A Replication of “What Will It Do For My EPS?”

- *A Straightforward But Powerful Motive for Mergers*

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1. Abstract

The purpose of this paper is to investigate the possibility of predicting what firms ultimately become targets in a merger and acquisition transaction, by replicating the results of Garvey, Milbourn & Xie in "*What Will It Do For My EPS*" (2013).

There are significant amounts of literature providing evidence that bidders are higher valued than their targets and that both parties in a takeover transaction tend to be in temporarily high-valued industries. Differences in valuation also indicate who will be an acquirer and when. The likelihood of being a target is higher when other firms in the industry can acquire the target using stock as consideration and if it has an accretive effect for the bidder, even when a significant premium is paid.

We find that the number of viable accretive bidders, controlling for other measures in the existing literature, is identifiably a strong target predictor. The results when trying to predict likely bidders are however not as clear. A firm is likely to be a bidder when there are more viable accretive targets in the industry, but unlike target prediction these results are somewhat obscured by existing measures, especially those related to misvaluation. Our results on target and bidder prediction are in line with what the original paper finds. Like Garvey, Milbourn & Xie (2013), we identify that the likelihood of a merger being stock financed increases with the targets number of viable accretive bidders.

2. Preface

This paper is written as the concluding part of our *Master of Science* in *Economics and Business Administration*, majoring in finance, at the *Norwegian School of Economics* (NHH).

After attending, both finance and strategy courses highlighting the different aspects, and the importance of mergers and acquisitions, we wanted to use our thesis as a possibility to investigate this field further. In particular, the fact that there are many different views on the determinants driving merger activity suggests that further research is desirable to fully comprehend the underlying mechanisms. During our work, we found that in addition to the ability to interpret historical data and empirical results, gathering reliable data and constructing a correct dataset is of great importance for the conclusions reached. This suggests that when reading and using existing work, one should pay attention not only to the findings, but also to the way they were obtained. We hope this paper can provide valid contribution to further work on merger activity. We are responsible for all errors.

We would like to extend a special thanks to our advisor, Francisco Santos (NHH), for helping us find an interesting topic and being both available and supportive at all times during the writing process. Further, his detailed and professional guidance has provided us with valuable insight and led us in the right direction for completing our thesis.

3. Introduction

The goal of this paper is to investigate the possibility of predicting what firms ultimately become targets in a merger and acquisition transaction. By replicating the results in Garvey, Milbourn & Xie's paper "*What will it do for my EPS*" (2013), we attempt to identify if the likelihood of ultimately becoming a target is related to the number of viable bidders. In line with their additional hypothesis, we also investigate if the number of viable bidders and targets carry predictive power regarding whether stock is used as the source of finance. Throughout this paper, we attempt to follow the exact approach as described in Garvey et al (2013) in order to achieve comparable results and highlight the validity of their findings.

Being able to predict mergers and acquisitions can benefit managers by assisting in the process of forming their firm's strategy. Further, it may supply relevant value-adding information to portfolio investors' stock picking decisions. This is of great importance as there is a significant amount of empirical evidence suggesting that the target's shareholders receive sizeable positive market returns following a takeover announcement[1] (Bruner, 2001).

Even though a range of studies have been undertaken in order to understand the dynamics of mergers and acquisitions, we still know relatively little about their determinants. Mergers and acquisitions are motivated by either managerial or value enhancing motives (Motis, 2007). Value enhancement can be achieved either by synergies, i.e. the value of the combined entity is greater than that of the two firms separately, or due to misvaluation of the target- or acquirer firm. This paper focuses on misvaluation and to what extent a firm that perceive themselves as overvalued by the market can utilize this mispricing to acquire relatively undervalued targets.

Recent literature argues that acquisitions are driven by stock market valuations more than synergies and managerial objectives as indicated in earlier literature (Schleifer & Vishny, 2003; Rhodes-Kropf & Viswanathan, 2004; Jensen 2005). Schleifer & Vishny (2003) suggest that acquirers tend to purchase underpriced assets with relatively overvalued stock and Dong et al. (2006) claim bidders tend to be more highly valued than their targets. Dong et al. (2006) and

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[1] Markets react much more to targets as they are harder to predict, hence the announcements are more surprising (Prabhala, 1997)

Rhodes-Kropf et al. (2005) furthermore claim that both parties tend to be in temporarily high valued industries. An economic shock that unevenly affects firm valuations in an industry could therefore motivate acquisitions of relatively cheaper firms by more highly valued firms.

Following the approach in Garvey et al (2013), we adopt the theories related to market misvaluation and target prediction in an attempt to, *ex ante*, identify what firms ultimately become acquirers and targets. They first define two viability measures based on earnings- and book values per share. Combining Schleifer & Vishny's (2003) model, with the basic "EPS bootstrap game" described by Brealey et al (2007) produces a model that qualifies any two firms in the same two digit SIC industry as viable candidates to merge simply if the party with the higher multiple can increase its earnings per share *(EPS)* or book value per share *(BVPS)* after paying the target a premium on the deal. This assumes that the market will apply the acquirer's multiple to the entire post-merger entity, increasing its *EPS* (or *BVPS*) when acquiring a target with a lower price-to-earnings (price-to-book) multiple. This simple approach developed in Garvey et al (2013) is the basis for our counts of viable bidders and targets for each firm.

Deviating from Garvey et al (2013), we exclude the approach based on the residual income model *(RIM)*, thus we only consider a pair to be viable, under the previously mentioned conditions, if the acquirer can increase its earnings- or book value per share.

In an attempt to add value to the findings, we expand upon some of Garvey et al's (2013) work. First, we add a third industry to investigate the relationship between the number of firms taken over and the number of firms in the industry. Further, as the main goal of our paper is to verify and investigate Garvey et al's (2013) results, we additionally run a more comprehensive sensitivity analysis related to the acquisition premium. We also place greater emphasis on describing the construction of the dataset to accommodate future replications.

In our empirical analysis, we apply an exhaustive set of controls following Garvey et al (2013) to affirm the robustness of our results and isolate the papers intended contribution. This includes a range of size and misvaluation measures. In line with the original paper, we use the misvaluation measures from Rhodes-Kropf et al (2005) as our main control variables. Our main variables of interest are thus the two viability measures and Rhodes-Kropf et al's (2005) three misvaluation components.

We are successful in finding clear evidence that the likelihood of being a target is in fact increasing with the number of viable accretive bidders in the industry. The results are evident using both earnings- and book values per share. This provides a strong indication that market mispricing is an important driver for merger likelihood, which is in line with the findings in the original work by Garvey et al (2013).

Moreover, our results suggest that there are additional relevant variables that should be taken into consideration when predicting the likelihood of being a target. First, we observe that the number of takeovers in a firm's industry has a strong predictive power. This is in line with Garvey et al (2013), pointing out that the wave variable indeed can help identify industries where high takeover activity and merger rates are observed. However, it does not distinguish between targets and bidders. Consistently across all of our results, the number of takeovers in the industry is an important variable being highly significant for identifying targets, acquirers and merger intensity at the firm level. Next, misvaluation resulting from a firm-specific error defined in Rhodes-Kropf et al (2005) proves to have a positive relationship to target likelihood. This suggests that firms, which are overvalued due to self-specific attributes, not connected to the market as a whole, have a greater chance of being taken over[2]. Lastly, we find a negative relationship with the firm's price-to-forecasted earnings ratio implying targets tend to have relatively cheaper earnings.

With our distinctive target results in hand, we shift our focus towards predicting acquirers. Although we find clear evidence that the number of viable targets available is related to the likelihood of being an acquirer, the results are not as robust to the inclusion of controls as for the target prediction. Predicting acquirers seems to be more related to various components of misvaluation rather than the sheer number of viable targets available. *Figure 1,* illustrating a summary of empirical distribution of measures for realized takeovers, highlights these unclear results. Even though acquirers have a significantly larger number of viable targets than the other two samples, they are also consistently distinguishable across almost all of the measures.

Turning our attention to the second hypothesis, namely that the number of viable bidders and targets are positively related to the likelihood of stock being used as the method of payment,

[2] Further analysis of the acquirers show that they tend to have an even higher self-specific overvaluation.

we are only able to find partially supporting evidence. Our findings suggest that only the target's number of accretive bidders is significant, thus proving to be the leading predictor in identifying, at the firm level, whether or not a deal will be financed with stock. Further, the acquirer’s number of accretive targets shows a positive relationship giving additional support for the hypothesis. Additionally, we find that both the target- and acquirer’s firm-specific misvaluation component has a strong positive significance, meaning that firm-specific overvaluation increase the likelihood of a deal being stock financed.

When predicting the medium of exchange at the industry level we observe the most conflicting results with what was found in the original paper. The industry average number of accretive bidders is mostly positive and significant, but shifts to negative when we manually control for industry fixed effects. This is conflicting in the sense that Garvey et al (2013) find it to be positive and significant across all regressions (even if the coefficients drop dramatically when controlling for industry fixed effects) and it is one of their main contributors to support the second hypothesis.

The dataset construction process requires gathering and combining data from a number of different sources. As there is no single correct way to combine these multiple datasets, due to limitations in unique identifiers and discrepancies in the data, this could be a potential source of differences between Garvey et al’s (2013) results and ours. Due to the originally substantial sample size and lack of information in Garvey et al’s (2013) paper regarding the sample construction, our focus has been on quality and not quantity of our observations, resulting in a somewhat lower sample size, but arguably more correct data points.

The proceeding sections of this paper are structured as follows: Chapter 4 provides a review of literature describing relevant topics for this paper. Chapter 5 presents the model development and the resulting hypotheses and chapter 6 provides a detailed description of how we constructed our dataset. Chapter 7 specifies the empirical models and key variables before we proceed to present our main empirical results in chapter 8. Lastly, chapter 9 sums up our paper and concludes.

4. Literature Review

As pointed out in the introduction there is a large amount of previous studies on the different aspects related to mergers and acquisitions. In this section, we will provide a brief review of literature relevant to this paper[3].

Closest to the work of Garvey et al (2013) is the model developed by Schleifer & Vishny (2003). Under the assumption of inefficient markets and fully rational managers, these models advocate that transactions are driven by stock market misvaluations of the merging firms. The idea that stock market misvaluations shape merger activity dates back to Nelson's publication of 1959, which indicates that mergers are not only related to prosperity but also the state of capital markets (Nelson, 1959). The key concept provided by Schleifer & Vishny (2003) is that acquirers take advantage of their overvalued stock and use it as consideration for acquiring relatively less overvalued targets. The target firm benefits in the short run from the premium, whilst the bidder is able to acquire a larger part of the combined firm due to the relative misvaluation.

Fuller & Jensen (2002) state that managers may engage in the earnings guidance game striving to meet analyst forecasts and often unrealistic expectations. Furthermore, Jensen (2005) finds that overvalued equity may lead to unfruitful acquisitions, reducing the fundamental long-run value of the firm. Hence, high stock prices and firm strategies driven by analyst forecasts could be damaging for the firm. This is consistent with our, and the original papers assumption that managers may carelessly believe the market will apply the acquirers higher multiple to the combined entity.

Identifying that stock prices deviate from their fundamental values on both sides of the transaction, Rhodes-Kropf & Viswanathan (2004) develop a model based on market misvaluation. Rhodes-Kropf & Viswanathan (2004) decompose the misvaluation effect into two main components, a market- or sector wide component and a firm-specific component. The market-wide component is common for both bidders and targets within the same sector while the firm-specific component is individual for each firm. The main issue for targets in a potential takeover is that they

[3] This literature review follows closely the one in the original paper by Garvey et al (2013), adding on some additional insights we find relevant.

are unable to determine how much of their own misvaluation is a result of the firm-specific component, and how much is caused by the market-wide component. When there is a high market-wide overvaluation, the more prone a target's manager is to underestimate the shared market-wide misvaluation component of the two entities. As a result, they underestimate the synergy effects of the merger. The target is not irrational, but due to this limited information, they may face problems correctly quantifying the sources of the total overvaluation and accept the deal.

Dong et al (2006) investigate both Q-theories and misvaluation of mergers. Q-theory bases itself on how bidders redeploy target assets. Brainard & Tobin (1968) apply price-to-book as a proxy for expected growth or managerial efficiency to investigate the Q-hypothesis. Previous literature indicates that a firm with a higher price-to-book ratio generates a higher return on their assets. Bidder and target valuations are here tied to the stock price-to-book ratios at the date of announcement. Takeovers of bad targets, i.e. targets with low price-to-book, by good bidders, i.e. bidders with high price-to-book, tend to improve efficiencies more than takeovers of good targets by bad bidders. The key difference between Dong et al (2006) and the original paper is that Garvey et al's (2013) tests include nearly all firms with public information and focus on predicting *ex ante* what firms become targets or acquirers, whilst Dong et al (2006) focus on deals that actually took place. Further, price-to-book and price-to-value (presented as RIM bidders and targets in Garvey et al (2013)) supply complementary information. Therefore, we limit our analysis of Q-theory based on price-to-book and price-to-forecasted earnings, as this seems sufficient for the intended contribution of this paper.

In an effort to test the models of Rhodes-Kropf & Viswanathan (2004) and Schleifer & Vishny (2003) empirically, Rhodes-Kropf et al (2005) use a more comprehensive valuation method. In order to better assess the sources of misvaluation they decompose the mispricing into three components using a model including *book values*, *net income* and *leverage*. They argue that misvaluation can be broken down into a firm-specific error, a sector mispricing error and a long-run mispricing error. Their results show that targets and acquirers have higher market-to-book values relative to firms not involved in merger activity. Furthermore, they find that high price to book firms tend to be acquired by even higher price to book firms. Additionally, the firm-specific error is greater for bidders than targets in both the total sample of takeovers and the subsample of takeovers using only stock as the medium of exchange.

Surprisingly however, they find that low long-run value-to-book firms tend to acquire high long-run value-to-book targets. This is somewhat conflicting with Q-theory, which argues that firms with high growth opportunities (i.e. firms with high long-run value-to-book) should buy firms with lower growth opportunities. Rhodes-Kropf et al (2005) argue that these contradicting results can be attributed to some form of market inefficiency and information asymmetries.

Several recent studies investigate the importance of merger waves as a reinforcement of overall merger activity and the underlying reasons for their occurrence. Gorton et al (2009) show that if managers value personal benefits of control sufficiently, they may engage in unprofitable defensive acquisitions. A technological or regulatory change that makes acquisitions profitable in some future states of the market can induce a pre-emptive wave of unprofitable, defensive acquisitions. Hardford (2005) also documents the idea that industry related shocks could cause merger waves. Further, Thakor & Goel (2010) show that envy can contribute to a positive cross-sectional correlation in mergers because a firm is more likely to acquire when another firm in its environment has acquired. Hence, acquisitions that would not have found place in the absence of previous acquisitions are now undertaken.

As stated in the introduction, this paper replicates the work and results presented in the paper "*What Will It Do For My EPS?*" by Garvey et al (2013). In their research, they investigate the possibilities of matching up and predicting potential targets and bidders. Their main results show that the number of viable bidders for firms that are actually taken over in the following year is far higher than for the firms that either are acquirers or not involved in any merger activity. Further, in support of their predictions, they expect to find that subsequent bidders have a far greater number of viable targets than either of the other two categories, target firms or firms not taking part in merger activity. After running probit regressions on target likelihood, their results show that the number of viable bidders is a far stronger target predictor than any other measure found in previous literature. These results are consistent with ours. Additionally, they find that the likelihood of being a bidder increases with the number of available targets. However, these results are not as impressive as for target prediction as they are obscured by several existing size and valuation measures. We reach the same conclusion, and find that specifically four factors: firm-specific error and long-run value-to-book from Rhodes-Kropf et al (2005), industry number of takeovers and leverage seem to be strong predictors of bidder likelihood.

Garvey et al (2013) also test if the number of viable bidders and targets are relevant predictors for the medium of exchange. Specifically they investigate whether the number of targets and bidders increase the likelihood of the deal being financed with stock both on the firm and industry level. In line with the original paper, we also find that the targets number of viable bidders is a strong predictor. However, Garvey et al (2013) also find that the acquirer's number of viable targets has strong predictive power. We find a positive, although not significant, relationship in our regressions. This paper follows the exact same approach as described in "*What Will It Do For My EPS?*" except we exclude the measures and analyses related to RIM.

5. Model and Resulting Hypothesis

In this section, we start by introducing Q-theory, which the formulas for counting viable bidders and targets are based upon. We then proceed to specify the assumptions before presenting the hypotheses. The description of Q-theory and the resulting formulas are to a great extent similar to the corresponding section found in the original paper. We feel however, that it is valuable to include, as it makes the following sections more intuitive and helps the reader form a better understanding of the central measures in the analyses. We follow the same structure as Garvey et al (2013) and present the same formulas, but also try to explain in more detail how they are, in practice, applied to our calculations.

The original paper by Garvey et al (2013) derives two empirically testable predictions and define a simple model of mergers based on Schleifer & Vishny (2003). Schleifer & Vishny (2003) denote a potential merger pair with $Firm_0$ and $Firm_1$. $Firm_0$ ($Firm_1$) has K_0 (K_1) units of capital with a stock price multiple of Q_0 (Q_1). We assume, without loss of generality, that the stock multiple of the prospective acquirer $Firm_1$ is higher than that of the prospective target $Firm_0$. Hence,

$$Q_1 > Q_0 \tag{1}$$

The synergy *(s)* the market attaches to the combined post-merger entity is the key parameter in Schleifer & Vishny (2003) and the estimated market value of the combined entity is:

$$[K_1 + K_0] \times [sQ_1 + (1 - s)Q_0] \tag{2}$$

This is referred to as the short-term market value; hence, the synergy may contain pricing errors. In the baseline case without synergies, assuming an efficient market, $\text{s} = \frac{K_1}{(K_1+K_0)}$. The target firm is able to cash out immediately following the deal. Therefore, they are not concerned with the long-term value. Hence, the only relevant variable for the viability of an acquisition is the bidding firm's view of *s*.

The second part of Schleifer & Vishny's (2003) model focuses on the long-term return to both the acquirer and target firm. As our analysis attempts to predict *ex ante* which firms will take part in a takeover, as either an acquirer or a target, the key component is that a bidder must pay a consideration including a non-zero premium given by a percentage of the target's market value.

Assuming without loss of generality that both firms have a single share outstanding and the acquirer issues additional shares (m) as consideration to the target, we have two conditions which must be satisfied for a firm pair to be viable for a merger.

First, the bidder must issue enough shares to cover the required premium of $\prod$.

$$\frac{m}{1+m}(sQ_1 + (1-s)Q_0)(K_1 + K_0) = Q_0 K_0 (1 + \prod) \qquad (3)$$

Second, the acquiring firm does not lose market value following the merger.

$$\frac{1}{1+m}(sQ_1 + (1-s)Q_0)(K_1 + K_0) \geq Q_1 K_1 \qquad (4)$$

These conditions are satisfied when:

$$\frac{Q_1+Q_0}{Q_0} > \frac{\prod K_0}{s(K_1+K_0)-K_1} \qquad (5)$$

The main issue when applying these conditions to the data is that the bidder's beliefs regarding the synergy effects are not observable. The extreme case put forward in the original paper, under the assumption of an efficient market where management do not believe in synergies,

$s = \frac{K_1}{(K_1+K_0)}$, the two conditions can never be satisfied for any $\prod > 0$. This is quite intuitive, as the bidder will not offer a premium if there are no perceived synergies to gain from the merger.

The opposite extreme case, where $s = 1$ and the bidder believes the market will apply the bidder's pre-merger multiple to the combined post-merger entity. By rearranging equation (5) and substituting for $s = 1$, all that is necessary, is for the bidders multiple to exceed the targets multiple by the premium. In this case, the first (3) and second (4) conditions are satisfied as long as:

$$Q_1 > (1 + \prod) \times Q_0 \qquad (6)$$

As mentioned in the original paper by Garvey et al (2013), this is a straightforward and relatively extreme bootstrapping result. Due to the extremity of this assumption, applying it to our real-life data requires considering three main issues.

When applied to the model, many firms will have multiple viable bidders for most reasonable premiums, resulting from the wide spread between valuation multiples in broadly defined industries. This implies that the likelihood of an actual takeover taking place is at least an order of magnitude greater than what is observed in the actual data. Following the original paper´s simple accommodation (Garvey et al, 2013), a fraction *X* of the population does not believe in the bootstrap game. As only one viable bidder is necessary for a firm to be taken over we denote the number of firms that satisfy the first (3) and second (4) condition by *n*. A potential target is thus taken over with the probability $1 - X^n$. The fraction of the population *X* is unknown, however this observation suggests we should apply a concave transformation to the number of viable bidders in the empirical tests.

Secondly, when $s = 1$, relative size does not matter. Under this assumption, the market will apply a small bidders multiple to the combined entity, even though the target is relatively larger. This might seem counterintuitive; however, Harford (1999) finds that targets are not on average small firms. We confirm this basic result in our data, where we cannot differentiate between the size of a target and a non-merger observation.

Additionally, in unreported robustness tests, implementing the requirement that the bidder´s assets are greater than those of the target, provide the same results. Garvey et al (2010) find that only 2% of actual merger deals involve a target buying a firm more than four times its asset size. We test for the restriction that prohibits a firm from buying a target whose total asset value is greater than four times its own, and our results hold up.

Lastly, in line with the original paper, we have adopted the modeling assumption put forward by Schleifer & Vishny (2003), that mispricing rather than valuation of differential cash flow and risk expectations causes deviations in multiples. Subsequent empirical literature provided by Dong et al (2006) and Rhodes-Kropf et al (2005) attempt to identify valuation models to isolate mispricing. This paper bases itself more on bidder behavior and beliefs. From the target's point of view, the deal is acceptable simply if it is offered the required premium. The deal is viable for the bidder as long as the deal increases it's per share value, either measured by forecasted earnings per share or book value per share. Furthermore, we argue that the likelihood of a merger taking place is a function of the number of viable bidders or targets available. Hence, the possibility for a firm to find a bidder, for it to sell itself to, who can provide the desired premium, increases with the number of viable bidders.

Following the original paper, the two hypotheses tested are:

Hypothesis 1 (H_1)

The likelihood of a firm being a target is positively related to the number of viable bidders.

As we argue that merger activity is driven by relative misvaluation, which is captured by our estimates of viable bidders and targets on stock financed deals, following the original paper, we adopt the additional prediction:

Hypothesis 2 (H_2)

The likelihood of the use of stock as method of payment is positively related to the number of viable bidders and viable targets.

Based on the findings in Garvey et al (2013), we have high confidence in H_1 linking the number of viable bidders to the probability of being a target. Initially Garvey et al (2013) were less confident in H_2 than H_1, as Boone & Mulherin (2007) find it likely that the presence of a viable stock-financed bidder may put a firm in play, but the successful bidder may end up using a significant amount of cash, particularly if there are many potential bidders. Garvey et al (2013) found supporting evidence of H_2, making it interesting to see if our results are mostly in line with theirs or Boone and Mulherin.

6. Data Construction

The following section provides a detailed description of how our dataset was constructed. We base our initial sample on all the firms in the Compustat universe, extracting historical merger observations from the SDC Platinum financial transaction database. Please see *Appendix 11.1 – 11.3* for definitions and item-codes from our databases.

The first step is extracting all domestic deals in the time-period 1981 to 2012 from the SDC database to match the original paper's sample-period. The search criteria include all deals taking the form of *Mergers*, *Acquisitions*, *Acquisition of Majority Interest* and *Acquisition of Assets* as well as transaction types *Disclosed Value*, *Undisclosed Value*, *Leveraged Buyouts* and *Tender Offers*. These filters provide us with a raw sample of *214,296* deal observations. For further filtering purposes, when extracting the report, we include the variables *Announcement Date*, *Deal Status*, *Firm's Public Status*, *CUSIP*, *Consideration Type* and a *Tender Offer Indicator*.

At this point, the dataset contains unwanted takeover observations resulting from merger activity between a firm and its parent. These intra-group acquisitions could be driven by other than value enhancing motives and are therefore removed. We therefore drop all duplicate records when the target's *CUSIP*, acquirer's *CUSIP, Announcement Date* and *Deal Status* are identical (dropping *149* observations). Further, we drop the record if either of the acquirer's *CUSIP* or acquirers' parent's *CUSIP* equals to of the target's *CUSIP* or the target's parent's *CUSIP*, accounting for both immediate and ultimate parent *CUSIPs* (dropping *5,840* observations).

The SDC data furthermore contains duplicate observations where an acquirer and target pair was recorded more than once in a year. Duplicate observations of the same exact deal will overweight the deals significance in the analysis; therefore, these duplicates in the same or the prior year are removed (dropping respectively *368* and *338* observations).

The analysis process involve multiple control variables based on balance sheet and other financial data, hence we require both acquirer and target to have a public status. This leaves us with *10,423* deal records (dropping *197,178* observations) prior to separating the sample into a target- and an acquirer sample.

To accurately follow the approach of Garvey et al (2013), we use *CUSIPs* as our company identifier[4]. A critical part of the dataset construction process is therefore to comprehend the nature of the *CUSIP* identifiers (e.g. how they are structured and how they might change over time), in order to successfully attach the correct financial data to each transaction observation. The SDC database provides six-digit historical *CUSIPs* (*name CUSIPs*) uniquely identifying the issuer of a security, but are subject to change over time. Compustat, our source of financial data, provides eight-digit header *CUSIPs* where the two last digits uniquely identify the issue number. Header *CUSIPs* are the last held *CUSIP* of a company, and can thus relate to several historical *CUSIPs* held by that particular company in the past.

Working with the target sample, we require all targets to have an eight-digit *CUSIP*. To achieve this we link the six-digit *CUSIPs* from SDC to the first six digits of the eight-digit historical *CUSIPs* in the file "*Stocknames*" from WRDS. For all matches we attach eight-digit historical- and header *CUSIPs* leaving us with *12,170* observations. This step however, creates artificial duplicate observations resulting from some of the six-digit *CUSIPs* from SDC matching with several historical *CUSIPs* in "*Stocknames*". To identify and keep the correct eight-digit *CUSIP* observation we drop the artificially created observations where the *Announcement Date* is not between the start- and end of *namedate* (dropping *3,843* observations). This step removes most of the artificial duplicates created in the previous step, however, some still remain due to overlapping *namedate* intervals. We keep the original unique observations, which do not have an announcement date between start- and end of *namedate*, but still match on *CUSIP*.

The SDC dataset contains unwanted duplicate data for our analysis, as a target may have multiple records with different acquirers within a year. A target, by definition, may only be taken over once[5], and these multiple observations can be attributed to announced, but not completed deals. Multiple observations of the same target within the same year will result in overweighting this target's data, hence we only allow a company to be recorded as a target once each year, and

[4] Several other identifiers are available, such as *PERMNO*/*PERMCO*, *GVKEY* and *TICKER*. We will not discuss the accuracy and viability of the different measures as our goal is to replicate Garvey et al (2013). In future research, one could extend the approach by using different/additional company identifiers.

[5] As we only consider mergers resulting in a majority interest which results in the parent company consolidating the target company into their financial statements.

drop the record if it was recorded the prior year (dropping respectively *386* and *175* observations). After applying these filters, we have a target sample of *7,766* records and each target has only one record per year and the preceding years.

We merge the SDC target sample with the CRSP Compustat Merged dataset (*CCM*), on eight-digit header *CUSIP*, to link financial data to the records. We obtain the calendar year from CCM by using the date at the end of the fiscal year, up to which the company reports its annual statement. Using the calendar year from CCM we find *9,664* matches with our SDC data either in the announcement year *(actual records)* or in the year before *(fictional).* We keep the fictional records where data is not available in the year of announcement (dropping *3,128* observations). The reason for creating these fictional records with financial data from the year prior to announcement is that many of the target firms do not provide annual reports in the year of which they were acquired.

As a final cleanup step, we drop the remaining artificial duplicates created during the process, as well as a few observations where it is indistinguishable which data from CCM is correct for the record. This reduces the sample slightly, but ensures correct data for the remaining sample (dropping *51* observations). Leaving us with *6,485* target firm year observations compiled of *3,150* observations with financial data the year of the announcement date, and *3,335* observations using financial data from the year prior to the announced year.

Turning our attention to the acquirer sample, we follow the exact process as for the targets, except we allow a company to be an acquirer more than once in a single year and in the preceding years. This results in an acquirer sample of *7,297* firm years observations with financial data the year of the announcement date, and *121* observations using financial data from the year prior to the announced year. The sample is slightly larger than that of the targets as more financial information is more readily available for the acquirers.

To construct the sample of firms not involved in merger activity we append the sample containing all firms in the Compustat universe removing all firm year observations that are included in either the target or acquirer sample. Following the same procedure as for the target and acquirer sample, we obtain eight-digit *CUSIP*s from “Stocknames” resulting in a sample of *184,405* non-merger firm year observations.

Finally, to complete the total sample, we drop all duplicate records where a firm was recorded as an acquirer more than once in a year. This is to make sure the same company is not counted as a viable bidder or target more than once for each potential counterpart and not weigh our regressions incorrectly due to identical balance sheet data. Appending the target-, acquirer- and non-merger samples completes our dataset used in the empirical the analyses.

From CCM we link balance sheet and price data to our sample, for earnings forecasts we turn to the I/B/E/S database. We obtain the mean analysts forecast at the point in time when the forecasts become the one-year forecast for the first time. In other words, the first forecast with forecast period end date (*fpedats*) from I/B/E/S one year after the financial data reporting date (*datadate*) from CCM. We merge in the EPS forecasts using eight-digit historical CUSIP and financial year (where the financial year from I/B/E/S is found by subtracting one year from *fpedats*). Many of the firms in our total sample do not find a match in the I/B/E/S database resulting in a significant reduction of observations when counting EPS accretive bidders and targets compared to book bidders and targets. As an alternative approach, we could have attempted to obtain additional matches by matching on tickers and company names. However, the ticker provided by I/B/E/S may change over time and/or be reused. Therefore, even if a match was found, it was not necessarily with the right firm. Since the sample is already sufficiently large to produce statistically significant results (*196,666* firm years), we valued the certainty in the correctness of the data more than increasing the sample size slightly.

Our dataset construction was conducted manually using Stata, and is most likely in practice somewhat different from Garvey et al's (2013) procedure (in regards to features of the software). We have included a comparison of the stages during the process where Garvey et al (2013) provide sample sizes, please see *Appendix 11.1.1* for details.

7. Empirical Specification and Key Variables

In this section, we begin by defining our variables and refine our controls. Then we continue by summarizing descriptive statistics as well as univariate findings from our initial empirical prediction that the likelihood of being a target is increasing with the number of viable bidders.

7.1 Empirical Specification

We follow the probit regression model for merger likelihood developed in Garvey et al (2013):

$$y_{i,t} = f(\alpha + \beta_1 V_{i,t-1} + \beta_2 X_{i,t-1} + \beta_3 Z_t + \beta_4 W_{t-1} + \mu_t + v_j) \tag{7}$$

Where the subscript *i* refers to firm *i*, subscript *t* refers to time in years and subscript *j* refers to industry *j*. μ_t refers to time fixed effects and v_j refers to industry fixed effects. Using the regression of target likelihood found in *Table 2* we illustrate the equation in practice. In this case, the dependent variable $y_{i,t}$ would take the value 1 if firm *i* was a target in year *t*, otherwise 0. The corresponding *V* is the number of viable bidders for the target measured by either book or EPS values for firm *i* in year *t-1*. *X* are the related control variables presented in *Table 1 Panel C-1* including firm *i*'s *size*, *leverage*, *price to book ratio*, *price to forecasted earnings ratio* etc. *Z* is the level and standard deviation of the related key variable within the industry at year *t*. *W* is the number of takeovers taking place in firm *i*'s industry *j* in year *t-1*. In the regressions for likelihood of using stock as a method of payment *y* is an indicator variable taking the value of 1 if the deal was financed only by stock, otherwise 0.

7.2 Test Variables

When computing the number of viable bidders for each firm we assume that any potential bidder will pay for the target with their own equity based on Q-theory and equation (6). Using our total sample of acquirers, targets and non-merger firms, we calculate for each firm each year the number of firms that are able to make an equity-financed deal, which is earnings per share accretive when paying a 20% premium to the target. For example, we consider $Firm_1$ as a viable bidder for $Firm_0$ if it uses its stock to pay a 20% premium for $Firm_0$'s equity (in market value terms) and the resulting earnings per share of $Firm_A$ increase after the acquisition.

Explained in more technical terms, $Firm_1$ is considered to be an earnings per share accretive bidder for $Firm_0$ in year *t* if $Firm_1$'s price over forecasted earnings ratio (P/FE_1) in year *t* is 1.2 (referring to a 20% premium) times that of $Firm_0$'s (P/FE_0) and they are both in the same two digit SIC industry.

$$\frac{P/FE_1 - P/FE_0}{P/FE_0} > \frac{0.2K_0}{s(K_1+K_0)-K_1} \qquad (8)$$

Based on the assumption that the acquirer expects the market to attach his multiple to the entire post-merge entity, an arguably extreme bootstrapping effect, applying $s = 1$ results in the equation:

$$P/FE_1 > (1.2) \times P/FE_0 \qquad (9)$$

In most of our analysis we apply lagged values as this paper is trying to convey insight into the possibility of predicting merger activity *ex ante*. The mean of analysts' earnings per share forecasts are obtained from the I/B/E/S database as proxy for expected earnings in our computations. We only use forecasts one year out.

I/B/E/S typically update their database with new forecasts each month and since Garvey et al's (2013) analyses are done on a yearly basis they only rely on one particular month's forecast. They choose the month in which the forecasted date becomes the one-year forecast for the first time. This usually happens the month a given firm publishes their financial reports and the analysts shift their attention to forecasting the next year's EPS. By following this method, we should be able to capture the new information available in the beginning of the financial year in question. When counting viable bidders and targets based on EPS, we exclude firms with negative earnings and denote them *Accretive Bidders* and *Accretive Targets.*

Summary statistics from our analysis of accretive bidders and targets are presented in *Table 1 Panel B-1*, including median and mean values for each of our three samples (numbers from the original paper are in *Panel B-2*). We run a simple multivariate regression without any controls shown in *Panel 1* of *Table A*. The results clearly portray that our median number of accretive bidders has a strong positive and significant relationship to the number of public firms actually being taken over on a yearly basis. Based on the same sample as the regression, *Figure 2* highlights the same message. Namely, that the median value of accretive bidders the same and the prior year, moves closely with the number of actual takeovers taking place.

We follow the same methodology to run an analogous exercise using book values. For example, we consider $Firm_1$ as viable book bidder for $Firm_0$ if it uses its stock to pay a 20% premium for $Firm_0$'s equity (in market value terms) and the resulting book value per share of $Firm_1$ increases after the acquisition. In practice this means that, $Firm_1$ is considered to be a book value per share accretive bidder for $Firm_0$ in year *t* if $Firm_1$'s price-to-book ratio (P/B_1) in year *t* is 1.2 (referring to a 20% premium) times that of $Firm_0$'s (P/B_0) and they are both in the same two digit SIC industry.

$$\frac{P/B_1 - P/B_0}{P/B_0} > \frac{0.2K_0}{s(K_1 + K_0) - K_1} \qquad (10)$$

Based on the same assumption previously introduced, the acquirer expects the market to attach his multiple to the entire post-merge entity, an arguably extreme bootstrapping effect, applying $s = 1$ results in the equation:

$$P/B_1 > (1.2)P/B_0 \qquad (11)$$

We exclude firms with negative book values of equity since it is hard to interpret their economic meaning. We denote the number of viable bidders for each firm based on book values as *Book Bidders* and the number of viable targets for each firm as *Book Targets*.

As the focus of this paper is to replicate Garvey et al (2013), we use the same approach for measuring viable bidders and targets. However, one could argue that this is a somewhat crude approach. For further work, it would be interesting to investigate the impact of using other, more comprehensive, ways of measuring accretion.

7.3 Control Variables

As pointed out in the introduction of this paper, a range of studies on the different aspects of merger likelihood have been performed. The findings imply that there are many possible drivers for mergers. Therefore, we apply an exhaustive set of controls highlighted in existing merger prediction literature, in line with those presented in Garvey et al (2013), to isolate and affirm the paper's intended contribution. We include all the controls in Garvey et al (2013) except the RIM measures.

Since the likelihood of being a target is shown to be positively related to the stock price to earnings ratio (Harford, 1999), we use this as a control. Cremers et al (2009) show that leverage has a significant and positive effect on the likelihood of being a target. Hasbrouck (1985) however does not find this statistically significant. To control for this, we include leverage measured as the book value of debt divided by total assets. According to past studies (Hasbrouck, 1985; Palepu, 1986; Mikkelson & Partch 1989), the size of the firm is negatively related to the likelihood of being a target. Varieties of different size measures exist, but we use the natural logarithm of assets as proxy for size in our regressions. Finally, as our main control variables, we adopt the valuation measures presented in the misvaluation paper by Rhodes-Kropf et al (2005).

These components are derived from the assumption presented by Rhodes-Kropf & Viswanathan (2004) that a firm has a true value (V) which can differ from the market value (M) and book value (B), thus for any measure of value we can use the following algebraic identity to decompose the misvaluation:

$$m - b = (m - v) + (v - b) \tag{12}$$

Rhodes-Kropf et al (2005) takes the breakdown of $m - b$ further suggesting that one component of $m - v$ is shared by all firms in a given sector or market, while another component of $m - v$ is firm-specific. Thus separating it into three components: firm-specific error, industry time-series error and long-run value-to-book error. The approach to estimating v involves expressing v as a linear function of firm-specific accounting information at a point in time, θ_{it}, and a vector of conditional accounting multiples, α, $v(\theta_{it}; \alpha)$.

Rewriting equation (12):

$$m_{it} - b_{it} = \left(m_{it} - v(\theta_{it}; \alpha_{jt})\right) + \left(v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)\right) + \left(v(\theta_{it}; \alpha_j) - b_{it}\right) \qquad (13)$$

$$m_{it} - v(\theta_{it}; \alpha_{jt}) \qquad (14)$$

Represents the firm-specific error, which captures purely firm-specific deviations from fundamental value.

$$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j) \qquad (15)$$

Represents the time-series error, when this figure is high, the sector wide valuation wave is near its peak.

$$v(\theta_{it}; \alpha_j) - b_{it} \qquad (16)$$

Represents the difference between long-run value and book value.

Rhodes-Kropf et al (2005) develop three separate models to identify the misvaluation components. Our control variables are based on the most comprehensive model, *Model III*[6], including *Market Value*, *Book Value*, *Net income* and *Leverage*[7].

$$m_{it} = \alpha_{0jt} + \alpha_{1jt}b_{it} + a_{2jt}\ln(NI)_{it}^{+} + \alpha_{3jt}I_{(<0)}\ln(NI)_{it}^{+} + \alpha_{4jt}LEV_{it} + \epsilon_{it} \qquad (17)$$

To obtain $v(\theta_{it}; \hat{\alpha}_{jt})$ we use fitted values from equation (17):

$$v(B_{it}, NI_{it}, LEV_{it}; \hat{\alpha}_{0jt}, \hat{\alpha}_{1jt}, \hat{\alpha}_{2jt}, \hat{\alpha}_{3jt}, \hat{\alpha}_{4jt}) = \hat{\alpha}_{0jt} + \hat{\alpha}_{1jt}b_{it} + \hat{\alpha}_{2jt}\ln(NI)_{it}^{+} + \hat{\alpha}_{3jt}I_{<0}\ln(NI)_{it}^{+} + \hat{\alpha}_{4jt}LEV_{it} \qquad (18)$$

To obtain $v(\theta_{it}; \hat{\alpha}_{j})$, we average over time $\frac{1}{T}\sum \alpha_{jt} = \bar{\alpha}_j$ for $\alpha_k, k = 0, 1, 2, 3, 4$ and calculate:

$$v(B_{it}, NI_{it}, LEV_{it}; \bar{\alpha}_{0j}, \bar{\alpha}_{1j}, \bar{\alpha}_{2j}, \bar{\alpha}_{3j}, \bar{\alpha}_{4j}) = \bar{\alpha}_{0j} + \bar{\alpha}_{1j}b_{it} + \bar{\alpha}_{2j}\ln(NI)_{it}^{+} + \bar{\alpha}_{3j}I_{<0}\ln(NI)_{it}^{+} + \bar{\alpha}_{4j}LEV_{it} \qquad (19)$$

One can argue that several other valuation metrics have been suggested as alternative controls[8]. However, since the valuation decomposition by Rhodes-Kropf et al (2005) overlap most of these, they seem to be sufficient to affirm our papers intended contribution. We also include

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[6] The lower case letters are values expressed in natural logs, whilst the upper case letters are standard units.

[7] *NI+* stands for the absolute value of net income and *I(<0) ln(NI)+* is an indicator function for negative net income observations. *LEV* is the leverage ratio, measured debt to total assets

[8] Hashbrouck (1985) uses market/book and argues that low values of this measure may indicate incompetent managers and low cost for acquirers. He also adds liquidity as a control variable as it is easier for an acquirer to get ownership in a liquid target. Cremers et al (2009) find that ROA (*return on assets*) is negatively related to the likelihood of being a target. Further, they control for Tobin's q and find a negative relationship to the target likelihood.

these misvaluation components in our regressions for acquirer likelihood, as we expect them to have the opposite effects than in target likelihood regressions.

In line with merger wave literature by Gorton et al (2009) we continue by counting the total number of takeovers within each two-digit SIC code each year. *Figure 2* highlights the generally agreed proposition that mergers happen more frequently in booming markets. To make sure our results are robust against picking up year effects or simply being caused by shocks affecting the entire economy or some industries, we control for industry- and year fixed effects and cluster the standard errors at the industry level when running our regressions. When shocks hit the entire economy or industry, we see the occurrence of overall stock price movements. However, in this paper we are only interested in how shocks create movement in relative stock price misvaluation and how this relates to observed merger activity.

We include industry dispersion (measured by interdecile range and standard deviation) of both the valuation metrics we consider (price-to-book and price-to-earnings) as additional controls to make sure our results are not driven by any changes to the industry as a whole. *Figure 2* reinforces this claim by showing the positive relation between the movement of price to book (i.e. price-to-book) dispersion and the number of deals each year. Finally, we include the number of firms in the industry as an additional control. This is because the number of viable bidders, unlike dispersion statistics, is related to the sheer number of firms in the industry.

7.4 Summary Statistics

In this section, we start by discussing our summary statistics presented in the five panels of *Table 1* and how they match up with Garvey et al's (2013) original results. We focus on the lagged values in each of the acquirer, target and non-merger sample. Finishing off, we take a closer look at takeover activity in three selected industries.

From *Panel B-1* we can see that the median number of both accretive and book bidders are significantly larger in the target sample than in the other two, acquirer- and non-merger sample. E.g., in the panel we can see that firms in the acquirer- and non-merger samples have a median of only 32 and 51 potential accretive bidders (*Lag Accretive Bidders*)[9], respectively, whereas firms in the target sample have a median of 61. Garvey et al's (2013) results displayed in *Panel B-2* portray results drawing a similar conclusion with a median number of potential bidders of 83 for the target sample, 50 for the non-merger sample and 68 for the acquirer sample.

Furthermore, in line with Garvey et al's (2013) results, we additionally find that the median number of viable targets in the acquirer sample, 61, is significantly greater than the other two samples, 34 and 33. This indicates strongly that our estimates of number of viable bidders and targets can participate in predicting if a firm ultimately becomes an acquirer or target[10]. We note that our mean and median values for both targets and bidders are lower than in the original paper; however, this only reflects the fact that we have smaller sample sizes.

The distribution of the data in the three samples are highly right-skewed. Therefore, when running the regressions, we follow Aggarwal & Samwick (1999) and transform the independent variables with the Cumulative Density Function *(CDF)*[11] for normalization purposes.

Applying the simple model, introduced by Garvey et al (2013), and presented earlier, with the observed probability of being a takeover target in the whole sample 3.21%[12] and the median number of EPS bidders for the entire sample (34) we estimate the fraction of the bidder population which do not believe in the bootstrap game based on the formula $1 - X^{34} = 3.21\%$. This results in a fraction of bidders who do not believe in the bootstrap game of 99.90%. If we apply this number with the median number of EPS bidders for the target sample (61) the probability for being a target increases with 2.48 percentage points to 5.69%, which is fairly close to the marginal effects of 0.030, 0.032 and 0.030 found in the three columns (1), (2) and (3) of *Table 2*.

[9] Variable names from the tables in parenthesis

[10] Using a simple T-Test. The mean differences are all significant at the 1% level

[11] The Cumulative Density Function describes the probability that a real-valued random variable *X* with a given probability distribution will be found to have a value less than, or equal to *X*.

[12] The observed probability of being a takeover target is found by dividing the number of targets by the size of the total sample.

When applying their numbers to the simple model above, Garvey et al (2013) find that the probability of being a target increases to 6.11%. This is slightly higher than our results, but significantly closer to their marginal effects of 0.053, 0.054 and 0.058. A potential explanation for our somewhat larger deviation from the marginal effects, compared to what is found in the original paper, is that our industry number of takeovers (*Lag Ind Num Takeover*) has coefficients ranging from 0.020 to 0.021, all significant at the 1% level. While this is evident throughout all our regressions, theirs are not.

Panel C-1 of *Table 1* reports the lagged means and medians of our control variables. Examining the target and the non-merger sample there are no obvious differences in the values except for the merger wave variable, industry number of takeovers, and the price over forecasted earnings ratio (*Lag P/FE*). As pointed out earlier, the number of takeovers in the industry is one of the most significant variables in our regressions for predicting merger likelihood. Our summary statistics are thus consistent with our regression findings, and mostly in line with Garvey et al (2013), showing that actual takeovers to a greater extent take place in the industries of our actual targets and acquirers. Contradicting Garvey et al's (2013) results displayed in *Panel C-2*, we fail to identify notable differences in the number of firms in the industry *(Lag Ind Num Firms)* between the target and non-merger sample.

Turning our attention to the differences between the mean values of the acquirer- and the non-merger sample, we find that they are mostly significant and almost always at the 1% level. The most striking differences are in size (*Lag Size*), P/FE ratio (*Lag P/FE*) and industry number of takeovers (*Lag Ind Num Takeover*) where, in line with Garvey et al (2013), we see that acquirers are both larger, have a higher P/FE ratio and are situated in industries with higher takeover rates than the firms in the non-merger sample. This is in accordance with existing literature; hence, the variables are arguably relevant controls for our tests. Further, we find that acquirers tend to have higher firm-specific error (*Lag Firm Specific Error*) meaning that acquirers are more overvalued (positively misvalued) than non-merger firms due to intrinsic factors. Our numbers are notably higher than Garvey et al's (2013). They identify a difference in the means of the non-merger and acquirer sample's firm-specific error of 0.06 in *Panel C-2*, whilst our data result in a difference of 0.19. Further, contradicting Garvey et al's (2013) results, our number of firms in the industry for the acquirer sample fails to deviate notably from the non-merger sample.

Highlighting what we see in *Figure 1*, these differences have already provided valuable information to *ex ante* identify the likelihood of being an acquirer, and therefore the number of viable targets does not stand out as the only relevant variable when attempting to predict the acquirers. The differences between the mean values of the merger- and non-merger samples further highlight the importance of the number of takeovers in the industry as pointed out earlier.

Panel D of *Table 1* portrays the correlations between the applied test variables. The book bidders and book targets are correlated at a 61.5% level indicating that the viability measures are accounting for different facets of managerial behavior. The correlation between accretive and book targets are very similar to that of the bidders at 61.3% and the correlation between viable targets and bidders are low, which are both in line with Garvey et al (2013) and to be expected.

Another important finding in *Panel D* of *Table 1* is the high correlations between the measures of viable targets and acquirers, and the number of takeovers in each industry. This is however a natural result as we count for viable bidders and targets at the firm level and the count is restricted to firms within the same industry. We define industries by two-digit SIC codes, and according to Garvey et al (2013), the results should not be overly sensitive to the choice of industry classification.

Panel E of *Table 1* portrays the correlations between merger rates and median number of accretive- and book bidders per firm, by industry, and by industry-year consecutively. There is a strong positive linear and monotonic relationship between the measures accretive- and book bidders, and the merger rates. The Spearman correlations (ρ) are 0.94 and 0.96 and the Pearson correlations (r) are 0.96 and 0.93. As the Spearman coefficient is positive, we can conclude that a greater number of viable bidders are associated with a greater number of takeovers. The merger rate by industry may not capture the dynamics of the merger activities, so we furthermore analyze the correlations based on industry each year. The Spearman- and Pearson correlations drop to 0.71, 0.73 and 0.83, 0.80 consecutively. Based on these correlations our methodology seems to work well in identifying hotbeds of merger activity. This prediction is different from the merger wave approach, as by construction the merger wave does not make predictions until after actual mergers have taken place (Garvey et al, 2013). Our correlation results are notably larger than the original paper's, indicating that our data sample provides a stronger relationship between these variables.

Moving on from the summary statistics, we now shift our focus to the time-series of mergers in three of the most active industries; *Depository Institutions*, *Business Services* and *Electronic and other Electrical Equipment and Components, except Computer Equipment*. In line with Garvey et al (2013), *Figures 3* and *4* illustrate how the lagged number of viable bidders relates to actual takeovers in the industries each year. We find analogous results that the merger wave variables and our measures of viable bidders tell a similar story in both industries. Book bidders however, seem to be even more closely related to industry takeovers for *Depository Institutions* than the accretive bidders are. Garvey et al (2013) argue that the rapid increase in the number of firms in *Figure 3* was caused by a large number of mutual banks going public in the 1990s. They claim that this also caused an increase in merger activity and that there is a clear relationship between industry number of firms and takeovers in the industry. The relationship however does not seem to be as clear in our results. Another point of interest shown in these figures is that the number of firms in the industries varies notably over time. Combined with the facts that the number of firms in the industry and the number of viable bidders and targets in the takeover and acquirer samples are larger than that in the non-merger sample and the two numbers are highly correlated suggests that we should also include number of firms in the industry as a control variable in our tests.

To further investigate the relationship between the number of firms and takeovers in an industry each year we add a third industry, *Electronic and other Electrical Equipment and Components, except Computer Equipment*. *Figure 5* portrays the same measures as *Figures 3* and *4* while we scale the number of firms and takeovers in *Figure 6* to provide a more illustrative depiction of the trends. The graphs show that the number of takeovers is considerably more volatile than the sheer number of firms and there is no obvious relationship between the two.

8. Main Empirical Results

With the data construction process complete, we proceed in testing the initial results identified in *Figure 1* and *Panel A* of *Table 1*.

8.1 Predicting Takeover Targets Based on Number of Viable Bidders

Testing their first hypothesis (H_1), if the likelihood of being a takeover target increases with the number of viable bidder firms, we run probit regressions where the dependent variable is a dummy variable taking the value of 1 if the firm is a takeover target and 0 otherwise. We transform the independent variables using the cumulative distribution function (*CFD*), to achieve comparability between the coefficients, cluster the standard errors at the industry level and control for year- and industry fixed effects. The results are presented as marginal effects in the tables.

Columns (1), (2) and (3) in *Table 2* show the effect of the number of viable accretive bidders the previous year (*Lag Accretive Bidders*) on the probability of being a takeover target. Column (1) is the baseline regression with controls for the standard deviation of the target's industry price over forecasted earnings ratio (*Ind P/FE SD*) alongside other relevant variables. The second column replaces the standard deviation with the interdecile range of P/FE (*Ind P/FE Interdecile*). The interdecile range is the range between the P/FE of the firms at the 90^{th}- and 10^{th} percentile in a given industry. The third column includes the three Rhodes-Kropf et al (2005) misvaluation components.

Strongly in support of the first hypothesis, we observe that the lagged number of accretive bidders are highly relevant for predicting the likelihood of being a target across all regressions. The coefficients are all positive and significant at the 1% level. Examining the marginal effects of the probit regressions, illustrates the significance of the findings. The coefficients of the accretive bidders in column (1), (2) and (3) of the marginal regression vary between 0.030 and 0.032, implying that if the number of viable bidders rises from the median of the CFD transformed variable to the maximum, the probability of being a target increases with (0,5 x 3.2%) = 1,6%. The magnitudes of the marginal effects for accretive bidders in our regressions are somewhat lower than the corresponding coefficients presented in the original paper ranging from 0.053 to 0.058. However, they are still significant and highly relevant. Further, we find that some of our controls seem to contribute to explaining the probability of being a target far better than in the original paper. The following paragraphs review these in more detail.

The coefficient of the number of takeovers in a firm's industry the previous year (*Lag Ind Num Takeover*) is both positive and significant at the 1% level ranging from 0.020 to 0.021, thus increasing the likelihood of being a target. This is supported by existing merger wave literature (Thakor & Goel, 2010; Gorton et al, 2009) and is both significant at a higher level and with a greater coefficient in our regressions than the original paper's non-significant coefficients ranging from 0.008 to 0.009.

Our results show that the number of firms in the industry *(Lag Ind Num Firms)* is not relevant in the prediction model, however the original paper have found a slightly negative significant coefficient ranging from -0.010 to -0.012. This is surprising as it suggests more firms in an industry lowers the probability of being a target, which seems counterintuitive and conflicting with the summary statistics.

Furthermore, our P/FE *(Lag P/FE)* ratio findings also contradict the original paper. Negative coefficients ranging from -0.023 to -0.037, significant at the 1% level, suggest that a firm with low P/FE has a significantly higher chance of being a target. Garvey et al (2013) do not find significant P/FE coefficients when controlling for accretive bidders. Our results are supported by Fuller & Jensen (2002) who argue that some CEOs engage in an earnings game and may mistakenly or carelessly acquire low P/FE firms believing that the market will apply the acquirer's high multiple for the combined entity.

We find that the firm-specific error *(Lag Firm Specific Error),* based on Rhodes-Kropf et al's (2005) misvaluation decomposition, increases the likelihood of being a target in all regressions with coefficients ranging from 0.09 to 0.017, similar to the findings of Garvey et al (2013) ranging from 0.012 to 0.014. This refers to cases in which a firm is overvalued due to pricing error of its own characteristics, and there is a discrepancy between its market- and fundamental value.

The effect of firm size *(Lag Size)* in our regression needs further explanation. Earlier literature agrees upon that small firms are likely to be targets. However Harford (1999), when applying the log value of the firm's assets as proxy for size, finds that the coefficient is not significant. Splitting our sample in two, at the median of firm size, indicates a non-linear relationship as we find that the coefficients for the sub samples have opposite signs. The original paper reports the same findings. As the effect of size on merger activity is not a primary issue in the original paper, we follow Garvey et al

(2013) and choose to simply add the square of size *(Lag Size Square)* to control for this non-linear relationship, resulting in insignificant sign and size of these coefficients[13].

Following our EPS bootstrap results, we test whether the likelihood of being a target increases by the number of viable book bidders. Column (4) portrays these results with the relevant controls. We find that the magnitude of the marginal effect of book bidders *(Lag Book Bidders)*, 0.025, is slightly lower than for the accretive bidders, 0.030 and significant at the 1% level. We find a similar reduction in Garvey et al (2013) as their coefficient drops from 0.058 to 0.016. All the Rhodes-Kropf et al (2005) misvaluation components turn positive and significant at the 1% level and the magnitude of the negative P/FE coefficient increases to -0.086.

We find some conflicting results from the original paper regarding the long-run value-to-book *(Lag Long Run V to B)* component of Rhodes-Kropf et al (2005), as this coefficient is only significant in our regression presented in column (4), when applying book bidders (as we will return to later) as the main independent variable, with a magnitude of 0.010. Garvey et al (2013) report a negative and statistically significant coefficient across the board, ranging from -0.006 to -0.022. Our results however, are somewhat in line with the findings of Rhodes-Kropf et al (2005) that low long-run value-to-book firms tend to acquire high long-run value-to-book targets. An argument in support of this proposition is that large firms with low expected future earnings acquire smaller firms with high expected earnings, in an attempt to increase their future expected earnings.

In column (5) we estimate the model controlling for both accretive- and book bidders. The impact of accretive bidders drops slightly from 0.030 to 0.027, and book bidders drops from 0.025 to 0.011, both still significant at the 1% level.

In line with the original paper, the number of viable accretive bidders seems to go a long way in explaining the likelihood of being a target. Other controls in our results seem to additionally carry a greater predictive power than in the original paper, such as previously mentioned industry number of takeovers and P/FE.

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[13] In unreported results we ran the regressions without the size square variable, resulting in a negative significant size measure for targets and the opposite for the acquirer sample

Overall, the results presented in *Table 2* are in line with the findings in Garvey et al (2013). They show strong support of the first hypothesis, that a firm is more likely to be a target if there are more viable accretive- and, although to a lesser extent, book bidders. We note that our measures remain strongly significant when including standard controls as well as the three Rhodes-Kropf et al (2005) misvaluation factors and Hardford's (2005) adjustment for the non-linear size variable.

8.2 Predicting Acquireres Based on the Number of Viable Targets

Next, we shift our attention to the models ability to predict the likelihood of being an acquirer. *Table 3* reports our results applying accretive targets (*Lag Accretive Targets*) as the main variable of interest, whilst adding other relevant variables as controls. Following Garvey et al (2013), we run probit regressions where the dependent variable is a dummy variable taking the value of 1 if the firm is an acquirer and 0 otherwise. As in *Table 2* the results reported are the marginal effects, the independent variables are CFD transformed, standard errors are clustered at the industry level and we control for year- and industry fixed effects.

The first regression displayed in column (1), includes only our main variable of interest, accretive targets. We find a marginal effect of 0.029 significant at the 1% level, similar to Garvey et al's (2013) coefficient of 0.032, suggesting that the likelihood of being a bidder is positively related to the number of viable targets.

In column (2), additional controls are added and the marginal effect of accretive targets drops to 0.015 but remains significant at the 1% level. Other control variables seem to have greater significance when attempting to predict if a firm becomes a bidder. The wave variable, (*Lag Ind Num Takeover*) has a marginal effect coefficient of 0.052, which is larger than the accretive targets variable and significant at the 1% level. This variable is clearly successful in predicting a bidder, even more so than predicting a target. Garvey et al (2013) report a somewhat similar result with a positive and significant coefficient for the merger wave variable. Their coefficients however are notably lower ranging from 0.009 to 0.010.

When we add control variables intended to capture misvaluation effects, i.e. P/FE and Rhodes-Kropf et al's (2005) three misvaluation components in column (3), (4) and (5), the number of accretive targets loses its predictive power and is longer no longer significant. In line with the original paper, accretive targets lose its significance when controlling for P/FE in columns (3) and (4). Our P/FE results however, contradict the original paper, as they are not statistically significant. We furthermore reach the same conclusions when adding the interdecile dispersion of the price to earnings variable in column (4).

In column (5) we add the three Rhodes-Kropf et al (2005) misvaluation measures revealing where these components really come into effect. Namely, as seen in Garvey et al's (2013) original paper, they show strong predictive power to the likelihood of being a bidder. Controlling for these variables do not reduce the magnitude of the other controls notably, but contribute additional predictive power. This is especially true for the firm-specific error and long-run value-to-book with coefficients of 0.035 and 0.020 respectively, both being significant at the 1% level. The time-series error *(Lag Time Series Error)* however, is not significant. Our results provide stronger support of this conclusion than the original paper, especially regarding the relevance of the firm-specific error with a coefficient at a higher significance level and with a greater value of 0.035 compared to their 0.010.

These results are in accordance with the findings of Rhodes-Kropf et al (2005), which conclude that when a firm itself has a temporarily elevated firm-specific misvaluation, it is more likely to be a bidder. The high and significant long-run value-to-book coefficient is in line with traditional Q-theory arguing that firms with high growth opportunities should buy firms with lower growth opportunities (Dong et al, 2006).

As reported in *Table 2*, the firms leverage ratio *(Lag Leverage)* was deemed not significant when predicting the likelihood of being a target. This is in accordance with the findings of Hasbrouck (1985). However, when predicting the likelihood of being an acquirer, in line with Garvey et al (2013), all of our regressions show a negative relationship significant at the 1% level. This suggests that the likelihood of being an acquirer is reduced as a firm's leverage increases, which can be supported by the findings of Billett & Qian (2005). The original paper's results support this conclusion but estimate a considerably smaller coefficient, ranging from -0.002 to -0.009, compared to ours. We find the coefficients ranging from -0.17 to -0.19, suggesting that Garvey et al (2013) underestimate the impact of leverage.

To sum up, we find similar results as Garvey et al (2013), namely that the number of viable targets available, to some extent, may contribute in predicting which firms will be an acquirer. However, the results are far less impressive than the target results. The main contributors in predicting the bidders seem to be the two Rhodes-Kropf et al (2005) measures of misvaluation, firm-specific error and long-run value-to-book, as well as the number of takeovers in the industry and the firms leverage ratio. Our results somewhat deviate from the original paper, as the predictive power of the mentioned variables are greater in magnitude in our results than theirs. In addition, we are successful in identifying leverage as a significant predictor for the likelihood of being an acquirer.

8.3 Predicting Merger Activity at Firm and Industry Levels

Next, we shift our focus to the models ability to predict merger activity at the firm and industry level. We run probit regressions where the dependent variable is a dummy variable taking the value of 1 if the firm was either a takeover acquirer or target, and 0 otherwise. The independent variables are CFD transformed, standard errors are clustered at the industry level and we control for year- and industry fixed effects. The marginal effects are displayed in *Table 4*.

We observe in the first regression, reported in column (1) without applying any controls, that the coefficient for both accretive bidders and targets are positive and significant at the 1% level. Garvey et al (2013) report an accretive targets coefficient of similar magnitude, however our accretive bidders coefficient (0.070) is substantially greater than theirs (0.046). When adding the merger wave control variable to the regression our coefficient of accretive targets loses its significance. This contradicts the original paper’s findings where the accretive targets variable is robust to the merger wave control. Our results suggest that the number of takeovers in the industry, which is positive and significant at the 1% level, does a better job at predicting if a firm will be involved in a takeover than the number of accretive targets.

Turning our attention to the valuation measures of Rhodes-Kropf et al (2005), we see that our estimated coefficients are quite similar, in both size and direction, to the ones found in Garvey et al (2013). As shown in column (3), we find that the firm-specific error and long-run value-to-book are significant at the 1% level with respectively positive and negative signs. Our firm-specific error coefficient of 0.039 is estimated to have substantially higher predictive power than in their results, showing a coefficient of only 0.018. The coefficients are slightly lower than reported in *Table 9* of Rhodes-Kropf et al (2005), however Garvey et al (2013) argue that this result stems from applying a finer industry partition (we apply SIC codes whereas Rhodes-Kropf et al (2005) rely on Fama-French 12 industry classification) and a longer sample period.

In line with Garvey et al (2013), the industry number of takeovers coefficient, is positive and significant when only including controls for these three misvaluation measures. We observe that our coefficient is significantly higher, with a value of 0.068 compared to Garvey et al's (2013) 0.021. When adding back the measures of viable bidders and targets in columns (4) and (5) we find a similar pattern as before. Accretive bidders stay positive and significant following both Garvey et al (2013) and Rhodes-Kropf et al (2005) and have incremental power to predict merger intensities at the firm level. Garvey et al (2013) report that the coefficient of long-run value-to-book is negative and significant across the board, though our results suggest that firm-specific error and accretive bidders are more important measures when trying to predict merger intensity at the firm level, cancelling out the long-run value-to-book's significance.

Next, in line with the original paper, we investigate whether our measures of viable bidders also predict merger waves at the industry level. The level of the industry merger wave is defined as the number of merger announcements in each industry every year. Following Garvey et al (2013) we run OLS panel regressions where our model's key predictive variable is the average number of accretive bidders in each industry each year (*Lag Ind Average Accretive Bidders*). We include several controls, such as the Rhodes-Kropf et al (2005) measures and the number of firms in the industry each year. Finally, we use lagged values in all regressions and control for year and industry fixed effects both in the regressions and with control variables. The results are reported in *Table 5*.

The first column (1) shows that our key variable of interest, the average number of accretive bidders in the industry, has a greater predictive power than Garvey et al (2013). We find a coefficient of 0.287 significant at the 1% level, compared to their coefficient of 0.193. In column (2), unlike Garvey et al (2013), we find that the number of firms in the industry is negatively related to the merger intensity. All though our results effect is marginal and only significant at the 10% level, Garvey et al (2013) find a positive coefficient of 0.0114 significant at the 1% level. Garvey et al (2013) furthermore illustrate these findings of a positive relationship between merger intensity and the sheer number of firms in the industry in their *Figure 3*, showing the development over time for *Depository Institutions*. They argue that a large number of mutual banks went public in the 1990s, driving more merger activity. However, the relationship does not seem to be that clear. For example, in the period 1982-1992 the number of firms in the industry almost triples, whereas the merger intensity remains almost constant. Further, as shown in *Figure 6* displaying a scaled plot of the two variables for *Electronic and other Electrical Equipment and Components except Computer Equipment*, there does not seem to be an obvious relationship in the trends. This supports our findings that the number of firms in the industry not necessarily plays a significant role in predicting merger intensity.

In columns (3), (4), (5) and (6) we sequentially include the industry average price-to-book ratio (*Lag Ind Average P/B*), total number of mergers in the previous year (*Total Mergers* $Year_{t-1}$) and the total number of mergers in the industry (*Total Mergers* Ind_j) using the last two as control variables for fixed effects. We observe that consistently across all panels, in line with Garvey et al (2013), the coefficient for our measure of the industry average accretive bidders remain positive and significant at the 1% level. Lastly, in columns (7), (8), (9) and (10) we include the Rhodes-Kropf et al (2005) measures of industry average time-series error *(Lag Ind Average Time Series Error)* and industry average long-run value-to-book ratio *(Lag Ind Average Long Run V to B)* as controls. Our primary variable, as in the original paper, remains a strong and significant predictor of industry level merger intensity. Note however that the coefficient drops slightly when manually controlling for industry fixed effects, lowering the R-squared, suggesting that accounting for fixed effects in the regressions provide better results.

8.4 Predicting the Medium of Exchange

We now shift our attention to the second hypothesis (H_2), namely that the number of viable bidders and targets are related to the use of stock as the medium of exchange in the acquisition.

In line with Garvey et al (2013), the dependent variable is a dummy variable taking the value of 1 if the deal only uses stock as a method of payment, and 0 otherwise. We run probit regressions controlling for year- and industry fixed effects and cluster the standard errors at the target's industry level. Following Garvey et al (2013), as an additional control variable to those applied in previous regressions, we add a dummy variable taking the value 1 if the deal is a tender offer. Existing literature furthermore finds that this is generally relevant for the choice of medium of payment (Garvey et al, 2013). In each regression, we pair the acquirer's number of viable targets with the target's number of viable bidders. As earlier, we CFD transform the independent non-dummy variables in the regression analysis and report the marginal effects in *Table 6 Panel A*. Several of the controls are not reported in the table partially due to space limitations, but primarily because they are less relevant for the conclusions reached. This procedure mimics the one in Garvey et al (2013).

We report the results based on accretive bidders and targets in columns (1), (2), (3) and (4) of *Table 6 Panel A*. In line with the work of Dong et al (2006), we include the target firms' corresponding acquirer's attributes in the tests. Hence, we report the number of viable targets and bidders for both the target and the acquirer. In column (1), as proxy for dispersion, we use the standard deviation of the target's industry price to forecasted earnings ratio, whereas in column (2), (3) and (4) rely on the interdecile range of the target's industry price to forecasted earnings ratio.

From columns (1) and (2) we observe that there is a positive relationship between the target's accretive bidders *(Lag Target Accretive Bidders)* and targets *(Lag Target Accretive Targets)* with the probability of the transaction being stock financed. However, the target measure is not significant. Garvey et al (2013) report that the positive relationship between the use of stock as a payment and the number of accretive targets is in accordance with existing literature. Specifically the proposition that a high number of accretive targets for the target firms indicate that when the target's valuation is elevated, it is also more likely to receive and accept stock as a method of payment. Surprisingly, we observe in Garvey et al's (2013) tables that the coefficient of their marginal effects in columns (1) and (2) are not significant, hence, they carry no predictive power to underscore their conclusion. Our regressions also fail to confirm the number of accretive targets for a target to be significant in predicting method of payment. The target's number of accretive bidders however, carries significant predictive power with coefficients ranging from 0.271 to 0.285.

A large number of accretive bidders might suggest that the target is, at least relative to other firms, undervalued. This is in line with Schleifer & Vishny (2003) who find that relatively overvalued bidders are more likely to use stock as a method of payment in the acquisition of undervalued targets.

In column (3) we add the three mispricing measures from Rhodes-Kropf et al (2005) for the targets. We find that all three are positively related to the use of stock as the method of payment, though time-series error *(Lag Target Time Series Error)* and long-run value-to-book *(Lag Target Long Run V to B)* are not significant. Garvey et al (2013) identify opposite results, as they find time-series error and long-run value-to-book to be positive and significant, whilst the target's firm-specific error *(Lag Target Firm Specific Error)* is not.

In column (4) we add the corresponding measures for the acquirers. We can see that the target's number of accretive bidders and accretive targets remain positive (although accretive targets is not significant), while the acquirer's own number of accretive targets *(Lag Acquirer Accretive Targets)* and accretive bidders *(Lag Acquirer Accretive Bidders)* are not significant. This is consistent with the results of Garvey et al (2013). We furthermore find that the firm-specific error for both targets *(Lag Target Firm Specific Error)* and acquirers *(Lag Acquirer Firm Specific Error)* are positive and significant. Thus, together with the targets number of accretive bidders, seems to be strong predictors of whether stock is used as the method of payment. Garvey et al (2013) find similar results regarding the firm-specific error of the acquirers, however as for the regression in column (3), the coefficient is not statistically significant for the targets.

Lastly we examine the relationship between book based viable bidders and targets and the use of stock as a method of payment, shown in column (5). Similar to Garvey et al (2013) we observe that the coefficient for the number of viable targets (*Lag Target Book Targets*) is positive and significant at the 1% level. Further, we find that none of the mispricing measures from Rhodes-Kropf et al (2005) are significant when applying the book-based measures for viable bidders *(Lag Target Book Bidders, Lag Acquirer Book Bidders)* and targets *(Lag Target Book Targets, Lag Acquirer Book Targets)*. The acquirer controls show an interesting result. The coefficient the acquirers number of book bidders is both negative and significant at the 1% level, indicating that when the number of the acquirer's viable bidders is higher, the less likely the acquirer is to finance the deal with 100% stock. Garvey et al (2013) find the opposite result for the acquirer's book targets, while our coefficient is both negative and not significant.

Garvey et al (2013) find that a firm with average attributes across the board has a probability of the method of payment being stock of 31.2%. Furthermore, they conclude in their paper, based on column (3) of *Table 6a*, that an increase from the median to the maximum of the number of viable targets for an acquirer will increase the probability of a deal being 100% stock financed by 20%. Garvey et al (2013) do not state whether this is the acquirer's book-, accretive- or RIM targets. Based on their model, a 20% increase in probability reflects a marginal coefficient of 0.1248, which is nowhere to be found in their table. The closest significant coefficient in the table is in regression (5) representing a 25% increase when an acquirer's book bidders increase from the median to the maximum.

These somewhat unidentifiable results lead us to some extent deviate in this calculation from what Garvey et al (2013) do in the original paper, as we apply the number of accretive bidders for a target to the model. This is both significant and positively related to a deal being stock financed with coefficients of 0.195. For a firm with average attributes across the board, including the number of viable targets and bidders, the unconditional probability of stock being the method of payment is 31.9%[14]. If the number of viable accretive bidders for a target firm goes up from the median to the maximum level, the probability of deals using only stock as the method of payment increases by 31%[15], which is a fairly substantial increase. The number of viable accretive targets for an acquirer however is not significant, hence unsuccessful in identifying stock based deals.

In *Table 6 Panel B*, we report the results from our regressions predicting the method of payment at the industry level. In line with Garvey et al (2013) we run OLS regressions using the number of 100% stock-financed merger announcements in each industry, each year, as our dependent variable. As our key test variable, we use the lagged values of the average accretive bidders in each industry each year (*Lag Ind Average Accretive Bidders*) and control for year- and industry fixed effects in the regressions and with control variables.

Garvey et al (2013) report that their results displayed in *Table 6b* of their paper, are similar to those in *Table 6a*, namely that the number of a target's accretive bidders have a strong positive effect in predicting the use of stock in merger deals. We obtain similar results from our data in regards to the relevance of accretive bidders. Columns (1), (2), (3), (4), (7) and (8) of *Table 6 Panel*

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[14] 3,325 stock financed deals out of 10,423 total deals announced

[15] $\left(\frac{31.9\%+(0.5*0.195)}{31.9\%}\right)-1$

B, where we control for fixed effects in the regressions, support their conclusion from *Table 6a* and our in *Table 6 Panel A*. Namely, that the number of accretive bidders is both significant and positive in regards to whether a takeover is stock financed or not, with coefficients ranging from 0.107 to 0.128.

Our results partially contradict Garvey et al's (2013) conclusion to hypothesis 2 (H_2) as the number of viable targets are deemed insignificant. However, a the number of viable bidders have a strong predictive power, and an increase of this variable results in a significantly higher probability of a stock financed deal taking place. Garvey et al (2013) conclude that a greater number of viable targets increase the probability of firms using stock as medium of consideration. This contradicts our results as we find the number of viable bidders as the only significant factor of the two. This partially confirms our second hypothesis (H_2) confirming that at least the number of viable bidders has predictive power.

8.5 Predicting Horizontal Mergers

In line with Garvey et al (2013), when calculating the numbers of viable bidders and targets, we restrict the count to companies within the same two-digit SIC industry. This causes us to believe that we may also do a better job at predicting horizontal mergers, i.e. within-industry mergers. We identify horizontal mergers in our sample of announced deals as mergers taking place between two firms within the same two-digit SIC industry and create a dummy variable *horizontal*, taking the value 1 when this constraint is satisfied. We denote the others as non-horizontal and give the horizontal dummy the value 0. Analogous to our previous analyses we run probit regressions, where the independent variables are CFD transformed, the standard errors are clustered at industry levels and we control for year- and industry fixed effects in some of the regression. The marginal effects are reported in *Table 7*.

If the measures of numbers of bidders and targets are more related to within industry valuation dispersion, it should predict a higher likelihood of horizontal mergers. In columns (1) and (2) we only control for year fixed effects. In line with Garvey et al's (2013) results, we observe that both measures of a target's viable targets and bidders (accretive and book) are positively related to horizontal mergers and highly significant, with coefficients of 0.321 and 0.306 respectively.

However, when adding industry fixed effects in columns (3) and (4), only book bidders for the targets remain significant and the number of accretive targets for the target turns negative. Hence, especially when applying book measures, horizontal mergers seem likely to be driven by industry specific characteristics, such as technological change, deregulation and other related industry shocks.

8.6 Sensitivity to the Acquisition Premium

Our assumed acquisition premium of 20% is somewhat arbitrary, but roughly in line with what is observed in practice (Petitt & Ferris, 2013). Following Garvey et al (2013) we additionally run sensitivity analyses with a range of different premiums[16]. We apply premiums of 10%, 50%, 100% and 200% in these sensitivity tests. We run the calculations for the number of viable accretive and book bidders for the mentioned premiums and repeat the regressions from columns (3) and (4) in *Table 2*. *Table 8, Panel A* and *B* portray the summary statistics, coefficients and p-values respectively.

In line with Garvey et al (2013), the number of viable bidders as well as the magnitude and significance of the coefficients drop with increasing premiums (although they report that the coefficient for book bidders increases from 0.016 to 0.018 when moving from a 20% to a 50% premium). Initially, our results, like Garvey et al's (2013), do not seem to be very sensitive to the premiums. The count of accretive bidders in both the acquirer and target samples are only reduced by about 50% with an increase of the premium from 10% to the unrealistic size of 100% as shown in *Panel B* (from 91.51 and 104.43 to 45.56 and 53.72 respectively).

Further examination of the coefficients reveals no surprising deviations between our findings and the results of Garvey et al (2013). In line with the original paper the coefficients for both book and accretive bidders drop with increasing premiums. An interesting observation is that their coefficients remain statistically significant for all premiums. Our accretive bidders p-value reaches 0.081 at a 100% premium, and is no longer statistically significant for predicting the likelihood of

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[16] We do not include negative premiums as they are rare and counterfactual, this would additionally result in the count of viable bidders approaching the number of firms in the industry, which we have included as controls in our regressions.

being a target. For book bidders however, our coefficient does not lose its significance until the premium is adjusted to 200% with a corresponding p-value of 0.760.

For further insight into the sensitivity of the premium on target prediction, we additionally ran the regressions from *Table 2* columns (1) through (5) with premiums of 10% and 50%, reporting our main control variables in *Table 8 Panel C* and *D*[17]. As we see from the tables, our results are robust to changes in premiums. When using a 10% premium in *Panel D* the coefficient of accretive bidders increase slightly across all panels and is significant at the 1% level. We see the same pattern for book bidders where the coefficient increases from 0.025 to 0.026 in column (3). In *Panel C*, applying a 50% premium, the coefficients for both accretive and book bidders drop and we observe a reduced significance. This is especially true for accretive bidders in column (3), where the significance drops from the 1% to the 5% level. The three misvaluation components from Rhodes-Kropf et al (2005) remain almost unchanged, compared to the baseline results with a 20% premium, and thus seem to be robust to changes in premium.

We follow the same procedure for acquirer prediction by running the regressions displayed in *Table 3* and report the results in *Panels E* and *F*. As we observed for the targets, the coefficient for our main variable of interest, accretive targets, increases slightly when applying a lower premium and decreases when applying a higher premium. As we observe in *Table 3*, the accretive targets coefficient is robust to the controls in columns (1) and (2) but not (3), (4) and (5). Again, we see that the firm-specific error and long-run value-to-book are highly significant and positive in column (5) and none of the three Rhodes-Kropf et al measures are sensitive to changes in the acquisition premiums to 10% and 50%.

To sum up, we find that our results are robust to changes in the acquisition premium within a reasonable range. Ferris & Petitt (2013) find that empirically the premium averages between 20% and 30%. This supports the use of a 20% premium in our analyses. By testing for premiums of 10% and 50%, we were able to confirm the robustness of the model and results presented in this paper.

[17] We do not report the remaining control variables used in the regressions, but note that they were not subject to any significant changes.

9. Conclusion

This paper follows Garvey et al's (2013) methods, investigating the possibility of *ex ante* predicting which firms ultimately become takeover targets. Specifically, they wanted to examine if the likelihood of being a target is related to the number of the firm's viable bidders. Founded on existing theory, suggesting that acquirers purchase underpriced assets using their overvalued stock, Garvey et al (2013) develop two viability measures based on earnings and book values per share. As an additional hypothesis, in line with Garvey et al (2013), we investigate if these numbers of viable bidders and targets carry predictive power in regards to whether stock is used as the source of finance.

Through our probit regressions, including controls for factors discussed in previous merger literature, we find clear evidence supporting Garvey et al's (2013) conclusion to the first hypothesis (H_1). The likelihood of being a target, controlling for an exhaustive set of variables, is both positively and significantly related to the number of viable bidders available. This is a strong indication that market mispricing is an important driver for merger likelihood.

Additionally, we are successful in identifying other relevant and significant variables for target prediction. Namely, the number of takeovers in the industry, Rhodes-Kropf et al's (2005) firm-specific error and a negative relationship to a firm's price over forecasted earnings. Predicting acquirers however, seems to be more related to the misvaluation components then the sheer number of viable targets. Again, our results are very much in line with the original paper.

Shifting our attention to the second hypothesis (H_2) we are only able to partially confirm the results presented in Garvey et al (2013). Our findings suggest that the target's number of accretive bidders seems to be the leading predictor in identifying whether or not a deal is financed by stock. Additionally, we find a strong positive and significant relationship to both the target and acquirers firm-specific misvaluation component, thus increasing the likelihood of the deal being stock financed.

Garvey et al (2013) claim that the number of firms in the industry is one of the main predictors for industry level merger intensity. Our results however contradict their findings and suggest this is insignificant. Further contradicting findings show that the probability of a takeover being stock financed is not driven by a target's number of accretive targets, but the target’s number of accretive bidders and both the target’s and acquirer’s firm-specific misvaluation. Throughout our regressions, the merger wave variable is consistently positive and significant, and carries a considerably higher predictive power than reported in Garvey et al’s (2013) paper.

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11. Appendix

11.1 SDC Data Details

Database Selection:

Mergers & Acquisitions: US Targets

Calendar Dates: *01/01/1981 – 12/31/2012*

Form of the Deal:

(M) Merger: A combination of business takes place or 100% of the stock of a public or private company is acquired.

(A) Acquisition: Deal in which 100% of a company is spun off or split off is classified as an acquisition by shareholders.

(AM) Acquisition of Majority interest: The acquirer must have held less than 50% and be seeking to acquire 50% or more, but less than 100% of the target company's stock.

(AA) Acquisition of Assets: Deals in which the assets of a company, subsidiary, division, or branch are acquired. This code is used in all transactions when a company is being acquired and the consideration sought is not given.

Deal Type:

(1) Disclosed Value: indicates all deals that have a disclosed dollar value and the acquirer is acquiring an interest of 50% or over in a target, raising its interest from below 50% to above 50%, or acquiring the remaining interest it does not already own.

(2) Undisclosed Value: indicates all deals that do not have a disclosed dollar value and the acquirer is acquiring an interest of 50% or over in a target, raising its interest from below 50% to above 50%, or acquiring the remaining interest it does not already own.

(3) Leveraged Buyouts: indicates that the transaction is a leveraged buyout. An "LBO" occurs when an investor group, investor, or firm offers to acquire a company, taking on an extraordinary amount of debt, with plans to repay it with funds generated from the company or with revenue earned by selling off the newly acquired company's assets. TF considers a deal an LBO if the investor group includes management or the transaction is identified as such in the financial press and 100% of the company is acquired.

(4) Tender Offers: indicates a tender offer is launched for the target. A tender offer is a formal offer of determined duration to acquire a public company's shares made to equity holders. The offer is often conditioned upon certain requirements such as a minimum number of shares being tendered.

Report Items:

(DA)	Date Announced
(ANL)	Acquirer Name
(TNL)	Target Name
(STAT)	Deal Status
(ACU)	Acquirer 6-digit CUSIP
(AIP)	Acquirer Immediate Parent 6-digit CUSIP
(AUP)	Acquirer Ultimate Parent 6-digit CUSIP
(TCU)	Target 6-digit CUSIP
(TIP)	Target Immediate Parent 6-digit CUSIP
(TUP)	Target Ultimate Parent 6-digit CUSIP
(APUB)	Acquirer Public Status
(TPUB)	Target Public Status
(CONSID_STRUCTURE)	Consideration Structure
(TEND)	Tender Offer Flag *(Y/N)*

11.1.1 Comparison of dataset process stages with Garvet et al (2013)

Step 1: After dropping no announcement date and duplicate records when all of the target's CUSIP, acquirer's CUSIP, date announced and status are the same. Step 2: After dropping deals where target's CUSIP or targets' parent CUSIP equals to either acquirer's CUSIP or acquirers parent CUSIP and if the same target and acquirer pair was recorded more than once in the same year or was recorded the prior year. Step 3: After requiring both target's and acquirer's status to be public. Step 4: After requiring all targets to have eight digit CUSIP and dropping the record if the same target was reported more than once in the same year and was reported the previous year

	Original Paper	Our sample	Deviation	
SDC data	-	214,296	-	-
Step 1	212,618	214,147	1,529	0.72 %
Step 2	199,496	208,307	8,811	4.42 %
Step 3	10,701	10,423	-278	-2.60 %
Step 4	7,367	7,766	399	5.42 %
Actual target records	3,427	3,150	-277	-8.08 %
Fictional target records	3,408	3,335	-73	-2.14 %
Target sample	6,835	6,485	-350	-5.12 %
Acquirer sample	7,404	7,418	14	0.19 %

11.2 CRSP Compustat Merged Dataset Details

We downloaded the CRSP Compustat merged annual fundamentals database from WRDS using the following filters: (Note that we choose wide filters in our search query in order to get as many records as possible).

Data Date:	*1980-01 - 2013-12*
Company codes format:	*CUSIP*
Screening variables:	*C, INDL, SDT, D, USD, CAD*, Active, Inactive
Linking options:	*LC, LU, LS, LX, LD, LN, NR, NU*
Fiscal period and link date requirements:	Any part of fiscal period is within link date range
Link information:	Historical CRSP Permco/Permno link to Compustat
Identifying information:	Com. name, *CUSIP*, Fiscal Year-End, Ticker Symbol

Company data for further analysis:

(AT)	Book value of assets
(BKVLPS)	Book value per share
(DLC)	Debt in Current Liabilities – Total
(DLTT)	Long-Term Debt - Total
(PRCC_F)	Price Close – Annual – Fiscal
(MKVALT)	Market Value – Total – Fiscal
(SEQ)	Stockholders’ Equity – Total
(CSHO)	Common Shares Outstanding
(SIC)	Standard Industry Classification Code
(NI)	Net Income

11.3 I/B/E/S Summary Details

IBES Statistical Period End: *1980-01 - 2013-12*

Company Identifier:	*CUSIP* (8-digit)
Measures:	*(EPS)* Earnings Per Share
Fiscal Period Indicator:	*(1)* Fiscal Year 1
Other Variables:	Forecast Period End Date, IBES Statistical Period, Mean Estimate

11.4 Empirical Variable Definition

The variables used in the analysis are defined as follows:

- Size is the natural logarithm of the book value of total assets.
- Size Square is the squared value of the CDF transformed Size variable.
- Leverage is the ratio of the sum of long-term and short-term debt to total assets.
- P/FE is the ratio of stock price to the one-year forecasted earnings per share.
- Ind Num Takeover is the number of takeovers for each two digit SIC industry.
- Ind Num Firms is the total number of firms in each two digit SIC industry.
- Tender Offer is a dummy variable equal to 1 if the deal form is tender offer, 0 otherwise.
- Stock is a dummy variable equal to 1 if the deal was financed with stock offer, 0 otherwise.
- Firm-Specific Error is the deviations of valuation implied by sector valuation multiples calculated in the year due to firm-specific pricing error. Please see Rhodes-Kropf et al (2005) for more details.
- Time-Series Error is the industry's deviations of valuation implied by its long-run multiples calculated in the year. Please see Rhodes-Kropf et al (2005) for more details.
- Long-run V to B is the difference between valuations implied by long-run multiples and current book values. Please see Rhodes-Kropf et al (2005) for more details.
- Ind P/FE SD is the standard deviation of the industry's P/FE ratio each year.
- Ind P/FE Interdecile is the difference between the industry's 90^{th} percentile P/FE ratio and the industry's 10^{th} percentile P/FE ratio each year.
- Ind P/B Interdecile is the difference between the industry's 90^{th} percentile P/FE ratio and the industry's 10^{th} percentile P/FE ratio each year.
- Accretive Bidders is the number of EPS based viable bidders for a firm
- Accretive Targets is the number of EPS based viable targets for a firm.
- Book Bidders is the number of book value based viable bidders for a firm.
- Book Targets is the number of book value based viable targets for a firm.

11.5 Tables and Figures

11.5.1 Table 1: Summary Statistics and Correlation tables

Panel A: Median Accretive Bidders and Number of Takeovers

This panel reports the results of OLS regressions of the number of takeovers on the median number of accretive bidders, S&P 500 index and the price to book dispersion (Interdecile). We use either the current or last year's value. The median number of accretive bidders is calculated as the median number of accretive bidders across all firms in the year. We report standard errors in parentheses. ***, ** and * represent 1%, 5% and 10% significance levels. *Panel B-1* contains summary statistics of our key variables, separated into three categories in the subsequent year: acquirers, targets and non-mergers. Lag accretive bidders is defined as the lagged value of the number of forecasted earnings per share (mean analysts' estimated earnings) based viable bidders for a firm and lag book bidders is the number of book value based viable bidders for a firm. Analogous definitions are given for lag accretive targets and lag book targets. See *Appendix 11.4* for all other variable definitions. *Panel C-1* summarizes our control variables according to the same subcategories. *Panel D* and *E* contain relevant correlations. *Panel B-2* and *C-2* represent Garvey et al's (2013) findings.

	(1)	(2)	(3)
Median Num Accretive Bidders Current Year	13.226***		
	(2.000)		
Median Num Accretive Bidders Last Year		17.192***	17.841***
		(2.470)	(2.220)
S&P 500 Index	-0.101**	-0.184***	
	(0.030)	(0.030)	
Market to Book Dispersion (Interdecile)	42.463**	52.352***	
	(14.460)	(13.400)	
S&P 500 Index Last Year			-0.192***
			(0.030)
Market to Book Dispersion (Interdecile) Last Year			40.126**
			(13.510)
Observations	32	31	31
R^2	0.777	0.789	0.786

Panel B-1: Summary Statistics for Key Variables

	Acquirer Sample			Target Sample			Non-Merger Sample		
	N	Mean	Median	N	Mean	Median	N	Mean	Median
Lag Accretive Bidders	4,406	82.79	51	3,129	95.53	61	78,019	62.40	32
Lag Book Bidders	5,390	97.84	54	4,947	135.72	81	130,547	102.54	53
Lag Accretive Targets	4,406	103.10	61	3,129	67.99	34	78,019	67.34	33
Lag Book Targets	5,390	166.63	103	4,947	119.08	63	130,547	100.76	50

Panel B-2: Summary Statistics for Key Variables in Garvey et al (2013)

	Acquirer Sample			Target Sample			Non-Merger Sample		
	N	Mean	Median	N	Mean	Median	N	Mean	Median
Lag Accretive Bidders	5,654	108.28	68	5,351	129.55	83	127,188	92.31	50
Lag Book Bidders	5,585	104.97	62	5,244	138.92	80	124,257	105.40	55
Lag Accretive Targets	5,654	141.64	87	5,351	105.26	58	127,188	93.78	48
Lag Book Targets	5,585	167.70	100	5,244	125.41	66	124,257	104.69	51

Panel C-1: Summary Statistics for Control Variables

	Acquirer Sample			Target Sample			Non-Merger Sample		
	N	Mean	Median	N	Mean	Median	N	Mean	Median
Lag Size	5,564	7.16	7.26	5,316	5.41	5.28	138,526	5.33	5.22
Lag Leverage	5,505	0.21	0.18	5,273	0.21	0.16	137,618	0.24	0.18
Lag P/FE	4,924	35.71	19.19	4,160	19.79	13.54	95,803	30.47	16.28
Lag Ind Num Takeover	6,972	20.43	12.00	6,251	19.08	10.00	181,906	11.36	6.00
Lag Firm Specific Errors	3,965	0.18	0.14	3,839	-0.03	-0.05	106,943	-0.01	-0.01
Lag Time Series Errors	3,974	0.08	0.09	3,841	0.04	0.07	107,133	0.03	0.06
Lag Long Run VtoB	3,974	0.66	0.65	3,841	0.73	0.70	107,133	0.68	0.65
Lag Ind Num Firms	6,272	383.29	348.00	6,251	362.34	320.00	181,906	382.65	273.00

Panel C-2: Summary Statistics for Control Variables in Garvey et al (2013)

	Acquirer Sample			Target Sample			Non-Merger Sample		
	N	Mean	Median	N	Mean	Median	N	Mean	Median
Lag Size	5,654	7.30	7.41	5,351	5.67	5.59	127,188	5.51	5.44
Lag Leverage	5,654	0.21	0.18	5,351	0.22	0.18	127,188	0.23	0.19
Lag P/FE	5,654	42.72	18.95	5,351	27.57	14.43	127,188	36.60	15.96
Lag Ind Num Takeover	5,654	19.87	11.00	5,351	19.07	10.00	127,188	11.76	5.00
Lag Firm Specific Errors	5,654	0.07	0.01	5,351	-0.01	-0.02	127,188	0.01	-0.03
Lag Time Series Errors	5,654	0.11	0.02	5,351	0.03	-0.01	127,188	0.03	-0.02
Lag Long Run VtoB	5,654	0.32	0.30	5,351	0.33	0.33	127,188	0.38	0.37
Lag Ind Num Firms	5,654	392.91	351.00	5,351	369.30	369.30	127,188	293.65	224.00

Panel D: Correlations Among Key Variables and Controls

	Accretive Bidders	Accretive Targets	Book Bidders	Book Targets	P/FE Interdecile	P/B Interdecile	Size	Leverage	P/FE	Ind Num Takeover	Ind Num Firms	Firm Specific Error	Time Series Error	Long Run V to B
Accretive Bidders	1.0000													
Accretive Targets	-0.0055	1.0000												
Book Bidder	0.6145	0.2954	1.0000											
Book Targets	0.3438	0.6129	0.0254	1.0000										
P/FE Interdecile	-0.0676	-0.0612	-0.0499	-0.0826	1.0000									
P/B Interdecile	0.1345	0.1259	0.1540	0.1328	0.0504	1.0000								
Size	0.0032	0.0294	-0.0694	0.0217	-0.2632	0.0155	1.0000							
Leverage	-0.1166	-0.2375	-0.1479	-0.2040	0.0374	-0.0041	0.2108	1.0000						
P/FE	-0.1323	0.1810	-0.0356	0.0883	0.0608	0.0070	-0.0336	-0.0525	1.0000					
Ind Num Takeover	0.6066	0.5787	0.5779	0.6053	-0.0249	0.2801	0.0229	-0.1966	0.0144	1.0000				
Ind Num Firms	0.5618	0.5411	0.5519	0.5775	-0.1338	0.1329	0.0516	-0.1023	0.0218	0.6770	1.0000			
Firm Specific Error	-0.1852	0.1816	-0.3756	0.3912	-0.0433	-0.0035	0.0678	-0.0117	0.1454	-0.0173	0.0290	1.0000		
Time Speries Error	0.0563	0.0872	0.0429	0.1044	-0.2758	0.3899	0.0859	-0.0120	0.0032	0.1509	0.0859	-0.0277	1.0000	
Long run V to B	0.0638	0.0115	-0.0604	0.2237	0.0721	-0.0046	-0.3411	-0.1298	0.0302	0.0366	-0.0229	-0.0267	-0.0722	1.0000

* All measures except P/FE interdecile and P/B interdecile are reported as lagged values

Panel E: Correlations Between Industry Merger Rates and the Number of Viable Bidders

Correlations Between Merger Rate and Median Viable Bidders by Industry

	Spearman	Pearson
	Merger Rate	Merger Rate
Median Accretive Bidders	0.94	0.96
Median Book Bidders	0.96	0.93

Correlations Between Merger Rate and Median Viable Bidders by Industry Year

	Spearman	Pearson
	Merger Rate	Merger Rate
Median Accretive Bidders	0.71	0.83
Median Book Bidders	0.73	0.80

11.5.2 Table 2: Likelihood of Being a Target and the Number of Viable Bidders

The dependent variable is a takeover dummy variable equal to 1 if a firm is a takeover target and 0 otherwise. The independent variables (except dummy variables) in the regressions are transformed by the empirical cumulative distribution function (CDF). We run probit regressions where our primary variables of interest are our measures of the number of viable bidders available for each candidate target firm and report the marginal effects in the table. We control for year- and industry fixed effects in all regressions, and cluster the standard errors at the industry level. We report standard errors in parentheses. ***, ** and * represent 1%, 5% and 10% significance levels.

	(1)	(2)	(3)	(4)	(5)
Lag Accretive Bidders	0.030***	0.032***	0.030***		0.027***
	(0.010)	(0.010)	(0.010)		(0.010)
Lag Book Bidders				0.025***	0.011***
				(0.003)	(0.004)
Lag Firm Specific Error			0.009***	0.017***	0.015***
			(0.003)	(0.003)	(0.004)
Lag Time Series Error			0.005	0.008***	0.006*
			(0.004)	(0.003)	(0.004)
Lag Long Run V to B			0.002	0.010***	0.005
			(0.004)	(0.003)	(0.004)
Ind P/FE SD	-0.013***				
	(0.004)				
Ind P/FE Interdecile		-0.015***	-0.014***		-0.012***
		(0.004)	(0.004)		(0.004)
Ind P/B Interdecile				-0.002	
				(0.005)	
Lag Ind Num Takeover	0.021***	0.020***	0.021***	0.027***	0.021***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)
Lag Size	0.079***	0.079***	-0.086***	0.085***	0.081***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)
Lag Size Square	-0.083***	-0.084***	-0.089***	-0.089***	-0.085***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Lag Leverage	-0.002	-0.002	-0.002	0.003	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Lag P/FE	-0.025***	-0.023***	-0.029***	-0.037***	-0.031***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Lag Ind Num Firms	0.000	-0.001	-0.001	-0.002	-0.006
	(0.015)	(0.016)	(0.017)	(0.010)	(0.016)
Observations	83,561	83,598	82,530	98,668	81,928
Pseudo R^2	0.059	0.059	0.061	0.050	0.060

11.5.3 Table 3: Likelihood of Being an Acquirer and the Number of Accretive Targets

The dependent variable is a takeover dummy variable equal to 1 if a firm is a takeover bidder and 0 otherwise. The independent variables (except dummy variables) in the regressions are transformed by the empirical cumulative distribution function (CDF). We run probit regressions where our primary variables of interest are our measures for the number of viable targets available for each candidate acquirer firm and report the marginal effects in the table. We control for year- and industry fixed effects in all regressions, and cluster the standard errors at the industry level. We report standard errors in parentheses. ***, ** and * represent 1%, 5% and 10% significance levels.

	(1)	(2)	(3)	(4)	(5)
Lag Accretive Targets	0.029***	0.015***	0.015	0.015	0.014
	(0.005)	(0.004)	(0.011)	(0.011)	(0.011)
Lag Firm Specific Error					0.035***
					(0.004)
Lag Time Series Error					0.005
					(0.005)
Lag Long Run V to B					0.020***
					(0.005)
Ind P/FE Interdecile				-0.001	0.002
				(0.004)	(0.004)
Ind P/FE SD		-0.007	-0.007		
		(0.005)	(0.004)		
Lag Ind Num Takeover		0.052***	0.052***	0.053***	0.053***
		(0.007)	(0.006)	(0.007)	(0.006)
Lag Size		0.007	0.007	0.007	0.025
		(0.034)	(0.034)	(0.034)	(0.034)
Lag Size Square		0.107***	0.107***	0.107***	0.091***
		(0.029)	(0.030)	(0.029)	(0.027)
Lag Leverage		-0.019***	-0.019***	-0.019***	-0.017***
		(0.005)	(0.005)	(0.005)	(0.005)
Lag P/FE			-0.000	-0.001	-0.011
			(0.009)	(0.009)	(0.009)
Lag Ind Num Firms		0.010	0.010	0.009	0.007
		(0.014)	(0.015)	(0.014)	(0.015)
Observations	85,353	83,400	83,400	83,436	82,376
Pseudo R^2	0.047	0.106	0.106	0.106	0.112

11.5.4 Table 4: Predicting Merger Intensity at the Firm Level

The dependent variable is a merger dummy variable equal to 1 if a firm is a takeover target or a bidder. The independent variables (except dummy variables) in the regressions are transformed by the empirical cumulative distribution function (CDF). Our primary variables of interest are our measures of the viable number of potential bidders and targets. We control for year- and industry fixed effects for all regressions, and cluster the standard errors at the industry level. We report standard errors in parentheses. ***, ** and * represent 1%, 5% and 10% significance levels.

	(1)	(2)	(3)	(4)	(5)
Lag Accretive Bidders	0.070***	0.042***		0.069***	0.068***
	(0.013)	(0.012)		(0.017)	(0.022)
Lag Accretive Targets	0.040***	0.010		0.011	0.011
	(0.012)	(0.009)		(0.012)	(0.013)
Lag Firm Specific Error			0.039***	0.058***	0.058***
			(0.005)	(0.009)	(0.009)
Lag Time Speries Error			0.001	0.009	0.008
			(0.004)	(0.007)	(0.010)
Lag Long Run V to B			-0.019***	0.001	0.001
			(0.005)	(0.010)	(0.010)
Lag Ind Num Takeover		0.087***	0.068***	0.081***	0.081***
		(0.011)	(0.009)	(0.011)	(0.011)
Lag Industry TS Error*Bidders					0.001
					(0.014)
Observations	85,515	85,515	143,691	82,530	82,530
Pseudo R^2	0.047	0.049	0.046	0.055	0.055

11.5.5 Table 5: Predicting Merger Intensity at the Industry Level

The dependent variable is the count of merger announcements in industry *j*, year *i*. The independent variables include the average number of bidders in industry *j*, the total number of firms in industry *j*, the log value of industry average price to book ratio, the industry average time-series error and the industry average of long-run value-to-book ratio. All values are lagged. We also include the total number of mergers at year *t-1* and the total number of mergers in industry *j*. We control for year fixed effects in all regressions except in column 4, 6, 8 and 10, in which we use total mergers at year *t*. We control for industry fixed effects except in column 5, 6, 9 and 10, in which we instead use the total mergers in industry *j*. We report standard errors in parentheses. ***, ** and * represent 1%, 5% and 10% significance levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lag Ind Average Accretive Bidders	0.287***	0.296***	0.295***	0.280***	0.180***	0.177***	0.295***	0.279***	0.182***	0.178***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Lag Ind Num Firms		-0.002*	-0.002*	-0.003**	-0.001	-0.001	-0.002	-0.002*	-0.001	-0.001
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag Ind Average P/B			0.723**	0.262	0.418*	0.365*				
			(0.300)	(0.250)	(0.240)	(0.210)				
Lag Ind Average Time Series Error							2.445***	0.525	2.209***	0.978**
							(0.630)	(0.400)	(0.700)	(0.430)
Lag Ind Average Long Run V to B							2.024***	2.949***	1.034***	1.486***
							(0.550)	(0.500)	(0.380)	(0.360)
Tota Mergers $Year_{t-1}$				0.003***		0.007***		0.003***		0.007***
				(0.000)		(0.000)		(0.000)		(0.000)
Total Mergers Ind_j					0.003**	0.004***			0.003**	0.003***
					(0.000)	(0.000)			(0.000)	(0.000)
Observations	2,079	2,079	2,079	2,079	2,079	2,079	2,079	2,079	2,079	2,079
R^2	0.797	0.797	0.798	0.781	0.734	0.724	0.800	0.785	0.736	0.726

11.5.6 Table 6: Predicting Method of Payment

Panel A: Predicting Method of Payment at the Firm Level

The dependent variable is a dummy variable equal to 1 if the deal only uses stock as method of payment and 0 otherwise. The independent variables (except dummy variables) in the regressions are transformed by the empirical cumulative distribution function (CDF). The control variables include the standard deviation of the target's industry P/FE in column 1, the target's industry P/FE interdecile range in column 2, 3 and 4 and the target's industry P/B interdecile range in column 5. In addition, in all columns we control for the number of deals in target's industry, the target's size and size squared, the target's leverage, the target's P/FE, the number of firms in target's industry and a dummy variable which equals to 1 if the deal is tender offer and 0 otherwise. In column 4, we also include the acquirer's information including acquirer's size, leverage, P/FE, acquirer's industry P/FE interdecile and the acquirer's industry P/B interdecile. All controls except P/FE and P/B interdecile are lagged. To save space, we do not report the coefficients of these control variables. We run probit regressions and report the marginal effects in the table. We control for year- and industry fixed effects in all regressions and cluster the standard errors at the industry level. We report standard errors in parentheses. ***, ** and * represent 1%, 5% and 10% significance levels.

	(1)	(2)	(3)	(4)	(5)
Lag Target Accretive Bidders	0.285**	0.271**	0.246**	0.195**	
	(0.112)	(0.111)	(0.102)	(0.097)	
Lag Target Accretive Targets	0.091	0.136	0.118	0.013	
	(0.096)	(0.095)	(0.095)	(0.102)	
Lag Target Book Bidders					0.001
					(0.059)
Lag Target Book Targets					0.323***
					(0.120)
Lag Acquirer Accretive Bidders				0.015	
				(0.110)	
Lag Acquirer Accretive Targets				0.142	
				(0.095)	
Lag Acquirer Book Bidders					-0.126***
					(0.096)
Lag Acquirer Book Targets					-0.080
					(0.108)
Lag Target Firm Specific Error			0.221***	0.209***	-0.027
			(0.058)	(0.065)	(0.092)
Lag Target Time Series Error			0.060	0.018	0.007
			(0.046)	(0.067)	(0.037)
Lag Target Long Run V to B			0.042	0.054	-0.139
			(0.049)	(0.058)	(0.109)
Lag Acquirer Firm Specific Error				0.205***	0.112
				(0.053)	(0.071)
Lag Acquirer Time Series Error				0.105	0.040
				(0.071)	(0.044)
Lag Acquirer Long un V to B				-0.001	0.044
				(0.048)	(0.045)
Observations	1,981	1,981	1,956	1,593	2,273
Pseudo R^2	0.309	0.312	0.323	0.346	0.293

Panel B: Predicting Method of Payment at the Industry Level

The dependent variable is the count of 100% stock-financed merger announcements in industry *j*, year *t*. The independent variables include the average number of bidders in industry *j*, the total number of firms in industry *j*, the log value of industry average price to book ratio, the industry average time-series error, the industry average of long-run value-to-book ratio. All values are lagged. We also include the total number of mergers at year *t-1* and the total number of mergers in industry *j*. We control for year fixed effects in all regressions except in column 4, 6, 8 and 10, in which we use total mergers at year *t*. We control for industry fixed effects except in column 5, 6, 9 and 10, in which we instead use the total mergers in industry *j*. We report standard errors in parentheses. ***, ** and * represent 1%, 5% and 10% significance levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lag Ind Average Accretive Bidders	0.107***	0.128***	0.125***	0.125***	-0.050***	-0.050***	0.122***	0.122***	-0.052***	-0.052***
	(0.005)	(0.005)	(0.008)	(0.008)	(0.009)	(0.009)	(0.005)	(0.005)	(0.009)	(0.009)
Lag Ind Num Firms		0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag Ind Average M/B			-0.780	-0.946	-0.814***	-0.825***				
			(1.890)	(1.898)	(0.248)	(0.250)				
Lag Ind Average Time Series Error							0.000***	0.000***	0.274	0.285
							(0.000)	(0.000)	(2.610)	(2.632)
Lag Ind Average Long Run V to B							-5.693***	-5.700***	-1.542***	-1.552***
							(0.873)	(0.880)	(0.360)	(0.363)
Tota Mergers $Year_{t-1}$				0.006***		0.006***		0.006***		0.006***
				(0.001)		(0.001)		(0.001)		(0.001)
Total Mergers Ind_j					0.023***	0.023***			0.023***	0.023***
					(0.001)	(0.001)			(0.001)	(0.001)
Observations	2,142	2,142	2,142	2,142	2,142	2,142	2,142	2,142	2,142	2,142
Pseudo R^2	0.445	0.445	0.445	0.427	0.429	0.411	0.445	0.447	0.431	0.413

11.5.7 Table 7: Likelihood of Horizontal Mergers and the Num Bidders and Targets

The dependent variable is horizontal dummy variable equal to 1 if the deal happened between two firms within the same two digit SIC industry and 0 otherwise. The independent variables (except dummy variables) in the regressions are transformed by empirical cumulative distribution function (CDF). We run probit regressions where our primary measures are the number of viable bidders and targets available to each firm, and report the marginal effects in the table. We control for year fixed effect in all regressions and industry fixed effects in columns 3 and 4, and cluster the standard errors at the industry level. We report standard errors in parentheses. ***, ** and * represent 1%, 5% and 10% significance levels.

	(1)	(2)	(3)	(4)
Lag Target Accretive Bidders	0.321**		0.006	
	(0.138)		(0.103)	
Lag Target Accretive Targets	0.186**		-0.042	
	(0.080)		(0.090)	
Lag Target Book Bidders		0.306***		0.168***
		(0.116)		(0.063)
Lag Target Book Targets		0.162*		0.930
		(0.093)		(0.061)
Observations	2,078	3,299	2,059	3,283
Pseudo R^2	0.053	0.041	0.216	0.211

11.5.8 Table 8: Sensitivity to Changes in the Acquisition Premium

In this table, we compute the number of accretive bidders and book bidders under alternative specifications of the deal premium. *Panel A* provides the summary statistics in the same manner as *Panel B-1* in *Table 1*. Panel B reports the regression results of the variables accretive- and book bidders following the empirical model in column 3 and 4 in *Table 2*. *Panel C* and *Panel D* report the main control variables from regressions in *Table 2* with premiums adjusted to 10% and 50% respectively. *Panel E* and *F* report the main control variables from regressions in *Table 3* with premiums adjusted to 10% and 50% respectively.

Panel A: Summary Statistics for Viable Bidders of Varying Premium

	Acquirer Sample		Target Sample		Non-merger Sample	
	Mean	Median	Mean	Median	Mean	Median
Premium of 10%						
Lag Accretive Bidders	91.51	57	104.43	67	67.87	36
Lag Book Bidders	111.66	66	149.58	92	112.05	60
Premium of 20%						
Lag Accretive Bidders	82.79	51	95.53	61	62.40	32
Lag Book Bidders	97.84	54	135.72	81	102.54	53
Premium of 50%						
Lag Accretive Bidders	63.85	37.5	74.99	46	49.95	25
Lag Book Bidders	68.73	33	102.51	54	80.02	38
Premium of 100%						
Lag Accretive Bidders	45.56	25	53.72	32	37.07	17
Lag Book Bidders	43.46	18	68.11	31	56.31	23
Premium of 200%						
Lag Accretive Bidders	28.14	13	32.45	18	24.07	9
Lag Book Bidders	23.38	8	37.76	14	22.37	12

Panel B: Sensitivity to Premium

	Premium of 10%		Premium of 20%		Premium of 50%		Premium of 100%		Premium of 200%	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Lag Accretive Bidders	0.032	0.001	0.030	0.003	0.025	0.030	0.020	0.081	0.017	0.115
Lag Book Bidders	0.026	0.000	0.025	0.000	0.020	0.000	0.013	0.004	0.002	0.760

Panel C: Likelihood of Being a Target and the Number of Viable Bidders, 10% premium

	(1)	(2)	(3)	(4)	(5)
Lag Accretive Bidders	0.032***	0.034***	0.032***		0.029***
	(0.010)	(0.010)	(0.010)		(0.010)
Lag Book Bidders				0.026***	0.010***
				(0.003)	(0.004)
Lag Firm Specific Error			0.009***	0.017***	0.015***
			(0.003)	(0.003)	(0.004)
Lag Time Series Error			0.005	0.008***	0.006*
			(0.004)	(0.003)	(0.003)
Lag Long Run V to B			0.002	0.010***	0.005
			(0.004)	(0.003)	(0.004)
Observations	83,561	83,598	82,530	98,668	81,928
Pseudo R^2	0.059	0.059	0.061	0.049	0.060

Panel D: Likelihood of Being a Target and the Number of Viable Bidders, 50% premium

	(1)	(2)	(3)	(4)	(5)
Lag Accretive Bidders	0.023**	0.026**	0.025**		0.022*
	(0.012)	(0.012)	(0.012)		(0.012)
Lag Book Bidders				0.020***	0.009**
				(0.004)	(0.003)
Lag Firm Specific Error			0.009***	0.015***	0.015***
			(0.003)	(0.003)	(0.004)
Lag Time Series Error			0.006	0.008***	0.007*
			(0.004)	(0.003)	(0.004)
Lag Long Run V to B			0.002	0.009**	0.005
			(0.004)	(0.003)	(0.004)
Observations	83,561	83,598	82,530	98,668	81,928
Pseudo R^2	0.059	0.059	0.061	0.049	0.060

Panel E: Likelihood of Being an Acquirer and the Number of Accretive Targets, 10% Premium

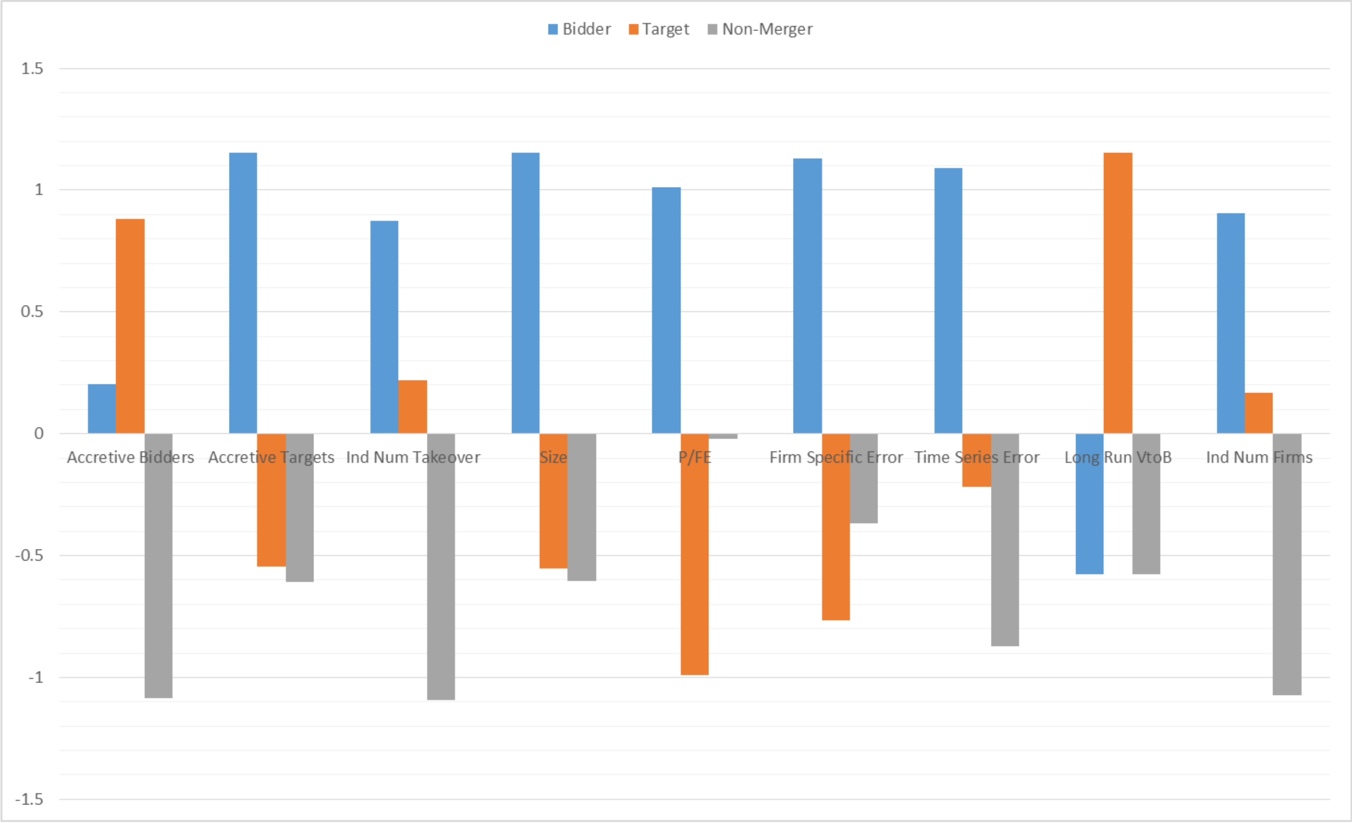
	(1)	(2)	(3)	(4)	(5)
Lag Accretive Targets	0.032***	0.016***	0.017	0.018	0.015
	(0.005)	(0.005)	(0.008)	(0.011)	(0.008)
Lag Firm Specific Error					0.035***
					(0.004)
Lag Time Series Error					0.005
					(0.005)
Lag Long Run V to B					0.020***
					(0.005)
Observations	85,353	83,400	83,400	83,436	82,376
Pseudo R^2	0.048	0.106	0.106	0.106	0.112

Panel F: Likelihood of Being an Acquirer and the Number of Accretive Targets, 50% Premium

	(1)	(2)	(3)	(4)	(5)
Lag Accretive Targets	0.025***	0.012***	0.008	0.008	0.008
	(0.005)	(0.004)	(0.013)	(0.012)	(0.012)
Lag Firm Specific Error					0.035***
					(0.004)
Lag Time Series Error					0.004
					(0.005)
Lag Long Run V to B					0.020***
					(0.005)
Observations	85,353	83,400	83,400	83,436	82,376
Pseudo R^2	0.047	0.106	0.106	0.106	0.112

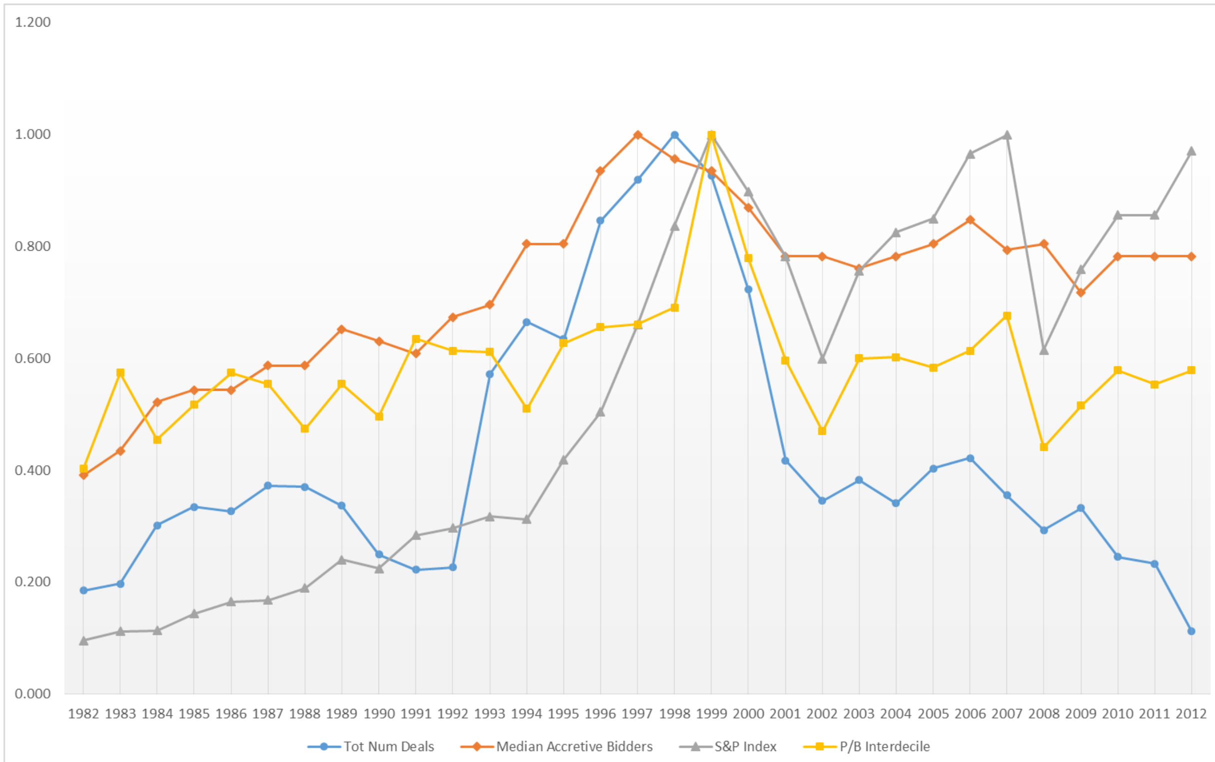
11.5.9 Figure 1: Summary of Empirical Distribution of Realized Acquisition Outcomes

Each trio of bares represent the three different firm samples, the first bar represents the bidders-, the second represents the target-, and the last bar represents the non-merger sample. The bars represent Z-scores and are calculated by computing the average and the standard deviation of the median values in each subsample in *Panel A* of *Table 1*. We then subtract the average from the median and divide it by the standard deviation.



11.5.10 Figure 2: Key Variables Across Time

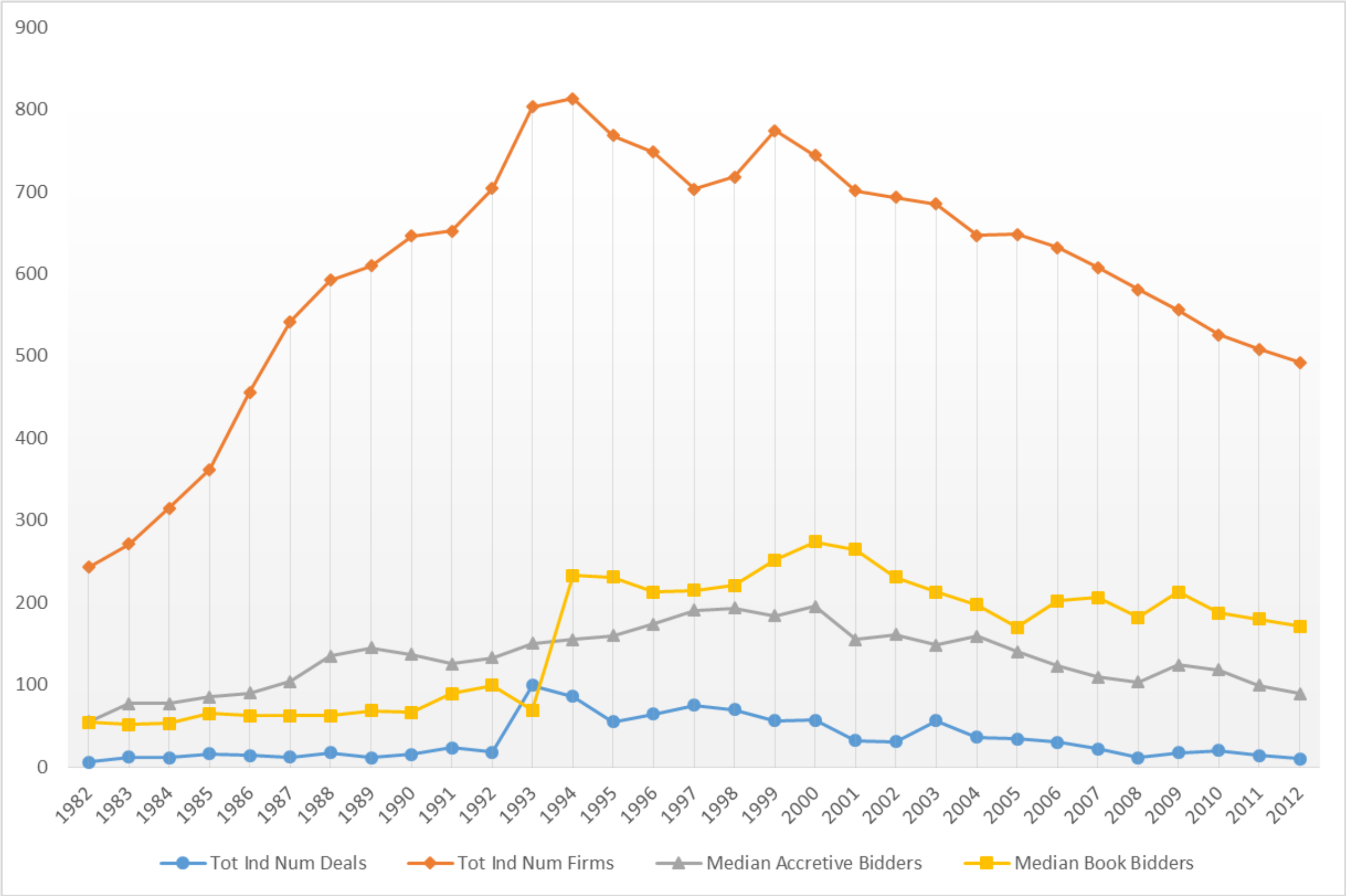
The sample covers the period from 1982 to 2012. The “Tot Num Deals” is the total number of deals announced. The “S&P Index” is the S&P 500 at the end of the calendar year. The “P/B Interdecile” is the median level of interdecile dispersion of the price-to-book ratio. The “Median Accretive Bidders” is the median of lag values of the number of accretive bidders each year. The graph is scaled to relative sizes of corresponding series and the data table is provided blow the graph.



Calendar Year	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Tot Num Deals	89	95	145	161	157	179	178	162	120	107	109	275	320	305	407	442	481	446	348	201	166	184	164	194	203	171	141	160	118	112	54
Median Accretive Bidders	18	20	24	25	25	27	27	30	29	28	31	32	37	37	43	46	44	43	40	36	36	35	36	37	39	37	37	33	36	36	36
S&P Index	141	165	167	211	242	247	278	353	330	417	436	466	459	616	741	970	1229	1469	1320	1148	880	1112	1212	1248	1418	1468	903	1115	1258	1258	1426
P/B Interdecile	3.40	4.84	3.84	4.36	4.85	4.68	4.00	4.68	4.19	5.36	5.18	5.16	4.31	5.29	5.54	5.58	5.83	8.44	6.58	5.03	3.97	5.06	5.08	4.92	5.18	5.71	3.72	4.35	4.88	4.67	4.88

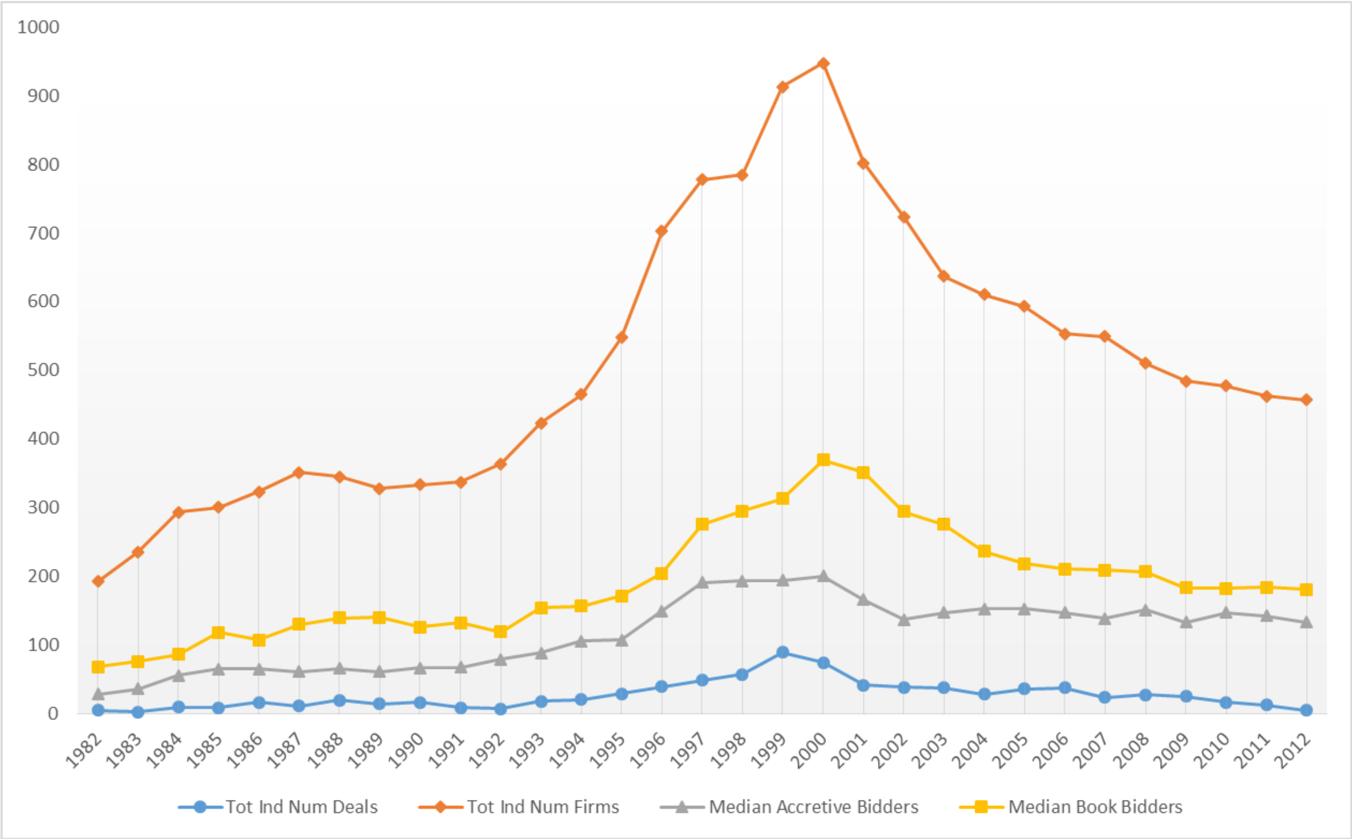
11.5.11 Figure 3: Actual Takeovers among Depository Institutions

The sample covers the period from 1982 to 2012. The "Tot Ind Num Deals" is the total number of deals announced in the *Depository Institutions* industry (SIC code 60) in each year. The "Tot Ind Num Firms" is the total number of firms in the *Depository Institutions* industry each year. The "Median Accretive Bidders" is the median of lag values of the number of accretive bidders each year. The "Median Book Bidders" is the median of the lag values of the number of book bidders each year.



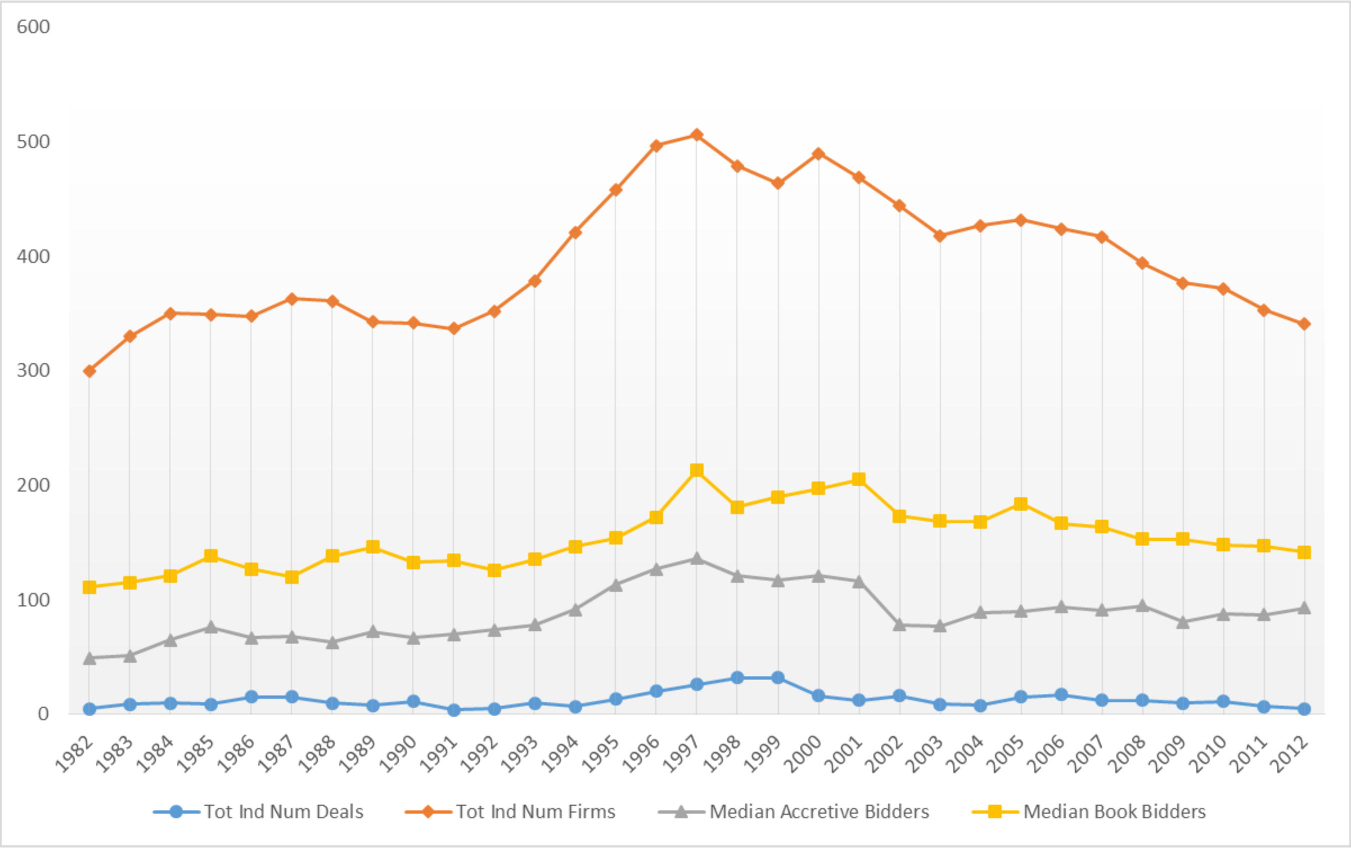
11.5.12 Figure 4: Actual Takeovers among Business Services Firms

The sample covers the period from 1982 to 2012. The "Tot Ind Num Deals" is the total number of deals announced in the *Business Services* industry (SIC code 73) in each year. The "Tot Ind Num Firms" is the total number of firms in the *Business Services* industry each year. The "Median Accretive Bidders" is the median of lag values of the number of accretive bidders each year. The "Median Book Bidders" is the median of the lag values of the number of book bidders each year.



11.5.13 Figure 5: Actual Takeovers, Electronic & other E. Equipment and Components[18]

The sample covers the period from 1982 to 2012. The "Tot Ind Num Deals" is the total number of deals announced in the *Electronic and other Electrical Equipment and Components, except Computer Equipment* industry (SIC code 36) in each year. The "Tot Ind Num Firms" is the total number of firms in the industry each year. The "Median Accretive Bidders" is the median of lag values of the number of accretive bidders each year. The "Median Book Bidders" is the median of the lag values of the number of book bidders each year.



[18] Except Computer Equipment firms

11.5.14 Figure 6: Tot Ind Num firms and Tot Ind Num Deals from Figure 5, scaled

The sample covers the period from 1982 to 2012. The "Tot Ind Num Deals" is the total number of deals announced in the *Electronic and other Electrical Equipment and Components, except Computer Equipment* industry (SIC code 36) in each year. The "Tot Ind Num Firms" is the total number of firms in the industry each year. The data series have been scaled according to max values for visual comparability.