Valuation Waves and Merger Activity: The Empirical Evidence

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Matthew Rhodes-Kropf, David T. Robinson and S. Viswanathan

Abstract

To test recent theories which suggest that valuation errors affect merger activity, we develop a decomposition that breaks M/B into three components: the firm-specific pricing deviation from short-run industry pricing; sector-wide, short-run deviations from firms' long-run pricing; and long-run pricing to book. We find strong support for recent theories by Rhodes-Kropf and Viswanathan (forthcoming) and Shleifer and Vishny (2003), which predict that misvaluation drives mergers. So much of the behavior of M/B is driven by firm-specific deviations from short-run industry pricing, that long-run components of M/B run counter to the conventional wisdom: *Low* long-run value to book firms buy *high* long-run value to book firms. Misvaluation affects who buys whom, as well as method of payment, and combines with neoclassical explanations to explain aggregate merger activity.

1 Introduction

The goal of this paper is to test the effect of misvaluation on merger activity. The last 125 years of business history indicate that periods of high M/B ratios

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coincide with periods of intense merger activity, especially for stock-financed deals.[1] This fact is open to two interpretations. Under the neoclassical view, this fact is evidence that assets are being redeployed towards more productive uses.[2] In contrast, if financial markets value firms incorrectly or managers have information not held by the market, this result can be interpreted as evidence that acquisition frenzies are driven by overvaluation. Indeed, the fact that each of the last five great merger waves on record ended with a precipitous decline in equity prices has led many to believe that misvaluation drives merger activity.

While this idea is compelling, it seems inconsistent with a broader equilibrium that endogenizes the target's response to the offer. To put it simply, why is the target fooled? Why would a value-maximizing target knowingly accept over-valued currency in a takeover offer?

Two recent theories offer answers to this question, and thus to the role that valuation waves play in merger activity. Rhodes-Kropf and Viswanathan (forthcoming, henceforth RKV) propose a rational theory based on correlated misinformation. In the RKV world, errors in valuing potential takeover synergies are correlated with overall valuation error. Merger waves occur during valuation waves because ex post, targets have mistakenly over-estimated synergies. Shleifer and Vishny (2003, henceforth SV) propose a theory based on an irrational stock market and self-interested target managers who can cash out quickly. SV posit that target managers do not maximize long-term shareholder value: they instead maximize their own short-run gain. Since these theories, although economically very different, do not model the source of the misvaluation, they yield parallel empirical predictions on the link between misvaluation and merger waves.

[1] See Maksimovic and Phillips (2001) or Jovanovic and Rousseau (2001) for recent evidence.
[2] See Servaes (1991) and Lang et al. (1989) for market reaction evidence consistent with this view.

In this paper we test the empirical predictions of RKV and SV and find strong support for the idea that misvaluation shapes merger activity. We show that misvaluation affects the level of merger activity, the decision to be an acquirer or target, and the transaction medium. To guard against the possible alternative interpretations for our findings, we run a battery of empirical horseraces between misvaluation and standard neoclassical explanations of takeover. Even if we attribute all spikes in merger activity to neoclassically motivated industry shocks, our results indicate that misvaluation is critical for understanding who buys whom in merger transactions.

To explore misvaluation empirically, we decompose M/B into two parts:

$$\text{Market} - \text{to} - \text{Book} \equiv \text{Market} - \text{to} - \text{Value} \times \text{Value} - \text{to} - \text{Book}. \quad (1)$$

If we had an accurate measure of value, we could assign labels to each of the two pieces on the right-hand side of Equation 1. The first piece would measure the discrepancy between price and true value, and would therefore measure misvaluation. This could be the result of a behavioral anomaly or due to asymmetric information between informed insiders and the rest of the market. In either case, the second piece would capture true value to book, which would then measure growth opportunities in a manner that is unadulterated by misvaluation.

Any breakdown of M/B rests critically on particular measures of 'value'. We use sector-level, cross-sectional regressions of firm-level market equities on firm fundamentals each year to derive a series of such measures. Average R^2 values indicate that this approach explains between 80% and 94% of within-sector variation in firm-level market values at a point in time. We then use the resulting regression coefficients to generate measures of value. These coefficients have natural interpretations as time-varying valuation multiples, and account for variation in the market's expectations of returns and growth over time and across industries.

Because RKV stresses the difference between sector-wide and firm-specific misvaluation, our empirical implementation of Equation 1 actually breaks M/B into three components: firm-specific error, time-series sector error, and long-run value to book. By exploiting the panel structure of our data, we measure *firm-specific error* with firm-specific deviations from valuations implied by contemporaneous sector multiples. This captures the idea that a firm may have an idiosyncratic misvaluation component. We measure *time-series sector error* by differences that arise when contemporaneous multiples differ from long-run multiples. This captures the idea that sectors, or entire markets, may be over-heated, and thus that firms in the same sector may share a common misvaluation component. The final piece is long-run value to book, which relates values implied by long-run valuation multiples to book value. This captures long-run growth opportunities.

Using this breakdown, we find support for each prediction of RKV and SV. In particular, we show the following:

- Acquiring firms are priced significantly higher than targets. The valuation difference is roughly 20% of the target's log M/B ratio.
- While the difference in M/B between acquirers and targets is large, it is dwarfed by differences in firm-specific error. Roughly 60% of the acquirer's M/B is attributable to firm-specific error. Almost none of the target's M/B is attributable to firm-specific error.
- Acquirers and targets cluster in sectors with high time-series sector error. Thus, acquirers and targets appear to share a common misvaluation component.

- Cash targets are undervalued—they have negative firm-specific error—while stock targets are slightly overvalued. Cash acquirers are less overvalued than stock acquirers.
- Increasing firm-specific error raises the probability that a firm will be involved in a merger, that it will be an acquirer, and that it uses stock. In contrast, M/B alone has no effect on the probability of merger once we control for year fixed effects. Similarly, sector-wide takeover activity increases with time-series sector error. This is especially true for stock merger intensity.
- When we examine long-run value to book, we find that *low* value-to-book firms buy *high* value-to-book firms. In fact, the long-run value to book component of M/B for targets is three to five times higher than that for acquirers.
- Misvaluation explains about 15% of merger activity at the sector level. Thus, while misvaluation is important for understanding patterns of merger activity at the industry level, neoclassical factors such as industry productivity shocks play an important role too.
- While roughly 40% of the total dollar volume of merger activity occurs during these merger waves, highly overvalued bidders are responsible for the bulk of these mergers. During merger waves, as much as 65% of merger activity comes from the quintile of most overvalued bidders. Thus, while neoclassical explanations are important for understanding merger activity at the sector level, misvaluation is critical for understanding who buys whom, regardless of whether the merger occurs during a time when productivity shocks may have caused a spike in merger activity.

Two alternative interpretations of our results that acquirers have higher firm specific errors than targets exist. The first is that misvaluation matters. Overvalued firms buy less overvalued firms in sectors which are themselves overvalued. Alternatively, one could view our decomposition as a refinement of q-theory, in which valuations implied by sector multiples provide better estimates of replacement costs than traditional accounting measures.

However, this second view must confront an unexpected finding, one that is a puzzle for existing theory. Namely, *low* long-run value-to-book firms buy *high* long-run value-to-book firms. In fact, long-run value to book for targets is three to five times higher than that for acquirers. Thus, so much of the 'high buys low' effect in the overall M/B ratio is driven by short-run valuation dynamics that the long-run components actually go in the opposite direction. This suggests that short-run misvaluation stemming from asymmetric information or behavioral phenomena masks Jensen (1986) agency-style motivations for takeover.[3]

Our robustness tests control for a number of potential neoclassical explanations. First, our misvaluation measures drive out q-theory based proxies for merger activity. Further, the "high buys low" result commonly offered as evidence in favor of q-oriented explanations of merger activity is stronger in failed deals than in successful ones. In contrast, misvaluation is higher in successful deals. Second, our misvaluation measures explain about 15% of sectoral merger activity based on Harford's (2003) classification of economic shocks. However, within these periods of economic flux, the bulk of acquirers come from the highest misvaluation decile. Thus, even during periods when economic shocks have caused spikes in merger activity at the industry level (Mitchell and Mulherin, 1996), misvaluation is still critical for understanding who buys whom and how they finance the acquisition. Based on these robustness tests, we conclude that while neoclassical explanations are important, misvaluation plays an important role in determining merger activity.

[3] See Rhodes-Kropf and Robinson (2004) for a model that nests the standard q-theory of mergers as a special case, but is also consistent with these findings.

This paper is related to a number of distinct literatures. It adds to a large empirical literature that examines trends in merger and acquisition activity (see Holmstrom and Kaplan (2001), Andrade, Mitchell, and Stafford (2001) for recent surveys). Our technique for calculating the pieces of our decomposition draws on the value relevance literature in accounting (see Francis and Schipper (1999), Barth et al. (2001), or Penman (1998) for recent examples). Our results linking valuation to merger waves complement contemporaneous empirical work by Harford (2003). In related work, Dong et al. (2002) and Ang and Chen (2004) follow a similar idea to that in this paper, but use analyst's estimates of future earnings instead of our regression-based approach. Recent work by Moeller, Schlingemann, and Stulz (forthcoming, JF) shows that the merger wave of the late 1990s destroyed almost ten times the dollar value per share as did mergers occurring during the merger wave of the 1980s, while Moeller, Schlingemann, and Stulz (forthcoming, JFE) shows that the bulk of this occurred with large acquirers. Our analysis of misvaluation and transaction size complements these findings.

The remainder of the paper is organized as follows. In section 2, we review current theories relating valuation waves to merger waves and determine our testable predictions. In section 3, we describe the data. Section 4 and 5 describe the conditional regression multiples approach in detail, and compare it to alternative specifications for value. Section 6 presents our findings. In section 7 we run an empirical horserace between misvaluation and neoclassical explanations for merger activity. Section 8 concludes.

2 Theoretical Background and Testable Implications

If firms use stock as an acquisition currency when their stock is overvalued, and this is widely known, then why are targets fooled? In this section, we review the main features of SV and RKV, which offer answers to this question. Then we explore their empirical implications.

In RKV, private information on both sides rationally leads to a correlation between stock merger activity and market valuation. In their theory misvaluation has a market- or sector-wide component as well as a firm-specific component. The target's and bidding firm's private information tells them whether they are over- or under-valued, but they cannot separately identify the sources of the misvaluation. A rational target correctly adjusts bids for potential overvaluation, but as a Bayesian puts some weight on high synergies as well. When the market-wide overvaluation is high, the estimation error associated with the synergy is high too, so the offer is more likely to be accepted. Thus, when the market is overvalued the target is more likely to overestimate the synergies because it underestimates the component of misvaluation that it shares with the bidders.

In contrast, SV posit inefficient capital markets and differences in managerial time-horizons as the key drivers of merger activity. They hypothesize that short-run managers sell their firm for stock in a long-run manager's firm when both firms are overvalued, even though the transaction price gives the short-run manager less than he knows his firm will be worth in the long run. The short run manager then sells his stock. The market is assumed to be irrational and therefore does not react to this deception/exploitation.

The remainder of this section uses these theories to establish empirically testable hypotheses to determine if valuation plays a fundamental roll in mergers.

2.1 Relative Value Predictions

In both models, overvaluation leads to mergers. Therefore, the central prediction of either theory is:

Empirical Prediction 1 *Overvalued firms use stock to buy relatively undervalued firms when both firms are overvalued.*

In SV this occurs because the overvalued short-run managers wish to sell out while their stock is overvalued. The acquirer is also overvalued because only long-run managers whose companies are more overvalued have room in their stock price to 'over pay' for a target that is also overvalued, and still make money in the long run.

In RKV, if the bidding firm has a large firm-specific overvaluation then it is more likely to win because the target cannot fully distinguish between a large synergy and a large firm-specific error. Furthermore, if the market or sector is overvalued then the target is more likely to accept an offer because, although the target makes the correct adjustment for potential market or sector overvaluation, as a Bayesian, the target puts some weight on high synergies as well. Therefore, an overvalued market leads to an overestimation of the synergies.

The above logic from both papers also suggests that:

Empirical Prediction 2 *Overall merger activity will be higher in overvalued markets. On average, firms in overvalued sectors should use stock to buy firms in relatively less overvalued sectors.*

The theories differ only slightly in their predictions about cash mergers. SV suggest that firms should only use cash to buy an undervalued firm because there is no role for true synergies in their model. In RKV cash targets should be less overvalued than stock targets, but could still be overvalued if high synergies outweigh the overvaluation. Furthermore, in both theories stock-financed deals are more likely to be completed when acquirers are more overvalued, therefore cash acquirers on average should be less overvalued than stock acquirers. Overall the theories suggest that cash mergers are driven by undervaluation and/or synergies, while stock mergers are driven by overvaluation. Thus, the theories suggest that:

Empirical Prediction 3 *Cash targets are more undervalued than stock targets. Cash acquirers are less overvalued than stock acquirers.*

2.2 Merger Intensity Predictions

The first three predictions relate to levels of relative misvaluation across types of transactions conditional on a merger. The SV and RKV theories also demonstrate how misvaluation can cause merger waves. Thus, the predictions from theory should also be stated in terms of how increases in misvaluation cause increases in merger activity. For the theories to have empirical relevance, merger activity should be more likely conditional on high valuation errors. Therefore, theory predicts:

Empirical Prediction 4 *Increasing misvaluation increases the probability that a firm is (a) in a merger, (b) is the acquirer, and (c) uses stock as the method of payment.*

In both theories the greater a firm's overvaluation the more likely it is to win the bidding for a target. RKV also predict that even the probability of being a *target* should increase with *sector* overvaluation. This is because in RKV, targets make mistakes evaluating synergies that are correlated with sector wide misvaluation.

Prediction 4 is about individual firms. A similar prediction should hold at the sector-level about aggregate merger intensity.

Empirical Prediction 5 *Increasing sector misvaluation increases merger activity, and the use of stock as method of payment, in that sector.*

These predictions allow us to examine the importance of valuation, and the components of valuation, in merger activity. However, it is important to note that there are a number of other prominent explanations for merger waves.[4] Therefore, to understand better how much merger activity can be attributed to misvaluation, and how much can be explained by more neoclassically oriented explanations, we not only test these empirical predictions but provide a battery of robustness checks and empirical horse races to ensure that our findings are not simply capturing more conventional explanations.

3 Data and Trends in Merger Activity

Our sample includes all merger activity between publicly traded bidders and targets listed on the SDC Merger and Acquisition Database between 1978 and 2001. Since our sample includes only publicly traded firms, this excludes transactions such as LBOs and MBOs. We then match these data with Compustat fiscal year-end accounting data and stock price data from CRSP to obtain a final sample.

We use the following conventions to merge data from the three sources. First, to calculate M/B, we match fiscal year-end data from Compustat with CRSP

[4] For example, Holmstrom and Kaplan (2001) argues that corporate governance issues led to the merger waves of the 80s and 90s. Andrade et al. (2001) and Mitchell and Mulherin (1996) argue that deregulation caused the 90s wave. Gorton et al. (2000) suggest that mergers are a defensive mechanism by managers. Jovanovic and Rousseau (2001, 2002) argue that technological changes caused the waves of the 1900, the 1920s, 1980s and 1990s, but not the 1960s.

market values occurring 3-months afterward. Since firms have different fiscal year end dates, this involves compensating for Compustat's year-of-record scheme, so that the year of the data corresponds to the year in which the accounting information was filed. Then, we associate this CRSP/Compustat observation with an SDC merger announcement if the announcement occurs at least one month after the date of the CRSP market value. If a merger announcement occurs between the fiscal year-end and one month after the CRSP market value, we associate the merger announcement with the previous year's accounting information.

Table 1 reports the time-series of merger announcements over our sample. While the SDC data span from 1978 to 2001, our data conventions associate the earliest mergers with fiscal year 1977 and the latest with fiscal year 2000. Requiring both firms to be on CRSP/Compustat, we have announcements from 4,325 acquirers corresponding to 4,025 target firms. (The difference owes to withdrawn or failed offers in multi-bidder takeover battles.) As the table shows, in many instances the SDC data do not indicate the method of payment of the transaction: we have 799 mixed payment, 1,218 all stock, and 1,542 all cash transactions.

Using Compustat, we calculate a variety of size, performance, and leverage ratios. Market Value is CRSP market equity plus Compustat book assets (item 6) minus deferred taxes (item 74) minus book equity (item 60). In addition, we obtain the following size-related measures: Total Plant, Property, Equipment (item 8), Total Cash (item 1), Long-term Debt (item 9), CAPEX (item 128) and Net Income (item 172). Return on assets and equity are calculated by dividing net income in year t by assets (item 6) or book equity (item 60) in year $t-1$. For leverage measures, we obtain the Current Ratio (items 4/5), Quick Ratio (items (4 - 3)/5), market leverage (1 - market equity/market value), and book leverage (1 - book equity/total book assets). Finally, the announcement and closing dates of mergers, the method of payment (when available), and a dummy for whether the merger was withdrawn were taken from SDC and merged to the Compustat/CRSP data.

Table 2 provides a comparison of these summary statistics based on whether or not a firm was involved in a merger, and if so, whether it was an acquirer or a target. Firms are flagged as merger observations in Table 2 in the year that a merger event is announced, therefore firms that ultimately are involved in mergers will be grouped in the non-merger category in the years in which they have no merger activity. Along virtually any conceivable size dimension, merger observations are larger than the typical non-merger firm on COMPUSTAT. However, this difference is driven by the fact that acquirers are much larger than average; target firms are about the same size, or a little smaller, than the average COMPUSTAT firm.

The market-to-book ratios for firms involved in mergers are considerably higher than those for non-merger firms. When we compare acquirers and targets, we find that M/B is significantly higher for acquirers than for targets. However, average M/B ratios for targets are statistically larger than for non-merger firms. Thus, the conventional wisdom that high M/B buys low M/B is somewhat misguided: high M/B firms buy lower M/B firms, but these targets have higher M/B ratios than the average firm. This is a first hint that mergers occur when both firms are overvalued, which is our main relative value prediction.

To say more about the tendency for mergers to cluster in particular sectors at a point in time (á la Andrade, Mitchell, and Stafford (2001) or Mitchell and Mulherin (1996)), we use industry classifications provided by Eugene Fama and Kenneth French.[5] These are described in Table 3, which reports verbal descriptions along with firm-counts and aggregate valuation and merger statis-

[5] We are grateful to Ken French for making these data available on his website.

tics. The firm-counts indicate that sector-year regressions, discussed in section 5, do not suffer from small sample problems.

The summary statistics from this section expand on existing results linking M/B to merger activity: high M/B firms are involved in mergers; the very highest M/B firms buy higher-than-average M/B firms. To build on these findings, we next discuss a technique for decomposing the M/B ratio that allows us to attach separate interpretations to these findings in terms of a firm-specific value component, a sector value component, and long-run value-to-book.

4 Decomposing Market-to-book

This section and the next discuss the two methodological innovations that we use to study how valuation waves affect merger waves. The theories of SV and RKV both suggest that a merger is more likely when a firm's market value, M, is greater than its true value, V. Therefore, both theories implicitly suggest that a firm's market to book ratio should be broken into two components: market value to true value, M/V, and true value to book, V/B. Thus, for any measure of value, we can use the following algebraic identity to decompose the market-to-book ratio:

$$m - b \equiv (m - v) + (v - b) \tag{2}$$

where m is market value, b is book value, and v is some measure of fundamental, or 'true' value, all expressed in logarithms. [6] Inserting a measure of value into the market-to-book ratio thus allows us to separate $\ln(M/B)$ into two

[6] Throughout our discussion, we will use lower-case letters to denote values expressed in logs, and upper case letters to denote the same values expressed in standard units.

components: a measure of price to fundamentals, $\ln(M/V)$, and a measure of fundamentals to book value, $\ln(V/B)$.

For the sake of argument, assume that a 'perfect' measure of v exists. Then, if markets perfectly anticipate future growth opportunities, discount rates, and cash flows, there would be no scope for pricing error to contaminate M/B, the term $m - v$ would always be equal to zero, and the term $v - b$ would be trivially equal to $\ln(M/B)$ at all times.

If, on the other hand, markets potentially make mistakes in estimating discounted future cash flows or, as in RKV, markets do not have all the information known by managers, then price-to-true-value, $m - v$, captures the part of $\ln(M/B)$ that is associated with misvaluation. This may or may not correspond to an asset-pricing sense of mispricing, depending on whether the information in v is known to the market. If the market price does not reflect true value, then $\ln(M/V)$ will be positive in times of overvaluation, and negative in times of under-valuation.

RKV takes the breakdown of $m_{it} - b_{it}$ further to suggest 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, we separate $\ln(M/B)$ into three components: (1) the difference between observed price and a valuation measure that reflects time-t fundamentals (firm-specific error); (2) the difference between valuation conditional on time-t fundamentals and a firm-specific valuation that reflects long-run value (time-series sector error); and (3) the difference between valuation based on long-run value and book value (long-run value to book).

As we discuss in the next section, our approach to estimating v conceptually 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.

Thus, writing $v(\theta_{it}; \alpha)$ as the predicted value based on some vector of multiples α, we can re-write Equation 2 as:

$$m_{it} - b_{it} = \underbrace{m_{it} - v(\theta_{it}; \alpha_{jt})}_{firm} + \underbrace{v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)}_{sector} + \underbrace{v(\theta_{it}; \alpha_j) - b_{it}}_{long-run} \quad (3)$$

The key difference in the $v(\theta_{it}; \cdot)$ expressions is that time-t multiples are represented as α_{jt} while long-run multiples are represented by α_j. The first term is the difference between market value and fundamental value conditional on time t and sector j valuation effects, $m_{it} - v(\theta_{it}; \alpha_{jt})$. We call this firm-specific error. Thus, if the market is 'overheated' at time t, this will show up in α_{jt} and therefore in $v(\theta_{it}; \alpha_{jt})$. Likewise, if industry j is 'hot' relative to other industries at time t, this too will appear in α_{jt}. This means that the firm-specific error, $m_{it} - v(\theta_{it}; \alpha_{jt})$, captures purely firm-specific deviations from fundamental value, since the v term captures all deviations common to a sector at a point in time.

The second component of $\ln(M/B)$ is time-t fundamental value to long-run value, $v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$. We call this time-series sector error, since the function $v(\theta_{it}; \alpha_j)$ captures sector-specific valuation that does not vary over time. When time-series sector error, $v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$, is high, the sector-wide valuation wave is near its peak. The parameters in α_j in some sense capture the long-run multiples for industry j. The final component is the difference between long-run value and book, $v(\theta_{it}; \alpha_j) - b_{it}$. Each of these three components varies at the firm-year level, and involve valuation multiples that vary across industries and over time. Thus, $v(\theta_{it}; \alpha_j)$ will vary over time at the firm level as accounting information changes (i.e., θ_{it} varies over t holding i constant), and will vary across firms within an industry as their accounting data differ (i.e., θ_{it} varies over i at a particular time t).

5 Estimating Market Value

In order to use our decomposition of M/B we must estimate the pieces of the decomposition that relate to time-t fundamental value and true value. This subsection describes our approach to calculating $v(\theta_{it};\alpha_{jt})$ and $v(\theta_{it};\alpha_j)$.

Our starting point is the definition of firm value, $\mathbf{M}_t$, as the present value of expected free cash flows (FCF),

$$\mathbf{M}_t = \int_t^{\infty} \mathrm{e}^{-\int_t^{\tau} r(\eta)d\eta}\mathbf{FCF}d\tau, \tag{4}$$

where $r(\eta)$ is a potentially time-varying discount rate. Following an idea that goes back to Marshall, we can rewrite the present value of free cash flows as the value of the assets in place plus the economic value added. In accounting terms the value of a firm is the book value of the assets plus the residual income generated by those assets:

$$\mathbf{M}_t = \mathbf{B}_t + \int_t^{\infty} \mathrm{e}^{-\int_t^{\tau} r(\eta)d\eta}\mathbf{RI}d\tau \tag{5}$$

where RI is residual income, defined as the excess of the economic flows arising from the assets over their opportunity cost. By defining residual income as the difference between the return on equity and the cost of capital, both multiplied by the previous period's capital stock, we can write equation 5 in discrete time as

$$\mathbf{M}_t = \mathbf{B}_t + \mathrm{E_t}\sum_{\tau=t+1}^{\infty} \frac{(ROE_\tau - r_\tau)\mathbf{B}_{\tau-1}}{(1+r_\tau)^\tau}. \tag{6}$$

There are a number of ways of implementing Equation 6 to get a measure of value. One approach is to use analyst's forecasts as proxies for expected future ROE values. Lee, Myers, and Swaminathan (1999) use this approach to study the intrinsic value of the Dow, and Dong et al. (2002) use this approach to study the relation between M/B and merger activity. However, as

Ritter and Warr (2002) point out, the particular form of the perpetuity calculation used by Dong et al. (2002) rests on a number of assumptions that make it difficult to conclude that mispricing (rather than differences in growth opportunities) is responsible for their findings. Moreover, their emphasis on behavioral explanations makes it difficult to see the impact of other theories.

To avoid these and other shortcomings, we take a different approach to obtain a measure of value. Our strategy is to impose identifying restrictions on Equation 6. This approach does not rely on analyst's forecasts which may include expectations of future merger activity, it does not bias our sample towards large transactions, and it allows us to recover the market's estimates of growth and discount rates. Depending on the identifying assumptions imposed, Equation 6 yields to a variety of econometric specifications. The remainder of this section discusses three possibilities.

5.1 Model I: Market Value and Book Value

We begin with a simple model linking market equity to book equity alone. To link current values of market equity to current values of book, two identifying restrictions are sufficient. The first is that expected future ROE is a constant multiple of expected future discount rates ($E_t(ROE_\tau) = \lambda E_t r_\tau \; \forall \; \tau > t$). This assumption can be motivated in terms of markup pricing, or in terms of the potential for competitive entry or technological change to force expectations of future profitability to be multiples of discount rates. The second assumption is that book equity is expected to grow at a constant rate over time. In that case, we can express Equation 6 as

$$\mathbf{M}_t = \alpha_{0t} + \alpha_{1t}\mathbf{B}_t. \tag{7}$$

where the particular values of α_{0t} and α_{1t} will depend on the particular identifying assumptions imposed. For example, if we assume that perfect competition forces the return on equity equal to its opportunity cost at all points in time ($\lambda = 1$ in the discussion above), then we no longer need to assume constant expected growth in book equity, and we have $\alpha_{0t} = 0$ and $\alpha_{1t} = 1$ for all t. In general, the α_{0t} and α_{1t} will be proportional to discount rates (costs of capital) and growth rates, which will likely vary over time.

To account explicitly for the possibility that discount rates and growth rates vary over time and across industries, we estimate equation 7 through the following equation for Model I:

$$\mathbf{m_{it}} = \alpha_{0jt} + \alpha_{1jt}\mathbf{b_{it}} + \epsilon_{it} \tag{8}$$

This is estimated in logs (hence the lower-case letters) to account for the right-skewness in the accounting data. To implement Equation 8, we group firms according to the 12 Fama-French industries and perform annual, cross-sectional regressions for each industry in question. By estimating separate equations for each industry-year, we do not require the growth rates or discount rates embedded in our multiples to be constant over time. This addresses concerns about time-varying risk premia and expected growth opportunities raised by Ang and Liu (2001) and Feltham and Ohlson (1999).

It is important to note that Equation 8 is not an asset-pricing equation—it does not relate expected returns to a particular set of priced risk factors in the economy. Nevertheless, since multiples reflect discount rates and expected growth rates, the α coefficients naturally embody risk characteristics of the average firm in the industry.

The industry classifications used for these regressions are discussed in Table 3. To interpret Equation 8, consider an industry average M/B multiple from Table 3. Equation 8 breaks this multiple into two pieces. Since the equation is estimated in logs, the first piece, α_{0jt}, is the average market value associated with a firm with \$1 MM book equity in industry j, year t. This term captures the amount of market value attributed to all firms on average, in a given industry at a point in time, regardless of their book value relative to other firms in their industry. This can be interpreted as the value of intangibles priced into the average firm in a sector at a point in time, since under OLS $\hat{\alpha}_{0jt} = \bar{m}_{jt} - \hat{\alpha}_{jt}\bar{b}_{jt}$. The second piece of the M/B multiple is the coefficient on book, α_{1jt}, which then measures the multiple associated with incremental book equity.

To generate estimates of $v(\theta_{it}; \alpha_{jt})$ and $v(\theta_{it}; \alpha_j)$ we use fitted values from Equation 8 above:

$$v(\mathbf{B}_{it}; \hat{\alpha}_{0jt}, \hat{\alpha}_{1jt}) = \hat{\alpha}_{0jt} + \hat{\alpha}_{1jt}\mathbf{b}_{it} \tag{9}$$

for each firm. To obtain $v(\theta_{it}; \overline{\alpha}_j)$, we average over time to obtain $\frac{1}{T}\sum \hat{\alpha}_{jt} = \overline{\alpha}_j$ for each set of parameters $\{\alpha\}$, then calculate

$$v(\mathbf{B}_{it}; \overline{\alpha}_{0j}, \overline{\alpha}_{1j}) = \overline{\alpha}_{0j} + \overline{\alpha}_{1j}\mathbf{b}_{it}. \tag{10}$$

The time-series averages from Model I are presented in the upper panel of Table 4. The variable $\overline{\alpha}_{0j}$ is recorded as $E_t(\hat{\alpha}_0)$, and varies considerably across industries. Moreover, the magnitudes of $E_t(\hat{\alpha}_0)$ are consistent with interpretations as capitalized intangible value, given the industry descriptions. For example, Utilities and Consumer non-durables have the lowest values of $E_t(\hat{\alpha}_0)$, while Telephone & TV, computers, and medicine have the highest values of intangibles according to our estimation scheme. Moreover, the values of $\overline{\alpha}_j$ are generally the highest in the same industries in which the constant terms are the lowest, suggesting that in these industries tangible book assets are most highly correlated with value. Finally, the average R^2 values are high across all industries, even in a simple model of log market value on log book value.

5.2 Model II: Market Value, Book Value, and Net Income

Recent scholarship in accounting has pointed to the importance of net income for explaining cross-sectional variation in market values.[7] To develop a valuation model that includes net income as well as book value, we can impose slightly less restrictive assumptions on Equation 6. For example, if we assume that book value and net income are growing at constant rates, we can re-write Equation 6 as

$$\mathbf{M}_t = \alpha_0 + \alpha_1 \mathbf{B}_t + \alpha_2 \mathbf{NI}_t. \tag{11}$$

Since net income is sometimes negative, we estimate the following equation for Model II:

$$\mathbf{m_{it}} = \alpha_{0jt} + \alpha_{1jt}\mathbf{b_{it}} + \alpha_{2jt}\ln(\mathbf{NI})^+_{\mathbf{it}} + \alpha_{3jt}\mathrm{I}_{(<0)}\ln(\mathbf{NI})^+_{\mathbf{it}} + \epsilon_{it} \tag{12}$$

where $\mathbf{NI}^+$ stands for the absolute value of net income and $\mathrm{I}_{(<0)}\ln(\mathrm{NI})^+_{\mathrm{it}}$ is an indicator function for negative net income observations. Since this equation is estimated in logs, and net income is often negative, this setup allows for net income to enter into the estimation without discarding all the firms with negative net income at a point in time. By estimating separate sets of parameters $\{\alpha_2\}$ and $\{\alpha_3\}$ for positive and negative net income, we allow negative net income observations to enter into the estimation without contaminating the 'earnings multiple' interpretation of α_2. Thus, if firms in a given industry are

[7] Examining the value-relevance of various accounting measures via equations similar in spirit to Equation 8 has a long tradition in the accounting literature. That literature is far too large to discuss fully here, but Holthausen and Watts (2001), Kothari and Zimmerman (1995), Kothari (2001), and Barth, Beaver, and Landsman (2001) contain excellent surveys of this literature and debates about the conclusions that can be drawn from it. A number of authors (for example Amir and Lev (1996), Lev (1997)) have argued that the value relevance of accounting has declined, in part because of the rise in importance of intangible assets that are not captured in book equity. Collins, Maydew, and Weiss (1997) counter that accounting information continues to be important in the face of intangibles, pointing instead to the increasing importance of net income for explaining cross-sectional variation in market value.

penalized for having negative net income in a given year, the α_{3jt} parameter will be negative.

To obtain $v(\theta_{it}; \hat{\alpha}_{jt})$ and $v(\theta_{it}; \hat{\alpha}_j)$ using Equation 12, we perform calculations analogous to Equation 9:

$$v(\mathbf{B}_{it}, \mathbf{NI}_{it}; \hat{\alpha}_{0jt}, \hat{\alpha}_{1jt}, \hat{\alpha}_{2jt}, \hat{\alpha}_{3jt}) = \hat{\alpha}_{0jt} + \hat{\alpha}_{1jt}\mathbf{b}_{it} + \hat{\alpha}_{2jt}\ln(\mathbf{NI})^{+}_{it} + \hat{\alpha}_{3jt}\mathrm{I}_{(<0)}\ln(\mathbf{NI})^{+}_{it}. \quad (13)$$

for each firm. To obtain $v(\theta_{it}; \alpha_j)$ under Model II, we average over time to obtain $\frac{1}{T}\sum \alpha_{jt} = \overline{\alpha}_j$ for α_k, $k = 0, 1, 2, 3$, then calculate

$$v(\mathbf{B}_{it}, \mathbf{NI}_{it}; \overline{\alpha}_{0j}, \overline{\alpha}_{1j}, \overline{\alpha}_{2j}, \overline{\alpha}_{3j}) = \overline{\alpha}_{0j} + \overline{\alpha}_{1j}\mathbf{b}_{it} + \overline{\alpha}_{2j}\ln(\mathbf{NI})^{+}_{it} + \overline{\alpha}_{3j}\mathrm{I}_{(<0)}\ln(\mathbf{NI})^{+}_{it}. \quad (14)$$

The second panel of Table 4 reports time-series average values of the $\{\alpha_j\}$ for each industry. The cross-industry comparisons match Model I, except that the addition of net income to the model uniformly increases average R^2 values. In addition, the interpretations of the loadings on the income variables make intuitive sense: the loading on net income for positive net income realizations is positive and about the same order of magnitude as the loading on the absolute value of the negative net income observations. The other noteworthy feature of this model is that including net income reduces the loading on book value; presumably this is arising from the time-series properties of net income.

5.3 Model III: Market Value, Book Value, Net Income and Leverage

Models I and II implicitly impose the restriction that firms be priced against the average multiples for firms in that industry-year. To account for the fact that within-industry differences in leverage could potentially influence this, we estimate a third model in which leverage also appears. Accounting for leverage allows for the fact that firms with higher or lower than industry-average leverage will have a different cost of capital, forcing them to differ from industry average multiples. Thus, Model III is:

$$m_{it} = \alpha_{0jt} + \alpha_{1jt}\mathbf{b_{it}} + \alpha_{2jt}\ln(\mathbf{NI})^{+}_{\mathbf{it}} + \alpha_{3jt}\mathrm{I}_{(<0)}\ln(\mathbf{NI})^{+}_{\mathbf{it}} + \alpha_{4jt}\mathbf{LEV}_{it} + \epsilon_{it} \quad (15)$$

where $\mathbf{LEV}_{it}$ is the leverage ratio. As in models I and II, this regression is estimated cross-sectionally in each industry-year, allowing the α_k, $k = 0, \ldots, 4$ to vary both over time and across industries. Cross-sectional and time-series variation in the parameters, in particular, captures the fact that some industries may be able to sustain high debt loads, while in other industries the optimal capital structure may be more tilted towards equity.

The third panel of Table 4 presents summary statistics for the Model III. Not surprisingly, the loading on leverage is negative and highly significant (Fama-Macbeth standard errors are reported below point estimates). Moreover, the value of intangibles rises when we account for cross-sectional differences in leverage. Finally, the average R^2 values range between 80% and 94%, indicating that accounting information and leverage alone explain the vast majority of cross-sectional variation in market values within a given industry at a point in time.

Looking across the three models reported in Table 4, it is generally easy to reject the null hypothesis that the average $\alpha_0 = 0$. There is less time-series volatility in the loadings on accounting variables for each industry than on the α_0 terms, however, which suggests that while discount rates and growth rates vary a great deal across industries, they are less variable within industries over time.

5.4 *Discussion*

Table 5 summarizes our decomposition methodology by identifying each component of our M/B decomposition and describing how it is calculated. It is important to stress that although the multiples used in our decomposition are calculated first at the industry-year level, and then at the long-run industry level, our valuation approach applies these multiples to firm-specific, time-varying accounting information. Therefore, each component of the decomposition will vary across firms and over time as the underlying accounting fundamentals change. Based on this approach, we can offer the following interpretations of our decomposition.

The term $m_{it} - v(\theta_{it}; \hat{\alpha}_{jt})$ is the regression error obtained from annual, industry-level, cross-sectional regressions. We label this piece *firm-specific error*. Since the multiples obtained from annual, cross-sectional regressions contain time-varying market expectations of industry average growth rates and discounts rates, firm-specific error can either be interpreted as one component of misvaluation, or as firm-specific deviations from contemporaneous, industry-average growth and discount rates. It is important to recognize that since average regression error is zero by construction, we designed a valuation measure that prices firms correctly on average relative to their industry valuation.

The term $v(\theta_{it}; \hat{\alpha}_{jt}) - v(\theta_{it}; \hat{\alpha}_j)$ captures the portion of M/B that is attributable to short-run industry multiples deviating from their long-run average values. We label this piece *time-series sector error*. If short-run multiples are higher than average, then when we apply them to a firm's accounting information, the resulting valuation will exceed what we would find by using lower, long-run average multiples instead. This difference reflects the fact that an entire sector may be 'over-heated' at a point in time. Of course, this is an inherently backward-looking calculation, since we are using ex-post knowledge about valuation levels to look back and discover when prices were high. There is no way that this information could be incorporated into prices at time t—it was not in investors' information sets at time t, unless we assume a particular form of stationarity in asset prices. Thus, accepting the interpretation that this measure proxies for misvaluation does not require the reader to believe that assets were mispriced in an asset-pricing sense. It does not rest on the inability of market participants to make full use of available information. This measure could proxy for knowledge held by the management that was unknown to the market at the time. Thus, this form of 'misvaluation' could be a part of a completely rational model, as it is in RKV. Of course, this measure can also be interpreted, along with firm-specific error, as another component of mispricing as well.

Finally, $v(\theta_{it}; \hat{\alpha}_j) - b_{it}$ represents long-run value to book. This represents the portion of M/B that cannot be attributed to firm-specific deviations from industry average values, or to industry-wide waves in valuation levels. The multiples used in this component of the breakdown are in some sense the Fama and MacBeth (1973) multiples for a given industry, and thus reflect the long-run average growth rates and discount rates that should apply to the average firm in the industry. Of course, this long-run value to book measure will vary over time and across firms, but this variation will be attributable solely to firm-specific variation in accounting fundamentals. Valuation effects that arise from hot industry effects or firm-specific misvaluation have been purged from this measure.

These interpretations of course rest on a correct measure of v. Since we are estimating v, we face the standard joint hypothesis problem: it is impossible to distinguish empirically between a purely behavioral explanation for misvaluation and one based on rational behavior in the presence of asymmetric information. However, it is possible to draw distinctions between these two theories and a class of explanations based on the idea that mergers occur as an efficient response to reorganization opportunities (see, for example, Gort

(1969) or Jovanovic and Rousseau (2002)). Therefore, we conduct an empirical horse race between these two groups of explanations at the end of the paper. The conclusions of that horse race suggest that our misvaluation measures are not a proxy for q based variables.

6 Tests and Findings

We now use our methodology to test the predictions discussed in Section 2. Since the SV and RKV theories explicitly link misvaluation levels to merger waves, we proceed in two steps. First, we examine the valuation characteristics of the sample of firms that actually participated in mergers. In subsection 6.1 we examine the relative value predictions.

To further examine the role of misvaluation in merger activity, we also study whether times of high aggregate valuation errors are times of high merger activity. These merger intensity predictions are tested in section 6.2.

6.1 Testing Relative Value Predictions

The first row of Table 6 reports differences in $m_{it}-b_{it}$ ratios by target, acquirer, and method of payment. From this we see that it is not the case that high M/B buys low M/B, but rather high M/B targets are bought by even higher M/B acquirers. Interestingly, this finding is driven by the characteristics of targets in stock transactions. In this group, both acquirers and targets have significantly higher M/B ratios than in other method of payment categories. When we examine cash-only or mixed payment transactions, we find no difference in M/B between target firms and non-merger firms.

The remainder of Table 6 reports the results of using the fitted values from Models I, II and III to break market to book into its three components:

$m_{it} - v(\theta_{it}; \hat{\alpha}_{jt})$, firm-specific error; $v(\theta_{it}; \hat{\alpha}_{jt}) - v(\theta_{it}; \overline{\alpha}_j)$, time-series sector error; and $v(\theta_{it}; \overline{\alpha}_j) - b_{it}$, long run value to book. Since the table is in logs, the three components of M/B for each model add to the $\ln(M/B)$ ratio reported in the top row. Table 6 reports values for all mergers (4,025 mergers), but also breaks the sample into 100% cash transactions (1,542 mergers), 100% stock transactions (1,218 mergers) and mixed transactions (799 mergers). (SDC omits method of payment for many mergers: we include missing method-of-payment transactions in the overall column but exclude them from any column that reports results by transaction type.) Within each group, Table 6 reports whether the difference between the target and the acquirer is significant.

Looking across models, we can compare how they attribute total M/B to its various components. For example, merger targets in cash acquisitions have an $m_{it} - b_{it}$ of 0.61. Model I attributes 0.59 of this to long-run value-to-book, 0.13 of this to sector-specific misvaluation, and the remaining -0.11 to firm-specific error. By comparison, Models II and III attribute 0.58 and 0.62 to long-run value-to-book, a slightly smaller 0.12 and 0.06 to sector-specific misvaluation, and a slightly larger -0.09 and -0.08 to firm-specific error. Overall the breakdown of M/B across the three models is remarkably consistent. Since the results are robust to different models, in what follows we will discuss the results only for Model III.

Table 6 allows us to test the first three predictions from the theory. The first prediction says that overvalued firms buy relatively undervalued firms when both firms are overvalued. This means that firm-specific error should be lower for targets than acquirers,

$$\underbrace{m_{it} - v(\theta_{it}; \hat{\alpha}_{jt})}_{target} < \underbrace{m_{it} - v(\theta_{it}; \hat{\alpha}_{jt})}_{acquirer} \tag{16}$$

but that the total of firm-specific and time-series sector error for firms in mergers should be greater than firms not involved in mergers:

$$\underbrace{m_{it} - v(\theta_{it};\hat{\alpha}_{jt}) + v(\theta_{it};\hat{\alpha}_{jt}) - v(\theta_{it};\overline{\alpha}_j)}_{target\ or\ acquirer} >$$
$$\underbrace{m_{it} - v(\theta_{it};\hat{\alpha}_{jt}) + v(\theta_{it};\hat{\alpha}_{jt}) - v(\theta_{it};\overline{\alpha}_j)}_{non-merger}. \quad (17)$$

This result should hold for the entire sample, but particularly for stock-financed acquisitions. Furthermore, cash targets should more undervalued than stock targets, and cash acquirers should be less overvalued than stock acquirers:

$$\underbrace{m_{it} - v(\theta_{it};\hat{\alpha}_{jt})}_{cash\ target\ or\ acquirer} < \underbrace{m_{it} - v(\theta_{it};\hat{\alpha}_{jt})}_{stock\ target\ or\ acquirer}. \quad (18)$$

We find support in the data for each of these predictions. Focusing on Model III, we see that firm-specific error is higher for acquirers than targets in the overall merger sample (0.32 for acquirers, but only 0.03 for targets) and for stock-financed mergers (0.44 for acquirers, but only 0.05 for targets). We also find that both firm-specific and time-series sector error are greater for firms involved in mergers than those not in mergers (0.18 firm-specific error in model III is greater than the -0.01 for non-merger firms, and the time-series sector error is 0.10 for merger-firms exceeds the 0.03 for non-merger firms).

The second prediction is that acquirers should come from sectors that are more overvalued than targets. Thus, time-series sector error, $v(\theta_{it};\hat{\alpha}_{jt}) - v(\theta_{it};\overline{\alpha}_j)$, should be greater for acquirers than targets. This effect holds for each of the three models, and across each type of method of payment. For example, in model III we see that the time-series sector error for mixed payment acquirers is 0.12, while it is only 0.08 for mixed payment targets. For stock transactions, acquirers have an average time-series sector error of 0.17, while targets have an average of only 0.12. This relationship also holds for cash transactions.

The last prediction that can be tested with Table 6 is Prediction 3. This also holds for all models. First, cash targets are more undervalued than stock targets. For example, in model III we see that the firm-specific error for stock targets (0.05) is larger than that of cash targets (-0.08). The same is true of time-series sector error for stock and cash targets (0.12 for stock targets is greater than 0.06 for cash targets).

In addition, firm-specific error is higher for stock acquirers than cash acquirers. From Model III, the stock acquirer firm-specific error is 0.44, while for cash acquirers it is only 0.29. Time-series sector error of 0.17 for stock acquirers exceeds the 0.14 for cash acquirers. Although the theory does not discuss mixed payment acquisitions, by extension it would seem that all stock acquirers should be more overvalued than mixed payment acquirers, which is supported by the data (0.44 (stock) versus 0.29 (mixed) for firm-specific, and 0.17 (stock) versus 0.12 (mixed) for sector-specific).[8] All reported inequalities are statistically significant.

Thus, to the extent that firm-specific error and time-series sector error proxy for misvaluation, Table 6 provides strong support for the central predictions of SV and RKV. It shows that merger firms are more over-valued than non-merger firms, that bidders are more over-valued than targets, and that method of payment determines whether a target is over- or under-valued. In cash acquisitions, targets are under-valued on average. In stock acquisitions, targets are over-valued. These latter findings support the idea that correlated misvaluation leads overvalued targets to accept takeover bids from overvalued bidders precisely because they over-estimate the expected synergies.

[8] We can say little about predictions for mixed offers because, except for Eckbo et al. (1990), there is little theoretical work modeling the use of mixed offers. If mixed offers allow the under and overvalued acquirers to separate, as suggested by Eckbo et al. (1990), then we might expect the predictions of RKV and SV not to hold for mixed offers. However, under a lose interpretation of RKV and SV we might expect mixed offers to fall between all cash and all stock offers.

6.1.1 Do Low Growth Firms Acquire High Growth?

Table 6 also contains a new finding that is not predicted by either efficient markets or the possibility of misvaluation. We find that although high M/B firms buy low M/B this difference between bidders and targets is driven by firm-specific deviations from short-run average value, not from fundamental differences between targets' and acquirers' long-run pricing. To see this in Table 6, compare the top row of the table, which reports $\ln(M/B)$ to the bottom row of each model, which reports long-run value-to-book. For example, the average log(M/B) of acquirers is 0.83 and the average log(M/B) of targets is 0.69, while, in model III, the average long-run value to book of acquirers is 0.39 and it is 0.58 for targets. In all of our models, we find that *low* long-run value to book firms acquire *high* long-run value to book targets, both in stock-financed and cash-financed transactions.

Thus, while it is true that high M/B acquirers buy lower M/B targets, so much of this is driven by short-run valuation dynamics that the long-run value to book measures work in the opposite direction. Note that long-run value is not lower due to the merger. Long-run value is a function of pre-merger accounting variables and long-run industry wide valuation multiples. Thus, a low long-run value arises from an industry with low long-run pricing. [9] This has important implications for questions relating to mergers, corporate governance, and economic efficiency.

The 'low buys high' long-run value finding is a puzzle for existing theory. Under a strict efficient markets interpretation, q theory would suggest that merger activity spikes when expected growth opportunities are high. However, these growth opportunities appear transient as the targets will be priced higher

[9] Of course, the accounting treatment of a recent merger would lead to distortions in the value of serial acquirers. To guard against this possibility, we discarded all multiple acquirers and repeated our analysis. This has no effect on the magnitude or significance of our results. We thank René Stulz for pointing out this possibility.

than the acquirer in the long-run. Thus, the short-run changes in growth rates and/or discount rates seem to mask underlying long-run fundamentals that go in the opposite direction. In a long-run sense, firms with low growth opportunities acquire targets that have better long-run growth opportunities.

This finding is reminiscent of Jensen (1986) motivations for mergers activity, since it suggests that firms with low growth prospects use acquisitions as a way of buying growth when the market's growth expectations are overblown. However, the fact that two countervailing effects are at work (high M/B buys low M/B, but low long run value to book buys high long run value to book) means that rational explanations cannot explain our findings unless it contains some element of asymmetric information as a key ingredient.

6.1.2 Robustness Checks on Relative Value Predictions

Table 6 contains striking evidence in support of the idea that temporary firm-specific and industry-specific fluctuations in value drive acquisition activity. However, a number of potential alternative explanations could be clouding the results in Table 6. Tables 7 and 8 provide robustness checks and further extensions to our primary relative value predictions.

One concern with the preceding analysis is that the results are being driven by the late 1990s, when (1) valuations were high, and (2) our long-run value calculations are the most backward-looking. To see why late-1990s mergers might be a problem for our analysis, consider a typical merger occurring in 1999. During this period, valuations were at all-time highs. Thus, $m_{it} - b_{it}$ is likely to be large, and α_{jt} values are likely to be above their long-term values, which towards the end of the sample are mostly backward looking (an $\overline{\alpha}$ contains only two years of forward-looking data in 1999). Moreover, since this period was a time of intense merger activity, such mergers may make up a disproportionate fraction of our sample.

To control for this possibility, Table 7 includes a column, labelled 'Pre-1996 Only', which repeats Table 6 except that only mergers occurring prior to 1996 are included. Thus, while $\overline{\alpha}$ is calculated using data out to 2001, the latest merger is in 1996, meaning that every merger in Table 7 has at least five years of forward-looking data built into $\overline{\alpha}$. The results are virtually unchanged. The main difference is that the long-run value to book measures are higher in Table 7 than in 6 for Models I and II. This shows that our results are not being solely driven by events in the late 1990s, when our long-run multiples are the most backward-looking.[10]

Table 7 includes a number of additional robustness checks. The fact that we get the same results when we split mergers according to whether they were within or across industry shows that our results cannot be attributed to explanations based on industry expansion or contraction.[11] Another potential concern is that firms at risk for LBO were systematically misvalued by our valuation technique because they had low growth prospects. This is not the case; excluding any firm that was ever in an LBO does not affect our findings. (Since our sample only includes deals between publicly traded firms, no LBO transaction is actually in our merger sample, but some firms were nevertheless also on the SDC LBO database at other points in their history.) Finally, what if misvaluations correct between the announcement and consummation of the merger, and the terms of the deal adjust? Evidence from Hietala et al. (2003) indicates that the terms of a transaction can change considerably if there is a long period of time between announcement and eventual success of the merger. The fact that we obtain our main findings in a sample of transactions that

[10] To guard against the possibility that isolated industries are influencing our decompositions, we summarized our breakdown on an industry-by-industry basis. Performing the means tests industry-by-industry also has the feature that since the sample sizes are much smaller, the t-statistics will not be overstated by assumptions about independence. None of t-statistics become insignificant.

[11] See Andrade and Stafford (2004); for brevity we have omitted results broken out by method of payment, but they match what is reported in Table 6.

close within 30 days of announcement suggest that misvaluation is unlikely to be driven away through protracted renegotiation.[12]

Table 8 provides additional robustness checks by showing that our results hold across all transaction size. This table reports our breakdown of $m_{it} - b_{it}$ according to transaction quintiles. Q1 are the smallest transactions; these deals involve small targets and are most often straight cash deals. As we move rightward in the table, towards Q5, deal size and the size of the target increases. In addition, the relative fraction of straight cash deals drops.

As transaction size increases, a number of distinct effects appear. Among the quintile of largest transactions (Q5), it is no longer the case that the $m_{it} - b_{it}$ of the acquirer is statistically larger than that of the target. However, in spite of the fact that the M/B values are roughly equal, it is still the case that the misvaluation differences between acquirers and targets are large and statistically significant. Moreover, it is still the case that low long-run value to book firms acquire higher long-run value to book firms.

Another striking feature of Table 8 is the pronounced change in the target's firm-specific misvaluation as we move from Q1 to Q5. For the smallest transactions (groups Q1 and Q2), target firm-specific misvaluation is negative and very large. Moving towards Q5, the firm-specific misvaluation of the target increases, growing positive between Q3 and Q4. The long-run value-to-book measures move in the opposite direction.

Finally, this table reports a row that adds together the sector-specific and long-run values into a single number. This is presented in order to guard against

[12] Another possible concern is that our valuation models are failing to price large firms well. In unreported robustness tests, we have replicated Table 6 for models that include squared and cubic terms for book value to capture non-linearities in size. In addition, we have repeated Table 6 using models that scale by shares outstanding, so that all variables are measured on a per-share basis. These are omitted for brevity, but are available upon request.

the possible criticism that our long-run value measure is inappropriate, since it uses forward-looking data. Even if we attribute all sector-specific valuation to long-run value, we still find that low value-to-book firms acquire high value-to-book firms.

In summary, this table shows that our decomposition results hold for all transaction sizes. In addition, the table removes the possibility that the decomposition results follow mechanically from differences in $m_{it} - b_{it}$ across targets and bidders. The results hold when differences in $m_{it} - b_{it}$ are large or small.

6.2 Overvaluation and Takeover Intensity

Now we turn the analysis from the previous section around and ask whether increases in valuation levels cause increases in merger activity. We approach this in two steps. First, at the firm level, we explore how valuation error affects the probability of being involved in a merger. Then, at the sector level, we relate aggregate merger activity to overall levels of valuation error. This allows us to test predictions 4 and 5 directly. First, we address the question of whether valuation error affects the probability of an individual firm being involved in a merger. This is presented in sub-section 6.2.1. In sub-section 6.2.2, we examine aggregate merger intensity.

6.2.1 Firm-Level Intensity Regressions

Panel A of Table 9 presents tests of the probability that a firm is involved in a merger as a function of its valuation characteristics. The panel reports Probit regressions in which the dependent variable is 1 if the firm in question was involved in a merger (either as an acquirer or a target), 0 otherwise. Column (1) shows that firms are more likely to be in mergers when their $m_{it} - b_{it}$ is high, corroborating widely cited evidence linking valuation levels to merger intensity. However, this effect is not robust to the inclusion of year fixed effects, as column (2) demonstrates. In column (2), the loading on $m_{it}-b_{it}$ diminishes, and loses statistical significance, indicating that the $m_{it}-b_{it}$ variable is picking up mostly time trends in overall valuation levels, not differences across firms in their probability of merger.

Columns (3)-(8) repeat the analysis of columns (1) and (2) but replace $m_{it}-b_{it}$ with the components of our decomposition. No matter which model we use, we see that firm-specific error and time-series sector error have a positive and statistically significant effect on the probability that a firm is involved in a merger, while long-run value to book has a negative, significant effect. Introducing year fixed effects eliminates the significance of the sector valuation error, but neither the firm-specific error nor the long-run value to book is affected. These findings hold across each of the three models.

In Panel B of Table 9, we focus only on the sample of mergers and tests the difference between acquirers and targets. Specifically, we report results from probit regressions in which the dependent variable is 1 if the firm is an acquirer and 0 if it is a target. Since the fraction of acquirers in the sample does not vary over time, year fixed effects would have no effect on the results, and are therefore omitted. This allows us to examine whether our decomposition explains the difference between acquirers and targets. It shows that a firm is much more likely to be an acquirer if it has higher firm-specific or time-series sector error. On the other hand, increasing long-run value-to-book decreases the probability that a firm is an acquirer. These results are highly statistically significant across each of the three models. While $\ln(M/B)$ is important for predicting whether a firm is an acquirer, our decomposition produces much stronger results, since the individual components of $\ln(M/B)$ affect this probability differently.

Panel C of Table 9 relates our decomposition to method of payment. It reports probit regressions in which the dependent variable is 1 if the acquisition was 100% stock-financed, 0 otherwise. It shows that high $\ln(M/B)$ firms are more likely to use stock. Each element of the decomposition has a positive, significant affect on this probability. This supports the findings of Martin (1996), which relates q to method of payment. It also supports the predictions of RKV and SV.

These findings show that positive firm-level deviations from industry pricing increase the probability that a firm is involved in a merger, that a firm is an acquirer, and that the acquisition is financed with stock. Thus, this table offers strong support for Prediction 4.

6.2.2 Sector-level Intensity Regressions

To test Prediction 5 we regress merger activity in sector j, year t, on a variety of aggregate valuation measures. These are reported in Table 10.

In Panel A, the dependent variable is a count of the total merger activity in sector j during year t. The first five columns regress this measure of merger activity on the average $\ln(M/B)$ in that sector, which is denoted $\bar{m}_t - \bar{b}_t$. Columns (6) through (10) instead regress this measure on average time-series sector error, $\bar{v}(\alpha_{jt}) - \bar{v}(\alpha_j)$, and long-run value-to-book, $\bar{v}(\alpha_{jt}) - \bar{b}_t$. The independent variables are obtained by averaging the firm-level data (this includes Compustat non-merger firms as well as firms engaged in merger activity) down to the sector level each year. In particular, since firm-specific error is zero at the sector-year level, this means that $\bar{m}_t$ is equal to $\bar{v}(\alpha_{jt})$.

The results from Column (1) indicate that merger activity loads positively and significantly on $\ln(M/B)$. Since this regression includes sector fixed effects, the interpretation is that sectors experience more merger activity as their valuation levels increase. In Column (2), however, we see that introducing year fixed effects destroys this result. In other words, once we control for the fact that in some years all sectors simultaneously experienced high levels of valuation and high levels of merger activity, we no longer find that increases in industry valuation levels lead to increases in merger activity. Thus, we cannot rule out the alternative explanation that some external factor such as deregulation or industry consolidation is responsible for both changes in overall $\ln(M/B)$ and changes in merger activity. This mirrors the finding in Table 9 which shows that firm-level $\ln(M/B)$ does not predict increased probability of merger once we control for year effects.

In columns (6) and (7), we repeat these regressions but replace $\bar{m}_t - \bar{b}_t$ with average time-series sector error, $\bar{v}(\alpha_{jt}) - \bar{v}(\alpha_j)$, and long-run value-to-book, $\bar{v}(\alpha_{jt}) - \bar{b}_t$. From these regressions, we see that the inclusion of sector and year fixed effects does not destroy the significance of our decomposition. In both cases, we see that increases in average sector valuation error lead to increases in merger activity. Since we control for sector and year fixed effects, the interpretation is that sectors with larger increases in valuation (relative to other sectors) experience greater increases in merger activity.

At the same time, we see that sector-average long-run value to book is negatively associated with sector-level merger activity. This gives us a better understanding of why the overall $\bar{m}_t - \bar{b}_t$ are so tenuous. The result indicates that $\bar{m}_t - \bar{b}_t$ is smearing two offsetting effects: short-run sector-level average valuation error, which is positively associated with merger activity, and sector-average long-run value-to-book, which is negatively related to it. Taken separately, each effect is statistically significant, but since they partially offset one another, this destroys the overall sector-average $\ln(M/B)$ effect when we control for sector and year fixed effects.

Since fixed effects seem to be important for understanding how valuation (and valuation error) affects merger activity, the remaining columns of Panel A explore possible explanations for the economic forces that year and sector fixed effects are capturing. In columns (3) and (8) we replace the year fixed effect with a count of the total number of mergers across all sectors in year t. This is intended to capture the idea that in some years merger activity spikes across all sectors. Introducing this variable does not drive out sector-average $\bar{m}_t - \bar{b}_t$, but at the same time this variable does not have a statistically significant relation to sector-level merger activity once we control for valuation level. Thus, we can conclude that while there are spikes in overall, economy-wide merger activity, these spikes do not explain away the relation between sector-level merger activity and sector-level valuation error.

Columns (4) and (9) drop the sector fixed effects and replace them with the total count of merger activity in that sector over the entire sample period. Like a sector fixed effect, this variable takes on only one value per sector, but instead of a dummy variable for each sector, the variable is higher for sectors that experience a great deal of merger activity. This variable is positive and highly significant, and it diminishes the loading on $\bar{m}_t - \bar{b}_t$ by a factor of three. This indicates that sectors in which mergers are common have an increased sensitivity to changes in valuation (or valuation error). Finally, columns (5) and (10) drop all fixed effects and include both sector-wide and year-total merger activity. In general, these regressions do not capture as much variation in merger activity as ones including year and sector fixed effects, indicating that the fixed effects are capturing more than just localized spikes in merger activity.

In Panel B we replace the dependent variable with the count of 100% stock-financed merger transactions and repeat the analysis conducted in Panel A. This allows us to test the second part of Prediction 5, which relates specifically to the frequency of stock-financed mergers as a function of aggregate valuation error. The results largely mirror the findings from Panel A. In particular, we again find that year fixed effects drive out market-to-book, but not our aggregate sector misvaluation measure. Again, $\bar{m}_t - \bar{b}_t$ smears two off-setting effects, a positive relation between sector misvaluation and merger activity, and a negative relation between long-run value to book and merger activity. Thus, taken together, Table 10 provides strong support for Prediction 5, relating aggregate merger activity to aggregate valuation error.

An alternative interpretation that does not make use of the SV and RKV predictions is that aggregate merger intensity is a function of growth opportunities. Our findings suggest that merger intensity spikes when short-run growth opportunities are high. The strongest evidence for this finding comes from column (7), which shows that sectors with relative increases in valuation error experience relative increases in merger activity. However, the long-run growth opportunities go in the opposite direction; they are negatively associated with merger intensity, as well as the use of stock. This suggests that the Martin (1996) finding relating q to method of payment is probably driven by short-run q variation (or by misvaluation, as discussed above), not by long-run measures of investment opportunities.

Finally, the inclusion of a variable that measures overall, economy-wide merger activity in a given year helps us to guard against a potential objection to our analysis, which is that there have been only a very small number of merger waves in our sample period of 1977-2001. If this were the case, then we would find a strong positive loading on the total number of mergers in year t, and this effect would drive down the significance of the loading on average sector valuation error. Instead, our results indicate that industries experience valuation-specific merger waves that differ from the overall, economy-wide trends in merger activity, corroborating evidence in Mitchell and Mulherin (1996) and Harford (2003), which shows that mergers cluster in time at the industry level.

7 A Horse Race Between Competing Theories of Merger Activity

The neoclassical explanation for merger activity is that mergers are an efficient response to reorganization opportunities that arise as a result of some underlying economic event (see, for example, Gort (1969)). The economic shock in question may come from a variety of sources: it may arise from industry overcapacity, the advent of a new technology, changing regulatory attitudes, or changes in access to capital markets that alter the optimal operating scale of firms. Explanations along these lines could potentially account for some of our findings if mergers cluster in times when opportunities for reorganization are rich, which in turn are periods of high valuation since markets bid up prices in anticipation of the restructuring.

To guard against the possibility that neoclassical explanations are responsible for our findings, we use two approaches. The first approach is based on arguments made by Jovanovic and Rousseau (2002) and others, who argue that dispersion in Tobin's q will reflect opportunities for organizational change. This 'q-theory' of mergers suggests that some exogenous economic shock occurs in an industry. Some firms are well positioned to take advantage of this shock, while others are not, thus creating fruitful opportunities for reorganization. Indeed, the stylized fact that mergers involve high M/B bidders acquiring lower M/B targets is often offered as support for q-theoretic explanations for merger activity.

Given the wide range of potential causes for economic shocks, the problem with the q-dispersion measure is that it may fail to capture many sources of organizational flux. Therefore, our second approach is to partition the data into two periods: an 'economic shock' sample, and a 'normal' sample. Our classification of economic shocks follows the merger wave classification discussed in Harford (2003). Under this strategy, we assume that all large spikes in merger activity are caused by some form of economic shock, and we ask whether misvaluation is still important for explaining merger activity.

The first approach probably gives too little weight to the neoclassical story by only looking at one potential neoclassical explanation for merger activity. Alternatively, the second approach may give too much weight to the neoclassical story, since it attributes neoclassical explanations, ex post, to all mergers that occurred during times of extreme merger activity. However, by running both types of empirical horse races, we can better see whether our misvaluation story stands up to alternative explanations. We first explore the q-theory of mergers alternative by comparing failed and successful acquisitions. The horse race in the second subsection pits misvaluation against the ex post classification of economic shocks.

7.1 Comparing Failed and Successful Mergers

Our first horse race comes from comparing successful acquisitions to failed acquisitions. Since assets are being efficiently reorganized, a q explanation would give a higher chance of completion to a merger between two firms with a larger disparity in M/B. Thus, if Tobin's q explains merger activity, then we would expect the bidder/target q-differential to be higher among successful deals than among failed deals. On the other hand, if misvaluation is driving merger activity, then we expect misvaluation levels to be higher in completed deals, and lower in failed deals.

Table 11 reports the same breakdown as in Table 6, but splits the sample according to whether or not the deal was successful. The q difference between bidder and target is higher in failed deals, not in successful deals. However, the absolute valuation levels are lower in failed deals.[13] Moreover, when we

[13] Interestingly, targets that are later successfully acquired have higher firm-specific error in the withdrawn deal than targets which are never subsequently taken over.

decompose the M/B ratio and compare success and failure, we see that failed deals have lower misvaluation, not higher misvaluation. Long-run q is higher in failed deals than in successful deals.

This cross-sectional horse race speaks against two alternatives. First, efficient asset redeployment is unlikely to be responsible for our findings, since q dispersion is higher in failed deals than in successful ones. Instead, misvaluation seems to be at work, since overall valuation levels are higher in successful than in failed bids, and more of the level is attributable to misvaluation in successful deals as well. Second, it seems unlikely that our analysis is simply capturing ex ante valuation differences that vanish between the announcement and consummation of the merger, since the overall misvaluation level is higher in deals that actually go through than in ones that are withdrawn.

7.2 Can Q-Dispersion Explain Merger Intensity?

Next, we conduct a horse race based on the merger intensity predictions by introducing dispersion in M/B as a proxy for reorganization opportunities. The measure of q-dispersion we use is the within-industry standard deviation in $m_{it} - b_{it}$ in a given year. Jovanovic and Rousseau (2001) argue that high levels of q-dispersion reflect the fact that there are opportunities to reshuffle assets from low-productivity to high-productivity uses. Thus, if the reorganization story were at work, we would expect q-dispersion to predict merger intensity, and for q-dispersion to drive out our measures of misvaluation.

Columns (1) and (2) of Table 12 support the neoclassical, optimal reorganization theory for mergers. When we include dispersion in q in a regression with ln(M/B), q-dispersion comes in positive and statistically significant, which indicates that mergers are more likely in times when there is dispersion in valuation.

However, the explanatory power of q-dispersion disappears when we introduce our valuation decomposition. In column (3), q-dispersion becomes statistically insignificant. This suggests that the short-run valuation dynamics that our decomposition captures are not being driven by the fact that the market anticipates reorganization opportunities and compounds them into prices.

The results from the left-hand portion of Table 12 guard against the explanation that valuation is merely a by-product of q-dispersion, which in turn reflects the root cause of merger activity. To push this further, we split each industry time-series into periods that are above and below the median level of sector misvaluation for that industry, and we re-examine the ability of q-dispersion to explain merger activity.

The right half of Table 12 reports these results. Comparing columns (4) and (6), we see that q-dispersion only predicts merger activity in the low valuation subsample. During high misvaluation periods, q-dispersion is not statistically significant. To ensure that this is not being driven by the fact that q-dispersion was low in the high value period, we checked the mean and standard deviation of the q-dispersion variable in each sub-sample. They are roughly the same (.897 in the low sample, .839 in the high sample, with standard deviations of .26 and .298, respectively), indicating that this is not being driven by a problem of limited variance in one sub-sample. This suggests that while q-dispersion may reflect some underlying economic force that drives merger activity, many mergers occur during periods of high misvaluation that are unrelated to these forces. Indeed, the large and statistically significant loadings on sector misvaluation suggest that misvaluation drives merger activity. The fact that q-dispersion works in times of low misvaluation, but not high misvaluation, indicates that misvaluation is not simply capturing liquidity.

7.3 Economic Shocks as an Alternative Explanation for Merger Intensity

One problem with the previous analysis is that there may be many potential neoclassical explanations for merger activity that do not involve dispersion in Tobin's q. If so, we may be giving too little weight to neoclassical explanations for merger activity. To guard against this potential objection, this section conducts a horse race using a measure designed to capture a broad range of potential neoclassical ex ante motivations for merger.

To do this, we use the classification of merger waves conducted by Harford (2003). The Harford (2003) technique builds on Mitchell and Mulherin (1996) and starts with the null hypothesis that merger activity is more or less uniformly distributed over time for each industry (though industries may differ in their overall level of merger activity). The technique then classifies an industry as undergoing a merger wave if, during a two-year window, an industry experiences so many mergers that it is statistically unlikely to have come from this null distribution. Harford (2003) then goes back and pinpoints the economic shocks—deregulation, the advent of new technology, consolidation, etc.—that precipitated each spike in merger activity.

Since Harford (2003) provides the likely rationale behind each merger wave from a variety of possible neoclassical motivations, our approach is to examine whether our misvaluation measures continue to explain mergers once we control for this classification. Because this measure was developed independently of our analysis, it is unlikely to be mechanically related to any of the measures we develop here, and thus provides an independent measure of neoclassically motivated merger activity.

First, we relate economic shocks to sector-level misvaluation measures. This is done in Panel A of Table 13, in which we run Probit regressions of merger waves on industry average valuation and misvaluation. The first row indicates that merger waves are generally times of high overall valuations; the average industry market-to-book ratio is statistically significant and explains about 7% of the variation in merger waves.

The next two rows replace the average market-to-book ratio with average sector-misvaluation and average sector long-run growth. These variables explain about twice as much of the variation in merger waves as does the log market-to-book ratio. Both variables are statistically significant for predicting whether a sector is in a merger wave.

Examining R^2 values across the three regressions illustrates an important point. While our regressions explain about twice as much variation in merger waves as does market-to-book, the regressions indicate that merger waves are being driven by much more than just sector-level misvaluation. A crude interpretation of Panel A is that while sector-level misvaluation is a crucial determinant of merger waves, it leaves 85% of merger waves unexplained. This is indirect evidence favoring Mitchell and Mulherin (1996), Andrade et al. (2001) and others who argue that economic shocks from a variety of potential sources are responsible for spikes in merger activity at the sector level.

At the same time, this evidence leaves open the question of who buys whom during merger waves. For this, we turn to panels B and C of Table 13. In Panel B, we provide several statistics of merger activity broken down according to the quantile of firm-specific misvaluation that the acquirer came from when the acquisition was announced. Panel B shows that the quintile of the most overvalued firms is responsible for 42% of merger transactions, and an even larger fraction (47%) of stock-financed transactions. This quintile is responsible for nearly 60% of the dollar volume of merger transactions.

In Panel C we repeat Panel B but focus only on the transactions that occur during Harford (2003) merger waves. Even though merger waves only comprise 70 of the roughly 1100 industry-years, 20% of overall activity and 39%

of merger dollar volume occurs during these periods. Nevertheless, we see from the breakdown across misvaluation quantiles that misvaluation continues to be important, even during economic shock periods. Almost 50% of the transactions, and over 65% of the dollar volume comes from acquirers in the top misvaluation quintile. The top misvaluation quintile is responsible for over one-half of stock-financed merger activity during periods of economic shocks.

Taken together, these results allow us to compare the neoclassical explanation for merger activity with misvaluation. The results show that while sector misvaluation is an important determinant of merger waves, many other factors are also important. Misvaluation is by no means the whole story at the sector level. Yet at the firm level, misvaluation is critical for understanding who participates in these merger waves. Even when the merger is part of a merger wave that is being driven by neoclassical considerations, we find that most merger activity is the work of misvalued firms. While roughly one-fifth of the transactions and almost one-half the dollar volume of mergers occurs in the relatively uncommon periods of economic shocks, the vast majority of transactions—whether or not they occur during these periods—involve highly overvalued bidders.

8 Summary and Conclusions

This paper uses regression techniques to decompose the M/B ratio into components that track misvaluation at the firm and sector levels, and a component that tracks long-run growth opportunities. This decomposition allows us to test recent theories that argue misvaluation drives merger activity. To summarize our main findings, our breakdown of M/B finds the following:

- Acquirers with high firm-specific error use stock to buy targets with relatively lower firm-specific error at times when both firms benefit from positive time-series sector error.
- Cash targets are undervalued relative to stock targets. Cash acquirers are less overvalued than stock acquirers.
- Merger intensity is highly positively correlated with short-run deviations in valuation from long-run trends, especially when stock is used as the method of payment. This holds for individual firms, as well as at the aggregate level.
- After controlling for firm-specific and time-series sector error, we find that *low* 'long-run value-to-book' firms actually buy *high* 'long-run value-to-book' targets.

Therefore, while it is generally true that higher M/B firms acquire targets with lower M/B, so much of this is driven by short-run deviations in fundamentals, both at the firm and sector level, that the results for fundamental value go in the opposite direction. In fact, the component of M/B attributable to fundamental value-to-book either has no effect or is negatively correlated with the intensity of merger activity over time.

The fact that *low* long-run value firms buy *high* long-run value targets is a puzzle for most theories of merger activity. What causes this finding? One possibility is that managers who face high short-run valuations acquire targets with high long-run value in order to substantiate the market's beliefs. Another is that value-maximizing, but low-skilled managers of low valued firms acquire managerial talent from outside, and try to adapt their organization to the newly acquired talent. Yet another possibility is that low-value managers acquire higher value targets as a way of further entrenching themselves. Sorting through these possibilities is a task for future theoretical and empirical research.

Pitting our predictions against neoclassical, q-oriented explanations for merger activity reveals that a significant fraction of merger activity is explained by misvaluation. Q theory suggests that successful transactions have large market-to-book differences between bidder and target. However, we find that failed transactions have larger differences than completed transactions, while successful deals display higher levels of misvaluation. Even in industries that appear to have experienced an economic shock, the bulk of acquirers come from the highest misvaluation quintile. Therefore, our findings support misvaluation theories based either on behavioral explanations or on asymmetric information between otherwise rational managers and markets. Economic shocks may well be the fundamental drivers of merger activity, but misvaluation affects how these shocks are propagated through the economy. Misvaluation affects who buys whom, as well as the method of payment they use to conduct the transaction.

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Table 1
Characteristics of Merger Sample

Mergers come from SDC merger database and are required to have Acquirer and Target information on CRSP and Compustat. (Withdrawn deals are included.) Mean Size is the average transaction value in millions of US dollars as reported by SDC. All stock and all cash refer to transactions that are known to be paid in 100% stock or cash, respectively. Mixed payment transactions include combinations of stock, cash, and derivative securities. Transactions of unknown type are omitted from the method of payment columns.

Year	Acquirer	Targets	All Stock	All Cash	Mixed	Mean Size
1977	11	9	4	7	0	434.7
1978	11	11	1	4	0	88.3
1979	18	21	0	3	0	310.2
1980	61	44	1	4	0	856.5
1981	63	55	0	0	0	270.6
1982	95	94	2	9	1	307.8
1983	104	109	7	34	4	251.6
1984	113	110	17	55	16	406.2
1985	144	145	14	81	15	300.1
1986	164	168	25	95	25	273.7
1987	141	135	20	70	18	175.0
1988	141	123	28	66	15	362.6
1989	101	103	19	49	13	274.4
1990	108	90	31	32	16	233.8
1991	99	83	24	43	16	227.9
1992	170	147	51	69	27	460.4
1993	255	219	96	98	34	259.5
1994	315	284	100	124	58	568.8
1995	367	342	141	116	78	716.7
1996	413	411	157	116	103	713.4
1997	426	409	154	127	104	1840.1
1998	451	410	160	160	104	1420.9
1999	395	363	124	137	95	1665.7
2000	159	140	42	43	57	993.9
Total	4,325	4,025	1218	1542	799	839.4

Table 2
Characteristics of Merger and Non-Merger Firms

Summary statistics for size, performance and leverage taken from Compustat between 1977 and 2000 to match the availability of the SDC data. 'Merger' observations are firms appearing on the SDC as either a bidder or target in the period 1977-2001. Observations are required to have book-to-market ratios below 100 and market equity larger than $10MM. Market Value of assets is market value of equity (CRSP Price * Shares Outstanding) + book assets (d6) - book equity (d60) - deferred taxes (d74). Quick ratio is (d4-d3)/d5. Current ratio is d4/d5. Leverage is debt to total assets: market leverage is 1 - mkt. equity/mkt. value; book leverage is 1 - bk. equity/bk. value. The column t(diff) reports the t-statistic for the hypothesis H(0): Non-merger - Merger = 0, or Target - Acquirer = 0, correcting for unequal variance across groups. Performance measures are winsorized to remove influential outliers.

Variable	Non-Merger	Merger	t(diff)	Target	Acquirer	t(diff)
Sample Size:	102,527	8,350		4,025	4,325	
Size Measures:						
Mkt. Value (Assets)	2700.32	10743.50	-17.62	2425.89	18486.55	-18.66
Book Assets	2352.61	6936.98	-14.95	2017.70	11516.44	-16.44
Mkt. Equity	889.40	5421.84	-16.15	789.94	9733.78	-16.79
Book Equity	487.24	1467.56	-19.13	338.49	2518.64	-22.85
PP&E	515.42	1121.06	-12.52	319.76	1869.88	-17.06
Debt, LT	377.09	976.55	-12.65	308.85	1596.73	-14.53
Cap. Ex.	93.97	271.89	-13.02	66.67	466.12	-15.37
Net Income	53.72	223.37	-17.17	32.09	401.63	-19.90
Performance Measures:						
ROA	0.0267	0.0297	-1.78	0.005	0.052	-14.98
ROE	0.0796	0.1019	-6.97	0.046	0.152	-17.46
Market/Book	2.75	3.13	-9.86	2.81	3.43	-7.89
Leverage Measures:						
Leverage (Book)	0.54	0.58	-14.09	0.56	0.59	-7.00
Leverage (Mkt.)	0.43	0.44	-3.16	0.44	0.44	0.08
Quick Ratio	2.46	2.21	5.25	2.42	2.00	5.43
Current Ratio	3.15	2.76	7.97	3.01	2.52	6.17

Table 3
Industry Characteristics

This table describes industry classifications used in the subsequent valuation models. Definitions are taken from Fama and French. Observations describes the min, mean, and max number of observations per year in each industry. All averages are equally weighted. Merger activity is measured by the number of firms involved in mergers in a given industry.

	Observations per year			Average Multiples		Average	Merger Activity:		
Industry	mean	min	max	p/e	m/b	Market Equity	Acquirers	Targets	Total
(1) Consumer Non-durables	406	336	495	19.37	2.43	792.1	242	196	438
(2) Consumer Durables	180	142	227	15.99	2.45	1033.4	106	99	205
(3) Manufacturing	796	639	904	16.51	2.44	445.4	453	377	830
(4) Energy	323	205	477	23.52	3.83	1454.4	161	141	302
(5) Chemicals	144	115	174	16.85	5.79	1211.7	104	80	184
(6) Computers, Software, etc.	1,037	388	1,811	19.05	5.48	780	788	782	1570
(7) Telephone & TV	165	66	333	31.53	6.96	3948.8	233	156	389
(8) Utilities	191	103	222	12.74	1.5	987.4	103	84	187
(9) Wholesale	687	532	883	22.47	2.81	430.1	286	331	617
(10) Medical	489	133	838	17.57	8.29	1205.4	401	378	779
(11) Finance	630	298	897	16.9	6.42	812.5	983	908	1891
(12) Everything Else	914	521	1,268	17.43	3.9	552.7	465	493	958

Table 4

Conditional Regression Multiples

This table illustrates the conditional regression multiples approach. Fama-French twelve industry classifications are reported across the top. Output from valuation regressions are reported in each row. Each model is estimated cross-sectionally at the industry-year level: The subscripts j and t denote industry and year, respectively. The variable $\mathrm{E}_t(\hat{\alpha}_0)$ is the time-series average of the constant term for each regression. Likewise, $\mathrm{E}_t(\hat{\alpha}_k)$ is the time-series average multiple from the regression associated with the k^{th} accounting variable. Fama-Macbeth time-series standard errors are printed below average point estimates. Finally, the time-series average R^2 is reported for each industry. Regressions are run annually for each industry from 1977 to 2000. This regression uses natural logs of market (M) and book value (B), natural log of the absolute value of net income (NI), and an indicator interacted with log net income (NI^+) to separately estimate net income for firms with negative net income (in model 2), and leverage (Lev). Natural logs are denoted with lower case letters.

	1	2	3	4	5	6	7	8	9	10	11	12
Model I:	$\mathrm{m}_{it} = \alpha_{0jt} + \alpha_{1jt}\mathrm{b}_{it} + \epsilon_i$											
$\mathrm{E}_t(\hat{\alpha_0})$	0.98	1.65	1.19	1.46	1.47	1.70	2.06	0.66	1.13	1.97	1.16	1.70
	0.06	0.11	0.06	0.08	0.09	0.07	0.12	0.10	0.07	0.05	0.07	0.05
$\mathrm{E}_t(\hat{\alpha_1})$	0.87	0.71	0.81	0.79	0.83	0.77	0.74	0.92	0.85	0.77	0.80	0.72
	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01
R^2	0.68	0.65	0.74	0.80	0.77	0.68	0.76	0.88	0.72	0.73	0.75	0.65
Model II:	$\mathrm{m}_{it} = \alpha_{0jt} + \alpha_{1jt}\mathrm{b}_{it} + \alpha_{2jt}\mathrm{ni^+}_{it} + \alpha_{3jt}(\mathrm{I}_{(<0)}\mathrm{ni^+})_{it} + \epsilon_i$											
$\mathrm{E}_t(\hat{\alpha_0})$	1.86	2.39	1.79	1.87	2.26	2.24	2.31	1.21	1.87	2.29	1.83	2.17
	0.06	0.13	0.05	0.08	0.06	0.07	0.07	0.09	0.06	0.06	0.05	0.05
$\mathrm{E}_t(\hat{\alpha_1})$	0.47	0.35	0.51	0.62	0.39	0.49	0.55	0.66	0.50	0.54	0.49	0.48
	0.02	0.03	0.02	0.02	0.03	0.03	0.03	0.04	0.02	0.02	0.02	0.01
$\mathrm{E}_t(\hat{\alpha_2})$	0.38	0.38	0.33	0.18	0.46	0.33	0.21	0.27	0.37	0.28	0.32	0.26
	0.02	0.02	0.02	0.02	0.04	0.02	0.05	0.04	0.02	0.02	0.01	0.01
$\mathrm{E}_t(\hat{\alpha_3})$	-0.35	-0.35	-0.22	-0.15	-0.23	-0.22	0.18	-0.03	-0.25	0.02	-0.14	-0.18
	0.04	0.10	0.04	0.04	0.07	0.04	0.06	0.04	0.05	0.05	0.06	0.05
R^2	0.73	0.71	0.78	0.82	0.82	0.73	0.79	0.89	0.77	0.77	0.79	0.68
Model III:	$\mathrm{m}_{it} = \alpha_{0jt} + \alpha_{1jt}\mathrm{b}_{it} + \alpha_{2jt}\mathrm{ni^+}_{it} + \alpha_{3jt}(\mathrm{I}_{(<0)}(\mathrm{ni^+})_{it} + \alpha_{4jt}\mathrm{Lev}_{it} + \epsilon_i$											
$\mathrm{E}_t(\hat{\alpha_0})$	2.39	2.56	2.20	2.35	2.38	2.55	2.91	2.15	2.44	2.68	2.21	2.60
	0.04	0.11	0.05	0.06	0.11	0.05	0.10	0.13	0.05	0.04	0.04	0.05
$\mathrm{E}_t(\hat{\alpha_1})$	0.64	0.56	0.64	0.66	0.64	0.59	0.60	0.85	0.62	0.61	0.58	0.60
	0.01	0.02	0.01	0.02	0.05	0.02	0.03	0.03	0.01	0.02	0.01	0.01
$\mathrm{E}_t(\hat{\alpha_2})$	0.27	0.30	0.27	0.23	0.31	0.29	0.26	0.12	0.28	0.26	0.30	0.25
	0.01	0.02	0.01	0.02	0.04	0.01	0.04	0.03	0.01	0.01	0.01	0.01
$\mathrm{E}_t(\hat{\alpha_3})$	0.08	0.05	0.10	0.00	0.13	-0.03	0.27	0.17	0.01	-0.09	-0.16	0.00
	0.03	0.06	0.03	0.04	0.06	0.04	0.05	0.04	0.04	0.05	0.05	0.04
$\mathrm{E}_t(\hat{\alpha_4})$	-2.59	-2.36	-2.09	-2.13	-2.43	-2.55	-2.27	-2.52	-2.11	-2.42	-1.06	-2.15
	0.05	0.09	0.07	0.15	0.19	0.11	0.18	0.23	0.06	0.10	0.05	0.09
R^2	0.84	0.80	0.86	0.88	0.90	0.83	0.87	0.94	0.86	0.85	0.82	0.80

Table 5

Defining the Components of the Decomposed Market-to-Book Ratio

This table is a guide to the analysis presented in the following tables. It describes the components of the M/B decomposition. In table 6, the variables below correspond to firm-level variables. In the merger intensity regression tables (Table 10), the same notation refers to annual industry average values, since the unit of observation is an intensity of merger activity in an industry-year.

$m_{it} - b_{it}$	The natural log of the market-to-book ratio for firm i at time t.
$\bar{m}_t - \bar{b}_t$	In Table 10, this notation refers to sector-average market-to-book in year t.
$v(\theta_{it}; \alpha_{jt})$	The fundamental value of the firm obtained by applying annual, sector- average regression multiples to firm-level accounting values. The individual time t values of the αs from Table 4 are used to obtain this number. Using model II, for instance, we would have $v = \hat{\alpha}_{0jt} + \hat{\alpha}_{1jt}\mathbf{ln(B)}_{it}$.
$v(\theta_{it}; \bar{\alpha}_j)$	The fundamental value of the firm obtained by applying long-run industry average multiples to firm-level accounting values. The long-run average values of α_j from Table 4 are used to obtain this number. Using model II, for instance, we would have $v = \overline{\alpha}_{0j} + \overline{\alpha}_{1j}\mathbf{ln(B)}_{it}$.
$m_{it} - v(\theta_{it}; \alpha_{jt})$	The component of $m_{it} - b_{it}$ that is due to firm-specific deviations from valuations implied by sector valuation multiples calculated at time t. This is called firm-specific error.
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \bar{\alpha}_j)$	The component of $m_{it} - b_{it}$ that is due to valuations implied by current sector multiples deviating from valuations implied by long-run multiples. In Table 6, this notation refers to firm-level observations calculated by applying sector multiples to firm-specific accounting information. This is called time-series sector error.
$\bar{v}(\alpha_{jt}) - \bar{v}(\bar{\alpha}_j)$	In Table 10 this notation refers to sector average time-series sector error.
$v(\theta_{it}; \bar{\alpha}_j) - b_{it}$	The component of $m_{it} - b_{it}$ that is attributable to the difference between valuations implied by long-run multiples and current book values. In Table 6, this notation refers to firm-level observations calculated by applying long-run sector multiples to firm-specific accounting information. This is called long-run value to book.
$\bar{v}(\alpha_{jt}) - \bar{b}_t$	In Table 10 this notation refers to sector average long-run value to book.

Table 6

Decomposing Market-to-Book at the Firm-Level

The data comprise 102,527 non-merger firm-level observations between 1977-2000 plus 8,350 firm-level merger observations, corresponding to 4,025 merger events occurring between bidders and targets listed on CRSP, Compustat, and SDC. The column 't(diff)' reports the t-statistic for the test H(0): Non-Merger - Merger = 0, or H(0): Target - Acquirer = 0. The data include 1,899 known all-cash transactions, 968 known mixed-payment transactions, and 1,436 known all-stock transactions.

Each model regresses log market equity on accounting information in annual, cross-sectional, industry-level regressions described in table 4. Model I corresponds to $\ln(M_{it}) = \alpha_{0jt} + \alpha_{1jt}\ln(B)_{it}$; model II adds net income; model III adds leverage. See table 5 for descriptions of the components of each model.

	Non-	Mergers					All Cash			Mixed			All Stock		
	Merger	All	t(diff)	Tar.	Acq.	t(diff)	Tar.	Acq.	t(diff)	Tar.	Acq.	t(diff)	Tar.	Acq.	t(diff)
$m_{it} - b_{it}$	0.59	0.76	-15.81	0.69	0.83	-6.95	0.61	0.79	-5.13	0.61	0.77	-3.29	0.87	1.12	-6.97
Model I:															
$m_{it} - v(\theta_{it};\alpha_{jt})$	-0.02	0.26	-26.81	0.01	0.50	-25.12	-0.11	0.49	-18.34	0.04	0.46	-9.20	0.11	0.64	-16.60
$v(\theta_{it};\alpha_{jt}) - v(\theta_{it};\bar{\alpha_j})$	0.07	0.15	-27.70	0.13	0.18	-8.08	0.13	0.19	-6.10	0.14	0.17	-2.54	0.18	0.26	-7.09
$v(\theta_{it};\bar{\alpha_j}) - b_{it}$	0.54	0.34	33.64	0.54	0.16	37.91	0.59	0.11	29.61	0.43	0.14	12.95	0.58	0.23	18.97
Model II:															
$m_{it} - v(\theta_{it};\alpha_{jt})$	-0.01	0.22	-24.48	0.02	0.41	-22.00	-0.09	0.38	-15.45	0.04	0.39	-8.27	0.11	0.57	-15.65
$v(\theta_{it};\alpha_{jt}) - v(\theta_{it};\bar{\alpha_j})$	0.06	0.15	-26.19	0.12	0.18	-9.11	0.12	0.19	-7.16	0.14	0.17	-2.65	0.17	0.25	-6.90
$v(\theta_{it};\bar{\alpha_j}) - b_{it}$	0.54	0.39	22.69	0.55	0.25	24.77	0.58	0.22	17.53	0.43	0.20	8.00	0.60	0.30	13.30
Model III:															
$m_{it} - v(\theta_{it};\alpha_{jt})$	-0.01	0.18	-25.21	0.03	0.32	-20.21	-0.08	0.29	-15.01	0.17	0.29	-3.46	0.05	0.44	-16.09
$v(\theta_{it};\alpha_{jt}) - v(\theta_{it};\bar{\alpha_j})$	0.03	0.10	-24.20	0.07	0.12	-8.73	0.06	0.14	-8.40	0.08	0.12	-3.97	0.12	0.17	-5.21
$v(\theta_{it};\bar{\alpha_j}) - b_{it}$	0.57	0.48	10.69	0.58	0.39	12.52	0.62	0.37	9.97	0.36	0.36	0.20	0.71	0.51	6.94

Table 7

The Robustness of Firm-Level Market-to-Book Decompositions

This table reproduces Table 6, except that it presents results from isolated sub-samples to control for alternative explanations. 'Pre-1996 Only' means that only transactions occurring before 1996 are used. Within-industry and across-industry describe whether the bidder and target belong to the same Fama-French 48 Industry classification. 'No LBO firms' indicates that no transaction is included involving a firm that was, at some point, involved in an LBO, whether before or after the merger in our sample (LBO transactions per se are excluded by our sample selection criteria). 'Quick-closing Deals' is the sub-sample of transactions that are effective within 30 days of the announcement date.

	Pre-1996 Only			Within Industry			Across Industry			No LBO Firms			Quick-Closing Deals		
	Tar.	Acq.	t(diff)	Tar.	Acq.	t(diff)	Tar.	Acq.	t(diff)	Tar.	Acq.	t(diff)	Tar.	Acq.	t(diff)
$m_{it} - b_{it}$	0.6	0.73	-5.87	0.63	0.8	-7.25	0.76	0.83	-2.29	0.69	0.83	-6.95	0.69	0.72	-0.48
Model I:															
$m_{it} - v(\theta_{it}; \alpha_{jt})$	-0.03	0.43	-23.01	0	0.47	-20.81	0.07	0.58	-16.72	0.01	0.5	-25.12	0.02	0.49	-8.34
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \bar{\alpha}_j)$	0.08	0.09	-1.98	0.13	0.19	-14.65	0.12	0.17	-6.48	0.13	0.18	-8.08	0.08	0.12	-2.94
$v(\theta_{it}; \bar{\alpha}_j) - b_{it}$	0.56	0.21	28.63	0.5	0.14	43.93	0.57	0.08	35.81	0.54	0.16	37.91	0.59	0.1	18.43
Model II:															
$m_{it} - v(\theta_{it}; \alpha_{jt})$	-0.02	0.36	-20.07	0	0.39	-17.67	0.08	0.47	-13.91	0.02	0.41	-22	0.01	0.39	-7.04
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \bar{\alpha}_j)$	0.06	0.08	-2.96	0.12	0.19	-14.51	0.11	0.17	-7.03	0.12	0.18	-9.11	0.06	0.13	-3.93
$v(\theta_{it}; \bar{\alpha}_j) - b_{it}$	0.56	0.29	18.24	0.51	0.22	23.36	0.57	0.19	21.24	0.55	0.25	24.77	0.62	0.2	11.65
Model III:															
$m_{it} - v(\theta_{it}; \alpha_{jt})$	0.02	0.29	-17.3	0.04	0.31	-14.96	0.05	0.37	-13.8	0.03	0.32	-20.21	-0.02	0.28	-6.98
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \bar{\alpha}_j)$	0.04	0.05	-2.26	0.07	0.13	-10.67	0.06	0.12	-7.43	0.07	0.12	-8.73	0.02	0.09	-5.05
$v(\theta_{it}; \bar{\alpha}_j) - b_{it}$	0.55	0.39	8.43	0.51	0.36	10.41	0.65	0.34	14.12	0.58	0.39	12.52	0.69	0.35	7.72

Table 8

Transaction Size and the Components of Market-to-Book

This table presents the same market-to-book decomposition results as Tables 6 and 7, but sorts the results according to transaction size. Q1 is the quintile of smallest transactions; Q5 is the largest transactions. Approximately 800 firms of each type (acquirers, targets) are in each quintile. T-statistics assume unequal variances across groups. The fourth row of each model adds the results of rows 2 and 3 to show that the 'low buys high' long-run value to book result holds even after accounting for time-series sector error.

	Q1			Q2			Q3			Q4			Q5		
Variable	Tar.	Acq.	t	Tar.	Acq.	t	Tar.	Acq.	t	Tar.	Acq.	t	Tar.	Acq.	t
$m_{it} - b_{it}$	0.69	0.86	-2.85	0.55	0.75	-4.19	0.54	0.82	-6.40	0.68	0.94	-6.11	0.92	0.93	-0.15
Model I:															
$m_{it} - v(\theta_{it}; \alpha_{jt})$	-0.23	0.34	-10.72	-0.32	0.31	-15.24	-0.19	0.45	-16.99	0.07	0.65	-15.64	0.51	0.80	-6.46
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \bar{\alpha_j})$	0.10	0.14	-2.47	0.09	0.14	-3.83	0.11	0.18	-5.24	0.14	0.20	-4.73	0.20	0.25	-3.30
$v(\theta_{it}; \bar{\alpha_j}) - b_{it}$	0.82	0.39	15.81	0.78	0.30	22.00	0.62	0.19	22.14	0.47	0.09	20.11	0.21	-0.12	16.73
$v(\theta_{it}; \alpha_{jt}) - b_{it}$	0.92	0.52	12.39	0.87	0.44	17.25	0.73	0.37	15.61	0.61	0.30	13.69	0.41	0.14	11.45
Model II:															
$m_{it} - v(\theta_{it}; \alpha_{jt})$	-0.19	0.26	-9.22	-0.26	0.25	-13.81	-0.16	0.39	-16.28	0.09	0.55	-13.27	0.45	0.67	-5.17
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \bar{\alpha_j})$	0.07	0.13	-3.30	0.08	0.14	-4.44	0.10	0.18	-5.60	0.14	0.20	-4.58	0.20	0.25	-3.55
$v(\theta_{it}; \bar{\alpha_j}) - b_{it}$	0.81	0.47	9.30	0.73	0.36	12.89	0.61	0.26	13.72	0.46	0.19	11.40	0.27	0.01	10.81
$v(\theta_{it}; \alpha_{jt}) - b_{it}$	0.88	0.60	7.18	0.81	0.50	10.18	0.71	0.44	9.81	0.59	0.39	7.72	0.47	0.26	7.47
Model III:															
$m_{it} - v(\theta_{it}; \alpha_{jt})$	-0.18	0.19	-8.87	-0.18	0.20	-12.22	-0.09	0.31	-13.77	0.08	0.44	-12.65	0.37	0.48	-3.63
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \bar{\alpha_j})$	0.02	0.09	-4.89	0.04	0.09	-3.68	0.06	0.12	-5.21	0.09	0.14	-4.59	0.14	0.19	-4.12
$v(\theta_{it}; \bar{\alpha_j}) - b_{it}$	0.85	0.59	5.63	0.69	0.47	6.10	0.58	0.39	5.52	0.51	0.36	4.88	0.42	0.26	5.20
$v(\theta_{it}; \alpha_{jt}) - b_{it}$	0.87	0.67	4.00	0.73	0.55	4.72	0.64	0.51	3.46	0.60	0.50	2.84	0.56	0.45	3.02

Table 9
Firm-Level Merger Intensity Regressions

This table reports Probit regressions of merger activity on valuation characteristics. The dependent variable in Panel A is a dummy for whether the firm in question is involved a merger (this includes acquirers and targets). Panel A uses the entire Compustat/SDC sample. Panels B and C focus only on the sample of merger observations.

			Model I		Model II		Model III	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: 1 if MERGER, 0 if NO MERGER								
$m_{it} - b_{it}$	0.088	-0.034						
	(15.95)	(1.19)						
$m_{it} - v(\theta_{it}; \alpha_{jt})$			0.153	0.119	0.162	0.151	0.209	0.206
			(23.63)	(3.26)	(22.86)	(3.74)	(24.13)	(4.02)
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \bar{\alpha_j})$			0.671	0.075	0.537	-0.011	0.722	-0.233
			(30.95)	(0.72)	(27.36)	(0.12)	(28.38)	(1.90)
$v(\theta_{it}; \bar{\alpha_j}) - b_{it}$			-0.392	-0.462	-0.174	-0.317	-0.083	-0.125
			(31.90)	(7.32)	(17.63)	(5.63)	(10.59)	(3.28)
Log Likelihood	-29492	-14867	-28189	-14831	-28631	-14840	-28782	-14850
χ^2	258.14	1.43	2864.90	71.43	1857.24	53.46	1555.31	32.78
Panel B: 1 if ACQUIRER, 0 if TARGET								
$m_{it} - b_{it}$	0.097							
	(6.86)							
$m_{it} - v(\theta_{it}; \alpha_{jt})$			0.279		0.302		0.379	
			(16.77)		(17.60)		(18.00)	
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \bar{\alpha_j})$			0.208		0.226		0.491	
			(3.81)		(4.71)		(8.39)	
$v(\theta_{it}; \bar{\alpha_j}) - b_{it}$			-0.974		-0.526		-0.229	
			(30.13)		(20.15)		(11.27)	
Log Likelihood	-5758		-4971		-5302		-5483	
χ^2	46.84		1621.19		937.73		575.22	
Panel C: 1 if STOCK, 0 if NOT								
$m_{it} - b_{it}$	0.232	0.179						
	(14.35)	(10.11)						
$m_{it} - v(\theta_{it}; \alpha_{jt})$			0.158	0.141	0.174	0.151	0.146	0.116
			(8.99)	(7.94)	(9.20)	(7.98)	(6.33)	(5.02)
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \bar{\alpha_j})$			0.707	0.404	0.636	0.374	0.643	0.373
			(13.33)	(6.52)	(12.88)	(6.81)	(10.53)	(5.70)
$v(\theta_{it}; \bar{\alpha_j}) - b_{it}$			0.326	0.331	0.239	0.225	0.236	0.219
			(10.55)	(10.44)	(9.06)	(8.35)	(10.87)	(9.92)
Log Likelihood	-4891	-4676	-4839	-4658	-4843	-4662	-4852	-4660
χ^2	215.28	102.11	320.36	167.68	292.50	144.09	274.03	148.17
Fixed Effects?		Year		Year		Year		Year

Table 10

Valuation Waves, Merger Intensity, and Method of Payment

In Panel A the dependent variable is the count of merger announcements in sector j, year t. In Panel B, the dependent variable is the count of 100% stock-financed merger announcements, as reported by SDC. Table 5 describes the independent variables, with the exception of Total mergers. (Note that $\bar{m}_t = \bar{v}(\alpha_{jt}.)$) 'Total mergers, year t' is the total number of mergers across all sectors in year t, while 'Total mergers, year j' is the total number of mergers across all years for sector j. Each regression contains 300 observations. Two asterisks denotes significance at the 1% level, one asterisk denotes 5%.

Panel A: Dependent Variable is Merger Count (Industry j, year t)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\bar{m}_t - \bar{b}_t$	24.673	12.676	24.640	8.260	19.117					
	(3.82)**	(1.82)	(3.81)**	(1.24)	(3.06)**					
$\bar{v}(\alpha_{jt}) - \bar{v}(\bar{\alpha_j})$						54.675	39.079	54.539	42.197	56.096
						(6.97)**	(4.11)**	(6.93)**	(4.10)**	(6.59)**
$\bar{v}(\bar{\alpha_j}) - \bar{b}_t$						-27.281	-21.054	-27.077	-17.403	-18.655
						(2.73)**	(2.04)*	(2.69)**	(2.02)*	(2.23)*
Total mergers,			0.004		0.005			0.001		0.002
year t			(0.83)		(0.94)			(0.27)		(0.42)
Total mergers,				0.013	0.012				0.015	0.015
sector j				(5.25)**	(4.69)**				(6.05)**	(5.98)**
Fixed Effects	Sector	Sector	Sector	Year	None	Sector	Sector	Sector	Year	None
		Year					Year			
R^2	0.05	0.20	0.05	0.12	0.13	0.16	0.25	0.16	0.18	0.23

Panel B: Dependent Variable is Stock-financed Merger Count (Industry j, year t)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\bar{m}_t - \bar{b}_t$	8.733	5.165	8.713	3.395	6.668					
	(2.83)**	(1.52)	(2.82)**	(1.04)	(2.23)*					
$\bar{v}(\alpha_{jt}) - \bar{v}(\bar{\alpha_j})$						20.067	15.822	19.911	18.132	21.246
						(5.23)**	(3.37)**	(5.17)**	(3.57)**	(5.12)**
$\bar{v}(\bar{\alpha_j}) - \bar{b}_t$						-10.961	-8.449	-10.728	-7.721	-8.255
						(2.24)*	(1.66)	(2.18)*	(1.82)	(2.02)*
Total mergers,			0.002		0.003			0.001		0.002
year t			(1.06)		(1.16)			(0.63)		(0.74)
Total mergers,				0.006	0.005				0.007	0.006
sector j				(4.59)**	(4.33)**				(5.26)**	(5.31)**
Fixed Effects	Sector	Sector	Sector	Year	None	Sector	Sector	Sector	Year	None
		Year					Year			
R^2	0.03	0.14	0.03	0.09	0.10	0.10	0.18	0.10	0.14	0.17

Table 11

Failed vs. Successful Targets

This table repeats the decomposition of the market-to-book ratio but examines targets and acquirers according to whether the deal was successful (Success) or whether it was withdrawn for any reason (Failed).

	Targets								
	All			Cash			Stock		
Variable	Success	Failed	t(diff)	Success	Failed	t(diff)	Success	Failed	t(diff)
$m_{it} - b_{it}$	0.71	0.58	3.45	0.64	0.43	4.09	0.87	0.89	-0.18
Model I:									
$m_{it} - v(\theta_{it}; \alpha_{jt})$	0.02	-0.00	0.62	-0.10	-0.22	2.40	0.12	0.14	-0.24
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \bar{\alpha_j})$	0.13	0.11	1.92	0.13	0.13	0.29	0.18	0.14	2.30
$v(\theta_{it}; \bar{\alpha_j}) - b_{it}$	0.56	0.47	4.41	0.61	0.52	2.67	0.57	0.62	-1.05
Model II:									
$m_{it} - v(\theta_{it}; \alpha_{jt})$	0.03	-0.00	0.93	-0.07	-0.17	2.10	0.12	0.10	0.23
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \bar{\alpha_j})$	0.12	0.10	2.00	0.11	0.12	-0.14	0.18	0.11	2.84
$v(\theta_{it}; \bar{\alpha_j}) - b_{it}$	0.56	0.49	3.06	0.60	0.48	2.73	0.58	0.68	-1.93
Model III:									
$m_{it} - v(\theta_{it}; \alpha_{jt})$	0.03	0.05	-0.86	-0.08	-0.09	0.31	0.06	0.04	0.32
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \bar{\alpha_j})$	0.07	0.06	1.72	0.06	0.07	-0.79	0.13	0.07	3.11
$v(\theta_{it}; \bar{\alpha_j}) - b_{it}$	0.60	0.47	4.47	0.65	0.44	4.04	0.70	0.79	-1.54
	Acquirers								
	All			Cash			Stock		
Variable	Success	Failed	t(diff)	Success	Failed	t(diff)	Success	Failed	t(diff)
$m_{it} - b_{it}$	0.85	0.74	2.32	0.80	0.72	1.29	1.14	1.02	1.48
Model I:									
$m_{it} - v(\theta_{it}; \alpha_{jt})$	0.53	0.31	5.49	0.52	0.30	3.78	0.67	0.40	3.96
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \bar{\alpha_j})$	0.19	0.12	5.93	0.20	0.14	3.20	0.27	0.15	5.84
$v(\theta_{it}; \bar{\alpha_j}) - b_{it}$	0.13	0.31	-8.39	0.08	0.28	-5.77	0.19	0.47	-7.08
Model II:									
$m_{it} - v(\theta_{it}; \alpha_{jt})$	0.44	0.25	5.13	0.41	0.22	3.62	0.60	0.37	3.80
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \bar{\alpha_j})$	0.19	0.12	5.80	0.20	0.13	3.28	0.27	0.16	4.64
$v(\theta_{it}; \bar{\alpha_j}) - b_{it}$	0.22	0.38	-6.51	0.20	0.36	-4.17	0.27	0.50	-5.07
Model III:									
$m_{it} - v(\theta_{it}; \alpha_{jt})$	0.34	0.23	3.76	0.30	0.19	2.53	0.46	0.29	3.48
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \bar{\alpha_j})$	0.13	0.07	5.48	0.14	0.11	2.16	0.18	0.10	4.23
$v(\theta_{it}; \bar{\alpha_j}) - b_{it}$	0.38	0.45	-2.20	0.36	0.42	-1.12	0.49	0.64	-2.57

Table 12
A Horse-Race Between Competing Theories of Merger

q-dispersion is the standard deviation in $ln(mb)$ within an industry in a given year. All other variables are defined in Table 5. Columns (4) and (5) use only the observations for which the industry valuation ($\bar{v}(\alpha_{jt}) - \bar{v}(\bar{\alpha_j})$) was below its time-series median. Columns (6) and (7) only use observations above the industry median valuation. The mean value (sd) of q-dispersion is .897 (.260) in the low-valuation sub-sample and .839 (.298) in the high valuation sub-sample.

	Full Sample			Low Valuation		High Valuation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\bar{m}_t - \bar{b}_t$	26.729	23.988		18.228		21.800	
	(4.31)	(3.73)		(2.54)		(1.78)	
q-dispersion	14.007	20.426	4.773	16.716	14.049	7.786	-9.189
	(1.65)	(2.10)	(0.50)	(2.03)	(1.55)	(0.51)	(0.47)
$\bar{v}(\alpha_{jt}) - \bar{v}(\bar{\alpha_j})$			53.829		49.383		117.355
			(6.70)		(4.09)		(4.78)
$\bar{v}(\bar{\alpha_j}) - \bar{b}_t$			-26.277		1.541		-46.934
			(2.57)		(0.13)		(2.95)
Observations	299	299	299	144	144	155	155
R^2	0.07	0.06	0.16	0.07	0.15	0.02	0.17
Industry Fixed Effects?		Yes	Yes		Yes		Yes

Table 13
Misvaluation and Merger Activity During Economic Shocks

Panel A reports Probit regressions that predict whether a sector is experiencing a merger wave based on levels of valuation ($m_{it} - b_{it}$) and misvaluation ($v(\alpha_{jt}) - v(\bar{\alpha_j})$). Merger Wave is defined in Harford (2003), which details when industries have experienced economic shocks that induced merger waves. Pseudo-R^2 values as well as χ^2 values of significance are reported. Standard errors appear in italics below point estimates. The regressions are based on 1187 industry-year observations across 48 Fama-French industries over the 1978-2001 time period.
In Panels B and C, merger activity is reported by firm-specific misvaluation quantile for the entire sample (Panel B) and for the sub-sample of observations that occur during merger waves (Panel C). Merger wave observations account for 12% of firm-years and 6.5% of industry-years in our sample.

Panel A:	$m_{it} - b_{it}$	$v(\alpha_{jt}) - v(\bar{\alpha_j})$	$v(\bar{\alpha_j}) - b_{it}$	R^2	χ^2
Pr(Merger Wave)	0.94			7.37	39.24
	0.16				
Pr(Merger Wave)		3.31		15.28	81.33
		0.47			
Pr(Merger Wave)		3.37	0.46	16.01	85.18
		0.47	*0.23*		

Panel B: Distribution of Mergers across Misvaluation Quantiles

	Lowest Quintile	$20^{th} - 50^{th}$ Percentile	$50^{th} - 80^{th}$ Percentile	Highest Quintile	Total
Acquisitions	8.21%	17.57%	32.02%	42.20%	4325
Dollar Volume	5.08%	10.01%	25.02%	59.89%	$6,112B
Stock Acquisitions	5.75%	12.64%	34.07%	47.54%	1218

Panel C: Merger/Misvaluation Distribution During Economic Shocks

	Lowest Quintile	$20^{th} - 50^{th}$ Percentile	$50^{th} - 80^{th}$ Percentile	Highest Quintile	Total
Acquisitions	10.78%	13.05%	27.24%	48.92%	881
(% of Overall Total)					(20%)
Dollar Volume	4.92%	12.65%	16.68%	65.75%	$2,391B
(% of Overall Total)					(39%)
Stock Acquisitions	7.92%	10.85%	28.15%	53.08%	341
(% of Overall Total)					(28%)