Target valuation complexity and takeover premiums

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Abstract: Firm- and deal-specific characteristics that complicate estimation of target value simultaneously increase the level and variance of takeover premiums. Specifically, the mean premium is higher and the precision of the premium as a signal is lower (i.e., the error variance higher) when targets belong to the tech industry, when target stock returns are more volatile, when the bidders are larger, and when the cost of deal advising is higher. We also find that deal characteristics that we believe reduce target valuation complexity (transactions involving private bidders or LBOs) result in a lower mean premium and dispersion of premiums. Conversely, deal characteristics that we believe increase target valuation complexity (such as tender offers and deals that take a long time to complete) result in a higher mean premium and higher dispersion of premiums. Overall, characteristics that complicate the valuation of targets feed back into the level of the premium through potential pricing errors and inflate the dispersion of premiums.

Keywords: mergers and acquisitions; M&A; takeover premiums; valuation complexity.

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1 Introduction

Recent work on mergers and acquisitions (M&A) emphasises the effect of divergence of perceived valuation between target and bidder and also among bidders on the total premium paid.[1] Moeller et al. (2007) study the relation between divergence of opinion and the bidder's abnormal return. Chatterjee et al. (2012) show that the total takeover premium is higher when investors' divergence of opinion is higher, and a positive shock in market sentiment increases investors' divergence of opinion. Jandik and Makhija (2005) show that factors that make takeovers more complex increase the target premium. The focus of these studies is on the level of the target premium. Numerous studies have investigated the determinants of takeover premiums (for a recent review, see Betton et al., 2008). However, none of the existing studies attempt to explain the variation in the dispersion of merger premiums over time.

We investigate whether and how the degree of complexity in the valuation of targets affects both the level and the variability of takeover premiums. Specifically, we identify firm- and deal-specific characteristics associated with higher degrees of target valuation complexity and study whether they result in both higher takeover premiums and larger dispersion in total takeover premiums.[2]

We document that the dispersion of takeover premiums is large, and changes considerably over time. We attribute the positive correlation between monthly mean takeover premium and monthly cross-sectional standard deviation of premiums to the existence of time-varying determinants that have the same directional influence on the level and dispersion of merger premiums. Just as Lowry et al. (2010) measure the complexity of IPO valuation, we measure target valuation complexity. We apply their method to explicitly model both the (conditional) mean premium and the variance of the error from the mean regression model (i.e., heteroskedasticity) as related to the same firm- and deal-specific characteristics that are used to proxy for target valuation complexity. Following the line of reasoning in Brunnermeier and Oehmke (2009), complexity becomes relevant anytime the investors are assumed to be 'boundedly rational'. When the rational expectations assumption is relaxed, the amount of available information per se does not define the complexity of a security; rather, for 'boundedly rational' investors, the 'quality' of the information disclosed in the signal is what defines the degree of 'complexity' of the security.

We find that the dispersion of total takeover premiums is higher when a target belongs to the Tech industry, lists on NASDAQ, or has a higher stock return volatility prior to the merger announcement. Further, the dispersion of takeover premiums is lower when the target belongs to the banking industry, or when deal advising (based on fees) is simpler. We find similar results whether in the cross-section or when we model takeover premiums as a time-series, using EGARCH and EGARCH-in-the-mean models.

We also test other deal characteristics that can proxy for target valuation complexity, and find that they influence the premium and dispersion of premiums among targets. Specifically, we argue that private bidders (and LBOs in particular) reflect less complex deals resulting in lower premiums and lower dispersion of premiums.[3] Conversely, tender offers and deals that take a long time to complete reflect high complexity of target valuation, and result in high premiums and higher dispersion of premiums. Overall, characteristics that serve as useful proxies for target valuation complexity surrounding the target's valuation affect the target premium and dispersion surrounding target premiums. These results are robust to alternative measures of the target's premium.

2 Complexity and valuation

Miller (1977) suggests that market prices reflect optimistic valuations, given high short-sale transaction costs preventing the revelation of the relatively more pessimistic opinions. Two sufficient conditions for the upward bias in market prices are the existence of boundedly rational investors and limited arbitrage (Diether et al., 2002). Consequently, bidders may not be equally informed about the value of the target because of their differential ability to estimate the value of a prospective target based on the available information (Povel and Singh, 2006). As a result, the level of difficulty, or complexity, in the valuation of a target can affect the takeover premium. For instance, Officer et al. (2009) find that target valuation complexity affects the method of payment in acquisitions, though they do not inspect merger premiums.

Additionally, according to Brunnermeier and Oehmke (2009), complexity can lead to less informed investment decisions (i.e., decisions of lower quality), and a larger dispersion in the quality of the decisions if investors have different abilities to process information.[4] Recent experimental evidence indicates that complexity affects valuation estimation errors as well as price volatility and trading frequency (Carlin et al., 2013). Thus, we hypothesise that complexity surrounding the valuation of targets influences the dispersion in premiums paid for targets over time.

To sum up, the literature predicts that the level and dispersion of takeover premiums increases when there is greater complexity in the valuation of targets (Brunnermeier and Oehmke, 2009; Carlin et al., 2013), or differential ability of bidders to value a target (Bazerman and Samuelson, 1983; Povel and Singh, 2006).

3 Sample description

We gather our initial sample from Thomson Financial Securities Data Corporation (SDC) Platinum database for the period from January 1985 to December 2015. We initially restrict the sample to cases where both the acquiring and target firms are publicly-listed US firms, and where the bid announcement is for a merger, acquisition, or acquisition of majority position, according to SDC. Only successful or completed acquisitions with available offer price or deal value on SDC are included. The initial sample includes 6,536 bid announcements.

Additionally, we require both bidder and target to list on the New York Stock Exchange or NASDAQ and to have information on CRSP on the market value of equity 42 days before the bid announcement. We exclude targets with a stock price 42 days before announcement lower than $1. The deal needs to have been completed within 365 days from announcement.

Our main measure of the bid premium (PREM) is the offer price minus the target stock price 42 days prior to bid announcement, divided by the target stock price 42 days prior to announcement (Officer, 2003; Moeller et al., 2004). Negative premiums are excluded. Our final sample includes 3,215 deals over the period 1985 to 2015. Sample sizes shown in tables of results vary because of data availability regarding firm and deal characteristics. We also use alternative measures for the target's premium as a robustness check to our main tests, which we discuss after presenting our main findings.

In Table 1, we report descriptive statistics for the average and standard deviation of takeover premiums, both cross-sectionally and over time. As shown in panel A, the time-series mean premium per month is 49% while the time-series mean of the cross-sectional standard deviation of premiums per month is 36%. Therefore, in an average month, the mean takeover premium of bid offers announced that month is 49%, while the standard deviation of premiums across takeovers in that month is 36%. The time-series mean of the interquartile range per month is 41%. Thus, there is considerable dispersion in premiums across takeovers per month. In addition, there is substantial variation in monthly mean takeover premiums and monthly cross-sectional dispersion levels over time. The standard deviation of the mean premium across the 364 months in the sample is 23%, while the standard deviation of the mean cross-sectional dispersion across months is 26%.

Furthermore, the correlation over time between the monthly average premium and the monthly standard deviation of premiums is 0.79. The correlation over time between the monthly average premium and the monthly interquartile range of premiums is 0.73. The strong positive correlation between the mean and standard deviation of the takeover premiums is early indication that there are economic determinants that simultaneously affect the level and variability of premiums.

Table 1 Descriptive statistics on the mean and volatility of takeover premiums

	N	*Mean*	*Median*	*Std. dev*	*Corr. (p-value)*
Panel A: 1985–2015, monthly					
Average premium (%)	364	0.49	0.45	0.23	1.00
CS standard deviation (%)	296	0.36	0.30	0.26	0.79 (0.0001)
CS interquartile range	349	0.41	0.36	0.30	0.73 (0.0001)
Panel B: 1985–2015, quarterly					
Average premium (%)	124	0.49	0.47	0.16	1.00
CS standard deviation (%)	122	0.39	0.33	0.24	0.78 (0.0001)
CS interquartile range	124	0.40	0.37	0.18	0.73 (0.0001)
Panel C: All-stock					
Average premium (%)	120	0.50	0.44	0.26	1.00
CS standard deviation (%)	99	0.42	0.31	0.35	0.82 (0.0001)
CS interquartile range	115	0.44	0.41	0.30	0.67 (0.0001)
Panel D: All-cash					
Average premium (%)	122	0.49	0.45	0.22	1.00
CS standard deviation (%)	90	0.31	0.28	0.17	0.73 (0.0001)
CS interquartile range	110	0.40	0.31	0.33	0.73 (0.0001)
Panel E: Statistics computed by industry (2 digits sic) before averaging by quarter					
Average premium (%)	124	0.49	0.45	0.18	1.00
CS standard deviation (%)	121	0.34	0.28	0.22	0.79 (0.0001)
CS interquartile range	124	0.38	0.34	0.24	0.72 (0.0001)

Notes: Takeover premium is computed as [Offer price / (Target price day – 42)] – 1. Each month (panel A) or quarter (panels B–E), the average, standard deviation, and interquantile range of the premium paid in mergers are measured. Summary statistics reflect the monthly or quarterly time series of the cross-sectional averages and standard deviations. Corr. represents the correlation between the averages and standard deviations, or ranges, over time. N is the number of months or quarters. Std. dev. (interquantile range) is computed only if there is a minimum of four (two) observations in the month or quarter.

When there are fewer than four takeovers in a month, we do not compute a standard deviation and use the standard deviation calculated using an interquartile range. We also provide descriptive statistics over quarters (see panel B), which allows for a larger number of takeovers per period than when months are used to compute descriptive statistics. Summary statistics are similar whether computed monthly or quarterly.

It is possible that the observed variability in takeover premiums is being driven by variability in the method of payment, whether cash or stock. We also consider that the mean and variability of takeover premiums could be related to merger activity at the industry-level (e.g., Harford, 2005). However, when we compute statistics at the industry level (two-digit sic code) each quarter, before averaging over time, premium dispersion is again similar to that for the full sample (panel E).

We hypothesise that the average and standard deviation of takeover premiums is higher in periods in which the valuation of a target is more complex, because of firm- or deal-specific characteristics that make the target more difficult to value.

As mentioned, the literature predicts that the level and dispersion of takeover premiums increases when there is greater complexity in the valuation of targets (Brunnermeier and Oehmke, 2009; Carlin et al., 2013), or differential ability of bidders to value a target (Bazerman and Samuelson, 1983; Povel and Singh, 2006). We broadly group the existing perspectives under the general notion of 'valuation complexity'.

4 Measures of valuation complexity

We consider the following characteristics, which proxy for the difficulty of accurately estimating the value of a target. To the extent possible, we have selected variables that can unambiguously contribute to valuation complexity.

4.1 Firm characteristics

1. *Technology status of target (TECH)*. Takeovers in the technology sector subject to 'industry shakeouts' are expected to have a final uncertain outcome and consequently a relatively high degree of complexity. According to the 'war of attrition' hypothesis of Bulow and Klemperer (1999), high tech industries like the Telecom industry are subject to frequent shakeouts as the firms are in a technological innovation race. In addition, most of the value in technology firms comes from growth opportunities rather than assets in place, what makes other things equal the valuation task of technological firms more complex than other sectors. Thus, we expect that valuations will be more difficult for targets that are classified in the technology sector. A dummy variable is set to equal 1.0 for targets that are in the technology sector and zero otherwise. We follow Lowry et al. (2010) and define the technology sector as biotech, computer equipment, electronics, communications, and general technology (as defined by SDC).
2. *Stock price volatility of target (TGTVOL)*. A target that exhibits high stock price volatility is presumed to have a relatively high degree of divergence of opinion given the lower precision of the signal. Following the literature, we define the precision of the signal as the inverse of the standard deviation. Other things equal, the lower is the precision of the signal; the lower is the quality of the information in the signal which makes the valuation task more complex. Just as it is difficult for investors to value this type of company, it may be difficult for a bidder to derive a fair bid for this type of company. Thus, we expect that bid pricing errors are more pronounced when the bidders value targets that have higher stock price volatility. The volatility is measured as the (log of) standard deviation of daily returns over the days from t-317 to t-64 relative to the bid announcement date, as in Boone and Mulherin (2007).
3. *Banking status of target (BANK)*. Banking is a sector heavily regulated and which is not subject to industry shakeouts given its role in the monetary transmission mechanism. The additional information that results from existing regulations and

governmental policies like too-big-to-fail is likely to limit the range of possible valuations, compared to non-bank firms. BANK is defined following the ten-industry classification in Fama and French (1997). We obtain similar results using a more broadly defined REGULATED variable, which includes utilities.

4 *Target size (TGTMVE)*. Smaller targets are typically younger, have more growth opportunities, and are followed by fewer analysts, all of which make valuation more difficult. We measure target size by the (log of) market value of equity 42 days prior to the acquisition announcement.

5 *Bidder size (BIDMVE)*. Moeller et al. (2004) find that large acquirers tend to pay higher premiums for targets. It is possible that bidder size may complicate the estimation of target value because it is more difficult to assess the likelihood of a successful integration and hence the synergies, when the bidder is larger. Also, the presence of large bidders is common in sectors with a natural oligopoly market structure and subject to wars of attrition. Thus, targets acquired by larger bidders may be more difficult to value or be subject to the uncertainty of an 'industry shakeout'. We measure bidder size as the (log of) the market value of equity of the acquirer measured 42 days prior to the announcement.

4.2 Deal characteristics

1 *Method of financing (CASH)*. According to Travlos (1987), cash acquisitions indicate that bidders are more confident of their ability to value the target. Similarly, Hansen (1987) predicts that bidders would rather use stock when targets are more difficult to value because of information asymmetry. We assign a dummy variable called *CASH* equal to 1 if the deal is financed with 100% cash and 0 otherwise.

2 *Degree of adviser participation (ADVISER)*. Servaes and Zenner (1996) find that the intensity of investment bank participation in mergers is related to the level of complexity of the transaction. However, merger premiums do not differ across the tier of the advising investment bank (Rau, 2000). A merger that involves a target that is difficult to value is likely to require a higher degree of adviser participation, hence, resulting in larger investment adviser fees. Thus, to measure the degree of adviser participation, we use total merger fees, as reported by SDC, divided by the market value of the target 42 days prior to the announcement. Because this variable is closely related to the target size (as measured by *TGTMVE*), we do not simultaneously include the two variables in our regression specifications.

3 *Merger activity (ACTIVITY)*. Harford (2005) illustrates how merger activity changes over time. A higher level of merger activity suggests more participants are in the market, and there is more information about the prevailing valuations in the market for corporate control. Merger activity is measured with the following proxies: total number of mergers in the same industry in the previous month, and total number of mergers in the previous month. Because results are similar using either proxy, we report results using the number of mergers in the same industry.

We also consider some additional deal characteristics that could also represent target valuation complexity, but leave them out of the initial analysis because they may overlap with some of the characteristics that are tested within the initial sample.

Table 2 Correlations between the monthly moments of takeover premiums and merger characteristics

	Mean	*Std. dev.*
TECH	–0.02	0.04
	(–0.7585)	(0.4372)
TGTVOL	0.36	0.36
	(0.0001)	(0.0001)
NASDAQ	0.17	0.14
	(0.0012)	(0.0089)
BANK	0.04	0.05
	(0.4027)	(0.3611)
TGTMVE	–0.38	–0.37
	(0.0001)	(0.0001)
BIDMVE	–0.17	–0.26
	(–0.0011)	(–0.0001)
CASH	–0.14	–0.07
	(–0.0056)	(–0.1945)
ADVISER	0.22	0.22
	(0.0001)	(0.0001)
ACTIVITY	0.02	0.09
	(0.6587)	(0.0973)

Notes: The table shows correlations (p-values) between the monthly averages and standard deviations of takeover premiums and the monthly averages of the following merger characteristics. TECH equals one for targets that are in the technology sector, as defined by SDC; otherwise TECH equals zero. TGTVOL is measured for each target as the (log of) standard deviation of daily returns over the days from t-364 to t-64 relative to the bid announcement date. NASDAQ equals one for targets that list on Nasdaq. BANK equals one for targets in the Banking sector, as defined by the ten-industry classification in Fama and French (1997). TGTMVE is measured for each target as the (log of) market value of equity 42 days prior to the acquisition announcement. BIDMVE is measured for each bidder as the (log of) the market value of equity of the acquirer 42 days prior to the announcement. CASH equals one if the method of payment is all cash. ADVISER is equal to total merger fees, as reported by SDC, divided by the market value of the target 42 days prior to the announcement. ACTIVITY equals the (log of) number of mergers in the target's industry in the month prior to the bid announcement. The sample consists of public bid announcements made over the period 1985 to 2015. Bidders and targets are US publicly-listed firms.

Additionally, we also investigate the impact of economic variables related to the business cycle or aggregate uncertainty. Specifically, we use (TERM) or the term spread calculated as the difference in percentages between the average yields of the ten year US Treasury note and the three month US Treasury Bill; (SPREAD) or the default spread calculated as the difference between the average yields of Baa rated corporate and ten-year Treasury bonds; and (VIX) or the 'risk-neutral' expected stock market variance for the US S&P500 contract computed from a panel of options prices.

As preliminary evidence, we compute monthly averages of the valuation complexity proxies and inspect the simple correlation coefficients between the proxies and the mean and volatility of takeover premiums. We report the sample correlations using monthly averages in Table 2. Premiums are higher and are more dispersed in periods when targets have higher return volatility, or when more targets list on NASDAQ. Conversely, premiums are lower and are less dispersed when bidders are larger or when a larger percentage of targets were acquired with cash. Additionally, premiums are larger and more dispersed when the average target size is smaller, and when advisers charge larger fees. Overall, the results of the preliminary analysis suggest that variables that proxy for valuation difficulty (simplicity) are positively (negatively) related to both the mean and standard deviation of the premiums.

5 The effects of merger-specific valuation complexity on takeover premiums

In this section, we use regression analysis to empirically investigate whether changes in the types of firms and deal characteristics that make the bid pricing decision more difficult affect both the level and the variance of takeover premiums.

More specifically, we model both the mean and variance of individual-firm takeover premiums as functions of firm- and deal-specific characteristics that proxy for target valuation complexity. Thus, we run regressions of the following type:

$$\begin{aligned} PREM_i = {} & \beta_0 + \beta_1 TECH_i + \beta_2 TGTMVE_i + \beta_3 BIDMVE_i + \beta_4 CASH_i \\ & + \beta_5 ACTIVITY + \varepsilon_i \end{aligned} \tag{1}$$

$$\begin{aligned} Log\left(\sigma^2\left(\varepsilon_i\right)\right) = {} & \gamma_0 + \gamma_1 TECH_i + \gamma_2 TGTMVE_i + \gamma_3 BIDMVE_i + \gamma_4 CASH_i \\ & + \gamma_5 ACTIVITY_i \end{aligned} \tag{2}$$

Following Lowry et al. (2010), the variance of the error from the regression model (1), ε_i, is assumed to be related to the same firm- and deal-characteristics that are expected to affect the level of takeover premiums, and the log of the variance of the regression error follows the model in (2). Maximum likelihood estimation (MLE) of (1) and (2) is essentially weighted least squares estimation of (1) using the standard deviations σ (ε_i) as weights. The advantage of this approach is that it permits estimation of the influence of each characteristic on both the level and the uncertainty of firm-level takeover premiums (Lowry et al., 2010).[5]

We report in Table 3 the descriptive statistics for the variables used in the regression analysis. The mean (median) premium, using individual takeover premiums (i.e., not monthly averages) is 46% (38%). The mean (median) of TGTVOL is 3% (3%). About 15% of the sample mergers take place in the Tech industry, and 32% in the banking industry. 70% of the targets list on NASDAQ. The mean (median) size is about \$1,032 (\$141) million for targets, and \$11,000 (\$1,515) for bidders. 21% of the sample takeovers are paid with 100% cash. The mean (median) adviser fee is 2% (1%) of target size. The average number of bids announced in the month prior to that of the bid announcement is 12.

In Table 4, we report sample correlation coefficients for the variables used in the regression analysis to assess potential multicollinearity problems. As predicted, takeover premiums are positively associated with TECH, TGTVOL, NASDAQ, and ADVISER; and negatively associated with BANK and TGTMVE. The three variables TECH, TGTVOL and NASDAQ are highly correlated. BANK is negatively correlated with TECH and TGTVOL. TGTMVE is highly correlated with all of the other variables (except TECH), but particularly with NASDAQ, BIDMVE, and ADVISER.

Table 3 Descriptive statistics of measures of valuation complexity

	N	*Mean*	*Median*	*Std. dev.*	*Min*	*Max*
PREM	3,193	0.46	0.38	0.33	0.00	1.98
TECH	3,193	0.15	0.00	0.36	0.00	1.00
TGTVOL	3,011	0.03	0.03	0.02	0.00	0.28
NASDAQ	3,193	0.70	1.00	0.46	0.00	1.00
BANK	3,193	0.32	0.00	0.47	0.00	1.00
TGTMVE (millions)	3,193	1,032.03	141.23	3,913.09	2.44	58,237.17
BIDMVE (millions)	3,004	11,000.52	1,515.13	32,839.70	6.02	535,107.95
CASH	3,193	0.21	0.00	0.41	0.00	1.00
ADVISER	2,321	0.02	0.01	0.02	0.00	0.53
ACTIVITY	3,193	12.59	11.00	7.77	1.00	34.00

Notes: The table reports descriptive statistics for the variables hypothesised to affect takeover premiums (PREM). Individual-firm takeover premiums (PREM) are computed as [Offer price / (Target price day – 42)] – 1. TECH equals one for targets that are in the technology sector, as defined by SDC; otherwise TECH equals zero. TGTVOL is measured for each target as the (log of) standard deviation of daily returns over the days from t-364 to t-64 relative to the bid announcement date. NASDAQ equals one for targets that list on Nasdaq. BANK equals one for targets in the Banking sector, as defined by the ten-industry classification in Fama and French (1997). TGTMVE is measured for each target as the (log of) market value of equity 42 days prior to the acquisition announcement. BIDMVE is measured for each bidder as the (log of) the market value of equity of the acquirer 42 days prior to the announcement. CASH equals one if the method of payment is all cash. ADVISER is equal to total merger fees, as reported by SDC, divided by the market value of the target 42 days prior to the announcement. ACTIVITY equals the (log of) number of mergers in the target's industry in the month prior to the bid announcement. The sample consists of public bid announcements made over the period 1985 to 2015. Bidders and targets are US publicly-listed firms.

In Table 5, we show results of MLE of equations (1) and (2) above. For comparison purposes, we also report in Table 5 the results of cross-sectional ordinary least squared (OLS) regressions of takeover premiums on the same set of firm- and deal-specific characteristics included in (1). Notice that there are three different model specifications (depending on the specific independent variables included), and that for each model specification, MLE results are displayed in two columns, one for the mean equation (1), and the other for the variance equation (2).

The results of the first specification, which includes the variables shown in (1) and (2) above, indicate that mean takeover premiums are significantly larger when the proportion of targets in the Tech industry is high, when targets are smaller, and when acquirers are larger.

Table 4 Correlation coefficients between measures of valuation complexity

	PREM	*TECH*	*TGTVOL*	*NASDAQ*	*BANK*	*TGTMVE*	*BIDMVE*	*CASH*	*ADVISER*
TECH	0.05	1.00							
	(0.0046)								
TGTVOL	0.30	0.21	1.00						
	(0.0001)	(0.0001)							
NASDAQ	0.11	0.06	0.31	1.00					
	(0.0001)	(0.0004)	(0.0001)						
BANK	–0.04	–0.29	–0.28	0.25	1.00				
	(0.0280)	(0.0001)	(0.0001)	(0.0001)					
TGTMVE	–0.24	0.12	–0.35	–0.42	–0.23	1.00			
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)				
BIDMVE	–0.03	0.13	–0.13	–0.18	–0.15	0.63	1.00		
	0.0557	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)			
CASH	0.01	0.03	0.03	0.08	–0.08	–0.11	0.12	1.00	
	(0.6387)	(0.0732)	(0.1437)	(0.0001)	(0.0001)	(0.0001)	(0.0001)		
ADVISER	0.23	0.06	0.26	0.08	–0.11	–0.30	–0.22	0.01	1.00
	(0.0001)	(0.0065)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.7242)	
ACTIVITY	0.03	0.00	0.07	0.03	0.03	0.00	0.00	–0.19	–0.02
	(0.1124)	(0.9833)	(0.0001)	(0.0809)	(0.0710)	(0.8098)	(0.8801)	(0.0001)	(0.2466)

Notes: The table reports sample correlation coefficients for the variables hypothesised to affect takeover premiums (PREM). Variable definitions are on Table 2. The sample consists of public bid announcements made over the period 1985 to 2015. Bidders and targets are US publicly-listed firms. Individual-firm takeover premiums (PREM) are computed as [Offer price / (Target price day – 42)] – 1.

Table 5 Relation between the mean and variance of takeover premiums and firm- and deal-specific proxies for complexity

	(1)			(2)			(3)		
	OLS mean	*MLE mean*	*MLE variance*	*OLS mean*	*MLE mean*	*MLE variance*	*OLS mean*	*MLE mean*	*MLE variance*
Intercept	0.48	0.46	–1.87	0.31	0.26	–2.69	0.52	0.48	–1.73
	(14.78)	(13.39)	(–12.31)	(8.56)	(7.05)	(–14.39)	(16.05)	(13.76)	(–11.03)
TECH	0.08	0.08	0.51						
	(4.82)	(3.90)	(5.84)						
TGTVOL				3.93	5.69	25.34			
				(12.19)	(10.89)	(11.76)			
BANK							–0.08	–0.06	–0.49
							(–5.44)	(–4.96)	(–7.31)
TGTMVE	–0.10	–0.09	–0.29	–0.08	–0.07	–0.22	–0.10	–0.09	–0.29
	(–13.73)	(–14.98)	(–9.15)	(–11.68)	(–11.39)	(–6.63)	(–14.67)	(-14.72)	(–9.04)
BIDMVE	0.07	0.06	0.10	0.06	0.05	0.08	0.07	0.07	0.12
	(10.16)	(10.54)	(3.46)	(9.87)	(9.57)	(2.57)	(10.62)	(10.73)	(3.79)
CASH	–0.05	–0.05	–0.34	–0.04	–0.05	–0.34	–0.06	–0.06	–0.35
	(–2.58)	(–3.31)	(–3.87)	(–2.2)	(–3.23)	(–3.81)	(–2.88)	(–3.52)	(–3.92)
ACTIVITY	0.01	0.01	0.09	0.01	0.00	0.00	0.01	0.01	0.10
	(0.96)	(1.27)	(2.01)	(0.54)	(0.37)	(0.07)	(1.09)	(1.45)	(2.14)
Adjusted R^2	0.0953			0.1348			0.1009		
Sample size	2,199	2,199		2,081	2,081		2,199	2,199	
Log-likelihood	–492.3249	–412.002		–405.1598	–244.9036		–485.5275	–404.172	

Notes: The columns labelled OLS show cross-sectional regressions of takeover premiums on firm- and deal-specific characteristics. For variable definitions, see Table 3. The *t*-statistics, shown in parenthesis, use White's (1980) heteroskedasticity-consistent standard errors. The columns labelled MLE show maximum likelihood estimates of the following type of regressions, in which the premium variance is assumed to be linearly related to the same characteristics that are included in the mean equation:

$$PREM_i = \beta_0 + \beta_1 TECH_i + \beta_2 TGTMVE_i + \beta_3 BIDMVE_i + \beta_4 CASH_i + \beta_5 ACTIVITY + \varepsilon_i$$

$$Log\left(\sigma^2\left(\varepsilon_i\right)\right) = \gamma_0 + \gamma_1 TECH_i + \gamma_2 TGTMVE_i + \gamma_3 BIDMVE_i + \gamma_4 CASH_i + \gamma_5 ACTIVITY_i$$

Turning to the variance portion of the MLE, there is evidence that the same characteristics that are significantly related to the level of premiums are significantly related to the variance of premiums, and in the same direction. That is, the variance of the premiums [i.e., the errors in equation (1)] is higher for targets in the Tech industry, and for smaller (larger) targets (acquirers). Each of these results is consistent with our hypotheses of how firm-specific characteristics that reflect bidders' divergence of opinion may affect the mean premium. ACTIVITY is positively and significantly related to the variance of premiums, but is not significant when the premium level is used as the dependent variable. CASH is significantly related to the mean and variance of premiums, controlling for the other variables.

The second specification in Table 5 includes TGTVOL in place of TECH. Results support our hypothesis that both the mean and variance of premiums are higher if targets have more volatile stock returns prior to the bid announcement; the results for the rest of the variables are similar to those in the first specification.

In the third specification in Table 5, BANK is included in place of TECH. Consistent with our hypothesis that complexity affects the bidding estimation process, both the mean and the variance of premiums are lower for targets in the banking industry, where the regulatory environment and governmental policies may narrow the range of possible valuations.

Modelling of both the mean and variance of takeover premiums results in significant improvements over modelling only the mean. Using a χ^2 test based on the difference in log-likelihoods, we reject the null that the MLE estimation does not explain the data better than the OLS estimation (e.g., Lowry et al., 2010).

In Table 6, we report results that include ADVISER in place of TGTMVE. As hypothesised, there is a significantly positive association between ADVISER and the mean and the variance of premiums, controlling for other variables. As in Table 5, there is a positive association between the mean and the variance of premiums and TECH and BIDMVE, although the association between BIDMVE and the premium variance is not significantly different from zero after controlling for ADVISER.

The second specification in Table 6 includes TGTVOL in place of TECH. We find that there is a strong positive association between the mean and volatility of premiums and TGTVOL and ADVISER. For this specification, BIDMVE remains positively and significantly associated with the mean premium, but is no longer significantly related to variance of premiums. In addition, CASH is significantly negatively associated with the variance of premiums.

In the third specification in Table 6, we include BANK in place of TECH and TGTVOL. Both the mean and the volatility of premiums are negatively associated with BANK as expected, but only the coefficient in the variance equation is significant.

Overall, the results suggest that the complexity of the bid pricing problem affects both the level and 'precision' of takeover premiums. Consistent with our predictions, targets in the Tech industry, or with higher return volatility, appear to be more difficult to value.[6] Small cap companies are followed by fewer analysts and more difficult to value. The value of targets in the banking industry is comparatively easier to estimate. Transactions in which investment advisers charge larger fees are also more difficult to value. Our findings are consistent with explanations of takeover premiums based on valuation complexity (Brunnermeier and Oehmke, 2009; Carlin et al., 2013).

Table 6 Relation between the mean and variance of takeover premiums and firm- and deal-specific proxies for complexity

	(1)			(2)			(3)		
	OLS mean	*MLE mean*	*MLE variance*	*OLS mean*	*MLE mean*	*MLE variance*	*OLS mean*	*MLE mean*	*MLE variance*
Intercept	0.17	0.20	–2.40	0.03	0.02	–3.53	0.15	0.18	–2.25
	(4.34)	(4.59)	(–11.7)	(0.61)	(0.37)	(–15.21)	(3.64)	(3.97)	(–10.45)
TECH	0.04	0.06	0.50						
	(2.41)	(2.82)	(5.05)						
TGTVOL				3.52	5.78	28.37			
				(9.56)	(9.19)	(10.40)			
BANK							0.02	0.01	–0.27
							(0.95)	(0.71)	(–3.48)
TGTMVE	0.01	0.01	–0.09	0.02	0.02	–0.03	0.01	0.01	–0.08
	(1.99)	(1.28)	(–4.49)	(4.05)	(3.37)	(–1.23)	(2.46)	(2.03)	(–4.07)
BIDMVE	0.01	0.00	–0.24	0.00	–0.01	–0.29	0.01	0.01	–0.25
	(0.22)	(0.22)	(–2.25)	(0.08)	(–0.49)	(–2.57)	0.30	(0.37)	(–2.27)
CASH	8.09	8.37	19.85	7.30	6.77	14.53	8.33	8.40	16.98
	(16.09)	(11.45)	(6.69)	(14.44)	(9.44)	(4.66)	(16.17)	(11.44)	(5.66)
ACTIVITY	0.02	0.02	0.05	0.02	0.01	0.00	0.02	0.02	0.06
	(2.26)	(1.96)	(1.02)	(2.12)	(1.12)	(–0.03)	(2.32)	(1.91)	(1.16)
Adjusted R^2	0.1055						0.1036		
Sample size	1,652	1,652		1,567	1,567		1,652	1,652	
Log-likelihood	–280.262	–223.1391		–216.939	–102.32		–282.069	–236.15	

Notes: The columns labelled OLS show cross-sectional regressions of takeover premiums on firm- and deal-specific characteristics. For variable definitions, see Table 3. The *t*-statistics, shown in parenthesis, use White's (1980) heteroskedasticity-consistent standard errors. The columns labelled MLE show maximum likelihood estimates of the following type of regressions, in which the premium variance is assumed to be linearly related to the same characteristics that are included in the mean equation:

$$PREM_i = \beta_0 + \beta_1 TECH_i + \beta_2 BIDMVE_i + \beta_3 CASH_i + \beta_4 ADVISER_i + \beta_5 ACTIVITY + \varepsilon_i$$

$$Log\left(\sigma^2(\varepsilon_i)\right) = \gamma_0 + \gamma_1 TECH_i + \gamma_2 BIDMVE_i + \gamma_3 CASH_i + \gamma_4 ADVISER_i + \gamma_5 ACTIVITY_i$$

6 Time-series variation in takeover premiums and premium dispersion

Recall that Table 1 indicates significant variation in both the level and dispersion of takeover premiums over time. In this section, we extend the analysis of the previous section by modelling explicitly the time variation in the mean and dispersion of takeover premiums. We are interested in whether the variables assumed to proxy for valuation complexity continue to affect the level and uncertainty of premiums after modelling the time series behaviour of premiums.

Methodologically, we follow Lowry et al. (2010) and treat the sample of takeover premiums as the realisation of a time series process. The approach is unorthodox because the individual observations represent different firms, and because the observations are not equally spaced in time. Nevertheless, as noted by Lowry et al. (2010), the use of Box and Jenkins's (1976) AR models to account for serial autocorrelation, and of Nelson's (1991) EGARCH models to account for residual heteroskedasticity results in an improvement over the standard OLS estimation procedure.

We adopt an AR(1)-EGARCH(1, 1) econometric specification. In Table 7, we show the results of the quasi maximum likelihood estimates (QMLE) assuming a Student's t distribution for the errors[7]:

$$PREM_t = \phi_1 PREM_{t-1} + X_t'\beta + \varepsilon_t, \text{ with } \varepsilon_t = h_t^{1/2} v_t \mid \Psi_{t-1} \sim D\left(0, h_t\right), \tag{3}$$

and

$$\ln h_t = \kappa + X_t'\delta + a_1 \ln h_{t-1} + b_1 \left[\left| v_{t-1} \right| - E\left| v_{t-1} \right| + \psi v_{t-1} \right], \tag{4}$$

where $\phi(L)$, $a(L)$ denote the autoregressive (AR) lag polynomial of order 1 i.e., $L = 1$, $b(L)$ the moving average (MA) lag polynomial of order 1, X_t is the vector of explanatory variables, β, δ are vector of coefficients, Ψ_{t-1} is the information set at time $t - 1$, ε_t is the error which follows some conditional distribution D, $\kappa = [1 - a_1]\zeta$, ζ is the intercept of the variance equation, ψ is a parameter for asymmetric effects, and $v_t \sim i.i.d.(0, 1)$.

A well-known advantage of this specification for heteroskedasticity is that no further restrictions need to be imposed in the coefficients to attain a positive variance.[8] Consequently, the numerical optimisation algorithm used in the estimation procedure is much more simple and flexible when compared to the standard GARCH specification.

In Table 7, we report parameter estimates and t-statistics using robust standard errors for the same specifications used in Table 5. Results are entirely consistent with those of the cross-sectional analysis disclosed in Table 5. The mean and variance of the premiums are significantly positively associated with TECH, TGTVOL, and BIDMVE, and negatively associated with TGTMVE and BANK. Therefore, we confirm that the complexity variables that help explain the cross-section of premiums also explain the time-series behaviour of premiums.

As shown in Table 7, there is evidence of persistency in the mean and variance premium equations consistent with previous empirical literature on takeover premiums.

In Table 8, we report results of the EGARCH regressions including ADVISER in place of TGTMVE. We use the same specifications as in Table 6. Consistent with Table 6, there is a significantly positive association between ADVISER and the mean and the volatility of premiums, controlling for other variables. Overall, the results of this section, in which we model the time series of premiums, are consistent with the results of the cross-sectional analysis performed in the previous section. There is evidence that variables that measure target valuation complexity affect both the level and uncertainty of takeover premiums.

Table 7 Relation between takeover premiums and proxies for complexity using AR (1)-EGARCH (1, 1) regressions

	(1)		*(2)*		*(3)*	
	QMLE mean	*QMLE variance*	*QMLE mean*	*QMLE variance*	*QMLE mean*	*QMLE variance*
Intercept	0.38 (11.26)	1.48	0.09 (0.83)	3.48	0.40 (14.26)	1.15
TECH	0.06 (3.34)	0.42 (3.81)				
TGTVOL			7.83 (15.86)	35.20 (14.88)		
BANK					–0.05 (–4.06)	–0.46 (–5.60)
TGTMVE	–0.08 (–12.79)	–0.35 (–7.78)	–0.05 (–9.60)	–0.16 (–3.93)	–0.08 (–8.98)	–0.37 (–8.52)
BIDMVE	0.06 (9.03)	0.15 (3.58)	0.04 (6.10)	0.04 (1.07)	0.06 (8.23)	0.16 (4.04)
CASH	–0.04 (–2.58)	–0.32 (–2.98)	–0.04 (–2.82)	–0.34 (–3.51)	–0.04 (–2.68)	–0.37 (–3.40)
ACTIVITY	0.01 (1.36)	0.04 (0.70)	0.01 (0.94)	0.04 (0.71)	0.01 (1.37)	0.04 (0.74)
AR1	0.08 (3.86)	0.38 (3.40)	0.04 (2.28)	0.13 (1.69)	0.08 (4.01)	0.40 (3.62)
MA1		0.22 (2.45)		0.07 (1.19)		0.24 (2.80)
Student's t $\sqrt{d.f.}$	2.19		2.86		2.20	
Adjusted R^2	0.10		0.20		0.11	
Sample size	2,197		2,114		2,197	
Log-likelihood	–292.81		–33.64		–281.84	

Notes: The table shows quasi-maximum likelihood estimates of regressions where the premium variance is assumed to be linearly related to the same characteristics that are included in the mean equation. The sample consists of takeover premiums between 1985 and 2015. See Table 3 for variable definitions. A Student's *t* distribution is assumed for the errors. The *t*-statistics, shown in parenthesis, are based on robust standard errors. Note that the intercept in the variance equation and the degrees of freedom in the Student *t* distribution have no natural zero hypothesis, consequently we do not show t-stats. Results were obtained running © James Davidson's Time Series Modelling software v4.32 under © Jurgen A. Doornik's OxEdit v5.10.

$PREM_t = \phi_1 PREM_{t-1} + X_t'\beta + \varepsilon_t$, with $\varepsilon_t = h_t^{1/2} v_t \mid \Psi_{t-1} \sim D(0, h_t)$.

$\ln h_t = \kappa + X_t'\delta + a_1 \ln h_{t-1} + b_1\left[|v_{t-1}| - E|v_{t-1}| + \psi v_{t-1}\right]$.

Table 8 Relation between takeover premiums and proxies for complexity using AR (1)-EGARCH (1, 1) regressions

	(1)		*(2)*		*(3)*	
	QMLE mean	*QMLE variance*	*QMLE mean*	*QMLE variance*	*QMLE mean*	*QMLE variance*
Intercept	0.12 (0.97)	2.27	–0.08 (–2.48)	3.71	0.09 (0.46)	2.18
TECH	0.04 (1.65)	0.33 (2.20)				
TGTVOL			8.00 (13.04)	37.82 (12.79)		
BANK					0.02 (1.33)	–0.15 (–1.56)
TGTMVE	0.01 (1.09)	–0.09 (–3.18)	0.01 (5.20)	–0.07 (–2.75)	0.01 (0.68)	–0.09 (–3.06)
BIDMVE	0.01 (0.33)	–0.26 (–1.75)	–0.01 (–0.68)	–0.40 (–3.06)	0.01 (0.52)	–0.28 (–1.86)
CASH	8.10 (8.82)	21.24 (5.22)	5.11 (8.09)	5.74 (1.52)	8.24 (4.66)	20.20 (4.88)
ACTIVITY	0.02 (0.81)	0.02 (0.24)	0.02 (2.09)	0.01 (0.13)	0.02 (1.23)	0.03 (0.49)
AR1	0.08 (3.31)	0.33 (2.60)	0.02 (1.02)	0.11 (1.35)	0.09 (3.23)	0.33 (2.35)
MA1		0.18 (1.65)		0.05 (0.95)		0.17 (1.37)
Student's t $\sqrt{d.f.}$	2.28		2.93		2.22	
Adjusted R^2	0.11		0.19		0.11	
Sample size	1650		1587		1650	
Log-likelihood	–154.08		43.64		–156.07	

Notes: The table shows quasi-maximum likelihood estimates of cross-sectional regressions where the premium variance is assumed to be linearly related to the same characteristics that are included in the mean equation. The sample consists of takeover premiums, ordered by the date of the acquisition announcement in SDC, between 1985 and 2015. Negative premiums are excluded. Both target and acquirer are US publicly listed companies. See Table 3 for variable definitions and Table 7 for model details. The *t*-statistics, shown in parenthesis, are based on robust standard errors. Note that the intercept in the variance equation and the degrees of freedom in the Student *t* distribution have no natural zero hypothesis; consequently, we do not show t-stats. Results were obtained running © James Davidson's Time Series Modelling software v4.32 under © Jurgen A. Doornik's OxEdit v5.10.

$PREM_t = \phi_1 PREM_{t-1} + X_t'\beta + \varepsilon_t$, with $\varepsilon_t = h_t^{1/2} v_t \mid \Psi_{t-1} \sim D(0, h_t)$.

$\ln h_t = \kappa + X_t'\delta + a_1 \ln h_{t-1} + b_1\left[|v_{t-1}| - E|v_{t-1}| + \psi v_{t-1}\right]$.

Table 9 Relation between takeover premiums and proxies for complexity using AR (1)-EGARCH (1, 1)-M regressions

	(1)		*(2)*		*(3)*	
	Mean	*Variance*	*Mean*	*Variance*	*Mean*	*Variance*
Intercept		2.36		3.26		2.19
TECH		0.19 (3.99)				
TGTVOL				14.17 (12.71)		
BANK						–0.21 (–5.23)
TGTMVE		–0.26 (–15.00)		–0.18 (–5.81)		–0.27 (–16.16)
BIDMVE		0.18 (9.28)		0.14 (3.45)		0.17 (5.94)
CASH		–0.12 (–2.54)		–0.08 (–2.00)		–0.13 (–2.74)
ACTIVITY		0.04 (1.22)		0.02 (0.67)		0.03 (0.63)
AR1	4.26 (15.42)		5.55 (16.86)		4.39 (14.67)	
MA1	0.06 (3.00)	0.05 (0.51)	0.03 (1.56)	0.07 (1.24)	0.05 (2.46)	0.14 (1.49)
Student's t $\sqrt{d.f.}$	2.10		2.48		2.14	
Adjusted R^2	0.11		0.18		0.12	
Sample size	2197		2114		2197	
Log-likelihood	–314.45		–127.66		–302.55	

Notes: The table shows the QMLE assuming a Student t distribution for the errors. Note that the intercept in the variance equation and the degrees of freedom in the Student t distribution have no natural zero hypothesis; consequently, we do not show t-stats. Results were obtained running © James Davidson's Time Series Modelling software v4.32 under © Jurgen A. Doornik's OxEdit v5.10.
$PREM_t = \phi PREM_{t-1} + \mu h_t + \varepsilon_t$, with $\varepsilon_t = h_t^{1/2} v_t \mid \Psi_{t-1} \sim D(0, h_t)$, and
$\ln h_t = \kappa + X_t'\delta + a_1 \ln h_{t-1} + b_1 \left[|v_{t-1}| - E|v_{t-1}| + \psi v_{t-1} \right]$.

In order to explore further the feedback effect between the variance of the premium and the mean premium without the confounding effects of the explanatory variables, we now proceed to model the drift equation as an AR(1) process function of only the EGARCH-M effect. In Table 9, we show the results of the QMLE assuming a Student's t distribution for the errors:

$$PREM_t = \phi PREM_{t-1} + \mu h_t + \varepsilon_t - \theta_1 \varepsilon_{t-1}, \text{ with } \varepsilon_t = h_t^{1/2} v_t \mid \Psi_{t-1} \sim D(0, h_t), \tag{5}$$

and

$$\ln h_t = \kappa + X_t'\delta + a_1 \ln h_{t-1} + b_1 \left[|v_{t-1}| - E|v_{t-1}| + v_{t-1} \right], \tag{6}$$

where μ is the parameter that captures the effect that a higher perceived dispersion in takeover premiums has on the level of takeover premiums; the rest of variables and parameters have been defined earlier. We expect the sign of this parameter to be positive because of the notion that the premium level and variance are positively related.

The results of the first specification using robust standard errors lead us to reject the null hypothesis that the variance of the premiums is unrelated to the level of premiums. The second specification in Table 9 includes TGTVOL in place of TECH. Results are similar to previous ones. In the third specification in Table 9, BANK is included in place of TECH. Again, the variance of premiums is lower for targets in the banking industry.

Although not reported in tabular form to save space, the results of the EGARCH-M regressions including ADVISER are similar to results already reported.

Overall, results using the E-GARCH-in-the-mean model are similar to previous results adding support the importance of valuation complexity for takeover premiums.

7 Evidence from additional complexity measures

While the proxies used so far are relatively simple and uncontroversial measures of deal complexity, in this section we consider some unique deal structure characteristics that could influence the degree of complexity surrounding target valuation. First, private acquirers may make a special effort to minimise target valuation errors, because the bidder managers engaged in the valuation process are likely large owners and would be highly exposed to errors from overpricing the target. Private acquirers often gain access to confidential information not available to public bidders; and at least a subset of private bidders are specialised investors (i.e., private equity).

A second deal characteristic that may serve as a proxy for target complexity is whether the acquisition is an LBO. The LBO serves as a special case for the private acquirers, as managerial efforts to minimise target valuation errors may be especially pronounced since their levered investments expose them to much risk. In addition, some of these LBOs involve managers who are familiar with the target and therefore may have private information that can minimise potential valuation errors. Thus, the complexity hypothesis predicts that premiums are lower and less dispersed for private acquirers, and especially for LBOs.

A third deal characteristic that may serve as a proxy for target complexity is whether the form of acquisition is tender offer versus a merger agreement. Targets that are subject to tender offers should exhibit a relatively high degree of complexity, because the respective acquirers have normally less information about the target than when a friendly merger agreement occurs. In addition, the target may resist any efforts by the acquirer, which can increase the complexity surrounding the potential synergies that could be extracted from the target. Thus, premiums should be higher and more dispersed for tender offers.

We also consider the time necessary to complete the transaction as a fourth proxy for target complexity. More complex deals are likely to take longer to complete; hence there should be a positive association between the time to complete a deal and the level and dispersion of premiums. We report results from testing these additional predictions in Table 10. The first set of regressions is applied to an expanded sample that includes tender offers. As predicted, tender offers are associated with both higher and less 'precise' (more dispersed) premiums. Results regarding the rest of variables are similar to those in Table 6, which uses a similar specification.

The second set of regressions is applied to a sample expanded to include tender offers and private bidders. The variables BIDMVE and ADVISER are dropped because of lack of data; instead, we use the log of deal value to measure deal size. Consistent with the complexity hypothesis, the coefficient for TENDER is positive and significant in explaining the dispersion in the target premium. The coefficient for TENDER is positive and significant at the 1% level when explaining the variation in the dispersion in the target premium. In addition, the coefficients of PRIVATE and LBO are consistently negative and significant, implying that mean and variance of target premiums is reduced when involving private acquirers and LBO acquirers. This result supports our hypothesis that target valuation complexity is attenuated when the acquiring firms are privately owned.

In the third set of specifications, we add the variable TIMETOCOMPLETE. The coefficient of this variable is positive and significant, which suggests that in transactions that take a longer time to complete, the level and dispersion of premiums is higher. Overall, all four deal characteristics appear to serve as useful proxies for complexity, and offer supplemental evidence of how complexity surrounding the target's valuation affects the target premium and dispersion surrounding target premiums.

The remaining results in Table 10 are focused on results that have been tested earlier. However, the interpretation of the results is different from the earlier analysis because the sample is less homogeneous. For example, the variable CASH when the sample includes public firms only is different from when the sample is expanded to include private bidders and tender offers. By their very nature, private bidders cannot offer (liquid) equity as a means of payment when the deal is more complex. Similarly, it is well-known that tender offers frequently involve cash. The proper analysis of previous variables using a heterogeneous sample would likely need to include too many interaction terms to be feasible. Thus, in Table 10, we treat the variables TECH, CASH, ACTIVITY, and DEALVALUE as controls. Nevertheless, we find the coefficients for the TECH variables are positive and significant, consistent with earlier results. The coefficients of the CASH variable are negative and typically significant, which implies lower premiums and less dispersion when cash is the method of payment used. The coefficients for the ACTIVITY variable are positive and typically significant, implying that merger activity increases the premium and dispersion of premiums.

We expect that valuation will be more difficult when targets list on NASDAQ, which are typically small, young, and high-tech (e.g., Lowry et al., 2010). The results using NASDAQ are similar to results using TGTVOL and TECH. To save space, we do not report regression results that include NASDAQ.

Finally, we test whether economic variables proxying for the phase of the real business cycle like TERM, SPREAD, and VIX affect the level and variability of premiums. We report results in Table 11. VIX and SPREAD both affect the level and variability of premiums, whereas TERM affects only the volatility of premiums. VIX and SPREAD are positively associated with the level and variance premiums; while TERM is negatively associated with the variance of premiums. The evidence from VIX and SPREAD in particular is consistent with the notion that premiums are higher and more dispersed when aggregate uncertainty is higher.

Table 10 Relation between the mean and variance of takeover premiums and proxies for complexity: expanded sample

	Initial sample + Tender offers			*Initial sample + Tender offers+ Private bidders*			*Initial sample + Tender offers+ Private bidders*		
	OLS mean	*MLE mean*	*MLE variance*	*OLS mean*	*MLE mean*	*MLE variance*	*OLS mean*	*MLE mean*	*MLE variance*
Intercept	0.01	0.03	–2.63	0.41	0.41	–2.16	0.31	0.30	–2.50
	(0.16)	(0.46)	(–8.93)	(12.34)	(11.67)	(–15.03)	(7.92)	(8.02)	(–14.71)
TECH	0.05	0.06	0.44	0.06	0.05	0.22	0.07	0.07	0.25
	(3.00)	(3.30)	(5.15)	(6.15)	(5.22)	(4.86)	(6.57)	(5.85)	(5.42)
BIDMVE	0.02	0.01	–0.06						
	(4.05)	(2.97)	(–3.31)						
CASH	0.00	0.00	–0.28	–0.01	–0.02	–0.12	0.00	0.00	–0.10
	(–0.16)	(–0.07)	(–3.19)	(–1.59)	(–1.72)	(–2.93)	(–0.41)	(–0.39)	(–2.32)
ADVISER	8.32	8.63	20.10						
	(18.96)	(13.71)	(7.87)						
ACTIVITY	0.04	0.04	0.04	0.01	0.01	0.04	0.02	0.02	0.10
	(3.58)	(3.72)	(0.65)	(1.73)	(1.38)	(1.50)	(2.55)	(2.71)	(3.06)
TENDER	0.04	0.04	0.08	0.11	0.11	0.23	0.11	0.11	0.25
	(2.17)	(2.24)	(0.89)	(11.02)	(10.42)	(5.02)	(10.55)	(10.34)	(5.30)
PRIVATE				–0.19	–0.18	–0.35	–0.14	–0.13	–0.29
				(–16.58)	(–15.9)	(–7.1)	(–10.91)	(–11.03)	(–5.2)
LBO				–0.08	–0.08	–0.32	–0.09	–0.09	–0.36
				(–4.86)	(–5.86)	(–4.67)	(–5.06)	(–6.56)	(–5.2)
DEAL VALUE				0.00	0.00	–0.05	–0.01	–0.01	–0.09
				(–0.85)	(–0.35)	(–4.96)	(–4.18)	(–5.34)	(–8.12)
TIMETOCOMPLETE							0.02	0.03	0.06
							(6.39)	(8.51)	(4.13)
Adjusted R^2	0.1288			0.1018			0.0793		
Sample size	2,044	2,044		7,277	7,277		6,560	6,560	
Log-likelihood	–353.928	–288.16		–1,999	–1,922		–1,881	–1,792	

Notes: The columns labelled OLS show cross-sectional regressions of takeover premiums on firm- and deal-specific characteristics. TENDER is an indicator variable that equals unity for tender offers; PRIVATE is an indicator variable for provide bidders (other than LBOs); LBO is an indicator variable for leverage buyouts. DEALVALUE equals the (log of) transaction deal value. TIMETOCOMPLETE equals the (log of) number days from announcement to completion. For other variable definitions, see Table 3. The *t*-statistics, shown in parentheses, use White's (1980) heteroskedasticity-consistent standard errors. The columns labelled MLE show maximum likelihood estimates of regressions in which the premium variance is assumed to be linearly related to the same characteristics that are included in the mean equation.

Table 11 Relation between the mean and variance of takeover premiums and economic determinants

	(1)			(2)			(3)		
	OLS mean	*MLE mean*	*MLE variance*	*OLS mean*	*MLE mean*	*MLE variance*	*OLS mean*	*MLE mean*	*MLE variance*
Intercept	0.42	0.38	–2.33	0.31	0.33	–2.37	0.51	0.49	–1.53
	(9.91)	(9.02)	(–11.9)	(6.57)	(6.75)	(–10.44)	(12.22)	(11.91)	(–7.34)
VIX	0.0029	0.0032	0.0189						
	(2.53)	(3.00)	(3.26)						
SPREAD				5.48	4.35	19.51			
				(4.44)	(3.59)	(3.13)			
TERM							–0.76	–0.71	–7.11
							(–1.11)	(–1.17)	(2.15)
TECH	0.09	0.08	0.51	0.07	0.07	0.41	0.08	0.07	0.45
	(4.95)	(3.86)	(5.45)	(4.30)	(3.64)	(4.56)	(4.74)	(3.94)	(5.10)
TGTMVE	–0.10	–0.10	–0.34	–0.10	–0.09	–0.31	–0.10	–0.09	–0.33
	(–13.19)	(–14.95)	(–9.68)	(–13.79)	(–15.1)	(–9.37)	(–13.6)	(–15.25)	(–10.1)
BIDMVE	0.07	0.07	0.16	0.07	0.06	0.12	0.07	0.06	0.13
	(9.91)	(10.71)	(4.70)	(10.31)	(10.55)	(3.71)	(10.20)	(10.76)	(4.11)
CASH	–0.06	–0.06	–0.34	–0.05	–0.06	–0.35	–0.05	–0.05	–0.34
	(–2.65)	(–3.39)	(–3.49)	(–2.63)	(–3.46)	(–3.86)	(–2.58)	(–3.34)	(–3.85)
ACTIVITY	0.01	0.01	0.09	0.03	0.03	0.14	0.00	0.00	0.02
	(0.96)	(1.43)	(1.74)	(2.77)	(2.54)	(2.76)	(0.01)	(0.29)	(0.38)
Adjusted R^2	0.1073			0.1068			0.0979		
Sample size	1,917	1,917		2,104	2,104		2,148	2,148	
Log-likelihood	–435.245	–355.009		–438.892	–357.602		–468.709	–379.4409	

Notes: The columns labelled OLS show cross-sectional regressions of takeover premiums on firm- and deal-specific characteristics. For variable definitions, see Table 3. VIX is the measure of implied market volatility. SPREAD is measured as difference between the yield on Baa rated corporate bond and ten-year Treasury yield. TERM is the difference between the yield on a ten-year Treasury bond and three-month T-Bill. The *t*-statistics, shown in parenthesis, use White's (1980) heteroskedasticity-consistent standard errors. The columns labelled MLE show maximum likelihood estimates of the following type of regressions, in which the premium variance is assumed to be linearly related to the same characteristics that are included in the mean equation:

$$PREM_i = \beta_0 + \beta_1 TECH_i + \beta_2 TGTMVE_i + \beta_3 BIDMVE_i + \beta_4 CASH_i + \beta_5 ACTIVITY + \varepsilon_i$$

$$Log\left(\sigma^2(\varepsilon_i)\right) = \gamma_0 + \gamma_1 TECH_i + \gamma_2 TGTMVE_i + \gamma_3 BIDMVE_i + \gamma_4 CASH_i + \gamma_5 ACTIVITY_i$$

8 Takeover premium measures

In this section, we investigate how our results change when we use alternative measures of takeover premium. In the previous sections, PREM was measured as the difference between the offer price and the target stock price 42 days prior to announcement, divided by the target stock price. Possible alternative measures of takeover premium are:

1. deal value, as reported in SDC, divided by the market value of the target 42 days prior to takeover announcement, minus one
2. deal value divided by the market value of the target the day prior to the announcement, minus one
3. the target market value the day of the announcement divided by the market value 42 days prior, minus one.

We make the following observations regarding the results using alternative measures (not reported in tabular form). First, the positive association reported in the previous sections between TGTVOL (or TECH) and the mean and dispersion of premiums is not sensitive to the measure of the premium. Second, the association between CASH, BIDMVE, and ACTIVITY, and the mean and dispersion of premiums, is sensitive to how the premium is measured. For example, although CASH is significantly negative when using the first two alternative measures of premium, it is significantly positive when using the third measure. Finally, comparison of the log-likelihoods between the MLE and the OLS models confirm that there are significant benefits from simultaneously modelling the level and uncertainty of takeover premiums, regardless of the actual measure of premium used.

9 Conclusions

We inspect the association between the degree of complexity in the valuation of targets and the level and variability of takeover premiums. Specifically, we test whether firm- and deal-specific characteristics that make valuation more difficult cause merger deals to exhibit larger premiums and larger dispersion in premiums. We apply the method used by Lowry et al. (2010) to test for IPO valuation complexity, and explicitly model both the (conditional) mean premium and the variance of the error from the mean regression model as related to the same firm-specific and deal-specific characteristics that are used to proxy for target valuation complexity.

We find that the mean takeover premium is higher and the precision lower (i.e., the error variance higher) when a relatively high proportion of targets belong to the tech industry, when target stock returns are volatile, when targets are smaller, when bidders are large, and when deal advising (as measured by fees) are more complicated. All of these characteristics cause higher levels of information asymmetry about target valuation, which increases the complexity of valuing targets. We also confirm using an EGARCH model that the relationships described above hold over time.

We also test unique deal characteristics that can proxy for target valuation complexity, and find that they influence the premium and dispersion of premiums among targets. Specifically, we argue that private bidders (and LBOs in particular) reflect low complexity of target valuation, while tender offers and deals that take a longer time to complete reflect high complexity of target valuation. We find that all four deal characteristics appear to serve as useful proxies for target valuation complexity, and offer supplemental evidence of how complexity surrounding the target's valuation affects the target premium and dispersion surrounding target premiums.

Finally, we find that economic variables proxying for the phase of the business cycle such as the default spread or with market volatility such as VIX are positively associated with both the level and variance of premiums. This is consistent with the notion that deal valuation complexity increases both the average and the dispersion of takeover premiums.

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Notes

1 Differences of opinion are typically modelled via asymmetric information. See the summaries of McAfee and McMillan (1987), Dasgupta and Hansen (2007), and Eckbo (2009) regarding auction theory and models of optimal bidding in the market for corporate control. A recent theoretical article by Povel and Singh (2006) shows that bidder asymmetry can affect takeover premiums.

2 We use 'takeovers', 'mergers', and 'acquisitions' interchangeably.

3 Note that this result is specific to the case of LBOs because of the presence of private information and not leverage. In this respect, Jandik and Makhija (2005) show that in general takeovers that involve targets with higher leverage are significantly more complex in the sense that take a longer time to complete, have multiple bidders, and several pricing revisions.

4 Two other consequences are possible market breakdown and sudden price adjustments.

5 Results of regression analysis are qualitatively similar, in terms of the sign and significance of the estimated coefficients, when we use the natural logarithm of the premium as the dependent variable, rather than the raw premium.

6 Although not shown in tabular form, the variable NASDAQ is also significantly positively associated with the mean and dispersion of premiums.

7 Nelson (1991) proposed as distribution the generalised error distribution (GED) $D(\varepsilon) = \eta \exp\left[-\frac{1}{2}(\varepsilon_t / \lambda)\right]^{\eta} \Big/ \lambda \cdot 2^{[(\eta+1)/\eta]}\,\Gamma(1/\eta),$ where η is some positive parameter driving the thickness of the tails of the distribution, $\Gamma(\cdot)$ is the gamma function and $\lambda = \sqrt{\left[2^{(2/\eta)}\Gamma(1/\eta)\big/\Gamma(3/\eta)\right]}$ is constant. For robustness purposes, we run the model assuming alternative distributions for the error ε_t and report the most significant results.

8 If we re-write equation (4) as $\ln h_t = \zeta + X_t'\delta + \pi_1\left[|v_{t-1}| - E|v_{t-1}| + \psi v_{t-1}\right]$ then we need that $\pi_1^2 < \infty$ in order to attain stationarity.