Journal of Financial Economics 110 (2013) 61–86

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Are small firms less vulnerable to overpriced stock offers? ☆

Anand M. Vijh [a,*], Ke Yang [b]

[a] Tippie College of Business, University of Iowa, Iowa City, IA 52242, USA
[b] College of Business and Economics, Lehigh University, Bethlehem, PA 18015, USA

ARTICLE INFO

Article history:
Received 10 November 2011
Received in revised form
24 July 2012
Accepted 20 February 2013
Available online 24 May 2013

JEL classification:
G34
G14

Keywords:
Firm size effect
Mergers and acquisitions
Overvaluation
Opinion divergence
Equity issuance

ABSTRACT

We show an inverted-U relation between targetiveness (probability of being targeted) and firm size. However, this pattern describes stock offers and is more pronounced during hot markets characterized by higher stock valuations. For cash offers we find a negative and monotonic relation. These contrasting patterns suggest that small firms (in the bottom NYSE size quartile) are less vulnerable to overpriced stock offers. In addition, we find that the stock acquirers of small targets are less overvalued than those of large targets, and that the announcement returns are less negative for stock acquirers of small targets than for those of large targets.

1. Introduction

Mergers and acquisitions are important events that create, destroy, and redistribute the wealth of target and acquirer shareholders. Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004) provide theoretical arguments that many stock acquisitions are motivated by the overvaluation of acquirer stocks relative to target stocks. Such acquisitions increase the wealth of long-term shareholders of acquirer firms and decrease the wealth of long-term shareholders of target firms who continue to hold the acquirer stock received as payment. Other researchers provide empirical evidence in support of this overvaluation hypothesis. For example, Loughran and Vijh (1997) and Rau and Vermaelen (1998) show that stock acquirers earn negative long-term excess returns on average. Savor and Lu (2009) provide further evidence by showing that while successful stock bidders earn negative long-term excess returns, they outperform otherwise similar but unsuccessful stock bidders.

The overvaluation hypothesis is important from a public policy perspective because of an underlying wealth redistribution or expropriation motive. While the existing literature provides empirical evidence in support of the overvaluation hypothesis from the acquirers' perspective, the unexplored question is whether one can identify a subset of potential target firms that are less vulnerable to this problem than others. In this paper we argue that small public firms belonging to the bottom NYSE size quartile are one such subset. In particular, we show that small firms are less vulnerable to overpriced stock offers that expropriate the wealth of their long-term shareholders than large firms.

☆ We are highly obliged to Sara Moeller, the referee, for several comments that substantially improved this paper. We also wish to thank Art Durnev, Jon Garfinkel, Wei Li, Amrita Nain, Raunaq Pungaliya, and seminar participants at Lehigh University, Renmin University, Shanghai Advanced Institute of Finance (SAIF), University of Iowa, and 2012 Financial Management Association meetings for useful comments. All errors are our own responsibility.

* Corresponding author.
E-mail address: anand-vijh@uiowa.edu (A.M. Vijh).

0304-405X/$ - see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.jfineco.2013.05.003

This key role of firm size in our vulnerability hypothesis is supported by many tests and it makes sense for two reasons. First, small targets offer only a small potential for diluting the stock overvaluation of large firms that make the majority of acquisitions in the U.S. economy. Thus, an overvalued large firm would have to acquire several small targets instead of one large target to achieve the same result. However, a sequence of stock acquisitions even of small targets would reveal its true intentions and correct its overvaluation. In addition, we conjecture that each acquisition incurs a certain fixed transaction cost component that depends on the acquirer size but does not depend on the target size (such as the cost of managers' time and a part of investment banker fees). This should further reduce the attraction of small target firms to large acquirer firms, especially if there are no obvious gains from merger other than diluting the overvaluation of acquirer stock.[1] Second, we argue that small firms make better decisions and resist overpriced stock offers that are not in the interests of their long-term shareholders.[2] While our results support both arguments, this paper does not delineate between them.

The flip side of lower vulnerability to overpriced stock offers is lower targetiveness of small firms. We define targetiveness as the probability rate that a firm under consideration will be successfully targeted (or acquired) during a one-year period. This prediction of our vulnerability hypothesis that small firms should have lower targetiveness driven by stock acquisitions contradicts a common belief that small firms are easier to acquire starting with Palepu (1986). To test this prediction, we carefully construct a comprehensive data set of all 5,990 acquisitions of U.S. public firms during 1981 to 2004, which supplements the standard sample of acquisitions reported by the Securities Data Company (SDC) with our manually collected sample. Using this data set we first show that there is an inverted-U relation between targetiveness and firm size. Specifically, the targetiveness value equals 3.77%, 4.34%, 3.94%, and 2.52% for firms belonging to the four NYSE size quartiles, from the smallest to the largest. This relation between targetiveness and firm size remains unchanged in multivariate regressions which include measures of opinion divergence besides other control variables.

We next examine 3,669 acquisitions for which both the target and acquirer are U.S. public firms and the payment method is known, which is necessary for testing other implications of our vulnerability hypothesis. We find that the targetiveness of small firms belonging to the bottom size quartile is in fact significantly lower than the targetiveness of all large(r) firms belonging to the upper three size quartiles. This definition of small versus large firms is the same as the definition used by Moeller, Schlingemann, and Stulz (2004) in comparing the performance of small versus large firms as acquirers.

In the following analysis we focus on a further subsample of 2,734 acquisitions for which the payment method is either all stock or all cash. Interestingly, we find that the lower targetiveness of small firms relative to large firms describes stock offers, but an opposite pattern describes cash offers. We next examine whether these contrasting patterns become more polarized during hot markets characterized by increased acquisition activity fueled by higher market-wide valuations. We divide our aggregate sample period into two subperiods: hot markets, spanning 1995–2000, and normal markets, spanning the remaining years, 1981–1994 and 2001–2004. In general, the targetiveness values increase sharply during hot markets relative to normal markets, and this increase is driven to a large extent by stock acquisitions. More interestingly, within the subset of stock acquisitions, the increase is significantly greater for large firms, by a factor of 3.91, than for small firms, by a factor of 3.03. In contrast, the targetiveness for cash acquisitions increases by a factor of 1.55 for large firms and 1.65 for small firms during hot markets relative to normal markets. To conclude this sequence of tests, we further show that the differences between market-to-book ratios of small firms and large firms, a measure of their relative valuation, become much greater during hot markets than during normal markets. In other words, when markets are hot, small target firms are even better buys per acquisition dollar than large target firms, yet the stock acquisition activity increases by a bigger factor in the latter case.

The combined evidence on targetiveness is consistent with our vulnerability hypothesis, which says that small targets are less attractive to overpriced stock acquirers due to their size differences or that small targets are more resistant to overpriced stock offers. We also examine whether this evidence can be explained by an alternate opinion divergence hypothesis proposed by Chatterjee, John, and Yan (2012). They show that there is greater opinion divergence about the value of small firms and that target firms with greater opinion divergence require higher acquisition premiums. This higher premium requirement can further reduce the appeal of small target firms to large acquirer firms that attempt to reduce their overvaluation by making stock acquisitions.

We examine four different measures of opinion divergence, which are analyst forecast dispersion, idiosyncratic volatility, change in breadth of mutual fund holdings, and ranked excess turnover around earnings releases. Using these measures we find some empirical support for the opinion divergence hypothesis in our targetiveness tests. However, this hypothesis does not explain our combined evidence for several reasons. First, the first three measures (fourth measure) suggest that opinion divergence increases (decreases) monotonically as firm size decreases,

[1] Hunter and Walker (1990) and McLaughlin (1992) find that investment banker fees contain a fixed component. As a counter-argument to the transaction costs argument, one can ask why small target firms are not acquired by overvalued small acquirer firms, of which there should be plenty. Empirically, we find that small firms make very few acquisitions, which can be due to lack of skills and resources.

[2] This argument is motivated by prior evidence that small firms make better decisions in other contexts. For example, Moeller, Schlingemann, and Stulz (2004) show that small firms earn higher returns as acquirers than large firms, McConnell and Nantell (1985) and Chan, Kensinger, Keown, and Martin (1997) show that small partners in joint ventures extract a higher percent return than large partners, and Berger, Miller, Petersen, Rajan, and Stein (2005) show that small banks are better able to collect and act on soft information than large banks to reduce their default risk.

which does not parallel the non-monotonic relation between targetiveness and firm size. Thus, the inverted-U relation remains significant after controlling for opinion divergence. Second, the opinion divergence hypothesis does not make predictions about the differential patterns in targetiveness across subsamples formed by payment method that we find. Third, we find split evidence on whether opinion divergence is higher or lower during hot markets relative to normal markets using different measures, which cannot explain why targetiveness more than doubles for both small and large firms during hot markets.

In the following sections we look at the valuation of acquirer firms before announcement, the choice of payment method, and acquirer announcement returns to provide more evidence on the vulnerability hypothesis. We start by testing the main prediction of our vulnerability hypothesis that small target firms accept stock offers from less overvalued acquirers. We employ two common proxies of acquirer overvaluation: prior-year excess returns and market-to-book ratios. The differences between prior valuations of the acquirers of small and large target firms are significantly negative within the subsample of stock acquisitions. For example, consider the stock acquirers belonging to the highest size quartile, which make the most acquisitions. If they happen to acquire small target firms, their prior-year excess returns average 15.8% and the log market-to-book ratios average 1.17. And if they happen to acquire large target firms, the corresponding figures are 46.9% and 1.40. In addition, the differences between the prior valuations of the acquirers of small and large targets are in the opposite direction if we look at cash acquisitions. Thus, the evidence suggests that, on average, small targets accept better-valued acquirers in stock acquisitions.

Further evidence on the role of acquirer overvaluation comes from multivariate analysis of the determinants of payment method. We report a logistic model test in which the dependent variable is the stock payment dummy. In addition to the known determinants of the payment method, we add two measures of firm-specific valuation (prior-year excess returns and industry-adjusted log market-to-book ratio) and one measure of market-wide valuation (the hot-market dummy). We then interact each of these valuation measures with the small target dummy to test the vulnerability hypothesis. Following Dittmar and Thakor (2007), we also include several variables to control for information asymmetry or disagreement between various parties to an acquisition (target volatility, hostile dummy, tender offer dummy, competing offer dummy, and market reactions to last earnings announcements of both target and acquirer firms). Finally, we add a variable to capture tax preferences of target shareholders (mutual fund ownership), and a variable to capture time-varying adverse selection (average volatility of all firms in the sample).

Consistent with the vulnerability hypothesis, we find that stock payment is significantly related to the overvaluation of acquirer stock, but that this relation is much weaker for small targets than for large targets. We also find that disagreement between various parties to an acquisition is negatively related to stock payment (or issuance), which provides an out-of-sample support to Dittmar and Thakor's hypothesis. In addition, we find that mutual fund ownership is negatively related to stock payment, perhaps because mutual funds are evaluated by their total returns and are less concerned about the tax implications of cash payment.

We next examine the acquirer announcement excess returns for additional evidence on the vulnerability hypothesis. If small targets are picked by (or they pick) less overvalued stock acquirers, then the negative market reaction to stock acquirers should be partially muted for acquisitions involving small targets. Univariate tests based on acquirer announcement returns provide preliminary support for this implied certification effect of small targets. To test this prediction in a multivariate setting, we start with a basic regression model of acquirer announcement returns and add the following variables. First, in separate regressions by payment method, we include the small target dummy to capture the predicted certification effect. Second, following Moeller, Schlingemann, and Stulz (2007), we include acquirer's opinion divergence and information asymmetry measures.

Using different models we estimate that in stock acquisitions the acquirer announcement return is about three percent higher for acquisitions involving a small target than for acquisitions involving a large target. That is about two percent higher than a similar effect in cash acquisitions. It shows that in stock payment deals the market perceives the acquirers of small targets to be less overvalued. Looking further, we find that this certification effect is also stronger when there is a greater need for certification. For example, the small target dummy in the acquirer announcement return regression has coefficients of 5.4% and 1.9% in subsamples formed by high and low volatility, and 13.7% and 1.9% in subsamples formed by negative and positive return on assets (ROA). In both cases the difference is statistically significant. Assuming that the certification need is greater when the acquirer stock is more volatile or the acquirer firm has negative ROA, this evidence provides strong support for the certification effect of small targets in particular and the vulnerability hypothesis in general.

Our primary results are thus consistent with the vulnerability hypothesis, which says that either overpriced stock acquirers find small targets to be unattractive or that the managers of small targets reject their offers. In the remainder of the paper we explore further explanations and present robustness tests before concluding that the combined evidence can only be explained by the vulnerability hypothesis. In particular, we explore the role of insider ownership of the target firm. On average, the chief executive officers (CEOs) of small firms own a 7.4% equity stake in their firms, compared to 4.5% for the CEOs of large firms. This implies that the CEOs of small firms exercise greater control over their firms, which should better enable them to reject overpriced stock offers. Further, consistent with Ambrose and Megginson (1992), we find that the CEO's ownership is not related to targetiveness in the sample of firm-years. We do find that the CEO's ownership is positively related to the likelihood of stock payment in the sample of successful acquisitions, possibly due to tax reasons. In view of this result in the broad sample of all small and large targets, our finding that small firms in particular are less likely to accept overpriced stock offers provides further support to the vulnerability hypothesis.

Our paper makes several contributions to the literature. First, contrary to a common belief, we show that the overall targetiveness does not increase monotonically with decreasing firm size. To the best of our knowledge, this is also the first paper to show that the relation between targetiveness and firm size depends on the payment method. Second, we show that small firms deliver better value to their long-term shareholders by picking the right stock acquirers. This evidence complements Moeller, Schlingemann, and Stulz (2004), who find that small public firms deliver better value for their shareholders as acquirers, and Alexandridis, Fuller, Terhaar, and Travlos (2013), who show that small public firms receive a higher acquisition premium as targets. A combined picture emerges from these studies that small public firms do well in many roles in the mergers and acquisitions process. Third, we illustrate a new certification effect whereby the market perceives less negative information about acquirer value in stock offers for small targets than in stock offers for large targets.

Section 2 discusses data and methods, and Section 3 examines the relation between targetiveness and firm size. Section 4 examines the prior valuation of acquirer stocks and the certification effect of small targets. Section 5 presents miscellaneous results and robustness tests, and Section 6 concludes.

2. Data and methods

2.1. Sample of firm-years and acquisitions

Many tests of the vulnerability hypothesis require us to measure targetiveness of different size firms. We do this measurement with comprehensive samples of firm-years and acquisitions. Our main sample includes all acquisitions announced during 1981–2004. The sample of firm-years includes all firms listed on the Center for Research in Security Prices (CRSP) database at the beginning of each year and having a share code of 10 or 11 (which excludes American Depository Receipts [ADRs], Real Estate Investment Trusts [REITs], units, certificates, and trusts). This gives a sample of 158,194 firm-years for which the market value of equity can be calculated as the number of shares outstanding multiplied by the stock price. Of this, 119,043 firm-years have the required information on Compustat to calculate the market value of assets as the market value of equity plus the book value of liabilities.

Table 1 describes the procedure followed to identify the subset of firm-years that are successfully targeted (or acquired). We first identify all acquisitions from the SDC database that satisfy the following criteria: (1) The acquisition is announced during 1981–2004. (2) The form of acquisition is coded as ‘Merger,’ ‘Acq. Maj. Int.,’ or ‘Acq. of Assets.’ (3) The acquirer holds less than 50% of target shares before acquisition and 100% after acquisition. (4) The target is a U.S. public firm and can be identified on CRSP. (5) The target share code is 10 or 11. (6) The completion date is between one and 1,000 days after the announcement date. (7) The target has nonmissing market value of equity. This procedure gives a sample of 5,710 firm-years that are successfully targeted.

Given our focus on small target firms, properly capturing the population of mergers and acquisitions is especially important to the targetiveness tests. Netter, Stegemoller, and Wintoki (2011) describe the potential biases due to some commonly used screens imposed on sampling mergers and acquisitions in the extant literature

Table 1

Procedure followed to identify a comprehensive sample of CRSP firms that were acquired following an acquisition announcement during 1981–2004.

The primary sample of acquired firms is retrieved from the SDC Mergers and Acquisitions file and the secondary sample is retrieved from the CRSP delisting file. The SDC sample is based on the acquisition announcement date and the CRSP sample is based on the firm delisting date. We therefore start with the SDC sample to cover the period 1981–2004 and the CRSP sample to cover 1981–2005.

Description	Frequency
Panel A: Primary sample of acquired firms retrieved from the SDC Mergers and Acquisitions file	
All acquisitions from the SDC database with announcement date between 1981 and 2004	124,137
Acquisition is completed	87,582
Form of acquisition is coded as ‘Merger,’ ‘Acq. Maj. Int.,’ or ‘Acq. of assets’[a]	64,557
Acquirer holds less than 50% of target shares before acquisition and 100% after acquisition	58,184
Target is a U.S. public firm and can be identified on CRSP	6,164
Target has CRSP share code 10 or 11[b]	5,932
Completion date is between one and 1,000 days after announcement date	5,793
Target has nonmissing market value of equity	5,710
Panel B: Secondary sample of acquired firms retrieved from the CRSP delisting file	
Number of firms delisted from CRSP which satisfy the following criteria: 1. Delisting date between 1981 and 2005, 2. Share code 10 or 11, 3. Delisting code between 200 and 299, 4. Last dividend distribution code 32, 37, or 38	6,281
Number of CRSP delisted firms not included in the SDC database	605
Number of CRSP delisted firms satisfying our other criteria upon verification of Factiva and Lexis/Nexis news reports	280
Panel C: Final sample	
Total sample of acquired firms for which firm size can be measured as the market value of equity from CRSP	5,990
Total sample of acquired firms for which firm size can be measured as the market value of assets from CRSP and Compustat	4,896

[a] This excludes the following forms of acquisition: ‘Acq. Cert. Asts.’ (1,016 cases), ‘Acq. Part. Int.’ (14,910 cases), ‘Acq. Rem. Int.’ (2,115 cases), ‘Acquisition’ (66 cases), ‘Buyback’ (4,705 cases), ‘Exchange Offer’ (160 cases), ‘Recapitalization’ (53 cases). According to SDC, ‘Acquisition’ applies to spinoffs and splitoffs.

[b] This excludes ADRs, REITs, units, certificates, and trusts.

which generally oversamples large deals. Thus, to be thorough, we supplement the sample extracted from SDC with all merger-related delistings from CRSP (identified with a delisting code between 200 and 299 and last dividend distribution code of 32, 37, or 38). Table 1 shows that 605 firms with these delisting and distribution codes are not identified as targets in the SDC data set. We hand-check all of these cases using Factiva and Lexis/Nexis reports to ascertain cases in which the delisting event is an acquisition satisfying our sampling criteria. This procedure identifies an additional 280 firm-years that are targeted. Overall, our exhaustive sampling procedure shows that 5,990 cases out of the CRSP sample of 158,194 firm-years and 4,896 cases out of the CRSP plus Compustat sample of 119,043 firm-years are successfully targeted during 1981–2004. We assume that a firm is targeted during the year when the acquisition is announced.

The top panel of Fig. 1 shows the sample distribution over time. This pattern corresponds well with the patterns reported in Holmstrom and Kaplan (2001), Andrade, Mitchell, and Stafford (2001), and Moeller, Schlingemann, and Stulz (2004, 2005). Notice there is a sharp increase in merger activity during the late 1990s. The bottom panel of Fig. 1 shows that there is a simultaneous increase in percent of all acquisitions that are paid entirely with acquirer stock. Following Faccio and Masulis (2005), we define cash deals as those financed with cash, liabilities, and newly issued notes, stock deals as those financed with acquirer stock that has full voting rights or inferior voting rights, and mixed deals as those financed by both. We include mixed deals in the initial tests of targetiveness but exclude them from other tests for clarity of tests and exposition.

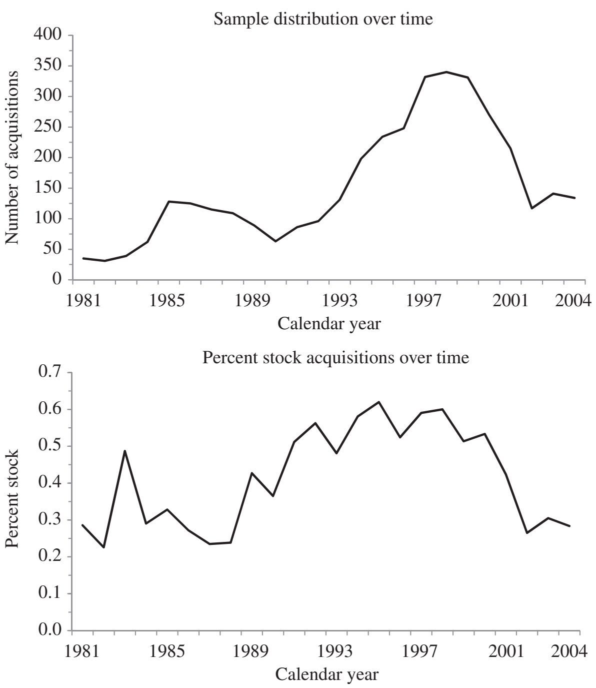

Fig. 1. Sample distribution and percent stock acquisitions over time. The sample of all acquisitions during 1981–2004 is described in Table 1. We define cash deals as those financed with cash, liabilities, and newly issued notes, stock deals as those financed with acquirer stock that has full voting rights or inferior voting rights, and mixed deals as those financed by both.

2.2. *Percentile rank as the measure of firm size*

Given our focus on the relation between firm size, targetiveness, and acquirer returns, the choice of a firm size measure becomes important. We measure the size of any given firm at any given point in time in relation to other firms at the same point in time. We follow the Fama-French procedure and rank all NYSE-listed firms by their market value of equity (alternately, market value of assets) at the beginning of each year. From this we determine the cutoff values at intervals of one-percentile. We assign a percentile rank to all firm-years using these cutoff values. This percentile rank is our basic size measure. We define the coarser firm size quartiles using the percentile ranks. Finally, following Moeller, Schlingemann, and Stulz (2004), we classify firms belonging to the bottom quartile as small firms and firms belonging to the other three quartiles as large firms.[3]

In the beginning of the sample period in 1981, the first, second, and third quartiles of market value of equity are \$76 million, \$231 million, and \$719 million (in nominal terms). By 2004, the corresponding values are \$721 million, \$1,741 million, and \$4,829 million. This shows two things. First, the small firms in our sample are quite substantial in terms of market value of equity (or assets). Second, the third quartile cutoff during 1981 is comparable in market value to the first quartile cutoff during 2004, so ranking within the year is necessary. However, for robustness we also try simple inflation-adjusted market values over the aggregate time period in our primary targetiveness tests.

2.3. *Identification of hot markets versus normal markets*

We identify the period 1995–2000 as a hot market and the remaining periods of 1981–1994 and 2001–2004 as a normal market for mergers and acquisitions due to several reasons. First, Fig. 1 shows that both the number of acquisitions and the percent stock acquisitions rose sharply around our hot-market period as also suggested by Shleifer and Vishny (2003). Second, to identify the first and last years of the hot market, we observe that the value-weighted market return (VWRETD) equals −0.8%, 35.7%, 21.2%, 30.3%, 22.3%, 25.2%, −11.1%, and −11.3% during each year from 1994 to 2001. Thus, we infer that the hot market started in 1995 with strong market returns. Further, a

[3] A question arises whether one should further measure firm size relative to same-industry firms. This would be inconsistent with our vulnerability hypothesis. Shleifer and Vishny (2003) propose that overvalued acquirers will make cross-industry acquisitions where better opportunities are more likely to exist. Note that in the often-cited example of the overvaluation-driven acquisition of Time Warner by America OnLine, the target and acquirer were in different industries. This is true regardless of whether one uses industry classification based on two-digit standard industry classification (SIC) code or Fama-French 48-industry, 12-industry, or 5-industry codes.

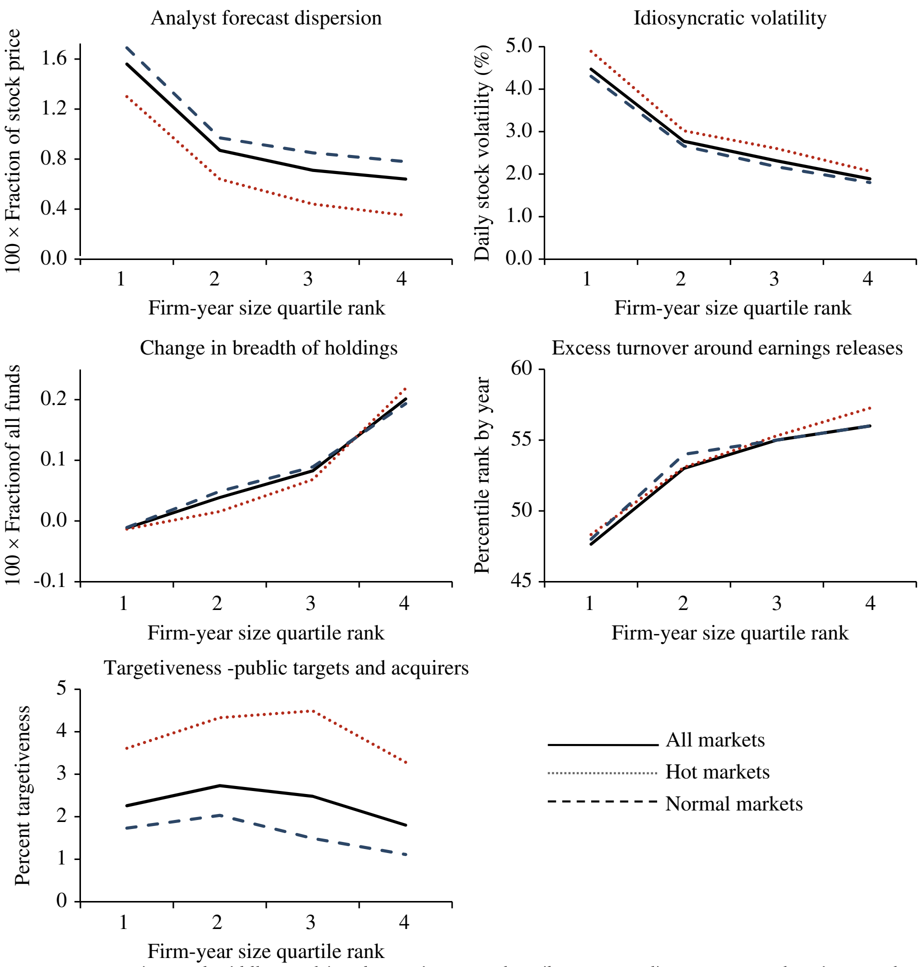

Fig. 2. Opinion divergence measures (top and middle panels) and targetiveness values (bottom panel) across comprehensive samples of firm-years sorted into NYSE size quartiles based on the market value of equity. The calculation of opinion divergence measures is described in Appendix A. Analyst forecast dispersion, idiosyncratic volatility, and ranked excess turnover around earnings releases are direct measures of opinion divergence, while change in breadth of holdings is an inverse measure. The samples for calculation of opinion divergence measures and targetiveness include all firm-years during 1981–2004 for which the relevant data are available. Targetiveness is defined as the percent probability of being successfully targeted (or acquired) by a U. S. public firm in a one-year period as defined in Tables 4 and 5.

number of stock indexes peaked in March 2000 and declined during the rest of 2000. The Standard and Poor's (S&P) 500 index declined 20% from its peak by the first quarter of 2001, which many investors regard as the beginning of a bear market. Thus, we infer that the hot market ended in 2000. Third, in support of our identification, we estimate that the S&P 500 index had an average price-to-earnings (P/E) ratio of 24.34 during 1995–2000, which was much higher than the corresponding ratio of 15.97 during 1981–1994 and 2001–2004.[4]

2.4. *Measures of opinion divergence*

Given the documented importance of opinion divergence in determining several aspects of mergers and acquisitions and stock issuance (Dittmar and Thakor, 2007; Moeller, Schlingemann, and Stulz, 2007; Chatterjee, John, and Yan, 2012), we construct four different measures as stated below. Appendix A reports the motivation and the calculation of these measures.

The top panels of Fig. 2 show the average values of the four measures across firm-year size quartiles (formed by the market value of equity). Recall that analyst forecast dispersion, idiosyncratic volatility, and ranked excess turnover around earnings releases are direct measures of opinion divergence and change in breadth of mutual fund holdings is an inverse measure. Taking this into consideration, three out of four measures suggest that opinion divergence decreases monotonically with increasing firm size while the fourth measure (ranked excess turnover) suggests an opposite pattern.

Fig. 2 also shows how the measures change from normal markets to hot markets across size quartiles. Averaged over the entire sample, analyst forecast dispersion decreases from 1.39% in normal markets to 1.01% in

[4] It is generally known that the stock overvaluations increased more sharply for technology stocks relative to other stocks during the hot-market period. An estimated 18% of the targets during normal markets and 20% during hot markets belong to the technology sector.

hot markets (exact numbers not shown in the figure). In comparison, idiosyncratic volatility increases from 3.69% to 4.16%, change in breadth of holdings decreases from 0.040% to 0.027%, and ranked excess turnover around earnings releases remains unchanged (since it is calculated by ranking within the year). This provides split evidence on whether opinion divergence increases or decreases from normal markets to hot markets. In particular, the evidence based on analyst forecast dispersion is counter-intuitive as it suggests that opinion divergence decreases during hot markets. While it may result from greater herding behavior on the part of analysts driven by their career concerns (Chevalier and Ellison, 1999; Hong, Kubik, and Solomon, 2000), it is not clear why analysts are more likely to herd during hot markets. Note that changes from normal markets to hot markets are usually in the same direction for all four size quartiles. Finally, for comparison, the lower panel of Fig. 2 shows the targetiveness values across size quartiles as defined below.

3. Firm size, payment method, and targetiveness

3.1. The vulnerability hypothesis

Song and Walkling (2000) argue that a firm's value comes from two sources: Its standalone value and its value to potential acquirers. These two values are joined through the firm's targetiveness, which is defined as the probability rate that the firm will be acquired over a one-year period. Thus, considerable finance research has been focused on understanding the cross-sectional determinants of targetiveness to get a better insight into the firm value. More recently, Cremers, Nair, and John (2009) show that there is a targetiveness factor in stock returns, which further emphasizes the importance of this issue.

While targetiveness in all payment forms is good for the short-term shareholders of target firms who cash out for a substantial acquisition premium, the same is not necessarily true for the long-term shareholders. An extensive literature cited in the introduction argues that many stock acquisitions are motivated by overvaluation reasons, in other words, an acquirer firm attempting to cash in on its stock overvaluation by merging with a relatively undervalued or even less overvalued target firm. The net effect of targetiveness on firm value is therefore ambiguous to some extent.

In most acquisitions the acquirer firm is substantially larger than the target firm. It is rare when a small firm can come up with the credibility and the resources to acquire a large firm using any payment method. Thus, on account of this factor, targetiveness decreases monotonically with firm size. However, the vulnerability hypothesis says that small firms make less attractive targets for overpriced large acquirer firms in stock acquisitions for two reasons. First, the potential acquirers may find that small targets do not offer a significant wealth expropriation potential. Second, we have argued that small firms are known to make better decisions in other contexts and are less likely to accept potentially overpriced stock offers. The combination of these influences predicts an inverted-U relation between targetiveness and firm size for stock offers. Further, since stock (and mixed) offers account for a large proportion of all offers, we predict a similar but less pronounced inverted-U relation between targetiveness in all payment forms, which for simplicity we also refer to as targetiveness without specifying a payment method, and firm size. For cash offers, however, we predict a more monotonic relation.

The relation between targetiveness in all payment forms and firm size has been the only topic of previous research, and arguably, this is all that matters to target shareholders who cash out after the acquisition. Appendix B lists 11 studies on this topic that were published during 1986–2009. Starting with Palepu (1986), all of these studies include a firm size variable to explain the cross-sectional differences in targetiveness. Two studies each find a significantly negative, significantly positive, or insignificant coefficient. In three studies the coefficient is both significantly negative and insignificant in different tests, and in one study it is both significantly negative and significantly positive in different tests. We conjecture that the mixed sign and significance of the coefficients of the size variable in these studies are explained by differences in their samples, which are often not comprehensive, and differences in their size variables, which can be the book value of assets, the market value of equity, or a log transform of either variable. More importantly, none of these previous studies analyzes a non-monotonic relation between targetiveness and firm size or the role of payment method. Thus, an important contribution of our study is to provide the first empirical analysis of both these issues.

3.2. The inverted-U relation between targetiveness and firm size

We investigate the relation between targetiveness and firm size starting with univariate tests. We sort the aggregate sample of firm-years by percentile size rank. As expected, there are an increasing number of firm-years with lower percentile size ranks. For each size tranche (i.e., aggregation of firm-years in a certain range of percentile size ranks), we calculate the targetiveness value as the number of targets divided by the number of firm-years. This measure follows from our definition of targetiveness, which is the probability that a firm will be acquired over a one-year period. We start with the aggregate sample of targets, which includes all cases in which the target is a U.S. public firm, but the acquirer can be public or private, foreign or domestic. This aggregate sample combines all payment methods.

The first set of columns in Panel A of Table 2 uses market value of equity as a size measure and shows that averaged over the entire sample, the targetiveness equals 3.79%. In the first size quartile the targetiveness equals 3.77%, and in the second, third, and fourth quartiles it equals 4.34%, 3.94%, and 2.52%. The second set of columns uses market value of assets as a size measure and shows that the targetiveness equals 4.05%, 4.89%, 4.24%, and 3.14% in the four size quartiles. There is a clear non-monotonic relation between targetiveness and firm size in either case.

Panel B of Table 2 shows univariate regressions of targetiveness value on percentile size rank using a

Table 2
Univariate analysis of targetiveness by firm size.

We define targetiveness as the probability of a firm getting successfully targeted (or acquired) within a year. Thus, for any given size tranche, we calculate a targetiveness frequency as the number of firm-years that are successfully targeted divided by the total number of firm-years. In this table the acquirers can be public or private, and foreign or domestic. Models (2.1.A) in Panel A and (2.1.B) in Panel B use the market value of equity as a size measure, and Models (2.2.A) in Panel A and (2.2.B) in Panel B use the market value of assets as a size measure. The market value of assets is calculated as the market value of equity plus the book value of liabilities. Thus, the dataset includes all firm-years during 1981 to 2004 listed in the CRSP database for (2.1.A) and (2.1.B), and both the CRSP and Compustat databases for (2.2.A) and (2.2.B). We further require that the included firm-years have a CRSP share code of 10 or 11 (which excludes ADRs, REITs, units, certificates, and trusts). Both the market value of equity and the market value of assets are calculated as of the beginning of the year. Table 1 describes the procedure for identification of 5,990 firm-years that were targeted in the sample using market value of equity as the size measure and 4,896 firm-years that were targeted in the sample using market value of assets as the size measure. Panel A reports targetiveness values by percentile size tranches arranged into quartiles. Panel B reports univariate regressions of targetiveness in which the dependent variable is the targetiveness frequency for each one-percentile size tranche and the independent variables are the percentile rank and its squared value. The inflexion point equals the negative of the coefficient of the linear term divided by two times the coefficient of the quadratic term. The *t*-statistics are reported in parentheses, and are based on White's heteroskedasticity-consistent standard errors. The notations [a,b,] and [c] denote significance at the 10%, 5%, and 1% levels.

Percentile size tranches	Market value of **equity** based size ranking (2.1.A)			Market value of **assets** based size ranking (2.2.A)		
	Number of firm-years	Number targeted	Targetiveness frequency (%)	Number of firm-years	Number targeted	Targetiveness frequency (%)
Panel A: Targetiveness by firm size arranged into one-percentile size tranches						
1–25	110,259	4,158	3.77	74,815	3,027	4.05
26–50	23,351	1,014	4.34	18,883	924	4.89
51–75	14,045	553	3.94	13,639	578	4.24
76–100	10,539	265	2.52	11,706	367	3.14
All	158,194	5,990	3.79	119,043	4,896	4.11

Panel B: Quadratic regression model fitted to one-percentile size tranches, Dependent variable is targetiveness frequency (%)

	Market value of **equity** based size ranking (2.1.B)	Market value of **assets** based size ranking (2.2.B)
Intercept	3.48^{c}	4.36^{c}
	(17.32)	(20.23)
Percentile rank of market value of **equity** $\times 10^{-2}$	2.92^{c}	
	(3.06)	
Square of percentile rank of market value of **equity** $\times 10^{-4}$	-5.08^{c}	
	(−5.47)	
Percentile rank of market value of **assets** $\times 10^{-2}$		3.54^{c}
		(3.26)
Square of percentile rank of market value of **assets** $\times 10^{-4}$		-5.64^{c}
		(−5.17)
Number of observations	100	100
Adjusted-R^2	0.545	0.449
Inflexion point	29	31

quadratic functional form. Regression (2.1.B) uses market value of equity as the size measure and Regression (2.2.B) uses the market value of assets. The adjusted-R^2 values are 0.545 and 0.449, showing a good model fit. In both regressions the coefficient of percentile rank is significantly positive and the coefficient of its squared term is significantly negative. The inflexion point of the curve lies around 29 percentile in the first case and 31 percentile in the second case. Overall, the univariate evidence of Table 2 provides strong support for an inverted-U relation between targetiveness and firm size.

3.3. Multivariate tests of targetiveness

We now report multivariate tests of targetiveness with the same percentile size rank variables, but using a different methodology that is commonly employed in the previous literature. We start with the aggregate samples of firm-years from Table 2 and test a logistic model in which the dependent variable is a targetiveness dummy. This dummy takes the value one if the firm is targeted during the year, and zero otherwise. The key independent variables of interest are the percentile size rank and its square value. The control variables are described as follows.

First, Chatterjee, John, and Yan (2012) propose a theory model in which increasing opinion divergence about a firm's value increases the expected premium to acquire that firm. In turn, the higher premium requirement decreases the targetiveness of the firm. They show empirical evidence in support of this opinion divergence hypothesis, so we include opinion divergence measures in our tests. Second, following Palepu (1986), we include: (1) Book-to-market, because undervalued firms are more attractive targets, (2) Cash flow, because cash-rich firms are more attractive targets, (3)

Table 3
Multivariate logistic analysis of targetiveness.

Our dataset starts with all firm-years included in the CRSP and Compustat databases during 1981–2004. We require that the included firms have a share code of 10 or 11 and the data on independent variables be available. The targeted firm-years are described in Table 1. Our dependent variable is the targetiveness dummy which takes the value of one if a firm-year is successfully targeted (or acquired), and zero otherwise. In this table the acquirers can be public or private, and foreign or domestic. Firm size percentile ranks are assigned using cutoffs based on the distribution of market values of equity of all NYSE-listed firms at the beginning of a year. In all regressions we test a quadratic form of the percentile size measure. We include four opinion divergence measures: Analyst forecast dispersion, idiosyncratic volatility, change in breadth of (mutual fund) holdings, and ranked excess turnover around earnings releases. The calculation of these variables is described in Appendix A. Change in breadth of holdings is an inverse measure of opinion divergence, the rest are direct measures. Book-to-market equals the ratio of book value divided by the market value of equity, cash flow equals the sum of earnings before extraordinary items and depreciation normalized by the market value of assets, and leverage equals the book value of long-term debt divided by the market value of assets. We measure the industry acquisition activity with the combined deal value of all acquisitions reported by the SDC for the corresponding year and the two-digit SIC code of target firm, divided by the combined book value of assets of all Compustat firms for the same year and the same two-digit SIC code. The prior-year excess return is computed as the difference between the cumulative return for the firm and the CRSP value-weighted market index during the last fiscal year ending before the acquisition. The growth-resource mismatch dummy takes the value of one if the firm has above industry average growth and below industry average cash flow, or vice versa. The *t*-statistics are reported in parentheses, and are based on White's heteroskedasticity-consistent standard errors. We omit *t*-statistics for control variables that are not of primary interest to the vulnerability hypothesis. The notations [a,b,] and [c] denote significance at the 10%, 5%, and 1% levels.

Dependent variable: Targetiveness dummy					
Variables	(3.1)	(3.2)	(3.3)	(3.4)	(3.5)
Percentile rank of market value of **equity** $\times 10^{-2}$	1.62[c]	1.29[c]	1.17[c]	0.60[b]	1.21[c]
	(8.05)	(6.19)	(5.54)	(2.53)	(5.73)
Square of percentile rank of market value of **equity** $\times 10^{-4}$	−2.55[c]	−2.25[c]	−2.20[c]	−1.58[c]	−2.02[c]
	(−10.04)	(−8.72)	(−8.54)	(−5.61)	(−7.66)
Analyst forecast dispersion		−2.40[c]			
		(−2.66)			
Idiosyncratic volatility			−5.01[c]		
			(−6.29)		
Change in breadth of holdings				−10.24[b]	
				(−2.00)	
Ranked excess turnover around earnings releases $\times 10^{-3}$					−0.46
					(−0.84)
Intercept	−3.25[c]	−3.16[c]	−3.04[c]	−3.11[c]	−3.17[c]
Book-to-market $\times 10^{-3}$	−0.20	−0.31	−0.22	−0.22	−0.24
Cash flow	0.28[c]	0.11[a]	0.16[c]	0.00	0.12[b]
Industry acquisition activity	1.49[c]	1.54[c]	1.73[c]	1.83[c]	1.61[c]
Prior-year excess return	−0.06[c]	−0.06[c]	−0.05[b]	−0.05[b]	−0.06[c]
Growth-resource mismatch dummy	0.05	0.05	0.06[a]	0.03	0.06[a]
Leverage	0.19[b]	0.17[a]	0.18[b]	0.04	0.12
Year dummies	Yes	Yes	Yes	Yes	Yes
N	112,264	100,598	111,840	72,715	91,710
N with dependent variable = 1	4,682	4,393	4,678	3,495	4,290
Pseudo-R^2	0.033	0.033	0.034	0.031	0.028

Industry acquisition activity, because industry shocks lead to merger waves, (4) Prior-year return, because inefficient managements are more likely targets, (5) Growth-resource mismatch dummy, because low-growth resource-rich firms and high-growth resource-poor firms are more likely targets, (6) Leverage, because it increases the potential for expropriation of wealth from bondholders, (7) Year dummies, because the aggregate acquisition activity varies over time. Table 3 defines these additional variables and presents the results.

All regressions of Table 3 use the market value of equity as a size measure. Regression (3.1) includes all control variables other than opinion divergence and shows that the percentile size rank has a positive coefficient and its square term has a negative coefficient, both highly significant. This result supports the inverted-U pattern between targetiveness and firm size. The pattern remains unchanged with the addition of opinion divergence measures in Regressions (3.2) to (3.5). Among the opinion divergence measures, two are significant in the predicted direction (analyst forecast dispersion and idiosyncratic volatility), one is insignificant (ranked excess turnover around earnings releases), and one is significant in the opposite direction (change in breadth of mutual fund holdings). Notice there are considerable differences between the samples of firm-years and acquisitions in Chatterjee, John, and Yan and this study and some necessary differences in the computation of opinion divergence measures as well (see Appendix A). In addition, the limited availability of some of the opinion divergence measures such as change in breadth of mutual fund holdings and ranked excess turnover around earnings releases lead to reduced sample sizes, especially at the lower end of the percentile size ranks. This affects the coefficients of both size and opinion divergence variables. Regression (3.3) includes idiosyncratic volatility, which is the most available measure of opinion divergence, and this regression shows strong

Table 4
Targetiveness by firm size and payment method in the sample of public targets and acquirers.

The sample analyzed in this table starts with the sample described in Tables 1 and 2 during 1981–2004, but further imposes the restriction that the acquirer is a U.S. public firm for which the relevant data on payment terms are available from the SDC, CRSP, or hard-copy sources. This restriction reduces the sample to 3,669 acquisitions. Following Faccio and Masulis (2005), we define cash deals as those financed with cash, liabilities, and newly issued notes, and stock deals as those financed with acquirer stock that has full voting rights or inferior voting rights. Mixed deals that are financed with both cash and stock are excluded. This exclusion leaves us with 2,734 pure stock or pure cash acquisitions that are analyzed in the remaining paper. The sorting of firm-years into NYSE size quartile ranks is described in Table 2. The firm size for this purpose is measured by the market value of equity. For each size quartile, we calculate the targetiveness frequency as the number of firm-years that are successfully targeted divided by the total number of firm-years. We test whether the difference between targetiveness values of small and large firms is significantly different from zero using a chi-square test and report the *p*-value in parentheses. The notations [a,b,] and [c] denote significance at the 10%, 5%, and 1% levels.

Firm size (market value of equity) quartile	N	**Stock** payment		**Cash** payment	
		Number targeted	Targetiveness frequency (%)	Number targeted	Targetiveness frequency (%)
Small	110,259	1,145	1.04	772	0.70
2	23,351	304	1.30	156	0.67
3	14,045	161	1.15	75	0.53
4	10,539	102	0.97	19	0.18
Large (2+3+4)	47,935	567	1.18	250	0.52
Difference (small-large) (p-value)			−0.14[b] (0.011)		0.18[c] (0.000)
All sizes	158,194	1,712	1.08	1,022	0.65

support for both the vulnerability and the opinion divergence hypotheses.

In untabulated tests we carry out many robustness tests of Table 3 results. First, we use the market value of assets as a size measure and find similar but somewhat stronger evidence in support of the vulnerability hypothesis. Second, we use the log of inflation-adjusted market value of equity as another size measure, and find similarly strong results. Third, since firm size and book-to-market are correlated, we verify that our results are virtually unchanged by the exclusion of book-to-market as a control variable. Fourth, we examine the correlations between opinion divergence measures and the remaining control variables. None of the correlations is too large, and the exclusion of any one control variable makes little difference to the regression results. Fifth, we use the same control variables as employed by Chatterjee, John, and Yan (2012) and find similar results. Overall, we find reasonable support for the opinion divergence hypothesis and strong support for the vulnerability hypothesis.

3.4. The role of payment method

The choice of payment method is an important consideration in mergers and acquisitions. For example, stock payment is an essential feature of overvaluation-driven acquisitions. An alternative would be a seasoned equity offering followed by a cash acquisition. However, that would likely incur higher transactions costs and delays in addition to a similar negative market reaction. Further, from the target shareholders' perspective, stock payment avoids capital-gains taxes. Boone, Lie, and Liu (2011) find that in mixed payment acquisitions for which target shareholders have a choice, they prefer stock payment even when the alternative cash payment is higher. Thus, an extensive mergers and acquisitions literature treats payment method as an important decision variable despite some possibility of a homemade alternative (i.e., target shareholders using cash payment to buy acquirer stock, or vice versa). Still, we are not aware of any previous studies of targetiveness that analyze the role of payment method.[5]

In the present context, Table 3 results contradict the popular notion of a monotonically decreasing relation between targetiveness and firm size by using a sample that includes all payment methods and acquirer types. However, our vulnerability hypothesis predicts this result mainly for stock acquisitions by public acquirers whose stock becomes overpriced from time to time. In the following tests we therefore start with the subset of 3,669 acquisitions by public acquirers, which can be categorized by the payment method. (This excludes only 12 cases for which the payment method could not be verified.) We measure firm size by the market value of equity for which the data are always available. Thus, the sample includes the 158,194 firm-years from Table 2. In untabulated results we again find that there is an inverted-U relation between targetiveness in all payment forms and firm size, captured by targetiveness values of 2.26%, 2.72%, 2.48%, and 1.81% for the four size quartiles from smallest to largest. However, the current focus is on whether this pattern differs across stock and cash payment. Since mixed payment can lie anywhere between stock and cash

[5] Before 2001, the acquirers could also use the pooling method of accounting with stock payment under which the target's assets and liabilities were transferred to the acquirer at their existing book value. Lys and Vincent (1995) find that AT&T paid a documented $50 million and possibly as much as $500 million to satisfy pooling accounting in its acquisition of NCR in 1991. This choice boosted earnings per share by 17% but left cash flows unchanged.

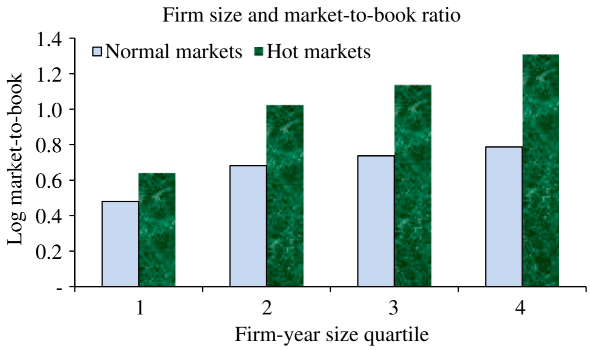

Fig. 3. The spread between log market-to-book ratios across firm size quartiles during normal markets and hot markets. The sample includes all firm-years during 1981–2004 as described in Table 2. We further require that the necessary data to calculate the market-to-book ratio are available from Compustat and CRSP. This ratio is calculated as the market value of equity divided by the book value as of the last fiscal year-end before acquisition announcement. It is log-transformed to adjust for skewness. This figure reports the average log market-to-book ratio during the concerned period for all firm-years included in a given size quartile. These size quartiles are based on the distribution of the market value of equity of all NYSE-listed firms at the beginning of the year. Years 1995–2000 are classified as hot markets, while years 1981–1994 and 2001–2004 are classified as normal markets.

payment, we exclude the 935 mixed payment cases from all subsequent analyses and focus on the remaining 1,712 stock and 1,022 cash payment cases.

Table 4 shows the targetiveness values across size quartiles separately for the subsamples of stock and cash payment. We find an inverted-U pattern in targetiveness with firm size for stock payment (targetiveness values of 1.04%, 1.30%, 1.15%, and 0.97% for the four size quartiles) but a monotonic pattern for cash payment (targetiveness values of 0.70%, 0.67%, 0.53%, and 0.18%). We further aggregate the firms belonging to the second, third, and fourth size quartiles as simply large firms and find that their targetiveness value equals 1.18% for stock payment and 0.52% for cash payment. The difference between the targetiveness values of small and large firms equals −0.14% for stock payment and is significantly different from zero with a p-value of 0.011 (using a chi-square test). In contrast, the difference between the targetiveness values of small and large firms for cash payment equals 0.18%, with a p-value of 0.000. The combined evidence supports our vulnerability hypothesis, which predicts lower targetiveness of small firms for stock payment but not for cash payment.

3.5. *Targetiveness values during hot markets versus normal markets*

Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004) argue that market-wide but unequal overvaluation of stocks causes an increase in merger activity. This increase is greater for stock acquisitions than for cash acquisitions. Bouwman, Fuller, and Nain (2009) further show that hot-market mergers lead to poor long-term returns. Our vulnerability hypothesis predicts that the targetiveness of small firms increases by less than the targetiveness of large firms during hot markets with higher valuations. We now test this prediction.

3.5.1. *Do small firms become relatively more or less attractive targets during hot markets?*

We compare the firm valuations across NYSE size quartiles during normal markets and hot markets. These valuations determine the expropriation potential in stock mergers. We use the log-transformed market-to-book ratio as the valuation measure. Fig. 3 shows that during normal markets the log market-to-book ratio had average values of 0.48, 0.68, 0.74, and 0.79 for firms belonging to the four size quartiles arranged in ascending order. The corresponding values during hot markets equal 0.64, 1.02, 1.14, and 1.31. Thus, the difference between log market-to-book ratios of firms belonging to the top and bottom quartiles equals 0.31 during normal markets and 0.67 during hot markets. Alternately, the market-to-book ratio of the bottom-quartile firms increases roughly by a factor of $\exp(0.64-0.48)=1.17$ for small firms and $\exp(1.31-0.79)=1.68$ for large firms in the top quartile (also 1.40 in the second quartile and 1.49 in the third quartile). The difference is statistically significant at the 1% level. We infer that per acquisition dollar, small firms are even better buys during hot markets than during normal markets. But does it mean that small firms are more likely to be targeted with stock offers during hot markets, by small or large acquirers? Below we show that the evidence is in the opposite direction.

3.5.2. *Targetiveness values*

Table 5 shows the targetiveness values during normal markets and hot markets for small and large firms. Including both sizes, there are an estimated 111,796 firm-years during the 18 years of normal markets and 46,398 firm-years during the six years of hot markets. Yet, there are 723 stock acquisitions during normal markets and 989 stock acquisitions during hot markets. This represents an increase in targetiveness using stock payment by a factor of 3.29 during hot markets relative to normal markets. Thus, there was a sharp increase in market valuation-driven stock acquisition activity during the hot markets of 1995–2000 as pointed out by Shleifer and Vishny (2003).

If we compare small firms and large firms, their targetiveness values in stock acquisitions equal 0.66% and 0.62% during normal markets and 2.00% and 2.41% during hot markets. While during both markets there is an inverted-U pattern across the four size quartiles as described in Table 5, the difference between targetiveness for small firms and large firms (which combine the upper three size quartiles) is an insignificant 0.04% during normal markets and a significant −0.41% during hot markets. Alternately, the targetiveness value increases by a ratio of $2.00/0.66=3.03$ for small firms and $2.41/0.62=3.91$ for large firms. We test the equality of these ratios by using a simulation procedure described in Table 5, which rejects their equality with a significance level of less than 1%.

Not unexpectedly, Table 5 also shows that during hot markets the cash acquisition activity does not increase as much as the stock acquisition activity. If we again compare small firms and large firms, their targetiveness values in cash acquisitions equal 0.59% and 0.44% during normal markets and 0.97% and 0.69% during hot markets. In both markets there is a monotonic pattern across the four size quartiles. The ratio of targetiveness values during hot markets and normal

Table 5
Are small firms less vulnerable to overpriced stock offers during hot markets?.

The sample analyzed in this table includes the acquisitions of U.S. public targets by U.S. public acquirers during 1981–2004 as described in Table 4. This table examines targetiveness across normal markets and hot markets. We define hot markets as the six-year period from 1995–2000 during which an estimated 48% of all acquisitions made by U.S. public firms over the 24-year period from 1981–2004 were announced. We define the remaining years as normal years. We define cash deals as those financed with cash, liabilities, and newly issued notes, and stock deals as those financed with acquirer stock that has full voting rights or inferior voting rights. Mixed deals that are financed with both cash and stock are excluded. We measure firm size by the market value of equity. Small firms are those with market value of equity in the bottom NYSE size quartile, and large firms are those in the upper three quartiles. For each size category, we calculate the targetiveness frequency as the number of firm-years that are successfully targeted divided by the total number of firm-years. The notations ^{a,b,} and ^{c} denote significance at the 10%, 5%, and 1% levels.

Payment method	Firm size	Normal markets 1981–1994 and 2001–2004			Hot markets 1995–2000			Ratio of targetiveness values during hot markets and normal markets	P-value to test whether ratio for large targets is greater than for small targets[‡]
		Number of firm-years	Number targeted	Target-iveness (%)	Number of firm-years	Number targeted	Targetiveness (%)		
Stock	Small (quartile 1)	78,942	520	0.66[!]	31,317	625	2.00	3.03	0.000^{c}
	Large (quartiles 2+3+4)	32,854	203	0.62	15,081	364	2.41	3.91	
	Difference (small-large)			0.04			-0.41^{c}		
	(*p*-value)[†]			(0.438)			(0.004)		
Cash	Small (quartile 1)	78,942	467	0.59	31,317	305	0.97	1.65	0.696
	Large (quartiles 2+3+4)	32,854	146	0.44	15,081	104	0.69	1.55	
	Difference (small-large)			0.15^{c}			0.28^{c}		
	(*p*-value)[†]			(0.002)			(0.002)		

[†] We calculate the statistical significance levels in these rows by using a chi-square test.

[!] In both normal markets and hot markets we find an inverted-U pattern in targetiveness for stock offers, with targetiveness values of 0.66%, 0.76%, 0.50%, and 0.45% for quartiles 1 to 4 in the former case and 2.00%, 2.53%, 2.47%, and 2.09% in the latter case. In contrast, in both markets we find a monotonic pattern in targetiveness for cash offers, with targetiveness values of 0.59%, 0.58%, 0.43%, and 0.14% in normal markets and 0.97%, 0.86%, 0.74%, and 0.27% in hot markets.

[‡] We calculate *p*-values in this column using a simulation procedure which is explained as follows. Consider the stock payment cases. For all firm sizes, the targetiveness equals (520+203)/(78,942+32,854)= 0.65% during normal markets and (625+364)/(31,317+15,081)=2.13% during hot markets. Thus, for all firm sizes, the targetiveness increases by a factor of 2.13/0.65=3.28. We test the null hypothesis that the increase is by the same factor of 3.28 for both small and large firms versus the alternate hypothesis that it is by a greater factor for large firms as follows. Under the null, the targetiveness during hot markets should equal $0.66 \times 3.28 = 2.16\%$ for small firms and $0.62 \times 3.28 = 2.03\%$ for large firms. So we draw 31,317 random numbers corresponding to the number of small firm-years during hot markets such that each random number takes the value of one with a probability of 2.16% and zero otherwise. Based on this draw, we calculate the simulated targetiveness of small firms during hot markets, which we denote by $p_{small,sim}$. We similarly calculate the simulated targetiveness of large firms during hot markets, which we denote by $p_{large,sim}$. The simulated ratios of targetiveness values during hot markets and normal markets thus equal $p_{small,sim}/0.66$ for small firms and $p_{large,sim}/0.62$ for large firms. We then test whether the simulated ratio of ratios, or $(p_{small,sim}/0.66)/(p_{large,sim}/0.62)$, is greater than 3.91/3.03, which is the observed ratio of ratios. We repeat the experiment 10,000 times. The reported *p*-value is calculated as the proportion of cases in which this test condition is met.

markets in this case equals 1.65 for small firms and 1.55 for large firms. Even though the difference between ratios is statistically insignificant, the contrasting patterns for stock offers and cash offers are still intriguing.[6] They suggest an active shift between the methods of payment for small versus large firms during hot markets that are characterized by higher valuations of acquirer stocks.

The combined evidence of Table 5 supports our main hypothesis. It shows that small firms are less vulnerable to overpriced stock offers, which tend to be more common during hot markets. This result contrasts with the corresponding result for cash offers and can be due to either of the two reasons stated in the introduction. However, the higher expropriation potential per acquisition dollar from small firms during hot markets suggests that at least part of the reason is greater vigilance and control exercised by their managers. Later we provide additional evidence of control based on deal hostility and tender offers to support such an interpretation.

3.6. Can opinion divergence explain the targetiveness patterns by payment method or hot markets?

This is unlikely for the following reasons. First, the opinion divergence hypothesis of Chatterjee, John, and Yan (2012) does not make predictions about the differential patterns in targetiveness across firm-size quartiles by payment method. Second, Fig. 2 shows split evidence on whether the average opinion divergence is higher or lower during hot markets relative to normal markets. It is higher based on idiosyncratic volatility and change in breadth of mutual fund holdings, lower based on analyst forecast dispersion, and the same based on ranked excess turnover around earnings releases. Thus, two measures predict lower targetiveness during hot markets, one predicts higher targetiveness, and one predicts no change. Ex-ante predictions of the opinion divergence hypothesis concerning targetiveness during hot markets versus normal markets are not obvious. Chatterjee, John, and Yan (2012) propose that market-wide investor sentiment is positively related to opinion divergence. Casual impression suggests that investor sentiment was more positive during the hot market of 1995–2000, which may be a necessary ingredient for higher valuations. However, this impression is supported by year-end sentiment data (obtained from the Website of Professor Jeffrey Wurgler), but not by month-end sentiment data. This obscures the picture on whether the average opinion divergence and in turn the average targetiveness should be higher or lower during hot markets than during normal markets.

The evidence on changes in opinion divergence thus does not correspond well with the large increase in targetiveness for both small and large firm-years during hot markets as shown in Table 5 besides differential increases with payment method and firm size. To summarize, opinion divergence is significantly related to targetiveness per se as shown in Table 3, but it cannot explain the patterns across payment methods and hot versus cold markets in Tables 4 and 5.

4. Are small firms less vulnerable to overpriced stock offers?

4.1. Summary statistics of targets and acquirers

So far our tests have examined samples of firm-years. The remaining tests examine samples of completed acquisitions. Table 6 shows several target, acquirer, and deal characteristics for this sample arranged by target size. We restrict attention to 2,734 stock or cash offers. Many target and acquirer characteristics are in line with those documented in previous studies, so we do not reproduce them here. However, looking at deal characteristics we find interesting evidence on greater control exercised by the managers of small targets. First, if managers of small firms exercise greater control, then it would be difficult for acquirers to launch hostile bids. We find that hostile bids are less frequent for small targets than for large targets (1.16% and 3.92%). Second, tender offers are usually hostile and less likely to succeed if managers exercise greater control. We find fewer tender offers for small targets than for large targets (16.76% and 20.00%), even though tender offers are almost always for cash which is easier for small targets. Third, we find fewer cases of competing bidders for small firms than for large firms (2.85% and 4.43%). Although not shown in Table 6, in each case the difference between percent frequencies is statistically significant. This evidence on greater control and discretion exercised by managers of small targets is important as it enables their firms to resist overpriced stock offers. Finally, we find that the acquirers of small targets earn higher announcement returns than the acquirers of large targets in both stock and cash offers. We explore the acquirer announcement returns in detail in Section 4.5 and show that they support our vulnerability hypothesis.

4.2. Acquirer valuations based on prior-year excess returns

We now examine the relative valuations of the acquirers of small and large target firms. We employ two popular measures of overvaluation used in the mergers and acquisitions literature. The first measure is the prior-year excess return, which we calculate as the difference between the buy-and-hold returns of an acquirer firm and its industry, size, and book-to-market matching firm over (−262,−11) days relative to the announcement date. The exact matching procedure is described in Fig. 4.

Averaged over all stock acquisitions, the prior-year excess returns equal 15.7% for acquirers of small targets and 42.3% for acquirers of large targets (t-statistics 7.47 and 7.79, not tabulated). The difference equals -26.6%, significant at the 1% level. Consistent with our vulnerability hypothesis, this evidence shows that the stock acquirers of small targets are less overvalued than the

[6] In untabulated results we find that the evidence for mixed payment as well as for all payments lies in between the evidence for stock and cash payment.

Table 6
Summary statistics for the sample of public targets and public acquirers.

The sample analyzed in this table includes the acquisitions of U.S. public targets by U.S. public acquirers during 1981–2004 as described in Table 4. It includes all cash and stock deals, but excludes mixed payment deals. Small targets are those with market value of equity at the beginning of the year in the bottom NYSE size quartile, and large targets are those in the upper three quartiles. Market value of equity and book value of assets reported below are obtained from the last annual statement on Compustat before acquisition announcement. Prior-year excess return is calculated as the difference between acquirer return and its industry, size, and book-to-market matching return as further described in Fig. 4. Market-to-book ratio is calculated as the market value of equity of acquirer stock divided by its book value. It is log-transformed to adjust for skewness. We analyze four opinion divergence measures: Analyst forecast dispersion, idiosyncratic volatility, change in breadth of (mutual fund) holdings, and ranked excess turnover around earnings releases. The calculation of these measures is described in Appendix A. Change in breadth of holdings is an inverse measure of opinion divergence, the rest are direct measures. CAR denotes cumulative abnormal return, and it is calculated as the cumulative market-adjusted abnormal return over a three-day window centered on the last earnings announcement date or the current acquisition announcement date. Acquirer's collateral is calculated as property, plant, and equipment divided by total assets, its leverage equals book value of long-term debt divided by the market value of assets, and its cash flow equals the sum of earnings before extraordinary items and depreciation divided by the market value of assets. Relative size equals the deal value divided by the market value of equity of acquirer. Hostile, tender offer, and competing offer dummies take the value of one if identified as such by SDC, and zero otherwise. We measure the target industry acquisition activity with the combined deal value of all acquisitions reported by the SDC for the corresponding year and the two-digit SIC code of target firm, divided by the combined book value of assets of all Compustat firms for the same year with the same two-digit SIC code. We force it to take a value between zero and one.

	Acquisitions of small targets			Acquisitions of large targets		
	Mean	Median	Std. dev.	Mean	Median	Std. dev.
		$N=1{,}917$			$N=817$	
Panel A: Target characteristics						
Market value of equity in $million	88	62	83	2,599	714	7,828
Book value of assets in $million	308	106	579	6,836	883	26,233
Mutual fund ownership	4.41	1.32	10.64	9.10	6.55	12.36
Target industry acquisition activity	3.65	1.33	7.05	4.60	1.61	6.89
CAR from last earnings announcement in percent (%)	−0.26	−0.43	9.71	−0.35	−0.37	8.25
CAR around acquisition announcements – stock deals (%)	17.09	13.13	23.61	15.31	12.72	18.19
CAR around acquisition announcements – cash deals (%)	29.40	23.34	32.88	26.68	23.76	23.79
Panel B: Acquirer characteristics						
Market value of equity $million	6,110	778	24,152	18,702	4,829	43,886
Book value of assets $million	10,272	1,439	28,791	28,902	5,959	77,593
Prior-year excess return	10.31	2.50	52.98	22.61	7.83	66.43
Log market-to-book ratio	0.84	0.76	0.72	1.03	0.96	0.78
Analyst forecast dispersion	0.0066	0.0030	0.0134	0.0048	0.0021	0.0114
Idiosyncratic volatility (%)	2.73	2.20	1.95	2.27	1.84	1.44
Change in breadth of holdings	−0.0002	−0.0006	0.0035	0.0003	−0.0003	0.0047
Ranked excess turnover around earnings releases	53	53	29	57	59	28
CAR from last earnings announcement in percent	0.42	0.24	7.18	1.04	0.37	7.09
CAR around acquisition announcement – stock deals (%)	−0.96	−1.10	14.04	−3.40	−2.98	8.73
CAR around acquisition announcement – cash deals (%)	0.95	0.14	6.35	−0.03	−0.21	5.89
Collateral	0.176	0.100	0.205	0.222	0.145	0.231
Financial leverage	0.138	0.111	0.128	0.142	0.121	0.124
Cash flow	0.065	0.041	0.195	0.048	0.039	0.078
Panel C: Deal characteristics						
Relative size	0.263	0.113	0.411	0.465	0.281	0.560
Hostile frequency in percent		1.16			3.92	
Tender offer frequency in percent		16.76			20.00	
Competing offer frequency in percent		2.85			4.43	
Same industry frequency in percent		68			66	

stock acquirers of large targets. In contrast, for cash acquisitions, the prior-year excess returns average 3.9% for acquirers of small targets and 0.7% for acquirers of large targets (t-statistics 2.69 and 0.38). The difference of 3.2% is in the opposite direction to the above, although statistically insignificant.

Since Fig. 3 shows a strong size factor in stock valuations, we next analyze these returns sorted by payment method and acquirer size quartile. The top panel of Fig. 4 shows that for stock payment the prior-year excess returns are uniformly lower for the acquirers of small targets relative to the acquirers of large targets. In the top acquirer size quartile these two values equal 15.8% and 46.9%. The corresponding values equal 18.7% and 29.5% in the third quartile, and 20.1% and 45.0% in the second quartile. We do not make a similar comparison in the bottom acquirer size quartile because there are hardly any acquisitions of large targets by small acquirers.

The bottom panel of Fig. 4 shows that the trend in prior-year excess returns for cash offers is the opposite of the trend for stock offers. In the top quartile the acquirers of small targets and large targets have prior-year excess returns of 5.8% and 2.5%. The corresponding values equal 1.5% and −11.2% in the third acquirer size quartile, and 6.4%

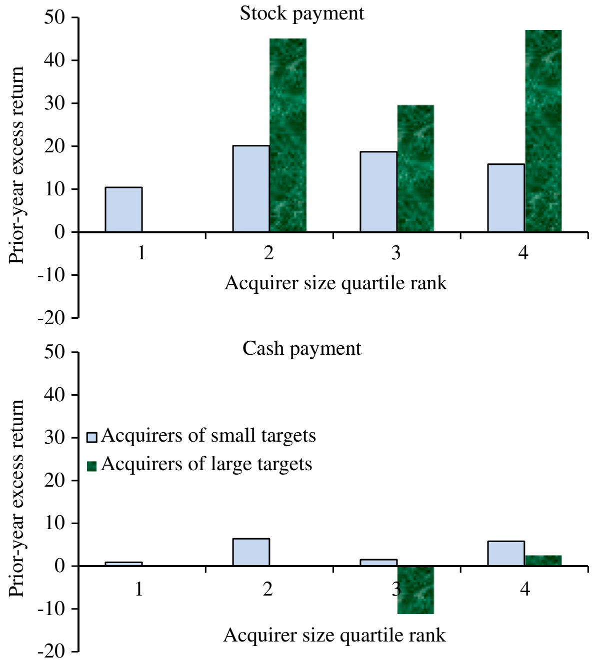

Fig. 4. Prior-year excess returns of acquirer stocks sorted by payment method and target size. The sample includes the U.S. public acquirers of all U.S. public targets during 1981–2004 as described in Tables 4 and 5. In addition, we require the prior returns data. Small targets belong to the bottom NYSE size quartile, and large targets belong to the remaining three size quartiles. Prior-year excess returns of acquirer firms are calculated over the period (−262, −11) days relative to the announcement date. We calculate excess returns as the difference between the buy-and-hold returns of the acquirer firms and the matching industry, size, and book-to-market firms. The returns are expressed in percent units. The matching procedure is described as follows. For each acquirer firm, we first identify all firms with the same two-digit SIC code and within ±30% of its market value. From this subset we identify the firm with the closest book-to-market. In a few cases this procedure does not result in a match, so we match by size alone. We keep up to five matching firms. Thus, if one firm gets delisted during the buy-and-hold period, we rollover its proceeds into the next matching firm, and so on. Since there are very few acquisitions of large targets by small acquirers in quartile 1, the extreme left panel shows only one vertical bar. There is a bar corresponding to acquirers of large targets in quartile 2 in lower panel, but it is only −0.1% tall, so almost invisible.

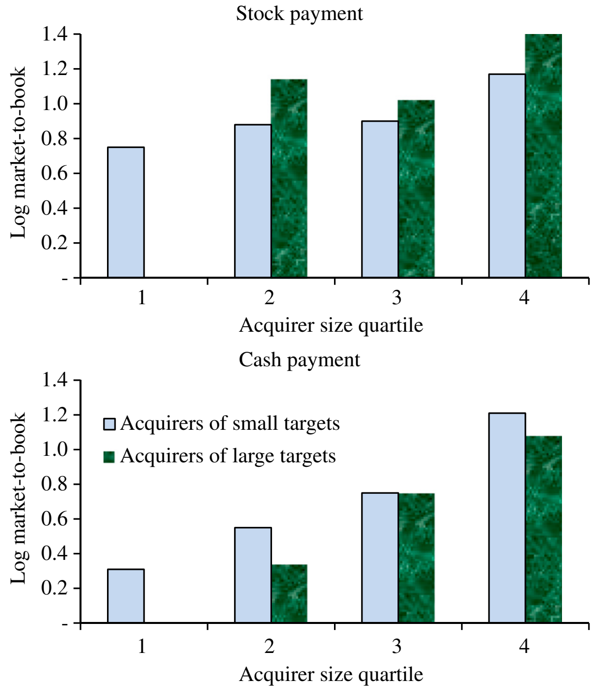

Fig. 5. Log market-to-book ratio of acquirer stocks before acquisition announcement sorted by payment method and target size. The sample includes the U.S. public acquirers of all U.S. public targets during 1981–2004 as described in Tables 4 and 5. In addition, we require that the market-to-book ratio data are available as of the last fiscal year-end before the announcement date of acquisition. This ratio is calculated as the market value of equity divided by the book value. The ratio is log-transformed to adjust for skewness. Small targets belong to the bottom NYSE size quartile, and large targets belong to the remaining three size quartiles. Since there are very few acquisitions of large targets by small acquirers in quartile 1, the extreme left panel shows only one vertical bar.

and −0.1% in the second quartile. The consistently opposite patterns for stock and cash acquisitions across acquirer size quartiles support the vulnerability hypothesis. The simple probability that all three differences are positive for stock acquisitions and negative for cash acquisitions by random chance is on the order of 0.5^6, or around 2%.

We should point out that in tests of Fig. 4 as well as in all subsequent tests of this paper, the main difference lies between small targets in the bottom NYSE size quartile and large targets in the remaining three quartiles (similar to Moeller, Schlingemann, and Stulz, 2004). There is no significant pattern across second, third, and fourth quartiles.

4.3. Acquirer valuations based on market-to-book ratios

The second valuation measure is the log-transformed market-to-book ratio. Fig. 5 shows that the patterns across payment methods and acquirer size quartiles with the log market-to-book ratio are similar to those with prior-year excess returns in Fig. 4. In every size quartile the log market-to-book ratio is higher for the acquirers of large targets relative to the acquirers of small targets in the case of stock acquisitions, and the trend is reversed in the case of cash acquisitions. Together, Figs. 4 and 5 provide strong support for our vulnerability hypothesis. Either small firms are less likely to receive offers from overvalued stock acquirers, or they reject some of their offers.

4.4. Multivariate tests of acquirer valuation and payment method

We have shown an association between hot markets and method of payment and between method of payment and prior valuations of acquirer stocks. We now ask a related but different question. In particular, we ask whether the method of payment is an active choice made by target and/or acquirer firms and whether its determination process differs across small and large target firms.

Faccio and Masulis (2005) show that stock payment is more likely when the acquirer valuations (prior-year raw return and market-to-book ratio) are high, the affordability of cash acquisition (relative size and acquirer's financial leverage, collateral, and log assets) is low, and the target and acquirer firms are in the same industry. We use their dependent variable, which is a stock payment dummy that takes the value of one for stock acquisitions, and zero for cash acquisitions. We next modify and supplement their list of independent variables to test our overvaluation variables and to take into consideration several new variables proposed in recent equity issuance literature. Regarding overvaluation, we include the acquirer's prior-year excess return and log market-to-book ratio besides a hot-market dummy. To make the first two variables focused on firm-specific overvaluation, we industry-adjust the log market-to-book ratio. The hot-market dummy is a market-wide measure which takes the value of one if an acquisition is announced during 1995–2000, and zero otherwise. To analyze the differential effects of overvaluation on the choice of stock payment, we include interaction terms between each overvaluation measure and a small target dummy. This dummy takes the value of one for target firms belonging to the bottom NYSE size quartile, and zero otherwise.

Recently, Dittmar and Thakor (2007) present a new theory to explain stock issues. In their model the manager of a firm considering a stock issue to finance a project is concerned about both the stock price immediately after the announcement and in the long run. The former depends on the degree of agreement between the manager and the outside investors about the project value. If the acquirer's managers have a similar objective function, then the choice of stock versus cash payment should also depend on the degree of agreement between managers and other parties involved in an acquisition. The empirical implementation of this agreement model raises several questions that we address below.

First, to complicate issues, in a seasoned equity offering, agreement involves the manager of an issuing firm and outside investors. However, in the contexts of acquisitions it would involve acquirer managers on one side and target managers (without whose agreement an offer may never be made), target shareholders (who vote on stock mergers), or outside investors (who determine the stock price that managers care about) on the other side. Second, to simplify issues, in the context of acquisitions the project is the target and the agreement about its value is easier to measure than that of a new project taken up with the proceeds of a seasoned equity offering. Specifically, we measure the (dis)agreement about the target (i.e., project) value by its idiosyncratic volatility over a three-month period ending 64 days before announcement. This works regardless of whose agreement is required. Further, because agreement between the managers of acquirer and target firms is the first and arguably the most important roadblock, we use alternate disagreement measures that include a hostile dummy, a tender offer dummy, and a competing offer dummy.[7] All of these measures are associated with disagreement by target managers as explained in Section 3.1. Finally, following Dittmar and Thakor (2007), we also use cumulative abnormal return (CAR) surrounding last earnings announcement for both target and acquirer firms as agreement variables. They argue that the greater the difference between actual and forecast earnings, which we proxy by CAR, the more the outside investors agree with their managers.

A negative relation between stock payment on one hand and hostile, tender offer, or competing offer dummies on the other hand (all disagreement proxies) is very likely. Other things equal, stock offers are known to be more friendly or agreeable than cash offers.[8] However, a negative relation between stock payment and target volatility predicted by Dittmar and Thakor is opposite to what follows from Hansen (1987). He argues that stock payment is a useful risk-sharing arrangement when there is greater information asymmetry about the target firm. These contrasting predictions make this an interesting variable to analyze in its own right.

Finally, we add two more variables. First, we add target's mutual fund ownership to capture tax effects. Mutual funds are evaluated on their total returns and are less likely to be concerned about the tax consequences of cash payment than individual shareholders. There is another reason for their lesser concern with taxes, that many mutual funds have fundholders in different tax brackets including an effective tax rate of zero for retirement accounts, charities, and university endowment funds (Sialm and Starks, 2012). Thus, we expect mutual fund ownership to be negatively related to stock payment. Second, we add average idiosyncratic volatility of all firms in our aggregate sample during the announcement year to capture time-varying adverse selection, which is proposed as a dynamic analog of the static pecking order theory by Dittmar and Thakor (2007).

Table 7 reports the logistic regressions of the stock payment dummy. We introduce the three acquirer valuation measures—prior-year excess return, industry-adjusted log market-to-book ratio, and hot-market dummy—one at a time in Regressions (7.1) to (7.3). Each valuation measure is positive and highly significant but its interaction with the small target dummy is negative and also highly significant. On average, the coefficient of an interaction term is around two-thirds of the coefficient of the corresponding valuation measure. The next Regression (7.4) shows that each valuation measure and its interaction with the small target dummy remains statistically significant in the presence of others.

Regressions (7.1) to (7.4) also show that the coefficient of target volatility is always negative and significant. This evidence is consistent with the agreement model of Dittmar and Thakor (2007) but inconsistent with the risk-sharing model of Hansen (1987). While these first four regressions provide considerable support for both the

[7] To highlight the importance of agreement by target managers, Dodd (1980) points out that in a sample of 151 stock mergers, the target shareholders approved the merger in all 151 cases.

[8] A recent acquisition of Cadbury by Kraft in 2010 shows why stock acquisitions are intrinsically more agreeable deals considering all involved parties. Warren Buffett, the largest shareholder of Kraft, disagreed with the deal. In response, Kraft changed the payment terms to include more cash so that shareholder approval (or agreement) was not required. (Under NYSE rules, acquirer firms are also required to seek shareholder vote if new equity issue exceeds 20% of old equity).

Table 7
Are small firms less vulnerable to overpriced stock offers? Logistic analysis of stock payment.

The sample analyzed in this table includes the acquisitions of U.S. public targets by U.S. public acquirers during 1981–2004 as described in Table 4. In addition, we require that the data on variables included in this table are available. The dependent variable in all logistic regressions reported in this table is a stock payment dummy, which takes the value of one for stock deals and zero for cash deals. Following Faccio and Masulis (2005), we define cash deals as those financed with cash, liabilities, and newly issued notes, and stock deals as those financed with acquirer stock that has full voting rights or inferior voting rights. Mixed deals that are financed with both cash and stock are excluded. The first set of independent variables constitutes the focus of this paper and includes three overvaluation measures as follows. First, acquirer's prior-year excess return (in fractional units) is calculated over the period (−262,−11) days relative to the announcement date by subtracting the return on an industry, size, and book-to-market matching firm. Second, acquirer's industry-adjusted log market-to-book ratio is the difference between log market-to-book ratio of the acquirer and the industry median firm. Market-to-book ratio is calculated as the market value of equity divided by the book value as of the last fiscal year ending before the announcement date, and industry is defined by the two-digit SIC code. Log transformation is done to remove skewness in market-to-book ratios. Third, a hot-market dummy equals one if the deal is announced during 1995–2000, and zero otherwise. The first two measures capture firm-specific overvaluation and the third captures market-wide overvaluation. Each of these three overvaluation measures is interacted with a small target dummy that equals one if the target firm has market value in the bottom quartile of all NYSE firms during the announcement year, and zero otherwise. The second set of independent variables includes several agreement measures based on Dittmar and Thakor (2007) as follows. Target's volatility is the idiosyncratic stock volatility calculated using the residuals from a market model applied to three-months of daily returns ending on day AD-64. Hostile, tender offer, and competing offer dummies take the value of one if identified as such by SDC, and zero otherwise. CAR from last earnings – acquirer/target is the cumulative market-adjusted abnormal return over a three-day window centered on the last earnings announcement date. The third set of independent variables includes target's mutual fund ownership, to capture tax preferences of target's shareholders, and average (idiosyncratic) volatility of all firms during the last calendar year, to capture time-varying adverse selection. The average volatility is omitted for all regressions containing a hot-market dummy as the two are related. The fourth set of independent variables includes remaining control variables from Faccio and Masulis (2005) as follows. Acquirer's collateral is calculated as property, plant, and equipment divided by total assets, acquirer's financial leverage is calculated as the book value of long-term debt divided by the market value of assets, and acquirer's log assets simply equals the log of book assets. All of these variables are calculated as of last fiscal year-end before acquisition announcement. Relative size equals the deal value divided by the market value of equity of acquirer, and same-industry dummy takes the value of one if the acquirer and the target have the same two-digit SIC code, and zero otherwise. The notations [a,b,] and [c] denote significance at 10%, 5%, and 1% levels. For the key variables of interest to the vulnerability hypothesis, we also report the *t*-statistics in parentheses.

Dependent variable: Stock payment dummy

Independent variables	(7.1)	(7.2)	(7.3)	(7.4)	(7.5)	(7.6)	(7.7)	(7.8)
Acquirer's prior-year excess return	1.22[c]			1.06[c]	1.06[c]	1.05[c]	1.03[c]	1.01[c]
	(6.23)			(4.89)	(4.76)	(3.87)	(4.71)	(4.16)
Acquirer's prior-year excess return × Small target dummy	−0.70[c]			−0.56[c]	−0.54[b]	−0.57[b]	−0.53[b]	−0.50[b]
	(−3.68)			(−2.67)	(−2.48)	(−2.16)	(−2.46)	(−2.13)
Acquirer's ind-adj log market-to-book ratio		0.87[c]		0.46[c]	0.33[b]	0.50[c]	0.31[b]	0.37[b]
		(6.65)		(3.08)	(2.29)	(2.65)	(2.24)	(2.24)
Acquirer's ind-adj log market-to-book ratio × Small target dummy		−0.62[c]		−0.31[a]	−0.19	−0.24	−0.18	−0.30
		(−4.24)		(−1.81)	(−1.14)	(−1.13)	(−1.13)	(−1.60)
Hot-market dummy			1.22[c]	0.92[c]	0.92[c]	0.98[c]	0.90[c]	1.24[c]
			(8.72)	(5.81)	(5.88)	(4.87)	(5.80)	(6.73)
Hot-market dummy × Small target dummy			−0.80[c]	−0.48[c]	−0.47[c]	−0.49[b]	−0.45[c]	−0.62[c]
			(−5.21)	(−2.75)	(−2.74)	(−2.24)	(−2.62)	(−3.06)
Target's volatility	−5.23[c]	−4.66[b]	−4.97[c]	−5.31[c]				
Hostile dummy					−2.11[c]			
Tender offer dummy						−4.43[c]		
Competing offer dummy							−1.14[c]	
CAR from last earnings – acquirer								−0.42
CAR from last earnings – target								−0.08
Target's mutual fund ownership	−2.22[c]	−2.33[c]	−2.39[c]	−3.25[c]	−0.11	0.79	−0.20	−2.60[c]
Average volatility of all firms	−2.05	−7.88						
Intercept	1.09[c]	1.30[c]	1.21[c]	0.97[c]	0.47[b]	1.01[c]	0.48[b]	0.70[c]
Acquirer's collateral	−0.98[c]	−1.22[c]	−1.24[c]	−1.12[c]	−1.15[c]	−0.32	−1.14[c]	−1.62[c]
Acquirer's financial leverage	−1.33[c]	−0.79[b]	−0.98[c]	−0.66[a]	−0.41	−1.21[b]	−0.40	−0.46
Acquirer's log assets	−0.06[b]	−0.08[c]	−0.10[c]	−0.10[c]	−0.07[c]	−0.06[a]	−0.08[c]	−0.10[c]
Relative size	0.18	0.19[a]	−0.00	0.18	0.25[b]	0.54[c]	0.20[a]	0.23[a]
Same-industry dummy	0.73[c]	0.72[c]	0.70[c]	0.72[c]	0.73[c]	0.41[c]	0.76[c]	0.62[c]
N	2,437	2,416	2,445	2,408	2,440	2,440	2,440	1,753
Pseudo-R^2	0.068	0.062	0.073	0.093	0.097	0.357[†]	0.093	0.107

[†] The large pseudo-R^2 for Regression (7.6) arises because tender offer dummy has a much higher correlation with the payment method than other variables.

vulnerability hypothesis and the agreement model, we push the analysis further in Regressions (7.5) to (7.8) with alternate measures of agreement between acquirer managers and outside participants in the acquisition process. These regressions continue to provide further support for both theories, although the coefficient of interaction term between industry-adjusted log market-to-book ratio and small target dummy becomes insignificant. As an additional result, we find that the coefficient of target's mutual fund ownership is negative in seven out of eight regressions and significant in five out of these seven regressions, which suggests that tax considerations of remaining shareholders favor stock payment. However, the time-varying adverse selection measure included in Regressions (7.1) and (7.2) is insignificant. (We do not include it in the remaining regressions since it is correlated with the hot-market dummy.)[9]

More important to our hypothesis, the effects of the three valuation measures and their interactions with a small target dummy remain reasonably consistent across various regression model specifications reported in Table 7. These results show that, in general, stock payment becomes more likely as the prior valuation of acquirer stock increases. However, this is less descriptive of small targets than of large targets. In other words, the same percent overvaluation increases the probability of a stock acquisition by a greater magnitude for large targets than for small targets. Finally, one can ask whether the sum of coefficients of each overvaluation measure and its interaction term with small target dummy is insignificant, which would mean that overpriced stock acquirers are not more likely to acquire small targets by making stock payment than by making cash payment. However, our evidence shows that this is usually not true, except for the log market-to-book ratio in several regressions.

4.5. *Does the market perceive less negative information about acquirer valuation in stock offers for small targets?*

An extensive finance literature explores the many determinants of acquirer announcement returns. A common theme emerges from this research, that the acquirer announcement returns are significantly lower for stock acquisitions than for cash acquisitions in samples of public targets and acquirers. The difference is usually attributed to negative information about acquirer valuation implicit in a stock offer. It stands to reason that the greater the perceived overvaluation, the more negative the market reaction.

We calculate three-day market-adjusted acquirer announcement excess returns by subtracting the cumulative value-weighted market returns from cumulative stock returns centered on the announcement date. Averaged over the subsample that includes all small targets, the acquirer announcement returns average −0.96% and 0.95% for stock and cash acquisitions (*t*-statistics −2.30 and 4.14). The corresponding returns for the subsample that includes all large targets average −3.40% and −0.03% (*t*-statistics −9.27 and −0.09). Thus, the presence of a small target instead of a large target is associated with an incremental acquirer return of 2.44% and 0.98% in stock and cash acquisitions (*t*-statistics 4.36 and 2.45). A question arises as to why there is a small target effect in cash acquisitions. It is possible that small targets are also picky about cash acquirers (although it does not affect their shareholders), or that acquisitions of small targets convey other positive information (such as more positive synergy effects). Thus, while one may characterize the entire small target effect of 2.44% in stock acquisitions as a certification effect, a more conservative interpretation would be that only the difference of differences given by 2.44%–0.98% = 1.46% is a certification effect (*t*-statistic 2.12, significant at the 5% level).

We next turn to multivariate tests. We start with the base multivariate regression model of acquirer announcement returns employed by Moeller, Schlingemann, and Stulz (2004) and make several modifications. First, in separate regressions for stock and cash acquisitions we add a small target dummy to capture the hypothesized certification effect. Second, we add several uncertainty variables suggested by Moeller, Schlingemann, and Stulz (2007). They argue that in a stock acquisition, the acquirer's float increases with the relative size of target, and that the adverse price impact of increased float increases with opinion divergence about its value. We therefore add an opinion divergence measure for acquirer and its interaction with relative size in the regression model for stock acquisitions. Since there is no increase in float for cash acquisitions, we do not add these variables to the corresponding regressions. They further argue that all acquisition announcements convey some information about stock valuation (Myers and Majluf, 1984), so a measure of asymmetric information should be added to the regression. We report our results with the inclusion of this variable, but caution that it will capture some of the small target effect that is also motivated as an information effect. Following Moeller, Schlingemann, and Stulz, our measure of asymmetric information is idiosyncratic volatility, which means that the opinion divergence measures are analyst forecast dispersion, change in breadth of mutual fund holdings, and ranked excess turnover around earnings releases.

Table 8 describes the remaining variables included in the acquirer announcement excess return regressions and gives the variable definitions. Regressions (8.1) and (8.6) first report the results with all control variables except the uncertainty measures. The small target dummy has a coefficient of 4.21% in stock acquisitions and 1.25% in cash acquisitions, both significant at the 1% level. The difference of 2.96% is significant at the 5% level and gives a conservative estimate of the certification effect of small targets in stock acquisitions as discussed before.

Regressions (8.2) to (8.4) next report the results for stock acquisitions with the addition of the uncertainty measures. From opinion divergence measures, acquirer's analyst forecast is significant in the predicted direction while change in breadth of holdings and ranked excess turnover around earnings releases are insignificant. The interactions of these measures with relative size are all insignificant. Acquirer's idiosyncratic volatility is significantly negative in one case, as predicted for stock acquisitions, and insignificant in the other two cases. More

[9] We also note that acquirer's collateral, acquirer's log assets, and same-industry dummy have the same sign and significance as in Faccio and Masulis (2005). However, acquirer's financial leverage has the opposite sign, although it is often insignificant. Finally, relative size is sometimes positive and significant. This has two interpretations. First, cash payment is less affordable for relatively large targets. Second, Hansen (1987) predicts that there is a greater reason for risk sharing through stock payment for relatively large targets. Considering the coefficients of both target volatility and relative size, our evidence provides mixed support for Hansen (1987).

Table 8
Does the market perceive less negative information about acquirer valuation in stock offers for small firms?.

The sample analyzed in this table includes the acquisitions of U.S. public targets by U.S. public acquirers during 1981–2004 as described in Table 4. In addition, we require that the data on variables included in this table are available. We drop mixed acquisitions for expositional reasons. The dependent variable in all regressions is the acquirer announcement excess return, calculated as the difference between the cumulative three-day stock return centered on the announcement date and the corresponding value-weighted market return. This return is expressed in percent units. The key variables of interest in this table are the coefficients of small target dummy in each regression (second row) and the differences between these coefficients across similar regressions for stock acquisitions and cash acquisitions (bottom row). The small target dummy takes the value of one for targets belonging to the bottom NYSE size quartile based on the market value of equity as of last year-end. We define cash deals as those financed with cash, liabilities, and newly issued notes, and stock deals as those financed with acquirer stock that has full voting rights or inferior voting rights. Mixed deals that are financed with both cash and stock are excluded. Relative size equals the deal value divided by the market value of equity of acquirer. Similar to Moeller, Schlingemann, and Stulz (2007), we include several opinion divergence and asymmetric information variables. The opinion divergence variables include acquirer's analyst forecast dispersion, change in breadth of mutual fund holdings, and ranked excess turnover around earnings releases. Each of these variables is interacted with relative size. The calculation of these variables is described in Appendix A. Conceptually, acquirer's opinion divergence matters only for stock acquisitions, so we do not include it for cash acquisitions. Asymmetric information is measured by idiosyncratic volatility, calculated over a three-month period ending on day -64 relative to acquisition announcement. However, since idiosyncratic volatility is also used as a measure of opinion divergence in Tables 3 and 7, Model (8.5) treats it as such, in which case it is interacted with relative size and no other measure of opinion divergence is included. Every regression uses additional control variables which are a small acquirer dummy, same-industry dummy, tender offer dummy, hostile dummy, competing offer dummy, acquirer's *q*, acquirer's leverage, acquirer's cash flow, and target industry acquisition activity. However, for expositional reasons their coefficients are not reported. Similar to small targets, small acquirers are those belonging to the bottom NYSE quartile based on the market value of equity as of last year-end. Same-industry dummy takes the value of one if the acquirer and the target have the same two-digit SIC code, and zero otherwise. Tender offer, hostile, and compete take the value of one if identified as such by SDC, and zero otherwise. Acquirer's *q* equals its market value divided by the book value of assets, acquirer's leverage equals its book value of long-term debt divided by the market value of assets, and acquirer's cash flow equals the sum of earnings before extraordinary items and depreciation divided by the market value of assets. We measure the target industry acquisition activity with the combined value of all acquisitions reported by the SDC for the corresponding year and the two-digit SIC code of target firm, divided by the combined book value of assets of all Compustat firms for the same year with the same two-digit SIC code. We force it to take a value between zero and one. The continuous control variables are measured as of the last fiscal year ending before the announcement year. Statistical significance levels are based on White's heteroskedasticity-consistent standard errors. The notations [a,b,] and [c] denote significance at 10%, 5%, and 1% levels.

Dependent variable: Acquirer's three-day market-adjusted announcement excess return (%)

	Stock acquisitions					Cash acquisitions	
Variables	(8.1)	(8.2)	(8.3)	(8.4)	(8.5)	(8.6)	(8.7)
Intercept	−6.41[c]	−3.07[c]	−3.14[c]	−6.21[a]	−0.01	−1.40[a]	−2.14[b]
	(−3.50)	(−2.96)	(−3.33)	(−1.83)	(−0.46)	(−1.67)	(−2.55)
Small target dummy	**4.21**[c]	**2.37**[c]	**2.55**[c]	**3.51**[c]	**2.35**[c]	**1.25**[c]	**1.03**[b]
	(3.28)	(3.58)	(4.15)	(3.17)	(3.89)	(2.63)	(2.13)
Relative size	7.95[b]	−1.28	2.56[a]	12.09	−0.04	1.72[b]	1.59[b]
	(2.04)	(−0.43)	(1.89)	(1.24)	(−1.50)	(2.46)	(2.23)
Acquirer's analyst forecast dispersion $\times 10^2$		−2.06[b]					
		(−2.04)					
Acquirer's analyst forecast dispersion × Relative size $\times 10^2$		6.45					
		(1.38)					
Acquirer's change in breadth of holdings $\times 10^2$			0.87				
			(1.43)				
Acquirer's change in breadth of holdings × Relative size $\times 10^2$			−1.69				
			(−0.67)				
Acquirer's ranked excess turnover around earnings releases				0.03			
				(0.81)			
Acquirer's ranked excess turnover around earnings releases × Relative size				−0.13			
				(−0.89)			
Acquirer's idiosyncratic volatility $\times 10^2$		0.05	−0.42[a]	0.09	−1.44[b]		0.67[b]
		(0.22)	(−1.74)	(0.30)	(−2.17)		(2.20)
Acquirer's idiosyncratic volatility × Relative size $\times 10^2$					2.89[a]		
					(1.81)		
Additional control variables (nine of them)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,426	1,331	1,341	1,201	1,417	896	891
Adjusted-R^2	0.118	0.140	0.050	0.080	0.123	0.049	0.061
Difference between coefficient of small target dummy for stock and cash acquisitions	**2.96**[b]	**1.34***	**1.52**[a]	**2.48**[b]	**1.32**[a]		
	(2.16)[†]	(1.63)[‡]	(1.94)[‡]	(2.26)[‡]	(1.71)[‡]		

[†] This is the difference between the coefficients of small target dummy in Regressions (8.1) and (8.6).
[‡] This is the difference between the coefficients of small target dummy in Regressions (8.2), (8.3), (8.4), and (8.5) for stock acquisitions and (8.7) for cash acquisitions.
* *P*-value of 0.103.

importantly, the coefficient of the small target dummy ranges between 2.37% and 3.51%, all significant at the 1% level. The bottom row of Table 8 shows that even after subtracting the coefficient of small target dummy for cash acquisitions from Regression (8.7), the minimum certification effect of small targets in stock acquisitions ranges between 1.34% and 2.48%, significant at 10% and 5% levels in two out of three cases.

Table 9
Do small target firms certify acquirer valuation? Evidence based on partitions formed by certification need.

This table continues the tests of Table 8, but with a few modifications. First, we restrict the sample to stock payment deals for which certification of acquirer value is a more relevant consideration. Second, we partition the sample along two measures of asymmetric information, which proxies for certification need. The first partition is based on above and below median acquirer's idiosyncratic volatility, and the second partition is based on positive and negative values of acquirer's return on assets (ROA). The latter partition in both cases has higher certification need. The dependent variable in all regressions is the acquirer announcement excess return, calculated as the difference between the cumulative three-day stock return centered on the announcement date and the corresponding value-weighted market return. The independent variables are described in Table 8, except ROA, which is defined as operating income before depreciation divided by total assets. The key variable is the small target dummy, which captures the certification effect. The unreported control variables include a small acquirer dummy, same-industry dummy, tender offer dummy, hostile dummy, competing offer dummy, acquirer's q, acquirer's leverage, acquirer's cash flow, and target industry acquisition activity. Statistical significance levels are based on White's heteroskedasticity-consistent standard errors. The notations [a,b,] and [c] denote significance at 10%, 5%, and 1% levels.

Payment method: All stock, Dependent variable: Acquirer's three-day market-adjusted announcement excess return (%)

	Partitions based on idiosyncratic volatility			Partitions based on acquirer's ROA		
	Low	High	Difference	ROA > 0	ROA≤0	Difference
Variables	(9.1)	(9.2)		(9.3)	(9.4)	
Intercept	−4.16[c]	−8.54[c]		−2.80[c]	−19.64[a]	
	(−2.98)	(−2.76)		(−3.08)	(−1.84)	
Small target dummy	**1.86**[c]	**5.36**[c]	**3.50**[b]	**1.94**[c]	**13.73**[b]	**11.79**[a]
	(3.62)	(3.24)	(2.02)	(3.91)	(2.23)	(1.91)
Relative size	1.44[a]	8.72		0.08	21.64[b]	
	(1.46)	(1.58)		(0.10)	(1.99)	
Acquirer's analyst forecast dispersion × 10^2	−0.29	−0.23		−0.31	−0.12	
	(−0.52)	(−0.43)		(−0.88)	(−0.07)	
Acquirer's idiosyncratic volatility × 10^2	−0.57	0.44		−0.29	0.93	
	(−0.99)	(1.37)		(−1.15)	(1.32)	
Additional control variables (nine of them)	Yes	Yes		Yes	Yes	
N	634	697		1,191	140	
Adjusted-R^2	0.030	0.088		0.022	0.202	

In an effort to control for the uncertainty effects proposed by Moeller, Schlingemann, and Stulz (2007) and Chatterjee, John, and Yan (2012), we are cognizant of the dual role for idiosyncratic volatility as a measure of information asymmetry (between managers and shareholders) proposed by the former and as a measure of opinion divergence (between shareholders) proposed by the latter. As a robustness test, we report Regression (8.5) for stock acquisitions in which we include idiosyncratic volatility but no other uncertainty variable. This regression views idiosyncratic volatility as an opinion divergence measure, so we also include its interaction term with relative size. Once again, we obtain a differenced certification effect of 1.32%, significant at the 10% level.

We next examine whether the certification effect is stronger in cases in which there is a greater need for certification. This should be the case when an acquirer firm has higher than average volatility of stock price or negative earnings. Thus, in Table 9 we report the analyses of stock acquisitions divided into two subsamples based on idiosyncratic volatility or return on assets (ROA). We report results with analyst forecast dispersion as a measure of opinion divergence, but drop its interaction term with relative size (which is insignificant in Table 8). Regressions (9.1) and (9.2) show that the small target dummy has coefficients of 1.86% and 5.36% in low and high volatility subsamples. The difference equals 3.50%, significant at the 5% level. Regressions (9.3) and (9.4) next show that the corresponding coefficients equal 1.94% and 13.73% in positive and negative ROA subsamples. Once again, the difference equals 11.79%, significant at the 10% level.[10]

In summary, Tables 8 and 9 show that the market correctly perceives the stock acquirers of small targets to be better valued than the stock acquirers of large targets. This certification effect is greater for acquirers suffering from more acute information asymmetry. The combined evidence again supports the vulnerability hypothesis.

5. Miscellaneous results and robustness tests

5.1. The role of insider ownership and corporate governance

A question arises whether our small firm effect can be explained as an insider ownership effect or a corporate governance effect. We investigate this possibility as follows. First, we obtain stock ownership of CEOs from ExecuComp. These data exist for 16,204 firm-years in our

[10] For comparison, we also analyze but do not tabulate the small target effect for cash acquisitions across the same type of subsamples. The difference equals 2.11% in the first case and −7.89% in the second case, significant in both cases, but with the wrong sign in the second case. The inconsistent sign suggests that the small target dummy effect for cash acquisitions is not a certification effect.

sample. Panel A of Table 10 shows that averaged across the four NYSE size quartiles in ascending order, the CEOs own 7.4%, 6.3%, 4.4%, and 2.6% of their firms. This shows that the CEOs of small firms exercise greater control over the key decisions of their firms, which should enable them to more effectively resist overpriced stock offers. However, it does not necessarily mean that their personal wealth incentives are greater. The dollar values of equity stakes show an opposite trend to percent values, averaging $14, $36, $67, and $116 million across small to large size quartiles. Besides, the personal wealth incentives can depend on how big their equity stake is relative to their unobserved total wealth.

Prior literature is ambiguous on the relation between insider ownership and targetiveness. For example, Ambrose and Megginson (1992) find an insignificant relation, and Song and Walkling (1993) find a significantly negative relation. Panel B of Table 10 reports our results. It shows that the CEO's percent ownership has an insignificant effect on targetiveness. However, Panel C of Table 10 next shows that the CEO's percent ownership is related to the likelihood of stock payment in successful acquisitions, which can be due to tax reasons. This finding can be interpreted as providing further support to the vulnerability hypothesis. Small firms have higher CEO ownership, higher CEO ownership is related to stock payment in the broad sample of all small and large firms, yet small firms are less likely to accept potentially overpriced stock offers. Unfortunately, given already reduced sample sizes, further tests within even smaller subsamples are not meaningful.

Chang (1998) and Fuller, Netter, and Stegemoller (2002) propose another type of insider ownership effect. They propose a monitoring hypothesis under which the higher acquirer announcement returns in stock acquisitions of private targets can be explained by the emergence of a new blockholder in the combined firm (i.e., owner of at least a 5% equity stake). Since small targets have higher CEO percent ownership, one may ask whether the small target effect can be explained as a blockholder effect. In untabulated results, we investigate this question using Dlugosz et al. (2006) blockholder data. The emergence of a new blockholder in the merged firm depends on both the prior existence of a blockholder in the target firm (which is more often for small targets) and the relative size of target to acquirer (which is lower for small targets). Thus, we find that there is not a significant difference between the frequency of new blockholders in acquisitions of small targets and large targets. We also find that the likely emergence of a new blockholder in the merged firm is not related to the frequency of stock payment.

We finally examine the role of corporate governance. Using the RiskMetrics database for 26,240 firm-years in our sample, we find that the average G-index value equals 9.0, 8.9, 9.3, and 9.5 across the four size quartiles in ascending order. A lower G-index value indicates more democratic governance, which is usually considered better governance. Thus, one can say that small firms have marginally better governance. However, Panel B of Table 10 shows that the G-index is not related to targetiveness in our sample consistent with Core, Guay, and Rusticus (2006), and Panel C of Table 10 shows that the G-index is not related to the likelihood of stock payment. More importantly, despite much smaller samples in Table 10 relative to previous tables, our small firm and small target measures remain significant. Overall, the results of this paper cannot be explained as an insider ownership effect or a corporate governance effect.

5.2. Are our results specific to hot-market years?

We repeated our tests by excluding the hot-market years of 1995–2000 (not tabulated). The results remain qualitatively similar. Thus, our small target effects are not confined to hot markets of the late 1990s. This is not surprising since both market-level and firm-specific measures of overvaluation are significant in multivariate tests of Table 7. Thus, small firms are less vulnerable to overpriced stock acquirers where overpricing may be firm-specific or market-wide.

5.3. Is there something unique about the manually collected sample of acquisitions?

We supplemented our sample of acquisitions from SDC with a manually collected sample starting with CRSP delistings and verified using hard-copy sources as described in Section 2.1. One can ask whether there is something unique about this manually collected sample in view of the evidence on data filters shown by Netter, Stegemoller, and Wintoki (2011). We therefore repeat our tests by excluding these observations and focusing on the sample retrieved from SDC files. We find that this has virtually no effect on our results (not tabulated).

6. Conclusion

This paper shows that small public firms are less vulnerable to overpriced stock offers that expropriate the wealth of their long-term shareholders. We reach this conclusion after comparing several measures of prior valuation of the public acquirers of small and large target firms. In addition, we compare their probabilities of becoming the targets of successful stock and cash acquisitions. Our sample includes all acquisitions of U.S. public firms announced during 1981–2004.

Our main results are as follows. We first estimate that over the aggregate sample period, the targetiveness of small firms belonging to the bottom NYSE size quartile is lower than the targetiveness of large firms belonging to the upper three size quartiles. However, this result is driven by stock (and mixed) acquisitions and is reversed for cash acquisitions. Interestingly, the differences in targetiveness become more polarized during hot markets characterized by greater differences in the valuations of small and large firms, which works to the advantage of the long-term shareholders of small target firms.

Our next set of tests focus on acquirer valuations. Using prior-year excess returns and market-to-book ratios, we show that the stock acquirers of small targets have significantly lower valuations than the stock acquirers of large targets. Conversely, we show that the overpricing

Table 10
Effects of CEO's ownership and governance on targetiveness and stock payment.

This table analyzes whether a CEO's ownership and governance affect targetiveness and stock payment choice. We obtain CEO ownership information during 1993–2004 from the ExecuComp database, and governance index information during 1991–2004 from the RiskMetrics database. For both variables the information is available only for a subset of the starting sample of firm-years described in Table 2. The corresponding sample of targets is described in Table 1. Panel A reports the summary statistics, Panel B reports the targetiveness tests, and Panel C reports the payment method tests. A lower value of the G-index shows a more democratic firm. The remaining variables are described in Tables 2, 3, and 7. Given the small number of observations, we include only one measure of acquirer overvaluation (the prior-year excess return) and one measure of market-wide overvaluation (the hot-market dummy) in Panel C on logistic model tests of stock payment dummy. The notations [a,b,] and [c] denote significance at 10%, 5%, and 1% levels. For the key variables we also report the *t*-statistics in parentheses.

	Firm size quartile rank					Difference small vs. large
Variables	Small	2	3	4	2+3+4	
Panel A: Mean values of ownership and governance variables						
CEO's ownership in percent	7.4	6.3	4.4	2.6	4.5	2.9[c]
CEO's ownership in million dollars	14	36	67	116	65	−51[c]
G-index	9.0	8.9	9.3	9.5	9.2	−0.2[c]

Variables	(10.1)	(10.2)
Panel B: Logistic regressions of targetiveness dummy		
Percentile rank of market value of equity × 10^{-2}	1.81[b]	1.06[a]
	(2.31)	(1.64)
Square of percentile rank of market value of equity × 10^{-4}	−2.12[c]	−1.81[c]
	(−3.04)	(−3.02)
CEO's ownership in percent	−0.05	
	(−0.15)	
G-index		0.02
		(1.16)
Analyst forecast dispersion	3.06	1.76
	(0.99)	(0.89)
Intercept	−3.76[c]	−3.55[c]
Book-to-market × 10^{-3}	0.09	−0.00
Cash flow	−0.22	−0.52[b]
Industry acquisition activity	2.57[c]	3.33[c]
Prior-year excess return	−0.10	−0.18[b]
Growth-resource mismatch dummy	−0.08	−0.11
Leverage	0.61[b]	0.29
Year dummies	Yes	Yes
N	13,521	17,798
N with dependent variable = 1	580	689
Pseudo-R^2	0.043	0.060

Independent variables	(10.3)	(10.4)
Panel C: Logistic regressions of stock payment dummy		
Acquirer's prior-year excess return	1.93[c]	1.92[c]
	(3.45)	(4.43)
Acquirer's prior-year excess return × Small target dummy	−1.66[b]	−1.35[b]
	(−2.02)	(−1.96)
Hot-market dummy	0.13	0.20
	(0.34)	(0.47)
Hot-market dummy × Small target dummy	−1.25[b]	−1.55[c]
	(−2.52)	(−3.43)
Target's CEO ownership	2.92[a]	
	(1.73)	
Target's G-index		−0.02
		(−0.31)
Target's volatility	−7.10	−21.68[b]
Target's mutual fund ownership	−5.34[b]	−3.44[a]
Intercept	1.23	1.34
Acquirer's collateral	−1.77[b]	−1.04[a]
Acquirer's financial leverage	−1.88	−0.56
Acquirer's log assets	−0.08	−0.04
Relative size	1.74[c]	0.63[b]
Same-industry dummy	1.34[c]	1.12[c]
N	282	395
Pseudo-R^2	0.212	0.171

of stock acquirers is more of a factor in stock payment for large targets than for small targets. Analysis of acquirer announcement returns shows that the market also perceives less negative information in stock acquisitions of small targets relative to large targets. Moreover, this certification effect of small targets concerning the valuation of stock acquirers is stronger in subsamples characterized by greater information asymmetry and higher need for certification.

Our tests control for a variety of alternate explanations before concluding in favor of the vulnerability hypothesis. In particular, we control for opinion divergence in tests of targetiveness and acquirer announcement returns, and agreement variables in tests of what explains the choice of stock payment. This leads to an interesting side result. Specifically, we provide out-of-sample evidence in favor of Dittmar and Thakor's (2007) theory that agreement between managers and outside investors increases the likelihood of stock issuance.

We propose two broad explanations for our results. First, we argue that small firms are less attractive to large acquirers that make the majority of stock acquisitions. This is because they offer only a small potential for diluting the overvaluation of acquirer stock, especially if there are significant transaction costs in the acquisition process. Second, we argue that small firms are more resistant to overpriced stock offers.

Our results complement an existing literature which suggests that small firms perform better in other contexts. For example, Moeller, Schlingemann, and Stulz (2004) show that small firms deliver better returns to their shareholders as acquirers, and Alexandridis, Fuller, Terhaar, and Travlos (2013) show that small target firms receive higher acquisition premium. We find that small firms also deliver better performance as targets, so a combined picture emerges that small firms do well in many roles in the mergers and acquisitions process. In addition, our results complement McConnell and Nantell (1985) and Chan et al. (1997) who show that small partners in joint ventures extract a higher percent return than large partners, and Berger, Miller, Petersen, Rajan, and Stein (2005) who show that small banks are better able to collect and act on soft information than large banks to reduce their default risk.

Appendix A. Opinion divergence measures

Below we describe the construction of opinion divergence measures. We face new challenges relative to the existing literature on this topic due to our focus on small firms belonging to the bottom NYSE quartile of market values. Thus, to ensure the robustness of our tests, we report four distinct measures of opinion divergence.

A.1. Analyst forecast dispersion

Following Diether, Malloy, and Scherbina (2002) and Chatterjee, John, and Yan (2012), our first measure is analyst forecast dispersion on the firm's one-year-ahead earnings. We calculate this measure as the standard deviation of the last available forecasts of all analysts who cover a stock during a given month divided by the month-end stock price. Unfortunately, analyst forecasts are available from the Institutional Brokers' Estimate System (I/B/E/S) database for only about one-fifth of small firm-years in our sample. In addition, the small firms for which analyst forecasts are available tend to be the larger small firms. Such limitation in data coverage poses a challenge to our study as our hypothesis testing requires sufficient presence of small firms in the sample. We therefore infer analyst forecast dispersion for the remaining stocks by using fitted values from cross-sectional regressions adopted from Diether, Malloy, and Scherbina.

Specifically, each year we regress the observed analyst forecast dispersion (averaged over 12 months of the year) on the firm's market beta, percentile rank of market equity, book-to-market ratio, momentum, residual coverage (the residual from yearly regressions of ln(1+analyst coverage) on percentile rank of market equity and ln(book-to-market)), average adjusted trading volume, average adjusted turnover, debt-to-assets ratio, sales-to-assets ratio, and standard deviation of earnings per share divided by the absolute value of mean earnings per share over the last five years.[11]

Using regression coefficients, we next infer the analyst forecast dispersion in cases in which a direct estimate is not available but the firm fundamentals are available. Following Chatterjee, John, and Yan, we use the last year's values of analyst forecast dispersion (besides other independent variables) in our targetiveness regressions. Given our methodology of inferring analyst forecast dispersion in many cases using annual data on firm fundamentals, we consistently use similarly calculated last year's analyst forecast dispersion in all the relevant tests throughout the paper. Notice we do not face this data limitation for the alternate opinion divergence measures of idiosyncratic volatility and change in breadth of (mutual fund) holdings. For those two measures we follow Chatterjee, John, and Yan and calculate more recent values as described below.

A.2. Idiosyncratic volatility

Gebhardt, Lee, and Swaminathan (2001), Danielsen and Sorescu (2001), and Chatterjee, John, and Yan (2012) use idiosyncratic volatility as a measure of opinion divergence, while Moeller, Schlingemann, and Stulz (2007) use it as a measure of asymmetric information. Given credible arguments on both sides, we explore both interpretations in different tests of our paper. Further, for targetiveness tests we measure idiosyncratic volatility as the standard deviation of daily abnormal stock returns over the previous year, and for tests of acquirer overvaluation, stock payment choice, acquirer announcement returns, and acquirer long-term returns, we follow Chatterjee, John, and Yan (2012) and employ a three-month period ending 64 days before the acquisition announcement date. We measure daily abnormal stock returns as the residuals from a market model regression.

[11] See Diether, Malloy, and Scherbina (2002) for further details.

A.3. Change in breadth of (mutual fund) holdings

Chen, Hong, and Stein (2002) argue that the change in breadth of mutual fund holdings is an inverse measure of opinion divergence. Using Thomson-Reuters Mutual Fund Holdings database, we calculate this measure as the change in the number of funds holding a given stock from the previous quarter to the current quarter divided by the total number of mutual funds in the previous quarter. However, in doing so we only consider those funds that exist in both current and previous quarters. Further, instead of taking the raw value of change in breadth of holdings (denoted $\Delta BREADTH$ by Chen, Hong, and Stein), we use the residual from a univariate regression of the raw value on the corresponding change in aggregate mutual fund holdings (denoted $\Delta HOLD$ by them). The resulting measure (denoted $RESIDUAL\Delta BREADTH$ by them) is our third measure of opinion divergence. Chen, Hong, and Stein argue that this final measure isolates changes in the composition of stockholdings within the mutual fund sector, as distinct from an overall movement of shares in and out of the mutual fund sector.

We average this measure over the four quarters of the previous year in targetiveness tests. In part, this treatment is motivated by the observation that the last calendar quarter's values are more negative than the other three quarters' values, possibly due to year-end window dressing. However, for tests of acquirer overvaluation, stock payment choice, and acquirer announcement returns, we use the last available change in breadth of holdings as of 64 days before the acquisition announcement date as suggested in Chatterjee, John, and Yan (2012).

A.4. Ranked excess turnover around earnings releases

Garfinkel (2009) constructs a measure of opinion divergence based on proprietary limit order and market order data. This measure equals the standard deviation of the percent distance between price at which an order is submitted and the market price prevailing at the time of order submission on any given day. He relates this measure to several proxies for opinion divergence and concludes that proxies based on unexplained turnover or volume work the best. However, Garfinkel's tests are based on a relatively short event period of January to March 2002 and a benchmark period of December 2001. Implementing his measures to a large panel data set of firm-years for which there is no explicit event as in targetiveness tests presents new challenges that we address as follows.

We argue that earnings announcements are very significant and periodic events associated with formation and revision of individual heterogeneous beliefs about the firm value (Scherbina, 2001). Accordingly, each year we define an event period as the 12 days surrounding the four earnings announcements for a given stock. In addition, we define a benchmark period as the remaining days of the year. Following Garfinkel and Sokobin (2006) and Garfinkel (2009), we first calculate unexplained market-adjusted turnover (denoted MATO by them) as follows:

$$\Delta TO_i = \left[\left(\frac{Vol_{i,t}}{Shs_{i,t}}\right)_{\text{firm}} - \left(\frac{Vol_t}{Shs_t}\right)_{mkt}\right]_{\text{averaged over earnings period}} - \left[\left(\frac{Vol_{i,t}}{Shs_{i,t}}\right)_{\text{firm}} - \left(\frac{Vol_t}{Shs_t}\right)_{mkt}\right]_{\text{averaged over non-earnings period}}$$

In this equation, Vol denotes shares traded and Shs denotes shares outstanding. Subscript i denotes firm and t denotes date.

Unexplained market-adjusted turnover around earnings announcements as calculated above has a strong time trend. There was a sharp increase in market turnover during both earnings and non-earnings announcement periods during the long period of our study. In fact, we find a Pearson correlation of 0.89 and a Spearman correlation of 0.95 between calendar year and unexplained market-adjusted turnover around earnings announcements. To abstract from this time trend, we calculate the percentile rank of this measure by year and use that rank as our fourth and final measure of opinion divergence. We refer to this measure as ranked excess turnover around earnings releases. Unfortunately, it has the limitation that it abstracts from any time trend in opinion divergence arising from changes in market-wide investor sentiment as hypothesized by Chatterjee, John, and Yan (2012). The required ranking by the year also means that we use the values as of last year in all tests of targetiveness, acquirer overvaluation, stock payment choice, and acquirer announcement returns.[12]

Appendix B. Previous literature on targetiveness (also known as takeover likelihood) models

Article	Topic	Sample	Size proxy	Coefficient of size proxy
Palepu (1986)	Examine whether takeover targets can be predicted with sufficient accuracy using public data	163 firms that were acquired and 256 firms that were not acquired during 1971–1979	Net book value of assets	Significantly negative
Ambrose and Meg-ginson (1992)	Analyze the role of asset structure, ownership structure, and takeover defenses in takeover likelihood	170 firms that were targeted and 273 firms that were not targeted during 1979–1986	Net book value of assets	Insignificant
Song and Walk-ling (1993)	Examine the role of managerial ownership in takeover	459 firms including 153 targets, 153 same-industry non-targets,	Within sample size decile rank based on market	Significantly negative in combined sample but insignificant

[12] We also test but do not report an alternate measure of opinion divergence based on standardized unexplained volume (SUV) as described by Garfinkel and Sokobin (2006) and Garfinkel (2009). It shows a similar time trend and requires ranking by the year. The results are similar.

	likelihood and target shareholder returns	and 153 random non-targets	value of equity	in subsamples
Billett (1996)	Examine the relationship between risky debt and takeover likelihood	448 firms for which credit ratings data were available during 1979–1990	Log of market value of equity adjusted by S&P 500 index to 1987 dollars	Significantly negative
Powell (1997)	Examine takeover likelihood function for hostile vs. friendly offers and role of industry characteristics	943 firms listed on London Stock Exchange (LSE) during 1984–1991, including 97 hostile targets, 314 friendly targets, and 532 non-targets	Log of total assets	Significantly positive in takeover likelihood of hostile targets, and significantly negative for friendly targets
North (2001)	Examine the role of managerial incentives and outside block ownership during the 1990s	342 banks that were acquired and 342 matching banks that were not acquired during 1990–1997	Log of total assets	Insignificant
Heron and Lie (2006)	Examine the role of poison pills and defensive payouts by takeover targets	526 firms that received unsolicited takeover offers during 1985–1998, 110 were acquired immediately and 330 within three years	Log of market value of equity	Significantly negative in one regression, insignificant in another regression
Cai and Vijh (2007)	Examine the role of illiquid stock and option holding of target and acquirer CEOs	8,704 firm-years listed on CRSP, Compustat, ExecuComp, and Investor Responsibility Research Center (IRRC) during 1993–2001	Log of market value of equity	Insignificant
Powell and Yawson (2007)	Build a takeover likelihood model with a comprehensive sample of firm-years	9,537 firm-years listed on LSE during 1992–2001	Log of total assets	Significantly positive during aggregate period and subperiods
Champagne and Kryzanowski (2008)	Examine the impact of past syndicate alliances on consolidation of financial institutions	60,692 syndicate loan deals from Dealscan during 1987–2004, and 5,014 merger deals	Log of book value of assets	Significantly positive
Cremers, Nair, and John (2009)	Examine whether there is a takeover factor in returns	83,752 firm-years during 1981–2004	Log of market value of equity	Significantly negative in three regressions, but with *t*-statistics of 1.92, 1.99, and 2.11 despite large sample, insignificant in one regression

References

Alexandridis, G., Fuller, K., Terhaar, L., Travlos, N., 2013. Deal size, acquisition premia and shareholder gains. Journal of Corporate Finance 20, 1–13.

Ambrose, B., Megginson, W., 1992. The role of asset structure, ownership structure, and takeover defenses in determining acquisition likelihood. Journal of Financial and Quantitative Analysis 27, 575–589.

Andrade, G., Mitchell, M., Stafford, E., 2001. New evidence and perspectives on mergers. Journal of Economic Perspectives 15, 103–120.

Berger, A., Miller, N., Petersen, M., Rajan, R., Stein, J., 2005. Does function follow organizational form? Evidence from the lending practices of large and small banks. Journal of Financial Economics 76, 237–269.

Billett, M., 1996. Targeting capital structure: the relationship between risky debt and the firm's likelihood of being acquired. Journal of Business 69, 173–192.

Boone, A., Lie, E., Liu, Y., 2011. Mixed-payment deals and target shareholder preferences for method of payment. Unpublished working paper. Texas A&M University, University of Iowa, and University of New Hampshire.

Bouwman, C., Fuller, K., Nain, A., 2009. Market valuation and acquisition quality: empirical evidence. Review of Financial Studies 22, 633–679.

Cai, J., Vijh, A., 2007. Incentive effects of stock and option holdings of target and acquirer CEOs. Journal of Finance 62, 1891–1933.

Champagne, C., Kryzanowski, L., 2008. The impact of past syndicate alliances on the consolidation of financial institutions. Financial Management 37, 535–570.

Chan, S., Kensinger, J., Keown, A., Martin, J., 1997. Do strategic alliances create value? Journal of Financial Economics 46, 199–221.

Chang, S., 1998. Takeovers of privately held targets, methods of payment, and bidder returns. Journal of Finance 53, 773–784.

Chatterjee, S., John, K., Yan, A., 2012. Takeovers and divergence of opinion. Review of Financial Studies 25, 227–277.

Chen, J., Hong, H., Stein, J., 2002. Breadth of ownership and stock returns. Journal of Financial Economics 66, 171–205.

Chevalier, J., Ellison, G., 1999. Career concerns of mutual fund managers. Quarterly Journal of Economics 114, 389–432.

Core, J., Guay, W., Rusticus, T., 2006. Does weak corporate governance cause weak stock returns? An examination of firm operating performance and investors' expectations. Journal of Finance 61, 655–687.

Cremers, K., Nair, V., John, K., 2009. Takeovers and the cross-section of returns. Review of Financial Studies 22, 1409–1445.

Danielsen, B., Sorescu, S., 2001. Why do option introductions depress stock prices? A study of diminishing short sale constraints. Journal of Financial and Quantitative Analysis 36, 451–484.

Diether, K., Malloy, C., Scherbina, A., 2002. Differences of opinion and the cross-section of stock returns. Journal of Finance 57, 2113–2141.

Dittmar, A., Thakor, A., 2007. Why do firms issue equity? Journal of Finance 62, 1–54.

Dlugosz, J., Fahlenbrach, R., Gompers, P., Metrick, A., 2006. Large blocks of stock: prevalence, size, and measurement. Journal of Corporate Finance 12, 594–618.

Dodd, P., 1980. Merger proposals, management discretion, and stockholder wealth. Journal of Financial Economics 8, 105–137.

Faccio, M., Masulis, R., 2005. The choice of payment method in European mergers and acquisitions. Journal of Finance 60, 1345–1388.

Fuller, K., Netter, J., Stegemoller, M., 2002. What do returns to acquiring firms tell us? Evidence from firms that make many acquisitions. Journal of Finance 57, 1763–1793.

Garfinkel, J., 2009. Measuring investors' opinion divergence. Journal of Accounting Research 47, 1317–1348.

Garfinkel, J., Sokobin, J., 2006. Volume, opinion divergence, and returns: a study of post-earnings announcement drift. Journal of Accounting Research 44, 85–112.

Gebhardt, W., Lee, C., Swaminathan, B., 2001. Toward an implied cost of capital. Journal of Accounting Research 39, 135–176.

Hansen, R., 1987. A theory for the choice of exchange medium in mergers and acquisitions. Journal of Business 60, 75–95.

Heron, R., Lie, E., 2006. On the use of poison pills and defensive payouts by takeover targets. Journal of Business 79, 1783–1807.

Holmstrom, B., Kaplan, S., 2001. Corporate governance and merger activity in the United States: making sense of the 1980s and 1990s. Journal of Economic Perspectives 15, 121–144.

Hong, H., Kubik, J., Solomon, A., 2000. Security analysts' career concerns and herding of earnings forecasts. RAND Journal of Economics 31, 121–144.

Hunter, W., Walker, M., 1990. An empirical examination of investment banking merger fee contracts. Southern Economic Journal 56, 1117–1130.

Loughran, T., Vijh, A., 1997. Do long-term shareholders benefit from corporate acquisitions? Journal of Finance 52, 1765–1790.

Lys, T., Vincent, L., 1995. An analysis of value destruction in AT&T's acquisition of NCR. Journal of Financial Economics 39, 353–378.

McConnell, J., Nantell, T., 1985. Corporate combinations and common stock returns: the case of joint ventures. Journal of Finance 40, 519–536.

McLaughlin, R., 1992. Does the form of compensation matter? Investment banker fee contracts in tender offers. Journal of Financial Economics 32, 223–260.

Moeller, S., Schlingemann, F., Stulz, R., 2004. Firm size and the gains from acquisitions. Journal of Financial Economics 73, 201–228.

Moeller, S., Schlingemann, F., Stulz, R., 2005. Wealth destruction on a massive scale? A study of acquiring-firm returns in the recent merger wave. Journal of Finance 60, 757–782.

Moeller, S., Schlingemann, F., Stulz, R., 2007. How do diversity of opinion and information asymmetry affect acquirer returns? Review of Financial Studies 20, 2047–2078.

Myers, S., Majluf, N., 1984. Corporate financing and investment decisions when firms have information that investors do not have. Journal of Financial Economics 13, 187–221.

Netter, J., Stegemoller, M., Wintoki, M., 2011. Implications of data screens on merger and acquisition analysis: a large sample study of mergers and acquisitions from 1992 to 2009. Review of Financial Studies 24, 2316–2357.

North, D., 2001. The role of managerial incentives in corporate acquisitions: the 1990s evidence. Journal of Corporate Finance 7, 125–149.

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

Powell, R., 1997. Modeling takeover likelihood. Journal of Business Finance and Accounting 24, 1009–1030.

Powell, R., Yawson, A., 2007. Are corporate restructuring events driven by common factors? Implications for takeover prediction. Journal of Business Finance and Accounting 34, 1169–1192.

Rau, P., Vermaelen, T., 1998. Glamour, value and the post-acquisition performance of acquiring firms. Journal of Financial Economics 49, 223–253.

Rhodes-Kropf, M., Viswanathan, S., 2004. Market valuation and merger waves. Journal of Finance 59, 2685–2718.

Savor, P., Lu, Q., 2009. Do stock mergers create value for acquirers? Journal of Finance 64, 1061–1097.

Scherbina, A., 2001. Stock prices and differences of opinion: empirical evidence that prices reflect optimism. Unpublished working paper. University of California, Davis.

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

Sialm, C., Starks, L., 2012. Mutual fund tax clienteles. Journal of Finance 67, 1397–1422.

Song, M., Walkling, R., 1993. The impact of managerial ownership on acquisition attempts and target shareholder wealth. Journal of Financial and Quantitative Analysis 28, 439–457.

Song, M., Walkling, R., 2000. Abnormal returns to rivals of acquisition targets: a test of the 'acquisition probability hypothesis.'. Journal of Financial Economics 55, 143–171.