Stock Merger Activity and Industry Performance

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Abstract

We propose a continuous merger activity variable (*MAV*) as an alternative to discrete industry merger waves. Ranking industries by *MAV* within a quarter removes the market-wide trend and gives a powerful measure of relative industry stock merger activity that is associated with strong patterns in before and after industry returns and operating performance. During 1989-2015, bucket 1 containing industries with lowest *MAV* rank earns alpha of 0.30% per month higher than bucket 12 containing industries with highest *MAV* rank. Our evidence is broadly consistent with industry misvaluation theory of stock merger activity by Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004).

Keywords: Merger Waves, Mergers, Acquisitions, Industry Performance, Long-Term Returns

JEL Classification: G34, G30, G12

November 2017

[*] Email: bo-meng@uiowa.edu and anand-vijh@uiowa.edu. We have benefited from comments of seminar participants at the University of Alabama, the University of Central Florida, the University of Iowa, Iowa State University, the University of Nebraska, the University of North Carolina at Greensboro, and the Northern Finance Association. We wish to thank Andrey Golubov, Kevin Mullally, and Ashish Tiwari for useful comments.

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1. Introduction

Merger waves connote sharp increases in industry-specific or market-wide merger activity over short periods. A large finance literature investigates the causes and consequences of industry merger waves. The neoclassical theory advanced by Gort (1969), Mitchell and Mulherin (1996), Maksimovic and Phillips (2001), and Harford (2005) argues that the increased merger activity is an efficient response to economic, regulatory, and technological shocks to an industry. These authors report many empirical results in support of their theory. The alternate overvaluation theory advanced by Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004) (also referred to as SV and RKV) argues that the overvaluation of certain industries causes merger waves as many firms in those industries use their overvalued stock to acquire other firms. In a related context, the overvaluation theory of stock mergers finds empirical support in several studies of long-term returns of *individual stock acquirers* (Loughran and Vijh 1997; Rau and Vermaelen 1998; Savor and Lu 2009; and many others). However, to date there is no documented evidence of the *misvaluation* of *entire industries* in the U.S. market in relation to their merger activity based on their before and after long-term excess returns or operating performance.[1] This paper proposes a new measure of industry stock merger activity that captures more information than traditional measures of industry merger waves and shows strong evidence consistent with return and performance implications of the industry misvaluation theory. We cover the full range of variation, from the most merger active industry to the least merger active industry, so we use the more general term of industry misvaluation rather than industry overvaluation. We also test whether the variations in industry stock merger activity are consistent with different features of the SV and RKV models.

Traditional measures of industry merger waves suffer from two limitations that reduce their ability to support the overvaluation theory. First, the merger wave versus non-wave framework is necessarily discrete, separating periods of higher merger activity than some cutoff level from the remaining periods. However, the empirical predictions of SV and RKV models are not limited to a discrete setting. For example, in the RKV model the managers of target firms rationally underestimate the overvaluation of

[1] Rhodes-Kropf, Robinson, and Viswanathan (2005) show that industry overvaluation is associated with stock merger activity using an accounting model of valuation that decomposes market-to-book ratios of individual firms.

acquirer stocks during periods of widespread overvaluation, which increases the acceptance rate of stock offers. By a similar argument, they would also underestimate the undervaluation of acquirer stocks during periods of widespread undervaluation, which would decrease the acceptance rate of stock offers. It is further reasonable to argue that the in-between levels of merger activity would produce in-between acceptance rates of stock offers. Now consider that a discrete zero-one merger wave variable reduces the detection power of test statistics, because one is ignoring information in the continuously variable merger activity, and because only a small number of industry-year observations (typically less than 10%) are usually identified as industry merger wave years. This limitation motivates our construction of a continuous merger activity variable (*MAV*). Specifically, for each industry j during quarter t, we define *MAV* as the number of stock merger offers made per firm-quarter over a four-quarter period $(t-3, t)$ divided by a similar number computed over the aggregate study period. Note that the average *MAV* value calculated over all quarters for any industry will equal one. Further, *MAV* values greater than one during any quarter will indicate higher than average merger activity for that industry in that quarter, while the opposite will be true for *MAV* values less than one. We focus on stock mergers, which is an essential ingredient of misvaluation driven merger activity in both SV and RKV models. (Later we also analyze cash mergers.)

Second, traditionally defined industry merger waves usually cluster in calendar time. We explore a procedure of identifying merger waves by Harford (2005) with our sample. If we treat the aggregate period from 1986 to 2015 as one period, we find only one two-year long merger wave in each of the Fama-French 12 industries, and all but one waves occur during a period of 4.5 years from 1996-Q3 (third quarter of 1996) to 2000-Q4. If we break the aggregate period into two subperiods, we still find one merger wave per industry in each period, largely clustered during the 1996-Q3 to 2000-Q4 period as before and the 2005-Q1 to 2007-Q4 period in addition. The evidence is similar, but less pronounced, when we try the Fama-French 48 industries. The clustering is likely driven by market-wide trends in merger activity in addition to industry-specific trends. More to our point, this clustering makes it difficult to find evidence in support of the industry misvaluation theory. That is because all models of excess return include the market return as one factor. This leads to a considerable washout of evidence as each industry undergoing a merger wave is benchmarked, in turn, against the market consisting of other industries undergoing a similarly defined merger wave. If the focus is on testing industry misvaluation theory of merger activity, then one needs to abstract from the market-wide trend in merger activity and returns. This makes the second step of our procedure described below critically important.

In this second step, we rank industries within a calendar quarter by our continuous *MAV*, which abstracts from the market-wide trend in merger activity and focuses on the *relative* intensities of industry-specific trends in merger activity. Thus, starting with Fama-French 12 industries, every quarter we assign one industry to each bucket numbered from 1 to 12, based on its *MAV* rank. This assignment procedure is the same for the extreme bull markets of 1998-1999 and for the extreme bear markets of 2008-2009. In every quarter, one industry that is relatively the least merger active industry is assigned to bucket number 1, and one industry that is relatively the most merger active is assigned to bucket number 12. This assignment procedure followed by the analysis of bucket returns gives powerful test statistics.

To understand the reasons, consider the following example. Suppose during a bull market the stock merger activity for industry A equals 3.0 times its normal activity and for industry B equals 2.0 times its normal activity. In addition, during a bear market the stock merger activity for industry A equals 0.4 times its normal activity and for industry B equals 0.6 times its normal activity. The overvaluation theory traditionally applied to discrete merger waves would say that during the first period both industries are in-wave and likely overvalued while during the second period both industries are out-wave and likely undervalued or fairly valued. However, our expanded industry misvaluation theory of stock merger activity applied to our new methodology says that during the first period, industry A is likely more overvalued than industry B, and also that during the second period industry A is likely more undervalued than industry B. Our expanded framework exploits more information, which increases the power of our tests. This is more so when we extend the ranking procedure to 12 industries and 108 quarters. Assuming that the misvaluation theory works, bucket number 12 constructed using our methodology will always include *relatively* the most overvalued (or *relatively* the least undervalued) industries, a tendency that will decrease successively as one goes to lower bucket numbers, all the way to bucket number 1.

Using our new framework, we document strong evidence in support of the industry misvaluation theory of stock merger activity. Here we summarize the main results. Our primary sample consists of Fama-French 12 industries during 1985-2015, and our primary tests analyze the industry returns and operating performance. At the end of each calendar quarter, we assign each industry a bucket number based on its ranked *MAV* during that quarter (calculated using stock merger activity), and keep it in that bucket for the following three years (or 12 quarters). From 1989-Q1 onwards, there are exactly 12 entries in each bucket at all times until 2015-Q4, although on average that consists of six distinct industries. We calculate monthly bucket returns in calendar time by averaging across the twelve value-weighted industry returns retrieved from Ken French's data library. Our results are as follows. A dollar invested in bucket number 1 (consisting of *relatively* the least stock merger active industries) in the beginning of 1989 grows to $24.13 by the end of 2015 while the same dollar invested in bucket number 12 (*relatively* the most stock merger active industries) grows to $6.77. In both cases, the cumulative amount is starkly different from $12.68 if invested in the CRSP value-weighted index, or $16.13 if invested in an equally weighted portfolio of all 12 industries at all times. There is an almost monotonically decreasing trend in cumulative returns as one goes from bucket number 1 to 12. We measure a correlation of -0.97 between returns and bucket numbers. Looking further, we find that with increasing bucket number, the average annual return decreases, the standard deviation of annual returns increases, and the Sharpe ratio decreases, in all cases by statistically and economically significant amounts.

These first tests are based on cumulative raw returns. We next risk-adjust the monthly bucket returns using the Fama-French three-factor model and find a similar and highly significant pattern in the alphas. On average, the post-*MAV* alphas *decrease* by 0.027% per month per bucket number, or by 0.30% per month between bucket numbers 1 and 12. Building on these strong post-*MAV* results, we further examine the pre-*MAV* returns following the same calendar-time methodology. More specifically, we create the same 12 buckets, but this time by adding industries during a 12-quarter period *before* the calculation of *MAV*. The pre-*MAV* alphas *increase* by an even bigger 0.044% per month per bucket number, thus following an opposite pattern to the post-*MAV* alphas across bucket numbers. We infer that the largest increases in industry stock merger activity (classified using ranked *MAV*) are preceded by the most positive excess returns and followed by the most negative excess returns, a pattern that is moderated as the merger activity decreases and eventually reversed as one goes towards the largest decreases in industry stock merger activity.

We turn attention to the preceding and following three-year operating performance, measured using annual operating income before depreciation normalized by the book value of assets calculated for entire industries. Changes in operating income from the base year y of bucket assignment to any of the following three years $y+1$, $y+2$, and $y+3$ are significantly negatively related to the bucket number. As an example, the operating income changes from year y to year $y+3$ by 0.48% for bucket number 1 and by -0.84% for bucket number 12. Thus, on average, industries with lower stock merger activity have an improving operating income and industries with higher stock merger activity have a deteriorating operating income during the years following the year of calculating the *MAV*. However, this parallel between industry excess returns and operating performance, both decreasing with increasing bucket numbers, is confined to the post-*MAV* period. Unlike returns, changes in the operating income from year $y-1$ to year y follow the same decreasing trend with increasing bucket numbers as from year y to year $y+3$, while there is no discernible trend going back to years before $y-1$. It appears that the downward (upward) trend in the operating performance of industries with higher (lower) ranked *MAV* had started a year before the base year of measuring merger activity and it simply continued on during the following years. It contrasts with the preceding one-year and three-year excess returns that are positive (negative) for industries with higher (lower) values of ranked *MAV*, leading to their overvaluation (undervaluation). The combined evidence is consistent with the basic setup of RKV model that managers of target firms in overvalued industries receive a private signal about their stock overvaluation, but due to its recentness they cannot be sure whether that overvaluation affects only their own firm or the entire industry. RKV show that under such conditions the target managers underestimate the overvaluation of bidder firms and over-accept their stock offers.

Overall, based on the tests of excess returns and operating performance, our evidence supports the industry misvaluation theory, which says that currently high (low) industry valuations increase (decrease) stock merger activity. We report many robustness checks of our results, such as using Fama-French 48 industries in place of 12 industries, using only historical information to calculate the average industry merger activity, calculating *MAV* with only the current quarter's merger activity instead of a moving average four-quarter merger activity, and analyzing event-time excess returns in place of calendar-time returns. More importantly, we repeat our main tests, post-*MAV* and pre-*MAV* excess returns and operating performance, with buckets formed by ranked cash-*MAV*. In other words, every quarter we make bucket 1 collect the industry with the lowest relative cash-merger activity and bucket 12 collect the industry with the highest relative cash-merger activity. We find that most test results with cash-*MAV* are insignificant, while one is significant in the opposite direction of the corresponding result with stock-*MAV* (which we have simply referred to as *MAV*). That is useful evidence, given that stock and cash merger activities are generally positively correlated, which to some extent aligns their results. This last positive correlation may be driven by other common reasons for both types of merger activity, such as neoclassical reasons. No doubt, the industry misvaluation theory and the neoclassical industry shocks theory are not mutually exclusive.

In the last section, we examine the long-term excess returns of individual stock acquirers in relation to their industry returns as determined by their ranked *MAV* (or bucket number). This part bears some resemblance to previous work by Rhodes-Kropf, Robinson, and Viswanathan (2005) who measure the industry-wide and firm-specific components of acquirer overvaluation. However, unlike their accounting multiples approach, we employ returns-based measures of overvaluation. In addition, we break down our sample by industry merger activity. Our results are as follows. First, a single calendar-time portfolio of all stock acquirers put together earns an alpha of -0.47% per month using a post-*MAV* three-year holding period. Second, we form 12 calendar-time portfolios of individual stock acquirers based on which bucket number their industries are assigned to on their merger announcement date. These portfolios all earn negative post-*MAV* alphas whereas the corresponding buckets of industries may earn positive or negative alphas. Thus, stock acquirers are overvalued even in undervalued industries. Third, acquirer alphas decrease sharply with increasing bucket numbers, at a rate of -0.066% per month per bucket number, compared to their industry alphas that also decrease with increasing bucket numbers, but at a lower rate of -0.027% per month per bucket number. This evidence suggests that the overvaluation of stock acquirers increases at a faster rate than the overvaluation of their industries as one moves to higher bucket numbers. Alternately, this evidence is also consistent with an agency hypothesis advanced by Duchin and Schmidt (2013). They find more negative buy-and-hold excess returns of acquisitions made during merger waves than of acquisitions made outside merger waves, which they attribute to higher agency costs leading to lower quality acquisitions during merger waves.

Section 2 of the paper discusses the relevant literature. Section 3 describes data and methodology. Sections 4, 5, and 6 present the main results and the robustness checks. Section 7 concludes.

2. Literature survey

In this paper, we treat industry-wide merger activity as a continuous variable. However, a large literature treats merger activity in discrete terms as consisting of a few merger waves, which are periods of concentrated merger activity, versus the rest. Therefore, that framework becomes our starting point for discussion. Many papers have documented the existence of industry merger waves, although they differ in the criteria used to define the merger waves. Below we discuss the main hypotheses proposed in these papers to explain the causes and consequences of industry merger waves.

2.1. The industry misvaluation hypothesis

This hypothesis is the focus of our investigation. Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004) model how firm and industry misvaluation lead to variation in merger activity, which is often captured as merger waves. The two models are motivated quite differently, although many of their implications are similar. In SV model, the acquirer firm is overvalued relative to the target firm and the acquirer managers exploit bullish market sentiments due to which investors overestimate the synergies from their mergers. The long-term acquirer shareholders benefit at the cost of long-term target shareholders who receive currently overvalued acquirer stock as payment. Target managers accept these exploitative bids because their time horizons are short (cash-out motives), or because they receive side payments. The SV model predicts industry overvaluation and increased dispersion of firm valuations within the industry besides stock payment as conditions for increases in merger activity. The greater the perceived synergies, the higher the stock merger activity in an industry. Because overvaluation and synergy are continuous variables, the SV model should predict continuous variation in merger activity.

While SV model is rooted in investor irrationality and differences between target manager and shareholder objectives, in RKV model private information on both sides rationally leads to a positive correlation between stock merger activity and industry valuation. For illustration, consider an industry that is overvalued on average, but firms in the industry have an additional positive or negative firm-specific error in valuation. At some point around the peak of an expansion, a target manager receives a private signal that his firm is overvalued. At the same time, he also receives a stock merger bid from an acquirer firm in the same industry. The target manager cannot tell what part of the overvaluation is specific to his firm and what part is common to all firms in the industry. Under such circumstances, RKV show that a rational target manager underestimates the industry-wide overvaluation that affects the acquirer firm, or equivalently overestimates the synergies from merger. The greater the industry overvaluation, the higher the estimated synergies, and the more likely it is that the target manager accepts the merger offer. Conversely, the greater the industry undervaluation, the lower the estimated synergies, and the less likely it is that the target manager accepts the merger offer. One of their key results is as follows:

> Theorem 4: *If the target only accepts offers with an expected value greater than the target's true value, X_T, but not all firms have access to cash, then, (1) mergers are more likely to occur in overvalued markets than in undervalued markets, and (2) the method of payment will include a greater fraction of stock deals in overvalued markets than in undervalued markets.*

Thus, the RKV model also treats merger activity and industry valuation as continuous variables, which motivates our *MAV* measure. The compounding of effects (1) and (2) in their Theorem 4 predicts a strong relation between the level of stock merger activity and industry misvaluation. High dispersion of firm valuations in an industry is a key requirement of merger activity in SV model and it exists in RKV model, since there is a firm-specific error term. However, it is not a key requirement in RKV model, because the industry overvaluation itself can be the driver of increased merger activity.

2.2. The neoclassical hypothesis

The neoclassical hypothesis says that merger waves occur as a rational response to economic, regulatory, and technological shocks to an industry, which makes it optimal for firms in that industry to consolidate. Gort (1969) argues that such economic disturbances render the future less predictable and increase the variance of firm valuations across investors. This makes it more likely that some investors consider the potential target firms to be attractively priced, which increases the merger rate in the industry. Mitchell and Mulherin (1996) examine the takeover activity of 51 Value-Line industries during 1982-1989 and find that in about half of these industries at least half of all takeover activity is clustered in a two-year period. They classify such periods as merger waves and relate them to four different types of shocks arising from deregulation, energy price volatility, foreign competition, and financing innovations. The clustering of takeover activity by industry in their paper contrasts with the more evenly distributed takeover activity for the whole market, which gives their merger waves an industry character.

Harford (2005) also examines specific industry shocks that lead to industry merger waves, using a different sample and methodology from Mitchell and Mulherin, and he arrives at a different conclusion.

Starting with Fama-French 48 industries during 1981-2000, he discovers 35 industry merger waves in 28 industries, which he defines as two years in length. He finds significant clustering of merger waves in his investigation as all except two of them start during 1985-1987 or 1996-1999. He attributes this clustering to capital market liquidity that is necessary to accommodate the reallocation of assets and affects all industries in the same way at any given point in time. Harford tests the implications of the neoclassical hypothesis and the misvaluation hypothesis (which he also refers to as the behavioral hypothesis). He finds strong support for the former but not the latter. Harford lists several implications of the misvaluation hypothesis, in particular, that merger waves should be preceded by high stock returns and followed by low stock returns. As we explain in the introduction, calendar-time clustering of industry merger waves would have reduced his ability to detect abnormal industry returns because each wave industry is benchmarked against the market portfolio that includes other wave industries.

Several other papers support the neoclassical theory of merger activity, including Jensen (1993), Andrade, Mitchell, and Stafford (2001), Maksimovic and Phillips (2001), and Ahern and Harford (2014). Clearly, this is a key hypothesis that explains the time variation in merger activity. While we discuss it at a few places in our paper for completeness, we do not run a horse race between the neoclassical and overvaluation hypotheses. That would be difficult within our framework that relies on continuous variation in merger activity rather than a few discrete and substantial industry shocks leading to intense but short-lived periods of merger activity that motivate the neoclassical hypothesis.

2.3. Other hypotheses

The *q*-theory of mergers, proposed by Jovanovic and Rousseau (2002), says that more efficiently managed firms with a higher *q* ratio acquire less efficiently managed firms with a lower *q* ratio. It is possible that after industry shocks some managers emerge as leaders who are more capable of dealing with change than others are. If these more efficient managers initiate many mergers, then the *q*-theory may explain some of the increased merger activity. Empirically, some of the implications of the *q*-theory overlap with the implications of the misvaluation hypotheses, in particular the SV model. That is because there is little difference between firm overvaluation and a higher *q* ratio. Just as SV model requires a wide dispersion in valuations, there should be a higher dispersion of *q* ratios in more merger active industries to justify efficiency-seeking mergers. The contrast lies in subsequent performance. The *q*-theory predicts a higher post-merger operating performance of acquirer firms, although it is not clear that the proportion of acquiring firms would ever be large enough to imply a measurable increase in industry performance. The misvaluation models predict lower industry performance after periods of intense merger activity.

Last, we discuss the agency theory of mergers. Duchin and Schmidt (2013) show that during periods of intense merger activity there is reduced monitoring of firm managers, so a greater number of self-motivated managers can make low-quality mergers that destroy shareholder wealth. They also show that mergers accomplished during merger waves have worse post-merger returns. Once again, given the relatively small number of acquiring firms in any industry, it is not clear that this hypothesis by itself can explain measurable amounts of higher preceding returns and lower subsequent returns of more merger active industries unless it is used in conjunction with the industry misvaluation hypothesis.

2.4. The prior empirical evidence

Rhodes-Kropf, Robinson, and Viswanathan (2005) (RKRV) empirically examine the causes of merger waves. They decompose the (log-transformed) market-to-book ratios of individual acquirers and targets into three components: a firm-specific error (in valuation), a time-series sector (or industry) error, and a long-run value-to-book ratio. This decomposition uses an accounting model of firm valuation that relates the market value to the book value, net income, and debt ratio. They find that the first two parts that represent firm and industry misvaluation are positive for all acquirers, but more positive for stock acquirers than for cash acquirers. They also show that the merger count in an industry-year is related to the average time-series sector error of firms in that industry.

RKRV present considerable evidence in support of the overvaluation theory of merger activity. However, a few aspects of their methodology motivate our very different approach to the same topic. First, while their paper is more focused on the overvaluation of individual acquirers, we focus on the relation between the industry stock merger activity and industry overvaluation. Second, although a higher market-to-book ratio is often used as a measure of firm (or industry) overvaluation in literature, it can represent other factors: for example, growth opportunities or low discount rates (i.e., higher capital liquidity). Harford (2005) argues that higher market-to-book ratios in the year preceding the merger wave year are evidence in favor of both the neoclassical hypothesis and the overvaluation hypothesis. Third, RKRV's valuation model implicitly assumes that current incomes of firms involved in mergers or all firms in merger active industries are not too high or too low relative to their long-term values. However, more recently Akbulut (2013) shows that the operating performance of individual stock acquirers declines after mergers, and this paper shows that industry merger activity is related to subsequent changes in operating performance. We propose that overvaluation (undervaluation) is better shown by higher (lower) preceding returns and lower (higher) subsequent returns and operating performance. To the best of our knowledge, such evidence *for entire industries* does not exist in the current literature, and it is the central question in this paper.[2]

3. Data and methodology

3.1. Sample of mergers

We retrieve our sample of mergers announced during 1985-2015 from the Securities Data Company (SDC) database. We use the simpler term ‘merger’ to connote all types of acquisitions in this paper. We start our sample in 1985 because the SDC mergers data on payment terms is less complete before then. The exact steps used to identify the sample are listed in Panel A of Table 1. The main features of our sample are summarized as follows: U.S. acquirers and targets; acquirers are public firms while targets may be public, private, or subsidiary firms; and deal value is at least $10 million in 2015 dollars. This procedure gives us a sample of 34,009 mergers, including both completed and incomplete deals.

Panel B of Table 1 breaks down the sample by payment method and target type. We divide all mergers into majority stock or majority cash payment deals. Boone, Lie, and Liu (2014) show that there has been a sharp increase in the number of mixed payment deals in the 21st century. Given our focus on the misvaluation hypothesis, we prefer that we do not lose the information in such deals. 50% of the 7,875 public targets, 30% of the private targets, and 9% of the subsidiary targets receive majority stock payment (henceforth, stock mergers). Given the smaller proportion of stock mergers for private and subsidiary targets, despite greater affordability of cash payment due to their smaller size, these deals may convey more information related to acquirer and industry overvaluation.

[2] Apart from methodological differences, there is a conceptual difference between RKRV and this study. Their “time-series sector error” measures the difference between firm valuations implied by current industry multiples and long-term average industry multiples, which combines the effects of market-wide and industry-wide overvaluations. In comparison, we measure “industry-wide overvaluation” by alpha, which implicitly benchmarks industry valuations to market valuation. Thus, our measure abstracts from market-wide overvaluation.

Figure 1 shows the sample distribution over time. Over the 31-year period of our study, there are an average of 34,009/31 = 1,097 mergers per year. The merger activity peaks during the late 1990s, reaching 2,582 mergers in 1998. However, even during the last market recession there are 532 mergers in 2009. Similar to Netter, Stegemoller, and Wintoki (2011), we find that the aggregate merger activity is a continuous variable, with the usual fluctuations, but it never totally busts during any year. Figure 1 also shows that there is a positive correlation between the aggregate merger activity and proportion of stock mergers. This proportion ranges between a low value of 11% in 2011 and 2012 and a high value of 48% in 2000, with an average value of 28% over the entire period. Finally, there is not a sustained upward or downward time trend in the market-wide merger activity or proportion stock deals.

We next examine the merger activity by acquirer's industry. We use Fama-French 12 industries, which are listed in the first column of Table 2. RKRV use the same industry classification, although other merger wave studies sometimes examine Fama-French 48 industries or standard industrial classification (SIC) code based industries. A finer industry classification increases the noise level in the quarterly merger activity variable *MAV* (defined below) because it means much fewer firms and mergers in any one industry-quarter, so we keep that as a robustness test.

We use the Compustat historic SIC codes from 1987 onwards and CRSP SIC codes before 1987 to identify which firm belongs to which industry in any year. We include only public firms listed on the NYSE, AMEX, or NASDAQ and with a market value of equity of at least $10 million in 2015 dollars. Table 2 shows that the 12 industries differ considerably in the number of firms and the number of mergers. As a proportion of all mergers, stock mergers account for between 14% for durables and nondurables industries and 38% for business equipment industry. Given our focus on the industry misvaluation hypothesis that requires stock payment, we focus on stock mergers in all our following tests. The last column of Table 2 shows that the mean number of stock mergers per firm quarter equals 0.0156 in the combined sample. However, it varies considerably from 0.0049 for durables and nondurables industries to 0.0296 for telecommunications industry. It therefore becomes necessary to use this number in defining *MAV* that follows.

3.2. Stock merger activity variable (MAV)

We propose a continuous stock merger activity variable as an alternative to discrete industry merger waves due to reasons explained in the introduction. Each quarter t, starting with 1985-Q4 and ending with 2015-Q3, we compute stock merger activity variable $MAV_{jt,stk}$ for industry j during quarter t as follows:

$$MAV_{jt,stk} = \frac{\sum_{\tau=t-3}^{t} m_{j\tau,stk} / \sum_{\tau=t-3}^{t} n_{j\tau}}{\sum_{\tau=1}^{T} m_{j\tau,stk} / \sum_{\tau=1}^{T} n_{j\tau}} \tag{1}$$

where $m_{j\tau,stk}$ denotes the number of stock mergers announced by all acquiring firms in industry j during quarter τ, $n_{j\tau}$ denotes the number of firm-quarters, and T is the total number of calendar quarters. In our case, the aggregate sample period extends from 1985 to 2015, or $T = 124$ quarters.

A few aspects of this stock merger activity variable require an explanation. First, the numerator is a measure of merger activity as of the current quarter, and it is actually an average of four-quarter merger activity. That is necessary to smooth out the noise in quarter-by-quarter activity. Often, a quarter of high activity is followed by a quarter of low activity, which leads to sharp swings in *MAV* and bucket assignment (described below), unless one uses a moving average procedure. This procedure is often used in financial analysis. For example, Netter, Stegemoller, and Wintoki (2011) use merger activity over the last 24 months to estimate the current merger activity, and Baker and Wurgler (2006) estimate the current market sentiment index based, in part, on the initial public offering (IPO) activity over the last 12 months. Our main results hold with just the current quarter's merger activity, but are predictably not as strong.

Second, the denominator of *MAV* is the long-term average merger activity, which is the natural benchmark for normalizing the current merger activity in the numerator. It makes the average value of *MAV* calculated over all quarters for any industry equal to one. This denominator is also the number reported in the last column of Table 2. Note that when standing in quarter t this variable includes some look-ahead information. This follows a common practice in the literature as merger waves are *always* identified by setting a cutoff that equals a multiple of the average merger activity over an aggregate period. Similarly, RKRV use the aggregate time-series of sector multiples to calculate the current sector misvaluation. This means that while tests of excess returns and operating performance that use this *MAV* definition are reasonable tests of the various hypotheses presented in Section 2, they do not represent an implementable portfolio strategy. Later, we show that our test results hold reasonably well even if we use only backward-looking information in constructing *MAV*.

Third, although industry stock merger activity is the focus of our paper, one can tweak Equation (1) to calculate other similar merger activity variables. For example, one can define industry cash merger activity $MAV_{jt,cash}$ by including only cash mergers, and industry total merger activity MAV_{jt} by including both stock and cash mergers. Similarly, one can define market-wide stock, cash, or total merger activity variables $MAV_{t,stk}$, $MAV_{t,cash}$, and MAV_{t} by including the appropriate type of mergers for all industries.

Visual examination of $MAV_{jt,stk}$ (often simply *MAV*) time series for the 12 industries shows that the stock merger activity is a continuous variable. First, we take the minimum and maximum values of this variable over the 1989-Q1 to 2015-Q4 period of our study for each industry, and average across industries. The average values equal 0.102 and 2.974, which shows a good dispersion. Second, only four industries with the lowest stock merger activity – nondurables, durables, chemicals, and utilities – have at least one quarter of zero *MAV*. Third, we look at histograms of *MAV* values at intervals of 0.2 from 0.0 to 2.0, and one cell for above 2.0. Only one cell in one industry – [0.0, 0.2] cell for money – has a zero frequency. All other cells for all industries are well populated.

3.3. Bucket assignment procedure and summary statistics

$MAV_{jt,stk}$ is our normalized measure of stock merger activity of industry j during quarter t. It includes the effect of both industry-specific and market-wide factors. To provide evidence on the latter, we measure the cross-industry correlation between $MAV_{jt,stk}$ and $MAV_{kt,stk}$ for all industries j and k, but $j \neq k$. This correlation has an average value of 0.53, which highlights the pronounced effect of market-wide factors on industry stock merger activity. While that may be interesting in its own right, it becomes necessary to filter out the effect of market-wide factors in order to test the industry misvaluation hypothesis. This is done as follows.

Every quarter we rank the Fama-French 12 industries from the lowest to the highest value of $MAV_{jt,stk}$ and assign them to buckets numbered 1 (least stock merger active industry) to 12 (most stock merger active industry), starting in quarter $t+1$. This ranking procedure assigns one industry to each bucket every quarter. The industry misvaluation hypothesis predicts that every quarter bucket 1 will collect *relatively* the most undervalued industry; bucket 12 will collect *relatively* the most overvalued industry, and so on for the in-between buckets. This is true regardless of market conditions, boom or bust.

Figure 2 shows the relation between industry stock merger activity and bucket number for three select industries by quarter. These industries – manufacturing, health care, and money – are chosen for illustration because they represent low, medium, and high overall stock merger activity during 1985-Q4 to 2015-Q4 (as shown in Table 3 next). Regardless of the level of overall stock merger activity, the bucket numbers for these industries are fairly well distributed over the range of 1 to 12.

Table 3 shows detailed information for industries included in each bucket, calculated at the time of entry and then averaged over all quarters. Because every industry spends about half the time in lower bucket numbers and half the time in higher bucket numbers, there is no clear correlation between bucket number and mean ratio of industry value to total stock market value. There is no correlation between bucket number and mean book-to-market of industries either. Of course, the correlations between bucket number and mean $MAV_{jt,stk}$ or mean number of stock mergers per firm quarter, all of them measures of industry stock merger activity in different ways, are high.

We keep each industry that is assigned to a bucket based on its $MAV_{jt,stk}$ in that bucket for a period of 12 quarters, from $t+1$ to $t+12$. This is our attempt to carry out calendar-time tests of excess returns that are common for portfolios of individual acquirers in literature. Every quarter one industry that was included 12 quarters ago is dropped while a new one is added. Every bucket has exactly 12 entries during every quarter, from 1989-Q1 to 2015-Q4, but the mean number of distinct entries (industries) ranges between 3.99 and 7.25 as shown in the last column of Table 3. This is not surprising since there tends to be a positive autocorrelation in $MAV_{jt,stk}$ time series. To explore the migration pattern of industries across buckets, we measure the first-order autocorrelation in the quarterly series of bucket numbers for each industry. This autocorrelation has a value of 0.77 averaged across the 12 industries. Alternately, we look at the average absolute change in bucket number from one quarter to the next for each industry and then average across industries. This number equals 1.52, showing once again that sharp swings in bucket numbers from one quarter to the next are rare, partly the result of our moving average procedure. Even measured over a four-quarter lag, the average absolute change in bucket number equals 3.26.

It helps to think of industries as ETFs (exchange-traded funds). These ETFs are added to different buckets at different times, depending on their recent stock merger activity. There is a finite number of 12 ETFs, which keep entering different buckets in different quarters. Given the assignment procedure, in any one bucket there may be multiple entries of some ETFs and no entries of other ETFs at any point in time. ETF returns are the value-weighted industry returns, and monthly bucket returns are calculated as a simple average of the monthly returns of 12 non-distinct ETF entries.

4. Main results: Stock merger activity and industry returns and operating performance

4.1. Post-MAV raw returns and alphas

We start by analyzing industry returns over a three-year period following the calculation of *MAV*. Section 3.3 above describes the construction of buckets ranked by *MAV* for this purpose and the calculation of monthly bucket returns. Figure 3 graphically depicts the timeline over which industries are included for calculation of post-*MAV* returns (as well as pre-*MAV* returns that follow). We analyze both raw returns and Fama-French 3-factor alphas for evidence on industry misvaluation.[3]

The first data column of Panel A in Table 4 shows the average annual return during 1989-2015 by bucket number. Annual return is calculated by compounding monthly returns within a calendar year. The average annual return declines almost monotonically from 14.07% for bucket 1 (least stock merger active industries) to 9.18% for bucket 12 (most stock merger active industries). In the bottom rows of next many tables, we show the correlation between the column variable and bucket number and the results of a univariate regression of the column variable on bucket number. The correlation equals -0.93 for average annual return, and the slope coefficient shows that it increases by -0.34% per bucket number.

The next column shows that the standard deviation of annual returns follows the opposite pattern to average return and it increases with increasing bucket number. The double whammy of lower average return and higher standard deviation implies a much lower Sharpe ratio for higher bucket numbers than for lower bucket numbers. The Sharpe ratio increases by -0.024 per bucket number, significant at 1% level.

[3] For individual acquirers, researchers often analyze buy-and-hold excess returns, calculated as the difference between the cumulative returns of the sample firm and a size and book-to-market matching firm over a holding period. Unfortunately, matching benchmarks within the space of twelve industry ETFs are not possible.

That implies a difference of 0.024×11 = 0.264 between buckets containing the least merger active and the most merger active industries.

In economic terms, the investor experience is better captured by cumulative returns shown in the last column of Panel A in Table 4. $1 invested in bucket number 1 in the beginning of 1989 would have grown to $24.13 by the end of 2015 compared to $6.77 in bucket number 12, a ratio of 3.56 to 1. The cumulative value of $1 has a correlation of -0.97 with bucket number, and it increases by -$1.38 per bucket number. We next discuss two benchmarks to compare the bucket returns: first, the CRSP value-weighted market portfolio (VWRETD), and, second, an equally weighted portfolio of all 12 industries that computes monthly portfolio returns as the arithmetic average of monthly industry returns (which are returns on value-weighted portfolios of industry stocks). The second benchmark is more relevant as it aggregates all industries in one bucket, similar to the main experiment but with no consideration given to the industry *MAV* values. The detailed statistics for both benchmarks are presented in Table 4. Briefly speaking, $1 invested in VWRETD in the beginning of 1989 would have grown to $12.68 by the end of 2015 and the corresponding amount invested in the equally weighted portfolio of all industries would have grown to $16.13. The latter value is right in the middle of the corresponding numbers for the 12 buckets formed by ranked *MAV* of industries.

Panel B of Table 4 shows the Fama-French 3-factor alpha calculated using 324 monthly returns for each bucket during 1989-2015. Alphas in Panel B show the same trend as the average annual (raw) returns in Panel A. The correlation between alphas and bucket numbers equals -0.89, and alphas increase by -0.027% per month per bucket number, which by annualizing gives an estimate close to the increase in average annual returns by -0.34% per bucket number. Apparently, risk adjustment does not alter our results concerning the differences between raw bucket returns. This is despite the fact that, inferred from the coefficients of *RMRF*, *SMB*, and *HML* risk factors, the market beta increases, average firm size increases, and average book-to-market ratio decreases with increasing bucket number.[4,5] Apparently, the effects on

[4] $RMRF$, SMB, and HML are factor returns, defined as the returns on zero-investment portfolios of market minus riskfree security, small minus big stocks, and high minus low book-to-market stocks (Fama and French 1993).

[5] One may point out that alphas of many buckets in Panel B of Table 4 are statistically insignificant. However, our primary question in this paper is whether bucket alphas and bucket numbers are related. That question is effectively addressed by the regression of bucket alphas on bucket numbers in Panel B of Table 4 and the one consolidated regression that is reported next in this section. In a similar light, one can show that the measured alpha for bucket 12 is statistically different from each of the measured alphas for buckets 1, 2, and 3 at 5% level or better.

returns of changes in different firm characteristics of buckets approximately balance out in our sample. Finally, for benchmarking, notice that the equally weighted portfolio of all 12 industries described above has a 3-factor alpha of 0.046 with a t-statistic of 1.24, about in the middle of the bucket alphas. The industry alphas are distributed around 0.046 rather than zero, because we are analyzing equally weighted portfolios of industry ETFs that are constructed by value weighting all industry stocks, making them a hybrid of the two weighting techniques.

To look at excess returns another way, we report the following consolidated regression by aggregating all 324×12 = 3,888 monthly returns for the 12 buckets:

$$bucket\ return - riskfree\ return = 0.224 - 0.027 \times bucket\ number + 0.902 \times RMRF$$
$$+0.009 \times RMRF \times bucket\ number + 0.037 \times SMB - 0.012 \times SMB \times bucket\ number$$
$$+0.350 \times HML - 0.022 \times HML \times bucket\ number + error$$

The coefficient of SMB alone is significant at 5% level while all other coefficients are significant at 1% level. In particular, the *t*-statistics of the intercept (first term) and $bucket\ number$ (second term) equal 4.34 and -3.90. The regression has an adjusted-R^2 of 0.88. Notice that the coefficients of interaction terms between *RMRF*, *SMB*, or *HML* and bucket number correspond closely to the univariate slope coefficients reported in the second from bottom row in Table 4.

Figure 4 plots the cumulative value of $1 from 1989 to 2015 against the bucket number in Panel A and the Fama-French 3-factor alphas against the bucket number in Panel B. Both panels show a remarkably close linear fit. The combined evidence of Table 4 and Figure 4 shows that there is a strong negative relation between *MAV* rank and post-*MAV* industry excess returns.

4.2. Pre-MAV alphas

As shown before in Figure 3, we measured preceding three-year returns over quarters $t-15$ to $t-4$ for evidence on overvaluation of high-*MAV* industries. This period precedes the four-quarter period $t-3$ to t over which we measure $MAV_{jt,stk}$. We use the same methodology that is used for measuring post-*MAV* returns. In particular, based on *MAV* ranks for quarter *t*, we drop the 12 industry ETFs in buckets with corresponding numbers, starting in quarter $t-15$ and ending in quarter $t-4$. We compute monthly bucket returns from 1985-Q1 to 2011-Q4, a period during which each bucket has exactly 12 entries.

Table 5 shows that 3-factor alpha has a correlation of 0.83 with bucket number. The pre-*MAV* alpha increases by 0.044% per month per bucket number, which compares with -0.027% per month per bucket number for post-*MAV* alpha. Figure 5 plots both pre-*MAV* and post-*MAV* alphas by bucket number. There is a negative correlation of -0.69 between the two variables, significant at 5% level. This negative correlation further suggests that the prior positive returns of more merger active industries were the result of overvaluation rather than emerging new growth opportunities. For nine cases, the pre-*MAV* alpha is negative and post-*MAV* alpha is positive, or vice versa.

In addition to preceding three-year returns, we also analyzed preceding one-year returns over quarters $t-7$ to $t-4$ following otherwise the same methodology. For brevity, we do not show these results in a table. However, the 3-factor alphas for buckets 1 to 12 are as follows: -0.260, -0.106, -0.046, 0.042, 0.038, 0.143, 0.112, 0.094, -0.089, -0.061, 0.313, and 0.381 (all in %). The correlation between post-*MAV* alpha and bucket number equals 0.72 and the slope coefficient equals 0.036% per month per bucket number, both significant at 1% level.

Our evidence on post-*MAV* and pre-*MAV* alphas is clearly consistent with the industry misvaluation theory of stock mergers. However, in a somewhat related context, Carlson, Fisher, and Giammarino (2006, 2010) argue that prior positive and subsequent negative excess returns of SEO (seasoned equity offering) firms can be explained by an alternate real options theory. According to this theory, SEO firms have emerging growth options before issuance that are cashed out after issuance. Consistent with their theory, Carlson, Fisher, and Giammarino show that the market betas of SEO firms increase before issuance and decrease after issuance. If mergers are a result of growth options exercised by acquirers, then one may expect some such effect in our sample. To test this possibility, we calculate the difference between post-*MAV* beta and pre-*MAV* beta for the 12 buckets that are reported in Tables 4 and 5. These differences are strongly *positively* related to bucket numbers, with a correlation of 0.87, significant at 1% level. This evidence is in the opposite direction to the predictions of real options theory and suggests that our excess return results cannot be explained by that theory.

4.3. Pre-MAV and post-MAV operating performance

We now examine the trends in industry operating performance relative to merger activity. Barber and Lyon (1996) recommend that operating performance should be measured by annual operating income before depreciation (OIBDP) normalized by assets (AT), so that is the measure we employ. Based on simulation evidence, they also recommend an industry and performance matching firm approach to calculate the abnormal performance of a sample of individual firms. However, we cannot follow this approach because our sample consists of 12 industries that differ by their *MAV* rank, and we hypothesize that *MAV* rank is related to the changes in operating performance. Therefore, we follow a different methodology that is fully described in Table 6 and briefly outlined below.

For industries ranked by *MAV* during the four quarters of 2004-Q3, 2004-Q4, 2005-Q1, and 2005-Q2, we take 2004 to be the base year y, and so on, for all years starting in 1989 and ending in 2014 (the last year for which we have complete accounting data). Thus, each year we have four industry ETF entries in each bucket, although these entries may not all be distinct. We calculate the industry operating income as the aggregate OIBDP of all firms included in the industry divided by the aggregate AT. The middle column in Table 6 shows the mean operating income for the base year calculated from 26×4 = 104 entries in each bucket. The columns to the right show the mean difference between the operating incomes for each of the following years, $y+1$, $y+2$, and $y+3$, and the base year y (later minus earlier). The columns to the left show a slightly different sequence, which is the mean difference between the operating incomes for the base year y and each of the preceding years, $y-3$, $y-2$, and $y-1$ (still, later minus earlier). The columns on which we focus our discussion are shown with shading while the remaining columns without shading test the stability of the evidence.

We find that the post-*MAV* changes in operating performance are significantly negatively related to the *MAV* rank. For example, from year y to $y+3$, mean operating income increases by 0.48% for bucket 1 and decreases by 0.84% for bucket 12. The correlation between change in operating income and bucket number equals -0.77, and the slope coefficient from the regression equals -0.098% per bucket number, both significant at 1% level. The evidence is quite similar if we examine the alternate windows from year y to y+1, or from year y to y+2, which means the operating performance changes fairly rapidly after the year of calculating *MAV*. Thus far, the evidence for post-*MAV* changes in operating performance in Table 6 is has the same direction as the evidence for post-*MAV* excess returns in Table 4.

Looking further, there is no parallel trend between pre-*MAV* changes in operating performance and pre-*MAV* excess returns. We do not find any significant trend in the change in operating income if we examine either of the windows, from year $y-3$ to y, or from year $y-2$ to y. However, looking over a shorter window that may reduce noise, we detect a significant trend in the change in operating income from year $y-1$ to y, and surprisingly it is in the same direction as the trend from year y to $y+3$. In other words, the operating income declines from year $y-1$ to y and from year y to $y+3$ for higher bucket numbers, while the opposite is true for lower bucket numbers. The last column of Table 6 combines these two changes to show one combined effect from year $y-1$ to $y+3$. The combined effect is economically significant, a fitted increase of -0.137% per bucket number from year $y-1$ to $y+3$. Notice these significant trends in changes in operating performance across bucket numbers occur despite negligible changes in operating performance averaged across all buckets and over all windows as shown in Table 6.

Figure 6 plots the trends in operating performance. Unlike Figure 5 that shows a negative correlation of -0.69 between pre-*MAV* and post-*MAV* excess returns across bucket numbers (significant at 5% level), Figure 6 shows a positive correlation of 0.54 between pre-*MAV* and post-*MAV* changes in operating performance (significant at 10% level).

We address a potential concern that the post-*MAV* operating performance of acquiring firms may be understated due to step-up of target assets after merger, which may in turn understate the performance of higher numbered buckets that contain a greater number of acquiring firms. At the outset, this should be a smaller concern with operating performance of entire industries than with individual acquiring firms since most firms in any industry are not involved in merger activity in any one year. In addition, before 2001 (about the midpoint of our sample) acquiring firms could avoid any step-up of target assets by choosing the pooling method of merger accounting, which they did whenever the alternate purchase method would have resulted in a substantial step-up (Aboody, Kasznik, and Williams 2000). Consistent with these conjectures, we find that the difference in step-up of target assets across buckets 1 to 12 is likely to be small and cannot explain the difference between changes in their post-*MAV* operating performance reported in Table 6.[6]

[6] Specifically, we estimate the total target assets before merger normalized by the total industry assets in the year of merger. Averaged over the years, this proportion has the following values (in percent) for buckets 1 to 12: 0.54, 0.96, 1.20, 1.63, 1.62, 1.13, 1.58, 1.43, 1.15, 1.27, 1.61, and 2.25. The difference in target assets scaled by industry assets between buckets 1 and 12 equals 1.71%. Based on numbers provided in Table 2 of Aboody, Kasznik, and Williams, we estimate that the mean step-up of target assets may be between 0.35 and 0.49 times the pre-merger target assets in cases where the purchase method of accounting was chosen. This would imply a difference in step-up of industry assets between buckets 1 and 12 of the order of $1.71\times(0.35+0.49)/2 = 0.7\%$ of industry assets post-2001 (when only purchase method was available) and much less pre-2001 (when both pooling and purchase methods were available).

4.4. Interpretation of the evidence on excess returns and operating performance

Our evidence supports the industry misvaluation theory of merger activity given by SV and RKV. First, we find that preceding excess returns over a three-year period (also a one-year period) are positive for industries with higher *MAV* ranks and negative for industries with lower *MAV* ranks. However, there is no parallel trend in their operating performance. In fact, during the preceding one year there is an opposite trend, with decreasing (increasing) operating incomes in industries with higher (lower) *MAV* ranks. That implies overvaluation (undervaluation) of industries with higher (lower) *MAV* ranks, or misvaluation in general. Second, the misvaluation reverses during subsequent years, with negative (positive) excess returns and continued decreasing (increasing) operating incomes in industries with higher (lower) *MAV* ranks. Thus, in sequence, we find a build-up of industry misvaluation, followed by an opportunistic but rational increase or decrease in the level of stock merger activity, followed by a correction of misvaluation.

The positive correlation between changes in operating performance from year *y*-1 to *y* and from year *y* to *y*+3 suggests that the eventual trend in industry earnings had started before the period of merger activity. However, it was likely private information at this stage, pending further confirmation through earnings releases and analyst interpretations. This evidence is further consistent with RKV model in which target managers receive a bid from an overvalued firm in the same industry. Given the recentness of signals regarding their own firm's overvaluation, they underestimate the overvaluation of the entire industry and therefore of the acquirer firms. Thus, they overestimate the merger synergies and over-accept the stock merger offers as outlined in Sections 1 and 2 of this paper.

The negative post-*MAV* excess returns and changes in operating performance of more merger-active industries in our study cannot be explained by the neoclassical theory. According to this theory, in cases where the increased merger activity occurs in response to emerging growth opportunities, one may even expect improvements in operating performance and positive excess returns. However, Mitchell and Mulherin (1996) and Harford (2005) argue that this improvement may not occur if the increased merger activity occurs in distressed industries, only that the subsequent performance may not be as bad as it would have been in the absence of merger activity. Undoubtedly, many merger waves (or simply periods of

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This effect cannot explain the difference in operating performance of the order of (0.48-(-0.84))/((13.96+15.17)/2) = 9.06% of prior industry operating performance between buckets 1 and 12 (see our Table 6).

increased stock merger activity in our framework) occur in distressed industries, but we find that is not the norm.[7] In unreported tests, we find that the average Standard and Poor's long-term issuer credit ratings for industries, a contrary measure of distress, are positively but insignificantly correlated with their bucket numbers (correlation 0.45, *p*-value 0.14, higher ratings are better ratings). Besides, the strong pre-*MAV* excess returns of industries with higher bucket numbers are inconsistent with their approaching financial distress. Thus, our evidence can only be explained by the industry misvaluation theory of mergers. (As a necessary caveat, we again point out the reasons mentioned in the introduction and the literature review related to the limited applicability of the neoclassical theory to our framework that considers continuous variation in merger activity rather than discrete merger waves.)

We investigate a few other features of our data for evidence on various theories of merger activity, with less success. First, both SV and RKV models predict a greater number of cross-industry mergers for more merger-active industries as overvalued acquirers seek relatively undervalued targets outside their industries. In contrast, the neoclassical theory predicts a greater number of same-industry mergers for more merger-active industries as potential target and acquirer firms in those industries deal with the impact of common industry shocks. In unreported tests, we find an insignificant correlation between the frequency of cross-industry mergers and bucket numbers, which does not favor either theory. Second, both SV and RKV models suggest an increased dispersion of firm values in more merger-active industries, and neoclassical arguments such as by Gort (1996) predict the same. However, we find an insignificant relation between interquartile spread of market-to-book ratios of industries and their bucket numbers.

5. Robustness tests of excess returns and operating performance

Results of Section 4 are broadly consistent with the industry misvaluation theory of stock mergers. In this section, we first report several robustness tests that change one feature of our methodology at a time. In these tests, we focus on our main results concerning the relation between bucket number and post-*MAV* returns, originally reported in Table 4. We then replicate the tests of Tables 4, 5, and 6 with cash mergers.

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[7] For example, Mitchell and Mulherin (1996) point out deregulation shock to the air transport industry and foreign competition shock to the apparel industry, both of which would have done worse without industry consolidation.

5.1. Fama-French 12 industries vs. 48 industries

We chose 12 industries for our main illustration because for most industries during most periods this classification gives a reasonably continuous *MAV* distribution. Using a finer industry classification gives a less continuous (or more discrete) distribution, with the result that some of the smaller industries with fewer stock mergers jump from a low bucket number to a high bucket number in adjacent quarters, or vice versa. This rapid migration tendency weakens our results. Nevertheless, we present our main results with Fama-French 48 industries for robustness. As before, we rank the 48 industries each quarter based on their $MAV_{jt,stk}$ values each quarter. We then assign the four lowest *MAV* industries to bucket 1, next four to bucket 2, and so on, until the four highest *MAV* industries are assigned to bucket 12. Table 7 shows that the average annual return, Sharpe ratio of annual return, cumulative value of $1 from 1989 to 2015, and 3-factor alpha, all remain negatively correlated with bucket number, significant in each case at 5% level or better.

5.2. Using only historical information to calculate MAV

In Section 3.2 we pointed out that $MAV_{jt,stk}$ defined by Equation (1) includes some forward-looking information similar to any other study of merger waves. In this subsection, we redefine this measure of stock merger activity to include only historical information until quarter t as follows:

$$MAV_{jt,stk} = \frac{\sum_{\tau=t-3}^{t} m_{j\tau,stk} / \sum_{\tau=t-3}^{t} n_{j\tau}}{\sum_{\tau=1}^{t} m_{j\tau,stk} / \sum_{\tau=1}^{t} n_{j\tau}} \quad (2)$$

The notations have the same meaning as before in Equation (1). The only difference between *MAV* definitions in Equations (1) and (2) is in the period over which the long-term average merger activity that appears in the denominator is calculated. In this section it is from quarter 1 to quarter t. Because our post-*MAV* return computation starts from quarter $t + 1$, there is no look-ahead bias with this measure. We require the first 10 years of historical information to start the *MAV* calculation. Since our mergers data starts in 1985, the first calculation of *MAV* and the corresponding assignment of industries to buckets occurs in 1995-Q1. All buckets continuously have 12 industries from 1997-Q4 onwards, so we begin our post-*MAV* returns experiment in 1998-Q1. That gives us a period of 18 whole years until 2015.

Table 8 shows that average annual return, Sharpe ratio of annual return, cumulative value of $1 from 1998 to 2015, and 3-factor alpha all remain negatively correlated with bucket number, significant at 1% level. This shorter period from 1998 to 2015 was characterized by lower annual market returns relative to the full period from 1989 to 2015. Despite that, our results show that our excess returns could have been captured using our bucket formation strategy.

5.3. Using only current quarter's stock merger activity instead of four-quarter activity

A moving averages procedure is often used to control noise in a monthly or quarterly time series. However, we try a variation of Equation (1) in which the numerator represents only the current quarter's stock merger activity as follows:

$$MAV_{jt,stk} = \frac{m_{jt,stk}/n_{jt}}{\sum_{\tau=1}^{T} m_{j\tau,stk}/\sum_{\tau=1}^{T} n_{j\tau}} \tag{3}$$

The notations have the same meaning as before in Equation (1). The only difference between *MAV* definitions in Equations (1) and (3) is that in the latter case the current stock merger activity in the numerator is calculated for the current quarter t. In unreported results, we find that our results related to the negative correlation between bucket number and average annual return, Sharpe ratio of annual return, and cumulative value of $1 from 1989 to 2015 are still significant at 5% level, while the negative correlation between bucket number and 3-factor alpha is significant at 10% level.

5.4. Calendar-time portfolio returns vs. event-time returns

The main results related to post-*MAV* returns in Tables 4 and 5 use techniques similar to calendar-time portfolio returns for individual stocks. As a robustness check, we also test event-time returns. Specifically, after assigning a bucket number to every industry based on its $MAV_{jt,stk}$ value during quarter t, we compute its 3-factor alpha over quarters $t+1$ to $t+12$. We average the 108 alphas, one per quarter for each bucket during the 27-year period of our study, to calculate the average post-*MAV* alpha for each bucket. We follow a similar procedure to calculate pre-*MAV* alpha for each bucket. In unreported results, we find that our results for bucket alphas across bucket numbers are strikingly similar to those shown in Figure 5. We therefore do not report these results for brevity.

5.5. Operating performance results based on top-line vs. bottom-line in income statement

The main results related to pre-*MAV* and post-*MAV* operating performance in Table 6 and Figure 6 employ operating income as the statistic. Operating income is a proxy for the bottom-line earnings in an income statement. An extensive accounting literature highlights the role of top-line sales revenue in addition to bottom-line earnings. We therefore analyze industry asset turnover, calculated as the aggregate sales (SALE) of all firms included in the industry divided by the aggregate assets (AT, average of beginning and end-of-year values). Table 9 shows that the results with industry asset turnover as a proxy for operating performance are similar to the results with OIBDP as a proxy for operating performance in Table 6. These results are also consistent with RKV model of misvaluation driven stock merger activity.

5.6. Cumulative growth over time of $1 invested in the beginning of 1989

Figure 7 shows that the relation between returns and bucket number is spread out over time, although it is more pronounced during the later years. Averaged across buckets numbered 1, 2, and 3, $1 invested in the beginning of 1989 grows to $4.69 by the end of 1997, $10.36 by the end of 2006, and $22.83 by the end of 2015. In comparison, averaged across buckets numbered 10, 11, and 12, the same $1 invested in the beginning of 1989 grows to $3.94 by the end of 1997, $6.86 by the end of 2006, and $10.22 by the end of 2015.

5.7. Cash merger activity and industry performance

Based on theory (RV and RKV) and empirical evidence (RKRV and this paper), we conclude that stock merger activity is higher during periods of industry overvaluation and lower during periods of industry undervaluation. However, there is no theory to suggest that the opposite is true for cash merger activity. Consider Theorem 4 of RKV that is spelled out in Section 2.1. It says that mergers are more likely in overvalued markets than in undervalued markets, and that the method of payment includes a greater fraction of stock deals in overvalued markets than in undervalued markets. Suppose there are a total of N_1 mergers in an overvalued market and N_2 mergers in an undervalued market, and the fraction of stock deals is f_1 in the overvalued market and f_2 in the undervalued market. It follows that the number of stock mergers equals $N_1 f_1$ in the overvalued market and $N_2 f_2$ in the undervalued market, while the corresponding number of cash mergers equals $N_1(1-f_1)$ and $N_2(1-f_2)$. From Theorem 4 of RKV, we know that $N_1 > N_2$, $f_1 >$

f_2, and $N_1 f_1 > N_2 f_2$. However, we cannot say whether $N_1(1 - f_1)$ is greater than or less than $N_2(1 - f_2)$. This highlights the difficulty of associating the variation in cash merger activity with the variation in industry valuation. In addition, the alternate theories of merger activity (the neoclassical theory, the q theory, and the agency theory) do not suggest any particular role for the payment method. Empirically, we find that the stock merger activity and cash merger activity are in fact positively related as the correlation between $MAV_{jt,stk}$ and $MAV_{jt,cash}$ averaged across the 12 industries equals 0.35. Thus, we have no clear predictions regarding the relation between cash merger activity and industry valuation. Nevertheless, for completion below we empirically document this relation.

Our sample for the following investigation includes 3,960 public cash acquisitions during 1985-2015 as described in Panel B of Table 1. We exclude private and subsidiary cash deals because acquisitions of private and subsidiary targets are predominantly for cash (in 70% and 91% of all cases), so they convey little information about industry valuation. We follow a similar methodology to that employed before for stock mergers. In other words, we calculate, in sequence, $MAV_{jt,cash}$, ranked $MAV_{jt,cash}$, bucket assignments, and then the post-*MAV* and pre-*MAV* excess returns and operating performance for bucket portfolios of industry ETFs. The main results are reported in Table 10.

We find that the correlation between post-*MAV* annual return and bucket number equals 0.58 for cash payment, which is significant at 5% level, and in the opposite direction to that for stock payment. The correlations with post-*MAV* and pre-*MAV* alphas are positive but insignificant. Also insignificant are the correlations of bucket number with the changes in operating performance from year y-1 to y, or from year y to y+3. Overall, we infer that, unlike stock merger activity, there is no clear relation between variations in cash merger activity and industry valuations.

6. Industry stock merger activity and overvaluation of individual stock acquirers

Previous literature has typically examined the total overvaluation of individual stock acquirers. To our knowledge, Rhodes-Kropf, Robinson, and Viswanathan (2005) provide the only empirical decomposition of this total overvaluation into an industry-wide and a firm-specific component (using an accounting model of firm valuation). However, they do not show how each of these component estimates varies by industry merger activity. In comparison, Duchin and Schmidt (2013) show that the acquirer overvaluation is higher during industry merger waves than outside industry merger waves (using a returns-based approach), but they do not decompose the total overvaluation into an industry-wide and a firm-specific component. In this section, we close some of these gaps. In particular, we provide a returns-based decomposition of the individual acquirer overvaluation and show how it varies by industry stock merger activity. In addition, we examine whether the effects of this merger activity are partially recognized by investors at the time of announcement of stock mergers.

We follow a calendar-time strategy parallel to that described in Table 4 for analyzing industry returns, but this time with individual stock acquirers. Thus, each quarter t, we sort all acquirers by the MAV rank of their industries and drop them in the corresponding buckets for a 36-month period from quarter $t+1$ to $t+12$. We calculate the monthly bucket returns as the equally weighted average of monthly returns of all acquirers included in that bucket. Using the time series of monthly bucket returns from 1989 to 2015, we calculate the bucket alphas. Other methodology details are given in Table 11.

We find a correlation of -0.82 between bucket number and bucket alpha for individual stock acquirers, significant at 1% level. This strong correlation occurs despite relatively few observations in lower numbered buckets. Regression results show that alpha decreases at a rate of -0.066% per bucket number, which is steeper than the rate of -0.027% per bucket number for industry alphas. Table 11 reports the results of regression lines fitted using the single independent variable of bucket number and the dependent variables of acquirer alpha and industry alpha. Figure 8 shows the evidence graphically. The solid line shows the (fitted) variation in acquirer alpha (an inverse measure of total acquirer overvaluation) with bucket number, and the broken line shows the variation in industry alpha (an inverse measure of industry-wide overvaluation). The distance between the solid line and the broken line shows the variation in acquirer's firm-specific alpha. The market-wide component of misvaluation has been dropped by including market return in the factor model.

A few results emerge from Table 11 and Figure 8. First, stock acquirers are always overvalued. This is unlike industries that may be undervalued or overvalued, which is natural since collectively the 12 industries are the market. (Notice the industry alphas do not center at zero for reasons pointed out in Section 4.1.) Second, we calculate implied percent overvaluation by multiplying each alpha by -36, because each acquirer or industry entry stays in a bucket for 36 months and a negative (positive) alpha indicates overvaluation (undervaluation). We find that stock acquirer overvaluation increases more steeply with bucket number (from 4.4% in bucket 1 to 30.4% in bucket 12) than industry overvaluation (from -7.1% in bucket 1 to 3.8% in bucket 12). This amounts to saying that the firm-specific overvaluation also increases with bucket number, from 11.4% in bucket 1 to 26.6% in bucket 12. Alternately, this evidence is consistent with an agency hypothesis advanced by Duchin and Schmidt (2013), who find that acquirer actions are subject to lower monitoring and lower penalties for underperformance from deals made during merger waves than from deals made outside merger waves. They argue that this reduced monitoring leads to lower quality mergers during merger waves. Third, related to the previous point, industry misvaluation increases by about 40% of the increase in industry plus firm-specific overvaluation between bucket numbers 1 and 12 (calculated as the ratio of slopes of the broken line and the solid line in Figure 8).

7. Conclusion

The overvaluation hypothesis is an important part of the equity issuance literature, which includes initial public offerings (IPOs), seasoned equity offerings (SEOs), and stock mergers. More specifically, Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004) theoretically model industry overvaluation as the reason for increased stock merger activity during merger waves. However, previous empirical evidence in support of the overvaluation hypothesis of stock mergers is based almost entirely on the long-term returns of individual stock acquirers. Similar returns-based evidence on the overvaluation (more generally misvaluation) of entire industries as a reason for merger waves has been lacking in the literature while there is other evidence in support of alternate reasons for merger waves, in particular, the neoclassical efficiency-based reasons that suggest that industry shocks lead to industry consolidation. This paper attempts to fill this gap in the literature.

We argue that traditionally defined merger waves are not the right framework in which to test the implications of the industry misvaluation theory for two reasons. First, there is a discreteness issue, which arises because very few industry-years are classified as wave years while the majority are classified as non-wave years, and there is no further distinction based on the intensity of merger activity within either subset of years. Second, traditionally defined merger waves cluster in calendar time, so each industry undergoing a merger wave is benchmarked against the market consisting of other industries undergoing a similarly defined merger wave. To overcome these limitations, we propose a continuous stock merger activity variable, or *MAV*. This variable helps us distinguish between industries even if by traditional definition many of them are simultaneously undergoing a discrete merger wave. Further adding industries each quarter by their *MAV* rank into 12 buckets produces strong evidence in favor of the industry misvaluation theory of changing stock merger activity. Consider, for example, that over the 27-year period from 1989 to 2015, $1 invested in bucket 1 (with relatively the least stock merger active industries) grows to $24.13 while the same $1 invested in bucket 12 (with relatively the most stock merger active industries) grows to $6.77, a ratio of 3.56 to 1. It is further remarkable that over the full range of merger activity there is a highly significant correlation of -0.97 between bucket return and bucket number.

While post-*MAV* returns are the most relevant tests of industry misvaluation, we provide further evidence based on pre-*MAV* returns and both pre-*MAV* and post-*MAV* operating performance that give additional support to the overvaluation theory. Pre-*MAV* returns over a three-year window are positively related to bucket number while pre-*MAV* changes in operating performance are not, which leads to the overvaluation (undervaluation) of industries with higher (lower) stock merger activity. The pre-*MAV* changes in operating performance over a shorter one-year window are in fact negatively related to bucket number, a trend that continues in the same direction into the post-*MAV* window. We explain that this evidence supports the RKV model of how industry-wide overvaluation leads to higher merger activity.

The later part of the paper provides a returns-based decomposition of total acquirer misvaluation into an industry-wide and a firm-specific component within our *MAV* framework. We document some new results. Stock acquirers are overvalued even in undervalued industries, both components of overvaluation increase as one goes from bucket 1 to bucket 12, and the firm-specific component of overvaluation increases at a greater rate. Finally, as a limitation of our analysis, we should point out that the analysis of market-wide misvaluation as a reason for stock merger activity is missing from our study. That is because all excess return models include market return as one factor, which washes out the market-wide valuation effects.

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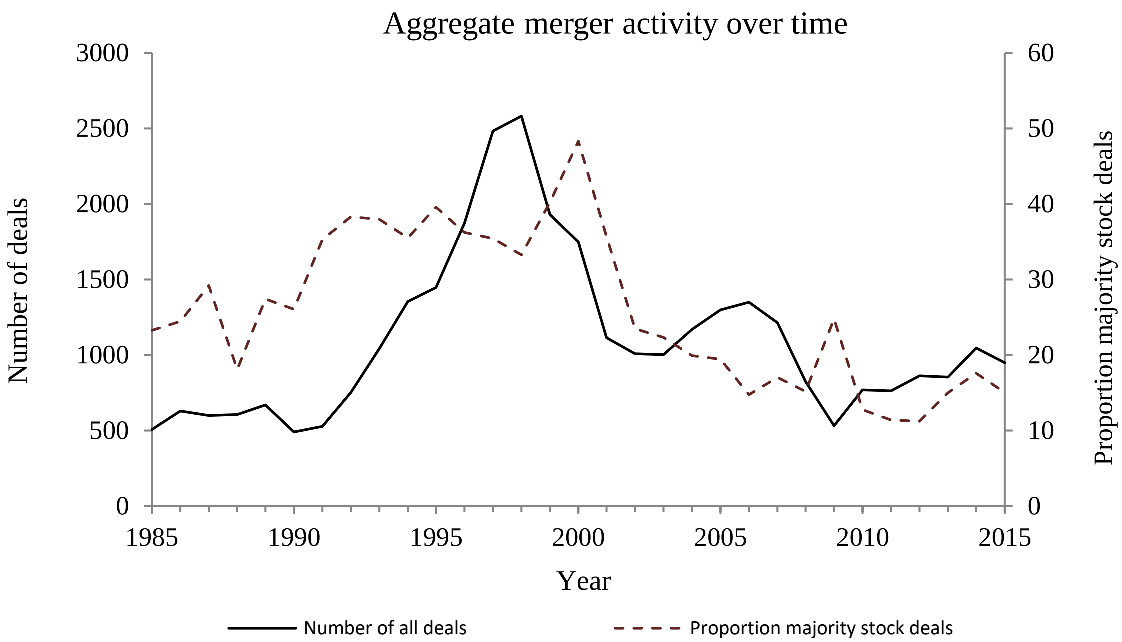

Figure 1: Aggregate merger activity over time. The sample of 34,009 acquisitions made by public acquirers during 1985-2015 is retrieved from the SDC database following criteria listed in Table 1, Panel A. It includes 7,875 public targets, 15,810 private targets, and 10,324 subsidiary targets. However, most of our analysis is confined to deals involving majority stock payment, or greater than 50% of consideration in the form of acquirer stock. This criterion leaves us with 3,915 public targets (50% of all public targets), 4,765 private targets (30%), and 897 subsidiary targets (9%). The solid line shows the number of all deals by year (left axis), and the broken line shows the proportion of deals involving majority stock payment (right axis).

The broken line shows the mean number of stock mergers per firm quarter using vertical scale on the right
The solid line shows the bucket number using vertical scale on the left

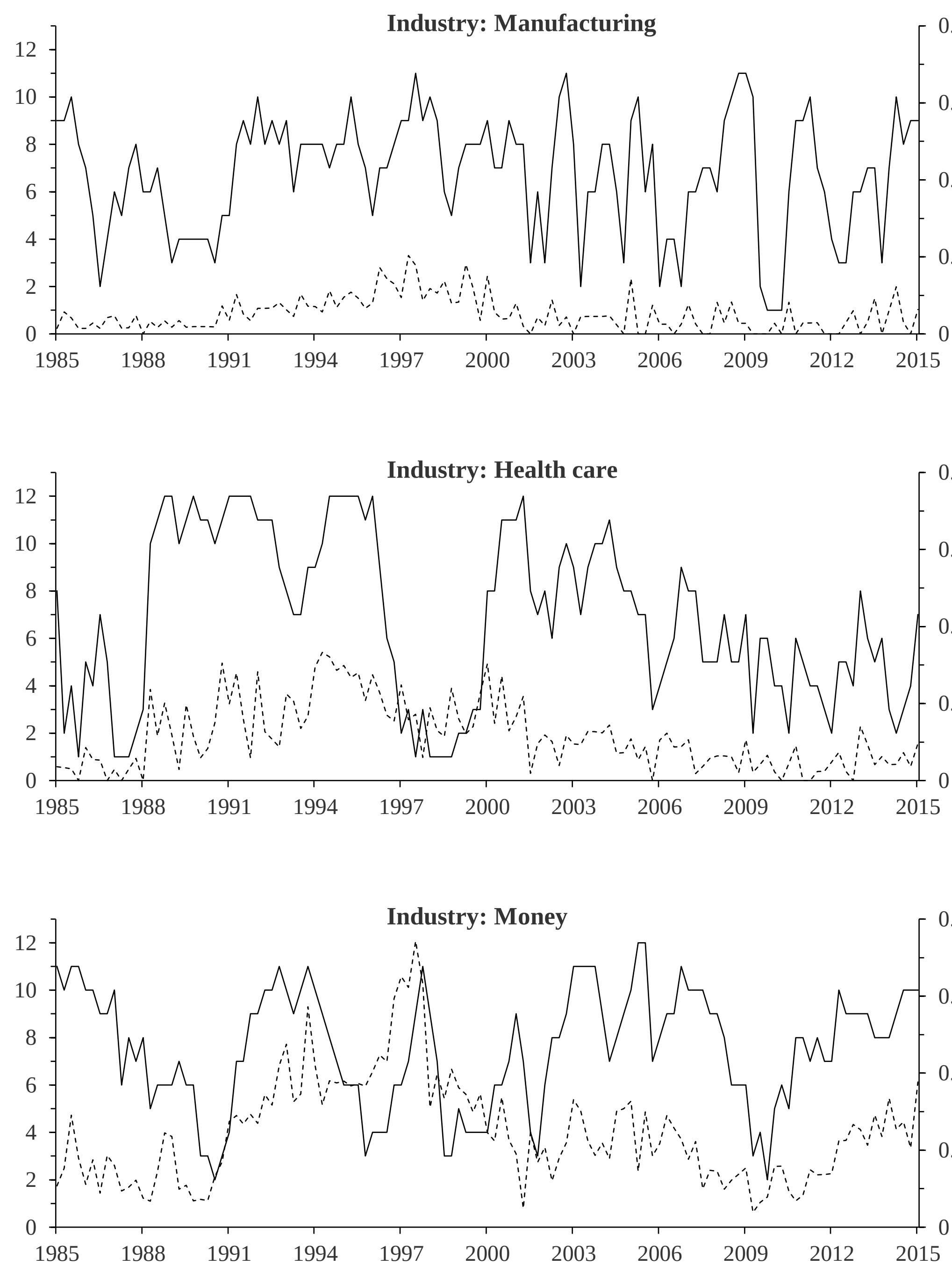

Figure 2: Relation between industry stock merger activity and bucket number for select industries by quarter. Quarterly industry stock merger activity is measured by the number of merger announcements divided by the number of firms in an industry over a calendar quarter. We calculate *MAV* for that industry during that quarter using Equation (1) in Section 3.2 and Table 3. We rank *MAV* for all Fama-French 12 industries within the quarter. Each industry is assigned to a bucket with the bucket number equal to its *MAV* rank. We choose three industries for illustration here that represent low, medium, and high overall stock merger activity during 1985-Q4 to 2015-Q4. Regardless of overall merger activity, the bucket numbers are about equally distributed over the range of 1 to 12.

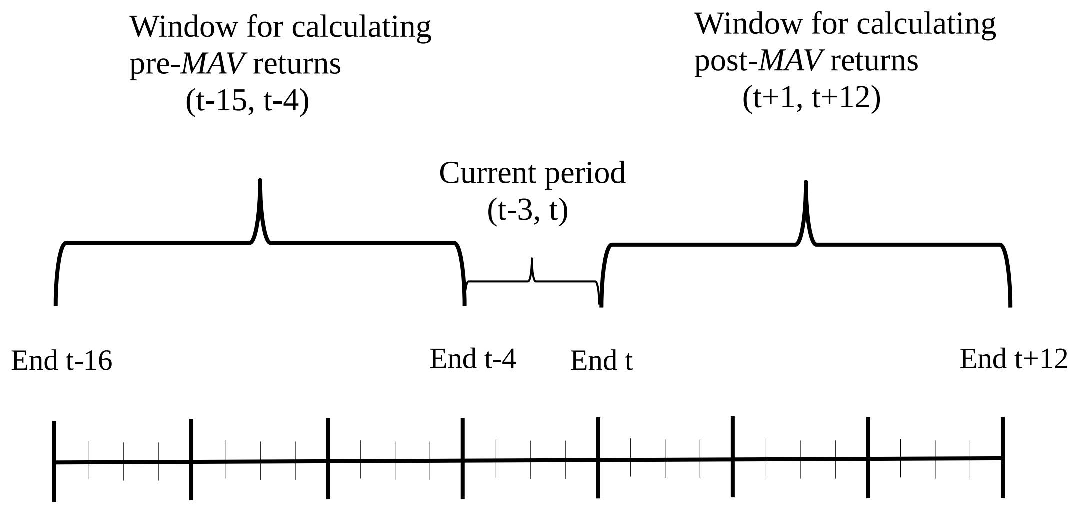

Figure 3: Timeline. $MAV_{jt,stk}$ for industry *j* during quarter t is calculated using majority stock mergers announced over the period from the beginning of quarter $t-3$ to the end of quarter t. See Section 3.2 and Equation (1) for further methodological details. The twelve industries *j* = 1 to 12 are next ranked within quarter t. For post-*MAV* returns, each industry *j* is added to an appropriate bucket based on its *MAV* rank, during the following period from the beginning of quarter $t+1$ to the end of quarter $t+12$. For pre-*MAV* returns, each industry *j* is added to an appropriate bucket based on its *MAV* rank, during the preceding period from the beginning of quarter $t-15$ to the end of quarter $t-4$.

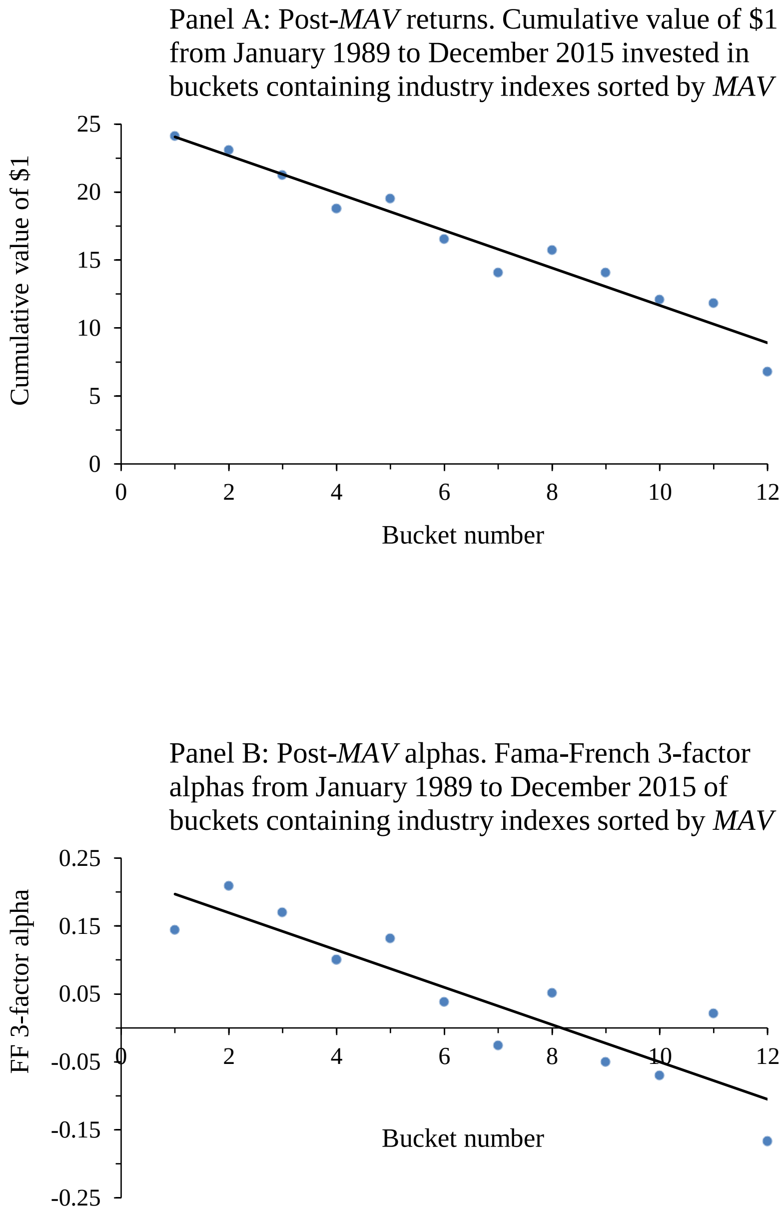

Figure 4: Post-*MAV* returns and alphas. This figure shows graphically the evidence presented in Table 4. We analyze the relation between stock merger activity of industries and their three-year post-merger activity returns. Please refer to Table 4 for all details of bucket formation and return and alpha calculations. Panel A of this figure shows the cumulative value of $1 invested in different buckets from the beginning of January 1989 to the end of December 2015 as numerically shown in the last column of Table 4, Panel A. In addition, Panel B of this figure shows the Fama-French 3-factor alphas for the same 12 buckets during the same period as numerically shown in the second column of Table 4, Panel B. The first graph has an adjusted-R^2 of 0.94, and the second graph has an adjusted-R^2 of 0.77.

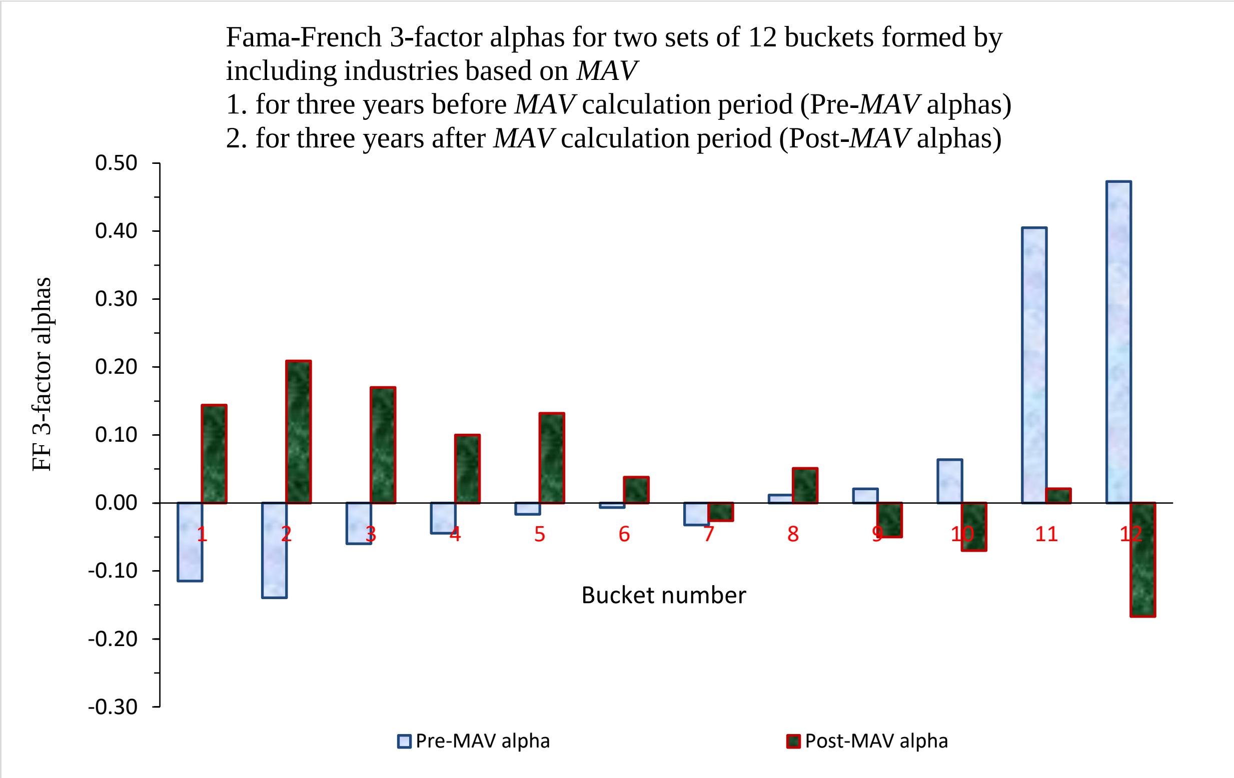

Figure 5: Contrasting pre-*MAV* and post-*MAV* alphas. We construct 12 buckets using industry stock merger activity variable $MAV_{jt,stk}$ for industry $j = 1$ to 12 and quarter t as described in Table 3. For the post-*MAV* alphas, we assign industries to 12 buckets based on their $MAV_{jt,stk}$ starting in quarter $t + 1$. Each entry to a bucket is held there for 12 quarters (i.e., until $t + 12$), and then dropped. Starting in 1989-Q1 and ending in 2015-Q4, at any time every bucket has 12 entries (industries), one entry during every one of the previous 12 quarters. Monthly returns for buckets are calculated as the arithmetic average of the value-weighted industry returns retrieved from Ken French's data library. We use this monthly return series to calculate post-MAV Fama-French 3-factor alphas. For the pre-*MAV* alphas, we assign industries to 12 buckets based on their $MAV_{jt,stk}$ starting in the quarter $t - 15$. Once again, each entry to a bucket is held there for 12 quarters (i.e., until $t - 4$), and then dropped. We calculate pre-MAV alphas from 1985-Q1 to 2011-Q4, a period during which each bucket has exactly 12 entries. The correlation between pre-*MAV* and post-*MAV* alphas equals -0.65 (significant at 5% level).

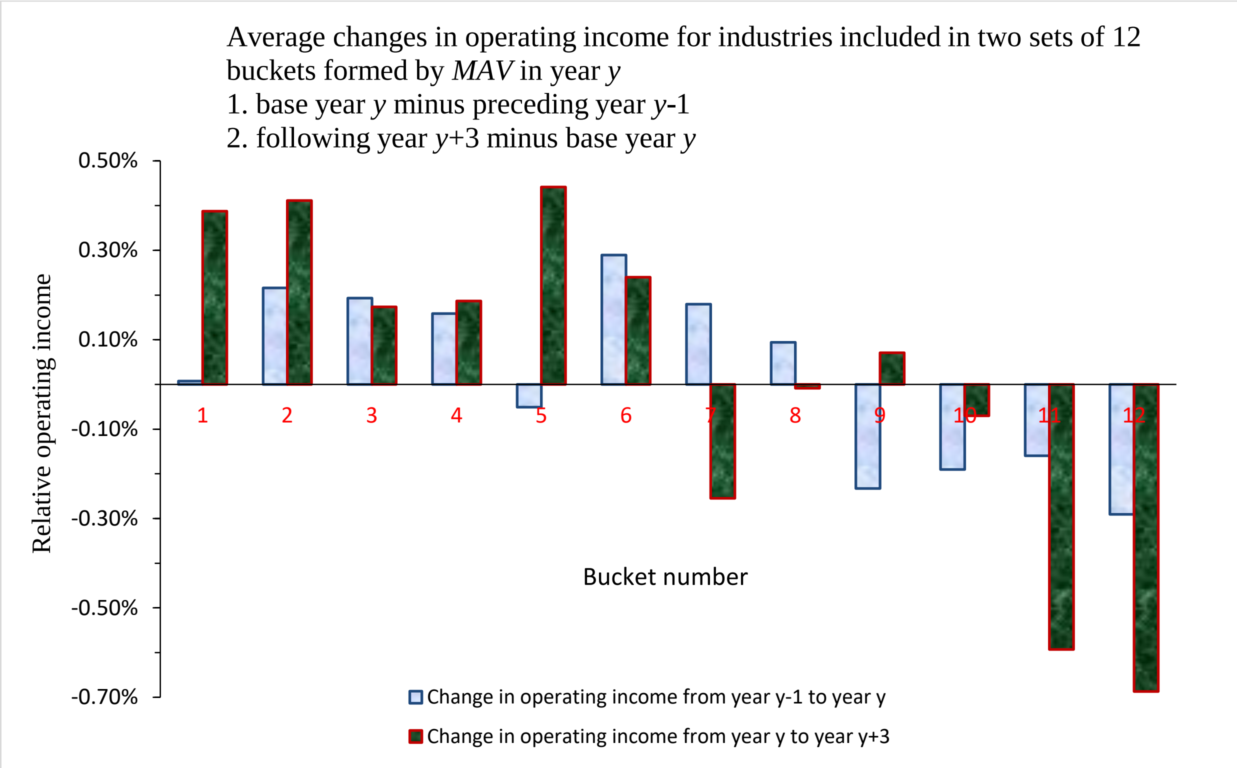

Figure 6: Changes in operating income. Table 6 describes the procedure of calculating the preceding and following three-year operating performance for industries assigned to 12 buckets based on their $MAV_{jt,stk}$ for industry j during quarter t. As noted, the first series (light-colored bars) represents mean change in operating income from year *y*-1 to year *y*, and the second series (dark-colored bars) represents mean change in operating income from year *y* to year *y*+3. The correlation between the two series equals 0.54 (significant at 10% level).

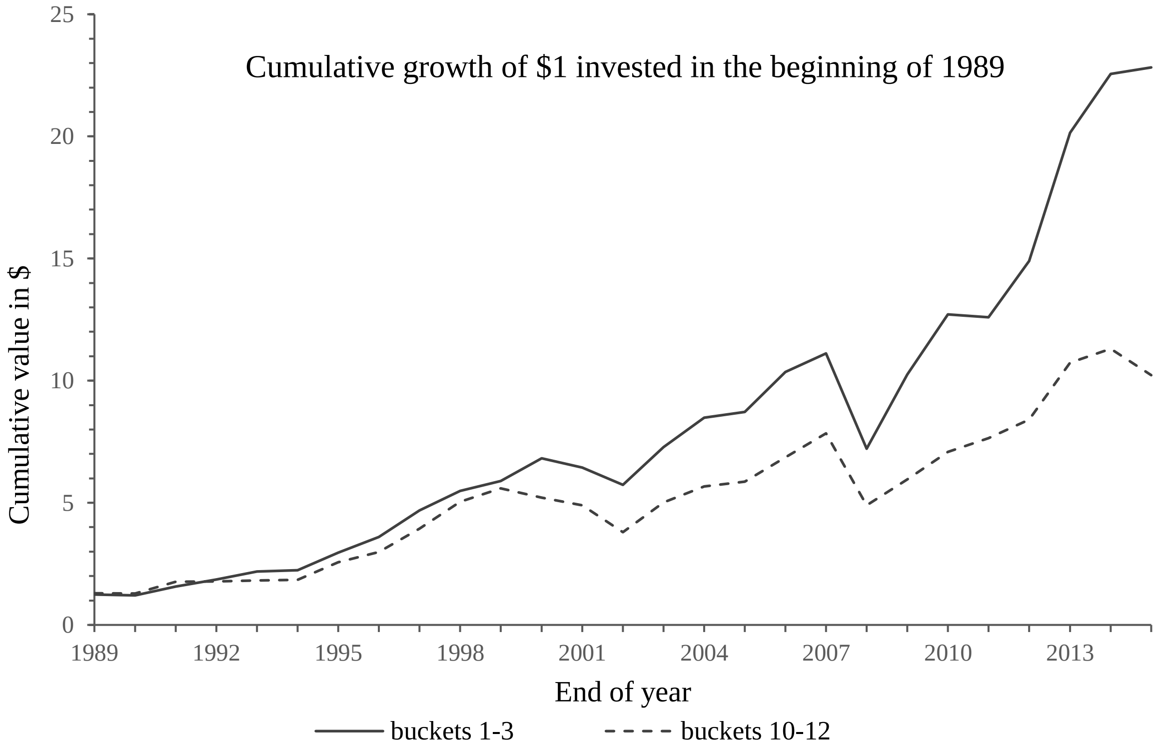

Figure 7: Cumulative growth over time of $1 invested in the beginning of 1989 by bucket number. For parsimony of presentation as well as to reduce noise, we show only two lines in this graph. First, the solid line is the average of cumulative growth over time for buckets numbered 1, 2, and 3. Second, the broken line is the average of cumulative growth over time for buckets numbered 10, 11, and 12. The bucket assignment procedure is based on the ranked value of *MAV* as described in Tables 3 and 4. Higher bucket numbers represent higher industry stock merger activity.

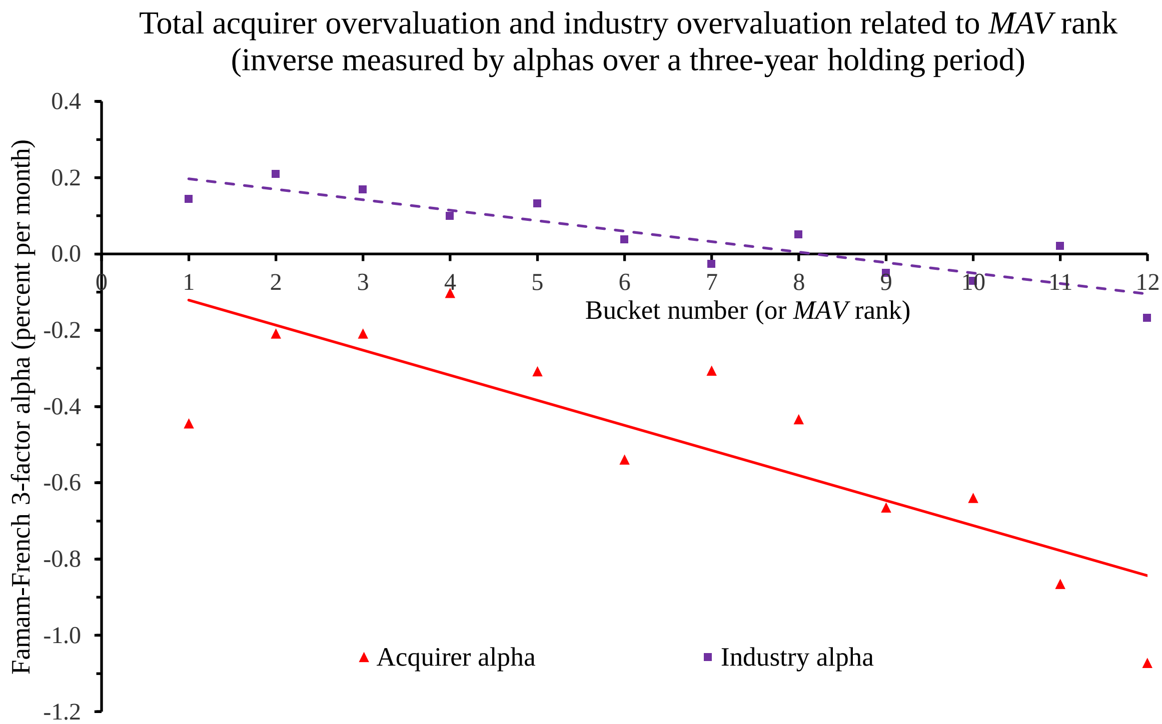

Figure 8: Components of total acquirer overvaluation related to bucket number (or *MAV* rank). The horizontal axis shows the bucket number, and the vertical axis shows the Fama-French 3-factor alphas. The solid line shows the acquirer alpha, which is calculated as described in Table 11 and is an inverse measure of total acquirer overvaluation. The broken line shows the corresponding industry alpha, which is calculated as described in Table 4 and is an inverse measure of the industry-wide component of total acquirer overvaluation. The distance between the two lines thus shows the firm-specific component of total acquirer overvaluation, all using a percent per month scale.

Table 1

Sample of mergers

Our sample period spans 1985-2015. We use the simpler term ‘merger’ to connote all types of acquisitions in this paper. Panel A of this table describes the procedure followed for identifying the sample of mergers, and Panel B describes the sample distribution by payment method and target type. Majority stock deals are those for which at least 50% of total payment is in the form of acquirer stock, and majority cash deals are those for which less than 50% of total payment is in the form of acquirer stock. Deal size, payment terms, and other merger details are obtained from the SDC database. Year (and later quarter) of merger is the calendar year (quarter) of announcement date.

Panel A: Sample retrieval

No.	Description	No of deals
1	All mergers done by U.S. public firms (acquirers) with U.S. targets during 1985-2015	125,914
2	Target firm is a public, private, or subsidiary firm	124,799
3	Deal form is ‘Merger’, ‘Acquisition of Assets’, or ‘Acq. Maj. Int.’	90,628
4	Percent of target shares owned by acquirer is 49% or less 6 months before announcement, and percent of shares acquired in transaction is 51% or more	90,595
5	In case of multiple offers for target within a 2-month window, include only the completed offer	89,940
6	Deal value is at least $10 million in 2015 dollars	34,009

Panel B: Sample distribution by payment method and target type

Target type → Payment method ↓	Public	Private	Subsidiary	All targets
Majority stock payment	3,915	4,765	897	9,577
Majority cash payment	3,960	11,045	9,427	24,432
All payment methods	7,875	15,810	10,324	34,009

Table 2

Merger activity by industry

The sample of all mergers is described in Table 1. We divide this sample by industry using the Fama-French 12-industry (FF-12) classification. We use the Compustat historic SIC codes from 1987 onwards and CRSP SIC codes before 1987 to identify which firm belongs to which industry in any year. We include only public firms listed on NYSE, AMEX, or NASDAQ and with a market value of equity of at least $10 million in 2015 dollars. The second column reports the mean number of firms at year-end, and the third and fourth columns show the number of all mergers during the aggregate period 1985-2015 as well as mergers that use majority stock payment. The last column reports the mean number of mergers per firm quarter that use majority stock payment. To understand the calculations, notice 161 (number of stock mergers during all years) divided by the product of 265 (mean number of firms) and 124 (number of calendar quarters) equals 0.0049 (mean number of stock mergers per firm-quarter) for the nondurables industry. That final figure is 0.31 times the corresponding figure of 0.0156 for all industries together reported in the last row.

		Number of mergers during all years 1985-2015		Mean number of mergers per firm-quarter
Industry	Mean number of firms at year-end	All payments	Majority stock payment (% of all payments in column to left)	Majority stock payment (proportion of all industries in last row)
1. Nondurables	265	1,176	161 (14)	0.0049 (0.31)
2. Durables	125	535	76 (14)	0.0049 (0.31)
3. Manufacturing	518	2,544	370 (15)	0.0058 (0.37)
4. Energy	171	1,873	336 (18)	0.0158 (1.01)
5. Chemicals	107	476	73 (15)	0.0055 (0.35)
6. Business Equipment	848	6,273	2,367 (38)	0.0225 (1.44)
7. Telecommunications	124	1,991	455 (23)	0.0296 (1.90)
8. Utilities	145	822	186 (23)	0.0103 (0.66)
9. Shops	500	2,128	506 (24)	0.0082 (0.52)
10. Healthcare	494	2,669	762 (29)	0.0124 (0.80)
11. Money	1,031	9,591	3,329 (35)	0.0260 (1.67)
12. Other	616	3,931	956 (24)	0.0125 (0.80)
All industries	4,944	34,009	9,577 (28)	0.0156 (1.00)

Table 3

Buckets formed by relative values of stock merger activity of industries

Each quarter t, starting with 1985-Q4 and ending with 2015-Q3, we compute stock merger activity variable $MAV_{jt,stk}$ for industry j during quarter t as follows:

$$MAV_{jt,stk} = \frac{\sum_{\tau=t-3}^{t} m_{j\tau,stk} / \sum_{\tau=t-3}^{t} n_{j\tau}}{\sum_{\tau=1}^{T} m_{j\tau,stk} / \sum_{\tau=1}^{T} n_{j\tau}}$$

where $m_{j\tau,stk}$ denotes the number of stock mergers announced by all acquiring firms in industry j during quarter τ, $n_{j\tau}$ denotes the number of firm-quarters, and T is the total number of calendar quarters. In our case, the aggregate sample period extends from 1985 to 2015, or $T = 124$ quarters. We then rank these 12 industries from lowest to highest values of $MAV_{jt,stk}$ and assign them one each to buckets numbered 1 (least stock merger active industry) to 12 (most stock merger active industry) starting in quarter $t+1$. Thus, the first quarter of bucket formation is 1986-Q1, and the last quarter is 2015-Q4. Each industry added to a bucket is kept there for 12 quarters. The first five columns of this table show the mean ratio of industry value to total market value (of equity), mean book-to-market, mean $MAV_{jt,stk}$, and number of mergers for industries added to a bucket, each variable calculated at the time of entry and then averaged over time. The last data column shows the mean number of distinct industries in any bucket in any quarter, from 1989-Q1 to 2015-Q4. (Our return measurement starts in 1989, which is the first full year when every month of the year we have 12 entries in each bucket, one entry during each of previous 12 quarters.) Industry book-to-market is calculated as the aggregate book value of all firms included in the industry divided by their aggregate market value at the end of quarter t. Only firms for which both book value and market value of equity data are available from Compustat and which lie within the 1 and 99 percentile of the distribution of book-to-market values are included. Notations *, **, and *** represent statistical significance at 10, 5, and 1 percent levels.

Bucket number	Mean ratio of industry value to total market value	Mean book-to-market of industries	Mean $MAV_{jt,stk}$ of industries	Mean number of stock mergers per firm-quarter of industries	Mean number of distinct industries in bucket in any quarter starting in 1989-Q1
	Below variables are computed at the time of entry of an industry to a bucket, and then averaged across all quarters				
1 (least merger active)	0.057	0.530	0.348	0.0039	4.94
2	0.079	0.462	0.495	0.0063	5.99
3	0.088	0.508	0.598	0.0093	6.35
4	0.088	0.512	0.667	0.0104	6.06
5	0.078	0.515	0.742	0.0094	6.54
6	0.087	0.516	0.823	0.0134	6.54
7	0.092	0.499	0.915	0.0122	7.25
8	0.094	0.522	1.007	0.0131	6.27
9	0.093	0.535	1.123	0.0155	6.44
10	0.083	0.550	1.246	0.0148	6.76
11	0.080	0.498	1.444	0.0160	4.97
12 (most merger active)	0.081	0.471	1.841	0.0204	3.99
Correlation between bucket number and variable	0.41	0.04	0.97^{***}	0.96^{***}	-0.21

Table 4

Stock merger activity of industries and their following three-year returns (Post-MAV raw returns and alphas)

This table analyzes the relation between stock merger activity of industries and their three-year **post**-merger activity returns. We construct 12 buckets using industry stock merger activity variable $MAV_{jt,stk}$ for industry $j = 1$ to 12 and quarter t as described in Sections 3.2 and 3.3 and Table 3. Starting in 1989-Q1 and ending in 2015-Q4, at any time every bucket has 12 entries (industries), one entry during every one of the previous 12 quarters. Alternately stated, every quarter every bucket gets one new entry based on the last quarter's stock merger activity and that entry stays in that bucket for 12 quarters. These 12 entries in a bucket usually represent fewer than 12 distinct industries as shown in Table 3. Figure 3 shows other timeline details. Monthly returns for buckets are calculated as the arithmetic average of value-weighted industry returns retrieved from Ken French's data library. This procedure is identical to what is typical for calendar-time portfolios of acquirers in the literature, except that instead of individual acquirers we enter value-weighted industry indexes (or ETFs). Annual returns for buckets are next calculated by cumulating monthly returns. Panel A analyzes post-merger activity raw returns for each bucket using statistics of average annual returns, standard deviation of annual returns, and Sharpe ratios. We also report the cumulative value of $1 invested in every bucket from the beginning of 1989 to the end of 2015 (a period of 27 years). Panel B reports the Fama-French 3-factor alphas and other model outputs. Variables $RMRF$, SMB, and HML are factor returns, defined as the returns on zero-investment portfolios of market minus riskfree asset, small minus big stocks, and high minus low book-to-market stocks (Fama and French 1993). Alpha values are in percent per month. The last rows of Panels A and B report results of a univariate regression of the corresponding column variable on the bucket number. Value-weighted market returns are measured by CRSP variable VWRETD. A better benchmark is an equally weighted portfolio of all 12 industries that computes monthly portfolio returns as the arithmetic average of monthly industry returns. Notations *, **, and *** represent statistical significance at 10, 5, and 1 percent levels.

Panel A: ***Raw returns*** *for buckets containing industries ranked by their stock merger activity, 1989-2015*

Bucket number	Average annual return	Standard deviation of annual return	Sharpe ratio of annual return	Cumulative value of $1 invested in the beginning of 1989 by the end of 2015
1 (least merger active)	14.07%	18.28%	0.596	$24.13
2	13.58	16.24	0.641	23.08
3	13.34	16.73	0.608	21.26
4	12.89	17.05	0.570	18.77
5	13.12	17.37	0.573	19.50
6	12.58	18.37	0.512	16.54
7	11.96	18.64	0.471	14.06
8	12.18	17.24	0.523	15.74
9	12.08	19.21	0.464	14.06
10	11.34	18.52	0.443	12.08
11	11.11	17.98	0.442	11.81
12 (most merger active)	9.18	19.76	0.304	6.77
Correlation between variable and bucket number	-0.93***	0.67**	-0.92***	-0.97***
Slope of variable regressed on bucket number, t-statistic in round brackets, and adj-R^2 in square brackets	-0.34% (-7.97)*** [0.85]	0.19% (2.81)** [0.39]	-0.024 (-7.63)*** [0.84]	-$1.38 (-13.16)*** [0.94]
Value-weighted market returns	11.54	18.47	0.455	12.68
Equally-weighted portfolio of all 12 industries	12.26	17.03	0.534	16.13

Table 4 continued …

Panel B: ***Fama-French 3-factor alphas*** *for buckets containing industries ranked by their stock merger activity, 1989-2015*

Bucket number	Alpha (t-statistic)	Coefficients of *RMRF*	Coefficients of *SMB*	Coefficients of *HML*	Adjusted-R^2
1 (least merger active)	0.144 (1.29)	0.959	0.010	0.445	0.80
2	0.209 (2.32)**	0.843	-0.023	0.286	0.83
3	0.170 (2.25)**	0.895	-0.007	0.182	0.89
4	0.100 (1.27)	0.951	-0.049	0.240	0.89
5	0.132 (2.06)**	0.920	0.024	0.144	0.92
6	0.038 (0.62)	0.983	-0.037	0.259	0.94
7	-0.026 (-0.49)	1.031	0.028	0.165	0.95
8	0.051 (0.98)	0.957	-0.010	0.134	0.95
9	-0.050 (-0.73)	1.058	-0.038	0.282	0.93
10	-0.070 (-0.92)	0.996	-0.029	0.299	0.90
11	0.021 (0.19)	0.932	-0.235	0.099	0.79
12 (most merger active)	-0.167 (-1.58)	0.991	-0.111	-0.059	0.84
Correlation between bucket number and variable	-0.89***	0.55*	-0.59**	-0.63**	
Slope of variable regressed on bucket number, *t*-statistic in round brackets, and adj-R^2 in square brackets	-0.027% (-6.20)*** [0.77]	0.009 (2.08)* [0.23]	-0.012 (-2.32)** [0.29]	-0.022 (-2.58)** [0.34]	
Equally-weighted portfolio of all 12 industries	0.046 (1.24)	0.960	-0.040	0.206	0.97

Table 5

Stock merger activity of industries and their preceding three-year returns (Pre-MAV alphas)

This table analyzes the relation between stock merger activity of industries and their **preceding** three-year excess returns. Each calendar quarter t, starting with 1985-Q4 and ending with 2015-Q3, we compute stock merger activity variable $MAV_{jt,stk}$ for $j = 1$ to 12 industries as described in Sections 3.2 and 3.3 and Table 3. We then rank these 12 industries from lowest to highest values of $MAV_{jt,stk}$ and add them to buckets numbered 1 (least stock merger active industry) to 12 (most stock merger active industry), this time over a period starting with the first month of quarter $t - 15$ and ending with the last month of quarter $t - 4$. Thus, each entry to a bucket stays there for exactly 12 quarters preceding the period from quarter $t - 3$ to t over which we calculate $MAV_{jt,stk}$. Figure 3 shows other timeline details. We calculate monthly bucket returns from 1985-Q1 to 2011-Q4, a period during which each bucket has exactly 12 entries. Notice the number of distinct industries that constitute these 12 entries in a bucket will be less than 12. Monthly returns for buckets are calculated as the arithmetic average of value-weighted industry returns retrieved from Ken French's data library. This table reports the Fama-French 3-factor alphas and other model outputs. Alpha values are in percent per month. The last row of this table reports results of a univariate regression of the corresponding column variable on the bucket number. Notations *, **, and *** represent statistical significance at 10, 5, and 1 percent levels.

Bucket number	Alpha (t-statistic)	Coefficients of			Adjusted-R^2
		RMRF	*SMB*	*HML*	
1 (least merger active)	-0.115 (-1.13)	1.009	-0.052	0.338	0.86
2	-0.139 (-1.46)	0.936	-0.008	0.344	0.86
3	-0.060 (-0.70)	0.986	-0.043	0.239	0.89
4	-0.044 (-0.53)	1.006	-0.069	0.222	0.90
5	-0.017 (-0.25)	0.960	-0.044	0.172	0.93
6	-0.007 (-0.12)	0.986	-0.064	0.289	0.95
7	-0.032 (-0.55)	1.065	-0.029	0.175	0.96
8	0.012 (0.22)	1.007	0.000	0.142	0.92
9	0.021 (0.28)	1.014	0.002	0.253	0.93
10	0.064 (0.84)	0.971	-0.016	0.164	0.91
11	0.405 (3.26)***	0.863	-0.103	0.166	0.75
12 (most merger active)	0.473 (4.35)***	0.851	-0.098	-0.154	0.81
Correlation between bucket number and variable	0.83***	-0.46	-0.24	-0.74***	
Slope of variable regressed on bucket number, *t*-statistic in round brackets, and adj-R^2 in square brackets	0.044% (4.67)*** [0.65]	-0.008 (-1.62) [0.13]	-0.002 (-0.77) [-0.04]	-0.027 (-3.46)*** [0.50]	

Table 6

Stock merger activity of industries and their preceding and following three-year operating performance

This table analyzes the relation between stock merger activity of industries and their preceding and following three-year operating performance. We use annual operating income data for this purpose. To understand the bucket assignment procedure, consider year $y = 2004$ as an example. Each calendar quarter from 2004-Q3 to 2005-Q2, we compute stock merger activity variable $MAV_{jt,stk}$ for $j = 1$ to 12 industries as described in Sections 3.2 and 3.3 and Table 3. We then rank these 12 industries from lowest to highest values of $MAV_{jt,stk}$ every quarter and add them to buckets numbered 1 (least stock merger active industry) to 12 (most stock merger active industry) every quarter. Given the annual nature of this experiment, we will have four industries, usually non-distinct, in every bucket, for year 2004. We extend this bucket assignment procedure to all years $y = 1989$ to 2014 (the last year of complete accounting data). We next calculate the mean operating income for the base year y for a bucket by averaging the operating income for every industry in that bucket during its year of entry. Industry operating income is calculated as the aggregate operating income before depreciation (OIBDP) of all firms included in the industry divided by the aggregate assets (AT, average of beginning and end of year values). Only firms for which OIBDP and AT are both available from Compustat and which lie inside the 1 and 99 percentile of the distribution of OIBDP/AT for a given industry and year are included. For the base year y we report the mean operating income in the middle column below, for the preceding years $y-3$ to $y-1$ we report the base year income minus the preceding year income, and for the following years $y+1$ to $y+3$ we report the following year income minus the base year income (in both cases, after minus before). The last column shows the cumulative change in operating income from year $y-1$ to $y+3$, the period over which a significant trend is detected. The last row reports results of a univariate regression of a column variable on the bucket number. Notations *, **, and *** represent statistical significance at 10, 5, and 1 percent levels.

	Mean value of base year operating income minus preceding year operating income			Mean operating income for base year of stock merger activity	Mean value of following year operating income minus base year operating income			Change in operating income from year $y-1$ to $y+3$
Bucket number	$y-3$	$y-2$	$y-1$	Year y	$y+1$	$y+2$	$y+3$	
1 (least merger active)	-0.44%	-0.18%	0.01%	13.96%	0.25%	0.43%	0.48%	0.49%
2	0.10	0.27	0.22	14.23	0.29	0.58	0.37	0.58
3	0.43	0.32	0.19	13.62	0.06	0.25	0.21	0.40
4	0.27	0.20	0.16	12.77	0.18	0.36	0.02	0.18
5	-0.17	-0.15	-0.05	13.14	0.23	0.50	0.60	0.54
6	-0.01	0.16	0.29	12.19	0.29	0.13	0.30	0.59
7	0.32	0.42	0.18	12.55	-0.13	-0.33	-0.31	-0.13
8	-0.12	0.07	0.09	12.24	0.01	-0.02	-0.02	0.08
9	-0.44	-0.54	-0.23	11.85	0.01	0.04	0.17	-0.06
10	-0.07	-0.06	-0.19	12.49	-0.12	-0.12	0.04	-0.15
11	0.94	0.38	-0.16	15.17	-0.33	-0.63	-0.82	-0.98
12 (most merger active)	-0.61	-0.41	-0.29	15.17	-0.51	-0.72	-0.84	-1.13
Average	0.02	0.04	0.02	13.28	0.02	0.04	0.02	0.03
Correlation between bucket number and variable	-0.03	-0.28	-0.70^{**}		-0.85^{***}	-0.88^{***}	-0.77^{***}	-0.85^{***}
Slope of variable regressed on bucket number, t-statistic in round brackets, and adj-R^2 in square brackets	-0.003% (-0.09) [-0.10]	-0.024% (-0.93) [-0.01]	-0.038% $(-3.08)^{**}$ [0.44]		-0.060% $(-5.06)^{***}$ [0.72]	-0.104% $(-5.87)^{***}$ [0.75]	-0.098% $(-3.78)^{***}$ [0.55]	-0.137% $(-5.14)^{***}$ [0.70]

Table 7

Stock merger activity of industries and their following three-year returns – Results using the alternate Fama-French 48 industry classification

This table analyzes the relation between stock merger activity of industries and their three-year **post**-*MAV* returns. It is similar to Table 4 in most respects, except that we use the Fama-French **48** industry classification here instead of the 12-industry classification in that table. This requires modification to the bucket assignment procedure as follows. We calculate $MAV_{jt,stk}$ for industry $j = 1$ to $\mathbf{48}$ and quarter t as described in Sections 3.2 and 3.3 and Table 3. We rank industries based on $MAV_{jt,stk}$, and assign 4 least stock merger active industries to bucket 1, next 4 to bucket 2, and so on, until the 4 most stock merger active industries are assigned to bucket 12. See Table 4 for details of performance measurement using raw returns in Panel A and Fama-French 3-factor alphas in Panel B below. We also report statistics for the CRSP value-weighted market returns (VWRETD). However, a better benchmark is an equally weighted portfolio of all 48 industries that computes monthly portfolio returns as the arithmetic average of monthly industry returns. Notations *, **, and *** represent statistical significance at 10, 5, and 1 percent levels.

Panel A: ***Raw returns*** *for buckets containing industries ranked by their stock merger activity, 1989-2015*

Bucket number	Average annual return	Standard deviation of annual return	Sharpe ratio of annual return	Cumulative value of $1 invested in the beginning of 1989 by the end of 2015
1 (least active)	14.97%	18.13%	0.651	$30.36
2	13.36	18.64	0.547	20.12
3	11.94	18.15	0.483	14.04
4	12.99	19.55	0.502	17.40
5	13.48	19.29	0.535	19.72
6	10.92	16.86	0.459	11.60
7	12.49	17.26	0.540	17.00
8	12.11	17.39	0.514	15.33
9	11.70	16.95	0.503	14.27
10	11.79	18.19	0.474	13.74
11	9.87	21.52	0.312	7.14
12 (most active)	11.69	19.06	0.447	13.07
Correlation between variable and bucket number	-0.74***	0.17	-0.70**	-0.73***
Slope of variable regressed on bucket number, *t*-statistic in round brackets, and adj-R^2 in square brackets	-0.27% (-3.49)*** [0.50]	0.06% (0.56) [-0.07]	-0.015 (-3.11)** [0.44]	-$1.16 (-3.42)*** [0.49]
Value-weighted market returns	11.54	18.47	0.455	12.68
Equally-weighted portfolio of all 48 industries	12.25	17.34	0.524	15.90

Table 7 continued … 48-industry classification …

*Panel B: **Fama-French 3-factor alphas** for buckets containing industries ranked by their stock merger activity, 1989-2015*

Bucket number	Alpha (t-statistic)	Coefficients of *RMRF*	Coefficients of *SMB*	Coefficients of *HML*	Adjusted-R^2
1 (least active)	0.374 (2.35)**	0.760	-0.085	0.258	0.55
2	0.034 (0.29)	1.015	0.263	0.488	0.82
3	-0.125 (-0.94)	1.098	0.326	0.567	0.81
4	-0.006 (-0.05)	1.023	0.277	0.451	0.80
5	0.054 (0.66)	1.037	0.186	0.251	0.91
6	-0.106 (-1.39)	0.988	0.134	0.369	0.91
7	0.041 (0.74)	1.001	0.049	0.184	0.95
8	0.008 (0.15)	1.002	0.074	0.175	0.95
9	-0.010 (-0.17)	1.004	0.097	0.144	0.94
10	-0.060 (-0.76)	1.034	0.086	0.314	0.91
11	-0.346 (-3.48)***	1.194	0.121	0.402	0.89
12 (most active)	-0.052 (-0.39)	1.012	0.096	0.346	0.76
Correlation between bucket number and variable	-0.59**	0.48	-0.26	-0.34	
Slope of variable regressed on bucket number, *t*-statistic in round brackets, and adj-R^2 in square brackets	-0.027% (-2.31)** [0.28]	0.013 (1.73) [0.15]	-0.008 (-0.84) [-0.03]	-0.012 (-1.12) [0.02]	
Equally-weighted portfolio of all 48 industries	-0.016 (-0.25)	1.014	0.135	0.329	0.93

Table 8

Stock merger activity of industries and their following three-year returns – Using MAV variable calculated using only historical information

This table is identical to Table 4 except in one respect: Unlike an extant literature that uses both backward and forward looking information in identifying industry merger waves, we construct an MAV variable that only uses backward looking (i.e., historical) information on industry stock merger activity. Thus, in some departure from the initial definition provided in Table 3, we calculate $MAV_{jt,stk}$ for industry j during quarter t as follows:

$$MAV_{jt,stk} = \frac{\sum_{\tau=t-3}^{t} m_{j\tau,stk} / \sum_{\tau=t-3}^{t} n_{j\tau}}{\sum_{\tau=1}^{t} m_{j\tau,stk} / \sum_{\tau=1}^{t} n_{j\tau}}$$

where $m_{j\tau,stk}$ denotes the number of stock mergers made by all acquiring firms in industry j during quarter τ, $n_{j\tau}$ denotes the number of firm-quarters, and $t = 1$ to T indexes the calendar quarters. Notice that the denominator only captures historical merger activity until quarter t, the quarter of calculating the industry stock merger activity variable. We next rank the Fama-French 12 industries from lowest to highest values of $MAV_{jt,stk}$, and assign them to corresponding buckets. We keep the industries entering the buckets for a period of three years, or 12 quarters. We require at least 10 years of historical information to calculate *MAV*. Since our mergers data starts in 1985, the first industry assignment occurs in 1995-Q1, and all of the buckets have a steady-state 12 industries only from 1997-Q4 onwards. We begin portfolio return computation in 1998-Q1 and end in 2015-Q4, a period of 18 years, or 216 months. Return calculation procedure and the corresponding performance statistics are the same as in Table 4. We also report statistics for the CRSP value-weighted market returns (VWRETD). However, a better benchmark is an equally weighted portfolio of all 12 industries that computes monthly portfolio returns as the arithmetic average of monthly industry returns. Notations *, **, and *** represent statistical significance at 10, 5, and 1 percent levels.

*Panel A: **Raw returns** for buckets containing industries ranked by their stock merger activity, 1998-2015*

Bucket number	Average annual return	Standard deviation of annual return	Sharpe ratio of annual return	Cumulative value of $1 invested in the beginning of 1998 by the end of 2015
1 (least active)	11.00%	21.58%	0.413	$4.62
2	9.43	17.53	0.419	3.97
3	10.62	17.62	0.484	4.80
4	11.04	18.32	0.489	5.03
5	9.61	17.77	0.424	4.03
6	9.05	16.81	0.415	3.81
7	9.62	19.74	0.382	3.80
8	8.55	20.00	0.323	3.15
9	8.31	17.64	0.353	3.24
10	7.74	21.15	0.268	2.62
11	8.71	16.41	0.404	3.57
12 (most active)	8.02	20.35	0.292	2.87
Correlation between variable and bucket number	-0.85***	0.05	-0.73***	-0.83***
Slope of variable regressed on bucket number, t-statistic in round brackets, and adj-R^2 in square brackets	-0.27% (5.07)*** [0.69]	0.03% (0.17) [-0.10]	-0.014 (-3.39)*** [0.49]	-$0.17 (-4.64)*** [0.55]
Value-weighted market returns	8.24	19.40	0.311	3.04
Equally-weighted portfolio of all 12 industries	9.27	17.72	0.406	3.81

Table 8 continued … Using only historical information to calculate *MAV* …

Panel B: ***Fama-French 3-factor alphas*** *for buckets containing industries ranked by their stock merger activity, 1998-2015*

Bucket number	Alpha (t-statistic)	Coefficients of *RMRF*	Coefficients of *SMB*	Coefficients of *HML*	Adjusted-R^2
1 (least active)	0.169 (1.02)	0.922	0.023	0.416	0.75
2	0.135 (1.41)	0.869	-0.062	0.256	0.89
3	0.217 (2.29)**	0.878	-0.061	0.283	0.89
4	0.228 (2.49)**	0.901	-0.068	0.322	0.90
5	0.150 (1.59)	0.914	-0.123	0.207	0.90
6	0.101 (1.46)	0.936	-0.085	0.229	0.95
7	0.055 (0.65)	1.000	0.000	0.327	0.93
8	-0.021 (-0.29)	1.038	-0.021	0.185	0.95
9	-0.012 (-0.14)	1.012	-0.039	0.312	0.93
10	-0.115 (-1.04)	1.061	0.060	0.153	0.90
11	0.120 (0.96)	0.878	-0.143	0.181	0.82
12 (most active)	0.025 (0.16)	0.998	-0.121	-0.038	0.79
Correlation between bucket number and variable	-0.71***	0.59**	-0.19	-0.73***	
Slope of variable regressed on bucket number, *t*-statistic in round brackets, and adj-R^2 in square brackets	-0.020% (-3.15)*** [0.45]	0.011 (2.33)** [0.76]	-0.003 (-0.61) [-0.06]	-0.023 (-3.33)*** [0.48]	
Equally-weighted portfolio of all 12 industries	0.088 (1.80)*	0.951	-0.053	0.236	0.97

Table 9

Stock merger activity of industries and their preceding and following three-year asset turnover

The bucket assignment and all other procedures in this table are identical to those in Table 6. This table analyzes industry asset turnover, calculated as the aggregate sales (SALE) of all firms included in the industry divided by the aggregate assets (AT, average of beginning and end of year values). Notations *, **, and *** represent statistical significance at 10, 5, and 1 percent levels.

Bucket number	Mean value of base year asset turnover minus preceding year asset turnover			Mean asset turnover for base year of stock merger activity	Mean value of following year asset turnover minus base year asset turnover			Change in asset turnover from year $y-1$ to $y+3$
	$y-3$	$y-2$	$y-1$	Year y	$y+1$	$y+2$	$y+3$	
1 (least merger active)	-2.09%	-0.79%	0.56%	91.26%	0.62%	1.52%	3.57%	4.13%
2	2.66	2.52	1.11	96.55	0.50	3.79	2.96	4.06
3	3.76	2.85	1.20	85.07	0.30	1.09	1.67	2.88
4	0.08	0.12	0.42	86.41	1.11	1.85	3.33	3.75
5	1.69	0.46	0.24	91.10	1.30	1.78	3.16	3.40
6	2.51	2.45	1.79	76.67	0.95	0.68	1.46	3.26
7	4.20	2.43	0.19	82.79	0.13	-0.90	-0.14	0.05
8	0.23	1.01	0.50	79.38	-0.23	0.88	0.37	0.87
9	0.38	-1.26	-0.28	75.35	0.70	1.50	2.07	1.79
10	0.17	-0.66	-0.87	80.07	-0.55	0.13	0.94	0.07
11	2.59	0.25	-1.21	93.19	-0.83	-1.35	-1.15	-2.36
12 (most merger active)	-2.69	-1.77	-0.76	89.91	-1.11	-3.37	-4.74	-5.50
Average	1.12	0.63	0.24	85.65	0.24	0.63	1.13	1.37
Correlation between bucket number and variable	-0.20	-0.48	-0.76***		-0.72***	-0.77***	-0.80***	-0.87***
Slope of variable regressed on bucket number, *t*-statistic in round brackets, and adj-R^2 in square brackets	-0.12% (-0.63) [-0.06]	-0.021% (-1.71) [0.15]	-0.019% (-3.69)*** [0.53]		-0.16% (-3.28)*** [0.47]	-0.39% (-3.86)*** [0.56]	-0.52% (-4.20)*** [0.60]	-0.71% (-5.66)*** [0.74]

Table 10

Cash merger activity of industries and their preceding and following returns and operating performance

The sample for investigation in this table begins with 3,960 public cash acquisitions during 1985-2015 as described in Panel B of Table 1. The bucket assignment is identical to that described in Table 3, except that we replace quarterly stock merger activity by quarterly public cash merger activity for industries. In other words, the terms $m_{j\tau,stk}$ and $MAV_{jt,stk}$ in the equation of Table 3 are replaced by the terms $m_{j\tau,cash}$ and $MAV_{jt,cash}$. We report below the main statistics from Tables 4 to 6 for cash merger activity. The calculation details of these statistics are shown in those tables. Notations *, **, and *** represent statistical significance at 10, 5, and 1 percent levels.

	Returns			Operating performance		
Bucket number	Post-MAV mean annual return for bucket	Post-MAV alpha (*t*-statistic)	Pre-MAV alpha (*t*-statistic)	Base year *y* minus prior year *y*-1 operating income	Mean operating income for base year *y*	Subsequent year *y*+3 minus base year *y* operating income
Compare to →	Table 4, Panel A	Table 4, Panel B	Table 5	Table 6	Table 6	Table 6
1 (least cash merger active)	12.85%	0.144 (1.50)	-0.056 (-0.46)	0.17%	12.65%	0.35%
2	10.82	-0.045 (-0.51)	0.029 (0.32)	-0.36	14.23	0.07
3	12.10	0.067 (0.70)	0.177 (2.10)**	0.02	13.89	0.01
4	11.68	-0.030 (-0.49)	-0.055 (-0.93)	0.01	12.59	0.22
5	12.00	0.033 (0.52)	0.033 (0.50)	0.07	12.64	0.19
6	11.69	-0.020 (-0.33)	0.065 (1.05)	0.14	13.31	-0.19
7	11.76	-0.032 (-0.50)	-0.015 (-0.26)	0.16	12.11	-0.28
8	12.26	-0.030 (-0.43)	0.151 (2.63)***	-0.01	13.69	0.09
9	13.40	0.124 (2.23)**	0.068 (1.04)	-0.03	13.29	0.00
10	13.16	0.064 (0.86)	-0.028 (-0.38)	0.08	13.07	-0.27
11	13.17	0.138 (1.60)	-0.044 (-0.44)	-0.13	13.52	0.41
12 (most cash merger active)	12.60	0.140 (1.19)	0.235 (2.05)**	0.12	14.37	-0.39
Correlation between variable and bucket number	0.58**	0.36	0.26	0.12		-0.42
Slope of variable regressed on bucket number, *t*-statistic in round brackets, and adj-R^2 in square brackets	0.12% (2.24)** [0.27]	0.008 (1.21) [0.04]	0.007 0.85 [-0.03]	0.000 (0.40) [-0.08]		-0.000 (-1.45) [0.09]

Table 11

Industry stock merger activity and individual stock acquirer overvaluation

The methodology and sampling in this experiment correspond closely with those in Table 4 for the industry alphas experiment. The main difference is that here we add individual stock acquirers to buckets instead of whole industries. Each quarter t from 1986-Q1 to 2015-Q3, and for each Fama-French industry $j = 1$ to 12, we calculate $MAV_{jt,stk}$, which is the stock merger activity variable as defined in Sections 3.2 and 3.3 and Table 3. We rank the 12 $MAV_{jt,stk}$ values during the quarter. We then add all stock acquirer firms in each industry to a bucket with the same number as that industry's MAV rank. The inclusion period is 36-month long, starting in quarter $t + 1$ and ending in quarter $t + 12$. Monthly bucket returns are calculated as equally weighted average of individual stock acquirer returns. We next calculate acquirer alphas using bucket returns during the 27-year period from January 1989 to December 2015. This is the exact same period as used for calculating industry alphas in Table 4, which are reproduced below from that table. We carry out univariate regressions of acquirer alphas and industry alphas on bucket numbers, and the results are as follows:

Acquirer alpha = -0.0553-0.0657×bucket number, Adj-R^2 = 0.64   Industry alpha = 0.2244-0.0275×bucket number, Adj-R^2 = 0.77

(Acquirer-Industry) alpha = -0.2797-0.0382×bucket number

The coefficient of bucket number in the acquirer alpha and industry alpha regressions is significant at 1% level, and in the (Acquirer-Industry) alpha regression at 5% level. Using these fitted trend-lines, we calculate the fitted acquirer alphas and industry alphas in the next two columns. We calculate the implied percent overvaluation by multiplying a fitted alpha by -36, because each entry stays in a bucket for 36 months and a negative (positive) alpha indicates overvaluation (undervaluation). The last three columns report percent overvaluation for stock acquirer firms by bucket number and its breakdown into an industry-wide and a firm-specific component. Notations *, **, and *** represent statistical significance at 10, 5, and 1 percent levels.

	Calendar-time portfolio excess return (% per month)			Fitted alphas based on regression model		Implied percent overvaluation of stock acquirers		
Bucket number	Acquirer alpha (t-statistic)	Number of firms	Industry alpha	Acquirer alpha	Industry alpha	Total	Industry-wide	Firm-specific
1 (least stock merger active)	-0.444 (-1.37)	161	0.144	-0.121	0.197	4.4	-7.1	11.4
2	-0.208 (-0.77)	335	0.209	-0.187	0.169	6.7	-6.1	12.8
3	-0.208 (-1.02)	629	0.170	-0.252	0.142	9.1	-5.1	14.2
4	-0.102 (-0.45)	769	0.100	-0.318	0.114	11.5	-4.1	15.6
5	-0.307 (-1.23)	546	0.132	-0.384	0.087	13.8	-3.1	16.9
6	-0.539 (-2.51)**	885	0.038	-0.450	0.059	16.2	-2.1	18.3
7	-0.305 (-1.66)*	965	-0.026	-0.515	0.032	18.5	-1.1	19.7
8	-0.433 (-2.17)**	847	0.051	-0.581	0.004	20.9	-0.2	21.1
9	-0.664 (-2.78)***	1,142	-0.050	-0.647	-0.023	23.3	0.8	22.4
10	-0.639 (-2.79)***	1,074	-0.070	-0.712	-0.051	25.6	1.8	23.8
11	-0.865 (-3.36)***	816	0.021	-0.778	-0.078	28.0	2.8	25.2
12 (most stock merger active)	-1.072 (-3.54)***	1,257	-0.167	-0.844	-0.106	30.4	3.8	26.6
All acquirers in one bucket	-0.474 (-3.30)***	9,426						
Correlation between bucket number and variable	-0.82***		-0.89***					