.1. For each deal the acquirer announcement return is computed using the method described in Online Appendix A.2.2. 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 ($\sigma_\varepsilon = 0.20$).



(a) Offer Premium



(b) Cash Fraction



(c) Acquirer Announcement Return

Figure 3: Comparing Simulated and Empirical Distributions

This figure compares the distributions of offer premium, cash fraction in the bid, and acquirer announcement return in the data and in the model. The model is solved under the parameters presented in Table 4 using the method described in Online Appendix A.2.1, and the variables of interest are computed using the method described in Online Appendix A.2.2.

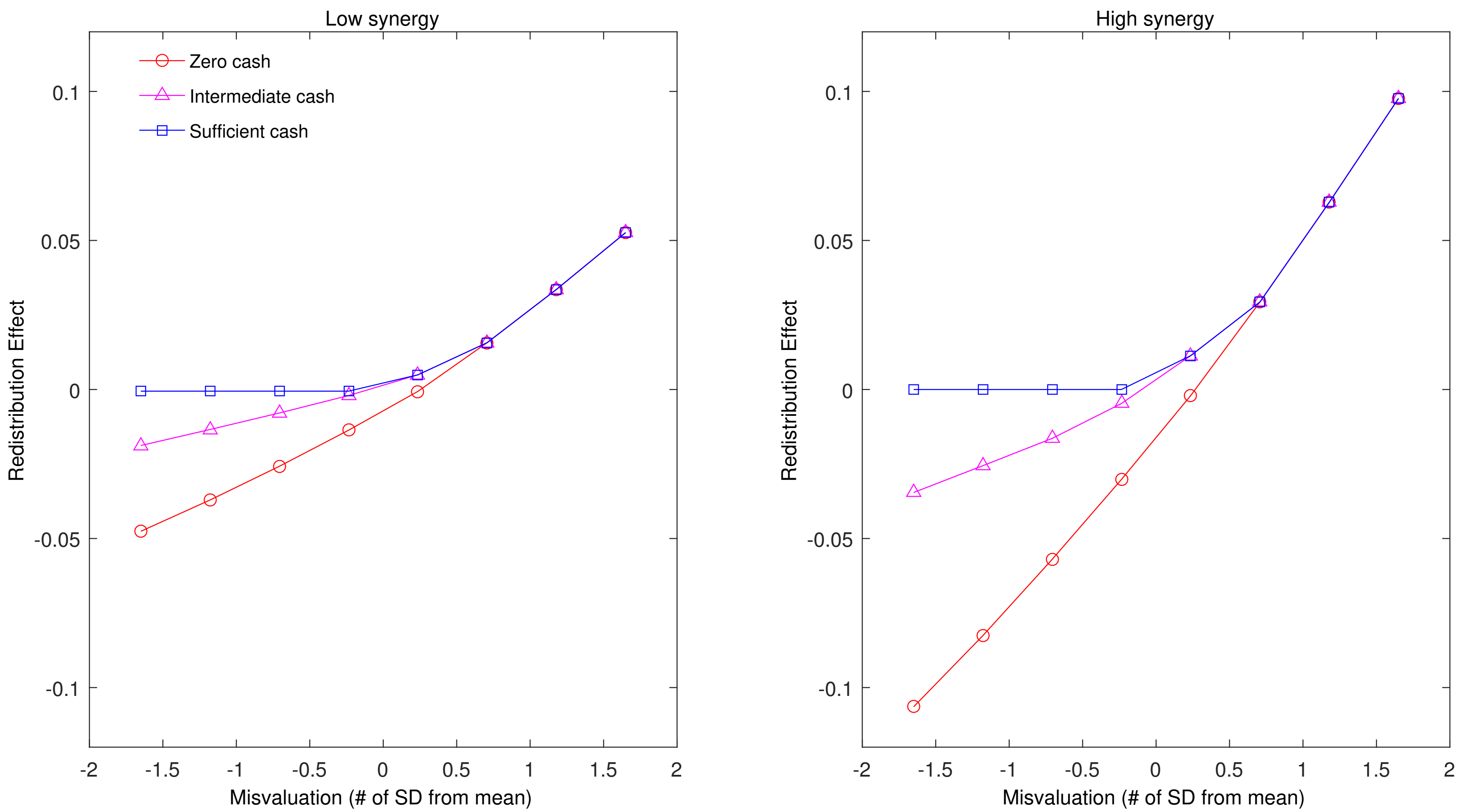


Figure 4: Redistribution Effect

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, Δ_i, varies with a bidder i's misvaluation, ceteris paribus. A bidder's misvaluation, denoted ε_i in the model, is measured in the number of standard deviation from the sample mean.

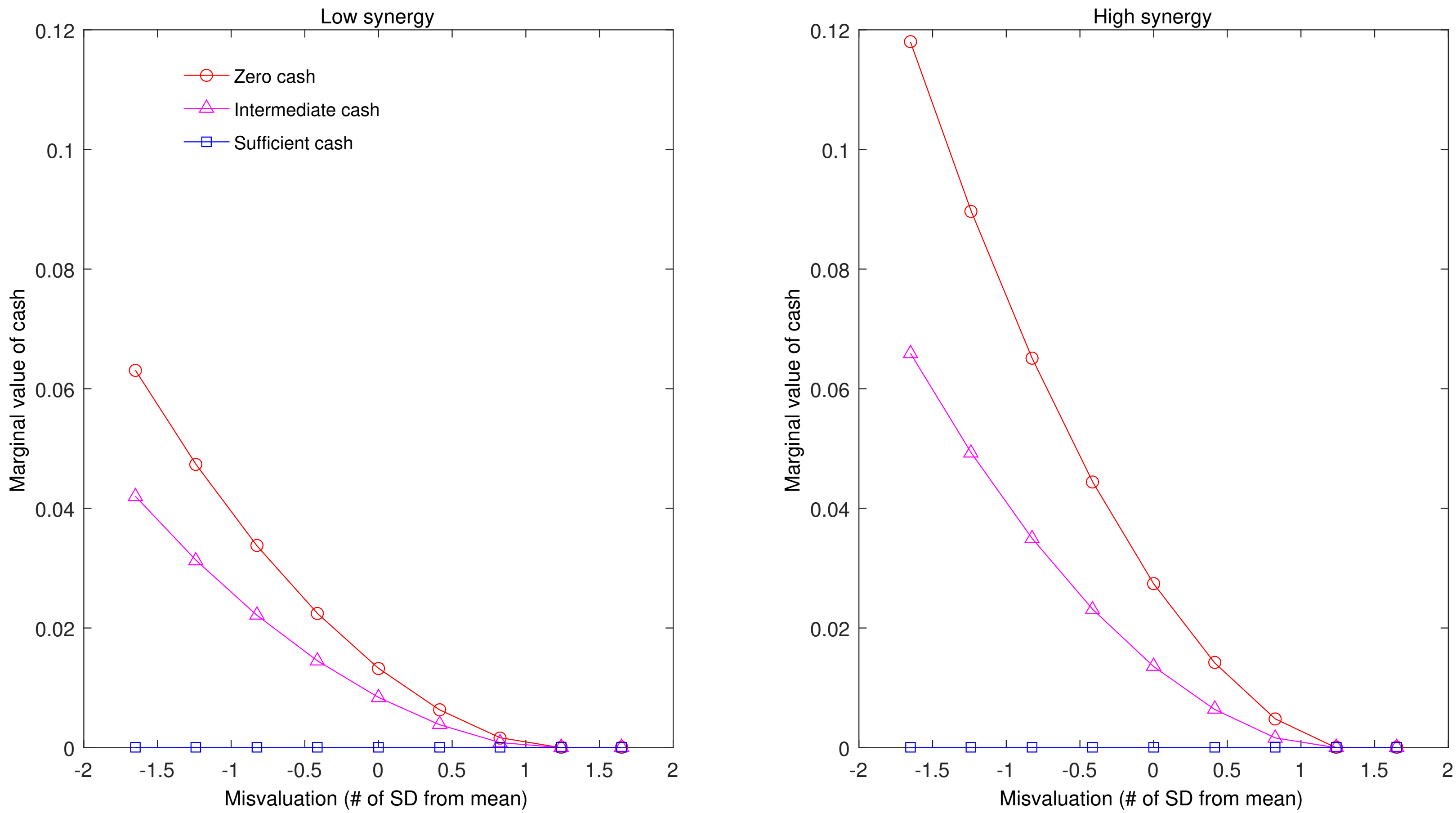


Figure 5: Marginal Value of Cash

This figure presents the marginal value of cash for different types of bidders. The marginal value of cash, which is measured by equation (10), is the partial derivative of a bidder's merger gain with respect to its cash capacity. The model is solved under the parameters in Table 4. The left panel shows the results for bidders with low synergy ($s = 0.4$) while the right panel for bidders with high synergy ($s = 0.8$). Each panel presents three curves representing bidders with zero, intermediate, and sufficient cash capacity, respectively. Bidders with intermediate cash capacity are able to pay the deal with 50% of cash, and bidders with sufficient cash capacity can pay the deal with all cash. Each curve describes how the marginal value of cash, λ_i^{Est}, varies with bidder i's misvaluation, denoted ε_i in the model. The figure measures ε_i in units 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 4 weeks before the bid announcement, minus one. Cash fraction is the fraction of the bid made up of cash rather than equity. Acq relative size is the market value of the acquirer divided by the market value of the target 4 weeks before the bid announcement. Acquirer AR, Combined-firm AR, and Target AR are the cumulative abnormal return in a 3-day event window around the bid announcement of the acquirer, the combined firm, and the target, respectively, computed based on the market model. Target size is the logarithm of the target market value (in millions) 4 weeks prior to the bid announcement. Target leverage is the ratio of debt and assets of the target. Target ME/BE is the market-to-book ratio of target equity. Target ROA is return on assets of the target. Target cash is the ratio of cash and book assets of the target. Number of obs. is the total number of observation for computing the statistics.

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

Table 2: Sensitivity of Moments to Parameters

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

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

Table 3: Model Fit

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 $E[AcqAR_i]$, the average acquirer announcement return. The fifth moment is b_1, the slope coefficient of acquirer announcement return on the fraction of cash used in the bid, from regression (6). The sixth moment is $E[CashFrac_i]$, the average fraction of cash in bids. The seventh moment is $\text{Var}(w_i)$, the conditional variance of $CashFrac$, measured using regression (7). The eighth moment is c_1, the slope coefficient of cash usage on the logarithm of relative firm size, from regression (7). Standard errors for the data moments are in parentheses. The lower panel reports results for untargeted moments. E[CombAR] and E[TarAR] are the average combined-firm and target announcement returns, including the 4-week runup. Var[AcqAR], Var[CombAR], and Var[TarAR] are the variances of the acquirer, combined firm, and target announcement returns. Corr[AcqAR, TarAR] is the Peason'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
t-stat.	(0.351)	(0.594)	(-0.041)	(-0.334)	(0.228)	(0.081)	(0.179)	(0.149)
	Panel B: Untargeted Moments							
	Var[AcqAR]	E[CombAR]	Var[CombAR]	E[TarAR]	Var[TarAR]	Corr[AcqAR,TarAR]		
Data	0.006	0.014	0.017	0.283	0.057	0.115		
Standard error	(0.001)	(0.003)	(0.001)	(0.005)	(0.002)	(0.020)		
Model	0.002	0.020	0.008	0.438	0.038	0.087		

Table 4: Parameter Estimates

This table reports 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 ε is assumed to follow a normal distribution $\mathcal{N}(\mu_\varepsilon, \sigma_\varepsilon^2)$; cash capacity is assumed to follow a normal distribution $\mathcal{N}(\mu_k, \sigma_k^2)$ that is left censored at zero; $\rho_{sM}$is the Spearman's rank correlation between synergy and acquirer relative size; and ρ_{kM} is the Spearman's rank correlation between cash capacity and acquirer relative size. E[s] and Stdev[s] are the average and standard deviation of synergy computed from the normal distribution $\mathcal{N}(\mu_s, \sigma_s^2)$ truncated at zero; E[ε] and Stdev[ε] are the average and standard deviation of misvaluation computed from the normal distribution $\mathcal{N}(\mu_\varepsilon, \sigma_\varepsilon^2)$; E[$k$] and 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.

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

Table 5: Estimated Efficiency Losses

This table reports the estimated efficiency losses in the baseline model. 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 loss in all deals, which equals the average efficiency loss across all deals (efficient and inefficient).

					Percentile		
Panel A: Percent of Deals That Are Inefficient							
	Estimate	7.01%					
	Standard Error	1.03%					
Panel B: Average Synergy Loss in Inefficient Deals							
		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: Where Is the Inefficiency Largest? Variation Across Deals

This table reports the model implications for M&A contests with different characteristics. Panel A reports the quantities implied by the parameter estimates, and Panel B reports the model implications in the corresponding subsamples. We simulate our model using the baseline estimates in Table 4, and we split the simulated contests into different subsamples based on the announcing bid's characteristics. The announcing bid is a random draw from the two competing bids, with 87% probability to be the winning bid and 13% probability to be the losing bid (see the Appendix for additional details). Columns 1-2 report the estimates for bids with different methods of payment (All Equity v.s. All Cash), Columns 3-4 report the estimates for deals with offer premiums in the bottom tercile (Low) or top tercile (High), and Column 5-6 report the estimates for deals with relative size ratio (i.e., the ratio of target pre-acquisition market value to acquirer pre-acquisition market value) in the bottom tercile (Low) or top tercile (High). 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		Relative Size (M)	
	All Equity	All Cash	Low	High	Low	High
	Panel A: Quantities Implied by Parameter Estimates					
E[s]	0.838	0.939	0.460	1.184	0.672	1.095
Stdev[s]	0.405	0.528	0.325	0.285	0.383	0.436
E[ε]	0.075	-0.028	0.057	0.065	0.067	0.061
Stdev[ε]	0.076	0.045	0.069	0.076	0.071	0.071
E[k]	0.328	2.377	0.805	1.032	0.347	1.542
Stdev[k]	0.92	0.57	0.97	1.20	0.62	1.16
	Panel B: Model Implications					
Percent of deals inefficient	7.82	5.11	10.75	4.28	8.94	4.89
Avg. loss in inefficient deals (%)	10.22	6.19	7.62	11.47	8.55	9.90
Avg. loss in all deals (%)	0.80	0.32	0.82	0.49	0.76	0.48

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 high (low) sentiment is comprised of M&A deals announced during months in the top (bottom) quintile of market sentiment measure; 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. 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.

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

Table 8: Robustness – Additional Subsample Results

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. The subsample of low (high) Entrenchment is comprised of M&A deals in which the acquirer's *E*-Index value is below (above) the median; the subsample of horizontal (diversifying) mergers is comprised of M&A deals in which the acquirer and target belong to the same (unrelated) industry; the subsample of overconfident acquirer CEOs is comprised of M&A deals in which the acquirer CEO is (is not) classified as overconfident; the subsample of No M&A or SEO Surrounding the Deal 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; the subsample of Excld. Top Target Intangibility Quintile excludes from the full sample all deals in which the target's asset intangibility measure ranks in the top quintile. 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.

	Entrenchment		Merger Type		Acq. Overconfidence		No M&A or SEO	Excld. Top Target
	Low	High	Horizontal	Diversifying	Yes	No	Surrounding Deal	Intangibility Quintile
	Panel A: Moments Implied by Parameter Estimates							
E[s]	0.622	0.590	0.663	0.716	0.612	0.572	0.637	0.644
Stdev[s]	0.395	0.356	0.421	0.452	0.392	0.350	0.393	0.418
E[ε]	0.055	0.049	0.048	0.056	0.060	0.057	0.055	0.055
Stdev[ε]	0.081	0.070	0.072	0.081	0.072	0.071	0.062	0.063
E[k]	0.690	0.706	0.794	0.864	0.691	0.759	0.622	0.698
Stdev[k]	0.749	0.650	0.906	0.940	0.749	0.763	0.693	0.814
r_{sM}	0.369	0.450	0.465	0.426	0.387	0.308	0.439	0.437
r_{kM}	0.464	0.466	0.464	0.469	0.461	0.482	0.372	0.381
	Panel B: Model Implications							
Percent of deals inefficient	8.30	7.52	7.01	7.32	7.62	7.81	6.67	6.35
Avg. loss in inefficient deals (%)	9.82	8.00	8.66	9.82	8.70	8.29	7.75	7.71
Avg. loss in all deals (%)	0.82	0.60	0.61	0.72	0.66	0.65	0.52	0.49

Table 9: Robustness – Alternative Model Specifications and Possible Omitted Factors

This table reports the model implications when alternative specifications and possible omitted variables are considered. The column Baseline reproduces Table 5's implications from the baseline model. The columns for $N > 2$ bidders report the model implications when contests involve more than two bidders. To do so, we keep the parameter estimates unchanged in the model and simulate multiple bidders (3, 4, or 5) in each bid contest. The column Negative s moves the lower bound of synergies (s) from 0 to -0.2 in the model. We then reestimate the model and compute the model implications. When s can be negative, there are two types of inefficiencies. The first type of inefficiency is the same as in our baseline model: the winner has a non-negative s, but the winner's s is lower than the loser's s. The second type of inefficiency is that the winner has a negative s. We define efficiency loss as the difference between the winner's s and the loser's s in the first type of inefficient deals, and as the gap between the winner's s and zero in the second type of inefficient deals. The columns Corr. Bidder Synergies assume that the synergy of competing bidders are correlated. We keep the parameter estimates unchanged and simulate bidders with correlated s. The column $\text{Corr}(\varepsilon, k)$ allows the acquirer's misvaluation to be correlated with its cash capacity. We set the correlation to the value shown in the table, then we reestimate the model and recompute its implications. The column Price Pressure controls for the negative price pressure induced by M&A arbitrageurs on acquirers' announcement returns in equity or mixed deals. We use the method of Mitchell, Pulvino, and Stafford (2004) to estimate the predicted change in short interest of acquirer stocks for equity or mixed bids, and we include the predicted change in the vector $Controls$ in regression (6). We also cut the average acquirer announcement returns to half following Mitchell, Pulvino, and Stafford (2004). We reestimate the model using the updated data moments and characterize the model implications based on the new parameters. The column Half Var(OfferPrem) reduces the conditional variance of offer premium measured in data by half, and it also reduces the loading of offer premium on $\ln(M)$ by $1/\sqrt{2}$. We reestimate the model using the updated data moments and characterize the model implications based on the new parameters. 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.

		$N > 2$ Bidders				Corr. Bidder Synergies		$\text{Corr}(\varepsilon, k)$		Price	Half
	Baseline	$N = 3$	$N = 4$	$N = 5$	Negative s	Corr$= +0.5$	Corr$= -0.5$	Corr$= +0.2$	Corr$= -0.2$	Pressure	Var(OfferPrem)
Percent of deals inefficient	7.01	10.08	12.39	14.04	5.98	10.13	5.33	7.57	6.92	6.17	9.29
Avg. loss in inefficient deals (%)	9.02	10.29	10.73	11.31	9.00	8.68	9.02	10.30	8.59	8.02	10.76
Stdev. of loss in inefficient deals (%)	8.31	9.22	9.53	9.99	7.76	8.14	8.10	9.51	7.65	7.41	11.42
Avg. loss in all deals (%)	0.63	1.04	1.33	1.59	0.54	0.88	0.48	0.78	0.59	0.49	0.99

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