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Does the CAPM drive misvaluations in M&As?

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Abstract

This paper confirms the positive empirical relationship between CAPM-implied target asset betas and bidder announcement returns originally documented by Dessaint et al. (Rev Financ Stud 34(1):1–66, 2021) for U.S. takeover bids. We successfully replicate the main regression results qualitatively for the original and an extended sample period. However, the relationship is statistically insignificant in the European market for corporate control, although it appears to be economically meaningful. Additional tests indicate that bidder announcement returns are only related to target asset betas during merger waves and in horizontal mergers and acquisitions. These findings suggest that the relationship between target asset betas and bidder announcement returns is not driven by a CAPM-induced misvaluation of target firms. Therefore, recommendations to abandon the CAPM for capital budgeting decisions do not seem warranted.

Keywords Mergers & acquisitions · CAPM · Capital budgeting · Valuation errors

JEL Classification G14 · G31 · G34 · G41

1 Introduction

The finance literature has frequently and thoroughly examined the capital asset pricing model (CAPM) introduced by Sharpe (1964), Lintner (1965), and Mossin (1966). While there is mounting empirical evidence against the use of the CAPM

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to predict stock returns (e.g., Black et al. 1972; Stambaugh 1982; Fama and French 1992; Frazzini and Pedersen 2014), it is still widely applied in practice, for example, to estimate discount rates for capital budgeting decisions or to evaluate the performance of portfolio managers (e.g., Graham and Harvey 2001; Fama and French 2004; Cain and Denis 2013; Graham 2022). Further, the CAPM is a centerpiece of corporate finance courses at universities (Da et al. 2012) and of typical corporate finance textbooks (e.g., Brealey et al. 2022). At first sight, this seems counterintuitive. Yet, both available empirical evidence (Berk et al. 1999) and theoretical reasoning (Da et al. 2012) indicate that it is not inconsistent to believe that stocks exhibit pricing errors relative to the CAPM and that betas calculated from stock returns are a valuable proxy for the underlying risk of investment projects (Stein 1996).

To determine whether the CAPM should be abandoned for capital budgeting objectives in favor of other models that forecast stock returns more accurately (Stein 1996), one must empirically investigate real-world capital budgeting decisions made by corporate executives and their observable value impacts. An ideal setting for such an evaluation are mergers and acquisitions (M&As) because these represent investment projects of large economic importance (Aktas et al. 2021), they are observable (Krüger et al. 2015), among the most critical financial decisions a firm faces (Dasgupta et al. 2024), and have a significant impact on the market value of a firm.

The first to provide such an empirical examination showing that the application of the CAPM leads to systematic valuation errors in M&As (relative to the market's view) are Dessaint et al. (2021) (hereafter: DOOT). Based on their findings, they caution against using the CAPM for capital budgeting decisions, particularly in an M&A context. Their intuition is as follows: Because stocks with a high (low) CAPM beta experience lower (higher) actual returns than predicted by the model, using the CAPM to estimate a target's value leads to systematic misvaluations. Thus, CAPM-implied values for targets with low (high) betas are above (below) their true valuation, such that bidders systematically overpay (underpay) for low-beta (high-beta) targets. This logic predicts that the bidders' stock market reaction is more favorable for announcements of bids with high-beta targets than low-beta targets. DOOT provide compelling empirical support for their hypothesis, based on a large sample of bids by U.S. public firms for private targets between 1977 and 2015. Their findings imply significant value destruction in M&As caused by using the CAPM to estimate the targets' cost of capital. The authors also argue that typical capital budgeting choices comprise non-tradeable projects, similar to acquisitions of private targets. Therefore, they conclude that their M&A results are likely a lower bound for CAPM-based valuation errors. This finding has a potentially large impact on academic teaching and on practitioners who use the CAPM to estimate the cost of capital. Ultimately, DOOT's findings suggest that we should abandon the CAPM for capital budgeting purposes in favor of a different asset pricing model.

However, despite the failure of the CAPM as a capital budgeting tool becomes a stylized fact and the profession starts rewriting all corporate finance textbooks, we believe additional empirical evidence is needed to buttress this claim. Therefore, we perform the first replication of DOOT focusing on their main result, i.e., applying the CAPM leads to systematic valuation errors in M&As, which we dub the "CAPM

misvaluation effect". While using their original methodology but extending the sample period by five years through the end of 2020, we are able to qualitatively replicate DOOT's main results. In the next step, we extend their findings in three dimensions: (1) geographically, (2) for different time periods, and (3) across different subsamples.

Due to the novelty of DOOT's approach, the evidence for the CAPM's influence on M&A bids is so far limited to U.S. bidders. However, there are significant institutional and economic differences across M&A markets, such as corporate governance structures, ownership, and stock market conditions that lead to systematically different M&A characteristics and outcomes, for example, in the U.S. and Europe (e.g., Faccio and Masulis 2005). Therefore, the question arises as to whether and how using the CAPM for target valuation affects M&A bids outside of the U.S. We provide the first empirical test using European M&A data. We find mixed evidence for the CAPM misvaluation effect in a large European data set including bids from 18 different countries between 1977 and 2020. Most regression coefficients lack statistical significance, but their implied economic impact is rather large.

Second, inspired by Welch (2019), we examine the sample period dependency of DOOT's findings. As we find the CAPM misvaluation effect to be present only prior to 2001, we investigate which time periods drive DOOT's results. Based on prior literature (e.g., Baker et al. 2012; Kolev et al. 2012; Duchin and Schmidt 2013) we know that acquisitions in merger waves are different from those outside of such waves. Therefore, we test the CAPM misvaluation effect's robustness across different time periods focusing on subsamples inside and outside of merger waves. We show that DOOT's findings primarily hold during merger wave periods, especially during the fifth merger wave (1992–2001) in the U.S., while they do not hold outside merger waves and during more recent years. Since there is no reason to believe that the CAPM is used differently by bidders inside and outside of merger waves, this result suggests that there might be a different underlying reason beyond the CAPM misvaluation effect proposed by DOOT for why target asset betas are related to bidder announcement returns.

Third, we propose a new test based on the idea that bidders are less likely to estimate the cost of capital using the CAPM for targets in their own industry (horizontal bids) than for targets from other industries (diversifying bids) because bidders have additional information about the cost of capital of targets within their own industry. In other words, the CAPM misvaluation effect should matter significantly more in diversifying than in horizontal bids. However, we find exactly the opposite. The CAPM misvaluation effect seems to exist only for horizontal but not for diversifying bids. Again, this finding casts doubt on the reasoning that suggests using the CAPM might cause target misvaluations in M&As.

Overall, our results all point in the same direction: Using the CAPM might not be the root cause of bidders misvaluing targets. Otherwise we would expect that the CAPM misvaluation effect (1) would also be strongly present in Europe, (2) would exist inside and outside of merger waves, and (3) would be stronger (not weaker) in diversifying acquisitions. We, therefore, conclude that the relationship between target asset betas and bidder announcement returns is more ambiguous than presented by DOOT.

We contribute to the existing literature mainly in two ways. First, we present new evidence on the question of whether the CAPM remains a valuable tool in capital budgeting, despite being unsuitable for predicting stock returns (Stein 1996). The literature's current stance on this matter is inconclusive. While some studies suggest that the CAPM might be valuable for estimating investment project risk (e.g., Berk et al. 1999; Da et al. 2012), others caution against its application (e.g., Dessaint et al. 2021). We provide new evidence on the implications of employing the CAPM as a capital budgeting tool in M&As.

Second, we add to the strand of literature questioning the extent to which insights from the U.S. capital market can be transferred to other regions. Although most finance research relies on U.S. data, economic activity is distributed more evenly worldwide (e.g., Karolyi 2016). This is also evident from our data set, as approximately one-third of the M&A bids in our entire sample involve European bidders. Furthermore, the presence of an effect in the U.S. does not necessarily indicate its global applicability. Hence, we examine whether DOOT's findings based on U.S. data carry over to the European market for corporate control.

In summary, we replicate the main results of DOOT but also find evidence that their conclusions may be premature. More research is needed to determine whether the CAPM causes systematic errors in capital budgeting. Thus, we believe it is too early to banish the model from corporate finance education and practice.

The remainder of the paper is organized as follows. Section 2 introduces the data sources, key variables, and summary statistics of our M&A sample. Section 3 presents the replication of DOOT's main findings for U.S. and European M&As. Section 4 provides two additional tests of the CAPM misvaluation effect, then Sect. 5 concludes.

2 Data

2.1 Sources

We form three M&A subsamples consisting of all takeover bids reported by the Securities Data Company (SDC). The first subsample, referred to as the "replication sample", focuses on bids from publicly listed firms based in the U.S. between January 1st, 1977, and December 31st, 2015, as in DOOT's paper. The second subsample, called the "extended sample", also requires the bidders to be listed and headquartered in the U.S. but extends the sample period until December 31st, 2020. The third subsample, which we name the "European sample", only considers bids between January 1st, 1977, and December 31st, 2020, submitted by public firms headquartered in one of the following 18 European countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. Following DOOT, we exclude bids with inflation-adjusted deal values below 50 million U.S. dollars (USD) from all M&A subsamples. This minimum threshold is adjusted using yearly values of the consumer price index (CPI). The base year of the CPI is set to 2015 in analogy to DOOT's study. Further,

we also exclude share repurchases and targets that SDC classifies as government owned, joint ventures, or mutually owned (Dessaint et al. 2021). Then, we divide each M&A subsample into two mutually exclusive groups depending on the targets' listing status. The first group consists of bids for listed firms, called "public targets" hereafter. The second group comprises bids for subsidiaries or privately held firms. This group is referred to as "private targets".

For U.S. firms, we obtain accounting data from Compustat, stock market data from the Center for Research in Security Prices (CRSP), and data on the statutory tax rate from Trading Economics.¹ For European firms, we draw both accounting and stock market data from Datastream and gather the data on the statutory tax rate on a country level from Tax Foundation.²

For the European data, we use additional filters to prevent data errors (e.g., Ince and Porter 2006; Griffin et al. 2010). First, we set monthly returns to missing if Datastream reports more than three consecutive months with returns of 0%, and we further delete all zero returns that Datastream reports after a stock's delisting. Second, we delete all observations past a firm's inactive date. Third, we drop all observations where the main accounting variables used in this study are missing simultaneously, as these indicate points in time before a firm started filing reports.

2.2 Variables

Dependent Variable. To examine the impact of a potential valuation bias in M&A bids induced by using the CAPM, we employ an event study methodology, calculating the bidders' cumulative abnormal returns (*Bidder CAR*) over a symmetric seven-day event window $[-3; +3]$ around the M&A announcement date ($t = 0$) in line with Krüger et al. (2015) and DOOT. Like DOOT, we use market-adjusted returns to calculate cumulative abnormal returns:

$$\widehat{CAR}_i [-3; +3] = \sum_{t=-3}^3 r_{i,t} - r_{m,t}, \quad (1)$$

where $r_{i,t}$ is the actual end-of-day return of company i at time t , and $r_{m,t}$ is the return of the applicable market index at time t . Following DOOT, *Bidder CAR* is win-sorized at the 1st and 99th percentiles to reduce the influence of outliers.

Independent Variables. Our main explanatory variable is the target's asset beta (*Target asset beta*) as defined in DOOT. It is calculated in four steps that are equal for the calculation of the bidder's asset beta (*Bidder asset beta*). First, we compute individual equity betas ($\beta_{i,t}^E$) for all public firms in the U.S. and all European countries considered in this study. Second, we delever each equity beta using the

¹ Trading Economics (<https://tradingeconomics.com/united-states/corporate-tax-rate>) was recommended to us for their precise U.S. tax data by KPMG, an accounting organization active worldwide.

² Tax Foundation is a U.S.-based independent tax policy nonprofit organization: <https://taxfoundation.org/data/all/global/corporate-tax-rates-by-country-2022/>.

formula given by Hamada (1972) to calculate individual asset betas ($\beta_{i,t}^A$) for all public firms in the U.S. and the European sample.^{3,4} Third, we compute the equal-weighted mean of $\beta_{i,t}^A$ across all public firms in the U.S. and Europe that share the same 3-digit Standard Industrial Classification (SIC) code. Fourth, we assign to the bidders and targets in our M&A subsamples the average asset beta of their respective industries at the end of the month before the bid announcement. Consequently, the same asset beta is attributed to bidders and targets operating in the same industry.

More specifically, for the replication sample and the extended sample, we estimate individual equity betas for all firms listed in CRSP. We regress monthly excess returns for every public firm i at the end of each month t on the excess return of the CRSP value-weighted portfolio (including dividends) using 60-month rolling windows. For the European sample, we use all firms listed in Datastream that are headquartered in one of the 18 European sample countries. Instead of the CRSP value-weighted portfolio, the MSCI Europe Value Weighted Index (including dividends) is used to proxy for the European market portfolio. Otherwise the procedure remains the same. In all three subsamples, we exclude all estimates of $\beta_{i,t}^E$ based on fewer than 36 monthly returns. Further, we drop all observations where the estimated equity beta is negative, and we drop an identical number of observations in the right tail of the equity beta distribution (Dessaint et al. 2021). This procedure is conducted separately for the replication sample, the extended sample, and the European sample to ensure consistency. The individual equity betas are delevered and then average 3-digit SIC industry asset betas are calculated. The average industry asset betas are winsorized at the 1st and 99th percentiles.

To control for the results of Krüger et al. (2015), who find that bidders use their own asset beta instead of that of their targets in valuations and, thus, do not adequately account for differences in asset risk between their targets and themselves, we also include a bid's *Beta spread* as an explanatory variable. The *Beta spread* reflects differences in asset risk across industries and is calculated by first subtracting the non-winsorized bidder's average industry asset beta from the non-winsorized target's average industry asset beta before winsorizing the difference at the 1st and 99th percentiles.

Following DOOT, we further control for a standard set of deal, acquirer, and target characteristics in the respective regressions (see, e.g., Moeller et al. 2007; Harford et al. 2012; El-Khatib et al. 2015; Dessaint et al. 2017). We briefly introduce all control variables used in the following and provide additional information in Table 8 in the Appendix. We include the same deal characteristics as DOOT. $\log(\text{Deal value})$ is the natural logarithm of the reported deal value by SDC in million

³ Hamada (1972) assumes a constant level of debt, which will never be paid down. Thus, the following formula is used to delever equity betas: $\beta_{i,t}^A = \beta_{i,t}^E / [1 + (1 - \tau) \times D_{i,t} / E_{i,t}]$, where τ is the nationwide statutory tax rate in the highest bracket, $D_{i,t}$ is the firm's total debt at the end of the last fiscal year, and $E_{i,t}$ is the market capitalization of firm i at the end of month t .

⁴ Our results are robust to using the alternative formulas of Miles and Ezzell (1980) and Harris and Pringle (1985) for deleveraging equity betas. Furthermore, changing DOOT's $\beta_{i,t}^D = 0$ assumption to $\beta_{i,t}^D = 0.3$ does not materially affect our results. The corresponding results are shown in Table A.4 in the Online Appendix.

USD winsorized at the 1st and 99th percentiles. *Equity (Cash)* is a dummy variable indicating whether a bid's payment mix includes stock (cash). We define *Toehold* as the fraction of the target's equity held by the acquirer before the bid announcement. If this information is missing in the SDC database, *Toehold* is set to zero. *Hostile* equals 1 if SDC classifies the bid as hostile and 0 otherwise. *Same industry* indicates whether the acquirer and target operate in the same 3-digit SIC industry. *Cross-border* equals 1 if the acquirer and target are headquartered in different countries and 0 otherwise. *Poison* is a dummy variable indicating whether the target uses a takeover defense. *Tender* equals 1 if SDC classifies the bid as a tender offer and 0 otherwise. *Multiple bidders* equals 1 if there is more than one bidder and 0 otherwise. *Relative size* is defined as the ratio of the reported deal value in SDC and the acquirer's market capitalization four days prior to the bid announcement. We define $\log(\text{Bidder size})$ as the natural logarithm of the market capitalization of the bidder in million USD four days prior to the bid announcement.

Furthermore, we follow, e.g., Baker et al. (2012) and DOOT by controlling for target and bidder characteristics in our analyses. Importantly, we include yearly balance sheet and income statement characteristics from the previous fiscal year before the M&A announcement such that no forward-looking information is used. In addition, we measure all variables in USD to ensure comparability across all M&A subsamples. In line with DOOT, we define a target's (bidder's) return on assets (ROA) as the ratio of net income before extraordinary items to total assets, while a target's (bidder's) market-to-book ratio is calculated as the ratio of the target's (bidder's) market capitalization and shareholders' equity. The target's (bidder's) leverage is calculated as the sum of long-term debt and current liabilities divided by total assets. In addition, we control for targets' and bidders' cash holdings scaled by total assets in our analyses. Finally, we include a target's (bidder's) cash flow, defined as net income before extraordinary items plus depreciation and amortization, divided by total assets in the set of controls. For private targets, we use the equally weighted mean of the respective characteristics calculated across all public firms operating in the same 3-digit SIC industry and year in the respective subsample, following the approach of DOOT for consistency.

2.3 Summary statistics

DOOT argue that corporate managers are more likely to use the CAPM to evaluate unlisted firms because there are no stock market prices available. Therefore, the main analyses in their paper focus on private targets. In line with that, we present the summary statistics only for private target bids in each of our subsamples in Table 1. In Panel A we also provide the summary statistics for what we refer to as the "original sample" from DOOT (Panel A of Table 1 in their paper). The descriptive statistics for public target bids in each subsample are reported in Table A.1 in the Online Appendix.

Table 1 Summary statistics – private targets

	N	Mean	St. Dev.	Min.	p25	Median	p75	Max.
Panel A: Original Sample								
<i>Bidder CAR (%)</i>	14,744	2.0	8.2	−20.5	−2.3	1.1	5.6	27.9
<i>Target asset beta</i>	17,885	0.86	0.33	0.17	0.62	0.86	1.11	1.55
<i>Bidder asset beta</i>	18,163	0.87	0.32	0.20	0.64	0.84	1.11	1.54
<i>Beta spread</i>	17,707	−0.01	0.25	−0.74	−0.06	0.00	0.03	0.76
<i>log(Deal value)</i>	18,485	4.91	1.07	3.29	4.09	4.70	5.52	9.08
<i>Deal value (in mio. USD)</i>	18,485	297	699	27	60	110	250	8799
<i>Deal value (in mio. USD, CPI adj.)</i>	18,485	388	882	51	82	148	334	11,437
<i>100% stock</i>	18,482	0.13	0.33	0.00	0.00	0.00	0.00	1.00
<i>Avg. discount rate (%)</i>	117	14.1	4.9	7.0	11.0	13.0	15.0	30.0
Panel B: Replication Sample								
<i>Bidder CAR (%)</i>	14,515	1.7	8.0	−21.8	−2.3	0.9	4.9	29.6
<i>Target asset beta</i>	17,366	0.80	0.32	0.16	0.57	0.78	1.06	1.43
<i>Bidder asset beta</i>	17,602	0.79	0.33	0.18	0.54	0.77	1.05	1.43
<i>Beta spread</i>	17,207	0.02	0.23	−0.69	−0.01	0.00	0.06	0.76
<i>log(Deal value)</i>	17,878	4.90	1.06	3.30	4.09	4.68	5.52	9.12
<i>Deal value (in mio. USD)</i>	17,878	297	718	27	60	108	250	9100
<i>Deal value (in mio. USD, CPI adj.)</i>	17,878	388	911	51	82	147	328	12,073
<i>100% stock</i>	17,878	0.12	0.33	0.00	0.00	0.00	0.00	1.00
<i>Avg. discount rate (%)</i>	110	14.3	5.0	6.5	11.5	13.0	15.0	30.0
Panel C: Extended Sample								
<i>Bidder CAR (%)</i>	17,488	1.8	8.2	−22.6	−2.3	0.9	4.9	30.6
<i>Target asset beta</i>	20,061	0.80	0.31	0.16	0.58	0.79	1.05	1.40
<i>Bidder asset beta</i>	20,348	0.78	0.31	0.18	0.53	0.76	1.03	1.40
<i>Beta spread</i>	19,886	0.02	0.23	−0.67	−0.01	0.00	0.07	0.75
<i>log(Deal value)</i>	20,645	5.00	1.11	3.31	4.14	4.79	5.63	9.26
<i>Deal value (in mio. USD)</i>	20,645	344	842	27	63	120	280	10,468
<i>Deal value (in mio. USD, CPI adj.)</i>	20,645	419	992	51	84	155	352	13,069
<i>100% stock</i>	20,645	0.12	0.32	0.00	0.00	0.00	0.00	1.00
<i>Avg. discount rate (%)</i>	147	13.6	4.7	6.1	10.5	12.5	15.0	30.0
Panel D: European Sample								
<i>Bidder CAR (%)</i>	7549	1.5	6.3	−16.2	−1.9	0.9	4.1	24.5
<i>Target asset beta</i>	11,478	0.43	0.14	0.15	0.33	0.42	0.53	0.79
<i>Bidder asset beta</i>	11,262	0.44	0.12	0.17	0.36	0.43	0.52	0.78
<i>Beta spread</i>	10,817	−0.01	0.12	−0.35	−0.06	0.00	0.02	0.37
<i>log(Deal value)</i>	12,431	5.05	1.11	3.43	4.19	4.82	5.70	9.23
<i>Deal value (in mio. USD)</i>	12,431	364	891	31	66	124	300	10,248
<i>Deal value (in mio. USD, CPI adj.)</i>	12,431	449	1067	51	84	154	373	12,270
<i>100% stock</i>	12,431	0.05	0.23	0.00	0.00	0.00	0.00	1.00
<i>Avg. discount rate (%)</i>	2	14.5	2.1	13.0	13.0	14.5	16.0	16.0

This table reports descriptive statistics for private target M&A bids. Panel A displays the summary statistics for the original sample of Dessaint et al. (2021) (Panel A of Table 1 in their paper). Panel B reports the values for the replication sample. Panel C shows the descriptive statistics for the extended

Table 1 (continued)

sample. Panel D describes the European sample. The summary statistics include the number of observations, sample mean, standard deviation, minimum, 25% quantile, median, 75% quantile, and maximum. *Bidder CAR* is the bidder's cumulative abnormal return in the symmetric seven-day window around the bid announcement. *Target (Bidder) asset beta* is the target's (bidder's) average 3-digit SIC industry asset beta. *Beta spread* is the difference between the target's and bidder's average 3-digit SIC industry asset beta. *Deal value* is the deal value reported by SDC in million USD. *100% stock* is a dummy equal to 1 for offers where the payment mix consists solely of equity and 0 otherwise. *Avg. discount rate* is the midpoint between the maximum and minimum discount rate reported in M&A fairness opinions in SDC. All non-binary variables are winsorized at the 1st and 99th percentiles. All variables are described in Table 8 in the Appendix

Private Targets. We observe only minor differences in summary statistics between the original sample (Panel A) and the replication sample (Panel B). The bidders in the replication sample display slightly lower cumulative abnormal returns (CARs) around the bid announcement than the bidders in the original sample (1.7% vs. 2.0%). Yet, both values are positive, consistent with Fuller et al. (2002) and Betton et al. (2008). For *Target (Bidder) asset beta*, we also observe smaller values in the replication sample. This gap shows up across the whole distribution of both variables. However, the standard deviation and the interquartile range for *Target (Bidder) asset beta* are very similar in both samples. Hence, the slightly smaller values of *Target (Bidder) asset beta* should not severely impact the following analyses, as their respective distributions are only slightly shifted. The average *Deal value* is about the same in both samples. Further, we observe that all-stock bids are similarly likely in the replication sample and the original sample (12% vs. 13%), while the average discount rate applied in fairness opinions is almost identical (14.3% vs. 14.1%). Overall, we can replicate the descriptive statistics for private targets bids quite well.

The same holds true for private target bids in the extended sample presented in Panel C of Table 1. Bidders experience, on average, lower CARs around bid announcements in the extended sample than in the original sample (1.8% vs. 2.0%). The distribution of *Target (Bidder) asset beta* is almost identical in Panel C and Panel A, but as in the replication sample, the values displayed in Panel C are marginally shifted compared to Panel A. Between 2015 and 2020, the average size of private targets increased, as the mean inflation-adjusted deal value in the extended sample is larger than during the original sample period (419 million USD vs. 388 million USD). At the same time, the tendency of bidders to fully pay with equity remained almost the same (12% vs. 13%), while the average discount rate used in fairness opinions decreased (13.6% vs. 14.1%) during the extended sample period. In summary, the extended sample shows quantitatively very similar descriptive statistics for private targets bids as the original sample.

The descriptive statistics for the European sample, presented in Panel D of Table 1, show about half as many announced M&A bids from listed European firms for private targets between 1977 and 2020 compared to the corresponding U.S. sample. The average CAR of European bidders for private targets is slightly smaller than for U.S. bidders (1.5% vs. 1.8%), but still positive, in line with the findings of Faccio et al. (2006). The mean *Target (Bidder) asset beta* is smaller in Europe than in the U.S. But, while the distribution of *Target (Bidder) asset beta* is shifted, the standard deviation is

also smaller than in the extended sample. The average inflation-adjusted *Deal value* is marginally larger in Europe than in the U.S. (449 million USD vs. 419 million USD). We also observe a rather large difference in the probability of acquiring private targets using stock as the only form of payment between European and U.S. bidders (5% vs. 12%). Regarding the average discount rate applied in fairness opinions, there is almost no information in SDC for the European sample. Overall, the summary statistics presented in Table 1 suggest that M&A bids in the U.S. differ from European acquisitions across many dimensions, emphasizing the relevance of examining the effects documented by DOOT in a European sample.

Public Targets. Table A.1 in the Online Appendix presents the descriptive statistics for bids from public U.S. and European firms for public targets. As evident from Panel A, B, and C, *Bidder CAR*, *Deal value*, *100% stock*, and *Avg. discount rate* are qualitatively very similar across the original sample, the replication sample, and the extended sample. The distribution of *Target (Bidder) asset beta* in the replication sample and the extended sample is again slightly shifted, with lower mean values than in the original sample but with similar standard deviations and interquartile ranges. In general though, we are able to replicate the descriptive statistics for public target bids for the U.S. subsamples.

The European sample of bids for public targets is again about half the size of the extended U.S. sample. Still, the means of *Deal value* and *Avg. discount rate* are in the same ballpark. For public targets, there are also fewer stock bids in Europe than in the U.S. and the distribution of *Target (Bidder) asset beta* is shifted, displaying a lower standard deviation. The most notable difference is that the mean value of *Bidder CAR* is slightly positive in the European sample but negative in the U.S. subsamples, consistent with prior literature (e.g., Schneider and Spalt 2022).

3 Target asset betas and announcement returns

We start our analyses by replicating the baseline findings of DOOT. Further, we examine whether DOOT's empirical results for the U.S. also hold true for our European sample. In providing new empirical evidence for Europe, we extend the analyses of DOOT to another major market for corporate control and test the robustness of their findings. As the CAPM is (likely) taught and used in the same way worldwide, a bidder's country of origin should not materially impact the main results of DOOT's analyses. We follow the original authors and focus our analyses on the effect of *Target asset beta* on *Bidder CAR* for private target bids. DOOT regress *Bidder CAR* on *Target asset beta* and find that bidder announcement returns increase in target asset betas. We implement the identical regression design and replicate their results for the original sample period, an extended sample period, and a European sample. In all three cases, the following OLS regression is estimated:

$$\begin{aligned} \text{Bidder CAR} = & \alpha + \beta \times \text{Target asset beta} + \gamma \times \text{Beta spread} + \delta' \times \text{Deal controls} \\ & + \eta' \times \text{Target controls} + \kappa' \times \text{Bidder controls} \\ & + \text{Bidder industry} \times \text{Year fixed effects} + \epsilon. \end{aligned} \quad (2)$$

The vector *Deal controls* comprises deal-specific characteristics, including *log(Deal value)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same industry*, *Cross-border*, *Poison*, *Tender*, *Multiple bidders*, *Relative size*, and *log(Bidder size)*. The vector *Target (Bidder) controls* accounts for target- (bidder-)specific characteristics, and it includes the target's (bidder's) market-to-book ratio, its leverage, and ROA, as well as its cash holdings and cash flow both scaled by total assets.⁵ All variables are defined in Table 8 in the Appendix. Following DOOT, we cluster standard errors by the target's 3-digit SIC industry.

Table 2 reports the respective regression results separately for the original sample (Panel A), the replication sample (Panel B), the extended sample (Panel C), and the European sample (Panel D). Column (1) controls for bidder industry \times year fixed effects only. In Column (2) *Deal controls* are added. *Target controls*, *Bidder controls*, and *Beta spread* are included subsequently in Columns (3), (4), and (5) in corresponding order.^{6,7} Following the table setup of DOOT and to preserve space, we do not report the estimated coefficients and *t*-statistics for all target and bidder control variables.

Like DOOT, we find a positive effect of the target's asset beta on bidder CARs in both of our U.S. subsamples. However, compared to DOOT's original results (Table 2 in their paper), shown in Panel A of Table 2, the coefficients and the corresponding *t*-statistics are smaller in the replication sample (Panel B) and the extended sample (Panel C). The point estimates for *Target asset beta* are smaller than the lowest number reported by DOOT in four (three) out of five specifications in the replication sample (extended sample). On average, the values of the coefficients are about 2.5 (1.6) times larger in Panel A than in Panel B (Panel C). Yet, the relative difference between the point estimates of Panel A and Panel B (Panel C) decreases the more control variables are included from Column (1) to Column (5). Regarding the statistical significance, the estimates reach the threshold for the 1% level only in one (two) of five columns in Panel B (Panel C) compared to all columns in Panel A. In two (one) of five columns, the estimated coefficients are statistically insignificant.⁸ However, the economic significance across the three U.S. samples is quite comparable. The point estimates ranging from 0.22 to 1.85 (0.54 to 1.66) imply that an increase in *Target asset beta* by its interquartile range (0.49 in Panel B; 0.47 in Panel C) increases *Bidder CAR*, on average, by 0.11 to 0.91 (0.25 to 0.78) percentage points. This corresponds to 1.53% to 12.64% (3.47% to 10.83%) of the interquartile range of *Bidder CAR* (7.2% in both panels). This is comparable

⁵ As outlined in Sect. 2.2, we follow DOOT and estimate *Target controls* for private targets by computing the equally weighted annual averages of the respective variables across all listed firms that operate in the same 3-digit SIC industry in the U.S. or Europe.

⁶ The number of observations (N) across the five columns fluctuates, because some variables are not available for all observations. We also discard all "singletons", i.e., instances of a single observation for a particular fixed effect (FE), before the regression model is estimated. This methodology is used for all tables presented.

⁷ The variable *Beta spread* in Column (5) already accounts partially for our control variable *Same industry*, i.e., when firms operate in the same industry, *Beta spread* is zero; otherwise, it deviates from zero. However, we still include *Same industry* in the regression model to be consistent with the approach of DOOT. Dropping *Same industry* from the set of controls does not change any of our results qualitatively, as displayed in Table A.5 in the Online Appendix.

⁸ In unreported results, we confirm that winsorization of non-binary variables does not alter our results.

Table 2 Target asset beta and bidder cars – private targets

	Dependent Variable: <i>Bidder CAR</i> (%)				
	(1)	(2)	(3)	(4)	(5)
Panel A: Original Sample					
<i>Target asset beta</i>	1.02*** (3.02)	1.34*** (4.20)	1.73*** (4.72)	1.49*** (4.14)	2.55*** (5.06)
<i>Beta spread</i>					−1.36*** (−2.60)
<i>log(Deal value)</i>		0.66*** (7.37)	0.65*** (7.34)	0.59*** (6.82)	0.59*** (6.69)
<i>Equity</i>		0.59** (2.24)	0.60** (2.26)	0.57* (1.87)	0.51* (1.69)
<i>Cash</i>		0.30 (1.07)	0.28 (0.98)	0.48 (1.45)	0.44 (1.34)
<i>Toehold</i>		−0.08 (−0.20)	−0.15 (−0.36)	−0.11 (−0.26)	−0.10 (−0.24)
<i>Hostile</i>		−2.26** (−2.19)	−2.44** (−2.26)	−2.82** (−2.26)	−3.22*** (−2.76)
<i>Same industry</i>		0.11 (0.65)	0.12 (0.71)	0.12 (0.82)	0.14 (0.96)
<i>Cross-border</i>		−0.14 (−0.63)	−0.14 (−0.61)	−0.06 (−0.26)	−0.09 (−0.37)
<i>Poison</i>		−0.60 (−0.87)	−0.66 (−0.90)	−0.51 (−0.49)	−0.47 (−0.45)
<i>Tender</i>		−0.30 (−0.29)	−0.36 (−0.34)	−0.57 (−0.49)	−0.72 (−0.63)
<i>Multiple bidders</i>		−0.40 (−0.54)	−0.38 (−0.51)	0.07 (0.09)	0.03 (0.04)
<i>Relative size</i>		−0.06*** (−7.25)	−0.06*** (−7.20)	−0.06*** (−7.51)	−0.06*** (−7.59)
<i>log(Bidder size)</i>		−0.94*** (−12.40)	−0.94*** (−12.33)	−0.96*** (−12.50)	−0.96*** (−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
N	13,916	13,599	13,486	12,209	12,109

Table 2 (continued)

	Dependent Variable: <i>Bidder CAR (%)</i>				
	(1)	(2)	(3)	(4)	(5)
Panel B: Replication Sample					
<i>Target asset beta</i>	0.22 (0.58)	0.48 (1.27)	0.94** (2.20)	0.90** (2.16)	1.85*** (3.18)
<i>Beta spread</i>					−1.18* (−1.93)
<i>log(Deal value)</i>		0.64*** (7.83)	0.64*** (7.74)	0.60*** (7.18)	0.61*** (7.23)
<i>Equity</i>		0.38 (1.35)	0.41 (1.44)	0.42 (1.45)	0.36 (1.28)
<i>Cash</i>		−0.03 (−0.19)	−0.03 (−0.18)	0.00 (0.01)	−0.02 (−0.11)
<i>Toehold</i>		−0.01 (−0.82)	−0.01 (−0.80)	−0.01 (−0.86)	−0.01 (−0.76)
<i>Hostile</i>		1.74 (0.73)	1.74 (0.73)	1.54 (0.64)	0.35 (0.15)
<i>Same industry</i>		0.11 (0.60)	0.12 (0.66)	0.12 (0.62)	0.11 (0.59)
<i>Cross-border</i>		−0.06 (−0.26)	−0.07 (−0.30)	−0.08 (−0.35)	−0.14 (−0.59)
<i>Poison</i>		−0.91 (−1.37)	−0.89 (−1.35)	−0.88 (−1.23)	−0.89 (−1.23)
<i>Tender</i>		−0.39 (−0.27)	−0.38 (−0.26)	−0.23 (−0.16)	−0.35 (−0.24)
<i>Multiple bidders</i>		0.12 (0.16)	0.14 (0.19)	0.23 (0.31)	0.21 (0.27)
<i>Relative size</i>		−0.01* (−1.74)	−0.01* (−1.75)	−0.01* (−1.96)	−0.01* (−1.83)
<i>log(Bidder size)</i>		−0.88*** (−9.18)	−0.88*** (−9.01)	−0.86*** (−8.95)	−0.86*** (−9.04)
Bidder SDC industry × Year FE	Yes	Yes	Yes	Yes	Yes
Target controls	No	No	Yes	Yes	Yes
Bidder controls	No	No	No	Yes	Yes
N	13,682	12,610	12,610	12,295	12,220
Adjusted R ² (%)	3.43	6.42	6.43	6.23	6.17

Table 2 (continued)

	Dependent Variable: <i>Bidder CAR (%)</i>				
	(1)	(2)	(3)	(4)	(5)
Panel C: Extended Sample					
<i>Target asset beta</i>	0.54 (1.54)	0.78** (2.46)	1.22*** (3.14)	0.99** (2.49)	1.66*** (3.00)
<i>Beta spread</i>					−0.78 (−1.39)
<i>log(Deal value)</i>		0.68*** (8.18)	0.67*** (8.13)	0.59*** (7.38)	0.59*** (7.32)
<i>Equity</i>		0.43** (2.14)	0.45** (2.23)	0.48** (2.19)	0.45** (2.12)
<i>Cash</i>		0.04 (0.32)	0.04 (0.34)	0.13 (0.95)	0.11 (0.77)
<i>Toehold</i>		−0.00 (−0.63)	−0.00 (−0.62)	−0.01 (−0.74)	−0.00 (−0.66)
<i>Hostile</i>		1.70 (0.75)	1.70 (0.75)	1.69 (0.76)	0.70 (0.32)
<i>Same industry</i>		0.12 (0.73)	0.14 (0.81)	0.13 (0.74)	0.12 (0.69)
<i>Cross-border</i>		−0.23 (−1.02)	−0.24 (−1.04)	−0.22 (−0.96)	−0.26 (−1.12)
<i>Poison</i>		−0.88 (−1.49)	−0.88 (−1.49)	−0.86 (−1.29)	−0.86 (−1.29)
<i>Tender</i>		−0.33 (−0.22)	−0.32 (−0.21)	−0.24 (−0.17)	−0.36 (−0.25)
<i>Multiple bidders</i>		−0.83 (−1.03)	−0.82 (−1.03)	−0.13 (−0.17)	−0.13 (−0.18)
<i>Relative size</i>		−0.01 (−1.17)	−0.01 (−1.19)	−0.01 (−1.40)	−0.01 (−1.59)
<i>log(Bidder size)</i>		−0.87*** (−10.87)	−0.87*** (−10.76)	−0.81*** (−9.87)	−0.81*** (−9.93)
Bidder SDC industry × Year FE	Yes	Yes	Yes	Yes	Yes
Target controls	No	No	Yes	Yes	Yes
Bidder controls	No	No	No	Yes	Yes
N	16,511	15,340	15,340	14,690	14,606
Adjusted R ² (%)	3.22	5.99	5.99	5.75	5.70

Table 2 (continued)

	Dependent Variable: <i>Bidder CAR (%)</i>				
	(1)	(2)	(3)	(4)	(5)
Panel D: European Sample					
<i>Target asset beta</i>	1.87** (2.11)	1.43* (1.68)	1.71* (1.82)	1.48 (1.07)	2.64 (1.18)
<i>Beta spread</i>					−1.64 (−0.94)
<i>log(Deal value)</i>		0.57*** (5.27)	0.59*** (5.63)	0.70*** (5.20)	0.69*** (5.05)
<i>Equity</i>		0.93* (1.79)	0.93* (1.79)	0.59 (1.05)	0.46 (0.83)
<i>Cash</i>		−0.11 (−0.53)	−0.14 (−0.68)	0.01 (0.05)	0.00 (0.01)
<i>Toehold</i>		−0.00 (−0.49)	−0.00 (−0.52)	−0.00 (−0.42)	−0.00 (−0.53)
<i>Hostile</i>		−2.97 (−0.50)	−2.99 (−0.51)	4.36*** (2.72)	4.60*** (2.93)
<i>Same industry</i>		0.28 (1.39)	0.27 (1.31)	0.16 (0.65)	0.17 (0.68)
<i>Cross-border</i>		0.45** (2.22)	0.43** (2.12)	0.20 (0.73)	0.15 (0.53)
<i>Poison</i>		3.21 (0.73)	3.23 (0.73)	4.62** (2.28)	4.50** (2.13)
<i>Tender</i>		−0.77 (−0.97)	−0.80 (−1.01)	0.58 (0.51)	0.65 (0.57)
<i>Multiple bidders</i>		−2.95** (−2.53)	−2.93** (−2.50)	−2.61* (−1.66)	−2.56 (−1.62)
<i>Relative size</i>		0.00 (0.45)	0.00 (0.45)	−0.00 (−0.01)	0.00 (0.03)
<i>log(Bidder size)</i>		−0.82*** (−10.92)	−0.83*** (−11.01)	−1.01*** (−9.11)	−0.98*** (−8.55)
Bidder SDC industry × Year FE	Yes	Yes	Yes	Yes	Yes
Target controls	No	No	Yes	Yes	Yes
Bidder controls	No	No	No	Yes	Yes
N	6619	6407	6341	3999	3925
Adjusted R ² (%)	7.03	11.95	11.92	14.39	14.38

Table 2 (continued)

This table presents results for OLS regressions regarding the sensitivity of a bidder's announcement return (*Bidder CAR*), measured as market-adjusted abnormal returns cumulated over a symmetric seven-day event window $[-3; +3]$, to its target's average 3-digit SIC industry asset beta (*Target asset beta*). Further independent variables are defined in Table 8 in the Appendix. A constant term is included but not reported. Panel A presents the original results from Dessaint et al. (2021) (Table 2 in their paper). Panel B shows the replicated results for the same sample period from 1977 to 2015, while in Panel C the sample period is extended to 2020. Panel D reports the results for bids from European acquirers between 1977 and 2020. 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 in the U.S. (in our European sample), these variables are average values of the corresponding variables across all public firms in Compustat (Datastream within the 18 European sample countries) operating in the same 3-digit SIC industry. The *t*-statistics in parentheses are based on standard errors clustered by the target's 3-digit SIC industry. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively

to DOOT's results, who find an increase in *Bidder CAR* by 6% to 16% of its interquartile range. The effect is also large in dollar terms ranging from a 10 to 85 (26 to 83) million USD increase in average bidder market capitalization for an interquartile range increase of *Target asset beta* in the replication sample (extended sample). This is equivalent to 3.37% to 28.62% (7.56% to 24.13%) of the average deal value (297 million USD in Panel B; 344 million USD in Panel C).

The *Deal controls* for our U.S. subsamples shown in Table 2 closely resemble DOOT's regression results and are broadly in line with prior literature (e.g., Chang 1998; Moeller et al. 2004). The only exceptions are the variables *Hostile*, which is significantly negative in Panel A but insignificantly positive in Panel B and C, and *Equity*, which is insignificant in Panel B.⁹ Like DOOT, we observe a better (worse) reception of bid announcements for larger targets (bidders). This is consistent with Schneider and Spalt (2022), who show that bidder and target size primarily affect *Bidder CAR* as scaling variables. Stock-financed takeovers of private targets are received positively by the U.S. stock market, which is in line with prior literature (Fuller et al. 2002; Slovin et al. 2005; Ma et al. 2019). All other *Deal controls* are insignificant in Panel B and C.

To sum up, we find quite similar results regarding *Target asset beta* in both the replication sample and the extended sample. There are some differences in the magnitude of the coefficients and their statistical significance compared to the original sample. However, these differences are less pronounced once we include more control variables. Overall, we can replicate DOOT's main finding quite well. Further, we observe the same baseline effect of *Target asset beta* on *Bidder CAR* for an extended sample period.

In contrast to the U.S. data, in the European sample the effect of target asset betas on bidder CARs becomes insignificant as more control variables are added to the

⁹ These inconsistencies may be attributable to changes in the data. For instance, Bollaert and Delanghe (2015) demonstrate that the data in SDC undergoes slight alterations over time. Additionally, SDC categorizes a relatively small number of deals involving private targets as hostile (41 in the extended sample). One might even argue that hostile takeovers of private targets are impossible, which would explain the insignificant coefficients observed in Panels B and C. Since the DOOT analysis includes the variable *Hostile*, we include it in our replication.

regression model (Panel D). While the t -value in Column (1) is above two, it drops to values slightly above one in Columns (4) and (5). However, the economic magnitude of the CAPM misvaluation effect appears to be meaningful in Europe, as the regression coefficients are, on average, almost twice as large as in the extended sample, ranging from 1.43 to 2.64. Several control variable coefficients diverge from those in Panel B and C, suggesting that the determinants of *Bidder CAR* differ between the U.S. and Europe, which is consistent with the findings of Faccio and Masulis (2005). First, we find no significant effect of *Equity* in Columns (4) and (5) in our European sample, opposed to significantly positive coefficients in the original sample and the extended sample. Thus, stock-financed takeovers of private targets, which are significantly less common in Europe (12.04% vs. 24.50% in the U.S.), are not associated with higher announcement returns when controlling for bidder characteristics. Second, we also observe differences in sign and significance level for *Hostile*, *Poison*, and *Cross-border*. In contrast, the sign, magnitude, and significance of the coefficients for bidder and target size ($\log(\text{Bidder size})$ and $\log(\text{Deal value})$, respectively) are in line with our findings for the U.S. market and the scaling explanation by Schneider and Spalt (2022) regarding the influence of bidder and target size on announcement returns.

For completeness, we also examine bids for public targets. The results are presented in Table A.6 in the Online Appendix. The *Target asset beta* coefficients in our U.S. subsamples are mostly positive but insignificant, in line with DOOT's results.¹⁰ The finding of no CAPM misvaluation effect for public target bids is also confirmed by our European sample shown in Panel C of Table A.6. In Europe, we find only insignificant but economically large negative *Target asset beta* coefficients for public target bids. These results also hold if we replace "individual" *Target controls* with equally weighted annual averages, as in Table 2 for private targets. In fact, most coefficients and t -values even decrease in magnitude compared to our results in Table A.6, as shown in Table A.8 in the Online Appendix. Therefore, we conclude that no statistically significant relation exists between *Target asset beta* and *Bidder CAR* for M&A bids involving public targets. This result is in line with DOOT's reasoning regarding public target bids: They conjecture that bidders and targets are less likely to rely on the CAPM to value public firms because their market valuations are observable and often act as a lower bound for takeover values (e.g., Baker et al. 2012).

In summary, we conclude that our results for the U.S. market are comparable to DOOT's results. Also, DOOT's main finding holds in our extended sample: *Bidder CAR* increases in *Target asset beta* regarding bids for private targets but not for public targets.¹¹ Within our European sample, we find mixed evidence for the

¹⁰ The original results of DOOT are presented in Panel A of Table A.7 in the Online Appendix (Table 5 in their paper). We replicate these results using the exact same setup with the replication sample, the extended sample, and the European sample in Panel B, C, and D of Table A.7, respectively.

¹¹ This is also evident from Fig. A.1 and A.2 in the Online Appendix replicating Fig. 2 in DOOT. While the relationship between *Target asset beta* and *Bidder CAR* is represented by a straight line for private target bids, the relation for public target bids is extremely noisy and statistically insignificant for most ranges of *Target asset beta*.

Table 3 Sample period split – private targets

	Dependent Variable: <i>Bidder CAR</i> (%)				
	(1)	(2)	(3)	(4)	(5)
Panel A: Bids Between 1977 and 2000					
<i>Target asset beta</i>	1.23*	1.88***	2.10***	1.73**	3.61***
	(1.78)	(2.86)	(2.98)	(2.35)	(3.38)
<i>Beta spread</i>					−2.22*
					(−1.84)
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
N	7303	6282	6282	5894	5845
Adjusted R ² (%)	1.76	3.83	3.93	3.50	3.52
Panel B: Bids Between 2001 and 2020					
<i>Target asset beta</i>	0.13	0.23	0.84*	0.73	0.92
	(0.39)	(0.66)	(1.95)	(1.65)	(1.55)
<i>Beta spread</i>					−0.22
					(−0.38)
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
N	9208	9058	9058	8796	8761
Adjusted R ² (%)	4.62	8.25	8.30	8.37	8.14

This table presents results for OLS regressions regarding the sensitivity of a bidder's announcement return (*Bidder CAR*), measured as market-adjusted abnormal returns cumulated over a symmetric seven-day event window $[-3; +3]$, to its target's average 3-digit SIC industry asset beta (*Target asset beta*). Further independent variables are defined in Table 8 in the Appendix. A constant term is included but not reported. Panel A presents results for bids between 1977 and 2000. Panel B shows the results for bids between 2001 and 2020. Only bids for private targets are included. *Deal controls* is a vector of deal characteristics: *log(Deal value)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same industry*, *Cross-border*, *Poison*, *Tender*, *Multiple bidders*, *Relative size*, and *log(Bidder size)*. *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 in the U.S., these variables are average values of the corresponding variables across all public firms in Compustat operating in the same 3-digit SIC industry. The *t*-statistics in parentheses are based on standard errors clustered by the target's 3-digit SIC industry. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively

CAPM misvaluation effect. The coefficients estimated for *Target asset beta* in the subsample of bids by European firms for private targets lose statistical significance once we control for bidder characteristics. However, they are positive and economically large.

4 Subsample tests of the CAPM misvaluation effect

4.1 Time periods

The differences in significance and magnitude of the regression coefficients for *Target asset beta* in the replication sample (Panel B) and the extended sample (Panel C) in Table 2 raise the question of whether the relationship between the target's asset beta and the bidder's announcement return in the U.S. market for corporate control is robust across different time periods. Inspired by Welch's (2019) call to examine the sample period dependency of previous empirical findings, we split the extended sample into two non-overlapping subsamples (1977–2000 and 2000–2020), similar to de Bodt et al. (2024). While this choice is somewhat arbitrary, it roughly cuts the extended sample period in half. We, then, examine the OLS regression model from Equation 2 across both subsamples focusing on bids for private targets as we do in Sect. 3. The results in Panel A of Table 3 include all observations that occurred through 2000, while Panel B includes all observations between 2001 and 2020. Columns (1) to (5) correspond to the columns presented for the baseline findings in Table 2. For brevity, we only show the results of the main explanatory variables (*Target asset beta* and *Beta spread*).

In Panel A of Table 3, we find large and statistically significant positive coefficients for *Target asset beta* in all columns, ranging from 1.23 to 3.61. Compared to the results for the full extended sample period (Panel C of Table 2), both economic and statistical significance are increased. In contrast, we find an economically and statistically attenuated effect of *Target asset beta* on *Bidder CAR* in Panel B. The coefficient estimates are all positive but, on average, 74% smaller than in Panel A, and only one out of five is marginally significant. Overall, these findings indicate that after 2000 *Target asset beta* no longer has a significant impact on *Bidder CAR*.

This obvious time dependency of the CAPM misvaluation effect raises the question of which time period drives the empirical results prior to 2001. During this period, the acquisition of private targets in high-beta industries must have coincided with higher bidder CARs. As Baker et al. (2012) show that favorable stock market valuations coincide with merger waves, these time periods represent a natural candidate for investigating differences across time in our M&A sample. In addition, as indicated by prior research, M&As during merger waves exhibit distinct characteristics and outcomes compared to those outside of such waves (for an overview, see, e.g., Kolev et al. 2012). For instance, Duchin and Schmidt (2013) find that merger waves coincide with increased uncertainty, reduced accuracy of analysts' forecasts, weaker corporate governance, and elevated agency problems, contributing to significantly worse long-term performance of M&As during merger waves.

We start our time series analysis by plotting the number of bids from public U.S. firms for private and public targets (Panel A) as well as the associated aggregated deal values in billion USD (Panel B) between 1977 and 2020 in Fig. 1. In general, the figure highlights the large deal volumes during the merger wave periods 1984–1989, 1992–2001, and 2004–2007, defined as in Gaughan (2017). More specifically, there is a large peak in the number of private target bids during the

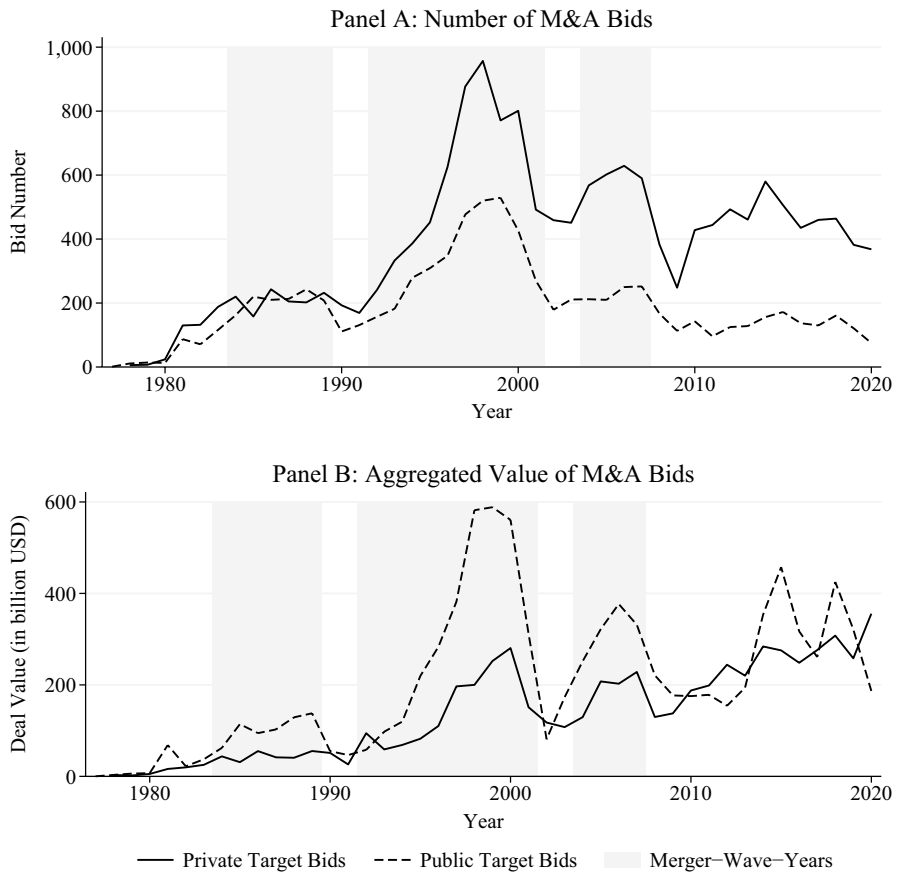


Fig. 1 Number of M&A Bids and Aggregated Deal Value in the U.S. This figure shows the annual number of M&A bids (Panel A) and the associated aggregated annual deal values in billion USD (Panel B) of public firms in the U.S. The solid line reports bids for private targets, while the dashed line reports bids for public targets. The shaded areas represent merger wave periods defined as in Gaughan (2017). The data on the number and value of M&A bids for the period from 1977 to 2020 is from SDC and is aggregated by calendar years

fifth merger wave between 1992 and 2001. This is of interest because DOOT mainly study bids for private targets, such that about 40% of their sample constitutes bids from this period. During the same time period, the aggregated deal value spikes for public targets. However, this is of minor concern for the OLS regressions conducted by DOOT, as those are not value weighted and already control for $\log(\text{Deal value})$.

Following our approach in Table 3, we perform another sample split for the extended U.S. sample. Based on Gaughan's (2017) merger wave periods, we group all observations into four non-overlapping subsamples. The first three subsamples include all observations during the fourth (1984–1989), fifth (1992–2001), and

Table 4 Merger waves – private targets

	Dependent Variable: <i>Bidder CAR (%)</i>				
	(1)	(2)	(3)	(4)	(5)
Panel A: Merger-Wave-Years Sample					
<i>Target asset beta</i>	0.58 (1.19)	1.03** (2.21)	1.41** (2.40)	1.19* (1.95)	2.39*** (2.65)
<i>Beta spread</i>					−1.44 (−1.61)
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
N	9375	8467	8467	8015	7968
Adjusted R ² (%)	2.44	5.15	5.13	4.89	4.88
Panel B: Non-Merger-Wave-Years Sample					
<i>Target asset beta</i>	0.48 (1.00)	0.52 (1.22)	1.10** (2.02)	0.87 (1.56)	1.06 (1.37)
<i>Beta spread</i>					−0.15 (−0.22)
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
N	7136	6873	6873	6675	6638
Adjusted R ² (%)	4.76	7.56	7.57	7.24	7.13
Panel C: Fourth Merger Wave (1984–1989)					
<i>Target asset beta</i>	1.17 (0.97)	1.96 (1.47)	1.57 (1.12)	1.01 (0.73)	2.91 (1.41)
<i>Beta spread</i>					−1.87 (−1.05)
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
N	1186	904	904	842	817
Adjusted R ² (%)	6.11	7.52	8.31	5.78	5.00

Table 4 (continued)

	Dependent Variable: <i>Bidder CAR (%)</i>				
	(1)	(2)	(3)	(4)	(5)
Panel D: Fifth Merger Wave (1992–2001)					
<i>Target asset beta</i>	1.25*	1.91***	2.64***	2.38***	3.74***
	(1.79)	(2.94)	(3.24)	(2.83)	(2.94)
<i>Beta spread</i>					−1.78
					(−1.30)
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
N	5844	5283	5283	4968	4952
Adjusted R ² (%)	2.02	4.45	4.42	4.23	4.24
Panel E: Sixth Merger Wave (2004–2007)					
<i>Target asset beta</i>	−0.71	−0.33	−0.34	−0.25	0.50
	(−1.17)	(−0.53)	(−0.40)	(−0.29)	(0.35)
<i>Beta spread</i>					−0.82
					(−0.61)
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
N	2345	2280	2280	2205	2199
Adjusted R ² (%)	4.93	10.42	10.24	10.84	10.88
Panel F: Extended Sample Excluding the Fourth and Fifth Merger Waves					
<i>Target asset beta</i>	0.11	0.21	0.71	0.57	0.91
	(0.31)	(0.60)	(1.61)	(1.30)	(1.53)
<i>Beta spread</i>					−0.34
					(−0.60)
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
N	9481	9153	9153	8880	8837
Adjusted R ² (%)	4.93	8.13	8.13	7.97	7.89

Table 4 (continued)

This table presents results for OLS regressions regarding the sensitivity of a bidder's announcement return (*Bidder CAR*), measured as market-adjusted abnormal returns cumulated over a symmetric seven-day event window $[-3; +3]$, to its target's average 3-digit SIC industry asset beta (*Target asset beta*). Further independent variables are defined in Table 8 in the Appendix. A constant term is included but not reported. In all panels the extended sample is used. Panel A presents results for bids during any year of a merger wave defined as in Gaughan (2017). Panel B shows the results for bids outside of merger wave years between 1977 and 2020. Panel C, D, and E display the results for bids during the fourth, fifth, and sixth merger wave, respectively. Panel F includes all bids between 1977 and 2020 excluding bids occurring during the fourth and fifth merger wave. Only bids for private targets are included. *Deal controls* is a vector of deal characteristics: *log(Deal value)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same industry*, *Cross-border*, *Poison*, *Tender*, *Multiple bidders*, *Relative size*, and *log(Bidder size)*. *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 in the U.S., these variables are average values of the corresponding variables across all public firms in Compustat operating in the same 3-digit SIC industry. The *t*-statistics in parentheses are based on standard errors clustered by the target's 3-digit SIC industry. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively

sixth (2004–2007) merger wave, respectively.¹² The fourth subsample, referred to as the “non-merger-wave-years sample”, comprises all bids that occurred outside of those years. To ease comparison between the three merger wave subsamples and the non-merger-wave-years sample, we pool all three merger wave subsamples into a “merger-wave-years sample”. We examine the same OLS regression models as above for all five subsamples, again focusing on bids for private targets. The results are presented in Table 4 in the same format as in Table 3, meaning we only show the coefficients of the main explanatory variables to conserve space. Panel A includes all observations that occurred during merger-wave-years, Panel B includes all other observations, i.e., all bids taking place in non-merger-wave-years. Panels C, D, and E present the separate results for the fourth, fifth, and sixth merger wave, respectively.

For the merger-wave-years sample presented in Panel A of Table 4, we find statistically significant positive coefficients for *Target asset beta* in Columns (2) to (5) ranging from 1.03 to 2.39. Compared to the extended sample (Panel C of Table 2), the economic significance is somewhat increased while the statistical significance is comparable. Thus, during merger-wave-years, we find a higher sensitivity of *Bidder CAR* to *Target asset beta*.

Consistently for the non-merger-wave-years sample, we find an economically and statistically attenuated effect of *Target asset beta* on *Bidder CAR* (Panel B of Table 4). In only one out of five specifications (Column (3)) we find a statistically significant coefficient. The coefficient estimates are all positive but between 18% and 56% smaller than in Panel A. Overall, the findings indicate that *Target asset beta* has less of an influence on *Bidder CAR* for bids occurring outside of merger waves.

To disentangle the effect of merger waves on the relationship between *Target asset beta* and *Bidder CAR*, we rerun our baseline regressions for each merger

¹² The first three merger waves in the U.S. occurred prior to SDC recording M&A bids.

wave in our sample period separately. The results presented in Panels C, D, and E of Table 4 show an interesting pattern. We find a positive and economically meaningful relationship between *Bidder CAR* and *Target asset beta* during the fourth (1984–1989) and fifth (1992–2001) merger waves. However, only the *Target asset beta* coefficients for the fifth merger wave (Panel D) are statistically significant. The M&A bids during 1992–2001 might have been impacted by the “dot-com bubble” (Ljungqvist and Wilhelm 2003), a period during which firms in high-risk industries, i.e., industries with a high asset beta, were disproportionately often targeted in M&As (Gaughan 2017). Maybe at the time, these bids were better received by the market compared to M&A deals in less risky industries; this could explain the larger coefficients in Panel D. The statistically insignificant results for the fourth merger wave (Panel C) might be due to the relatively small sample size ($N \approx 900$). In contrast, the coefficients for the sixth merger wave (2004–2007), presented in Panel E, are mostly negative and insignificant, despite $N > 2,000$. These results imply that the statistically and economically significant positive relationship between *Target asset beta* and *Bidder CAR* prevailing during the entire sample period from 1977 to 2020 and particularly between 1977 and 2000 is mainly (partially) driven by bids during the fifth (fourth) merger wave.

To highlight the difference between M&A bids during the fourth and fifth merger waves and all other years more explicitly, we provide another sample split in Panel F of Table 4. Here, we exclude observations occurring during the fourth and fifth merger waves from the extended sample. The influence of *Target asset beta* on *Bidder CAR* vanishes almost completely for this subsample.¹³ Overall, the results presented in Tables 3 and 4 indicate that the relationship between *Bidder CAR* and *Target asset beta* not only loses significance toward the end of the sample period but is mainly driven by the fifth, and in part also by the fourth, merger wave in the U.S.¹⁴

Our U.S. results regarding the impact of merger waves on the CAPM misvaluation effect are confirmed by our European sample. When we split the sample period according to merger waves, a statistically significant effect emerges for *Target asset beta* on CARs of European bidders around M&A announcement dates only during merger-wave-years. The results are shown in Table A.11 in the Online Appendix. The *Target asset beta* coefficients vary notably between merger-wave-years and non-merger-wave-years not only in terms of statistical significance but also in terms of economic impact. While the coefficients (*t*-values) range from 2.31 to 6.50 (1.50 to 2.46) during merger-wave-years, they are below 0.90 (0.70) during non-merger-wave-years.¹⁵

¹³ When we only exclude observations during the fifth merger wave from the extended sample, *Target asset beta*’s influence on *Bidder CAR* is still positively significant at the 10% level in Columns (2) and (5), as displayed in Table A.9 in the Online Appendix. This confirms that the observations during the fourth and fifth merger wave combined drive the original results of DOOT.

¹⁴ For public target bids, we do not find any differences across sample periods, in line with DOOT and our prior results showing that for public target bids there is no effect of *Target asset beta* on *Bidder CAR*. The results are presented in Table A.10 in the Online Appendix.

¹⁵ When we define merger waves according to European M&A activity as in Vancea (2013), i.e., 1987–1991, 1997–2000, and 2003–2007, the difference in the regression coefficients and *t*-values between European merger-wave-years and European non-merger-wave-years even increases, while our conclusion remains unchanged. The corresponding results are presented in Table A.12 in the Online Appendix.

In summary, the evidence suggests that the positive relationship between *Target asset beta* and *Bidder CAR* in the extended U.S. sample is driven by the fact that 43% of private target bids occur during the fourth and fifth merger waves. It appears that DOOT's main finding is strongly time dependent and linked to merger waves. Both facts seem inconsistent with DOOT's conclusion that there is a causal relationship between target misvaluation and the usage of the CAPM, since one would expect the CAPM to be used in a similar way both inside and outside merger waves. It might be worthwhile to investigate this connection further to understand what ultimately drives the *Target asset beta* and *Bidder CAR* relationship.

4.2 M&A types

DOOT argue that CAPM-based beta estimates are biased in general but (almost) exclusively used by bidders estimating private M&A targets' cost of capital due to the lack of alternative information sources (e.g., market prices). Consequently, this means that bidders, who have access to additional sources of information for private targets' cost of capital beyond the CAPM estimate, should be less likely to rely (solely) on systematically biased CAPM-based measures during the evaluation process.

We argue that, in general, bidders have a fairly good estimate of their own cost of capital and thus of the cost of capital within their own industry. This implies that "horizontal bidders", i.e., bidders, operating in the same 3-digit SIC industry as their target, do not base their estimate of the target's cost of capital entirely on the CAPM-based measure but also take into account their knowledge of the cost of capital in their industry. As "diversifying bidders", i.e., bidders operating in different 3-digit SIC industries than their targets, do not have the same knowledge regarding the cost of capital within the target's industry as horizontal bidders, our reasoning suggest that horizontal bidders have an informational advantage over diversifying bidders.

Based on this argument, we hypothesize that diversifying bidders are more likely to rely on potentially biased CAPM-based *Target asset beta* estimates than horizontal bidders and, thus, are more susceptible to the CAPM misvaluation effect when estimating the target's cost of capital and value. This implies a stronger positive relationship between *Target asset beta* and *Bidder CAR* in diversifying bids compared to horizontal bids. Overall, combining DOOT's argument regarding the effect of *Target asset beta* on *Bidder CAR* for private and public M&A targets and our reasoning, we propose that diversifying bidders are more prone to using biased CAPM-based beta estimates in target evaluations than horizontal bidders. This means we expect a larger *Target asset beta* coefficient for diversifying bids compared to horizontal bids.

Table 5 provides descriptive statistics of the main variables for horizontal and diversifying private target bids in our extended sample separately. We report the mean and median values of the variables along with the difference in means between

Table 5 Summary statistics – comparison of horizontal and diversifying private target bids

	Horizontal		Diversifying		Difference in Means	
	Mean	Median	Mean	Median	Difference	<i>t</i> -value
<i>Bidder CAR (%)</i>	2.2	1.2	1.5	0.8	0.6***	(4.98)
<i>Target asset beta</i>	0.82	0.81	0.78	0.78	0.04***	(8.79)
<i>Bidder asset beta</i>	0.82	0.81	0.74	0.74	0.08***	(17.59)
<i>Beta spread</i>	0.00	0.00	0.04	0.03	−0.04***	(−11.67)
<i>log(Deal value)</i>	5.01	4.78	4.99	4.79	0.02	(1.12)
<i>Deal value (in mio. USD)</i>	371	119	325	120	46***	(3.89)
<i>Deal value (in mio. USD, CPI adj.)</i>	454	154	395	155	59***	(4.19)
<i>100% stock</i>	0.13	0.00	0.11	0.00	0.03***	(5.59)
<i>Avg. discount rate (%)</i>	13.2	12.5	13.9	12.3	−0.76	(−0.98)

This table displays the mean and the median for the main variables of interest for horizontal (Columns (1) and (2)) and diversifying (Columns (3) and (4)) private target bids from public firms headquartered in the U.S. between 1977 and 2020 (extended sample). The last two columns display the difference in means between horizontal and diversifying bids and the corresponding *t*-value for each variable. *Bidder CAR* is the bidder's cumulative abnormal return in the symmetric seven-day window around the bid announcement. *Target (Bidder) asset beta* is the target's (bidder's) average 3-digit SIC industry asset beta. *Beta spread* is the difference between the target's and bidder's average 3-digit SIC industry asset beta. *Deal value* is the deal value reported by SDC in million USD. *100% stock* is a dummy equal to 1 for offers where the payment mix consists solely of equity and 0 otherwise. *Avg. discount rate* is the midpoint between the maximum and minimum discount rate reported in M&A fairness opinions in SDC. All non-binary variables are winsorized at the 1st and 99th percentiles. All variables are described in Table 8 in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively

both groups.¹⁶ We find that the average *Bidder CAR* is significantly larger for horizontal bids than for diversifying bids (2.2% vs. 1.5%), which is in line with earlier findings in the literature showing that diversifying bids are, on average, less profitable for bidders (e.g., Morck et al. 1990). The mean *Target asset beta* is significantly larger by 0.04 for horizontal bids. While we observe that horizontal bids are, on average, larger than diversifying bids (454 million USD vs. 395 million USD inflation-adjusted deal value), the difference in *log(Deal value)* between both groups is statistically insignificant. Additionally, there are significantly more fully stock-financed horizontal than diversifying M&As (13% vs. 11%). Overall, we find evidence that the two subsamples differ significantly.

In our European sample, we make similar observations when splitting the sample into horizontal and diversifying private target bids. Again, *Bidder CAR* and *Target asset beta* are significantly larger for horizontal than for diversifying bids. In addition, horizontal bids are significantly larger according to *log(Deal value)* than diversifying bids in Europe. The summary statistics for this sample split are presented in Table A.3 in the Online Appendix.

We test our hypothesis that the relationship between *Target asset beta* and *Bidder CAR* is stronger for diversifying bids by using the same cross-sectional test

¹⁶ We provide the full descriptive statistics for horizontal and diversifying private target bids in Table A.2 in the Online Appendix.

employed by DOOT in their Table 4. We interact all independent variables and fixed effects with a dummy variable, called *Diversifying*, allowing the coefficients of all explanatory variables to vary across the two M&A types. *Diversifying* equals 1 if bidder and target are active in different 3-digit SIC industries and 0 otherwise. We run this test using our extended sample for private target bids. Table 6 provides the results in the same format as Table 2. The interaction term of *Target asset beta* and *Diversifying* is negative in all specifications and statistically significant in four out of five specifications, clearly rejecting the hypothesis that the relationship between *Target asset beta* and *Bidder CAR* is stronger for diversifying private target bids. This result implies that the positive effect of *Target asset beta* on *Bidder CAR* for private target bids originally documented by DOOT and successfully replicated in Table 2 is surprisingly driven by horizontal bids.¹⁷

For a better illustration on how *Target asset beta* influences *Bidder CAR* in both M&A type subsamples, we provide a sample split of bids for private targets (all targets) in Table 7 with horizontal bids presented in Panel A (C) and diversifying bids shown in Panel B (D). The setup is the same as in Table 4, meaning we only display the coefficients of the main explanatory variables to conserve space.

We observe economically and statistically significant coefficients for *Target asset beta* ranging from 1.99 to 3.12 for horizontal private target bids in Panel A of Table 7. These estimates imply that an interquartile range increase in *Target asset beta* (0.47 in Panel A) raises *Bidder CAR*, on average, by 0.98 to 1.53 percentage points. This is equivalent to 11.95% to 18.66% of the interquartile range of *Bidder CAR* (8.2% in Panel A), which is substantially larger than DOOT's results and our baseline regression in Table 2. In terms of dollars, the effect is also considerable, ranging from a 89 to 139 million USD increase in average bidder market capitalization for a one-interquartile-range increase in *Target asset beta*. Such an increase corresponds to 23.99% to 37.47% of the average deal value (371 million USD) for this subsample. Our results show that the effect size measured in USD is about 1.7 to 3.4 times larger for horizontal private target bids than for private target bids overall.

In contrast, for diversifying private target bids (Panel B), we observe *Target asset beta* coefficients between 76% and 92% smaller than in Panel A, which are statistically insignificant throughout (*t*-statistics ranging from 0.51 to 1.19). The same "horizontal bid effect" is observable when we pool all bids for private and public targets and split the sample into horizontal (Panel C) and diversifying bids (Panel D). The two panels show that *Target asset beta* only impacts *Bidder CAR* when bidder and target operate in the same 3-digit SIC industry, independent of the target's listing status.¹⁸

These findings underline that the positive effect of *Target asset beta* on *Bidder CAR* is only present for horizontal bids. A similar horizontal bid effect is not

¹⁷ This finding is consistent with our results in Sect. 4.1, where we show that the positive relationship between *Target asset beta* and *Bidder CAR* is primarily evident during the fifth merger wave, which is characterized by consolidating deals – referred to as "roll-ups" (Gaughan 2017).

¹⁸ If we only study bids for public targets, the same horizontal bid effect is observable. *Target asset beta* has a significantly positive effect on *Bidder CAR* in the group of horizontal bids and no significant effect for diversifying bids. The results are shown in Table A.13 in the Online Appendix.

Table 6 Industry interaction – private targets

	Dependent Variable: <i>Bidder CAR</i> (%)				
	(1)	(2)	(3)	(4)	(5)
<i>Target asset beta</i>	1.99*	2.66**	3.12**	3.04***	3.04***
	(1.82)	(2.45)	(2.51)	(2.63)	(2.63)
<i>Target asset beta</i> × <i>Diversifying</i>	−1.52	−2.26*	−2.53*	−2.79**	−2.45*
	(−1.21)	(−1.80)	(−1.75)	(−2.08)	(−1.77)
<i>Beta spread</i>					−0.26
					(−0.42)
<i>log(Deal value)</i>		0.95***	0.95***	0.84***	0.84***
		(8.57)	(8.58)	(7.14)	(7.14)
<i>Equity</i>		0.44	0.44	0.37	0.37
		(1.34)	(1.34)	(0.88)	(0.88)
<i>Cash</i>		0.07	0.06	0.22	0.22
		(0.29)	(0.25)	(0.93)	(0.93)
<i>Toehold</i>		−0.01	−0.01	−0.01	−0.01
		(−0.82)	(−0.86)	(−1.07)	(−1.07)
<i>Hostile</i>		8.75	8.64	9.48*	9.48*
		(1.57)	(1.55)	(1.70)	(1.70)
<i>Cross-border</i>		−0.54	−0.54	−0.49	−0.49
		(−1.46)	(−1.48)	(−1.34)	(−1.34)
<i>Poison</i>		−1.00	−1.01	−1.43	−1.43
		(−1.07)	(−1.08)	(−1.21)	(−1.21)
<i>Tender</i>		−4.09*	−4.07*	−3.70	−3.70
		(−1.75)	(−1.73)	(−1.55)	(−1.55)
<i>Multiple bidders</i>		−1.77	−1.72	−1.04	−1.04
		(−0.92)	(−0.89)	(−0.58)	(−0.58)
<i>Relative size</i>		0.09	0.10	0.08	0.08
		(0.71)	(0.72)	(0.61)	(0.61)
<i>log(Bidder size)</i>		−0.83***	−0.83***	−0.76***	−0.76***
		(−6.17)	(−6.19)	(−5.63)	(−5.63)
Bidder SDC industry × Year FE (interacted)	Yes	Yes	Yes	Yes	Yes
Deal controls (interacted)	No	Yes	Yes	Yes	Yes
Target controls (baseline & interacted)	No	No	Yes	Yes	Yes
Bidder controls (baseline & interacted)	No	No	No	Yes	Yes
N	15,803	14,644	14,644	13,995	13,907
Adjusted R ² (%)	4.05	6.60	6.55	6.40	6.31

This table presents results for OLS regressions regarding the sensitivity of a bidder's announcement return (*Bidder CAR*), measured as market-adjusted abnormal returns cumulated over a symmetric seven-day event window $[-3; +3]$, to its target's average 3-digit SIC industry asset beta (*Target asset beta*). Further independent variables are defined in Table 8 in the Appendix. A constant term is included but not reported. The sample covers bids from listed firms in the U.S. between 1977 and 2020 (extended sample). 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

Table 6 (continued)

Cash to assets. For private targets in the U.S., these variables are average values of the corresponding variables across all public firms in Compustat operating in the same 3-digit SIC industry. (*Interacted*) indicates that all independent variables and fixed effects are interacted with *Diversifying*, allowing their coefficients to depend on the value of the dummy variable. The *t*-statistics in parentheses are based on standard errors clustered by the target's 3-digit SIC industry. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively

observable for the other significant explanatory variables, as shown in Table A.14 in the Online Appendix. The coefficients for $\log(\text{Deal value})$ ($\log(\text{Bidder size})$) are significantly positive (negative) for both horizontal and diversifying private target bids, as is the case for all three U.S. samples in the baseline regression model presented in Table 2.

Table A.15 in the Online Appendix re-estimates Table 6 for our European sample of private target bids. All estimates for the interaction term *Target asset beta* \times *Diversifying* are insignificant. However, they are large in magnitude and negative in all specifications, as in the U.S. sample.¹⁹ We, therefore, conclude that the large magnitude of the *Target asset beta* coefficients in the baseline regression model, shown in Panel D of Table 2, is mainly driven by horizontal bids in our European sample.

Overall, we find strong evidence that *Target asset beta* has a significantly positive effect on *Bidder CAR* for horizontal bids in the U.S., independent of a target's listing status. Our European results lack statistical significance but point in the same direction. In sum, our results in this subsection reject the hypothesis that bidders in diversifying deals are more susceptible to the CAPM misvaluation effect. In our view, this finding is inconsistent with the idea that target misvaluations in M&As are caused by using the CAPM to estimate a target's cost of capital.

5 Conclusion

DOOT predict that bidder CARs are increasing in target asset betas due to the fact that the CAPM prices risk differently than the market. They provide convincing empirical evidence consistent with their conjecture showing that low (high) target asset betas lead to lower (higher) bidder announcement returns. Based on these results, DOOT caution against using the CAPM in capital budgeting decisions, in particular in the context of M&As, as they find large valuation errors (relative to the market's view) of about one-quarter of average M&A deal values. In this paper, we replicate DOOT's main findings using their methodology for the same and an extended sample period. Our results confirm the positive relationship between target asset betas and bidder announcement returns

¹⁹ Qualitatively similar results can be found when splitting the European sample of private target bids into horizontal and diversifying bids, as shown in Table A.16 in the Online Appendix. There are almost no significant coefficients for *Target asset beta* in both subsamples. However, the estimates (*t*-values) are, on average, 4.2 (1.5) times larger for horizontal than for diversifying private target bids.

Table 7 Industry split

	Dependent Variable: <i>Bidder CAR (%)</i>				
	(1)	(2)	(3)	(4)	(5)
Panel A: Horizontal Private Target Bids					
<i>Target asset beta</i>	1.99* (1.81)	2.66** (2.43)	3.12** (2.49)	3.04*** (2.62)	3.04*** (2.62)
Bidder SDC industry \times 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
N	6618	6099	6099	5815	5815
Adjusted R ² (%)	1.54	3.95	3.88	3.80	3.80
Panel B: Diversifying Private Target Bids					
<i>Target asset beta</i>	0.48 (1.16)	0.40 (1.02)	0.59 (1.19)	0.25 (0.51)	0.58 (0.82)
<i>Beta spread</i>					-0.26 (-0.42)
Bidder SDC industry \times 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
N	9185	8545	8545	8180	8092
Adjusted R ² (%)	5.91	8.61	8.56	8.34	8.22
Panel C: All Horizontal Bids					
<i>Target asset beta</i>	2.13** (2.56)	2.44*** (2.88)	2.42*** (2.76)	2.61*** (3.05)	2.61*** (3.05)
Bidder SDC industry \times 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
N	11,310	10,310	9272	8950	8950
Adjusted R ² (%)	3.83	5.64	5.15	5.43	5.43
Panel D: All Diversifying Bids					
<i>Target asset beta</i>	0.23 (0.71)	0.33 (0.98)	0.47 (1.23)	0.30 (0.74)	0.45 (0.72)
<i>Beta spread</i>					-0.13 (-0.25)
Bidder SDC industry \times 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
N	12,939	11,857	11,052	10,616	10,486
Adjusted R ² (%)	4.25	6.03	6.57	6.61	6.35

Table 7 (continued)

This table presents results for OLS regressions regarding the sensitivity of a bidder's announcement return (*Bidder CAR*), measured as market-adjusted abnormal returns cumulated over a symmetric seven-day event window $[-3; +3]$, to its target's average 3-digit SIC industry asset beta (*Target asset beta*). Further independent variables are defined in Table 8 in the Appendix. A constant term is included but not reported. The sample covers bids from listed firms in the U.S. between 1977 and 2020 (extended sample). Panel A (Panel C) presents results for bids toward private targets (all targets) operating in the same 3-digit SIC industry as the bidder. Panel B (Panel D) shows the results for bids for private targets (all targets) operating in a different 3-digit SIC industry than the bidder. *Beta spread* is omitted in Panel A and C as the variable always equals zero for horizontal bids, given the computation of *Target asset beta* and *Bidder asset beta*. *Same industry* is omitted in all panels as its value does not vary within each subsample. Thus, *Deal controls* is a vector of the following deal characteristics: *log(Deal value)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Cross-border*, *Poison*, *Tender*, *Multiple bidders*, *Relative size*, and *log(Bidder size)*. *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 in the U.S., these variables are average values of the corresponding variables across all public firms in Compustat operating in the same 3-digit SIC industry. The *t*-statistics in parentheses are based on standard errors clustered by the target's 3-digit SIC industry. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively

for U.S. bidders. However, our three extension tests do not confirm DOOT's general predictions. First, we rerun the original analysis for M&A bids from 18 European countries and only find mixed evidence for the CAPM misvaluation effect in the European market for corporate control. Second, we split the sample into bids inside and outside of merger waves and find stark differences. We find the positive relationship between target asset betas and bidder announcement returns to be confined to merger waves in the U.S. and in Europe. If this relationship is actually caused by using the CAPM for target valuations, we should not see any strong time period dependence, as the application of the CAPM is unlikely to change for bids inside and outside of merger waves. Third, we provide a new test based on the hypothesis that bidders are less inclined to rely on (incorrect) CAPM beta estimates for horizontal bids, as they have additional information available for estimating the cost of capital for targets within their own industry. However, we find that the CAPM misvaluation effect only exists in the subsample of horizontal bids and not in diversifying bids. This result rejects the hypothesis above and again casts doubt on DOOT's conclusion that using the CAPM causes target misvaluations.

To sum up, we provide three new empirical tests that all point in the same direction: The positive relationship between target asset betas and bidder announcement returns does not seem to be caused by using the CAPM for target valuations. The empirical patterns we uncover are not consistent with such a conclusion. Therefore, we are skeptical that there is convincing empirical evidence to claim that using the CAPM results in systematic errors in capital budgeting decisions. We believe it is too early to strike the CAPM from corporate finance textbooks and valuation courses or to advocate for ceasing its practical application.

Appendix

See Table 8.

Table 8 Variable definitions

Variable	Variable Definition
<i>Avg. discount rate</i>	Mean of the highest and lowest discount rate (SDC: Fairness Opinion DCF Percent High and Fairness Opinion DCF Percent Low, respectively) used in discounted cash flow analyses as stated in M&A fairness opinions recorded by SDC. The final distribution is winsorized at the 1% level in each tail and expressed in percentage points.
<i>Asset beta</i>	Equally weighted average asset beta of all public firms in CRSP (Datastream within the 18 European sample countries) with the same 3-digit SIC industry code. Asset betas are computed assuming a constant level of debt as in Hamada (1972): $\beta_{i,t}^A = \beta_{i,t}^E / [1 + (1 - \tau) \times D_{i,t} / E_{i,t}]$, where $\beta_{i,t}^E$ is a firm's equity beta, τ is the nationwide statutory tax rate in the highest bracket in the respective country, $D_{i,t}$ is a firm's total debt, and $E_{i,t}$ is the market capitalization of a firm. For the U.S. subsamples, we calculate $D_{i,t}$ as the sum of long-term debt (Compustat: DLTT) plus debt in current liabilities (Compustat: DLC). For our European sample, we obtain a firm's total debt directly from Datastream (Datastream: WC03255). Similarly, we calculate $E_{i,t}$ as price or bid/ask average (CRSP: PRC) times number of shares outstanding (Compustat: CSHO) for our U.S. subsamples, while we obtain a firm's market capitalization directly from Datastream (Datastream: MV) for our European sample. $\beta_{i,t}^E$ is estimated by regressing five years of monthly excess returns on excess returns of the CRSP value-weighted portfolio (including dividends) proxying for the American market portfolio. For our European sample, we use raw returns instead of excess returns and use the MSCI Europe Value Weighted Index (including dividends) to proxy for the European market portfolio. Estimates for $\beta_{i,t}^E$ based on less than 36 months of return data are dropped. Further, observations for which $\beta_{i,t}^E$ is negative and the same number of observations in the right tail of the distribution of $\beta_{i,t}^E$ are dropped.
<i>Beta spread</i>	Difference between the target's unwinsorized average 3-digit SIC industry asset beta (similar to <i>Target asset beta</i>) and the bidder's unwinsorized average 3-digit SIC industry asset beta (similar to <i>Bidder asset beta</i>). The final distribution is winsorized at the 1% level in each tail.
<i>Bidder asset beta</i>	Equally weighted average asset beta of all public firms in CRSP (Datastream within the 18 European sample countries) with the same 3-digit SIC industry code as the bidder, estimated one month prior to the bid announcement. We refer to <i>Asset beta</i> for the details on the estimation of individual asset betas. The final distribution is winsorized at the 1% level in each tail.
<i>Bidder CAR</i>	The bidder's cumulative abnormal return in a symmetric seven-day event window $[-3; +3]$ around the M&A announcement date. The abnormal returns are market adjusted. The final distribution is winsorized at the 1% level in each tail and expressed in percentage points.

Table 8 (continued)

Variable	Variable Definition
<i>Bidder SDC industry</i>	Bidder mid-level industry classification (SDC: Acquiror Mid Industry).
<i>log(Bidder size)</i>	Natural logarithm of the market capitalization of the bidder in million USD four days prior to the bid announcement. In the U.S. subsamples, a firm's market capitalization is calculated as price or bid/ask average (CRSP: PRC) times number of shares outstanding (Compustat: CSHO). In the European sample the market capitalization is obtained directly from Datastream (Datastream: MV).
<i>Cash</i>	Dummy equal to 1 if the payment mix includes cash and 0 otherwise (SDC: Final Consideration Structure).
<i>Cash flow to assets</i>	Ratio of net income before extraordinary items (Compustat: IB Datastream: WC01551) plus depreciation and amortization (Compustat: DP Datastream: WC01151) to total assets (Compustat: AT Datastream: WC02999). If information on depreciation and amortization is missing in Compustat or Datastream, it is set to zero.
<i>Cash to assets</i>	Ratio of cash and cash equivalents (Compustat: CHE Datastream: WC02001) to total assets (Compustat: AT Datastream: WC02999).
<i>Cross-border</i>	Dummy equal to 1 if the target is headquartered in a different country than the bidder and 0 otherwise (SDC: Target Nation and Acquiror Nation, respectively).
<i>log(Deal value)</i>	Natural logarithm of the value of the takeover bid in million USD (SDC: Deal Value). The final distribution is winsorized at the 1% level in each tail.
<i>Deal value (in mio. USD)</i>	Value of the takeover bid in million USD (SDC: Deal Value). The final distribution is winsorized at the 1% level in each tail.
<i>Deal value (in mio. USD, CPI adj.)</i>	Value of the takeover bid in million USD (SDC: Deal Value) inflation-adjusted to 2015 using the Consumer Price Index. The final distribution is winsorized at the 1% level in each tail.
<i>Debt to assets</i>	Ratio of long-term debt (Compustat: DLTT) plus debt in current liabilities (Compustat: DLC) to total assets (Compustat: AT Datastream: WC02999). For the European sample, total debt (Datastream: WC03255) is used in the nominator instead of long-term debt plus debt in current liabilities. If only values for long-term debt or debt in current liabilities are available in Compustat, then only the value available is used to proxy for total debt, assuming there is no debt in current liabilities or long-term debt, respectively.
<i>Diversifying</i>	Dummy equal to 1 if target and bidder operate in a different 3-digit SIC industry and 0 otherwise (SDC: Target Primary SIC and Acquiror Primary SIC, respectively).
<i>Equity</i>	Dummy equal to 1 if the payment mix includes stock and 0 otherwise (SDC: Final Consideration Structure).
<i>Hostile</i>	Dummy equal to 1 if the bid is classified accordingly by SDC and 0 otherwise (SDC: Deal Attitude).

Table 8 (continued)

Variable	Variable Definition
<i>Market-to-book</i>	Ratio of market capitalization to shareholder's equity (Compustat: CEQ Datastream: WC05476). In the U.S. subsamples, a firm's market capitalization is calculated as price or bid/ask average (CRSP: PRC) times number of shares outstanding (Compustat: CSHO). In the European sample the market capitalization is obtained directly from Datastream (Datastream: MV).
<i>Multiple bidders</i>	Dummy equal to 1 if there is more than one bidder and 0 otherwise (SDC: Number of Bidders).
<i>Poison</i>	Dummy equal to 1 if the target uses a defense mechanism and 0 otherwise (SDC: Defensive Tactics Flag).
<i>Public target</i>	Dummy equal to 1 if the target is publicly listed and 0 otherwise (SDC: Target Public Status).
<i>Relative size</i>	Ratio of the value of the takeover bid in million USD (SDC: Deal Value) to the bidder's market capitalization in million USD four days prior to the bid announcement. In the U.S. subsamples, a firm's market capitalization is calculated as price or bid/ask average (CRSP: PRC) times number of shares outstanding (Compustat: CSHO). In the European sample the market capitalization is obtained directly from Datastream (Datastream: MV).
<i>ROA</i>	Return on assets defined as the ratio of net income before extraordinary items (Compustat: IB Datastream: WC01551) to total assets (Compustat: AT Datastream: WC02999).
<i>Same industry</i>	Dummy equal to 1 if target and bidder operate in the same 3-digit SIC industry and 0 otherwise (SDC: Target Primary SIC and Acquiror Primary SIC, respectively).
<i>Target asset beta</i>	Equally weighted average asset beta of all public firms in CRSP (Datastream within the 18 European sample countries) with the same 3-digit SIC industry code as the target, estimated one month prior to the bid announcement. We refer to <i>Asset beta</i> for the details on the estimation of individual asset betas. The final distribution is winsorized at the 1% level in each tail.
<i>Tender</i>	Dummy equal to 1 if the bid is classified accordingly by SDC and 0 otherwise (SDC: Tender Offer Flag).
<i>Toehold</i>	Percentage of the target's equity held by the bidder before the bid announcement (SDC: Percentage of Shares Held at Announcement). If the data is missing in SDC, <i>Toehold</i> is set to zero.
<i>100% stock</i>	Dummy equal to 1 if the bids constitute stock only (SDC: Final Consideration Structure).
$\mathbb{1}\{a < \textit{Target asset beta} \leq b\}$	Dummy equal to 1 if <i>Target asset beta</i> is larger than a but smaller or equal to b and 0 otherwise.
$\mathbb{1}\{\textit{Target asset beta} < p_{25}\}$	Dummy equal to 1 if <i>Target asset beta</i> is in the bottom quartile of its distribution and 0 otherwise.
$\mathbb{1}\{\textit{Target asset beta} > p_{75}\}$	Dummy equal to 1 if <i>Target asset beta</i> is in the top quartile of its distribution and 0 otherwise.

In this table, we define all variables used in the paper. In brackets, we report the item codes from Compustat, CRSP, Datastream, and SDC where applicable. If a single bracket is divided in two by a vertical line, the first item code represents the data source for our U.S. subsamples and the second item code represents the data source for our European sample

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Declarations

Conflict of interest The authors declare that they have no competing financial interests, non-financial, or personal relationships that could have appeared to influence the work reported in this paper.

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