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CAPM-Based Company (Mis)valuations

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There is a discrepancy between CAPM-implied and realized returns. Using the CAPM in capital budgeting—as recommended in textbooks—should thus have real effects. For instance, low beta projects should be valued more by CAPM users than by the market. We test this hypothesis using M&A data and show that bids for low-beta private targets entail lower bidder returns. We provide further support by testing several ancillary predictions. Our analyses suggest that using the CAPM when valuing targets leads to valuation errors (relative to the market's view) corresponding on average to 12% to 33% of the deal values. (*JEL* G31, G34, G41)

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The capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) is the predominant model of risk and return taught by academics in universities and business schools in undergraduate, MBA, and executive education programs. The CAPM is also widely used in practice, in particular,

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to estimate firms' cost of (equity) capital.[1] However, it is well known that the CAPM does not fit the data. The average realized returns of low beta securities are higher and those of high beta securities lower than the CAPM predicts. In other words, the slope of the empirical security market line (SML) is less steep than implied by the CAPM (e.g., Black, Jensen, and Scholes 1972; Fama and French 2004; Baker, Bradley, and Wurgler 2011; Frazzini and Pedersen 2014).

We show that the widespread use of the CAPM for cost of capital computations has real effects, in particular, for firms' capital budgeting decisions and the market's reaction thereto. The intuition is as follows. For low beta investments, the cost of capital implied by the CAPM is lower than the cost of capital implied by the empirical SML. Equivalently, the "CAPM-based valuation" of low beta investments exceeds their market valuation. Consequently, managers who use the CAPM for capital budgeting are willing to undertake low beta projects at prices that the market deems too high. The reverse holds for high beta projects. It follows that the stock market reaction to low beta investments is less favorable than to high beta investments. To test this prediction, we study mergers and acquisitions. This is a suitable setting, because acquisitions are examples of large-scale investments, and their known announcement dates allow us to observe the stock market reaction. Further, because standard capital budgeting decisions involve projects that are not publicly traded, our main test focuses on bids for private targets. In particular, using data from SDC Platinum on more than 12,000 takeover bids for private targets during the period from 1977 to 2015, we show that bids for low beta targets entail more negative stock market reactions than bids for high beta targets. To the best of our knowledge, we are the first to document this relation. Specifically, we find that a difference in target betas of one interquartile range (0.49) is associated with a difference in bidder cumulative abnormal returns (CARs) of 0.5 to 1.2 percentage points, corresponding to 6% to 16% of the interquartile range of bidder CARs. This relation is not explained by any of the CAR determinants that have been documented in the prior literature and does not depend on the model we use to estimate betas or CARs.

Potential concerns are that our beta estimates may be noisy proxies for the actual beta estimates used by managers in practice or that target betas may be correlated with unobserved determinants of bidder CARs. For example, acquisitions of high beta targets may be associated with larger synergies. We mitigate such concerns by estimating two-stage least squares (2SLS) regressions. To do so, we rely on mutual fund fire sales as a source of nonfundamental variation in realized stock returns (i.e., noise), which in turn translates into nonfundamental variation in beta estimates (i.e., noise in the

[1] Among the chief financial officers (CFOs) at public firms surveyed by Graham and Harvey (2001), p. 201), "the CAPM is by far the most popular method of estimating the cost of equity capital: 73.5% of respondents always or almost always use the CAPM." Jacobs and Shivdasani (2012, p. 120) report that "about 90% of the respondents in a survey conducted by the Association for Financial Professionals use the capital asset pricing model (CAPM) to estimate the cost of equity." In a survey of valuation professionals, Mukhlynina and Nyborg (2016), p. 22) find that "76% of respondents use the CAPM almost always or always" to compute the cost of equity.

coefficient estimates from a regression of excess stock on excess market returns). Using the scaled in-sample covariance between the estimated noise components in realized excess stock returns and excess market returns as an instrument for the beta estimates corroborates our results: We find a positive and statistically significant relation between target betas and bidder CARs with a magnitude that is similar to the ordinary least squares (OLS) estimates. We also show that high beta targets have lower bid-implied valuations and receive lower offer premiums, that betas do not predict cash flows, and that there is no relation between target betas and the *combined* CARs of bidders and targets. All of these findings are at odds with the idea that acquisitions of high beta targets are associated with larger synergies. Further, we show that the discount rates used in fairness opinions on the bids increase with the targets' beta, supporting the premise that the CAPM is used to estimate the cost of capital in practice.

We also test several cross-sectional predictions. The positive relation between target betas and bidder CARs is stronger if the targets' growth rate and relative size are high. The intuition is that higher growth and larger size amplify the difference between the CAPM-implied value of a target and the market's assessment thereof. The relation, instead, is weaker when the empirical SML has a steeper slope and thus diverges less from the CAPM-implied SML. We also find that the relation is stronger for bidders that are more likely to use the CAPM (as proxied by mentioning the CAPM in their SEC filings) and weaker if bidders are more likely to rely on valuation multiples (as proxied by the availability of publicly listed peers of the target). When examining bids for public firms, we find a significant relation between target betas and bidder CARs only for low, but not for high, beta targets and an insignificant relation for public targets overall. A possible explanation is that readily available market prices dampen the impact of using the CAPM, in particular for targets with high betas (and thus low CAPM-implied valuations) because bids below current market prices are unlikely to be successful. The sum of the cross-sectional patterns is important as it supports the idea that the positive relation between target betas and bidder CARs is indeed due to bidders' use of the CAPM. Any alternative story must explain not only this main finding but also all of the cross-sectional results.

Our contribution is to show that using the CAPM has real effects: CAPM-users are willing to buy (sell) low (high) beta assets at prices that the market deems too high (low). The resultant valuation discrepancies are economically significant. In the M&A market for private targets, we estimate discrepancies that correspond, on average, to 23% of the deal values (USD 66 million, inflation adjusted to December 2015). This estimation is based on the calibration of a simple model in which corporate managers use the CAPM whereas the market values targets based on the flatter empirical SML. The model turns out to match the empirical relation between target betas and bidder CARs reasonably well and, given data on actual takeovers, allows us to estimate the valuation discrepancy for each deal. The average discrepancy implied by our regression results is in line with the model-implied estimates and ranges from 12% to 33% of the deal values. Moreover, the insight that using the CAPM leads to a valuation error (relative to the market's view) is not specific to the M&A market but applies to capital budgeting decisions more generally. New investment projects are typically not publicly traded (as is the case for private targets), and the CAPM is commonly used to compute the projects' cost of capital. Our estimate of the valuation error in the M&A context is thus likely to be a lower bound for the total error due to using the CAPM also in other contexts.

The normative implications of our study ultimately depend on how the debate about the veracity of the CAPM is settled. One view is that the CAPM holds in the long run, but that the market is inefficient. According to this view, our findings reflect temporary mispricing by the market, and managers are right to use the CAPM. An alternative view is that the market is efficient and the CAPM fails to explain expected returns, even in the long run. According to that view, our findings reflect valuation mistakes by bidders and sellers, and managers should not use the CAPM. It is difficult to empirically distinguish these alternatives, but we provide some suggestive evidence that managers should not use the CAPM (at least not in its simple textbook form and in an M&A context). First, we do not find any return reversal in the long run, suggesting long-lasting wealth effects for investors. Second, we find that the relation between target betas and bidder CARs is weaker for bidders with stronger corporate governance (as proxied by the presence of institutional investors and a higher wealth-performance-sensitivity of the bidder's CEO) and for bidders with less entrenched managers (as proxied by the number of antitakeover provisions). These findings suggest that managers' reliance on the CAPM may not be in the interest of shareholders.

Regarding the existing literature, most closely related to our paper is the work of Baker, Hoeyer, and Wurgler's (2019), henceforth BHW, who start from the same observation as we do: the realized returns of high beta stocks are lower than implied by the CAPM. BHW assume that managers are right to use the CAPM and focus on the effect on *financing* decisions: They predict that leverage is a decreasing function of beta. We instead focus on *investment* decisions. This distinction is important not only because financing and investment are two different activities but also because whether and how using the CAPM affects financing decisions is very different from the effect on investment decisions. As BHW point out, *financing* decisions are affected *only* if there is a risk anomaly in the equity market, but not in the debt market (or, at least, if the risk anomaly in the debt market is weaker). The effect on *investment* decisions (and the corresponding market reaction thereto) does instead *not* depend on market segmentation. In other words, the key condition for BHW's prediction that leverage is negatively related to asset risk is that equity and debt markets are segmented, that is, that risk is priced differently by equity investors compared to debt investors. In contrast, the key condition for our prediction that bidder CARs are positively related to target asset betas is that risk is priced differently by the market compared to corporate managers. Another difference is that we study not only firms' decisions (takeover bids) but also their effect on firm value (through bidder CARs). This is a distinct advantage of the M&A setting: takeovers constitute large investments with known announcement dates, allowing us to quantify the value implications of managers' use of the CAPM, at least if one accepts the premise that the stock market is efficient and bidder CARs reflective of value creation or destruction.

Our paper is also related to recent work on the real effects of the practice of capital budgeting. Krüger, Landier, and Thesmar (2015) assume that firms apply the beta of their core division even to investments with different risks and hence expect targets to be undervalued by *high beta bidders*. We instead expect *high beta targets* to be undervalued. These are two different mechanisms, but to make sure our findings are not driven by bidders using their own cost of capital when valuing targets, we check that our results are unchanged when controlling for the bidders' beta. Jagannathan et al. (2016) offer survey evidence that high beta firms use higher discount rates than low beta firms, which supports the premise that firms use the CAPM to compute discount rates. Levi and Welch (2017) recommend that betas be computed with a double shrinkage, which would be consistent with an interpretation of our results whereby managers overestimate the slope of the true SML. Finally, our paper is related to van Binsbergen and Opp's (2019) recent study on the impact of asset pricing anomalies on the real economy. They explore a wider set of anomalies than we do but perform a very different exercise from ours: they make a model-based quantification of the real impact of anomalies, whereas we attempt to trace out the impact of one anomaly on firm behavior in the data.

1. Predictions

1.1 Target betas and bidder abnormal returns around bid announcements

To provide a framework for our analysis, we now introduce a simple model that formalizes our arguments. As a typical capital budgeting case is arguably an investment in a new project that is not publicly traded and thus more similar to a bid for a private target, we restrict attention to private targets here and consider the case of a public target in Appendix A. Acquisitions of private targets are also much more common, accounting for almost 90% of all M&A transactions by U.S. bidders between 1977 and 2015 in the SDC Platinum database (including transactions with undisclosed deal values but excluding share repurchases).

Our model has three players: (1) *the bidder*, a public firm that seeks to acquire a private target;[2] (2) *the seller*, the target's current owners; and (3) *the market*, other investors in the market place. The bidder and the seller value assets by discounting expected future cash flows at the cost of capital implied by the CAPM. The market, instead, values assets in line with the empirical SML (by construction), which may differ from the CAPM-implied SML.[3] This is the only relevant difference between the market and the other two players.

[2] We consider an acquisition of less than 100% of the target's equity in Appendix A.

[3] Our predictions are qualitatively unchanged if the bidder and seller use other methods (e.g., multiples) in addition to a DCF valuation as long as they place at least some weight on the DCF-implied value. Note further that we do not assume anything about the valuation model used by the market, except that the empirical SML that it generates may differ from the CAPM-implied SML.

The value of the target's equity conditional on an acquisition and as assessed by the bidder and seller is

$$E_t = V_t^A + \Delta_t - D_t + S_t \tag{1}$$

$$= \sum_{\tau=t+1}^{\infty} \frac{FCF_\tau}{(1+r_A)^{\tau-t}} + \sum_{\tau=t+1}^{\infty} \frac{\delta_\tau}{(1+r_\Delta)^{\tau-t}} - \sum_{\tau=t+1}^{\infty} \frac{d_\tau}{(1+r_D)^{\tau-t}} + \sum_{\tau=t+1}^{\infty} \frac{s_\tau}{(1+r_S)^{\tau-t}}, \tag{2}$$

where V_t^A is the stand-alone enterprise value of the target if it were entirely equity financed, Δ_t is the net benefit of leverage (e.g., tax savings minus distress costs), D_t is the value of the target's debt, and S_t is the value of synergies between the bidder and the target.[4]

The bidder pays a price B_t for the target's equity that is determined through bilateral Nash bargaining:

$$B_t = V_t^A + \Delta_t - D_t + \alpha S_t, \tag{3}$$

where $\alpha \in (0,1)$ denotes the seller's relative bargaining power vis-à-vis the bidder. The seller thus receives the stand-alone value of the target's equity plus a fraction α of the synergies.

The cumulative abnormal return of the bidder's stock in response to the bid (CAR_t^{Bidder}) is equal to the difference between the value of the target's equity as assessed by the market ($\widetilde{E}_t$) and the price paid by the bidder (B_t), scaled by the bidder's market capitalization (E_t^{Bidder}), that is,[5]

$$CAR_t^{Bidder} = \frac{\widetilde{E}_t - B_t}{E_t^{Bidder}}. \tag{4}$$

For ease of exposition, we now assume the following: (AI) The systematic risk of the synergies, debt, and net benefits of leverage does not depend on the systematic risk of the target's operating free cash flows on a stand-alone basis. (AII) The empirical SML is flat. We relax both assumptions in Appendix A and show that our key prediction is qualitatively unchanged as long as the empirical SML is not too steep. Using $r_A = r_f + \beta_A \times \mu$, the first assumption implies

$$\frac{\partial B_t}{\partial \beta_A} = -\frac{\partial r_A}{\partial \beta_A} \times \sum_{\tau=t+1}^{\infty} \frac{(\tau-t) \times FCF_\tau}{(1+r_A)^{\tau-t+1}} = -\mu \sum_{\tau=t+1}^{\infty} \frac{(\tau-t) \times FCF_\tau}{\left(1+r_f+\beta_A \times \mu\right)^{\tau-t+1}} < 0, \tag{5}$$

where r_f, β_A, and μ denote the risk-free rate, target's asset beta, and market risk premium.

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4 FCF_τ are expected operating free cash flows on a stand-alone basis; δ_τ are net benefits of leverage; d_τ are payments to debt holders; and s_τ are synergies in period τ. The corresponding discount rates are r_A, r_Δ, r_D, and r_S. We assume $FCF_\tau \geq 0$ and $s_\tau \geq 0$ for all $\tau > t$ and $FCF_\tau > 0$ for at least one $\tau > t$. We further assume that the target is financed only with equity E_t and debt D_t and does not hold excess cash. Otherwise, D_t should be interpreted as the value of all financing other than E_t and net of excess cash.

5 We assume that the bidder's share of the gains or losses from the takeover accrues to the bidder's shareholders rather than the bidder's creditors. Note also that being private does not imply that the market does not form a belief about the target's value.

The second assumption implies that the market's assessment of the target's equity value does not depend on the target's asset beta, that is,

$$\frac{\partial \widetilde{E}_t}{\partial \beta_A} = 0. \tag{6}$$

It follows that

$$\frac{\partial CAR_t^{Bidder}}{\partial \beta_A} = \frac{\mu}{E_t^{Bidder}} \sum_{\tau=t+1}^{\infty} \frac{(\tau - t) \times FCF_\tau}{\left(1 + r_f + \beta_A \times \mu\right)^{\tau - t + 1}} > 0, \tag{7}$$

which motivates our main prediction:

Prediction 1. The bidder's cumulative abnormal return around the bid announcement is increasing in the target's asset beta.

1.2 Additional predictions

Our framework implies a number of additional predictions. We state each prediction below, together with a short description of the underlying intuition. Appendix A provides formal derivations.

Prediction 2. The positive relation between the bidder's CAR and target's asset beta is stronger if the growth rate of the target's expected operating free cash flows on a stand-alone basis is larger.

Higher growth amplifies the difference between the value implied by the CAPM versus the empirical SML.

Prediction 3. The positive relation between the bidder's CAR and target's asset beta is stronger if the relative size of the bid vis-à-vis the bidder's market capitalization is larger.

Misvaluing a target has a bigger effect if the target is large relative to the bidder.

Prediction 4. The positive relation between the bidder's CAR and target's asset beta is stronger if the bidder relies more on the CAPM-based valuation of the target (relative to other valuation methods).

Bidders overvalue low- and undervalue high-beta targets relative to the market's assessment because they use the CAPM. Consequently, there is more over- or underpayment if bidders rely more on the CAPM.

Prediction 5. The positive relation between the bidder's CAR and target's asset beta is weaker if the empirical SML has a steeper slope.

The reason the CAPM-based value of a target differs from the market's assessment thereof is that the empirical SML is less steep than the CAPM-implied SML. Consequently, the difference between the CAPM-based value and the market value becomes smaller when the empirical SML becomes steeper.

Prediction 6. The positive relation between the bidder's CAR and target's asset beta is weaker if the target is publicly listed, in particular, if its asset beta is high.

As the current market valuations of public targets are observable, bidders are likely to rely relatively less on the CAPM. Further, owners of public targets can sell their shares at the current price in the stock market. Bids for high beta public targets (whose market prices exceed their CAPM-based values) must thus reflect the beta-insensitive market prices. Both effects weaken the relation between bidder CARs and target betas.

2. Data

Data on takeover bids come from Thomson Financial's SDC Platinum M&A database. We use all observations between 1977 and 2015, excluding share repurchases, with a U.S. public bidder and a deal value of at least USD 50 million (inflation adjusted to December 2015). Table 1 presents descriptive statistics.[6] We distinguish between bids for private targets (panel A) and bids for public targets (panel B).

The average cumulative abnormal return of the bidders' stock around the bid announcements (from $t=-3$ to $t=+3$ for a bid announced on date $t=0$) is positive for private targets (2.0%) and negative for public targets (-0.6%), consistent with the existing literature (e.g., Betton, Eckbo, and Thorburn 2008; Schneider and Spalt 2019). The average deal value is USD 388 million for private and USD 1,258 million for public targets (inflation-adjusted to December 2015). Bidders offer an all-stock payment in 13% (33%) of the cases if the target is private (public). The average discount rate used in fairness opinions on the proposed deals is 14.1% for private and 13.1% for public targets.

The private (public) targets in our sample have an average asset beta of 0.86 (0.82) with a standard deviation of 0.33 (0.36). The distribution of bidder asset betas is very similar. All betas are computed as follows: First, for each public firm i in CRSP at the end of each month t, we regress monthly excess stock returns (RET in CRSP minus the risk-free rate from Kenneth French's Web page[7]) during the previous 5 years, that is, from month $t-60$ to month t,

[6] All continuous variables are winsorized at the 1st and 99th percentiles. Table A.1 in the appendix defines the variables.

[7] *http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html*

Table 1
Descriptive statistics

A. Private targets	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:	Bids for private targets with a CPI-adjusted deal value ≥ \$50M, 1977–2015							
Variable:	Observations	Mean	SD	Min.	*p*25	*p*50	*p*75	Max.
Bidder CAR	14,744	2.0%	8.2%	−20.5%	−2.3%	1.1%	5.6%	27.9%
Target asset beta	17,885	0.86	0.33	0.17	0.62	0.86	1.11	1.55
Bidder asset beta	18,163	0.87	0.32	0.20	0.64	0.84	1.11	1.54
Beta spread	17,707	−0.01	0.25	−0.74	−0.06	0.00	0.03	0.76
log(Deal value)	18,485	4.91	1.07	3.29	4.09	4.70	5.52	9.08
Deal value (in \$M)	18,485	297	699	27	60	110	250	8,799
Deal value (in \$M, CPI adjusted)	18,485	388	882	51	82	148	334	11,437
100% stock	18,482	0.13	0.33	0	0	0	0	1
Avg. discount rate	117	14.1%	4.9%	7.0%	11.0%	13.0%	15.0%	30.0%

B. Public targets	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:	Bids for public targets with a CPI-adjusted deal value ≥ \$50M, 1977–2015							
Variable:	Observations	Mean	SD	Min.	*p*25	*p*50	*p*75	Max.
Bidder CAR	7,296	−0.6%	7.7%	−20.5%	−4.6%	−0.7%	3.1%	27.9%
Target asset beta	7,879	0.82	0.36	0.17	0.53	0.82	1.11	1.55
Bidder asset beta	7,932	0.81	0.34	0.20	0.55	0.80	1.09	1.54
Beta spread	7,794	0.01	0.21	−0.74	0.00	0.00	0.00	0.76
log(Deal value)	8,095	5.59	1.49	3.29	4.38	5.33	6.55	9.08
Deal value (in \$M)	8,095	921	1,852	27	80	206	699	8,799
Deal value (in \$M, CPI adjusted)	8,095	1,258	2,430	51	121	307	1,019	11,437
100% stock	8,091	0.33	0.47	0	0	0	1	1
Avg. discount rate	1,064	13.1%	3.9%	7.0%	10.5%	12.3%	14.5%	30.0%

This table presents descriptive statistics for our sample of bids for private (panel A) and public (panel B) targets between 1977 and 2015. *Bidder CAR* is the bidder's cumulative abnormal return around the bid announcement. *Target (bidder) asset beta* is the target's (bidder's) asset beta. *Beta spread* is the difference between the target's and bidder's asset beta. *Deal value* is the value of the bid (in \$M). *100% stock* is an indicator for all-stock offers. *Avg. discount rate* is the midpoint between the maximum and minimum discount rate used in M&A fairness opinions. All continuous variables are winsorized at the 1st and 99th percentiles. Table A.1 in the appendix defines the variables.

on the corresponding excess returns of the CRSP value-weighted portfolio (including dividends). The regression coefficient is the CAPM (equity-)beta β_{it}^E.[8] To ensure reasonable precision, we drop estimates based on less than 36 monthly returns. Further, we drop observations for which the estimated beta is negative, and we drop the same number of observations in the right tail of the distribution of estimated betas. Our findings are unchanged if we winsorize the estimates at the 1% level instead. Second, we delever each beta using the formula $\beta_{it}^A = \beta_{it}^E / [1 + (1-\tau) \times D_{it}/E_{it}]$, where τ is the statutory tax rate in the highest bracket, D_{it} is total debt at the end of the most recently completed fiscal year ($DLT + DLC$ in Compustat), and E_{it} is the market capitalization of firm i at the end of month t. Third, we compute the equally weighted average of β_{it}^A of all public firms in CRSP with the same 3-digit primary SIC code. Finally, we attribute to the target and bidder the equally weighted average asset

[8] We use share codes 10 and 11 and compute the value-weighted average beta in case of multiple securities per firm.

beta of their respective industries as of the last completed month before the bid announcement. Hence, if the bidder and target operate in the same industry, they have the same asset beta.

To test our predictions, we require estimates of the betas used by managers in practice. Thus, our goal is not to estimate the "true" CAPM-betas but to replicate as closely as possible the estimation procedure most likely used by the bidders in our sample. Consequently, we follow common industry practice and rely on 5 years of monthly returns, use the standard (textbook) delevering formula, and compute the equally weighted average asset beta of each target's public peers. Our results, however, are not materially affected when using alternative methodologies to estimate, delever, or aggregate betas.

3. Results

3.1 Cumulative abnormal returns of bidders' stock around bid announcements

We now test our main prediction: the bidder's cumulative abnormal return around the bid announcement is increasing in the target's asset beta (Prediction 1). For the purpose of this analysis, we focus on private targets. Tests of our model's differential predictions for public targets are provided in Section 3.5.

We estimate the following OLS regression:

$$\begin{aligned} \textit{Bidder CAR} = {} & \alpha + \beta \times \textit{Target asset beta} + \gamma \times \textit{Beta spread} + \delta' \textit{Deal controls} \\ & + \eta' \textit{Target controls} + \kappa' \textit{Bidder controls} \\ & + \textit{Bidder industry} \times \textit{Year fixed effects} + \varepsilon. \end{aligned} \tag{8}$$

Bidder CAR is the bidder's cumulative abnormal return during the seven days around the bid announcement (i.e., from date $t-3$ to date $t+3$ for a bid announced on date $t=0$).[9] *Target asset beta* is the target's asset beta. *Beta spread* is the difference between the target's and bidder's asset beta. We include this variable to control for the effect of bidders using their own beta rather than the target's beta to compute the cost of capital (Krüger, Landier, and Thesmar 2015). *Deal controls* are characteristics commonly used as control variables in the M&A literature.[10] Specifically, we control for *log(Deal value)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same industry*, *Cross-border*, *Poison*, *Tender*, *Multiple bidders*, *Relative size*, and *log(Bidder size)*. Table A.1 in the appendix defines the variables. *Target controls* are the target's market-to-book ratio, return on assets, and leverage, as well as cash holdings and cash flow (both scaled by

[9] Our findings are robust to using alternative event windows, for example, from $t-2$ to $t+2$ or from $t-1$ to $t+1$.

[10] See, for example, Moeller, Schlingemann, and Stulz (2004), Masulis, Wang, and Xie (2007), Golubov, Petmezas, and Travlos (2012), Harford, Humphery-Jenner, and Powell (2012), and Dessaint, Golubov, and Volpin (2017).

assets).[11] *Bidder controls* are defined analogously. The standard errors are clustered by target industry.[12]

Table 2 presents the results.[13] In Column 1, we do not include any control variables other than fixed effects. We add the deal controls in Column 2, target controls in Column 3, and bidder controls in Column 4. In Column 5, we also add *Beta spread*. To conserve space, we do not report the coefficient estimates and t-statistics of all control variables. The coefficient estimates on *Target asset beta* are positive and statistically significant at the 1% level in all five columns.[14] The point estimates range from 1.02 in Column 1 to 2.55 in Column 5 and imply that an increase in *Target asset beta* by its interquartile range (0.49) is associated with an increase in *Bidder CAR* by 0.5 to 1.2 percentage points, corresponding to 6% to 16% of *Bidder CAR*'s interquartile range (7.9%).

3.2 Instrumental variable estimation

Potential concerns regarding our analysis are measurement error and omitted, correlated variables. Specifically, the procedures and data that managers use in practice to estimate beta may differ from the procedures and data we use to construct *Target asset beta*. In that case, *Target asset beta* = *Beta actually used* + *Measurement error*, and the OLS estimator would suffer from an attenuation bias. Target betas also may be correlated with determinants of bidder CARs that are not captured by the control variables and fixed effects. We control for the determinants that have been documented in the literature (e.g., Golubov, Yawson, and Zhang 2015; Moeller, Schlingemann, and Stulz 2004; Masulis, Wang, and Xie 2007; Harford, Humphery-Jenner, and Powell 2012), but we cannot rule out that there might be other, omitted variables that are (conditionally) correlated with both target asset betas and bidder CARs. As the existing literature does not provide clear guidance on what these omitted variables may be and how they may be correlated with target betas, however, we cannot make a clear-cut prediction whether the resultant bias in the OLS estimator would be positive or negative. For example, if bidder hubris, synergies, or sellers' relative bargaining power were correlated with target asset betas, then the OLS estimator could be either upward or downward

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[11] For private firms, we use the equally weighted average of these variables computed across all public firms that operate in the same industry (based on the first three digits of the firms' primary SIC code).

[12] Our findings are unchanged if we use block bootstrap standard errors instead.

[13] The reported number of observations refers to the observations that are effectively used in the estimation procedure and varies between the different columns because some control variables are not available for all observations and cases with only a single observation for a given fixed effect ("singletons") are dropped in an iterative procedure. This note applies to all subsequent tables.

[14] Table A.2 in the appendix shows that this finding does not depend on the model used to estimate *Bidder CAR*. Table A.3 shows that the results are similar when we use the targets' equity betas instead of their asset betas. When controlling for *Bidder asset beta* instead of *Beta spread*, the coefficient on *Target asset beta* (*Bidder asset beta*) is 1.28 (1.22) with a t-statistic of 3.28 (2.41) in the full sample and 0.95 (0.79) with a t-statistic of 1.90 (1.27) in the subsample where the two betas differ.

Table 2
Bidder cumulative abnormal returns around bid announcements

	(1)	(2)	(3)	(4)	(5)
Sample:			Private targets		
Dependent variable:			Bidder CAR (in percentage points)		
Target asset beta	1.02***	1.34***	1.73***	1.49***	2.55***
	(3.02)	(4.20)	(4.72)	(4.14)	(5.06)
Beta spread					−1.36***
					(−2.60)
log(Deal value)		0.66***	0.65***	0.59***	0.59***
		(7.37)	(7.34)	(6.82)	(6.69)
Equity		0.59**	0.60**	0.57*	0.51*
		(2.24)	(2.26)	(1.87)	(1.69)
Cash		0.30	0.28	0.48	0.44
		(1.07)	(0.98)	(1.45)	(1.34)
Toehold		−0.08	−0.15	−0.11	−0.10
		(−0.20)	(−0.36)	(−0.26)	(−0.24)
Hostile		−2.26**	−2.44**	−2.82**	−3.22***
		(−2.19)	(−2.26)	(−2.26)	(−2.76)
Same industry		0.11	0.12	0.12	0.14
		(0.65)	(0.71)	(0.82)	(0.96)
Cross-border		−0.14	−0.14	−0.06	−0.09
		(−0.63)	(−0.61)	(−0.26)	(−0.37)
Poison		−0.60	−0.66	−0.51	−0.47
		(−0.87)	(−0.90)	(−0.49)	(−0.45)
Tender		−0.30	−0.36	−0.57	−0.72
		(−0.29)	(−0.34)	(−0.49)	(−0.63)
Multiple bidders		−0.40	−0.38	0.07	0.03
		(−0.54)	(−0.51)	(0.09)	(0.04)
Relative size		−0.06***	−0.06***	−0.06***	−0.06***
		(−7.25)	(−7.20)	(−7.51)	(−7.59)
log(Bidder size)		−0.94***	−0.94***	−0.96***	−0.96***
		(−12.40)	(−12.33)	(−12.50)	(−12.56)
Bidder SDC industry × Year FE	Yes	Yes	Yes	Yes	Yes
Target controls	No	No	Yes	Yes	Yes
Bidder controls	No	No	No	Yes	Yes
Observations	13,916	13,599	13,486	12,209	12,109

This table presents OLS estimates of the sensitivity of the cumulative abnormal return of the bidder's stock during the 7-day window around the bid announcement (*Bidder CAR*) to the target's asset beta. The sample period is 1977 to 2015. Only bids for private targets are included. *Target (bidder) controls* is a vector of target (bidder) characteristics: *Market-to-book*, *ROA*, *Cash flow to assets*, *Debt to assets*, and *Cash to assets*. For private targets, these variables are average values of the corresponding variables across all public firms in Compustat with the same 3-digit primary SIC code. Tables 1 and A.1 in the appendix define the variables. t-statistics, based on standard errors clustered by the target's (SIC3-) industry, are reported in parentheses. *p <.1; **p <.05; ***p <.01.

biased, depending on the sign of the correlations between these variables and *Target asset beta*.

To mitigate the above-mentioned concerns, we construct an instrument for *Target asset beta* and estimate the effect on bidder CARs in a two-stage-least-squares (2SLS) framework. To do so, we rely on mutual fund fire sales as a source of nonfundamental variation in realized stock returns (i.e., noise), which in turn translates into nonfundamental variation in beta estimates (i.e., noise in the coefficient estimates from a regression of excess stock on excess market returns). The intuition is as follows.

In practice, a firm's equity-beta is typically estimated by regressing realized stock returns in excess of a proxy for the risk-free rate on realized excess returns of a market proxy. The beta estimate is then defined as

$$\widehat{\beta} \equiv \frac{\widehat{\sigma}_{r,m}}{\widehat{\sigma}_m^2}, \tag{9}$$

where $\widehat{\sigma}_{r,m}$ denotes the in-sample covariance between the excess stock return r and the excess market return r_m, and $\widehat{\sigma}_m^2$ denotes the in-sample variance of r_m.[15]

The realized excess stock return can be written as the sum of a fundamental and a noise component,

$$r = r^* + u, \tag{10}$$

where r^* denotes the fundamental component, and the noise component is defined as $u \equiv r - r^*$. It follows that the beta estimate ($\widehat{\beta}$) can be decomposed into a "fundamental beta" ($\widehat{\beta^*}$) and a "noise beta" ($\widehat{\beta_u}$), that is,

$$\widehat{\beta} = \frac{\widehat{\sigma}_{r,m}}{\widehat{\sigma}_m^2} = \frac{\widehat{\sigma}_{r^*,m}}{\widehat{\sigma}_m^2} + \frac{\widehat{\sigma}_{u,m}}{\widehat{\sigma}_m^2} = \widehat{\beta}^* + \widehat{\beta}_u, \tag{11}$$

where $\widehat{\sigma}_{r^*,m}$ and $\widehat{\sigma}_{u,m}$ are the in-sample covariances between r^* and r_m and u and r_m. This decomposition suggests that the scaled in-sample covariance ($\widehat{\beta_u}$) between nonfundamental shocks to realized excess stock returns and excess returns of the market proxy can be used as an instrument for the beta estimate ($\widehat{\beta}$).

To implement this strategy, we rely on mutual fund fire sales as a source of nonfundamental variation in realized returns. Coval and Stafford (2007) show that stock sales by funds that experience large outflows create large, positive supply shocks for the liquidated stocks and thus negatively affect realized returns. Fund managers, however, can exercise discretion when deciding which of their positions to liquidate. To mitigate the concern that the decision of which shares to sell introduces a correlation between fire sales and fundamentals, we follow Edmans, Goldstein, and Jiang (2012) and rely on hypothetical mutual fund fire sales (*HMFFS*) rather than actual sales.[16] In particular, for each stock, we compute the total dollar amount of hypothetical mutual fund fire sales scaled by the total dollar amount of trading in the stock, assuming that each position in an affected fund's portfolio is liquidated in proportion to its portfolio weight (so that the overall composition of the portfolio remains unchanged).[17] This approach ensures that the variable *HMFFS* is not affected by fund managers' discretion regarding which stocks to sell after a large outflow.[18]

15 Some data providers (e.g., Bloomberg) also offer "adjusted beta" estimates that are a weighted average between the "raw beta" estimate and one (e.g., $\widehat{\beta}_{adj.} = \frac{2}{3} \times \widehat{\beta} + \frac{1}{3}$). We abstract away from such adjustments, which complicate the exposition, but doing so does not change the intuition behind our identification strategy.

16 See also Lou (2012).

17 We provide a detailed description of the construction of *HMFFS* in Appendix B.

18 Wardlaw (2018) argues that scaling the amount of hypothetical mutual fund fire sales by the trading volume may be problematic. Doing so could lead to a correlation between *HMFFS* and returns for reasons other than the fire sales. We discuss this concern in detail in Appendix C and show that our findings are robust to the use of alternative measures not subject to this critique.

Next, we use *HMFFS* to estimate the nonfundamental noise component in firms' stock returns. Specifically, for each public firm in the CRSP database and for each beta-estimation period in our sample, we regress the firm's realized excess stock return r on *HMFFS*,

$$r = \alpha + \gamma \times HMFFS + \upsilon. \tag{12}$$

Importantly, because we estimate this regression separately for each firm and 5-year beta-estimation period, α in (12) is effectively a firm $\times$ estimation-period fixed effect that absorbs all characteristics that do not vary during the 5-year estimation period. The estimated effect of *HMFFS* is therefore only based on within-firm, time-series variation, but not on cross-sectional variation between firms, during the estimation period. This is worth noting because it mitigates the potential concern that the occurrence and extent of fire sales may be correlated with the characteristics of the firms whose shares are sold.[19]

Next, we use the fitted value from (12)—the predicted excess return due to mutual fund fire sales—as an estimate of the nonfundamental noise component in the return (i.e., $\widehat{u} = \widehat{\gamma} \times HMFFS$) and define[20]

$$\widehat{\beta_{\widehat{u}}} \equiv \frac{\widehat{\sigma_{\widehat{u},m}}}{\widehat{\sigma}_m^2}, \tag{13}$$

where $\widehat{\sigma_{\widehat{u},m}}$ is the in-sample covariance between the estimated noise component and the realized excess return of the market proxy. Finally, in analogy to the construction of *Target asset beta*, we delever the firm-level estimates $\widehat{\beta_{\widehat{u}}}$ and compute the equally weighted average at the industry level. The resultant variable, denoted *Target noise beta*, is our instrument for *Target asset beta*.[21]

To be a valid instrument, *Target noise beta* must satisfy two conditions. First, it must be correlated with *Target asset beta*. This condition can be tested using the first stage of the 2SLS procedure. The results show that the correlation between *Target noise beta* and *Target asset beta* is positive and highly statistically significant (Table 3, panel A). With t-statistics above ten, the implied F-statistics are an order of magnitude larger than the threshold suggested by Stock, Wright, and Yogo (2002) to guard against weak instruments.[22] To mitigate concerns about the robustness of this finding,

19 Berger (2019), p. 4), for example, argues that "large outflows are more likely among funds that invest in small firms."

20 Our identification strategy does not require that *HMFFS* explain the entire noise term. In particular, assume that u is the sum of unexplained noise η and noise ν due to mutual fund fire sales: $r = r^* + \eta + \nu$. In that case, we have $\widehat{\beta} = \widehat{\beta}^* + \widehat{\beta}_\eta + \widehat{\beta}_\nu$, so $\widehat{\beta}_\nu$ can be used to instrument $\widehat{\beta}$.

21 To ensure that *Target noise beta* and *Target asset beta* are constructed based on the same sample of observations, we exclude $\widehat{\beta}_u$ estimates if the corresponding $\widehat{\beta}$ estimates are missing. Further, we set *Target noise beta* to missing if the average estimated effect of *HMFFS* on r at the industry level is in the top or bottom percentile of the sample distribution. This procedure mitigates the concern that *Target noise beta* may be driven by outliers in the distribution of estimated noise components.

22 *Target noise beta* is an estimated quantity, so the first-stage t-statistics may be overstated. Importantly, this does not affect the asymptotic distribution of the second-stage estimator as long as *Target noise beta* is consistent and

Table 3
Two-stage least squares instrumental variable estimation

A. 1st stage of 2SLS	(1)	(2)	(3)	(4)	(5.a)	(5.b)
Sample:	Private targets					
Dependent variable:	Target Asset beta	Target Asset beta	Target Asset beta	Target Asset beta	Target Asset beta	Beta Spread
Target noise beta	3.35***	3.32***	2.06***	2.06***	2.09***	2.22***
	(10.38)	(10.74)	(14.44)	(14.22)	(13.61)	(12.14)
Bidder noise beta					−0.10	−2.45***
					(−0.67)	(−11.63)
Bidder SDC industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Deal controls	No	Yes	Yes	Yes	Yes	Yes
Target controls	No	No	Yes	Yes	Yes	Yes
Bidder controls	No	No	No	Yes	Yes	Yes
Observations	13,360	13,062	12,953	11,720	11,719	11,719

B. 2nd stage of 2SLS	(1)	(2)	(3)	(4)	(5)
Sample:	Private targets				
Dependent variable:	Bidder CAR (in percentage points)				
Target asset beta (instrumented)	2.09**	2.27***	3.60**	3.38**	4.70*
	(2.26)	(2.55)	(2.25)	(1.98)	(1.77)
Beta spread (instrumented)					−1.92
					(−0.92)
Bidder SDC industry × Year FE	Yes	Yes	Yes	Yes	Yes
Deal controls	No	Yes	Yes	Yes	Yes
Target controls	No	No	Yes	Yes	Yes
Bidder controls	No	No	No	Yes	Yes
Observations	13,360	13,062	12,953	11,720	11,719

This table presents 2SLS estimates of the sensitivity of *Bidder CAR* to *Target asset beta*. The sample period is 1980 to 2015. Only bids for private targets are included. *Deal controls* is a vector comprising all deal-level controls included in Columns 2 to 4 of Table 2: *log(Deal value)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same industry*, *Cross-border*, *Poison*, *Tender*, *Multiple bidders*, *Relative Size*, and *log(Bidder size)*. Tables 2 and A.1 in the appendix define all other variables. t-statistics, based on standard errors clustered by the target's (SIC3-) industry, are reported in parentheses. $^*p<.1$; $^{**}p<.05$; $^{***}p<.01$.

we explore the correlation between the two variables in further detail. Figure A.1 in the appendix shows the estimated coefficients from a regression of *Target asset beta* on indicators for different ranges of *Target noise beta*. This analysis reveals a strong and monotone relation that corroborates the first-stage results reported in Table 3, panel A.

The second condition is that *Target noise beta* must be uncorrelated with the error term in the regression of *Bidder CAR* on *Target asset beta*. The key exogeneity assumption in our setting is therefore that the unexplained part of a bidder's CAR around the bid for a private target is uncorrelated with the average covariance between the market return and the estimated noise components in the returns of other, public firms in the industry during the 5 years before the takeover bid: $cov[\textit{Target noise beta}, \varepsilon]=0$, where ε is the error term in (8). A sufficient condition is that mutual fund fire sales are exogenous and

the error in the regression of *Bidder CAR* on *Target asset beta* has a conditional mean of zero given the data used to estimate *Target noise beta* (Wooldridge 2002). Both are maintained assumptions in our analysis. Further, note that even if the "true" t-statistics were up to three times smaller than those reported, the implied F-statistics would still exceed the threshold suggested by Stock, Wright, and Yogo (2002).

introduce random noise into the public firms' excess stock returns. The evidence documented by a growing number of papers supports this premise: Mutual fund fire sales trigger a drop in stock prices that is followed by subsequent reversal, and corporate insiders trade against these shocks.[23] Both findings are consistent with the notion that mutual fund fire sales represent temporary, nonfundamental supply shocks.[24]

Importantly, however, this is not a necessary condition. Even if the fire sales were correlated with the characteristics of the public firms in the funds' portfolios, it is difficult to argue that this would translate into a correlation between the average covariance of the market return and the estimated noise components in the public firms' excess returns (*Target noise beta*) and the unexplained part of a bidder's CAR around the bid for a different, private target several years after the fire sale, in particular, after conditioning on the large number of control variables and fixed effects in the regressions. Our exogeneity assumption $cov[\textit{Target noise beta}, \varepsilon] = 0$ is thus weaker than the assumption that the mutual fund fire sales themselves are exogenous. This is another reason the potential concern that *HMFFS* may be correlated with the characteristics of the firms whose shares are sold is unlikely to be important in our setting.

It is also unclear why the realized, in-sample covariance between excess market returns and nonfundamental noise in the return realizations of public firms during the 5 years before a deal would affect a bidder's CAR around a bid announcement for a different, private firm through any channel other than the effect on the beta estimate. Taken together, plausibly random assignment and a single channel through which bidder CARs are affected suggest that *Target noise beta* satisfies the exclusion restriction.

Table 3 displays the results of the 2SLS estimation.[25] In panel A, Columns 1 to 4, we present the results of the first-stage regressions of *Target asset beta* on *Target noise beta*. In Columns 5A and 5B, we instrument *Target asset beta* and *Beta spread* with *Target noise beta* and *Bidder noise beta*.[26] The coefficient estimates on *Target noise beta* in all columns are positive and strongly significant. Similarly, the coefficient on *Bidder noise beta* in Column 5B is negative and highly significant.

Panel B shows the second-stage results. The IV estimates of the coefficients on *Target asset beta* are noisier than the corresponding OLS estimates reported in Table 2 but remain positive and statistically significant at the 5% level in Columns 1, 3, and 4, at the 1% level in Column 2, and at the 10% level in Column 5. Further, while estimated with lower precision, the IV estimates are

23 See Ali, Wei, and Zhou (2011), Goldman (2017), Honkanen and Schmidt (2018), and Dessaint et al. (2019).

24 Other papers using mutual fund fire sales as nonfundamental shocks to prices/returns include Edmans, Goldstein, and Jiang (2012), Phillips and Zhdanov (2013), Acharya et al. (2014), and Eckbo, Makaew, and Thorburn (2017).

25 The sample period for this analysis is 1980 to 2015; data on mutual funds flows are not available prior to 1980.

26 We construct *Bidder noise beta* in analogy to *Target noise beta*.

comparable in magnitude to the OLS estimates. Indeed, the 10% confidence intervals around the IV estimates include the corresponding OLS estimates, and Durbin-Hausman-Wu tests indicate that the difference between the IV and the OLS estimates is not statistically significant. The IV results thus corroborate our earlier findings of a positive relation between *Target asset beta* and *Bidder CAR*.

The finding that the 2SLS estimates are a bit larger than (though not statistically different from) the OLS estimates is consistent with the initially mentioned concern about a potential attenuation bias in the OLS estimator. It is also worth noting that the IV estimates capture a local average effect that could potentially differ from the average effect captured by OLS. Specifically, the IV coefficients capture the relation between *Target asset beta* and *Bidder CAR* for those acquisitions where the beta estimate used by the managers is influenced by fire sale induced noise in stock returns. Imagine now that there is heterogeneity in bidder sophistication: more sophisticated bidders know that simple regression betas can be distorted by noise and therefore adjust the estimation procedure or put less emphasis on the CAPM-implied value of the target. In that case, the IV coefficients would primarily reflect the relation between *Target asset beta* and *Bidder CAR* for less sophisticated bidders who continue to use the CAPM with simple beta estimates even when there is fire-sale-induced noise. Hence, if less sophisticated bidders rely more on the textbook version of the CAPM—thus generating a stronger relation between *Target asset beta* and *Bidder CAR*—then the local average effect captured by the IV estimation could be larger than the average effect captured by OLS.

3.3 Model calibration and implied valuation errors

We now explore whether the magnitude of the regression coefficients that we estimate is consistent with the model of Section 1. For this purpose, we assume that the bidder seeks to acquire a fraction $\pi \in [0,1]$ of the target's equity and that the takeover succeeds with probability $\rho \in [0,1]$.[27] In that case, our model implies

$$CAR_t^{Bidder} = \rho \times \frac{\pi \widetilde{E}_t - B_t}{E_t^{Bidder}}. \tag{14}$$

We make three simplifying assumptions: (I) The operating cash flows and synergies have the same systematic risk and grow at a constant rate g. (II) The level of debt is permanent, and the net benefit of leverage is equal to the tax shield. (III) The bidder, seller, and market use the book value of debt as a proxy for the debt's market value. We show in Appendix A that the bidder's CAR

[27] Unlike in the model in Section 1, some bids in the data fail. We introduce the parameter ρ to capture this empirical pattern.

then can be written as

$$CAR_t^{Bidder} = \frac{\rho}{E_t^{Bidder}} \times \left\{ \pi\,(FCF_{t+1}+s_{t+1}) \times \left[\frac{1}{\widetilde{r}_A - g} - \frac{1}{r_A - g} \right] + (1-\alpha)\,\frac{s_{t+1}}{r_A - g} \right\}. \tag{15}$$

Finally, we assume that the CAPM-implied and empirical SML cross at the average asset beta ($\overline{\beta}_A$) and allow for different degrees of steepness of the empirical SML, so that discount rate used by the market is

$$\widetilde{r}_A = r_f + \left[\gamma \times \beta_A + (1-\gamma) \times \overline{\beta}_A\right] \times \mu, \tag{16}$$

where $\gamma \in [0,1]$ determines the steepness of the empirical SML (relative to the CAPM). For example, $\gamma = 0$ means that the empirical SML is flat, and $\gamma = 1$ means that the empirical and CAPM-implied SML coincide.

We then use Equations (15) and (16) to compute CAR_t^{Bidder} for different values of β_A. We assume the following parameter values: We set ρ equal to 0.92 and E_t^{Bidder} equal to USD 10,269 million based on the average bidder market value and bid acceptance rate in the sample of 12,109 observations used to estimate Column 5 in Table 2. We use the average yield on 20-year U.S. bonds during the sample period (5.0%) as a proxy for r_f, the average nominal GDP growth (5.4%) to proxy for g, and we assume a market risk premium (μ) of 6%. We use the average asset beta of all public firms in Compustat (0.84) to proxy for $\overline{\beta}_A$, set α to 0.5, and consider three different degrees of steepness of the empirical SML: $\gamma = 0$, $\gamma = 0.5$, and $\gamma = 1$. Finally, we set s_{t+1} and $\pi\,(FCF_{t+1}+s_{t+1})$ to the values implied by $s_{t+1} = \widetilde{S}_t(\widetilde{r}_A - g)$ and [28]

$$\pi\,(FCF_{t+1}+s_{t+1}) = B_t\,[1+(1-\tau)L](r_A - g) + s_{t+1}\,[1-\alpha+(1-\tau)L(1-\pi-\alpha)], \tag{17}$$

which we compute using the average synergy value ($\widetilde{S}_t$) of USD 58 million that we estimate based on the combined CARs of bidders and targets around bids for public firms, the average bid value (B_t) of USD 314 million, average tax rate (τ) of 36%, average ratio of debt to equity (L) of 0.59, and average target asset beta of 0.9 in the sample used to estimate Column 5 in Table 2. All other parameter values are as before.

Next, we compute the implied coefficients in a regression of CAR_t^{Bidder} on indicator variables for different ranges of β_A, relative to the base case of $\beta_A =$ 0.9. We contrast these model-implied coefficients with the actual coefficients obtained in our empirical analysis. Figure 1 presents the results. The dashed blue line represents the model-implied coefficients for a flat empirical SML ($\gamma = 0$), and the dashed gray line represents the coefficients corresponding to an empirical SML that coincides with the CAPM ($\gamma = 1$). The solid blue line represents the coefficients corresponding to an empirical SML that is half as steep as the CAPM-implied SML ($\gamma = 0.5$). The solid red line represents the

[28] We derive this relation in Appendix A.

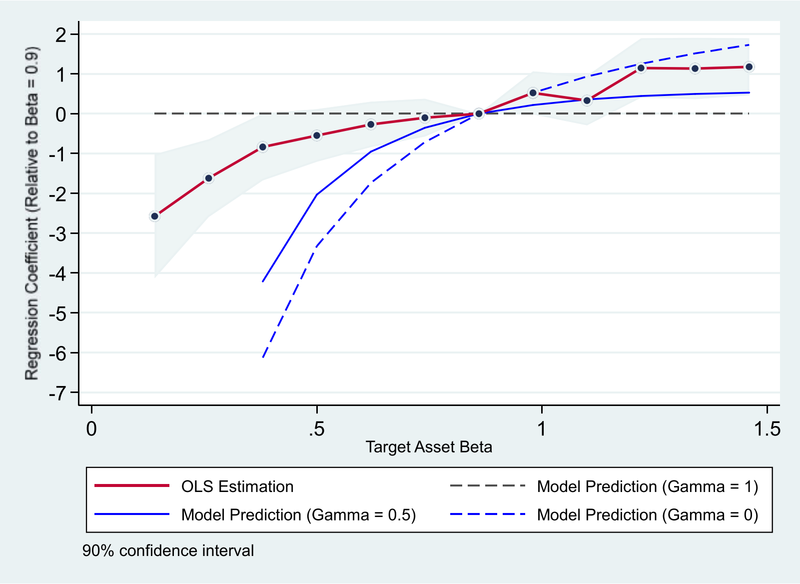

Figure 1
Model calibration
This figure shows the model-implied coefficients from a regression of CAR_t^{Bidder} on indicator variables for different ranges of target asset betas (β_A), relative to the base case of $\beta_A = 0.9$, for different degrees of steepness of the empirical SML. The different model parameters are chosen to match the average values of the corresponding proxy variables in our sample of bids made by public bidders for private targets between 1977 and 2015. We consider three different degrees of steepness of the empirical SML: $\gamma = 0$ (blue dashed line), $\gamma = 0.5$ (blue solid line), and $\gamma = 1$ (gray dashed line). The figure also shows the OLS coefficient estimates of indicator variables for different ranges of β_A (relative to the base case of $\beta_A = 0.9$, the average asset beta of the private targets in the sample), as reported in Table A.4 in the appendix (red solid line).

coefficient estimates from our empirical analysis (using the same controls as in Column 5 of Table 2).[29] Overall, except for very low asset betas, the model fits the empirical relation between *Bidder CAR* and *Target asset beta* reasonably well. Put differently, our regression estimates are quantitatively consistent with our model.

Our model also allows us to assess the magnitude of the valuation error (relative to the market's view) that is due to managers' reliance on the CAPM. The idea is that we observe the actual bids B_t in the data and can use the model to back-out the implied counterfactual bids $\widetilde{B}_t$ that would have been made had the managers relied on the empirical SML instead of the CAPM. The implied valuation error can then be computed as the absolute value of the difference between the actual and counterfactual bids, where we use the absolute value because all losses to bidders are gains to targets (and vice versa).

29 We report the numerical values of these coefficient estimates in Table A.4 in the appendix.

Specifically, for each completed takeover in our sample, we estimate the valuation error as[30]

$$|B_t - \widetilde{B}_t| = |(1-\alpha)s_{t+1} - \pi(FCF_{t+1} + s_{t+1})| \times \left| \frac{1}{\widetilde{r}_A - g} - \frac{1}{r_A - g} \right|, \tag{18}$$

where we use $s_{t+1} = \widetilde{S}_t(\widetilde{r}_A - g)$ and

$$\pi(FCF_{t+1} + s_{t+1}) = B_t[1+(1-\tau)L](r_A - g) + s_{t+1}[1-\alpha+(1-\tau)L(1-\pi-\alpha)] \tag{19}$$

computed using the bid-specific values of B_t, π, and β_A as well as (target SIC3-) industry specific estimates of $\widetilde{S}_t$, τ, and L. For all other model parameters, we make the same assumptions as before.

The valuation errors implied by this analysis correspond, on average, to 23% of the deal values (USD 66 million per takeover, inflation adjusted to December 2015). This model-implied estimate is in line with the estimates obtained from regressing *Bidder CAR* on *Target asset beta* (Tables 2 and 3), which provide an alternative way to gauge the valuation errors. Specifically, for each deal, we can compute the regression-implied valuation error by multiplying the coefficient estimate on *Target asset beta* with the absolute difference between *Target asset beta* and 0.84 (our estimate of $\overline{\beta}_A$) and the bidder's market capitalization. Doing so implies average valuation errors of 12% to 33% of the deal values (based on the coefficient estimates reported in Columns 1 to 5 of Table 2).[31]

3.4 Cross-sectional variation

We now test Predictions 2 to 5 regarding cross-sectional variation in the relation between bidder CARs and target asset betas. To do so, we define five indicators. *Target growth high* is equal to one if the growth rate of aggregate sales in the target's industry over the past 3 years is larger than the sample median. *Target relative size high* is equal to one if the relative size of the bid vis-à-vis the bidder's market capitalization is larger than the sample median. *Bidder mentions CAPM* is equal to one if the words "CAPM" or "Capital Asset Pricing Model" occur in the bidder's 10K, 10Q, and 8K filings during the 3 years prior to the bid announcement. *Listed peer available* is equal to one if the target is a U.S. firm, and there is at least one other publicly listed U.S. firm with the same primary 3-digit SIC code whose market capitalization is neither smaller than 50% nor larger than 150% of the target's bid-implied equity value. The idea is that a comparable public peer should come from the same geographic region,

30 We derive Equation (18) in Appendix A.

31 As a robustness check, we have also computed the model-implied valuation errors using equity instead of asset betas. Doing so yields valuation errors that correspond, on average, to 14% of the deal values (USD 38 million, inflation adjusted to December 2015). A point worth noting is that the model-implied estimates correspond to the valuation errors that are due to using the CAPM in the M&A context, not the total errors due to using the CAPM in general. An implication is that the model-implied estimates of the valuation errors in the M&A context may understate the *total* errors from using the CAPM across *all* contexts.

operate in the same industry, and have a similar size. We use *Bidder mentions CAPM* and *Listed peer available* as proxies for bidders' reliance on the CAPM relative to other valuation methods. The intuition is that bidders who rely on the CAPM should be more likely to mention the CAPM, and that bidders are more likely to complement a CAPM-based valuation with a multiple-based valuation if there are comparable, publicly listed peers. Finally, we define the indicator *Steep empirical SML* that is equal to one if, during the month of the bid announcement, the slope of the empirical SML estimated following Hong and Sraer (2016) is larger than the sample median.[32]

Next, we estimate OLS regressions in which we interact *Target asset beta* with the above indicators.[33] Table 4 presents the results. We find that the relation between bidder CARs and target betas is stronger if the growth in the target's industry is high and if the bid is large relative to the bidder's market capitalization. Further, the relation is stronger if the bidder is more likely to rely on the CAPM (as proxied by *Bidder mentions CAPM*) and weaker if the bidder is more likely to complement a CAPM-based valuation with a multiple valuation (as proxied by *Listed peer available*).[34] Finally, the relation is weaker when the empirical SML is steep. All of these findings support the cross-sectional predictions that are implied by our model.[35]

3.5 Private versus public targets

We now test Prediction 6. Specifically, we consider both private and public targets and examine whether and how the relation between bidder CARs and target asset betas varies between the two types of targets.

The key difference between a private and a public target in our model is the seller's outside option when negotiating with the bidder. The owners of a public target can decide between accepting the bid, keeping the shares, and selling the shares at their current price in the stock market. The owners of a private target can only choose between selling to the bidder and retaining the shares. The owners of a public target thus have a better outside option when bargaining with the bidder, in particular, when the target's CAPM-beta is high (i.e., when the market price is larger than the CAPM-implied value). Further, because the market price is less sensitive to beta than the CAPM-implied value, the relation

32 We thank David Sraer for sharing the code and data.

33 We also interact all controls and fixed effects with the indicators, thus allowing their coefficients to vary with the indicators.

34 Similarly, we find that the relation is weaker if the fairness opinions on the proposed deals include multiple valuations based on comparable, traded peers. A caveat is that this information is only available for a very small subsample of the deals.

35 The finding that the relation between *Bidder CAR* and *Target asset beta* is stronger if the relative deal size is larger is consistent not only with our model but also with alternative models in which bidder CARs and target betas are related for reasons other than managers' use of the CAPM. Taken in isolation, this finding does thus not distinguish our model from such alternatives. However, the sum of our cross-sectional findings, all of which are predicted by our model, is difficult to reconcile with alternative explanations.

Table 4
Cross-sectional variation

	(1)	(2)	(3)	(4)	(5)
Sample:			Private targets		
Dependent variable:			Bidder CAR (in percentage points)		
Target asset beta × Target growth high	2.71**				
	(2.08)				
Target asset beta × Target relative size high		2.86**			
		(2.31)			
Target asset beta × Bidder mentions CAPM			10.95**		
			(2.03)		
Target asset beta × Listed peer available				−2.63**	
				(−1.99)	
Target asset beta × Steep empirical SML					−2.03*
					(−1.70)
Target asset beta	1.44*	1.39**	2.37***	4.11***	3.43***
	(1.93)	(2.07)	(4.24)	(4.10)	(3.80)
Bidder SDC industry × Year FE (interacted)	Yes	Yes	Yes	Yes	Yes
Deal controls (interacted)	Yes	Yes	Yes	Yes	Yes
Target controls (interacted)	Yes	Yes	Yes	Yes	Yes
Bidder controls (interacted)	Yes	Yes	Yes	Yes	Yes
Observations	11,518	11,503	12,109	10,716	10,823

This table presents OLS estimates of the sensitivity of the cumulative abnormal return of the bidder's stock during the 7-day window around the bid announcement (*Bidder CAR*) to the target's asset beta as function of cross-sectional characteristics. The sample period is 1977 to 2015. Only bids for private targets are included. *Target growth high* is an indicator equal to one if the compound annual growth rate of aggregate sales in the target's (SIC3-) industry during the 3 years preceding the takeover bid is larger than the sample median. *Target relative size high* is an indicator equal to one if *Relative size* is larger than the sample median. *Bidder mentions CAPM* is an indicator equal to one if the bidder's 10K, 10Q, or 8K filings of the 3 years prior to the bid announcement contain the words "CAPM" or "capital asset pricing model". *Listed peer available* is an indicator equal to one if, at the time of the acquisition, there is at least one U.S.-listed firm in the target's (SIC3-) industry whose market capitalization is larger than 50% but smaller than 150% of the target's equity value as reported in SDC. *Steep empirical SML* is an indicator equal to one if the slope of the empirical SML during the month of the bid announcement is larger than the sample median. *Deal controls* is a vector comprising all deal-level controls included in Column 5 of Table 2: *Beta spread*, *log(Deal value)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same Industry*, *Cross-border*, *Poison*, *Tender*, *Multiple bidders*, *Relative size*, and *log(Bidder size)*. Tables 2 and A.1 in the appendix define the variables. *(Interacted)* indicates that all control variables and fixed effects are interacted with the cross-sectional characteristic of interest, allowing their coefficients to depend on the value of *Target growth high*, *Target relative size high*, *Bidder mentions CAPM*, *Listed peer available*, and *Steep empirical SML*. t-statistics, based on standard errors clustered by the target's (SIC3-) industry, are reported in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

between the target's beta and the takeover price offered by the bidder (and thus ultimately the bidder's CAR) is weaker for high beta public targets.

Another difference between private and public targets is the ease with which observable prices can be used to complement a CAPM-based valuation. For a public target, the bidder may consider not only the CAPM-based value but also the target's current market capitalization. For a private target, the market prices of public firms that are deemed "comparable" may play a role (e.g., in the form of valuation multiples). We consider this possibility in an extension of our model (in Appendix A). In particular, we assume that the bidder's assessment of the target's equity value is a weighted average of the CAPM-based value and another, market-based value (e.g., the current market price for a public target and a multiple-implied value for a private target). As a current

Table 5
Private versus public targets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:		Private targets			Public targets		All targets	
Dependent variable:				Bidder CAR (in percentage points)				
Target asset beta	2.55***			0.40			1.57***	2.55***
	(5.06)			(0.32)			(3.34)	(5.00)
Target asset beta × Public target								−2.15*
								(−1.75)
Public target							−2.84***	
							(−12.20)	
$\mathbb{1}\{$Target asset beta $< p25\}$		−0.59**			−1.20**			
		(−2.09)			(−2.36)			
$\mathbb{1}\{$Target asset beta $> p75\}$		0.88***			−0.04			
		(3.27)			(−0.07)			
$\mathbb{1}\{-\infty <$ Target asset beta $\leq 0.25\}$			−2.25***			−1.75*		
			(−4.19)			(−1.88)		
$\mathbb{1}\{0.25 <$ Target asset beta $\leq 0.48\}$			−1.16***			−1.74***		
			(−3.27)			(−2.69)		
$\mathbb{1}\{0.48 <$ Target asset beta $\leq 0.71\}$			−0.50*			−0.52		
			(−1.88)			(−0.94)		
$\mathbb{1}\{0.94 <$ Target asset beta $\leq 1.17\}$			0.54*			−0.72		
			(1.91)			(−1.32)		
$\mathbb{1}\{1.17 <$ Target asset beta $\leq 1.40\}$			1.22***			0.00		
			(3.53)			(0.00)		
$\mathbb{1}\{1.40 <$ Target asset beta $< \infty\}$			1.29***			−1.10		
			(3.04)			(−0.89)		
Bidder SDC industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Target controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bidder controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Public target (interacted)	No	No	No	No	No	No	No	Yes
Observations	12,109	12,109	12,109	3,894	3,894	3,894	16,547	16,003

This table presents OLS estimates of the sensitivity of the cumulative abnormal return of the bidder's stock during the 7-day window around the bid announcement (*Bidder CAR*) to the target's asset beta. The sample period is 1977 to 2015. *Public target* is an indicator for public targets. $\mathbb{1}\{$Target asset beta $< p25(> p75)\}$ is an indicator equal to one if the target's asset beta is in the bottom (top) quartile of the distribution of asset betas in the sample. $\mathbb{1}\{a <$ Target asset beta $\leq b\}$ is an indicator equal to one if the target's asset beta is larger than a but smaller than (or equal to) b. *Deal controls* is a vector comprising all deal-level controls included in Column 5 of Table 2: *Beta spread*, *log(Deal value)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same industry*, *Cross-border*, *Poison*, *Tender*, *Multiple bidders*, *Relative size*, and *log(Bidder size)*. Tables 2 and A.1 in the appendix define all other variables. *(Interacted)* indicates that all control variables and fixed effects are interacted with the indicator *Public target*, allowing their coefficients vary with the listing status of the target. t-statistics, based on standard errors clustered by the target's (SIC3-) industry, are reported in parentheses. *p <.1; **p <.05; ***p <.01.

market price is arguably considered a more accurate assessment than a multiple-implied value, we conjecture that the weight given to a public target's market capitalization is higher than the weight given to a multiple-implied value for a private target. Thus, because the market-based value is less sensitive to beta than the CAPM-based value, we expect the takeover bid (and consequently, the bidder's announcement CAR) to be less sensitive to the target's asset beta if the target is public.

To test this prediction, we regress *Bidder CAR* on *Target asset beta* separately for private and public targets. Table 5 shows the results for private targets in Columns 1 to 3 and for public targets in Columns 4 to 6. Columns 1 and 4 correspond to Column 5 of Table 2. We find a positive and statistically significant relation between bidder CARs and target asset betas for private targets, but not for public targets.

Columns 2 and 5 show the coefficient estimates for variables indicating whether a target's asset beta falls within the bottom or top quartile of the sample distribution. For both private and public targets, the results indicate that bids for targets with betas in the bottom quartile of the distribution are associated with lower bidder CARs (relative to bids for targets with betas in the middle of the distribution). Bids for targets with betas in the top quartile, however, are associated with higher bidder CARs only for private, but not for public, targets. The null-hypothesis that the coefficients on $\mathbb{1}\{\textit{Target asset beta} > p75\}$ in Columns 2 and 5 are the same is rejected by a Wald test at the 10% level and at the 5% level by a Fisher nonparametric permutation test based on 5,000 simulations (see, e.g., Cleary 1999).

Columns 3 and 6 show the estimated coefficients on indicators for different ranges of asset betas. For private targets, we find negative and significant coefficients for low asset betas and positive and significant coefficients for high asset betas (relative to bids for targets with asset betas in the middle of the distribution). For public targets, the coefficient estimates are negative and significant for low asset betas, but not statistically different from zero for high asset betas. Figure 2 provides a graphical representation of these findings. For private targets, the relation between *Target asset beta* and *Bidder CAR* is positive over the entire range of asset betas. In contrast, the relation for public targets is only significant if the asset betas are low. For high-beta public targets, the relation is much flatter and not statistically significant.

Finally, in Columns 7 and 8 of Table 5, we pool the bids for private and public targets. The regression in Column 7 corresponds to the one in Columns 1 and 4, except for the indicator *Public target*, which we include as an additional control. The estimated coefficient on *Target asset beta* is positive and statistically significant. This shows that the relation between *Target asset beta* and *Bidder CAR* is significantly positive not only in the sample of bids for private targets but also in the pooled sample of all bids. The coefficient on *Public target* is negative and significant, consistent with prior studies that document lower bidder CARs around bids for public targets (e.g., Betton, Eckbo, and Thorburn 2008; Schneider and Spalt 2019). In Column 8, we again use the pooled sample of all bids but interact *Target asset beta* with *Public target*, thus allowing the relation between *Target asset beta* and *Bidder CAR* to vary with the targets' listing status.[36] We find a positive and statistically significant coefficient estimate on *Target asset beta* and a negative and significant estimate on the interaction with *Public target*.

[36] We also interact *Public target* with all control variables and fixed effects.

Figure 2
Private versus public targets
This figure shows the OLS coefficient estimates of indicator variables for different ranges of β_A (relative to the base case of $\beta_A = 0.9$, the average asset beta of the private targets in the sample) for the sample of private targets (left panel) and the sample of public targets (right panel), as reported in Columns 3 and 6 of Table 5. The sample period is 1977 to 2015.

3.6 Probability of receiving takeover bids

Our model also has implications for the probability with which public firms receive takeover bids. A bid for a public firm is only made if the firm's CAPM-implied equity value exceeds its current market capitalization. Hence, because the CAPM-implied equity value is decreasing in beta (whereas the market capitalization is less sensitive to beta), a public firm's probability of receiving a takeover bid should be decreasing in its beta.[37] To test this prediction, we estimate the following OLS regression for all public firms in Compustat:[38]

$$Bid_t = \alpha + \beta \times Asset\ beta_{t-1} + \gamma' Firm\ characteristics_{t-1} + Year \times IPO\ cohort\ fixed\ effects + \varepsilon. \quad (20)$$

We distinguish between two types of bids. *Controlling bid* is an indicator equal to one if a firm receives an offer from a bidder that seeks to acquire

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[37] We provide a formal derivation of this prediction in Appendix A.

[38] Table A.5 in the appendix presents descriptive statistics for this sample. The SDC data are very sparse before 1981, so we cannot reliably identify the occurrence or absence of bids in earlier years. The sample period is thus 1981 to 2015. Also, we cannot examine the relation between private firms' betas and the probability of receiving takeover bids, because we only observe those private firms that receive bids, but not the private firms that do not receive bids and thus do not show up in our data.

Table 6
Probability of receiving takeover bids

	(1)	(2)	(3)	(4)
Sample:	Public firms in Compustat			
Dependent variable:	Controlling bid		Any bid	
Asset beta	−1.30*	−1.26**	−1.47**	−1.39**
	(−1.78)	(−2.18)	(−2.06)	(−2.18)
log(Assets)		0.09**		0.33***
		(2.11)		(4.96)
ROA		−6.57***		−11.05***
		(−2.70)		(−3.61)
Debt to assets		0.11		2.49***
		(0.24)		(3.97)
Cash to assets		0.39		1.49
		(0.43)		(1.54)
Cash flow to assets		6.22**		9.91***
		(2.48)		(3.20)
Tobin's q		−0.32***		−0.39***
		(−6.82)		(−7.19)
PPE to assets		−1.62***		−2.09***
		(−2.83)		(−3.02)
IO block		1.37***		1.89***
		(7.57)		(8.43)
Year × IPO cohort FE	Yes	Yes	Yes	Yes
Observations	154,788	139,517	154,788	139,517

This table presents OLS estimates of the sensitivity of public firms' propensity to receive a controlling takeover bid (*Controlling bid*) or any bid (*Any bid*) to the firms' asset beta. All reported coefficient estimates have been multiplied with 100 to improve readability. The sample period is 1981 to 2015. All public firms in Compustat are included. Table A.1 in the appendix provides detailed definitions of all variables. Year × IPO cohort fixed effects are based on the year of the observation and the IPO cohort of the firm, defined by the number of years since the firm's first appearance in CRSP. *t*-statistics, based on standard errors clustered by the firms' (SIC3-) industry, are reported in parentheses. *p <.1; **p <.05; ***p <.01.

a controlling stake. *Any bid* is equal to one if a firm receives any bid (i.e., controlling or not). *Asset beta* is our estimate of firms' asset beta, and *Firm characteristics* is a vector of control variables that have been used in the literature to explain takeover probabilities (e.g., Hasbrouck 1985; Palepu 1986; Ambrose and Megginson 1992; Cremers, Nair, and John 2009): *log(Assets)*, *ROA*, *Debt to assets*, *Cash to assets*, *Cash flow to assets*, *Tobin's q*, *PPE to assets*, and *IO block*.[39] Each firm's IPO cohort is defined by the number of years since the firm's first appearance in CRSP.

Table 6 shows the results. The estimated coefficients on *Asset beta* are negative in all four columns and statistically significant at the 10% level in Column 1 and at the 5% level in Columns 2 to 4. This finding supports the prediction that public firms' probability of receiving bids decreases with their asset beta.[40]

39 The explanatory variables for a bid in year t are measured at the end of year $t-1$. The standard errors are clustered by industry.

40 An unreported robustness check confirms that the estimated coefficients on *Asset beta* are also negative and statistically significant if we estimate a conditional logit model instead of the linear probability model reported in Table 6.

A closely related prediction is that the average beta of private targets is larger than that of public targets. The intuition is that the owners of private firms do not have the outside option of selling their shares in the stock market. Consequently, while public targets tend to have lower average betas as successful bids must exceed their beta-insensitive market valuations, this effect is less present for private targets. As a result, private targets tend to have higher betas than public targets. A simple t-test suggests that the average asset beta of the private targets in our data is indeed larger than that of the public targets. When we cluster the standard errors by target industry, the difference in average asset betas becomes statistically insignificant if we only consider acquisitions with nonmissing deal values of at least USD 50 million (as we do in our analyses of bidder CARs). However, the difference remains significant if we consider all acquisitions by U.S. bidders in SDC (excluding share repurchases).

3.7 Method of payment

We now examine the relation between bidders' asset betas and the method of payment in takeovers. Bidders who believe their own stock to be overvalued by the market are more likely to propose payment in stock than in cash (Shleifer and Vishny 2003). Hence, if bidders rely on the CAPM when assessing the value of their own equity, high beta bidders should be more likely than low beta bidders to propose stock as the method of payment.[41] To test this prediction, we estimate the following OLS regression:

$$\begin{aligned} \textit{100\% stock} = {} & \alpha + \beta \times \textit{Bidder asset beta} + \gamma \times \textit{Target asset beta} + \delta' \textit{Deal controls} \\ & + \eta' \textit{Target controls} + \kappa' \textit{Bidder controls} + \textit{Target industry} \\ & \times \textit{Year fixed effects} + \varepsilon, \end{aligned} \tag{21}$$

where *100% stock* is an indicator equal to one if the bidder proposes to pay entirely with stock.[42] *Bidder (Target) asset beta* are the bidder's and target's asset beta. All other variables are defined as before. The standard errors are clustered by bidder industry.

Table 7 presents the results. The estimated coefficients on *Bidder asset beta* are positive and statistically significant in all five columns, supporting the prediction that high beta bidders are more likely to offer stock based payment rather than cash. This is consistent with Baker, Hoeyer, and Wurgler's (2019) finding that firms' leverage decreases with beta. In the same spirit, another related prediction would be that, even in the absence of M&A activity, high beta firms should be more likely to issue equity and less likely to repurchase shares. Appendix E presents empirical evidence consistent with this prediction.

41 An implicit assumption is that bidders do not perceive cash as being equally misvalued as equity.

42 Table A.6 in the appendix shows that our findings are robust to using other variables to capture the propensity to pay with stock, and Table A.7 shows that using equity betas rather than asset betas does not change the results.

Table 7
Method of payment

	(1)	(2)	(3)	(4)	(5)
Sample:			Private and public targets		
Dependent variable:			100% stock		
Bidder asset beta	9.50***	13.58***	8.20***	7.95***	8.26***
	(4.01)	(6.60)	(5.23)	(4.65)	(4.61)
Target asset beta					−1.22
					(−0.53)
log(Deal value)		3.41***	3.47***	3.47***	3.49***
		(7.00)	(7.04)	(7.05)	(7.10)
Toehold		−7.11***	−6.22***	−6.38***	−6.41***
		(−2.93)	(−2.64)	(−2.67)	(−2.69)
Hostile		−7.57***	−8.48***	−8.84***	−8.75***
		(−3.99)	(−3.65)	(−3.79)	(−3.75)
Same industry		0.39	0.09	0.04	−0.02
		(0.30)	(0.11)	(0.04)	(−0.02)
Cross-border		−5.55***	−5.45***	−5.33***	−5.15***
		(−5.47)	(−5.58)	(−5.58)	(−5.59)
Poison		15.91***	16.16***	16.18***	15.94***
		(8.71)	(8.81)	(9.10)	(9.23)
Tender		−16.92***	−16.05***	−15.75***	−15.81***
		(−10.28)	(−10.52)	(−10.55)	(−10.60)
Multiple bidders		−0.37	−0.42	−0.43	−0.39
		(−0.28)	(−0.27)	(−0.28)	(−0.25)
Relative size		−0.14***	−0.11***	−0.12***	−0.12***
		(−3.57)	(−3.00)	(−3.13)	(−3.17)
log(Bidder size)		−1.52***	−1.26***	−1.27***	−1.28***
		(−4.97)	(−4.44)	(−4.40)	(−4.41)
Target SDC industry × Year FE	Yes	Yes	Yes	Yes	Yes
Bidder controls	No	No	Yes	Yes	Yes
Target controls	No	No	No	Yes	Yes
Observations	25,772	21,063	18,762	18,423	18,348

This table presents OLS estimates of the sensitivity of the propensity to offer an all-stock payment to the bidder's asset beta (*Bidder asset beta*). The sample period is 1977 to 2015. *100% stock* is an indicator equal to one if the proposed payment is 100% stock. Tables 2 and A.1 in the appendix define all other variables. t-statistics, based on standard errors clustered by the bidder's (SIC3-) industry, are reported in parentheses. *p <.1; **p <.05; ***p <.01.

4. Alternative Explanations

4.1 Do managers really use the CAPM?

Our prediction of a positive relation between bidder CARs and target betas rests on the premise that managers use the CAPM to compute discount rates. Surveys among corporate executives and valuation professionals support this assumption: The vast majority of respondents state that they always or almost always use the CAPM (Graham and Harvey 2001; Jacobs and Shivdasani 2012; Mukhlynina and Nyborg 2016).

To provide further support, we test the basic implication that the discount rate used to value a target is increasing in its asset beta. To do so, we obtain data on the maximum and minimum discount rates used in fairness opinions on the proposed takeovers. SDC Platinum provides this information for 1,181 bids in our sample. For each of these bids, we compute the average of the maximum and minimum discount rate used in the fairness opinion (*Avg. discount rate*) and estimate by OLS:[43]

$$\begin{aligned} \textit{Avg. discount rate} &= \alpha+\beta\times \textit{Target asset beta}+\gamma\times \textit{Beta spread} \\ &\quad +\delta\times \textit{log(Deal value)}+\eta\times \textit{Public target} \\ &\quad +\textit{Year fixed effects}+\varepsilon. \end{aligned} \tag{22}$$

We control for *log(Deal value)* and *Public target* because the providers of fairness opinions may adjust the discount rate upwards for small and private targets due to their lower liquidity.

Panel A of Table 8 presents the results. In Column 1, we only control for year fixed effects. In Column 2, we add *log(Deal value)* and *Public target*. In Column 3, we add *Beta spread*. The standard errors are clustered by target industry. The coefficient estimate on *Target asset beta* is positive and statistically significant at the 1% level in all three columns. This finding supports the premise that the CAPM is used to estimate discount rates in practice. The magnitude of the coefficient estimate (3% to 4%) is likely to be a lower bound for the market risk premium used in the fairness opinions. One reason is an attenuation bias due to measurement error: *Target asset beta* may be a noisy estimate of the beta actually used to compute the discount rate. Another reason is that, for public targets, fairness opinion providers may upward-adjust (downward-adjust) the market risk premium used to compute the discount rate if the implied value of the target exceeds (falls short of) its current market capitalization by a sufficiently large amount. Adjusting the market risk premium—and thus the discount rate—in this manner to bring the fairness opinion closer to the current market price naturally reduces the coefficient estimate on *Target asset beta* in our regressions.

Another way to assess whether the CAPM is used in practice is to examine how closely the cost of capital that is implied by *Target asset beta* corresponds to the average discount rate that is used in the fairness opinions (*Avg. discount rate*). In Appendix D, we thus regress this average discount rate on the cost of capital that is implied by *Target asset beta* when making the same assumptions regarding all other parameters as in the model calibration in Section 4.3. We find that the "*Target asset beta*-implied" cost of capital indeed corresponds closely to the variable *Avg. discount rate* precisely in those cases where the spread between the maximum and minimum rate in the fairness opinion is small, that is, if the midpoint between the two rates is more likely to be an accurate estimate of the discount rate that was actually used by the bidder.

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43 We use a simple average of the two discount rates for simplicity. If the providers of the fairness opinions pick the maximum and minimum discount rate so that the average target value that is implied by the two rates is equal to the actual bid (thereby making the bid look "fair"), then a simple average overestimates the actual discount rate used for the bid. The reason is Jensen's inequality: $\frac{1}{2}\left(\frac{1}{r_{max}}+\frac{1}{r_{min}}\right)=\frac{1}{r_{actual}} \Rightarrow \textit{Avg. discount rate} \equiv \frac{r_{max}+r_{min}}{2} \geq 2\left(\frac{1}{r_{max}}+\frac{1}{r_{min}}\right)^{-1}=r_{actual}$. An alternative thus would be to use a harmonic average, that is, to define $\textit{Avg. discount rate} \equiv 2\left(\frac{1}{r_{max}}+\frac{1}{r_{min}}\right)^{-1}$. Doing so does not qualitatively change our findings.

Table 8
Discount rates used in fairness opinions, bid-implied valuations, and takeover premiums

A	(1)	(2)	(3)
Sample:	Private and public targets		
Dependent variable:	Avg. discount rate used in fairness opinion DCF (in percentage points)		
Target asset beta	3.03***	3.69***	3.99***
	(5.76)	(12.92)	(11.19)
Beta spread			−1.81**
			(−2.46)
log(Deal value)		−1.30***	−1.30***
		(−8.90)	(−9.17)
Public target		−0.88***	−0.94***
		(−2.85)	(−2.99)
Year FE	Yes	Yes	Yes
Observations	1,174	1,174	1,171

B	(1)	(2)	(3)	(4)
Sample:	Private and public targets			
Dependent variable:	log(Deal value)	FV/sales	FV/EBIT	Premium
Target asset beta	−0.20***	−2.58***	−8.47***	−0.49***
	(−2.63)	(−2.72)	(−2.66)	(−2.51)
Bidder SDC industry × Year FE	Yes	Yes	Yes	Yes
Deal controls	Yes	Yes	Yes	Yes
Target controls	Yes	Yes	Yes	Yes
Bidder controls	Yes	Yes	Yes	Yes
Observations	18,370	4,196	3,116	3,935

This table presents OLS estimates of the sensitivity of the average discount rate (*Avg. discount rate*) used in fairness opinions on M&A bids (panel A) as well as bid-implied target valuations and takeover premiums (panel B) to the target's asset beta. The sample period is 1977 to 2015. *Public target* is an indicator for public targets. *FV/sales* and *FV/EBIT* are the ratios of the bid-implied target values to sales and EBIT. *Premium* is the percentage premium of the bid-implied equity value over the target's market capitalization 6 months prior to the bid. As prebid market prices are available only for public targets, *Premium* is missing for private targets. *Deal controls* comprises *Beta spread*, *log(Deal value)* (omitted in Column 1 of panel B), *Equity*, *Cash*, *Toehold*, *Hostile*, *Same industry*, *Cross-border* (omitted in Columns 2 and 3 of panel B), *Poison*, *Tender*, *Multiple bidders*, *Relative size*, and *log(Bidder size)*. Tables 2 and A.1 in the appendix define the variables. t-statistics, based on standard errors clustered by the target's (SIC3-) industry, are reported in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

We test another basic implication of using the CAPM: The bidder's assessment of the target's value and the takeover premium are decreasing in beta. Specifically, we estimate by OLS:

$$\begin{aligned}&\textit{Bid-implied valuation (Premium)}\\&\quad=\alpha+\beta\times \textit{Target asset beta}+\gamma\times \textit{Beta spread}\\&\qquad+\delta'\textit{Deal controls}+\eta'\textit{Target controls}+\kappa'\textit{Bidder controls}\\&\qquad+\textit{Bidder industry}\times\textit{Year fixed effects}+\varepsilon,\end{aligned}\tag{23}$$

where *Bid implied valuation* and *Premium* are the value of the target and the takeover premium as implied by the bid. All other variables are defined as before. The standard errors are clustered by target industry.

Panel B of Table 8 presents the results. In Column 1, we use the natural logarithm of the value of the bid (in USD million) as the dependent variable.[44] In Column 2, we us the bid-implied firm value (FV) scaled by the target's sales. In Column 3, we scale the firm value by EBIT.[45] In Column 4, we use the bid-implied premium relative to the target's market capitalization 6 months prior to the bid announcement.[46]

The coefficient estimates on *Target asset beta* are negative and statistically significant at the 1% level in all four columns. This finding is important for three reasons. First, it corroborates the premise that the CAPM is used to compute discount rates. Second, it supports the basic prediction that a bidder's assessment of a target's value is decreasing in the target's asset beta. Third, it suggests that acquisitions of high beta targets do not generate larger synergies than acquisitions of low beta targets. Otherwise, one would expect the bid-implied valuations and premiums to be increasing in beta. This last point is important as it implies that the positive relation between bidder CARs and target asset betas is unlikely to be driven by a positive correlation between the targets' asset betas and the value of synergies. The findings in Table 8 also give additional credibility to our measure *Target asset beta*. Although this measure may be noisy, it is strongly correlated with the average discount rate used in fairness opinions and the bid-implied valuations and takeover premiums.

4.2 Do CAPM-betas correlate with future cash flows or synergies?

A potential concern regarding the interpretation of our findings is that firms' asset betas may be correlated with the firms' expected free cash flows or the synergies that can be generated by a takeover. In that case, bids for high beta targets may entail higher bidder CARs because acquisitions of high beta firms create more value. Our IV analysis suggests that such biases cannot be too large (as the IV estimates are not statistically different from the OLS estimates) but to double check, we now examine the relation between firms' asset betas and future (realized) free cash flows as well as the relation between targets' asset betas and the combined cumulative abnormal returns of bidders and targets. We begin with the relation between asset betas and future (realized) free cash flows and estimate the following OLS regression for all public firms in Compustat between 1977 and 2015:

$$\frac{FCF}{assets} = \alpha + \beta \times Asset\ beta + \gamma' Firm\ characteristics + Year\ fixed\ effects + \varepsilon. \tag{24}$$

[44] As a consequence, we do not include *log(Deal value)* as a control variable in Column 1.

[45] Information on sales and EBIT is missing for non-U.S. targets in our sample. The indicator for cross-border bids (*Cross-border*) is therefore not included in Columns 2 and 3.

[46] Our findings are robust to using the 1-day, 1-month, 3-month, or 9-month premium instead.

Table 9
Future realized free cash flows

	(1)	(2)	(3)	(4)
Sample:	Public firms in Compustat			
Dependent variable:	$\frac{\text{FCF}_t}{\text{assets}_t}$	$\frac{\text{FCF}_{t+1}}{\text{assets}_{t+1}}$	$\frac{\text{FCF}_{t+2}}{\text{assets}_{t+2}}$	$\frac{\text{FCF}_{t+3}}{\text{assets}_{t+3}}$
Asset beta$_{t-1}$	−0.32	−0.10	−0.34	−0.43
	(−0.20)	(−0.06)	(−0.22)	(−0.29)
log(Market capitalization)$_{t-1}$	1.06***	1.29***	1.45***	1.47***
	(4.42)	(4.94)	(5.87)	(6.16)
Market-to-book$_{t-1}$	−0.42***	−0.40***	−0.34***	−0.29***
	(−6.22)	(−5.58)	(−4.81)	(−3.66)
Cash to assets$_{t-1}$	−17.14***	−16.07***	−15.04***	−14.30***
	(−6.50)	(−4.65)	(−3.88)	(−3.50)
Debt to assets$_{t-1}$	5.18***	4.67***	3.80**	3.28**
	(3.22)	(2.78)	(2.21)	(1.98)
ROA$_{t-1}$	−4.84	4.09	2.81	7.43
	(−0.51)	(0.41)	(0.36)	(0.89)
Cash flow to assets$_{t-1}$	36.21***	24.57**	22.96***	15.86*
	(3.54)	(2.33)	(2.83)	(1.88)
Year FE	Yes	Yes	Yes	Yes
Observations	208,399	187,045	168,898	152,541

This table presents OLS estimates of the sensitivity of a firm's realized free cash flows in future periods scaled by total assets (*FCF/assets*) to the firm's lagged asset beta. All reported coefficient estimates have been multiplied with 100 to improve readability. The sample period is 1977 to 2015. All public firms in Compustat are included. Table A.1 in the appendix provides detailed definitions of all variables. t-statistics, based on standard errors clustered by (SIC3-) industry, are reported in parentheses. *p <.1; **p <.05; ***p <.01.

FCF/assets is free cash flows scaled by total assets.[47] *Firm characteristics* comprises the following variables: *log(Market capitalization)*, *Market-to-book*, *Cash to assets*, *Debt to assets*, *ROA*, and *Cash flow to assets*. All variables are defined as before. The standard errors are clustered by industry.

Table 9 presents the results. We do not find any evidence of a relation between asset betas and future free cash flows. This result suggests that the relation between bidder CARs and target asset betas is unlikely to be driven by a correlation between asset betas and free cash flows.

Next, we assess the relation between synergies and asset betas by regressing the combined CARs of bidders and targets (*Combined CAR*) on the targets' asset betas.[48] Specifically, we estimate by OLS:

$$\begin{aligned}\textit{Combined CAR} = {} & \alpha+\beta\times \textit{Target asset beta}+\gamma\times \textit{Beta spread}+\delta'\textit{Deal controls}\\ & +\eta'\textit{Target controls}+\kappa'\textit{Bidder controls}\\ & +\textit{Bidder industry}\times \textit{Year fixed effects}+\varepsilon \end{aligned} \tag{25}$$

All variables are defined as before. The standard errors are clustered by target industry.

[47] *FCF/assets* is [EBIT $\times(1-\tau)$+D&A−CAPEX−ΔNWC]/ASSETS, where τ is the tax rate, D&A depreciation and amortization, CAPEX capital expenditures, ΔNWC the increase in net working capital, and ASSETS the book value of total assets.

[48] A caveat is that we can compute the combined CAR of bidders and targets only if the targets are public.

Table 10
Combined CARs of bidders and targets

	(1)	(2)	(3)	(4)
Sample:	Public targets			
Dependent variable:	Combined CAR (in percentage points)			
Target asset beta	−0.60	−0.85	−0.76	0.21
	(−1.07)	(−1.29)	(−1.04)	(0.18)
Beta spread				−1.29
				(−1.17)
Bidder SDC industry × Year FE	Yes	Yes	Yes	Yes
Deal controls	Yes	Yes	Yes	Yes
Target controls	No	Yes	Yes	Yes
Bidder controls	No	No	Yes	Yes
Observations	5,079	4,261	3,992	3,949

This table presents OLS estimates of the sensitivity of the combined cumulative abnormal returns of the bidder's and target's stock during the 7-day window around the bid announcement (*Combined CAR*) to the target's asset beta. The sample period is 1977 to 2015. Only public targets are included. *Deal controls* is a vector comprising all deal-level controls included in Columns 2 to 4 of Table 2: *log(Deal value)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same industry*, *Cross-border*, *Poison*, *Tender*, *Multiple bidders*, *Relative size*, and *log(Bidder size)*. Tables 2 and A.1 in the appendix define the variables. t-statistics, based on standard errors clustered by the target's (SIC3-) industry, are reported in parentheses. *p <.1; **p <.05; ***p <.01.

Table 10 presents the results. We do not find any evidence of a relation between *Target asset beta* and *Combined CAR*. This result is another piece of evidence suggesting that the relation between bidder CARs and target asset betas is not driven by unobserved differences in synergies.

5. Are CAPM-Using Managers Rational?

5.1 Why do managers use the CAPM?

Our findings raise the question why managers use the CAPM in the first place. We do not take a strong stance on this issue. Instead, based on existing survey evidence and the CAPM's prominent role in major textbooks, we take the use of the CAPM as given and focus on the consequences thereof.[49] Nonetheless, we now delineate a number of potential explanations for the widespread use of the CAPM in practice.

One possibility is that the CAPM is the true model of the relation between risk and expected returns in the long run, but that the stock market is inefficient. In that case, using the CAPM can be optimal for rational managers that seek to maximize the long-term value of financially unconstrained firms, even if returns deviate from the CAPM in the short run (Stein 1996).[50] Another possibility is that the CAPM is not the true model but that managers are not aware of this.

49 See, for example, Berk and DeMarzo (2017), Brealy, Myers, and Allen (2016), Graham and Harvey (2001), Jacobs and Shivdasani (2012), Mukhlynina and Nyborg (2016), and Ross et al. (2016).

50 It is further possible that the CAPM is the correct model of the relation between risk and expected returns for firms' individual investment projects, but not for the firms' shares, which are backed not only by the firms' projects but also by the real options to start, modify, or abandon these projects (Berk, Green, and Naik 1999; Da, Guo, and Jagannathan 2012).

In particular, corporate managers and their M&A advisors may not be aware of the relation between target betas and bidder CARs. Learning about this relation may be difficult because most managers experience only a limited number of takeovers and thus receive only infrequent feedback on their M&A decisions. M&A advisors experience a larger number of deals but are typically organized in sector teams and specialize on particular industries. As a result, they may not experience sufficient variation in target betas to learn about the relation to bidder CARs. It is also possible that managers and their advisors are aware of the divergence between CAPM-implied and realized returns but that they underestimate the extent to which the CAPM fails empirically or the importance of using accurate discount rates. In that case, they may prefer to use the CAPM instead of alternative models that are more accurate but also more difficult to implement or communicate to clients, colleagues, or superiors.

Related to the question why corporate managers and their M&A advisors use the CAPM is the question why other investors (e.g., traders in the stock market) use different models. One possibility are differences in rationality: corporate managers and their M&A advisors may be irrational while market traders are rational or vice versa. Differences in beliefs may then lead to differences in model usage. Another possibility is that corporate managers, M&A advisors, and market traders are constrained (e.g., in terms of time, attention, or resources) and in response focus on what they believe to be their relative advantage: Managers may believe that they create value through real actions (e.g., choosing a better corporate strategy or developing better products) rather than identifying undervalued assets. Consequently, they may be willing to rely on of-the-shelve valuation techniques, including the CAPM, even though they know that these techniques are not perfect. M&A advisors may see their competitive advantage in negotiating takeovers and deal management, not in estimating discount rates.[51] Instead, market traders who focus on identifying misvalued assets may see their edge in using better valuation models than the CAPM.

5.2 Should managers use the CAPM?

Closely related to the question *why* managers use the CAPM is the normative question if they *should* use the CAPM. The answer crucially depends on the question of market efficiency. One possibility is that the stock market is efficient in the sense that prices reflect fundamentals and expected returns compensation for risk only. This would imply that the difference between the empirical SML and the CAPM-implied SML reflects compensation for risk, and the higher

[51] Consistent with this view, Mukhlynina and Nyborg (2016), p. 1) quote one of the respondents to their survey as saying: “there seem to be lots of academics asking how analysts in the real world use CAPM or calculate the cost of capital. The answer is, people don’t waste time on this. No one ever lost/made money because they calculated the WACC better than consensus.”

(lower) bidder CARs around bids for higher (lower) beta targets are due to valuation mistakes by CAPM-using managers. This view would be consistent with the lack of conclusive evidence in favor of the CAPM in the existing asset pricing literature. In that case, the normative implication is that managers should not use the CAPM but instead rely on whatever statistical model provides the best estimate of the relation between project risk and expected returns (Stein 1996).

The other possibility is that the market is inefficient, and the higher (lower) bidder CARs around bids for higher (lower) beta targets are due to temporary mispricing by the market. In that case, managers should use the model that correctly maps risk to expected returns in the long run, even if it has no predictive power in the short run (Stein 1996).[52] That is, if the market is inefficient, managers should use the CAPM if it is the "true" model of the relation between risk and expected returns.[53] This would be consistent with Cohen, Polk, and Vuolteenaho's (2009) finding that betas based on accounting cash flows forecast long-term returns.

The answer to the question "Should managers use the CAPM?" thus depends on the answer to (1) "Is the stock market efficient in the sense that prices reflect fundamentals and expected returns compensation for risk only?" and, if not, (2) "Is the CAPM the true model of the relation between risk and expected returns?"[54] We (and the existing asset pricing literature) cannot provide a definitive answer to these questions. However, in what follows, we present some suggestive evidence that managers should not use the CAPM (at least not in its simple textbook form and in an M&A context).

5.3 Some suggestive evidence

We first examine bidders' abnormal returns in the long run. The idea is as follows. If the CAPM is a good model of expected returns in the long run, then the relation between bidder abnormal returns and target asset betas observed during short periods around bid announcements should disappear over longer horizons as the market eventually learns that managers were right to use the CAPM. We thus compute the bidders' buy-and-hold abnormal returns (*Bidder*

[52] Here, we assume that the objective is to maximize the long-term value of financially unconstrained firms. If firms are financially constrained or managers interested in maximizing short-term stock prices, relying on whatever statistical model produces the best prediction of returns in the short run, even if the predictability is due to mispricing, can be optimal (Stein 1996).

[53] This poses a well-known conundrum: It is difficult to empirically validate the CAPM with data generated in an inefficient market, that is, if realized prices and returns may reflect mispricing rather than fundamentals and compensation for risk.

[54] The well-documented discrepancy between the empirical SML and the CAPM-implied SML is inconsistent with the hypothesis that the market is efficient and the CAPM true, so we do not consider this alternative.

BHAR) over different horizons and estimate the following OLS regression:

$$\begin{aligned} \textit{Bidder BHAR} = {} & \alpha+\beta\times \textit{Target asset beta}+\gamma\times \textit{Beta spread} \\ & +\delta'\textit{Deal controls}+\eta'\textit{Target controls} \\ & +\kappa'\textit{Bidder controls}+\textit{Bidder industry}\times\textit{Year fixed effects}+\varepsilon. \end{aligned} \tag{26}$$

All explanatory variables are defined as before. The standard errors are clustered by target industry.

Table 11 shows the results. Column 1 mirrors the findings of Table 2. The bidders' buy-and-hold abnormal returns during the 7 days around the bid announcements are increasing in the targets' asset betas. Columns 2 to 5 show no evidence of subsequent reversal: The abnormal buy-and-hold returns are not statistically different from zero starting from four trading days after the bid announcements. The positive and statistically significant coefficient estimates in Columns 6 to 9 corroborate this result: Bidder BHARs from three trading days before the bid announcements up to 400 trading days after the announcements are positively related to target asset betas. This finding suggests that bidders' use of the CAPM has long-lasting wealth effects for investors. A caveat is that this test lacks power (as do most long-run return studies).

As a second test, we examine if the relation between bidder CARs and target asset betas depends on bidders' corporate governance and managerial entrenchment. The idea is rooted in bounded rationality: using a more accurate model than the CAPM is cognitively costly, so managers only do it when they have something to gain from it. Assuming that better governance and lower entrenchment make managers act more in line with what shareholders want, bidders with better corporate governance and less entrenched managers should thus be less likely to use the CAPM if shareholders believe that doing so is "wrong."

To test this prediction we estimate OLS regressions in which we interact *Target asset beta* with proxies for bidder governance and entrenchment:[55] *Institutional ownership* is the fraction of shares owned by institutional investors. *Insider ownership* is the fraction of shares owned by the five highest paid executives. *Wealth performance sensitivity* is the performance sensitivity measure of Edmans, Gabaix, and Landier (2009). *Board independence* is the fraction of independent directors. *Antitakeover index* is the antitakeover index of Bebchuk, Cohen, and Ferell (2004). The standard errors are clustered by target industry.

Table 12 presents the results. We find that the relation between bidder CARs and target betas is significantly weaker if the bidders have higher institutional ownership, if the bidder CEOs' wealth-performance-sensitivity is higher, and if the bidders' management is less entrenched through antitakeover provisions.

55 We also interact all controls and fixed effects.

Table 11
Bidder buy-and-hold abnormal returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample:	Private targets								
Dependent variable:	Bidder BHAR (in percentage points)								
Event window:	[−3, +3]	[+4, +100]	[+4, +200]	[+4, +300]	[+4, +400]	[−3, +100]	[−3, +200]	[−3, +300]	[−3, +400]
Target asset beta	2.75***	0.42	2.82	4.50	6.47	3.63*	6.21**	7.49*	8.95*
	(4.29)	(0.22)	(0.96)	(1.09)	(1.35)	(1.75)	(2.08)	(1.88)	(1.88)
Bidder SDC ind. × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Target controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bidder controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,281	10,220	10,038	9,817	9,578	10,219	10,037	9,816	9,577

This table presents OLS estimates of the sensitivity of the buy-and-hold abnormal return of the bidder's stock over different event windows (*Bidder BHAR*) to the target's asset beta. [x,y] denotes an event window from $t=x$ to $t=y$ for a bid announced on date $t=0$. The sample period is 1977 to 2015. Only bids for private targets are included. *Deal controls* is a vector comprising all deal-level controls included in Column 5 of Table 2: *Beta spread*, *log(Deal value*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same industry*, *Cross-border*, *Poison*, *Tender*, *Multiple bidders*, *Relative size*, and *log(Bidder size)*. Tables 2 and A.1 in the appendix define the variables. t-statistics, based on standard errors clustered by the target's (SIC3-) industry, are reported in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

Table 12
Variation in corporate governance and managerial entrenchment

	(1)	(2)	(3)	(4)	(5)
Sample:	Private targets				
Dependent variable:	Bidder CAR (in percentage points)				
Target asset beta × Institutional ownership	−7.46***				
	(−2.56)				
Target asset beta × Insider ownership		−3.30			
		(−1.25)			
Target asset beta × Wealth-performance sensitivity			−0.02**		
			(−2.25)		
Target asset beta × Board independence				−1.92	
				(−1.05)	
Target asset beta × Antitakeover index					1.07**
					(1.96)
Target asset beta	7.51***	2.88*	2.46***	2.96**	−1.66
	(3.70)	(1.93)	(3.56)	(2.09)	(−0.97)
Bidder SDC industry × Year FE (Interacted)	Yes	Yes	Yes	Yes	Yes
Deal controls (interacted)	Yes	Yes	Yes	Yes	Yes
Target controls (interacted)	Yes	Yes	Yes	Yes	Yes
Bidder controls (interacted)	Yes	Yes	Yes	Yes	Yes
Observations	11,784	1,942	7,017	4,467	5,561

This table presents OLS estimates of the sensitivity of the cumulative abnormal return of the bidder's stock during the 7-day window around the bid announcement (*Bidder CAR*) to the target's asset beta as a function of the bidder's corporate governance and managerial entrenchment. The sample period is 1977 to 2015. Only bids for private targets are included. *Institutional ownership* is the percentage of outstanding shares of the bidder that are owned by institutional investors. *Insider ownership* is the percentage of outstanding shares of the bidder owned by the five highest paid executives of the bidder. *Wealth performance sensitivity* is the performance sensitivity measure of Edmans, Gabaix, and Landier (2009) for the bidder's CEO. *Board independence* is the percentage of independent directors on the bidder's board. *Antitakeover index* is the antitakeover index of Bebchuk, Cohen, and Ferell (2004) for the bidder. *Deal controls* is a vector comprising all deal-level controls included in Column 5 of Table 2: *Beta Spread*, *log(Deal value)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same industry*, *Cross-border*, *Poison*, *Tender*, *Multiple bidders*, *Relative size*, and *log(Bidder size)*. Tables 2 and A.1 in the appendix define the variables. *(Interacted)* indicates that all control variables and fixed effects are interacted with the governance or entrenchment characteristic of interest. t-statistics, based on standard errors clustered by the target's (SIC3-) industry, are reported in parentheses. *p <.1; **p <.05; ***p <.01.

The coefficient estimates on the interaction terms between *Target asset beta* and *Insider ownership* and *Board independence* are also negative, but not statistically significant.

In sum, the results indicate that better governance and lower entrenchment make bidders less likely to use the CAPM. One possible explanation for this finding is that shareholders know that the CAPM is "wrong" but that using a more accurate model is cognitively costly, so that managers only do so if governance is good or entrenchment low. Another possibility, however, is that shareholders merely believe that the CAPM is "wrong," even though it is not. Consequently, the results of Table 12 cannot conclusively rule out the possibility that the CAPM is "right."

Using the CAPM appears not to be what shareholders want, so a natural question is what should be done instead. Ultimately, managers of unconstrained firms with long horizons should use the model that correctly describes the true relation between risk and expected returns (Stein 1996). The problem is that the existing asset pricing literature does not agree about what this model is. This lack of consensus prevents us from providing a clear-cut prescription *which* model should be used. A pragmatic approach might be to start with the CAPM, which is appealing for both its simplicity and theoretical foundation, but to shrink the beta estimates as suggested in Levi and Welch (2017). This would be consistent with an interpretation of our results whereby managers overestimate the slope of the true SML. The results could then be complemented with estimates from multifactor or characteristics based models, models that exploit information in option prices, and valuations based on multiples, so as to produce a valuation range for a potential takeover target.[56]

6. Conclusion

The CAPM is the predominant model of risk and return taught by academics and used by practitioners to estimate the cost of capital. However, the CAPM does not fit the data: The empirical SML is flatter than the CAPM implies. We show that the widespread use of the CAPM has real effects, in particular, for firms' capital budgeting decisions and the market's reaction thereto. Using M&A data on bids for private targets, we show that acquirers experience significantly lower cumulative abnormal returns when announcing bids for low rather than high beta targets and estimate that using the CAPM in this context leads to valuation errors (relative to the market's view) that correspond, on average, to 12% to 33% of the deal values.

The normative implications of our study ultimately depend on how the debate about the veracity of the CAPM is settled. One view is that the CAPM holds in the long run, but that the market is inefficient. According to this view, our findings reflect temporary mispricing by the market, and managers are right to use the CAPM. An alternative view is that the market is efficient and the CAPM fails to explain expected returns, even in the long run. According to that view, our findings reflect valuation mistakes by bidders and sellers, and managers should not use the CAPM. While it is difficult to empirically distinguish the two alternatives, our analyses provide some suggestive evidence that managers should not use the CAPM (at least not in its simple textbook form and in an M&A context).

Appendix to "CAPM-Based Company (Mis)valuations"

Appendix A. Model Extensions and Derivations

A.1 Model Extension: Relaxing Assumptions (AI) and (AII)

We consider a bidder that seeks to acquire a fraction $\pi \in (0,1]$ of a private firm's equity. If acquired, the value of the equity stake as assessed by the bidder and seller is[57]

$$\pi E_t = \pi \times \left[V_t^A + \Delta_t - D_t + S_t(\pi)\right]. \tag{A1}$$

[56] See, for example, Carhart (1997), Daniel et al. (1997), Daniel and Titman (1997), Fama and French (1993), Liu, Nissim, and Thomas (2002), and Martin and Wagner (2018).

[57] We allow the value of the synergies to depend on the fraction of equity acquired by the bidder to capture the notion that the size of the stake may affect the bidder's ability and incentives to unlock synergies.

In exchange for the fraction $\pi \in (0,1]$ of the target's equity, the bidder offers an amount B_t. The seller's outside option is to reject the bidder's offer and retain an equity stake valued at

$$V_t^A + \Delta_t - D_t. \tag{A2}$$

Alternatively, the seller can accept the offer and retain an equity stake valued at

$$(1-\pi)\times\left[V_t^A + \Delta_t - D_t + S_t(\pi)\right]. \tag{A3}$$

The Nash bargaining solution implies that the bidder's offer must satisfy

$$V_t^A + \Delta_t - D_t + \alpha S_t(\pi) \;=\; (1-\pi)\times\left[V_t^A + \Delta_t - D_t + S_t(\pi)\right] + B_t \tag{A4}$$

$$\Leftrightarrow$$

$$B_t \;=\; \pi\times\left[V_t^A + \Delta_t - D_t\right] + \alpha S_t(\pi) - (1-\pi)\times S_t(\pi). \tag{A5}$$

The bid corresponds to the stand-alone value of the equity stake, plus a fraction α of the synergies, minus the increase in value of the seller's remaining equity stake that is due to the synergies.[58] The cumulative abnormal return of the bidder's stock in response to the bid announcement is given by

$$CAR_t^{Bidder} = \frac{\pi\,\widetilde{E}_t - B_t}{E_t^{Bidder}}, \tag{A6}$$

where

$$\pi\,\widetilde{E}_t = \pi\times\left[\widetilde{V}_t^A + \widetilde{\Delta}_t - \widetilde{D}_t + \widetilde{S}_t(\pi)\right] \tag{A7}$$

is the value of the equity stake (conditional on its acquisition by the bidder) as assessed by the market, and E_t^{Bidder} is the bidder's market capitalization. Equations (A5) and (A7) can be written as

$$B_t = \pi\sum_{\tau=t+1}^{\infty}\left[\frac{FCF_\tau}{(1+r_A)^{\tau-t}} + \frac{\delta_\tau}{(1+r_\Delta)^{\tau-t}} - \frac{d_\tau}{(1+r_D)^{\tau-t}}\right] - (1-\pi-\alpha)\sum_{\tau=t+1}^{\infty}\frac{s_\tau(\pi)}{(1+r_S)^{\tau-t}} \tag{A8}$$

and

$$\pi\,\widetilde{E}_t = \pi\sum_{\tau=t+1}^{\infty}\left[\frac{FCF_\tau}{(1+\widetilde{r}_A)^{\tau-t}} + \frac{\delta_\tau}{(1+\widetilde{r}_\Delta)^{\tau-t}} - \frac{d_\tau}{(1+\widetilde{r}_D)^{\tau-t}}\right] + \pi\sum_{\tau=t+1}^{\infty}\frac{s_\tau(\pi)}{(1+\widetilde{r}_S)^{\tau-t}}. \tag{A9}$$

The appropriate discount rates as assessed by the bidder and market are given by

$$r_i = r_f + \beta_i \times \mu \;\; for\;\; i \in \{A, \Delta, D, S\} \tag{A10}$$

and

$$\widetilde{r}_A = r_f + \left[\gamma\times\beta_A + (1-\gamma)\times\overline{\beta}_A\right]\times\mu, \tag{A11}$$

where r_f is the risk-free rate, μ the market risk premium, and $\overline{\beta}_A$ the average asset beta in the economy.[59] That is, we assume that the empirical SML has a slope of $\gamma\times\mu$ for some $\gamma\in[0,1]$

[58] The derivation assumes that the bidder does not have a toehold in the target when making the bid. If the bidder has a toehold $\omega\in(0,1)$, then the seller must decide between rejecting the bid and retaining a stake valued at $(1-\omega)\times\left[V_t^A + \Delta_t - D_t\right]$ or accepting the bid and retaining a stake valued at $(1-\pi-\omega)\times\left[V_t^A + \Delta_t - D_t + S_t(\pi)\right]$. In that case, the bidder's offer must satisfy $B_t = \pi\times\left[V_t^A + \Delta_t - D_t\right] + \alpha S_t(\pi) - (1-\pi-\omega)\times S_t(\pi)$.

[59] If the portfolio of all assets in the economy constitutes the true (CAPM-)market portfolio, then the average asset beta is equal to one (by construction). Note, however, that our predictions do not depend on $\overline{\beta}_A = 1$, so we do not impose this condition.

and crosses the CAPM-implied SML at the average asset beta ($\overline{\beta}_A$). We assume that the systematic risk of the net benefits of leverage, debt, and synergies is weakly increasing in the systematic risk of the target's operating free cash flows on a stand-alone basis, that is,

$$\frac{\partial \beta_i}{\partial \beta_A} \geq 0 \text{ and } \frac{\partial \widetilde{\beta}_i}{\partial \beta_A} \geq 0 \text{ for } i \in \{\Delta, D, S\}. \tag{A12}$$

We further assume

$$\frac{\partial}{\partial \beta_A}\left(V_t^A + \Delta_t - D_t\right) < 0, \tag{A13}$$

which rules out that an increase in the systematic risk of the operating free cash flows increases the stand-alone value of the target's equity (all else equal), and

$$\alpha + \pi \geq 1, \tag{A14}$$

which implies that the bid is at least equal to the stand-alone value of the acquired stake, that is,

$$B_t \geq \pi \times \left(V_t^A + \Delta_t - D_t\right). \tag{A15}$$

This would be the case, for example, if any synergies are split evenly between the bidder and the seller ($\alpha = 0.5$) but can only be achieved if the bidder acquires a majority stake ($\pi > 0.5$). Given the above assumptions, we have

$$\frac{\partial CAR_t^{Bidder}}{\partial \beta_A} = -\frac{1}{E_t^{Bidder}} \times \left[\pi \times \frac{\partial}{\partial \beta_A}\left(V_t^A + \Delta_t - D_t\right) - (1 - \pi - \alpha)\frac{\partial S_t}{\partial \beta_A}\right] > 0 \text{ if } \gamma = 0, \tag{A16}$$

and

$$\frac{\partial CAR_t^{Bidder}}{\partial \beta_A} = \frac{1 - \alpha}{E_t^{Bidder}} \times \frac{\partial S_t}{\partial \beta_A} \leq 0 \text{ if } \gamma = 1. \tag{A17}$$

Continuity in γ thus implies that a $\gamma^* \in (0, 1)$ exists, such that

$$\frac{\partial CAR_t^{Bidder}}{\partial \beta_A} > 0 \text{ for } \gamma < \gamma^*. \tag{A18}$$

That is, the bidder's cumulative abnormal return $\left(CAR_t^{Bidder}\right)$ around the bid announcement is increasing in the target's asset beta (β_A) as long as the empirical SML is not too steep ($\gamma < \gamma^* < 1$).

A.2 Model Extension: Public Target

We assume that the key difference compared to a private target is that the seller of a public target can sell the shares at the prevailing market price $\widehat{E}_t$ instead of selling them to the bidder at price B_t.[60] Consequently, the seller's outside option when negotiating with the bidder depends on the target's current market price $\widehat{E}_t$. Specifically, if the target's stand-alone value as assessed by the

[60] Note that $\widehat{E}_t$ denotes the market's assessment of the target's equity value on a stand-alone basis, whereas $\widetilde{E}_t$ denotes the market's assessment of the target's equity value conditional on an acquisition by the bidder (i.e., including synergies).

bidder and seller is higher than the current market price ($V_t^A + \Delta_t - D_t \geq \widehat{E}_t$), then bilateral Nash bargaining implies

$$B_t = V_t^A + \Delta_t - D_t + \alpha S_t, \tag{A19}$$

which in turn implies[61]

$$\frac{\partial CAR_t^{Bidder}}{\partial \beta_A} = \frac{\mu}{E_t^{Bidder}} \sum_{\tau=t+1}^{\infty} \frac{(\tau - t) \times FCF_\tau}{\left(1 + r_f + \beta_A \times \mu\right)^{\tau - t + 1}} > 0. \tag{A20}$$

If, instead, the market price is higher than the stand-alone value but lower than the value including synergies ($V_t^A + \Delta_t - D_t < \widehat{E}_t \leq V_t^A + \Delta_t - D_t + S_t$), then the bidder pays

$$B_t = (1 - \alpha) \times \widehat{E}_t + \alpha \times \left(V_t^A + \Delta_t - D_t + S_t\right), \tag{A21}$$

and we have

$$\frac{\partial CAR_t^{Bidder}}{\partial \beta_A} = \alpha \times \frac{\mu}{E_t^{Bidder}} \sum_{\tau=t+1}^{\infty} \frac{(\tau - t) \times FCF_\tau}{\left(1 + r_f + \beta_A \times \mu\right)^{\tau - t + 1}} > 0. \tag{A22}$$

If the target's current market price exceeds the equity value including synergies as assessed by the bidder and seller ($\widehat{E}_t > V_t^A + \Delta_t - D_t + S_t$), then no bid is made because the seller's outside option dominates any bid that the bidder would be willing to make.

A.3 Derivations of Additional Predictions

Derivation of Predictions 2 and 3: We assume $FCF_{t+1} > 0$ and that the expected operating free cash flows on a stand-alone basis grow at a constant rate $g < r_A$ thereafter. This implies

$$\frac{\partial CAR_t^{Bidder}}{\partial \beta_A} = \frac{\mu}{E_t^{Bidder}} \times \frac{FCF_{t+1}}{\left(r_f + \beta_A \times \mu - g\right)^2} > 0, \tag{A23}$$

which can be rewritten as

$$\frac{\partial CAR_t^{Bidder}}{\partial \beta_A} = \frac{\mu}{r_f + \beta_A \times \mu - g} \times \left(R - \frac{\Delta_t - D_t + \alpha S_t}{E_t^{Bidder}}\right), \tag{A24}$$

where $R \equiv B_t / E_t^{Bidder}$ is the relative size of the bid vis-à-vis the bidder. We thus have

$$\frac{\partial^2 CAR_t^{Bidder}}{\partial \beta_A \partial g} = \frac{2\mu}{E_t^{Bidder}} \times \frac{FCF_{t+1}}{\left(r_f + \beta_A \times \mu - g\right)^3} > 0 \tag{A25}$$

and

$$\frac{\partial^2 CAR_t^{Bidder}}{\partial \beta_A \partial R} = \frac{\mu}{r_f + \beta_A \times \mu - g} > 0. \tag{A26}$$

Derivation of Prediction 4: We assume that the bidder's and seller's assessment of the target's equity value is a weighted average of the CAPM-based value and a market-based (i.e., non-CAPM-based) value,

$$E_t = \omega \times E_t^{\text{CAPM-based}} + (1 - \omega) \times E_t^{\text{Market-based}}, \tag{A27}$$

where $\omega \in [0, 1]$ is the weight on the CAPM-based value. $E_t^{\text{Market-based}}$ could be the current market price for a public target and a multiple-implied price for a private target (e.g., based on listed peers). Assuming

$$\frac{\partial E_t^{\text{Market-based}}}{\partial \beta_A} > \frac{\partial E_t^{\text{CAPM-based}}}{\partial \beta_A} \tag{A28}$$

(e.g., $\partial E_t^{\text{Market-based}} / \partial \beta_A = 0$) then implies

$$\frac{\partial^2 CAR_t^{Bidder}}{\partial \beta_A \partial \omega} > 0. \tag{A29}$$

[61] To derive Equation (A20), we assume (AI) and (AII) as in Section 1.

Derivation of Prediction 5: We assume that the empirical SML is given by

$$\widetilde{r}_i = r_f + \left[\gamma \times \beta_i + (1-\gamma) \times \overline{\beta}_A\right] \times \mu, \tag{A30}$$

for some $\gamma \in [0,1]$, and that the bidder seeks to acquire a fraction $\pi \in (0,1]$ of the target's equity. Given

$$\frac{\partial CAR_t^{Bidder}}{\partial \beta_A} = -\frac{1}{E_t^{Bidder}} \times \left[\pi \times \frac{\partial}{\partial \beta_A}\left(V_t^A + \Delta_t - D_t\right) - (1-\pi-\alpha)\frac{\partial S_t}{\partial \beta_A}\right] > 0 \text{ } if \text{ } \gamma = 0, \tag{A31}$$

and

$$\frac{\partial CAR_t^{Bidder}}{\partial \beta_A} = \frac{1-\alpha}{E_t^{Bidder}} \times \frac{\partial S_t}{\partial \beta_A} \le 0 \text{ } if \text{ } \gamma = 1, \tag{A32}$$

continuity in γ implies that two cutoffs $\underline{\gamma}$ and $\overline{\gamma}$ with $0 < \underline{\gamma} \le \overline{\gamma} < 1$ exist such that $\partial CAR_t^{Bidder} / \partial \beta_A$ is larger for all $\gamma < \underline{\gamma}$ than for all $\gamma > \overline{\gamma}$.

Derivation of Prediction 6: Assuming $\alpha < 1$, Equations (A20) and (A22) imply that the relation between a bidder's CAR and target's asset beta is weaker for a public than for a private target if the public target's stand-alone value as assessed by the bidder and seller $\left(V_t^A + \Delta_t - D_t\right)$ is lower than its current market price ($\widehat{E}_t$). This condition is more likely to be satisfied for high than for low beta public targets because

$$\frac{\partial\left(V_t^A + \Delta_t - D_t\right)}{\partial \beta_A} < \frac{\partial \widehat{E}_t}{\partial \beta_A}. \tag{A33}$$

Further, assuming that the weight given to a public target's market capitalization in Equation (A27) is greater than the weight given to a multiple-implied value for a private target (e.g., because the current market price is considered a more accurate assessment than a multiple-implied value), Prediction 4 also implies that the relation between bidder CARs and target asset betas is weaker for public than for private targets.

Derivation of the Prediction Regarding the Probability of Receiving a Takeover Bid: We assume that organizing a takeover costs $c > 0$ and that the value of synergies as assessed by the bidder and seller is a random variable with cumulative distribution function F and density function $f > 0$ for $S_t \in \mathbb{R}_+$. To avoid a mechanical relation between a firm's asset beta and the probability of receiving a takeover bid, we assume that F does not depend on β_A.[62] Differences in beta thus do not imply differences in potential synergies (and thus attractiveness as a takeover target) *per se*. For a private firm, a bidder makes a bid if the present value of the synergies exceeds the costs of organizing the takeover ($S_t > c$). Hence, the probability of a bid does not depend on the firm's asset beta:

$$\Pr(\text{Bid}) = \Pr(S_t > c) = 1 - F(c). \tag{A34}$$

For a public firm, a bid is made if the value of the synergies exceeds the costs of organizing the takeover ($S_t > c$) and the firm's current market price is lower than its equity value including

62 As long as the value of the synergies is not increasing in the firm's asset beta, our prediction would not qualitatively change even if F depends on β_A. In that case, however, the probability $1 - F(x)$ that S_t exceeds some cutoff x justifying a takeover—and hence the probability of a bid—would depend on β_A even if the empirical SML and the CAPM-implied SML coincide.

synergies as assessed by the bidder and seller ($\widehat{E}_t < V_t^A + \Delta_t - D_t + S_t$). The bid probability is therefore

$$\Pr(\text{Bid}) = \Pr\left(S_t > \max\left\{c; \widehat{E}_t - V_t^A - \Delta_t + D_t\right\}\right) \tag{A35}$$

$$= 1 - F\left(\max\left\{c; \widehat{E}_t - V_t^A - \Delta_t + D_t\right\}\right) \leq 1 - F(c), \tag{A36}$$

Assuming (AI) and (AII) as in Section 1, we further obtain[63]

$$\frac{\partial \Pr(\text{Bid})}{\partial \beta_A} = \begin{cases} -f\left(\widehat{E}_t - V_t^A - \Delta_t + D_t\right) \\ \times \mu \sum_{\tau=t+1}^{\infty} \frac{(\tau - t) \times FCF_\tau}{\left(1 + r_f + \beta_A \times \mu\right)^{\tau - t + 1}} & \text{if } c < \widehat{E}_t - V_t^A - \Delta_t + D_t \\ 0 & \text{if } c > \widehat{E}_t - V_t^A - \Delta_t + D_t, \end{cases} \tag{A37}$$

implying that a public firm's probability of receiving a takeover bid is weakly decreasing in its asset beta.

Derivation of the prediction regarding the average asset betas of private versus public targets: The derivation of the prediction regarding the probability of receiving a takeover bid implies that the expected asset beta in a sample of private targets is equal to the average asset beta in the population of private firms. The reason is that each private firm's probability of receiving a takeover bid is $1 - F(c)$, regardless of its asset beta. It follows that the sample of private targets constitutes a random draw from the population of private firms. For public firms, instead, the probability of receiving a takeover bid is weakly decreasing in the asset beta. Consequently, because public firms with a higher asset beta have a weakly lower probability of receiving a takeover bid, the expected asset beta in a sample of public targets is weakly smaller than the average asset beta in the population of public firms. Hence, if the average asset beta in the population of private firms is the same as in the population of public firms, then the expected asset beta in a sample of private takeover targets is weakly larger than the expected asset beta in a sample of public takeover targets.

A.4 Derivation of Equations (15), (17), and (18)

We build on the model extension introduced at the beginning of this appendix and use a tilde ($\widetilde{\ }$) to indicate the market's beliefs and assessments. $L = \overline{D}_t / E_t^s$ denotes the target's book leverage and τ the tax rate. We assume: (I) The operating cash flows and synergies have the same systematic risk and grow at a constant rate (g). (II) The level of debt is permanent and the net benefit of leverage is equal to the tax shield. (III) The bidder, seller, and market use the book value of debt ($\overline{D}_t$) as a proxy for the debt's market value.

63 (AI) and (AII) are not necessary (but sufficient) to obtain $\partial \Pr(\text{Bid}) / \partial \beta_A \leq 0$. The (weaker) necessary and sufficient condition is that an increase in the asset beta entails a smaller reduction in the market's than the bidder's assessment of the target's equity value on a stand-alone basis, so that $\frac{\partial}{\partial \beta_A}\left(\widehat{E}_t - V_t^A - \Delta_t + D_t\right) > 0$.

Derivation of Equation (15):

$$
\begin{aligned}
CAR_t^{Bidder} \times \frac{E_t^{Bidder}}{\rho} &= \pi\,\widetilde{E}_t - B_t && \text{(A38)}\\
&= \pi\left(\widetilde{V}_t^A + \widetilde{\Delta}_t - \widetilde{D}_t + \widetilde{S}_t\right) - \pi\left(V_t^A + \Delta_t - D_t + S_t\right) + (1-\alpha)\,S_t && \text{(A39)}\\
&= \pi\left(\frac{FCF_{t+1}+s_{t+1}}{\widetilde{r}_A - g} + \frac{\delta_{t+1}-d_{t+1}}{\widetilde{r}_D}\right) - \pi\left(\frac{FCF_{t+1}+s_{t+1}}{r_A - g} + \frac{\delta_{t+1}-d_{t+1}}{r_D}\right)\\
&\quad +(1-\alpha)\,\frac{s_{t+1}}{r_A - g} && \text{(A40)}\\
&= \pi\left(\frac{FCF_{t+1}+s_{t+1}}{\widetilde{r}_A - g} + \frac{\tau d_{t+1}-d_{t+1}}{\widetilde{r}_D}\right) - \pi\left(\frac{FCF_{t+1}+s_{t+1}}{r_A - g} + \frac{\tau d_{t+1}-d_{t+1}}{r_D}\right)\\
&\quad +(1-\alpha)\,\frac{s_{t+1}}{r_A - g} && \text{(A41)}\\
&= \pi\left(\frac{FCF_{t+1}+s_{t+1}}{\widetilde{r}_A - g} - (1-\tau)\,\frac{d_{t+1}}{\widetilde{r}_D}\right) - \pi\left(\frac{FCF_{t+1}+s_{t+1}}{r_A - g} - (1-\tau)\,\frac{d_{t+1}}{r_D}\right)\\
&\quad +(1-\alpha)\,\frac{s_{t+1}}{r_A - g} && \text{(A42)}\\
&= \pi\left(\frac{FCF_{t+1}+s_{t+1}}{\widetilde{r}_A - g} - (1-\tau)\,\widetilde{D}_t\right) - \pi\left(\frac{FCF_{t+1}+s_{t+1}}{r_A - g} - (1-\tau)\,D_t\right)\\
&\quad +(1-\alpha)\,\frac{s_{t+1}}{r_A - g} && \text{(A43)}\\
&= \pi\left(\frac{FCF_{t+1}+s_{t+1}}{\widetilde{r}_A - g} - (1-\tau)\,\overline{D}_t\right) - \pi\left(\frac{FCF_{t+1}+s_{t+1}}{r_A - g} - (1-\tau)\,\overline{D}_t\right)\\
&\quad +(1-\alpha)\,\frac{s_{t+1}}{r_A - g} && \text{(A44)}\\
&= \pi\,(FCF_{t+1}+s_{t+1})\left(\frac{1}{\widetilde{r}_A - g} - \frac{1}{r_A - g}\right) + (1-\alpha)\,\frac{s_{t+1}}{r_A - g} && \text{(A45)}\\
&\Leftrightarrow\\
CAR_t^{Bidder} &= \frac{\rho}{E_t^{Bidder}} \times \left\{\pi\,(FCF_{t+1}+s_{t+1}) \times \left[\frac{1}{\widetilde{r}_A - g} - \frac{1}{r_A - g}\right] + (1-\alpha)\,\frac{s_{t+1}}{r_A - g}\right\}\\
& && \text{(A46)}
\end{aligned}
$$

Derivation of Equation (17):

$$
B_t = \pi\left(V_t^A + \Delta_t - D_t + S_t\right) - (1-\alpha)\,S_t = \pi\left[V_t^A - (1-\tau)\,\overline{D}_t + S_t\right] - (1-\alpha)\,S_t \qquad \text{(A47)}
$$

with

$$
\overline{D}_t = L \times E_t^s = L \times \left[V_t^A + \Delta_t - D_t\right] = \frac{L}{\pi} \times \left[B_t + (1-\pi-\alpha)\,S_t\right] \qquad \text{(A48)}
$$

implies

$$\begin{aligned} B_t &= \pi\left[V_t^A-(1-\tau)\overline{D}_t+S_t\right]-(1-\alpha)S_t && \text{(A49)}\\ &= \pi\left(V_t^A+S_t\right)-(1-\tau)L\left[B_t+(1-\pi-\alpha)S_t\right]-(1-\alpha)S_t && \text{(A50)}\\ &\Leftrightarrow \\ B_t\left[1+(1-\tau)L\right] &= \pi\left(V_t^A+S_t\right)-S_t\left[1-\alpha+(1-\tau)L(1-\pi-\alpha)\right] && \text{(A51)}\\ &= \pi\frac{FCF_{t+1}+s_{t+1}}{r_A-g}-\frac{s_{t+1}}{r_A-g}\left[1-\alpha+(1-\tau)L(1-\pi-\alpha)\right] && \text{(A52)}\\ &\Leftrightarrow \\ \pi\left(FCF_{t+1}+s_{t+1}\right) &= B_t\left[1+(1-\tau)L\right](r_A-g)+s_{t+1}\left[1-\alpha+(1-\tau)L(1-\pi-\alpha)\right] && \text{(A53)} \end{aligned}$$

Derivation of Equation (18):

$$\begin{aligned} B_t-\widetilde{B}_t &= \pi\times\left[V_t^A+\Delta_t-D_t+S_t\right]-(1-\alpha)S_t-\pi\times\left[\widetilde{V}_t^A+\widetilde{\Delta}_t-\widetilde{D}_t+\widetilde{S}_t\right]\\ &\quad +(1-\alpha)\widetilde{S}_t && \text{(A54)}\\ &= -\pi\left(FCF_{t+1}+s_{t+1}\right)\times\left[\frac{1}{\widetilde{r}_A-g}-\frac{1}{r_A-g}\right]\\ &\quad +(1-\alpha)s_{t+1}\times\left[\frac{1}{\widetilde{r}_A-g}-\frac{1}{r_A-g}\right] && \text{(A55)}\\ &= \left[(1-\alpha)s_{t+1}-\pi\left(FCF_{t+1}+s_{t+1}\right)\right]\times\left[\frac{1}{\widetilde{r}_A-g}-\frac{1}{r_A-g}\right] && \text{(A56)}\\ &\Leftrightarrow \\ \left|B_t-\widetilde{B}_t\right| &= \left|(1-\alpha)s_{t+1}-\pi\left(FCF_{t+1}+s_{t+1}\right)\right|\times\left|\frac{1}{\widetilde{r}_A-g}-\frac{1}{r_A-g}\right| && \text{(A57)} \end{aligned}$$

Figure A.1
Nonparametric regression of *Target asset beta* on *Target noise beta*
This figure shows the coefficient estimates from an OLS regression of *Target asset beta* on indicator variables for different ranges of *Target noise beta*. The sample period is 1980 to 2015.

Table A.1
Variable definitions

Variable	Definition
Above 50% stock	Indicator equal to one if the proposed payment consists of more than 50% stock
Antitakeover index	Antitakeover index of Bebchuk, Cohen, and Ferell (2004)
Asset beta	Equally weighted average asset beta of all public firms in CRSP with the same 3-digit primary SIC code. Asset betas are computed as $\beta_A = \beta_E / [1+(1-\tau)\times D/E]$, where β_E is the equity beta, τ is the statutory tax rate in the highest bracket, D is total debt ($dltt+dlc$), and E is the market value of equity. Using alternative methodologies to delever the equity betas does not materially affect the results. Equity betas are estimated by regressing 5 years of monthly excess returns (ret minus the risk-free rate obtained from Kenneth French's Web page, *http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html*) on excess returns of the CRSP value-weighted portfolio (including dividends). We use CRSP sharecodes 10 and 11 and compute the value-weighted average beta in case of multiple securities per firm. We drop estimates based on less than 36 months of return data. Further, we drop observations for which the estimated beta is negative, and we drop the same number of observations in the right tail of the distribution of estimated betas
log(Assets)	Natural logarithm of the book value of assets in USD million
Beta spread	*Target asset beta* minus *Bidder asset beta*
Beta spread (equity)	*Target equity beta* minus *Bidder equity beta*
Bidder asset beta	Equally weighted average asset beta of all public firms in CRSP with the same 3-digit primary SIC code as the bidder, estimated 1 month prior to the bid announcement (see *Asset beta* for details of the estimation of individual betas)
Bidder BHAR	Buy-and-hold abnormal return of the bidder's stock. [x,y] denotes an event window from $t=x$ to $t=y$ for a bid announced on date $t=0$. The buy-and-hold abnormal return for bidder i is given by $\text{BHAR}_i \equiv \text{BH}_i - \text{BH}_i^{\text{Match}}$, where BH_i is the buy-and-hold return of bidder i (during the event window from $t=x$ to $t=y$), and $\text{BH}_i^{\text{Match}}$ is the buy-and-hold return on a portfolio of firms matched to bidder i based on industry, size, and Tobin's q (e.g., Savor and Lu 2009). We first match bidder i to all public firms in CRSP with the same 3-digit primary SIC code. Next, we compute the Mahalanobis distance to all matched firms in terms of size and Tobin's q to identify the ten closest industry peers. $\text{BH}_i^{\text{Match}}$ is then computed as the weighted average buy-and-hold return of these ten closest industry peers, where the weights are chosen such that closer peers receive greater weight. If there are fewer than ten peers (because there are not enough firms in the same industry), the matched portfolio contains less than ten firms. The weight assigned to peer j of bidder i is $w_{i,j} = K\left(d_{i,j}/h_i\right)/\sum_{k=1}^{N_i} K\left(d_{i,k}/h_i\right)$, where N_i is the number of peers matched to bidder i, $d_{i,j}$ is the Mahalanobis distance between bidder i and peer j, $K(\cdot)$ is the Gaussian density function, and h_i is equal to the Mahalanobis distance to the nearest matched peer (see, e.g., Todd 1999)
Bidder CAR	Cumulative abnormal return of the bidder's stock over the 7-day window around the bid announcement (i.e., from $t=-3$ to $t=+3$ for a bid announced on date $t=0$). Abnormal returns are market adjusted returns of CRSP share codes 10 and 11, using the CRSP value-weighted portfolio as the market proxy. Outliers are dropped by trimming the final distribution of CARs at the 0.5% level in each tail
Bidder equity beta	Equally weighted average equity beta of all public firms in CRSP with the same 3-digit primary SIC code as the bidder, estimated 1 month prior to the bid announcement (see *Asset beta* for details of the estimation of individual betas)
Bidder mentions CAPM	Indicator equal to one if the bidder's 10K, 10Q, or 8K filings of the 3 years prior to the bid announcement contain the words "CAPM" or "capital asset pricing model"
Bidder noise beta	Equally weighted average noise beta of all public firms in CRSP with the same 3-digit primary SIC code as the bidder, estimated 1 month prior to the bid announcement (see *Noise beta* for details of the estimation of individual betas)
Bidder SDC industry	Bidder mid-level industry classification code (SDC item ATF_MID_CODE)
log(Bidder size)	Natural logarithm of the market capitalization of the bidder in USD million 4 days prior to the bid announcement

(*Continued*)

Table A.1
(Continued)

Variable	Definition
Board independence	Percentage of independent directors on the board
Cash	Indicator equal to one if the proposed payment includes cash
Cash flow to assets	Net income (ib) + D&A (dp) / total assets (at)
Cash to assets	Total cash and cash equivalents (che) / total assets (at)
Combined CAR	Weighted average of the cumulative abnormal returns of the bidder's and target's stock over the 7-day window around the bid announcement (see *Bidder CAR* for details of the estimation of the cumulative abnormal returns)
Cross-border	Indicator equal to one if the target's and bidder's headquarters are located in different countries
log(Deal value)	Natural logarithm of the value of the takeover bid in USD million
Deal value (in $M)	Value of the takeover bid in USD million
Deal value (in $M, CPI adjusted)	Value of the takeover bid in USD million (inflation-adjusted to December 2015)
Debt to assets	Total debt (dlc + dltt) / total assets (at)
Equity	Indicator equal to one if the proposed payment includes stock
FCF/assets	$[\text{EBIT}\times(1-\tau)+\text{D\&A}-\text{CAPEX}-\Delta\text{NWC}]/\text{ASSETS}$, where EBIT is earnings before interest and taxes (Compustat item ebit, or oiadp if ebit is missing, or pi + xint − spi − nopi if both ebit and oiadp are missing), τ is the statutory tax rate in the highest bracket, D&A is depreciation and amortization (Compustat item dp, or xdp if dp is missing, or dpc if both dp and xdp are missing), CAPEX is capital expenditures (Compustat item capx, or capxv if capx is missing), ΔNWC is the increase in net working capital (Compustat items recch + invch + apalch + aoloch, or if missing: − (rect − rect_{t-1}) − (invt − invt_{t-1}) + (ap − ap_{t-1}) − (aco − lco − aco_{t-1} + lco_{t-1})), and ASSETS is the book value of total assets (Compustat item at)
FV	Bid-implied firm value of the target, defined as EV+ASSETS−BVE. EV is the bid-implied equity value of the target, defined as the equity value indicated in SDC, or the deal value divided by the percentage of equity acquired if the equity value is missing but the deal is completed, or the deal value divided by the percentage of equity sought if the equity value is missing and the deal is withdrawn. ASSETS is the book value of total assets (Compustat item at), and BVE is the book value of equity (Compustat item ceq)
FV/EBIT	Bid-implied firm value of the target divided by the target's EBIT
FV/sales	Bid-implied firm value of the target divided by the target's sales
HMFFS	Dollar amount of hypothetical mutual fund fire sales, assuming that each position in an affected fund's portfolio is liquidated in proportion to its portfolio weight, scaled by the dollar volume of trading in the stock
HMFFS*	Variant of HMFFS, where the dollar amount of trading used to scale the dollar amount of hypothetical fire sales is computed using the share price at the beginning of the quarter
HMFFS**	Number of shares sold in hypothetical mutual fund fire sales, assuming that each position in an affected fund's portfolio is liquidated in proportion to its portfolio weight
HMFFS***	Dollar value of hypothetical mutual fund fire sales, assuming that each position in an affected fund's portfolio is liquidated in proportion to its portfolio weight
Hostile	Indicator equal to one if the initial bid is hostile
Insider ownership	Percentage of outstanding shares of the bidder that are owned by the five highest paid executives of the bidder
Institutional ownership	Percentage of outstanding shares of the bidder that are owned by institutional investors
IO block	Indicator equal to one if an institutional investor owns more than 5% of the firm's outstanding shares
Listed peer available	Indicator equal to one if the target is a U.S. firm and, at the time of the acquisition, there is at least one other publicly listed U.S. firm with the same primary 3-digit SIC code whose market capitalization is neither smaller than 50% nor larger than 150% of the target's bid-implied equity value reported in SDC
log(Market capitalization)	Natural logarithm of the market value of equity in USD million

(*Continued*)

Table A.1
(Continued)

Variable	Definition
Market-to-book	Market capitalization (prc × csho) / shareholders' equity (ceq)
Multiple bidders	Indicator equal to one if there is more than one bidder
Noise beta	In-sample covariance between the estimated noise component in a firm's realized excess stock returns and the realized excess returns on the market proxy, scaled by the in-sample variance of the excess market returns. The noise components are estimated as the fitted values from a regression of realized excess returns on hypothetical mutual fund fire sales. Individual firms' noise betas are delevered and aggregated at the industry level in analogy to the construction of *Asset beta*
Poison	Indicator equal to one if the target uses a defense mechanism
PPE to assets	Property, plant, and equipment (ppent) / total assets (at)
Predicted WACC	Weighted average cost of capital implied by *Target asset beta* and the same assumptions as in the model calibration in Section 3.3
Premium	Percentage premium of the bid-implied equity value over the target's market capitalization 6 months prior to the bid
Public target	Indicator equal to one if the target is listed
Relative size	Deal value divided by the market capitalization of the bidder 4 days prior to the bid announcement.
Repurchase	Indicator equal to one if a firm repurchases shares
ROA	Return on assets (ib / at)
Same industry	Indicator equal to one if the bidder and target operate in the same industry as defined by the first three digits of their primary SIC codes
SEO	Indicator equal to one if a firm does a seasoned equity offering
Steep empirical SML	Indicator equal to one if the slope of the empirical SML (estimated following Hong and Sraer 2016) during the month of the bid announcement is larger than the sample median
Stock versus cash	Indicator equal to one (zero) if 100% of the proposed payment is in stock (cash). Deals for which the proposed payment comprises both stock and cash are excluded
Target asset beta	Equally weighted average asset beta of all public firms in CRSP with the same 3-digit primary SIC code as the target, estimated 1 month prior to the bid announcement (see *Asset beta* for details of the estimation of individual betas)
Target equity beta	Equally weighted average equity beta of all public firms in CRSP with the same 3-digit primary SIC code as the target, estimated 1 month prior to the bid announcement (see *Asset Beta* for details of the estimation of individual betas)
Target growth high	Indicator equal to one if the compound annual growth rate of aggregate sales in the target's (SIC3-) industry during the 3 years preceding the takeover bid is larger than the sample median
Target noise beta	Equally weighted average noise beta of all public firms in CRSP with the same 3-digit primary SIC code as the target, estimated 1 month prior to the bid announcement (see *Noise beta* for details of the estimation of individual betas)
Target relative size high	Indicator equal to one if *Relative size* is larger than the sample median
Target SDC industry	Target mid-level industry classification code (SDC item TTF_MID_CODE)
Tender	Indicator equal to one if the bid is a tender offer
Tobin's q	[Assets (at) + market capitalization (prc × csho) − equity (ceq)] / assets (at)
Toehold	Fraction of the target's equity held by the bidder before the bid
Avg. discount rate	Average of the maximum and minimum discount rate (SDC items FO_DCF_RATE_HI and FO_DCF_RATE_LOW) used for discounted cash flow analyses in M&A fairness opinions
100% stock	Indicator equal to one if 100% of the offered payment is in stock
Wealth performance sensitivity	Performance sensitivity measure of Edmans, Gabaix, and Landier (2009)
$\mathbb{1}\{a < \text{Target asset beta} \leq b\}$	Indicator equal to one if the target's asset beta is larger than a but smaller than (or equal to) b
$\mathbb{1}\{\text{Target asset beta} < p25\}$	Indicator equal to one if the target's asset beta is in the bottom quartile of the distribution
$\mathbb{1}\{\text{Target asset beta} > p75\}$	Indicator equal to one if the target's asset beta is in the top quartile of the distribution

Table A.2
Alternative CAR models

	(1)	(2)	(3)	(4)
Sample:		Private targets		
Dependent variable:		Bidder CAR (in percentage points)		
CAR model:	Market adjusted	Market model	3 factors	4 factors
Target asset beta	2.55***	2.19***	2.13***	2.23***
	(5.06)	(4.61)	(4.43)	(4.66)
Bidder SDC industry × Year FE	Yes	Yes	Yes	Yes
Deal controls	Yes	Yes	Yes	Yes
Target controls	Yes	Yes	Yes	Yes
Bidder controls	Yes	Yes	Yes	Yes
Observations	12,109	12,061	12,061	12,060

This table presents OLS estimates of the sensitivity of the cumulative abnormal return of the bidder's stock during the 7-day window around the bid announcement (*Bidder CAR*) to the target's asset beta. The sample period is 1977 to 2015. Only bids for private targets are included. In Column 1, *Bidder CAR* is defined as the return of the bidder's stock minus the return of the CRSP value-weighted portfolio. In Column 2, *Bidder CAR* is defined as the return of the bidder's stock minus the expected return implied by the CAPM. In Columns 3 and 4, *Bidder CAR* is defined as the return of the bidder's stock minus the expected return implied by the Fama-French 3-factor model (Fama and French 1993) and Carhart 4-factor model (Carhart 1997), respectively. *Deal controls* is a vector comprising all deal-level controls included in Column 5 of Table 2: *Beta spread*, *log(Deal value*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same industry*, *Cross-border*, *Poison*, *Tender*, *Multiple bidders*, *Relative size*, and *log(Bidder size)*. Tables 2 and A.1 in the appendix define the variables. t-statistics, based on standard errors clustered by the target's (SIC3-) industry, are reported in parentheses. *p <.1; **p <.05; ***p <.01.

Table A.3
Sensitivity of bidder CAR to target equity beta

	(1)	(2)	(3)	(4)
Sample:		Private targets		
Dependent variable:		Bidder CAR (in percentage points)		
Target equity beta	1.41***	1.64***	1.37***	2.16***
	(4.95)	(5.24)	(4.38)	(4.69)
Beta spread (equity)				−1.06**
				(−2.27)
Bidder SDC industry × Year FE	Yes	Yes	Yes	Yes
Deal controls	Yes	Yes	Yes	Yes
Target controls	No	Yes	Yes	Yes
Bidder controls	No	No	Yes	Yes
Observations	13,610	13,490	12,211	12,112

This table presents OLS estimates of the sensitivity of the cumulative abnormal return of the bidder's stock during the 7-day window around the bid announcement (*Bidder CAR*) to the target's equity beta. The sample period is 1977 to 2015. Only bids for private targets are included. *Target equity beta* is the equity beta of the target. *Beta spread (equity)* is the difference between the target's and the bidder's equity beta. *Deal controls* is a vector comprising all deal-level controls included in Columns 2 to 4 of Table 2: *log(Deal value)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same Industry*, *Cross-border*, *Poison*, *Tender*, *Multiple Bidders*, *Relative Size*, and *log(Bidder size)*. Tables 2 and A.1 in the appendix define the variables. t-statistics, based on standard errors clustered by the target's (SIC3-) industry, are reported in parentheses. *p <.1; **p <.05; ***p <.01.

Table A.4
Nonparametric estimation of the sensitivity of bidder CAR to target asset beta

	(1)
Sample:	Private targets
Dependent variable: Bidder CAR (in percentage points)	
$\mathbb{1}\{-\infty < \text{Target asset beta} \leq 0.20\}$	-2.66^{***}
	(-2.83)
$\mathbb{1}\{0.20 < \text{Target asset beta} \leq 0.32\}$	-1.67^{***}
	(-2.87)
$\mathbb{1}\{0.32 < \text{Target asset beta} \leq 0.44\}$	-0.88^{*}
	(-1.74)
$\mathbb{1}\{0.44 < \text{Target asset beta} \leq 0.56\}$	-0.58
	(-1.47)
$\mathbb{1}\{0.56 < \text{Target asset beta} \leq 0.68\}$	-0.30
	(-0.88)
$\mathbb{1}\{0.68 < \text{Target asset beta} \leq 0.80\}$	-0.13
	(-0.44)
$\mathbb{1}\{0.92 < \text{Target asset beta} \leq 1.04\}$	0.55^{*}
	(1.68)
$\mathbb{1}\{1.04 < \text{Target asset beta} \leq 1.16\}$	0.39
	(1.00)
$\mathbb{1}\{1.16 < \text{Target asset beta} \leq 1.28\}$	1.21^{***}
	(2.64)
$\mathbb{1}\{1.28 < \text{Target asset beta} \leq 1.40\}$	1.21^{***}
	(2.66)
$\mathbb{1}\{1.40 < \text{Target asset beta} < \infty\}$	1.25^{***}
	(2.84)
Bidder SDC industry × Year FE	Yes
Deal controls	Yes
Target controls	Yes
Bidder controls	Yes
Observations	12,109

This table presents OLS estimates of the sensitivity of the cumulative abnormal return of the bidder's stock during the 7-day window around the bid announcement (*Bidder CAR*) to the target's asset beta. The sample period is 1977 to 2015. Only bids for private targets are included. $\mathbb{1}\{a < \text{Target Asset Beta} \leq b\}$ is an indicator equal to one if the target's asset beta is larger than a but smaller than (or equal to) b. *Deal controls* is a vector comprising all deal-level controls included in Column 5 of Table 2: *Beta spread*, *log(Deal value)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same industry*, *Cross-border*, *Poison*, *Tender*, *Multiple bidders*, *Relative size*, and *log(Bidder size)*. Tables 2 and A.1 in the appendix define the variables. t-statistics, based on standard errors clustered by the target's (SIC3-) industry, are reported in parentheses. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

Table A.5
Descriptive statistics: Public firms in Compustat (bid probability sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:			Public firms in Compustat					
Variable:	Observations	Mean	SD	Min.	*p*25	*p*50	*p*75	Max.
Controlling bid	154,831	0.05	0.22	0	0	0	0	1
Any bid	154,831	0.08	0.28	0	0	0	0	1
Asset beta	154,831	0.85	0.34	0.17	0.60	0.86	1.11	1.55
log(Assets)	152,023	5.27	2.31	−2.06	3.59	5.21	6.87	10.76
ROA	151,848	−0.07	0.42	−9.03	−0.03	0.02	0.06	0.30
Debt to assets	150,928	0.23	0.25	0.00	0.04	0.18	0.35	4.15
Cash to assets	151,567	0.17	0.21	0.00	0.02	0.08	0.23	0.95
Cash flow to assets	147,434	−0.02	0.42	−9.30	0.00	0.06	0.11	0.37
Tobin's q	151,898	1.95	2.47	0.54	1.02	1.29	1.99	62.40
PPE to assets	150,803	0.26	0.24	0.00	0.06	0.18	0.38	0.91
IO block	147,780	0.61	0.49	0	0	1	1	1

This table presents descriptive statistics for all public firms in Compustat considered when estimating the sensitivity of public firms' propensity to receive takeover bids to the firms' asset beta (Table 6). The sample period is 1981 to 2015. All continuous variables are winsorized at the 1st and 99th percentiles. Table A.1 in the appendix defines the variables.

Table A.6
Alternative method of payment definitions

	(1)	(2)	(3)
Sample:		Private and public targets	
Dependent variable:	Equity	Above 50% stock	Stock versus cash
Bidder asset beta	10.18***	8.50***	10.78***
	(4.81)	(4.73)	(5.41)
Target asset beta	−0.19	−0.95	−0.86
	(−0.06)	(−0.31)	(−0.28)
Target SDC industry × Year FE	Yes	Yes	Yes
Deal controls	Yes	Yes	Yes
Target controls	Yes	Yes	Yes
Bidder controls	Yes	Yes	Yes
Observations	18,348	17,631	13,237

This table presents OLS estimates of the sensitivity of the propensity to offer different types of payment to the bidder's asset beta (*Bidder asset beta*). The sample period is 1977 to 2015. *Equity* is an indicator equal to one if the proposed payment includes stock. *Above 50% stock* is an indicator equal to one if the proposed payment consists of more than 50% stock. *Stock versus cash* is an indicator equal to one if 100% of the proposed payment is in stock and zero if 100% of the proposed payment is in cash. Deals for which the proposed payment comprises both stock and cash are excluded from Column 3. *Deal controls* is a vector comprising all deal-level controls included in Columns 2 to 4 of Table 7: *log(Deal value)*, *Toehold*, *Hostile*, *Same industry*, *Cross-border*, *Poison*, *Tender*, *Multiple bidders*, *Relative size*, and *log(Bidder size)*. Tables 2 and A.1 in the appendix define the variables. *t*-statistics, based on standard errors clustered by the bidder's (SIC3-) industry, are reported in parentheses. **p* <.1; ***p* <.05; ****p* <.01.

Table A.7
Method of payment and target equity beta

	(1)	(2)	(3)	(4)
Sample:	Private and public targets			
Dependent variable:	100% stock			
Bidder equity beta	7.61***	7.62***	5.54***	5.52***
	(3.86)	(3.90)	(3.54)	(3.47)
Target equity beta				0.01
				(0.00)
Target SDC industry × Year FE	Yes	Yes	Yes	Yes
Deal controls	Yes	Yes	Yes	Yes
Target controls	No	Yes	Yes	Yes
Bidder controls	No	No	Yes	Yes
Observations	21,082	20,471	18,428	18,354

This table presents OLS estimates of the sensitivity of the propensity to offer an all-stock payment to the bidder's equity beta. The sample period is 1977 to 2015. *Bidder (target) equity beta* are the bidder's and target's equity beta, respectively. *Deal controls* is a vector comprising all deal-level controls included in Columns 2 to 4 of Table 7: *log(Deal value)*, *Toehold*, *Hostile*, *Same industry*, *Cross-border*, *Poison*, *Tender*, *Multiple bidders*, *Relative size*, and *log(Bidder size)*. Tables 2 and A.1 in the appendix define the variables. t-statistics, based on standard errors clustered by the bidder's (SIC3-) industry, are reported in parentheses. *p <.1; **p <.05; ***p <.01.

Appendix B. Construction of Hypothetical Mutual Fund Fire Sales

The following description is based on Dessaint et al. (2019). For each stock i, we construct $HMFFS_{i,q,t}$, a measure of hypothetical sales of stock i during quarter q of year t that are due to large outflows in mutual funds owning the stock. Our approach follows the three-step approach proposed by Edmans, Goldstein, and Jiang (2012). First, in each year t, we estimate quarterly mutual fund flows for all U.S. funds that are not specialized in a given industry using CRSP mutual funds data. For every fund, CRSP reports the monthly return and the total net assets (TNA) by asset class. The average return of fund j during month m of year t is given by

$$RETURN_{j,m,t} = \frac{\sum_k (TNA_{k,j,m,t} \times RETURN_{k,j,m,t})}{\sum_k TNA_{k,j,m,t}}, \tag{B1}$$

where k indexes asset classes. We compound monthly fund returns to estimate average quarterly returns and aggregate TNAs across asset classes in March, June, September, and December to obtain the TNA of fund j at the end of every quarter in each year. An estimate of the net inflow experienced by fund j during quarter q of year t is then given by

$$FLOW_{j,q,t} = \frac{TNA_{j,q,t} - TNA_{j,q-1,t} \times (1+RETURN_{j,q,t})}{TNA_{j,q-1,t}}, \tag{B2}$$

where $TNA_{j,q,t}$ is the total net asset value of fund j at the end of quarter q of year t, and $RETURN_{j,q,t}$ is the return of fund j during quarter q of year t. $FLOW_{j,q,t}$ is therefore an estimate of the net inflow experienced by fund j during quarter q of year t as a percentage of its net asset value at the beginning of the quarter. Second, we calculate the dollar value of fund's j holdings of stock i at the end of every quarter using data from CDA Spectrum/Thomson. CDA Spectrum/Thomson provides the number of stocks held by all U.S. funds at the end of every quarter. The total value of the participation held by fund j in firm i at the end of quarter q of year t is

$$SHARES_{i,j,q,t} \times PRC_{i,q,t}, \tag{B3}$$

where $SHARES_{j,i,q,t}$ is the number of shares i held by fund j at the end of quarter q of year t, and $PRC_{i,q,t}$ is the price of stock i at the end of quarter q of year t. For all mutual funds for which $FLOW_{j,q,t} \leq -0.05$, we then compute

$$HMFFS^{USD}_{i,q,t} = \sum_j (FLOW_{j,q,t} \times SHARES_{j,i,q-1,t} \times PRC_{i,q-1,t}). \tag{B4}$$

This variable corresponds to the hypothetical net selling of stock i, in U.S. dollars (USD), by all mutual funds subject to extreme outflows (i.e., outflows greater or equal to 5%). We also compute the dollar volume of trading in stock i during quarter q of year t ($VOL_{i,q,t}$) as[64]

$$VOL_{i,q,t} = \sum_m Shares\ Traded_{i,m,q,t} \times PRC_{i,m,q,t} \tag{B5}$$

where $Shares\ Traded_{i,m,q,t}$ is the total number of shares i traded during month m in quarter q of year t, and $PRC_{i,m,q,t}$ is the price of the shares at the end of month m. Finally, we define the measure of hypothetical mutual fund fire sales ($HMFFS$) as

$$HMFFS_{i,q,t} \equiv \frac{HMFFS^{USD}_{i,q,t}}{VOL_{i,q,t}} = \frac{\sum_j (FLOW_{j,q,t} \times SHARES_{j,i,q-1,t} \times PRC_{i,q-1,t})}{VOL_{i,q,t}}. \tag{B6}$$

[64] An alternative is to compute the total dollar volume of trading in stock i during quarter q of year t as $VOL_{i,q,t} = Total\ Number\ of\ Shares\ Traded_{i,q,t} \times PRC_{i,q,t}$. Doing so does not qualitatively change the results.

Appendix C. Robustness of IV Estimation to Critique by Wardlaw (2018)

Wardlaw (2018) argues that using the dollar volume of trading during quarter q when computing $HMFFS_{i,q,t}$ may be problematic if $HMFFS_{i,q,t}$ is subsequently used as an instrument for stock i's return. For example, using $VOL_{i,q,t} = Total\ Number\ of\ Shares\ Traded_{i,q,t} \times PRC_{i,q,t}$ implies

$$HMFFS_{i,q,t} \equiv \frac{\sum_j (FLOW_{j,q,t} \times SHARES_{j,i,q-1,t} \times PRC_{i,q-1,t})}{VOL_{i,q,t}}$$

$$= \frac{\sum_j (FLOW_{j,q,t} \times SHARES_{j,i,q-1,t})}{Total\ Number\ of\ Shares\ Traded_{i,q,t}} \times \frac{PRC_{i,q-1,t}}{PRC_{i,q,t}}, \tag{C1}$$

where the last term, $PRC_{i,q-1,t}/PRC_{i,q,t}$, is equal to the inverse of the stock's realized gross return, so that there is a "mechanical" relation between the return and $HMFFS_{i,q,t}$.[65] This concern can be addressed by computing the dollar volume of trading using the price at the beginning of the quarter, that is, $VOL^*_{i,q,t} = Number\ of\ Shares\ Traded_{i,q,t} \times PRC_{i,q-1,t}$, and defining

$$HMFFS^*_{i,q,t} \equiv \frac{\sum_j (FLOW_{j,q,t} \times SHARES_{j,i,q-1,t} \times PRC_{i,q-1,t})}{VOL^*_{i,q,t}}$$

$$= \frac{\sum_j (FLOW_{j,q,t} \times SHARES_{j,i,q-1,t})}{Total\ Number\ of\ Shares\ Traded_{i,q,t}}, \tag{C2}$$

so that the term $PRC_{i,q-1,t}/PRC_{i,q,t}$ is no longer present. Panels A.1 and B.1 of Table C.1 show that our results are robust to using $HMFFS^*_{i,q,t}$ instead of $HMFFS_{i,q,t}$ in the IV analysis.[66] Wardlaw (2018) also argues that the total number of shares traded during the quarter could be correlated with the return, so that scaling by $Total\ Number\ of\ Shares\ Traded_{i,q,t}$ may be problematic, too. To address this concern, we define two alternative measures that do not include $Total\ Number\ of\ Shares\ Traded_{i,q,t}$:

$$HMFFS^{**}_{i,q,t} \equiv \sum_j (FLOW_{j,q,t} \times SHARES_{j,i,q-1,t}) \tag{C3}$$

$$HMFFS^{***}_{i,q,t} \equiv \sum_j (FLOW_{j,q,t} \times SHARES_{j,i,q-1,t} \times PRC_{i,q-1,t}). \tag{C4}$$

Panels A.2, B.2, A.3, and B.3 of Table C.1 show that our results are also robust to using $\ln(1+HMFFS^{**}_{i,q,t})$ and $\ln(1+HMFFS^{***}_{i,q,t})$ instead of $HMFFS_{i,q,t}$ in the IV analysis.

65 Using $VOL_{i,q,t} = \sum_m Shares\ Traded_{i,m,q,t} \times PRC_{i,m,q,t}$ as we do complicates the exposition without changing the intuition.

66 The correlation between the original measure $HMFFS_{i,q,t}$ and the new measure $HMFFS^*_{i,q,t}$ is 0.975.

Table C.1
Two-stage least-squares IV estimation using HMFFS*, ln(1+*HMFFS*), and ln(*HMFFS****) instead of HMFFS**

A.1 1st stage of 2SLS	(1)	(2)	(3)	(4)	(5.a)	(5.b)
Sample:			Private targets			
Dependent variable:	Target asset beta	Target asset beta	Target asset beta	Target asset beta	Target asset beta	Beta spread
Target noise beta	3.77***	3.73***	2.34***	2.36***	2.34***	2.40***
constructed using HMFFS*	(9.34)	(9.46)	(11.92)	(11.67)	(10.89)	(9.75)
Bidder noise beta					0.06	−2.56***
constructed using HMFFS*					(0.30)	(−8.84)
Bidder SDC industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Deal controls	No	Yes	Yes	Yes	Yes	Yes
Target controls	No	No	Yes	Yes	Yes	Yes
Bidder controls	No	No	No	Yes	Yes	Yes
Observations	13,334	13,048	12,939	11,707	11,706	11,706

B.1 2nd stage of 2SLS	(1)	(2)	(3)	(4)	(5)
Sample:			Private targets		
Dependent variable:			Bidder CAR (in percentage points)		
Target asset beta (instrumented)	2.29*	2.58***	3.99**	3.72**	5.15*
	(1.92)	(2.31)	(2.15)	(1.93)	(1.91)
Beta spread (instrumented)					−2.07
					(−0.95)
Bidder SDC industry × Year FE	Yes	Yes	Yes	Yes	Yes
Deal controls	No	Yes	Yes	Yes	Yes
Target controls	No	No	Yes	Yes	Yes
Bidder controls	No	No	No	Yes	Yes
Observations	13,334	13,048	12,939	11,707	11,706

(*Continued*)

Table C.1
(Continued)

A.2 1st stage of 2SLS	(1)	(2)	(3)	(4)	(5.*a*)	(5.*b*)
Sample:			Private targets			
Dependent variable:	Target asset beta	Target asset beta	Target asset beta	Target asset beta	Target asset beta	Beta spread
Target noise beta	3.23***	3.21***	1.97***	1.99***	1.98***	2.00***
constructed using ln(1+HMFFS**)	(10.63)	(10.78)	(11.61)	(11.76)	(10.62)	(9.39)
Bidder noise beta					0.05	−2.20***
constructed using ln(1+HMFFS**)					(0.28)	(−9.04)
Bidder SDC industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Deal controls	No	Yes	Yes	Yes	Yes	Yes
Target controls	No	No	Yes	Yes	Yes	Yes
Bidder controls	No	No	No	Yes	Yes	Yes
Observations	13,358	13,051	12,942	11,708	11,707	11,707

B.2 2nd stage of 2SLS	(1)	(2)	(3)	(4)	(5)
Sample:			Private targets		
Dependent variable:			Bidder CAR (in percentage points)		
Target asset beta (instrumented)	3.69**	3.75***	5.95**	5.67**	6.49**
	(2.67)	(2.76)	(2.44)	(2.25)	(2.01)
Beta spread (instrumented)					−1.22
					(−0.51)
Bidder SDC industry × Year FE	Yes	Yes	Yes	Yes	Yes
Deal controls	No	Yes	Yes	Yes	Yes
Target controls	No	No	Yes	Yes	Yes
Bidder controls	No	No	No	Yes	Yes
Observations	13,358	13,051	12,942	11,708	11,707

(*Continued*)

Table C.1
(Continued)

A.3 1st stage of 2SLS	(1)	(2)	(3)	(4)	(5.a)	(5.b)
Sample:			Private targets			
Dependent variable:	Target asset beta	Target asset beta	Target asset beta	Target asset beta	Target asset beta	Beta spread
Target noise beta	3.23***	3.21***	2.04***	2.07***	2.06***	2.08***
constructed using ln(1+HMFFS***)	(12.33)	(12.53)	(12.85)	(13.12)	(11.66)	(10.42)
Bidder noise beta					0.05	−2.26***
constructed using ln(1+HMFFS***)					(0.28)	(−10.06)
Bidder SDC industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Deal controls	No	Yes	Yes	Yes	Yes	Yes
Target controls	No	No	Yes	Yes	Yes	Yes
Bidder controls	No	No	No	Yes	Yes	Yes
Observations	13,353	13,052	12,943	11,715	11,714	11,714

B.3 2nd stage of 2SLS	(1)	(2)	(3)	(4)	(5)
Sample:			Private targets		
Dependent variable:			Bidder CAR (in percentage points)		
Target asset beta (instrumented)	2.70**	2.90***	4.43**	4.58**	5.20*
	(2.20)	(2.38)	(2.09)	(2.06)	(1.69)
Beta spread (instrumented)					−0.93
					(−0.42)
Bidder SDC industry × Year FE	Yes	Yes	Yes	Yes	Yes
Deal controls	No	Yes	Yes	Yes	Yes
Target controls	No	No	Yes	Yes	Yes
Bidder controls	No	No	No	Yes	Yes
Observations	13,353	13,052	12,943	11,715	11,714

This table presents 2SLS estimates of the sensitivity of *Bidder CAR* to *Target asset beta*. For panels A.1 and B.1, we use HMFFS* instead of HMFFS to construct *Target noise beta* and *Bidder noise beta*. For panels A.2 and B.2, we use ln(1+*HMFFS***). For panels A.3 and B.3, we use ln(1+*HMFFS****). The sample period is 1980 to 2015. Only bids for private targets are included. *Deal controls* is a vector comprising all deal-level controls included in Columns 2 to 4 of Table 2: *log(Deal value)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same industry*, *Cross-border*, *Poison*, *Tender*, *Multiple bidders*, *Relative size*, and *log(Bidder size)*. Table A.1 in the appendix defines the variables. t-statistics, based on standard errors clustered by the target's (SIC3-) industry, are reported in parentheses. *p <.1; **p <.05; ***p <.01.

Appendix D. Reconciling *Target Asset Beta* and *Avg. Discount Rate*

To examine how well the cost of capital implied by *Target asset beta* lines up with *Avg. discount rate* (the midpoint between the maximum and minimum rate in fairness opinions), we estimate the OLS regression

$$\textit{Avg. discount rate} = \alpha + \beta \times \textit{Predicted WACC} + \varepsilon, \tag{D1}$$

where *Predicted WACC* is the cost of capital implied by *Target asset beta* and the same assumptions as in the model calibration in Section 3.3. Specifically, we estimate regression (D1) for various subsamples based on the spread between the maximum and minimum rate used in the fairness opinions, defined as

$$\Delta \equiv \frac{r_{max} - r_{min}}{\textit{Avg. discount rate}}. \tag{D2}$$

The reason for this approach is as follows. *Avg. discount rate* is not the actual discount rate used by the bidder (which is unobserved) but only a proxy thereof. However, assuming that the discount rate used by the bidder lies between the maximum and minimum discount rate used in the fairness opinion, *Avg. Discount rate* should be a more accurate proxy if the spread between the maximum and minimum rate is small. Table D.1 displays the results of this analysis. In Column 1, we include all fairness opinions. In Columns 2 to 11, we impose increasingly tight restrictions on the spread Δ between the maximum and minimum discount rate. For example, in Column 6, we only use cases were $\Delta < 0.2$. In Column 11, we only use cases were $\Delta < 0.1$. We find that the coefficient estimate ($\widehat{\beta}$) on *Predicted WACC* approaches one as the spread between the maximum and minimum discount rate in the fairness opinion decreases. Similarly, the estimated regression constant ($\widehat{\alpha}$) approaches zero. Indeed, in Columns 7 to 11, one cannot reject the hypotheses that the coefficient on *Predicted WACC* is equal to one and that the regression constant is zero. That is, as the range of discount rates used in the fairness opinion becomes increasingly tight—so that the variable *Avg. discount rate* becomes more likely to be an accurate estimate of the discount rate that was actually used by the bidder—one cannot reject the hypothesis that the discount rate implied by *Target asset beta* is equal to *Avg. discount rate*.

Table D.1
Relation between the predicted WACC and the midpoint between the maximum and minimum discount rate used in fairness opinions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Sample:	Fairness opinions on bids for private and public targets										
Dependent variable:	Midpoint between maximum and minimum discount rate used in fairness opinion DCF (in percentage points)										
Restriction:	None	$\Delta < \frac{1}{1}$	$\Delta < \frac{1}{2}$	$\Delta < \frac{1}{3}$	$\Delta < \frac{1}{4}$	$\Delta < \frac{1}{5}$	$\Delta < \frac{1}{6}$	$\Delta < \frac{1}{7}$	$\Delta < \frac{1}{8}$	$\Delta < \frac{1}{9}$	$\Delta < \frac{1}{10}$
Predicted WACC	0.61***	0.64***	0.62***	0.64***	0.74***	0.69***	0.76***	1.04***	1.08***	0.98***	1.01***
	(4.20)	(4.44)	(4.32)	(5.42)	(5.65)	(4.92)	(5.38)	(6.24)	(5.00)	(3.95)	(4.70)
Constant	0.07***	0.07***	0.07***	0.06***	0.05***	0.05***	0.05***	0.02	0.02	0.03	0.03
	(5.06)	(4.77)	(4.93)	(5.33)	(3.94)	(4.02)	(3.41)	(1.29)	(0.88)	(1.27)	(1.39)
Observations	1,174	1,162	1,121	1,022	768	607	426	266	207	161	112

This table presents results from the OLS regression *Avg. discount rate*$=\alpha+\beta\times$*Predicted WACC*$+\varepsilon$, where *Avg. discount rate*$=(r_{max}+r_{min})/2$ and r_{max} and r_{min} are the maximum and minimum discount rate used for DCF valuations provided in fairness opinions on takeover bids. *Predicted WACC* is the weighted average cost of capital for the target that is implied by *Target asset beta* and the same assumptions that we make for the model calibration in Section 3.3. Δ is the difference between r_{max} and r_{min} scaled by the midpoint between r_{max} and r_{min}. t-statistics, based on standard errors clustered by the target's (SIC3-) industry, are reported in parentheses. *p <.1; **p <.05; ***p <.01.

Appendix E. Share Repurchases and Seasoned Equity Offerings

Our results on the relation between bidders' asset betas and the method of payment extend beyond takeover bids. We have shown that high beta bidders are more likely to use equity to pay for the target, but if our framework is correct, then the propensity to issue equity should be higher for high beta firms whether or not they make acquisitions. To a CAPM-using manager of a high beta firm, raising funds by issuing equity at the market price looks like a positive net present value (NPV) transaction, regardless of the planned use of these funds (M&A, capital expenditures, other investments, capital structure changes, or even payouts). Repurchasing shares at the market price, on the other hand, looks like a negative-NPV investment. Thus, we now move away from the setting of takeover bids and examine the relation between firms' asset betas and their propensity to repurchase shares or conduct seasoned equity offerings. The intuition is as follows. Firms that believe to be overvalued by the market are more likely to issue equity and less likely to repurchase shares (Baker and Wurgler 2013). Indeed, two-thirds of CFOs state that "the amount by which our stock is undervalued or overvalued by the market" is an important or very important determinant of the decision to issue equity (Graham and Harvey 2001, p. 2016). More than 85% of financial executives state that the "market price of our stock (if our stock is a good investment, relative to its true value)" is an important or very important determinant of the decision to repurchase shares (Brav et al. 2005, p. 496). Hence, we predict a negative relation between a firm's asset beta and *Repurchase*, an indicator equal to one if a firm repurchases shares, and a positive relation between a firm's asset beta and *SEO*, an indicator equal to one if a firm conducts a seasoned equity offering. To test this prediction we estimate the following OLS regression for all public firms in Compustat:[67]

$$Repurchase_t\ (SEO_t) = \alpha + \beta \times Asset\ beta_{t-1} + \gamma' Firm\ characteristics_{t-1} + Industry \times Year\ FE + \varepsilon. \tag{E1}$$

Firm characteristics is a vector of control variables commonly used in the literature on firms' share repurchase or equity issuance decisions (e.g., Dittmar 2000; Alti and Sulaeman 2012; Baker and Xuan 2016): the natural logarithm of the firm's market capitalization, the firm's market-to-book ratio, and the ratios of cash holdings, debt, and cash flows to assets. The standard errors are clustered by industry. Table E.1 presents the results. As predicted, we find a negative and highly significant relation between *Asset beta* and *Repurchase* and a positive and highly significant relation between *Asset beta* and *SEO*. Table E.2 shows that the results are similar when we use firms' equity betas instead of their asset betas.

[67] The sample period is 1977 to 2015.

Table E.1
Share repurchases and seasoned equity offerings

	(1)	(2)	(3)	(4)
Sample:	Public firms in Compustat			
Dependent variable:	Repurchase		SEO	
Asset beta	−10.95***	−11.01***	18.33***	17.07***
	(−5.45)	(−6.49)	(10.68)	(10.56)
log(Market capitalization)		4.86***		4.91***
		(21.74)		(18.33)
Market-to-book		−0.42***		0.38***
		(−6.79)		(3.81)
Cash to assets		−2.72		1.43
		(−0.79)		(0.53)
Debt to assets		−10.77***		−3.37
		(−5.30)		(−1.09)
ROA		2.60		9.25**
		(0.77)		(2.46)
Cash flow to assets		4.12		−13.70***
		(1.19)		(−3.24)
SIC2 industry × Year FE	Yes	Yes	Yes	Yes
Observations	319,143	219,486	318,771	219,162

This table presents OLS estimates of the sensitivity of the propensity to repurchase shares (*Repurchase*) and to conduct seasoned equity offerings (*SEO*) to the firm's asset beta (*Asset beta*). The sample period is 1977 to 2015. All public firms in Compustat are included. t-statistics, based on standard errors clustered by the firm's (SIC2-) industry, are reported in parentheses. *p <.1; **p <.05; ***p <.01.

Table E.2
Share repurchases, seasoned equity offerings, and equity beta

	(1)	(2)	(3)	(4)
Sample:	Public firms in Compustat			
Dependent variable:	Repurchase_t		SEO_t	
Equity beta_{t-1}	−6.60**	−9.73***	15.50***	11.18***
	(−2.29)	(−6.08)	(5.07)	(6.41)
$\text{log(Market capitalization)}_{t-1}$		4.85***		4.92***
		(21.53)		(18.35)
$\text{Market-to-book}_{t-1}$		−0.44***		0.40***
		(−7.09)		(3.89)
$\text{Cash to assets}_{t-1}$		−3.10		2.50
		(−0.90)		(0.92)
$\text{Debt to assets}_{t-1}$		−9.94***		−4.68
		(−5.04)		(−1.48)
ROA_{t-1}		2.81		8.51**
		(0.82)		(2.18)
$\text{Cash flow to assets}_{t-1}$		3.90		−12.97***
		(1.11)		(−2.96)
SIC2 industry × Year FE	Yes	Yes	Yes	Yes
Observations	333,001	219,584	332,629	219,260

This table presents OLS estimates of the sensitivity of the propensity to repurchase shares (*Repurchase*) and to conduct seasoned equity offerings (*SEO*) to the firm's equity beta (*Equity beta*). The sample period is 1977 to 2015. All public firms in Compustat are included. t-statistics, based on standard errors clustered by the firm's (SIC2-) industry, are reported in parentheses. *p <.1; **p <.05; ***p <.01.

References

Acharya, V., H. Almeida, F. Ippolito, and A. Perez. 2014. Credit lines as monitored liquidity insurance: Theory and evidence. *Journal of Financial Economics* 112:287–319.

Ali, A., K. Wei, and Y. Zhou. 2011. Insider trading and option grant timing in response to fire sales (and purchases) of stocks by mutual funds. *Journal of Accounting Research* 49:595–632.

Alti, A., and J. Sulaeman. 2012. When do high stock returns trigger equity issues? *Journal of Financial Economics* 103:61–87.

Ambrose, B., and W. Megginson. 1992. The role of asset structure, ownership structure, and takeover defenses in determining acquisition likelihood. *Journal of Financial and Quantitative Analysis* 27:575–89.

Baker, M., B. Bradley, and J. Wurgler. 2011. Benchmarks as limits to arbitrage: understanding the low-volatitliy anomaly. *Financial Analyst Journal* 67:1–15.

Baker, M., M. Hoeyer, and J. Wurgler. 2019. Leverage and the beta anomaly. *Journal of Financial and Quantitative Analysis*. Advance Access published April 22, 2019, 10.1017/S0022109019000322.

Baker, M., and J. Wurgler. 2013. Behavioral corporate finance: an updated survey. In *Handbook of the Economics of Finance, Volume 2A*, ed. G. Constantinides, M. Harris, and R. Stulz, 357–424. Amsterdam: North Holland.

Baker, M., and Y. Xuan. 2016. Under new management: Equity issues and the attribution of past returns. *Journal of Financial Economics* 121:66–78.

Bebchuk, L., A. Cohen, and A. Ferrell. 2009. What matters in corporate governance? *Review of Financial Studies* 22:783–827.

Betton, S., E. Eckbo, and K. Thorburn. 2008. Corporate takeovers. In *Handbook of corporate finance, vol. 2*, ed. E. Eckbo, 291–429. Amsterdam, the Netherlands: North Holland.

Berger, E. 2019. Selection bias in mutual fund flow-induced fire sales: Causes and consequences. Working Paper, Cornell University.

Berk, J., and P. DeMarzo. 2017. *Corporate finance*. Essex, UK: Pearson Education.

Berk, J., R. Green, and V. Naik. 1999. Optimal investment, growth options, and security returns. *Journal of Finance* 54:1553–607.

van Binsbergen, J. H., and C. C. Opp. 2019. Real anomalies. *Journal of Finance* 74:1659–706.

Black, F., M. Jensen, and M. Scholes. 1972. The capital asset pricing model: Some empirical tests. In *Studies in the theory of capital markets*, ed. M. Jensen, 79–121. New York, NY: Praeger.

Brav, A., J. Graham, C. Harvey, and R. Michaely. 2005. Payout policy in the 21st century. *Journal of Financial Economics* 77:483–527.

Brealy, R., S. Myers, and F. Allen. 2017. *Principles of corporate finance*. New York: McGraw-Hill.

Carhart, M. 1997. On persistence in mutual fund performance. *Journal of Finance* 52:57–82.

Cleary, S. 1999. The relationship between firm investment and financial status. *Journal of Finance* 54:673–92.

Cohen, R., C. Polk, and T. Vuolteenaho. 2009. The price is (almost) right. *Journal of Finance* 64:2739–82.

Coval, J., and E. Stafford. 2007. Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics* 86:479–512.

Cremers, M., V. Nair, and K. John. 2009. Takeovers and the cross-section of returns. *Review of Financial Studies* 22:1409–45.

Da, Z., R. Guo, R., and R. Jagannathan. 2012. CAPM for estimating the cost of equity capital: interpreting the empirical evidence. *Journal of Financial Economics* 103:204–20.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers. 1997. Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance* 52:1035–58.

Daniel, K., and S. Titman. 1997. Evidence on the characteristics of cross sectional variation in stock returns. *Journal of Finance* 52:1–33.

Dessaint, O., T. Foucault, L. Frésard, and A. Matray. 2019. Noisy stock prices and corporate investment. *Review of Financial Studies* 32:2625–72.

Dessaint, O., A. Golubov, and P. Volpin. 2017. Employment protection and takeovers. *Journal of Financial Economics* 125:369–88.

Dittmar, A. 2000. Why do firms repurchase stock? *Journal of Business* 73:331–55.

Eckbo, E., T. Makaew, and K. Thorburn. Forthcoming. Are stock-finance takeovers opportunistic? *Journal of Financial Economics*.

Edmans, A., X. Gabaix, and A. Landier. 2009. A multiplicative model of optimal CEO incentives in market equilibrium. *Review of Financial Studies* 22:4881–917.

Edmans, A., I. Goldstein, and W. Jiang. 2012. The real effects of financial markets: the impact of prices on takeovers. *Journal of Finance* 67:933–71.

Fama, E., and K. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33:3–56.

Fama, E., and K. French. 2004. The capital asset pricing model: theory and evidence. *Journal of Economic Perspectives* 18:25–46.

Frazzini, A., and L. Pedersen. 2014. Betting against beta. *Journal of Financial Economics* 111:1–25.

Graham, J., and C. Harvey. 2001. The theory and practice of corporate finance: evidence from the field. *Journal of Financial Economics* 60:187–243.

Goldman, J. 2017. Do directors respond to stock mispricing? Evidence from CEO turnovers. Working Paper, University of Toronto.

Golubov, A., D. Petmezas, and N. Travlos. 2012. When it pays to pay your investment banker: new evidence on the role of financial advisors in M&As. *Journal of Finance* 67:271–311.

Golubov, A., A. Yawson, and H. Zhang. 2015. Extraordinary acquirers. *Journal of Financial Economics* 116:314–30.

Harford, J., M. Humphery-Jenner, and R. Powell. 2012. The sources of value destruction in acquisitions by entrenched managers. *Journal of Financial Economics* 106:247–61.

Hasbrouck, J. 1985. The characteristics of takeover targets q and other measures. *Journal of Banking and Finance* 9:351–62.

Hong, H., and D. Sraer. 2016. Speculative betas. *Journal of Finance* 71:2095–144.

Honkanen, P., and D. Schmidt. 2018. Learning from noise? Price and liquidity spillovers around mutual fund fire sales. Working Paper, HEC Paris.

Jacobs, M., A. Shivdasani. 2012. Do you know your cost of capital? *Harvard Business Review* 7/8:118–24.

Jagannathan, R., D. Matsa, I. Meier, and V. Tarhan. 2016. Why do firms use high discount rates? *Journal of Financial Economics* 120:445–63.

Krüger, P., A. Landier, and D. Thesmar. 2015. The WACC fallacy: the real effects of using a unique discount rate. *Journal of Finance* 70:1253–85.

Levi, Y., and I. Welch. 2017. Best practice for cost-of-capital estimates. *Journal of Financial and Quantitative Analysis* 52:427–63.

Lintner, J. 1965. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics* 47:13–37.

Liu, J., D. Nissim, and J. Thomas. 2002. Equity valuation using multiples. *Journal of Accounting Research* 40:135–72.

Lou, D. 2012. A flow-based explanation for return predictability. *Review of Financial Studies* 25:3457–89.

Martin, I. W. R., and C. Wagner. 2019. What is the expected return on a stock? *Journal of Finance* 74:1887–929.

Masulis, R., C. Wang, and F. Xie. 2007. Corporate governance and acquirer returns. *Journal of Finance* 62:1851–89.

Moeller, S., F. Schlingemann, and R. Stulz. 2004. Firm size and the gains from acquisitions. *Journal of Financial Economics* 73:201–28.

Mossin, J. 1966. Equilibrium in a capital asset market. *Econometrica* 34:768–83.

Mukhlynina, L., and K. Nyborg. 2016. The choice of valuation techniques in practice: education versus profession. Working Paper, University of Zurich.

Palepu, K. 1986. Predicting takeover targets: A methodological and empirical analysis. *Journal of Accounting and Economics* 8:3–35.

Phillips, G., and A. Zhdanov. 2013. R&D and the incentives from merger and acquisition activity. *Review of Financial Studies* 26:34–78.

Ross, S., R. Westerfield, J. Jaffe, and B. Jordan. 2016. *Corporate finance*. New York: McGraw-Hill.

Savor, P., and Q. Lu. 2009. Do stock mergers create value for acquirers? *Journal of Finance* 64:1061–97.

Schneider, C., and O. Spalt. 2019. On the use of proxy variables in Finance: Why does size matter so much for bidder announcement returns? Working Paper, Tilburg University.

Sharpe, W. 1964. Capital asset prices: a theory of market equilibrium under conditions of risk. *Journal of Finance* 19:425–42.

Shleifer, A., and R. Vishny. 2003. Stock market driven acquisitions. *Journal of Financial Economics* 70:295–311.

Stein, J. 1996. Capital budgeting in an irrational world. *Journal of Business* 69:429–55.

Stock, J., J. Wright, and M. Yogo. 2002. A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics* 20:518–29.

Todd, P. 1999. A practical guide to implementing matching estimators. Working Paper, University of Pennsylvania.

Wardlaw, M. 2018. Measuring mutual fund flow pressure as shock to stock returns. Working Paper, University of Michigan.

Wooldridge, J. 2002. *Econometric analysis of cross section and panel data*. Cambridge: MIT Press.