Are small firms less vulnerable to overpriced stock offers?

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Abstract

We document 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 with greater overvaluations. 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 attractive to overpriced stock acquirers, and also that their managers are less receptive to overpriced stock offers which expropriate the wealth of their long-term shareholders. Several additional results support this hypothesis. First, the stock acquirers of small targets are less overvalued than the stock acquirers of large targets, but an opposite result holds for cash acquirers. Second, the acquirer announcement returns following stock offers are less negative for small targets than for large targets. Moreover, this certification effect increases for acquirers facing greater information asymmetry. Third, the stock acquirers of small targets earn higher long-term returns than the stock acquirers of large targets.

Keywords: Firm size effect; mergers and acquisitions; overvaluation; uncertainty; opinion divergence; asymmetric information; equity issuance

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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) document that stock acquirers earn negative long-term excess returns on average. Savor and Lu (2009) provide further evidence by documenting 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 empirically demonstrate that small firms are less vulnerable to overpriced stock offers that expropriate the wealth of their long-term shareholders than large firms.

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 may depend 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 the managers of small firms exercise greater control over the key decisions of their firms (Demsetz and Lehn, 1985; Morck, Shleifer, and Vishny, 1988; Mikkelson and Partch, 1989; this paper).[2] This makes them more resistant to overpriced stock offers that are not in the interests of their long-term shareholders (including themselves).

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 contradicts a common belief that small firms are easier to acquire (starting with Palepu, 1986). To test this prediction, we carefully construct a comprehensive dataset of 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.[3] Using this dataset 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 focus on the 3,669 acquisitions where both the target and acquirer are U.S. public firms, 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 identical to the definition used by Moeller, Schlingemann, and Stulz (2004) in comparing the performance of small versus large firms as acquirers.

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[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 may 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 may be due to lack of skills and resources.

[2] Consistent with this argument of greater control, we show that the proportions of hostile offers, contested offers, and tender offers made directly to target shareholders are lower for small target firms than for large target firms.

[3] We further require post-acquisition returns for three years after completion, which extends the data period to 2008.

Interestingly, we find that the lower targetiveness of small firms relative to large firms in the aggregate sample describes stock and mixed 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 market-wide overvaluation. We divide our aggregate sample period into two subperiods: hot markets, spanning 1995 to 2000, and normal markets, spanning the remaining years, 1981 to 1994 and 2001 to 2004. If we combine all payment methods and firm sizes, the targetiveness during hot markets is 2.21 times the targetiveness during normal markets. Not surprisingly, this increase is also driven by a greater increase in the number of stock acquisitions relative to the number of cash acquisitions. More interestingly, within the subset of stock acquisitions, the increase is greater for large firms, by a factor of 3.91, than for small firms, by a factor of 3.03. In contrast, cash acquisitions increase 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 document 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 the managers of 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 document 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 may 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, 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 document. 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, acquirer announcement returns, and acquirer long-term 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. More interestingly, the differences between the overvaluation measures become smaller if we look at mixed acquisitions and even change direction if we look at cash acquisitions. 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 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 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. To test this prediction 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 price effects. 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 earnings, this evidence provides strong support for the certification effect of small targets in particular and the vulnerability hypothesis in general.

In the following tests we examine long-term returns for differences in the overvaluation of the acquirers of small and large target firms. We compute industry, size, and book-to-market adjusted buy-and-hold excess returns for acquirer stocks over a three-year period after the acquisition completes. These excess returns average 2.4% for stock acquirers of small target firms and -20.1% for stock acquirers of large target firms. The difference of 22.5% is highly significant. We also find that the long-term excess returns of acquirers are related to each of the three overvaluation measures (prior-year return, log market-to-book ratio, and hot market dummy) in the case of stock acquisitions.

So far our results are 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 overtures. However, this may not be the sole explanation for all of the stylized facts in our paper. Thus, in the remaining paper we explore a few alternate explanations before concluding that the combined evidence can only be explained by the vulnerability hypothesis.

Chang (1998) and Fuller, Netter, and Stegemoller (2002) propose that the higher acquirer announcement returns to stock acquisitions of private targets can be explained by the emergence of a new blockholder in the combined firm who monitors the managers. If stock acquisitions of small public targets are more likely to result in a new blockholder than stock acquisitions of large targets, it might offer an alternate explanation of our results. In particular, acquirers may avoid stock payment to small targets if it would create a potentially contentious new blockholder, but the market may react more positively to stock acquisitions of small targets given the higher incidence of new monitoring blockholders. However, our investigation does not support this explanation. The emergence of a new blockholder depends on the existence of a large blockholder in the target firm, which is more likely for small targets, but also its relative size, which is lower for small targets. Thus, we find that there is no significant difference between

the frequency of new blockholders in acquisitions of small targets and large targets. We also find that the emergence of a new blockholder is not related to the likelihood of stock payment.

We next 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. Thus, 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 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. We finally explore the role of corporate governance and find that it cannot explain our results.

Our paper makes several contributions to the literature. First, contrary to a common belief, we show that targetiveness does not increase monotonically with decreasing firm size. 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 et al. (2012), 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 all roles in the mergers and acquisitions process. Third, our paper relates to the asset pricing literature on firm size. Many papers document that there is a small firm premium in returns. These papers analyze returns until a firm ceases to exist, due to dissolution, bankruptcy, or acquisition. Our paper suggests that the difference between returns to shareholders of small and large firms may be even higher if one includes their performance for a few years beyond the date when their original firm ceases to exist but they continue to hold the acquirer stock received in merger.

Section 2 discusses data and methods. Section 3 examines the relation between targetiveness and firm size, and Section 4 examines the prior valuation of acquirer stocks. Section 5 examines the long-term returns, and Section 6 reports miscellaneous results and robustness tests. Section 7 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 to 2004, but our tests require three-year returns after acquisition completion, which extends the data period to 2008. 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 to 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 US public firm and can be identified on CRSP. 5. The target share code is 10 or 11. 6. The completion date is between 1 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.

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 merger-related delistings included in the CRSP database are not included in the SDC dataset. We hand-check all of these cases using Factiva and Lexis/Nexis reports to identify instances where 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 to 2004. We assume that a firm is targeted during the year when the acquisition is announced.

The top panel of Figure 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 Figure 1 also shows that there is a simultaneous increase in percent of all acquisitions that were 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 mix 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 cut-off 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.[4]

Figure 2 shows the upper cutoffs corresponding to the first, second, and third NYSE size quartiles using market value of equity in the top panel and market value of assets in the bottom panel. In the beginning of the sample period in 1981, these cutoffs are $76 million, $231 million, and $719 million for

[4] 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 SIC code or Fama-French 48-industry, 12-industry, or even 5-industry code.

market value of equity. 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. (The same goes for market value of assets in the bottom panel.) Second, the third quartile cutoff during 1981 is comparable in value to the first quartile cutoff during 2004, so ranking within the year is necessary.

2.3. Identification of hot markets versus normal markets

We identify the period 1995 to 2000 as a hot market and the remaining periods of 1981 to 1994 and 2001 to 2005 as a normal market for mergers and acquisitions due to several reasons. First, Figure 1 shows that both the number of acquisitions and the percent stock acquisitions rose sharply during this period as suggested by Shleifer and Vishny (2003). Second, to identify the first and last years of hot market, we note 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 number of stock indexes peaked in March 2000 and declined during the rest of 2000. The 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 to 2000, which was much higher than the corresponding ratio of 15.97 during 1981 to 1994 and 2001 to 2004.[5]

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 1 reports the motivation and the calculation of these measures.

The top panels of Figure 3 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

[5] 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.

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.

Figure 3 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 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. Note that the changes are usually in the same direction for all size quartiles. Finally, for comparison the lower panel of Figure 3 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 firm's targetiveness, which is defined as the probability rate that the firm will be acquired over a one-year period. Considerable finance research has been focused on understanding the cross-sectional determinants of targetiveness to get a better insight to firm value. More recently, Cremers, Nair, and John (2009) show that there is a strong targetiveness factor in stock returns, which further emphasizes the importance of this issue.

While targetiveness in all forms is good for short-term shareholders of target firms who cash out for a substantial acquisition premium, the same is not necessarily true for 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, with greater control over key decisions of their firms the managers of small firms may be less likely to accept potentially overpriced stock offers. The combination of these influences predicts an inverted-U relation between targetiveness and firm size.

To the best of our knowledge previous literature has not proposed or tested such a non-monotonic relation. As an example, Appendix 2 lists eleven studies published during 1986 to 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 size coefficient in previous literature reflect two common reasons. First, each study uses a linear functional form of firm size, which is typically the book value of assets or the market value of equity, or a log-transform of either variable. However, our hypothesis predicts an inverted-U relation, which suggests a quadratic functional form. Second, many previous studies pool together book values or market values of firms over several years with little or no adjustment for the time trend in these variables. As described in Figure 2 and Section 2.2, there has been a strong time trend in book values and market values of U.S. firms. We therefore measure a firm's size relative to all firms at a given point in time using the Fama-French procedure based on NYSE percentile ranks. Below we report the results of targetiveness analysis with these innovations.

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 samples of firm-years by percentile rank. Recall that the aggregate sample includes all acquisitions for which the target is a U.S. public firm, but the acquirer can be public or private, foreign or

domestic. The aggregate sample also combines all payment methods. As expected, there are an increasing number of firms with lower ranks. For each size tranche 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.

The first set of columns in Panel A of Table 2 use market value of equity as a size measure and show 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 use market value of assets as a size measure and show 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 quadratic functional form. Regression (2.1) uses market value of equity as the size measure and Regression (2.2) 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. 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 control variables are described below.

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 document empirical evidence in support of this opinion divergence hypothesis, so we include opinion divergence in our multivariate tests. In addition, 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. 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.[6]

Regressions (3.1) to (3.5) in Panel A 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. This 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 completed acquisitions in Chatterjee, John, and Yan and this study and some necessary differences in the computation of opinion divergence measures as well (see Appendix 1).

Regressions (3.6) to (3.10) in Panel B of Table 3 use the market value of assets as a size measure and find similar results to Regressions (3.1) to (3.5). 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 may 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

[6] We also try control variables similar to those used by Chatterjee, John, and Yan (2012) and find similar results.

payment acquisitions where 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 home-made 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.[7]

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 and mixed acquisitions by public acquirers whose stock becomes overpriced from time to time. In the following tests we therefore focus on the subset of 3,669 acquisitions by public acquirers, which can be categorized by the payment method.[8] We measure firm size by the market value of equity for which the data are always available. The sample includes the 158,194 firm-years from Table 2.

Table 4 shows that for stock payment the targetiveness values equal 1.04%, 1.30%, 1.15%, and 0.98% across the four size quartiles arranged in ascending order. When we aggregate the firms belonging to the second, third, and fourth size quartiles as large firms, their targetiveness value equals 1.18%. The difference between the targetiveness values of small and large firms thus equals -0.14% for stock payment and is significantly different from zero with a *p*-value of 0.011 (using a chi-square test). Looking further, the difference between the targetiveness values of small and large firms is even bigger at -0.23% for mixed payment, with a *p*-value of 0.000. However, in sharp contrast with stock and mixed payment cases, the targetiveness values decrease monotonically with increasing size quartile rank for cash acquisitions, equaling 0.70%, 0.67%, 0.53%, and 0.18%. The difference between the targetiveness values of small and large firm-years for cash payment equals 0.18%, with a *p*-value of 0.000.

[7] Before 2001 acquirers could also use 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.

[8] This excludes only 12 cases for which the payment method could not be identified.

The results of Table 4 show that the inverted-U relation between targetiveness and firm size in the aggregate sample is driven by stock and mixed payment acquisitions made by public acquirer firms. This evidence is consistent with our vulnerability hypothesis.

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 document 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 overvaluation-driven hot markets. 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. Figure 4 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 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. In the aggregate sample combining all payment methods, the targetiveness value of small firms equals 1.73% during normal markets and 3.61% during hot markets. The corresponding values for large firms equal 1.67% and 4.14%. The targetiveness value increases by a ratio of 3.61/1.73 = 2.09 for small firms and 4.14/1.67 = 2.48 for large firms. We test the equality of these ratios by using a simulation procedure described in Table 5. It rejects their equality with a significance level of 1%.

We next separate our sample by payment method. The ratios of targetiveness values during hot markets and normal markets are the highest for stock acquisitions, taking values of 3.03 for small firms and 3.91 for large firms. The difference is statistically significant at 1% level. The evidence is in the same direction but weaker for mixed acquisitions, still significant at 5% level. More interestingly, the evidence is in the opposite direction for cash acquisitions. The ratio of targetiveness values during hot markets and normal markets in this case equals 1.65 for small firms and 1.55 for large firms. Even though the difference is statistically insignificant in this last case, the contrasting patterns for stock offers and cash offers are still intriguing. They suggest an active shift between the methods of payment for small vs. large firms during hot markets characterized by greater overvaluation 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 may 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, Figure 3 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.[9] This evidence does not correspond well with the doubled 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 divided by target size. While the target and acquirer characteristics are in line with those documented in previous studies, looking at deal characteristics we find interesting evidence on greater control exercised by the managers of small targets as follows. First, if managers of small firms exercise greater control, it may 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

[9] 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 to 2000, which may be a necessary ingredient for higher valuations. However, this impression is supported by year-end sentiment data (obtained from the web-site 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.

frequencies is statistically significant. Overall, we find that the managers of small target firms exercise greater control over their key decisions, which make them less vulnerable to overpriced stock offers.

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 Figure 5.

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 1% level. Consistent with our vulnerability hypothesis, this evidence shows that the stock acquirers of small targets are less overvalued than the 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, although statistically insignificant. The evidence for mixed payment cases lies in between the stock and cash payment cases.

Since Figure 4 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 Figure 5 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 middle panel of Figure 5 shows that the above trend is moderated for mixed payment, but it is generally in the same direction as stock payment. In contrast, the trend is reversed in all three acquirer size quartiles for cash payment. 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% and -0.1% in the second quartile. The consistently opposite patterns for stock and cash acquisitions across acquirer size quartiles support the vulnerability hypothesis.[10]

We should point out that in tests of Figure 5 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. Figure 6 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 Figure 5. 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. The evidence for mixed payment cases lies between the cash and stock payment cases.

Figures 5 and 6 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 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. To this we add a hot market dummy as another measure of acquirer valuation. This

[10] Keeping aside the *t*-statistics that are examined in Table 7, the simple probability that all three differences are positive for stock acquisitions and negative for cash acquisitions by random chance is the order of 0.5^6, or around 1%. Mixed acquisitions lie in between stock and cash acquisitions and increase this significance level.

dummy takes the value of one if acquisition is announced during 1995 to 2000, and zero otherwise. More importantly, we include an interaction effect of each valuation measure with a small target dummy, which takes the value of one for target firms belonging to the bottom NYSE size quartile, and zero otherwise. The dependent variable is a stock payment dummy that takes the value of one for stock acquisitions, and zero for cash acquisitions. Mixed acquisitions are excluded from this test.

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 may 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 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 firm is the first and arguably the most important roadblock, we also use alternate disagreement measures that include a hostile dummy, a tender offer dummy, and a competing offer dummy.[11] 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

[11] 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.

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.[12] 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, 2009). 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 valuation measures – prior-year excess return, log market-to-book ratio, and hot market dummy – one at a time in Regressions (7.1) to (7.3). The results are striking. Each valuation measure is positive and highly significant but its interaction with 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

[12] 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.)

measure. Finally, multivariate 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) 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). Regressions (7.5) to (7.8) provide further support for the agreement model. We also find that the coefficient of target's mutual fund ownership is negative and usually significant, which suggests that tax considerations of remaining shareholders favor stock payment. However, the time-varying adverse selection measure is insignificant.[13,14]

More important to our hypothesis, the effects of the three valuation measures and their interactions with a small target dummy remain 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 much less descriptive of small targets than of large targets. In alternate terms, the same percent overvaluation increases the probability of a stock acquisition by a greater magnitude for large targets than for small targets. This evidence supports our main hypothesis that small firms are less vulnerable to overpriced stock offers.

4.5. Does 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

[13] In reported results we do not include time-varying adverse selection measure in regressions that include the hot-market dummy since the two have similar motivation. However, in untabulated tests we tried adding each of three different measures of time-varying adverse selection to Regression (7.4) (average volatility, a dummy that takes the value one if acquisition is announced within 30 days of an earnings announcement following Dittmar and Thakor, or investor sentiment). The time-varying adverse selection measures were either insignificant or significant in the opposite direction. However, the coefficients of the hot-market dummy and its interaction with the small target dummy were qualitatively similar.

[14] 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. 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).

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%, -0.30%, and 0.95% for stock, mixed, and cash acquisitions (*t*-statistics -2.30, -0.93, and 4.14). The corresponding values for the subsample of all large targets equal -3.40%, -2.19%, and -0.03% (*t*-statistics -9.27, -5.59, 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%, 1.89%, and 0.98% in stock, mixed, and cash acquisitions (*t*-statistics 4.36, 3.71, 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 is 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 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 main 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 may 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.[15]

Table 8 describes the remaining variables included in the acquirer announcement excess return regressions and gives the variable definitions. Regressions (8.1) and (8.5) 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 1% level. The difference of 2.96% is significant at 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 also insignificant. Acquirer's idiosyncratic volatility is significantly negative in one case, as predicted for stock acquisitions, and insignificant in the other two cases. More importantly, the coefficient of the small target dummy ranges between 2.37% and 3.51%, all significant at 1% level. The bottom row of Table 8 shows that even after subtracting the coefficient of small target dummy for cash acquisitions from Regression (8.6) 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.

We next examine whether the certification effect is stronger in cases where 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

[15] Notice the dual role of idiosyncratic volatility as a measure of information asymmetry (between managers and shareholders) in Moeller, Schlingemann, and Stulz (2007) and opinion divergence (between shareholders) in Chatterjee, John, and Yan (2012). We ignore this ambiguity and include both idiosyncratic volatility and another opinion divergence measure in our regressions to control for known empirical effects.

forecast dispersion, which is the only opinion divergence measure significant as predicted in Table 8, but drop its interaction with relative size, which is insignificant. 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 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 10% level.[16]

In summary, Tables 8 and 9 shows 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 supports the vulnerability hypothesis.

5. Long-term returns to the acquirers of small and large targets

5.1. Payment method, target size, acquirer size, and long-term returns

The cumulative evidence of previous tables and figures strongly suggests that stock acquirers of small targets are better-valued than stock acquirers of large targets. This should lead to differences in their long-term returns. Besides, from an investor's perspective it is important to know which type of acquirer stocks yield superior long-term returns.

We calculate long-term excess returns as the difference between buy-and-hold returns of the acquirer firms and the industry, size, and book-to-market matching firms over the period (+1,+757) days relative to the completion date of the acquisition. Loughran and Vijh (1997) argue that buy-and-hold returns capture the investor experience better than monthly rebalanced returns. Besides, buy-and-hold returns can be related to firm characteristics to derive a better understanding of their causal factors. Lyon, Barber, and Tsai (1999) show that in random samples buy-and-hold excess returns using only size and book-to-market control firms and conventional *t*-statistics are well-specified over all holding periods of up to five years. However, they caution that in non-random samples showing industry clustering one may

[16] 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.

need to control for industry effects. Our sample does not show industry clustering, but to be conservative we select matching firms that control for industry factors in addition to size and book-to-market factors in long-term returns. The matching procedure is described in Table 10.

As usual, we arrange our aggregate sample of acquirers into subsets formed by payment method and target size. On average, the stock acquirers of small targets earn three-year post-acquisition buy-and-hold excess returns of 2.4%, insignificant, and the stock acquirers of large targets earn -20.1%, significant at 1% level. The difference between these excess returns equals 22.5%, significant at 1% level. The corresponding difference between excess returns for mixed and cash acquirers equals -2.7%, insignificant, and 16.4%, significant at 1% level. While our vulnerability hypothesis explains the long-term evidence for stock acquirers, it cannot explain the evidence for cash acquirers. It is possible that this latter evidence is partly explained by variants of the wealth destruction hypothesis such as those advanced by Moeller, Schlingemann, and Stulz (2005).

5.2. Are long-term excess returns explained by prior overvaluation of acquirer stocks?

We next examine whether the differences between the long-term returns of the acquirers of small targets and large targets can be partly explained by the differences in their prior valuations. Table 10 reports multivariate regressions of the three-year post-acquisition buy-and-hold excess returns separately for each payment method. We winsorize the long-term returns and prior-year returns and the log market-to-book ratios at 1% level to reduce the influence of outliers in regressions.

Regressions (10.1) to (10.3) report the evidence for stock payment. Regression (10.1) shows a univariate analysis with small target dummy as the only independent variable. It has a coefficient of 15.99%, significant at 1% level. Regression (10.2) next introduces all three overvaluation measures at the same time. Each measure is economically and statistically significant. The strongest relation is between the long-term excess returns and prior-year excess returns. Thus, there is a strong pattern of reversals in returns. The coefficient of prior-year excess return equals -0.13, significant at 1% level, which suggests a 0.13% reversal for every 1.00% of prior return. In addition, the coefficient of acquirer's log market-to-book ratio equals -9.60, significant at 5% level, and the coefficient of hot market dummy equals -9.81, significant at 10% level. Recall from Section 4 that the acquirers of small targets have lower log market-

to-book ratios than the acquirers of large targets, and that small firms are relatively resistant to accepting stock offers during hot markets. The coefficient of small target dummy equals 10.88%, which is a reduction of 5.11% from the corresponding coefficient in univariate Regression (10.1). Thus, roughly one-third of the small target effect in long-term returns (alternately, poor long-term returns to acquirers of large targets) is explained by the differences in prior valuation measures. Notice we compute excess returns using industry, size, and book-to-market matching firms, which washes away some of the effect of prior variables that may be a growth-firm effect common to all other firms.

Regression (10.3) introduces three more control variables: acquirer's idiosyncratic volatility, a tender offer dummy, and a hostile dummy. This has little effect on the results from Regression (10.2). Among the additional variables, only acquirer's idiosyncratic volatility is significant. This is interesting. Moeller, Schlingemann, and Stulz (2007) show that acquirer announcement returns are negatively related to volatility in stock acquisitions, which was partially supported by our results in Table 8. The new evidence in Table 10 shows that this evidence extends to acquirer's long-term returns.

Regressions (10.4) and (10.5) next report the multivariate analysis of mixed payment and cash payment cases. All coefficients of prior valuation measures are insignificant in these regressions. This suggests that in mixed and cash payment cases these valuation measures mainly represent a normal growth-firm or value-firm effect common to all other firms and not a significant overvaluation effect. The coefficient of small target dummy in cash payment cases remains significant, suggesting that there may be other influences behind the target size effect in long-term returns. As an interesting side result, the coefficient of acquirer's idiosyncratic volatility is insignificant for mixed payment and significantly positive for cash payment. This strengthens the evidence that there is adverse selection in mergers and acquisitions that increases with information asymmetry and affects long-term returns.

6. Miscellaneous results and robustness tests

6.1. Is the small target effect explained by the formation of new blockholders in merged firms?

Chang (1998) and Fuller, Netter, and Stegemoller (2002) 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 (owner of at least a 5% equity stake). If stock acquisitions of small public targets are also more likely to result in a new blockholder than stock acquisitions of large targets, it might offer an alternate explanation of our results. In particular, acquirers may avoid stock payment to small targets if it would create a potentially contentious new blockholder, but the market may react more positively to stock acquisitions of small targets on average given the higher incidence of new monitoring blockholders.

We use the blockholder dataset created by Dlugosz et al. (2006). This dataset includes 7,649 firm-years during 1996 to 2001, a period of high acquisition activity. We merge this data with our sample of firms that were successfully targeted. This gives 402 matches including 112 small targets and 290 large targets. In 361 cases (90% of total) there is at least one blockholder in the target firm. However, this blockholder's ownership in the merged firm falls to (Prior Ownership × Relative size / (1 + Relative size)) after a stock acquisition, which may or may not exceed 5%. Thus, even though small target firms have higher ownership concentration, given smaller relative size their stock acquisitions are not necessarily more likely to create new blockholders in the merged firm.

We conduct a few tests of the above conjecture. First, we estimate that in 77 out of 402 cases a new blockholder in the merged firm would have emerged if stock payment were used. However, the actual frequency of stock payment does not differ significantly across the 77 cases where a blockholder would have emerged or the remaining 325 cases where a blockholder would not have emerged. Second, we repeat the multivariate tests of stock payment choice in Table 7. Despite much fewer observations our focus variables remain significant but a dummy variable that equals one if stock payment would result in a blockholder is not significant. Third, looking across acquisitions of small and large targets we find that in 22% and 17% of cases there is a new blockholder and the difference between these frequencies is not significant. We conclude that our results are not explained by different likelihood of a new blockholder emerging in acquisitions of small and large targets.

6.2. The role of insider ownership and corporate governance

The next question is whether our small target effect is an insider ownership effect (even if not of the magnitude that creates a new blockholder in the merged firm) or a corporate governance effect. We

explore these questions as follows. First, we obtain stock ownership of CEOs from ExecuComp. These data exist for 16,204 firm-years in our sample. Panel A of Table 11 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 target firms exercise greater control over the key decisions of their firms, which should make them more resistant to 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 may 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 11 reports our results. It shows that the CEO's percent ownership has an insignificant effect on targetiveness. However, Panel C of Table 11 next shows that the CEO's percent ownership is related to the likelihood of stock payment in successful acquisitions, which may be due to tax reasons. This finding can be interpreted as providing further support to the vulnerability hypothesis. Small firms have higher CEO's ownership, higher CEO's 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.

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 to be better governance. Thus, one may say that small firms have marginally better governance. However, Panel B of Table 11 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 11 shows that the G-index is not related to the likelihood of stock payment. More importantly, despite much smaller samples in Table 11 relative to previous tables, our small firm and small target measures remain significant.

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

We repeated our tests by excluding the hot market years of 1995 to 2000 (not tabulated). The results remain qualitatively similar. Thus, our small target effects are not confined to hot markets of late 1990s. This is not surprising since both market-level and firm-specific measures of overvaluation are significant in multivariate tests of Tables 7 and 10. Thus, small firms are less vulnerable to overpriced stock acquirers where overpricing may be firm-specific or market-wide.

6.4. Does our small target effect overlap with the small acquirer effect?

Moeller, Schlingemann, and Stulz (2004) document an acquirer size effect, which raises the question of whether our small target effect overlaps with their small acquirer effect. We consider this to be unlikely for several reasons. First, our regressions of acquirer announcement returns in Tables 8 and 9 control for the small acquirer effect. Second, in the tests of acquirer overvaluation presented in Figures 5 and 6 the small target effect is visually prominent among acquisitions by large acquirers. Third, we nevertheless repeat the tests of Tables 7, 8, 9, and 10 by excluding small acquirers. Our results are qualitatively similar (not tabulated). Thus, our small target effect is not explained by the small acquirer effect.

6.5. Why are small target firms not acquired by small overvalued stock acquirers?

This remains anomalous to some extent and can be a topic for future research. In untabulated tests, we calculate that the acquisitiveness values of firms belonging to the four size quartiles equal 0.007, 0.030, 0.061, and 0.124 (defined as the average number of acquisitions of other public firms made by a public firm in a given size quartile over one year). While not the focus of our study, the much lower acquisitiveness of small firms helps further in understanding the lower targetiveness of small firms.

6.6. Are there other instances where small firms outperform large firms?

There is some evidence on the superior performance of small firms in other contexts. In the context of mergers and acquisitions, Moeller, Schlingemann, and Stulz (2004) show that small firms earn higher returns as acquirers than large firms. Outside this context, Berger et al. (2005) argue that small banks are better able to collect and act on soft information than large banks, which reduces their default

risk. In addition, McConnell and Nantell (1985) and Chan et al. (1997) find that smaller partners in joint ventures extract a higher percent return than larger partners. Prior literature also finds that small firms have more focused operations and that focused firms command higher valuations. Finally, an extensive literature on asset pricing finds that small firms earn higher risk-adjusted returns than large firms (using risk measures other than firm size). Our study complements these studies on the superior performance of small firms in other contexts.

7. 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 and subsequent performance 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 to 2004.

Our 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. This works to the advantage of the long-term shareholders of small target firms as we demonstrate in the following tests.

Our second 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. 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 greater need for certification. Our third set of tests look at long-term returns to understand the implications for long-term shareholders of

target firms. We find that the three-year post-acquisition returns are insignificant (but positive) for stock acquirers of small targets, and significantly negative for stock acquirers of large targets. Further, these differences in long-term returns are related to the differences in prior valuations of acquirer stocks.

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 several side results. For example, 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. In addition, while Moeller, Schlingemann, and Stulz (2007) show that increasing information asymmetry decreases (increases) the acquirer announcement returns in stock (cash) acquisitions, we show a similar result for acquirer's long-term returns.

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 the managers of small firms do a better job of protecting the interests of their long-term shareholders by being less receptive to overpriced stock offers.

Our results complement the results of Moeller, Schlingemann, and Stulz (2004), who find that small firms deliver better returns to their shareholders as acquirers. We find that small firms also deliver better returns as targets, especially to their long-term shareholders who hold on to the acquirer stock received as payment. Together, a picture emerges that small firms do a better job from both sides of the table in the mergers and acquisitions process.

Appendix 1: 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.

A1.1. 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 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 twelve 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.[1]

Using regression coefficients we next infer the analyst forecast dispersion in cases where 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

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

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.

A1.2. 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.

A1.3. 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 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).

A1.4. 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 dataset of firm-years for which there is no explicit event as in targetiveness tests presents new challenges that we address as follows.[2]

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 twelve 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:

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

[2] We wish to thank Jon Garfinkel for a discussion on these issues.

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.[3]

[3] We also test but do not report an alternate measure 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.

Appendix 2: 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 Megginson (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 Walkling (1993)	Examine the role of managerial ownership in takeover likelihood and target shareholder returns	459 firms including 153 targets, 153 same industry non-targets, and 153 random non-targets	Within sample size decile rank based on market value of equity	Significantly negative in combined sample but insignificant 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 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 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 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-year 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

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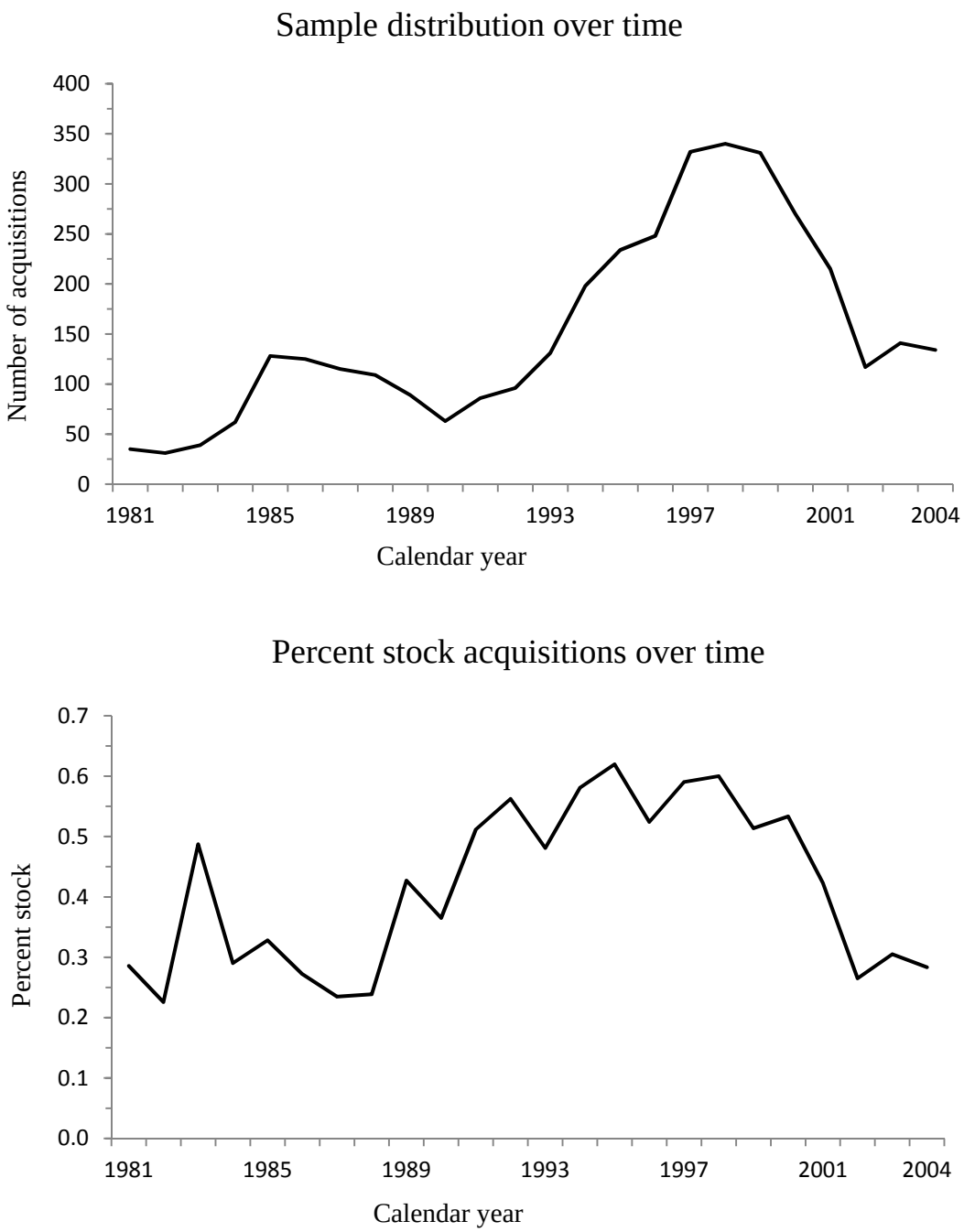

Figure 1: Sample distribution and percent stock acquisitions over time. The sample of all acquisitions during 1981 to 2004 is described in Table 1. We define cash deals as those financed with cash, liabilities, and newly-issued notes, stock deals as those financed with acquirer stock that has full voting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

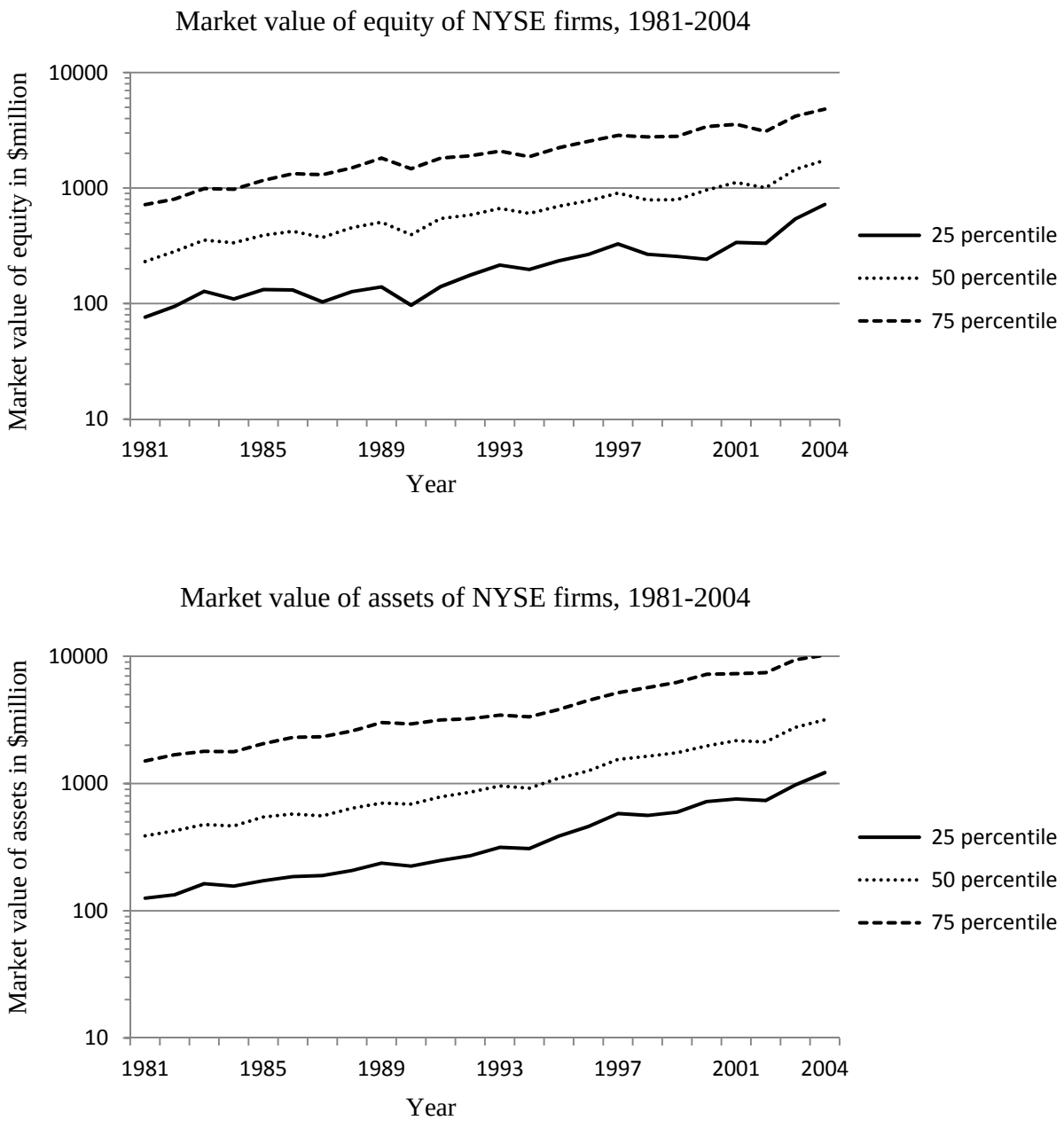

Figure 2: Market value of equity and assets of NYSE firms, 1981-2004. We calculate the market value of equity as the number of shares outstanding at the beginning of a calendar year multiplied by the stock price. The market value of assets equals the market value of equity plus the book value of all liabilities. We form one-percentile tranches of firm size by the year using cutoffs based on the distribution of the market value of equity (or the market value of assets) of all NYSE-listed firms at the beginning of the year. From this we calculate the 25, 50, and 75 percentile cutoffs.

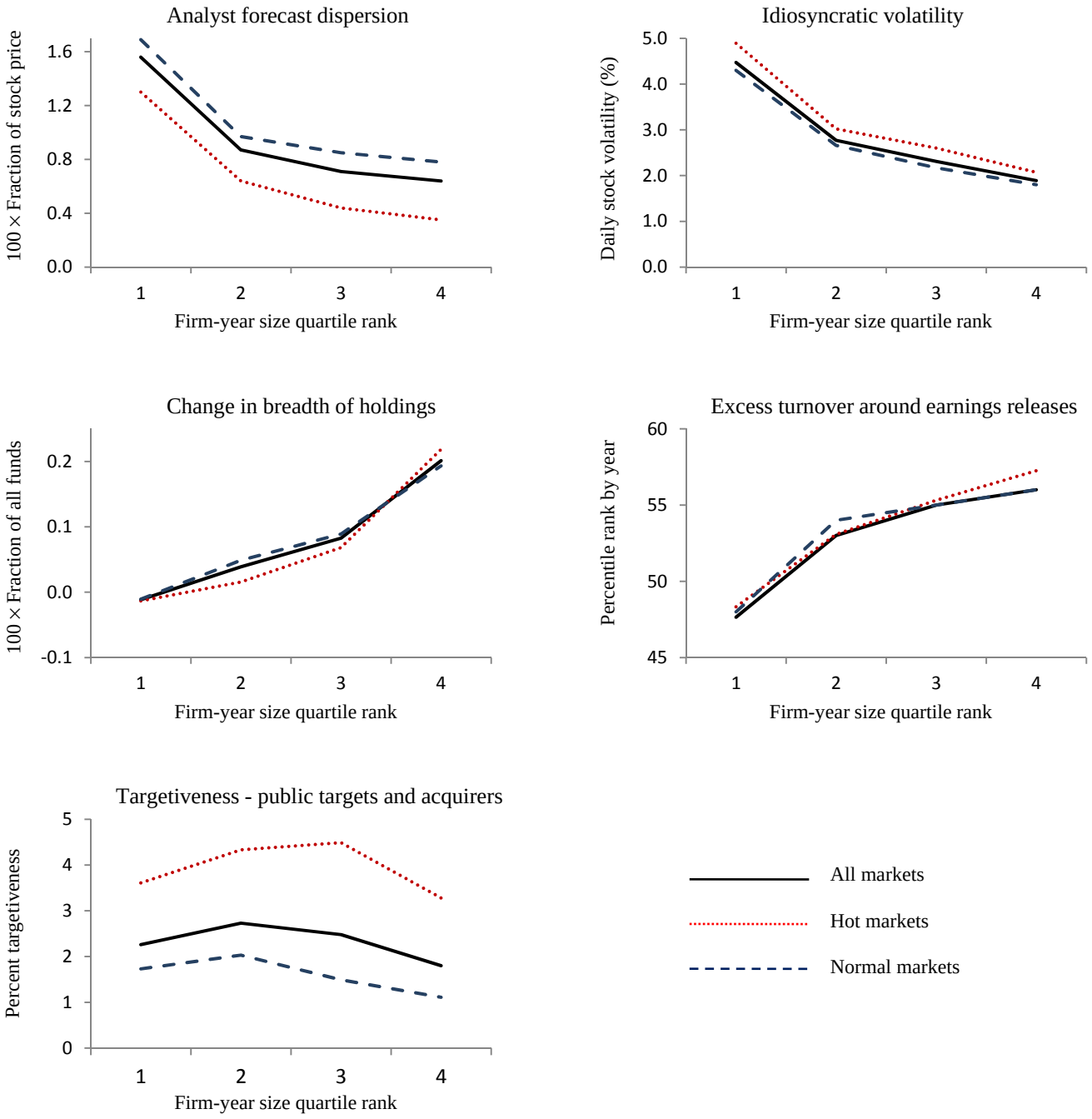

Figure 3: Opinion divergence measures (top and middle panels) and targetiveness values (bottom panel) across comprehensive samples of firm-years sorted into NYSE size quartiles based on the market value of equity. The calculation of opinion divergence measures is described in Appendix 1. Analyst forecast 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 to 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.

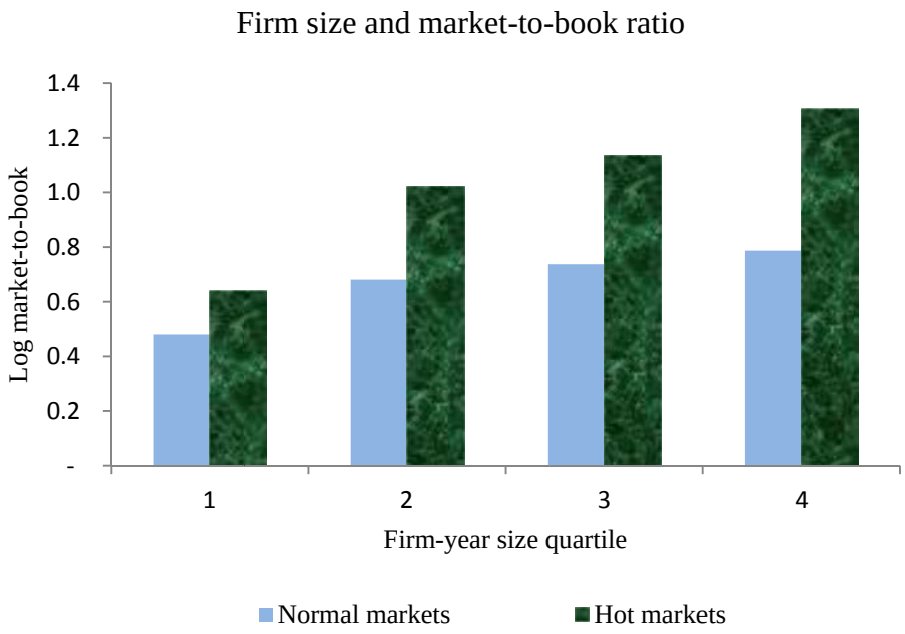

Figure 4: The spread between log market-to-book ratios across firm size quartiles during normal markets and hot markets. The sample includes all firm-years during 1981 to 2004 as described in Table 2. We further require that the necessary data to calculate the market-to-book ratio are available from 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. The ratio 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 to 2000 are classified as hot markets, while years 1981 to 1994 and 2001 to 2004 are classified as normal markets.

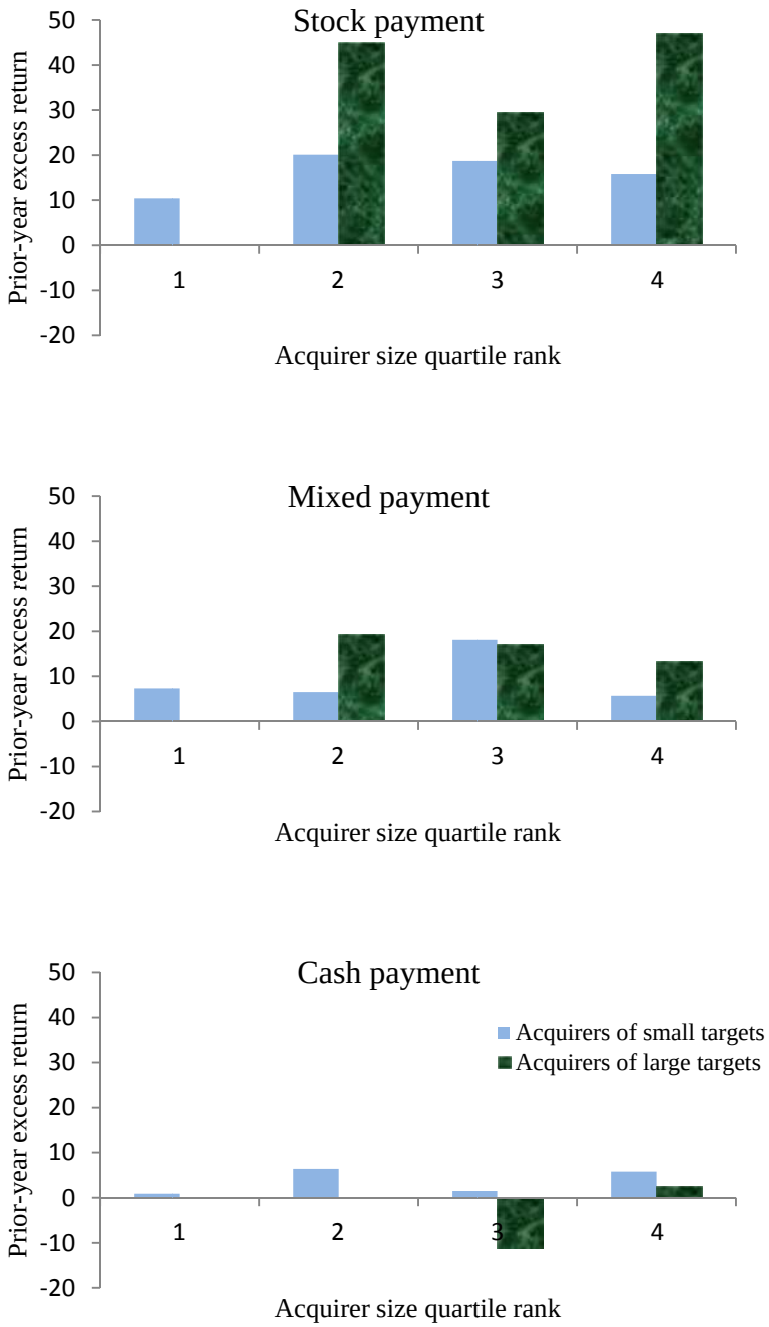

Figure 5: Prior-year excess returns of acquirer stocks sorted by payment method and target size. The sample includes the U.S. public acquirers of all U.S. public targets during 1981 to 2004 as described in Tables 4 and 5. In addition, we require the prior returns data. Small targets belong to the bottom 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 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 bottom panel, but it is only -0.1% tall, so almost invisible.

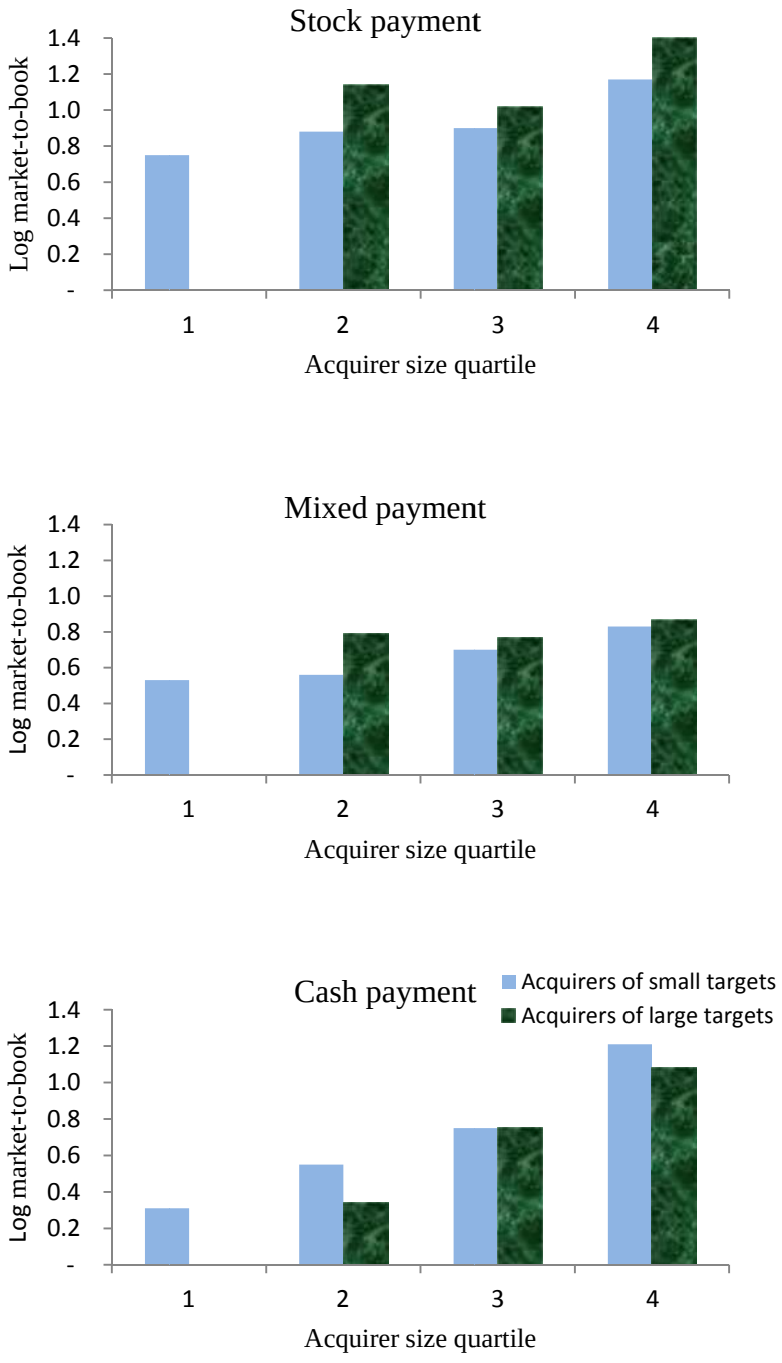

Figure 6: Log market-to-book ratio of acquirer stocks before acquisition announcement sorted by payment method and target size. The sample includes the U.S. public acquirers of all U.S. public targets during 1981 to 2004 as described in Tables 4 and 5. In addition, we require that the market-to-book 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 acquirers in quartile 1, the extreme left panel shows only one vertical bar.

Table 1

Procedure followed to identify a comprehensive sample of CRSP firms that were acquired after an acquisition announcement during 1981 to 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 to 2004 and the CRSP sample to cover 1981 to 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 US 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 1 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.

Table 2

Univariate analysis of targetiveness by firm size

We define targetiveness as the probability of a firm getting acquired within a year. In this table the acquirers can be public or private, and foreign or domestic. In Panel A, we focus on the percent of firm-years that were acquired for different firm-size tranches. Model (2.1) uses the market value of equity as a size measure. Model (2.2) uses the market value of assets as a size measure, which is defined 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), and both the CRSP and Compustat databases for (2.2). We require that the included firms have a CRSP share code of 10 or 11 (which excludes ADRs, REITs, units, certificates, and trusts). We form one-percentile tranches of firm size by the year using cutoffs based on the distribution of the market value of equity (or the market value of assets) of all NYSE-listed firms at the beginning of the year. For each size tranche, we calculate the targetiveness frequency as the number of firm-years that are successfully targeted divided by the total number of firm-years. The sample of targeted firm-years is described in Table 1. In Panel B, we report univariate regressions of targetiveness. The dependent variable is the targetiveness frequency for each of the one-percentile tranches, and the independent variables are the percentile rank and its squared value. The inflexion point equals the negative of the coefficient of linear term divided by two times the coefficient of quadratic term. The *t*-statistics are reported in parentheses, and are based on White's heteroscedasticity-consistent standard errors. The notations [a], [b], and [c] denote significance at the 10%, 5%, and 1% levels.

	Market value of equity based size ranking (2.1)			**Market value of assets** based size ranking (2.2)		
Percentile size tranches	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 to 25	110,259	4,158	3.77	74,815	3,027	4.05
26 to 50	23,351	1,014	4.34	18,883	924	4.89
51 to 75	14,045	553	3.94	13,639	578	4.24
76 to 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)	**Market value of assets** based size ranking (2.2)
Intercept	3.48[c]	4.36[c]
	(17.32)	(20.23)
Percentile rank of market value of **equity** x 10^{-2}	2.92[c]	
	(3.06)	
Square of percentile rank of market value of **equity** x 10^{-4}	-5.08[c]	
	(-5.47)	
Percentile rank of market value of **assets** x 10^{-2}		3.54[c]
		(3.26)
Square of percentile rank of market value of **assets** x 10^{-4}		-5.64[c]
		(-5.17)
Number of observations	100	100
Adjusted-R^2	0.545	0.449
Inflexion point	29	31

Table 3

Multivariate Logit analysis of targetiveness

Our dataset starts with all firm-years included in the CRSP and Compustat databases during 1981 to 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 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 (or the market value of assets) of all NYSE-listed firms at the beginning of a year. Market value of assets is defined as the market value of equity plus the book value of liabilities. 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 1. 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 value of all acquisitions reported in Table 1 for the corresponding year and the 2-digit SIC code, divided by the combined book value of assets of all Compustat firms for the same year and the 2-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 heteroscedasticity-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)
Panel A: ***Market value of equity*** *based size ranking*					
Percentile rank of market value of **equity** $\times 10^{-2}$	1.62 (8.05)[c]	1.29 (6.19)[c]	1.17 (5.54)[c]	0.60 (2.53)[b]	1.21 (5.73)[c]
Square of percentile rank of market value of **equity** $\times 10^{-4}$	-2.55 (-10.04)[c]	-2.25 (-8.72)[c]	-2.20 (-8.54)[c]	-1.58 (-5.61)[c]	-2.02 (-7.66)[c]
Analyst forecast dispersion		-2.40 (-2.66)[c]			
Idiosyncratic volatility			-5.01 (-6.29)[c]		
Change in breadth of holdings				-10.24 (-2.00)[b]	
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

Table 3 continued

Dependent variable: ***Targetiveness dummy***					
Variables	(3.6)	(3.7)	(3.8)	(3.9)	(3.10)
Panel B ***Market value of assets*** *based size ranking*					
Percentile rank of market value of **assets** $\times 10^{-2}$	2.00 (10.39)[c]	1.65 (8.31)[c]	1.67 (8.25)[c]	0.87 (3.87)[c]	1.43 (7.08)[c]
Square of percentile rank of market value of **assets** $\times 10^{-4}$	-2.64 (-11.07)[c]	-2.31 (-9.52)[c]	-2.40 (-9.92)[c]	-1.54 (-5.83)[c]	-1.94 (-7.82)[c]
Analyst forecast dispersion		-1.85 (-2.19)[b]			
Idiosyncratic volatility			-3.60 (-4.53)[c]		
Change in breadth of holdings				-12.92 (-2.67)[c]	
Ranked excess turnover around earnings releases $\times 10^{-3}$					-0.73 (-1.33)
Intercept	-3.34[c]	-3.26[c]	-3.18[c]	-3.20[c]	-3.22[c]
Book-to-market $\times 10^{-3}$	-0.18	-0.28	-0.20	-0.19	-0.21
Cash flow	0.21[c]	0.04	0.13[b]	-0.05	0.07
Industry acquisition activity	1.51[c]	1.53[c]	1.65[c]	1.76[c]	1.62[c]
Prior-year excess return	-0.07[c]	-0.07[c]	-0.07[c]	-0.06[b]	-0.07[c]
Growth resource mismatch dummy	0.07[b]	0.07[c]	0.07[b]	0.05	0.08[c]
Leverage	0.13	0.15[a]	0.17[a]	0.10	0.09
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	0.032	0.033	0.029	0.027

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 in Tables 1 and 2, 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. 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. 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		**Mixed** payment		**Cash** payment		**All** payments	
		Number targeted	Target-iveness frequency (%)	Number targeted	Target-iveness frequency (%)	Number targeted	Target-iveness frequency (%)	Number targeted	Target-iveness frequency (%)
Small	110,259	1,145	1.04	577	0.52	772	0.70	2,494	2.26
2	23,351	304	1.30	177	0.76	156	0.67	637	2.72
3	14,045	161	1.15	112	0.80	75	0.53	348	2.48
4	10,539	102	0.98	69	0.65	19	0.18	190	1.81
Large (2+3+4)	47,935	567	1.18	358	0.75	250	0.52	1,175	2.45
Difference (small-large)			-0.14 (0.011)[b]		-0.23 (0.000)[c]		0.18 (0.000)[c]		-0.19 (0.022)[b]
All sizes	158,194	1,712	1.08	935	0.59	1,022	0.65	3,669	2.32

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 to 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 to 2000 during which an estimated 48% of all acquisitions made by U.S. public firms over the 24-year period from 1981 to 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, 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 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.[1]

		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
Payment method	Firm size	Number of firm-years	Number targeted	Target-iveness (%)	Number of firm-years	Number targeted	Target-iveness (%)		
All	Small (quartile 1)	78,942	1,364	1.73	31,317	1,130	3.61	2.09	0.000[c]
	Large (quartiles 2+3+4)	32,854	550	1.67	15,081	625	4.14	2.48	
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	
Mixed	Small (quartile 1)	78,942	377	0.48	31,317	200	0.64	1.34	0.013[b]
	Large (quartiles 2+3+4)	32,854	201	0.61	15,081	157	1.04	1.70	
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	

[1] We calculate *p*-values using a simulation procedure which is explained as follows. Consider the first row. For all payment methods and all firm sizes, the targetiveness equals (1364+550)/(78942+32854) = 1.71% during normal markets and (1130+625)/(31317+15081) = 3.78% during hot markets. Thus, for all firm sizes, the targetiveness increases by a factor of 3.78/1.71 = 2.21. We test the null hypothesis that the increase is by the same factor of 2.21 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 1.73×2.21 = 3.82% for small firms and 1.67×2.21 = 3.70% for large firms. So we draw 31,317 random numbers corresponding to the number of small firm-years during hot market such that each random number takes the value one with a probability of 3.82% 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 $p_{small,sim}/1.73$ for small firms and $p_{large,sim}/1.67$ for large firms. We then test whether the simulated ratio of ratios, or $(p_{small,sim}/1.73)/(p_{large,sim}/1.67)$, is greater than 2.48/2.09, 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.

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 to 2004 as described in Table 4. 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 described in Figure 5. 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 1. 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. 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 value of all acquisitions reported by SDC for the corresponding year and the 2-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 2-digit SIC code. We force it to take a value between 0 and 1.

	Acquisitions of small targets			Acquisitions of large targets		
	Mean	Median	Std. dev.	Mean	Median	Std. dev.
	N = 2494			N = 1175		
Panel A: Target characteristics						
Market value of equity in $million	93	62	157	2467	760	6882
Book value of assets in $million	348	113	1092	6152	1089	22517
Mutual fund ownership	4.31	1.37	10.32	9.07	6.60	11.85
Target industry acquisition activity	3.55	1.17	6.80	4.50	1.47	7.07
CAR from last earnings announcement in percent	0.04	-0.26	9.82	-0.13	-0.31	7.92
Panel B: Acquirer characteristics						
Market value of equity $million	5560	714	24752	16374	4460	39262
Book value of assets $million	9779	1326	29026	26604	6152	75005
Prior-year excess return	10.04	3.25	50.99	19.96	7.68	60.93
Log market-to-book ratio	0.79	0.71	0.72	0.94	0.85	0.79
Analyst forecast dispersion	0.0067	0.0032	0.0126	0.0051	0.0025	0.0102
Idiosyncratic volatility in percent	2.62	2.15	1.80	2.14	1.81	1.31
Change in breadth of holdings	-0.0002	-0.0006	0.0034	0.0004	-0.0002	0.0047
Ranked excess turnover around earnings releases	52	52	29	56	59	28
CAR from last earnings announcement in percent	0.41	0.25	7.07	1.05	0.61	6.55
Collateral	0.181	0.096	0.215	0.250	0.177	0.241
Financial leverage	0.142	0.116	0.131	0.156	0.136	0.126
Cash flow	0.065	0.041	0.184	0.051	0.045	0.068
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	

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 to 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. Mixed payment deals are dropped. 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. The first set of independent variables constitutes the focus of this paper and includes several overvaluation measures as follows. 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. Acquirer's market-to-book ratio is calculated as the market value of equity divided by the book value as of last fiscal year ending before the announcement date. It is log-transformed to adjust for skewness. A hot market dummy equals one if the deal is announced during 1995 to 2000, and zero otherwise. 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 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 2-digit SIC codes, 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.

Table 7 continued

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] (6.23)			1.04[c] (4.74)	1.04[c] (4.63)	1.00[c] (3.65)	1.02[c] (4.60)	1.00[c] (4.06)
Acquirer's prior-year excess return × Small target dummy	-0.70[c] (-3.68)			-0.54[b] (-2.53)	-0.51[b] (-2.32)	-0.52[b] (-1.96)	-0.50[b] (-2.30)	-0.49[b] (-2.03)
Acquirer's log market-to-book ratio		0.78[c] (7.87)		0.40[c] (3.28)	0.28[b] (2.41)	0.55[c] (3.61)	0.26[b] (2.23)	0.30[b] (2.20)
Acquirer's log market-to-book ratio × Small target dummy		-0.52[c] (-5.26)		-0.29[b] (-2.20)	-0.21[a] (-1.67)	-0.32[a] (-1.93)	-0.20 (-1.62)	-0.26[a] (-1.79)
Hot market dummy			1.22[c] (8.72)	0.80[c] (4.51)	0.81[c] (4.66)	0.77[c] (3.43)	0.81[c] (4.66)	1.15[c] (5.66)
Hot market dummy × Small target dummy			-0.80[c] (-5.21)	-0.35[a] (-1.73)	-0.35[a] (-1.75)	-0.29 (-1.14)	-0.33[a] (-1.69)	-0.51[b] (-2.19)
Target's volatility	-5.23[c]	-5.06[b]	-4.97[c]	-5.32[c]				
Hostile dummy					-2.15[c]			
Tender offer dummy						-4.42[c]		
Competing offer dummy							-1.15[c]	
CAR from last earnings – acquirer								-0.42
CAR from last earnings – target								-0.04
Target's mutual fund ownership	-2.22[c]	-3.25[c]	-2.39[c]	-3.56[c]	-0.16	0.65	-0.24	-2.78[c]
Average volatility of all firms	-2.05	-2.58						
Intercept	1.09[c]	1.13[c]	1.21[c]	0.93[c]	0.45[a]	0.88[c]	0.48[a]	0.69[b]
Acquirer's collateral	-0.98[c]	-1.34[c]	-1.24[c]	-1.16[c]	-1.18[c]	-0.40	-1.16[c]	-1.62[c]
Acquirer's financial leverage	-1.33[c]	-0.56	-0.98[c]	-0.62	-0.42	-1.10[b]	-0.42	-0.44
Acquirer's log assets	-0.06[b]	-0.09[c]	-0.10[c]	-0.10[c]	-0.08[c]	-0.06[a]	-0.08[c]	-0.10[c]
Relative size	0.18	0.12	-0.00	0.15	0.22[a]	0.51[c]	0.17	0.21
Same industry dummy	0.73[c]	0.72[c]	0.70[c]	0.72[c]	0.73[c]	0.42[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	0.067	0.073	0.092	0.097	0.357†	0.093	0.107

† The large pseudo-R^2 for Regression (8.6) arises because tender offer dummy has a much higher correlation with the payment method than other variables.

Table 8

Does 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 to 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, 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. 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 1. 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. 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 2-digit SIC codes, 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 SDC for the corresponding year and the 2-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 2-digit SIC code. We force it to take a value between 0 and 1. The continuous form control variables are measured as of the last fiscal year ending before the announcement year. Statistical significance levels are based on White's heteroscedasticity-consistent standard errors. The notations [a], [b], and [c] denote significance at 10%, 5%, and 1% levels.

Table 8 continued …

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)
Intercept	-6.41[c] (-3.50)	-3.07[c] (-2.96)	-3.14[c] (-3.33)	-6.21[a] (-1.83)	-1.40[a] (-1.67)	-2.14[b] (-2.55)
Small target dummy	**4.21**[c] (3.28)	**2.37**[c] (3.58)	**2.55**[c] (4.15)	**3.51**[c] (3.17)	**1.25**[c] (2.63)	**1.03**[b] (2.13)
Relative size	7.95[b] (2.04)	-1.28 (-0.43)	2.56[a] (1.89)	12.09 (1.24)	1.72[b] (2.46)	1.59[b] (2.23)
Acquirer's analyst forecast dispersion × 10^2		-2.06[b] (-2.04)				
Acquirer's analyst forecast dispersion × Relative size × 10^2		6.45 (1.38)				
Acquirer's change in breadth of holdings × 10^2			0.87 (1.43)			
Acquirer's change in breadth of holdings × Relative size × 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 × 10^2		0.05 (0.22)	-0.42[a] (-1.74)	0.09 (0.30)		0.67[b] (2.20)
Additional control variables (nine of them)	Yes	Yes	Yes	Yes	Yes	Yes
N	1,426	1,331	1,341	1,201	896	891
Adjusted-R^2	0.118	0.140	0.050	0.080	0.049	0.061
Difference between coefficient of small target dummy for stock and cash acquisitions	**2.96**[†] (2.16)[b]	**1.34**[‡] (1.63)[*]	**1.52**[‡] (1.94)[a]	**2.48**[‡] (2.26)[b]		

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

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 each case 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 heteroscedasticity-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	

Table 10

Are acquirer long-term excess returns explained by prior overvaluation of acquirer stocks?

The sample analyzed in this table includes the acquisitions of U.S. public targets by U.S. public acquirers during 1981 to 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 regressions reported in this table is the long-term excess return of acquirer stock. This return is calculated over the period (+1,+757) days relative to the completion date of the acquisition as the difference between the buy-and-hold return of the acquirer firm and the matching industry, size, and book-to-market firm. The matching procedure is described as follows. For each acquirer firm, we 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. We also require that the matching firm should not have made an acquisition of another public firm during three years before the matching year. In a few cases the industry, size, and book-to-market matching 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. 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. The independent variables are as follows. The 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. Acquirer's prior-year excess return 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. Acquirer's market-to-book ratio is calculated as the market value of equity divided by the book value as of last fiscal year ending before the announcement date. Hot market is a dummy variable that equals one if the deal is announced during 1995 to 2000, and zero otherwise. Acquirer's idiosyncratic volatility is calculated as the standard deviation of residuals from a market model carried out over the period (-126,-64) days relative to the announcement date. The tender offer dummy and hostile dummy equal one if identified as such by SDC, and zero otherwise. Both long-term return and prior-year excess returns are expressed in percent units and winsorized at 1% level. The log market-to-book ratio is also winsorized at 1% level. The *t*-statistics are reported in parentheses, and are based on White's heteroscedasticity-consistent standard errors. The notations [a], [b], and [c] denote significance at 10%, 5%, and 1% levels.

Dependent variable: ***Three-year post-acquisition buy-and-hold excess return*** *of acquirer firms in percent*

	Stock payment			Mixed payment	Cash payment
Independent variable	(10.1)	(10.2)	(10.3)	(10.4)	(10.5)
Intercept	-18.32[c] (-5.52)	2.79 (0.51)	9.69[a] (1.65)	9.58 (1.18)	-13.52 (-1.52)
Small target dummy	**15.99**[c] (3.49)	**10.88**[b] (2.40)	**12.49**[c] (2.75)	**-5.65** (-0.89)	**12.59**[b] (2.11)
Acquirer's prior-year excess return		-0.13[c] (-4.05)	-0.12[c] (-3.44)	-0.02 (-0.25)	-0.04 (-0.44)
Acquirer's log market-to-book ratio		-9.60[b] (-2.33)	-9.13[b] (-2.14)	-3.00 (-0.47)	2.70 (0.57)
Hot market dummy		-9.81[a] (-1.89)	-9.86[a] (-1.87)	-1.25 (-0.18)	0.71 (0.11)
Acquirer's idiosyncratic volatility			**-3.06**[b] (-2.10)	**-0.63** (-0.20)	**5.66**[a] (1.79)
Tender offer dummy			-3.45 (-0.29)	-0.72 (-0.06)	-8.68 (-1.36)
Hostile dummy			13.33 (1.18)	-28.11 (-1.52)	17.65 (1.13)
N	1,589	1,589	1,569	846	893
Adjusted R-square	0.006	0.026	0.028	-0.004	0.005

Table 11

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

This table analyzes whether CEO's ownership and governance affect targetiveness and stock payment choice. We obtain CEO's ownership information during 1993 to 2004 from the ExecuComp database, and governance index information during 1991 to 2004 from the RiskMetrics database. Panel A reports the summary statistics, Panel B reports the targetiveness tests, and Panel C reports the payment method tests. A lower value of 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 Logit 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.

*Panel A: Mean values of **ownership** and **governance** variables*

	Firm size quartile rank					Difference small vs. large
Variables	Small	2	3	4	2+3+4	
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]

*Panel B: Logit regressions of **Targetiveness dummy***

Variables	(11.1)	(11.2)
Percentile rank of market value of **equity** $\times 10^{-2}$	1.81[b] (2.31)	1.06[a] (1.64)
Square of percentile rank of market value of **equity** $\times 10^{-4}$	-2.12[c] (-3.04)	-1.81[c] (-3.02)
CEO's ownership in percent	-0.05 (-0.15)	
G index		0.02 (1.16)
Analyst forecast dispersion	3.06 (0.99)	1.76 (0.89)
Intercept	-3.76[c]	-3.55[c]
Book-to-market $\times 10^{-3}$	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

Table 11 continued

Dependent variable: ***Stock payment dummy***		
Independent variables	(11.3)	(11.4)
Acquirer's prior-year excess return	1.93[c] (3.45)	1.92[c] (4.43)
Acquirer's prior-year excess return × Small target dummy	-1.66[b] (-2.02)	-1.35[b] (-1.96)
Hot market dummy	0.13 (0.34)	0.20 (0.47)
Hot market dummy × Small target dummy	-1.25[b] (-2.52)	-1.55[c] (-3.43)
Target's CEO's 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