# 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 consistent with industry misvaluation theory of stock merger activity by Rhodes-Kropf and Viswanathan (2004) rather than neoclassical theory.

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# Stock Merger Activity and Industry Performance

## 1. Introduction

Merger waves connote sharp increases in industry-specific or market-wide merger activity over short periods. An extensive finance literature investigates the causes and consequences of industry merger waves that are the focus of this study. The neoclassical theory advanced by Gort (1969), Mitchell and Mulherin (1996), Maksimovic and Phillips (2001), Harford (2005), and Ahern and Harford (2014) argues that the increased merger activity is an efficient response to economic, regulatory, and technological shocks to an industry. These authors report many empirical tests in support of their theory. The alternate overvaluation theory advanced by Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004) (henceforth 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* over an aggregate period or inside versus outside merger waves (Loughran and Vijh 1997; Rau and Vermaelen 1998; Duchin and Schmidt 2013; and many others). However, to date there is no documented evidence of overvaluation of *entire industries* in the U.S. market in relation to their merger activity and as evidenced by their before and after long-term excess returns or operating performance. This paper proposes a new measure of industry stock merger activity that captures more information than the traditional measures of industry merger waves and documents strong evidence consistent with this direct implication of the overvaluation theory.

Traditional measures of industry merger waves suffer from two limitations that reduce their ability to test the overvaluation theory. First, these measures are 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 RKV model the managers of target firms rationally underestimate the overvaluation of 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 are usually identified as industry merger wave years (7.3% in Harford 2005). 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. We focus on stock mergers, which is an essential ingredient of misvaluation driven merger activity in both SV and RKV.

Second, traditionally defined industry merger waves often cluster in calendar time. Over the period 1981-2000, 33 of 35 industry merger waves identified by Harford (2005) started during 1985-1987 or 1996-1999, which is seven out of 20 years. Harford explains that this clustering is the result of calendar-time variation in capital liquidity, or ease of financing, which is a necessary ingredient in all mergers. Similarly, Ahern and Harford (2014) report that 65% of the 471 industries in their sample experience a merger wave during 1998. This raises the concern that the industry merger waves identified in previous literature were really parts of a few market-wide merger waves. The neoclassical economic arguments given by Ahern and Harford predict a spillover of industry merger waves across a network of industries through customer-supplier links. Unfortunately, the resultant clustering makes it difficult to find evidence in support of the alternative overvaluation theory if one sticks to the framework of discrete industry merger waves. The clustering reduces the power of tests to detect industry misvaluation as an industry return is benchmarked against the market return consisting of other industries many of which are experiencing a similarly defined merger wave.

To alleviate this concern, we rank industries within a calendar quarter by our continuous *MAV*, which ignores 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 their *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, and it greatly increases the power of our 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. Thus, our expanded framework exploits more information, which increases the power of our tests. It follows that, under the overvaluation hypothesis, 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 monotonically 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 setting 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. Therefore, they underestimate the overvaluation of bidder firms and over-accept their stock offers.

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, including substitution of 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. In our setup, the misvaluation theory emerges as so powerful that it may have suppressed implications of the neoclassical efficiency-based theory according to which there should be an improvement in the post-*MAV* operating performance of more merger active industries (notice the two theories are not mutually exclusive). However, we must point out that the neoclassical theory has been proposed in the existing literature to explain increases in merger activity following significant industry shocks in a discrete merger wave setting and its full implications for the extended range of merger activity analyzed in this paper are not obvious. Besides, the neoclassical theory does not restrict to stock mergers.

We next 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, they employ an accounting multiples based decomposition of market-to-book ratios while we employ returns-based measures of overvaluation, and they do not break down their 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. Recall that in our study we replace merger waves by *MAV* rank, or bucket number.

Finally, we report tests of acquirer announcement returns and acquisition premiums. Significant long-term excess returns earned by acquirer stocks show that it takes markets a long time to recognize their overvaluation (which is, of course, necessary to sustain valuation-driven merger activity). However, there may be some recognition on the announcement date as well. In support of this conjecture, we find some evidence that acquirer announcement returns are negatively related to industry stock merger activity (because acquirer shareholders partly recognize and correct for the overvaluation) while acquisition premiums are positively related to industry stock merger activity (because target shareholders demand an extra premium as they also partly recognize the overvaluation). These results share some similarity with the results of Moeller, Schlingemann, and Stulz (2005) who examine mergers announced during the period 1998-2001, a part of which was characterized by market-wide overvaluation and increased merger activity, and find large negative acquirer announcement returns (wealth destruction on a massive scale).

Section 2 of the paper discusses salient features of the relevant literature. Section 3 describes data and methodology. Sections 4 and 5 discuss the main results, and Section 6 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 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 behavioral hypothesis (which is another name for the overvaluation or misvaluation or market-timing hypothesis). He finds strong support for the former but not the latter hypothesis. That is somewhat surprising as 25 out of 35 merger waves in his sample start during 1995-1999, a period often recognized as suffering from market-wide overvaluation. Harford lists several implications of the behavioral 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.

### *2.2. The misvaluation hypothesis*

Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004) (SV and RKV) model how firm and industry misvaluation can cause merger activity and merger waves. However, there are many differences between their model settings and implications. In SV model, the acquirer firm is overvalued relative to the target firm and the acquirer managers exploit market sentiments due to which investors overestimate the synergies from their combination. 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 or because they receive side payments. Merger waves in SV model occur as multiple acquirers in an overvalued industry seek relatively undervalued targets. Their model predicts industry overvaluation and increased dispersion of firm valuations within the industry besides stock payment as conditions for merger waves.

While SV model is mostly rooted in investor irrationality and differences between 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 as follows. Consider an overvalued industry that includes both target and acquirer firms. At some point, a target manager receives a private signal that his firm is overvalued, and he 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 own firm and what part is common to all firms in his industry, which includes the acquirer firm. RKV show that under such circumstances, a rational target manager underestimates the industry-wide overvaluation that affects the acquirer firm, or equivalently he overestimates the synergies from merger. The higher the industry overvaluation, the higher the estimated synergies, and the more likely it is that the target manager accepts the merger offer, to the detriment of target shareholders and the benefit of acquirer shareholders. The resulting correlation between merger activity and industry valuation covers the full range, from extreme overvaluation to extreme undervaluation. This is laid out in their Theorem 4 as follows:

> *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.*

The RKV model treats merger activity and industry valuation as continuous variables. This feature is important for our empirical setup and it increases the power of our tests. 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 that is the basis of our empirical tests. However, unlike the SV model, the RKV model does not require higher dispersion of firm valuations within more merger active industries or a higher frequency of cross-industry mergers from such industries as overvalued acquirers seek relatively undervalued targets in other industries.

### *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 SV model of overvaluation driven merger activity, 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 SV model predicts 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*

In addition to the studies mentioned above, 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 market value to 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. First, while their research 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 factors other than overvaluation: for example, growth opportunities or low discount rates (i.e., higher capital liquidity). Using this argument, 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 net 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 individual stock acquirers have a significant decline in operating performance after mergers, and in this paper we show that industry merger activity is related to subsequent changes in operating performance. Overall, following Harford (2005), we propose that the evidence of overvaluation (undervaluation) is best 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 our paper.[1]

## 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 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 21$^{st}$ 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 potent information related to acquirer and industry 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.

[1] Apart from methodological differences, there is another conceptual difference between Rhodes-Kropf, Robinson, and Viswanathan (2005) 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, and it 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.

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 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 information 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:

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

where $m_{j\tau,stk}$ denotes the number of stock mergers announced by all acquiring firms in industry $j$ during quarter $\tau$, $n_{j\tau}$ 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 features 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. This denominator is 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. As explained in the introduction, it becomes necessary to filter out the effect of market-wide factors in order to test the industry misvaluation hypothesis. This is done two different ways as follows.

First, 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 is our main procedure, and it 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. Second, we carry out one consolidated regression of $MAV_{jt,stk}$ values for all industries and all quarters on only the year dummies. The residuals from this regression are denoted by $MAVresid_{jt,stk}$. These residuals constitute another measure of industry stock merger activity that abstracts from the time trends in market-wide stock merger activity. One may think of $MAVresid_{jt,stk}$ as the continuous variable counterpart of bucket number, which is a discrete variable. We use it as an alternative to bucket number in some of our later tests.

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

## 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 2 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.[2]

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. That implies a difference of $0.024 \times 11 = 0.264$ 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

[2] 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.

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 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, in all cases by statistically significant amounts. Apparently, the effects on returns of changes in different firm characteristics of buckets approximately balance out in our sample.[3,4] 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,

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[3] $RMRF$, $SMB$, 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).

[4] 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.

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 a factor return and bucket number correspond closely to the univariate slope coefficients reported in the bottom row of Table 4.

Figure 3 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 3 shows that there is a strong negative relation between *MAV* rank and post-*MAV* industry excess returns.

*4.2. Pre-MAV alphas*

Figure 2 shows that we measure 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 4 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.

*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 to 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 5 plots the trends in operating performance. Unlike Figure 4 that shows a negative correlation of -0.69 between pre-*MAV* and post-*MAV* excess returns across bucket numbers (significant at 5% level), Figure 5 shows a positive correlation of 0.54 between pre-*MAV* and post-*MAV* changes in operating performance (significant at 10% level).

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

Our evidence supports the industry misvaluation theory of merger activity in general and RKV model in particular. First, we find that preceding excess returns over a three-year period (as well as 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 over time 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 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. This evidence strongly supports the industry misvaluation theory of stock merger activity.

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 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 their entire industry and therefore of the acquirer firms. Thus, they overestimate the merger synergies and over-accept the stock merger offers as outlined in the introduction and the literature review section of this paper.

We also consider whether our evidence is consistent with alternative theories of merger activity. First, Shleifer and Vishny (2003) model requires greater dispersion of firm valuations within an industry or a greater number of cross-industry mergers to support an increase in stock merger activity. However, in unreported tests, we find an insignificant correlation between interquartile spread of market-to-book ratios or the percent frequency of cross-industry mergers for an industry and that industry's *MAV* rank. Second, we examine the implications for the neoclassical theory of mergers. Mitchell and Mulherin (1996) and Harford (2005) argue that the neoclassical theory of industry merger waves does not necessarily predict an improvement in post-wave operating performance. They argue that many merger waves occur in distressed industries, so the (unobservable) performance of target and acquirer firms would have been worse without mergers. Undoubtedly, many merger waves (or periods of increased stock merger activity in our framework) occur in distressed industries.[5] However, we find that this is not the norm. In unreported tests, we find that the average Standard and Poor's long-term issuer credit ratings within industries 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 *MAV* ranks are inconsistent with their approaching financial distress. Thus, our evidence cannot be explained by the neoclassical theory of mergers. (Recall also the reasons mentioned in the introduction and literature review related to the limited applicability of neoclassical theory to our framework.) Last, we consider the *q*-theory of mergers. Decreasing (increasing) industry operating performance of industries with higher (lower) *MAV* ranks is inconsistent with this theory, which says that mergers are motivated by synergy gains extracted by the more efficient acquirer firms.

### *4.5. Robustness tests of excess returns and operating performance*

In this section, we report several robustness tests that change one variable or one feature of our methodology at a time. We focus on our main results concerning the relation between bucket number and post-*MAV* excess returns, originally reported in Table 4.

#### *4.5.1. 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 than some industries, especially 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

[5] 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.

1989 to 2015, and 3-factor alpha all remain negatively correlated with bucket number, significant in each case at 5% level or better.

*4.5.2. 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:

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

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 $t$. Thus, given that our post-*MAV* return computation starts from quarter $t + 1$, there is no look-ahead bias. 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 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.

*4.5.3. 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.

*4.5.4. 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 4. We therefore do not report these results for brevity.

*4.5.5. 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 5 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.

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

Figure 6 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.

*4.5.7. Cash acquisitions and industry performance*

Stock payment is an integral part of the overvaluation hypothesis. However, the alternate hypotheses of industry merger activity (the neoclassical hypothesis, the $q$ theory, and the agency hypothesis) do not require any particular payment method. For completion, we also investigate the link between cash acquisition activity and industry performance.

We find a significant correlation between the quarterly time series of $MAV_{jt,stk}$ that includes majority stock acquisitions within industry $j$ and $MAV_{jt,cash}$ that includes majority cash acquisition within the same industry. Averaged across industries, this correlation equals 0.35. This positive correlation can be explained by the above alternate hypotheses, the presence of some stock payment in majority cash acquisitions, and the possibility that in some cases a cash acquisition may be financed by a public stock issue. We next examine the pre-*MAV* and post-*MAV* excess returns using $MAV_{jt,cash}$ as the input to bucket formation (not reported in a table). The pre-*MAV* (cash) excess returns are increasing with bucket number, although at 0.6 times the rate of pre-*MAV* (stock) excess returns reported in Table 5. More importantly, the post-*MAV* (cash) excess returns are unrelated to bucket number, unlike the post-*MAV* (stock) excess returns reported in Table 4. Finally, all results are similar if we use all cash acquisitions instead of majority cash acquisitions to calculate $MAV_{jt,cash}$.

Harford (2005) points out that the positive excess returns preceding industry merger waves can be explained by both the neoclassical and overvaluation hypotheses. The insignificant relation between subsequent excess returns and bucket number further suggests that variation in cash merger activity may be explained by the neoclassical hypothesis.

## 5. Industry stock merger activity and individual stock acquirer returns

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). 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 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.

*5.1. Overvaluation of stock acquirers as a function of MAV rank*

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 10.

We find a correlation of -0.82 between bucket numbers and bucket alphas for individual stock acquirers, significant at 1% level. This strong correlation occurs despite relatively few observations in lower numbered buckets. Regression results show that the 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 10 reports the results of regression lines fitted using the single independent variable of bucket number and the three dependent variables of acquirer alpha, industry alpha, and difference between acquirer and industry alphas. Figure 7 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 overvaluation, if any, has been dropped by including market return in the factor model.

A few results emerge from Table 10 and Figure 7. 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 7).

### *5.2. Announcement date effects*

Thus far, we have shown that an increase in industry stock merger activity is associated with higher industry-wide and firm-specific valuations of stock acquirers in that industry. The deviations from fair value show up as long-term excess returns that are related to current industry stock merger activity. This delayed adjustment shows that it takes investors some time to realize the economic relevance of stock merger activity. A question arises whether the market even partially recognizes this relevance at the time of merger announcements. Previous literature provides some evidence that this may be so at some level of aggregation of merger activity. Specifically, using acquirer announcement returns, Moeller, Schlingemann, and Stulz (2005) find that there were an unusually large number of large loss deals during the late 1990s period of a market-wide increase in merger activity (see Figure 1), and that these deals involved a greater proportion of stock payment than at other times.

Table 11 starts the investigation around announcement dates with acquirer side of the picture. If investors partially understand the valuation information conveyed by stock merger activity, then the cumulative abnormal returns (CAR) of acquirer firms over a three-day announcement period should be negatively related to bucket number, or perhaps another similar measure of stock merger activity. An increase in agency costs of control, such as an increased empire-building tendency on part of acquirer managers, may exacerbate this effect. Panel A of Table 11 shows mean CARs across the 12 buckets. We break down the aggregate sample of acquirers by the target type: public targets, private targets, and subsidiary targets. Previous literature shows that CARs differ starkly by the target type (Moeller, Schlingemann, and Stulz 2004), a result that we confirm in our analysis.

We find only weak evidence of a univariate relation between mean CAR and bucket number. The correlation between these two variables is insignificant for public targets and subsidiary targets, but significantly negative for private targets at 10% level. We next report a multivariate analysis of CAR in Panel B of Table 10. The control variables follow Moeller, Schlingemann, and Stulz (2004) and Vijh and Yang (2013) and are defined in the table. The analysis is restricted to the subset of public targets as many control variables (such as target size, tender offer, hostile, and conglomerate) are not relevant or not available for private and subsidiary targets. Our focus is on various measures of stock merger activity as follows. Regression (11.1) shows that CAR is not significantly related to the bucket number. Regression (11.2) includes $MAV_{jt,stk}$, which is the unranked measure of stock merger activity for industry $j$ during quarter $t$ as defined in Equation (1), and its coefficient is significantly negative at 10% level. Regression (11.3) includes $MAVresid_{jt,stk}$, which is the residual term from a regression of $MAV_{jt,stk}$ on just the year dummies and may be thought of as a continuous variable counterpart of bucket number (see Section 3.3), and its coefficient is significantly negative at 5% level. Regression (11.4) includes $MAV_{t,stk}$, which is a measure of market-wide stock merger activity, and its coefficient is significantly negative at 1% level.

The multivariate analysis of CAR suggests that investors partially recognize the valuation implications of current stock merger activity in some form on the announcement date, but not in the form that is related to long-term returns in our analysis. That latter form, the bucket number, combines information from 12 industries over a four-quarter period ending with the current quarter. This entire information is not available to investors on the merger announcement date, although bits and pieces may be available and have some effect on the announcement returns.

We next analyze the target side of the picture. If the target suspects overvaluation of acquirer stock, over and above its own, then it may demand an extra premium. Alternately, the overvalued acquirer may offer a higher premium to increase the probability of success. The effect may be exacerbated by higher agency costs of control during periods of increased merger activity. Table 12 analyzes the determinants of acquisition premium, with focus on the industry stock merger activity variables. We carefully construct a measure of acquisition premium that is described in the table legend, as also the control variables. Notice the acquisition premium critically requires a pre-merger target price, so it can be calculated only for public targets.

Panel A of Table 12 shows that in a univariate setting the target acquisition premium is unrelated to bucket number. In a multivariate setting, the acquisition premium is related to $MAV_{jt,stk}$ and $MAVresid_{jt,stk}$, but unrelated to bucket number and $MAV_{t,stk}$. We interpret this as weak evidence that the acquisition premium increases with industry stock merger activity.

## 6. 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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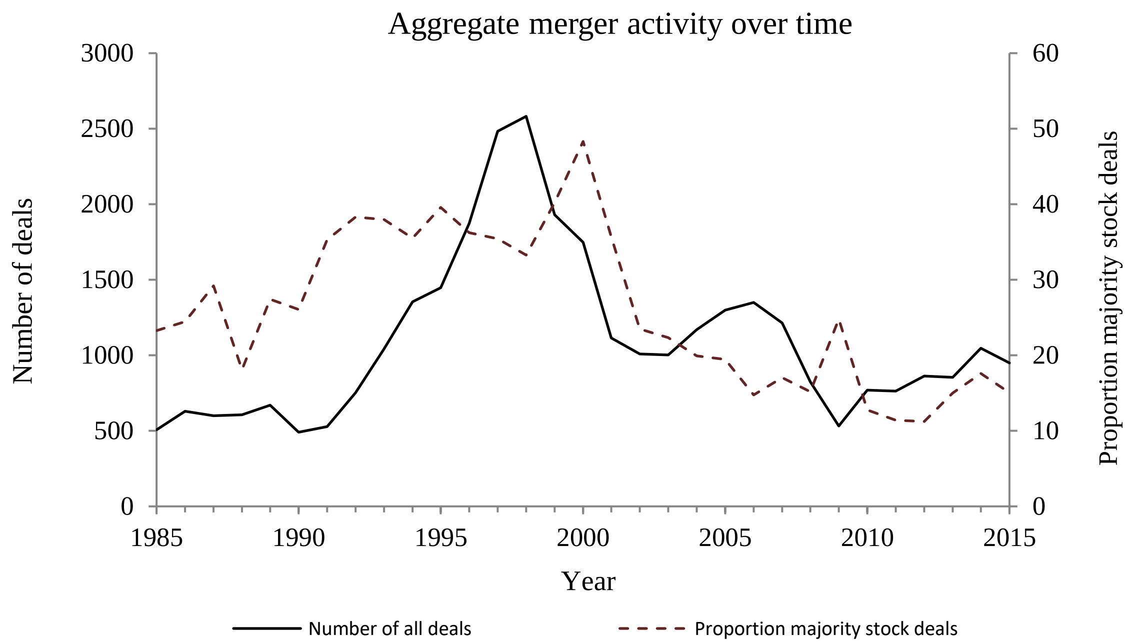



**Figure 1: Aggregate merger activity over time.** The sample of 34,009 acquisitions made by public acquirers during 1985-2015 is retrieved from the SDC database following criteria listed in Table 1, Panel A. It includes 7,875 public targets, 15,810 private targets, and 10,324 subsidiary targets. However, 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).

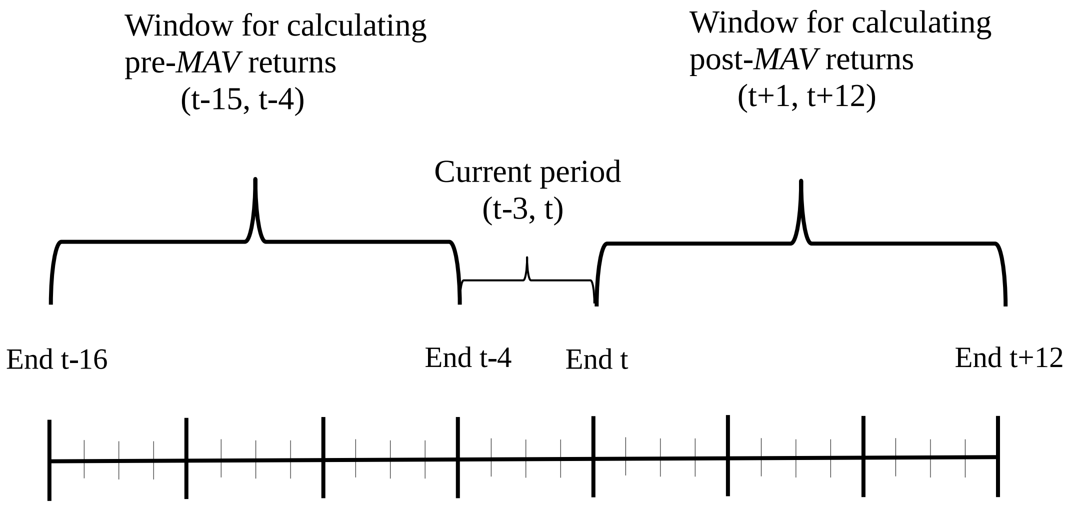
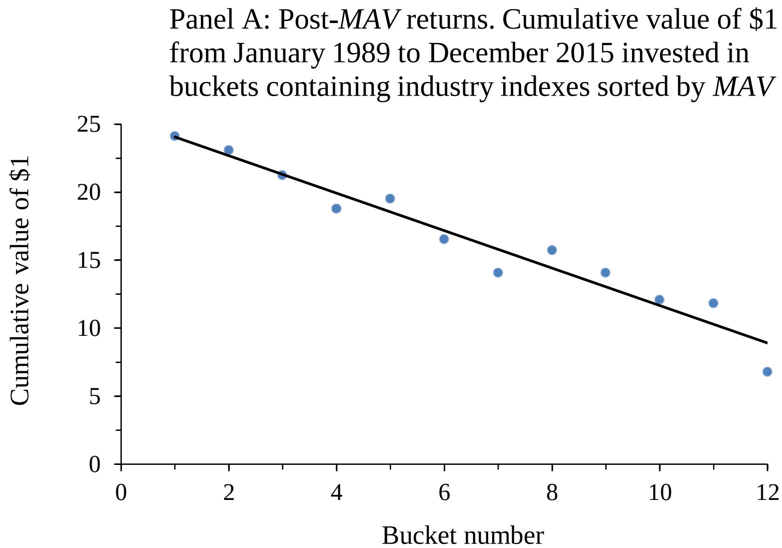



**Figure 2: Timeline.** $MAV_{jt,stk}$ for industry *j* during quarter *t* is calculated using majority stock mergers announced over the period from the beginning of quarter $t-3$ to the end of quarter $t$. See Section 3.2 and Equation (1) for further methodological details. The twelve industries *j* = 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 $t-4$.



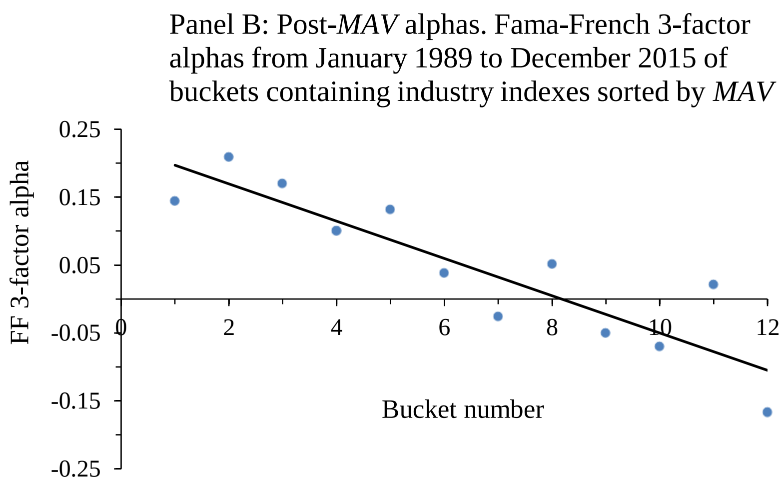




**Figure 3: Post-*MAV* returns and alphas.** This figure shows graphically the evidence presented in Table 4. We analyze the relation between stock merger activity of industries and their three-year post-merger activity returns. Please refer to Table 4 for all details of bucket formation and return and 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.

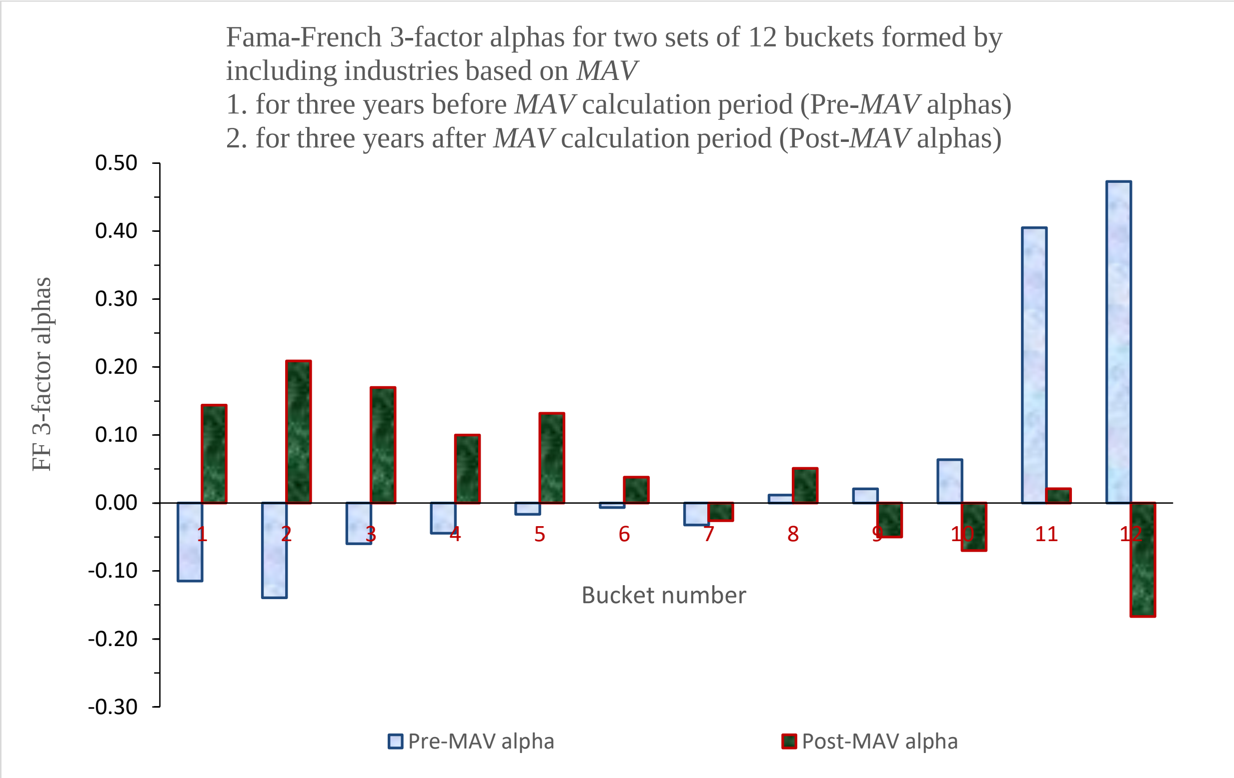



**Figure 4: Contrasting pre-*MAV* and post-*MAV* alphas.** We construct 12 buckets using industry stock merger activity variable $MAV_{jt,stk}$ for industry $j = 1$ to 12 and quarter $t$ as described in Table 2. For the post-*MAV* alphas, we assign industries to 12 buckets based on their $MAV_{jt,stk}$ 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).

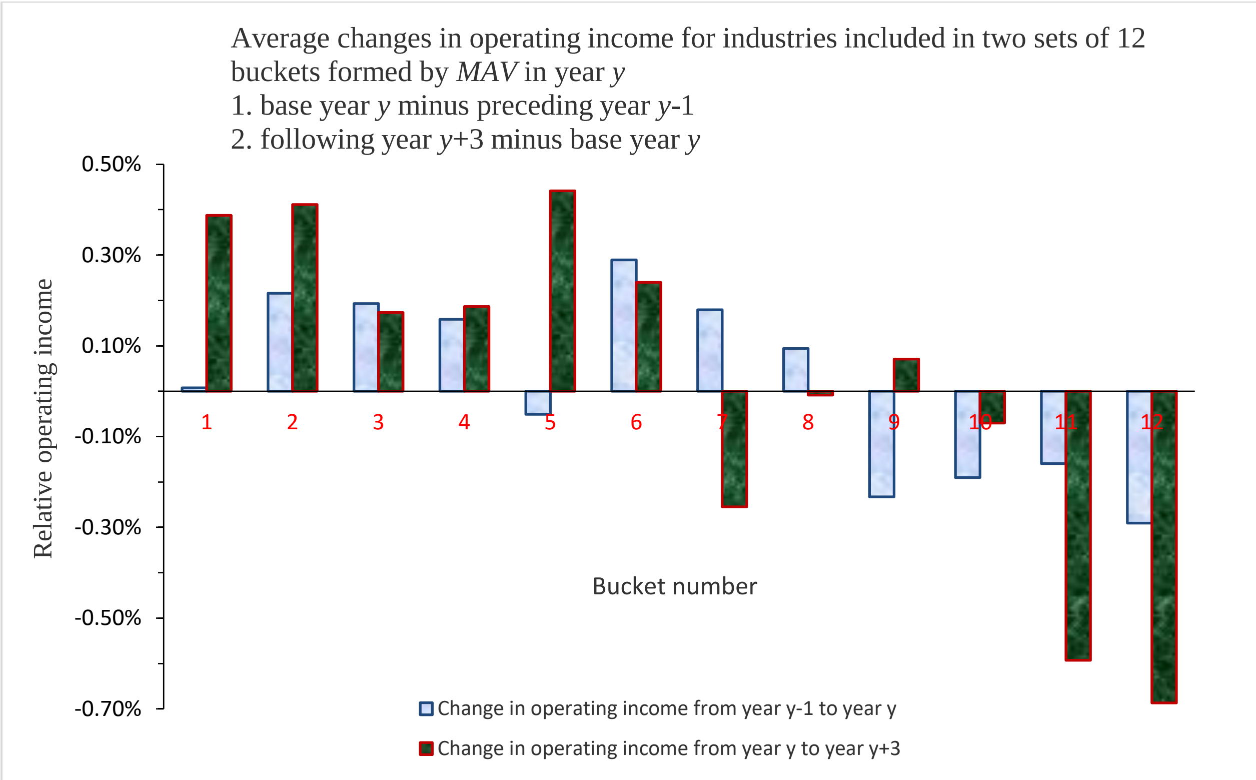



**Figure 5: Changes in operating income.** Table 6 describes the procedure of calculating the preceding and following three-year operating performance for industries assigned to 12 buckets based on their $MAV_{jt,stk}$ for industry $j$ during quarter $t$. As noted, the first series (light-colored bars) 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).

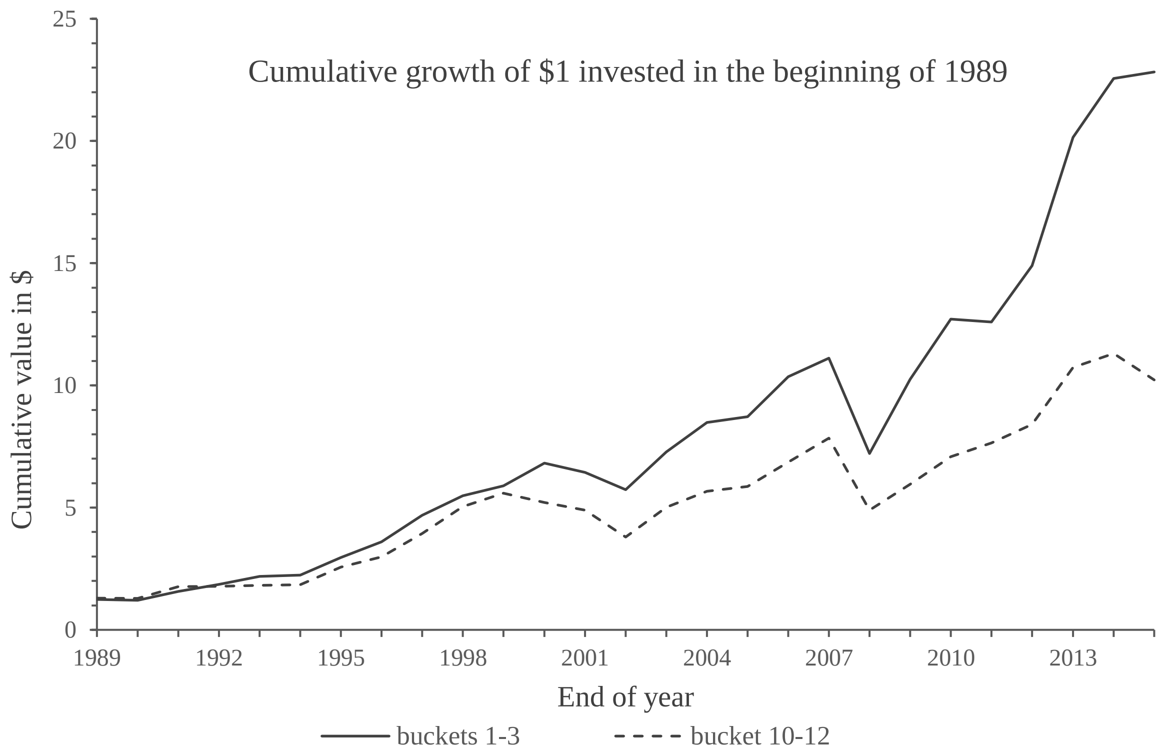



**Figure 6: Cumulative growth over time of $1 invested in the beginning of 1989 by bucket number.** For parsimony of presentation as well as to reduce noise, we show only two lines in this graph. First, the solid line is the average of cumulative growth over time for buckets numbered 1, 2, and 3. Second, 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.

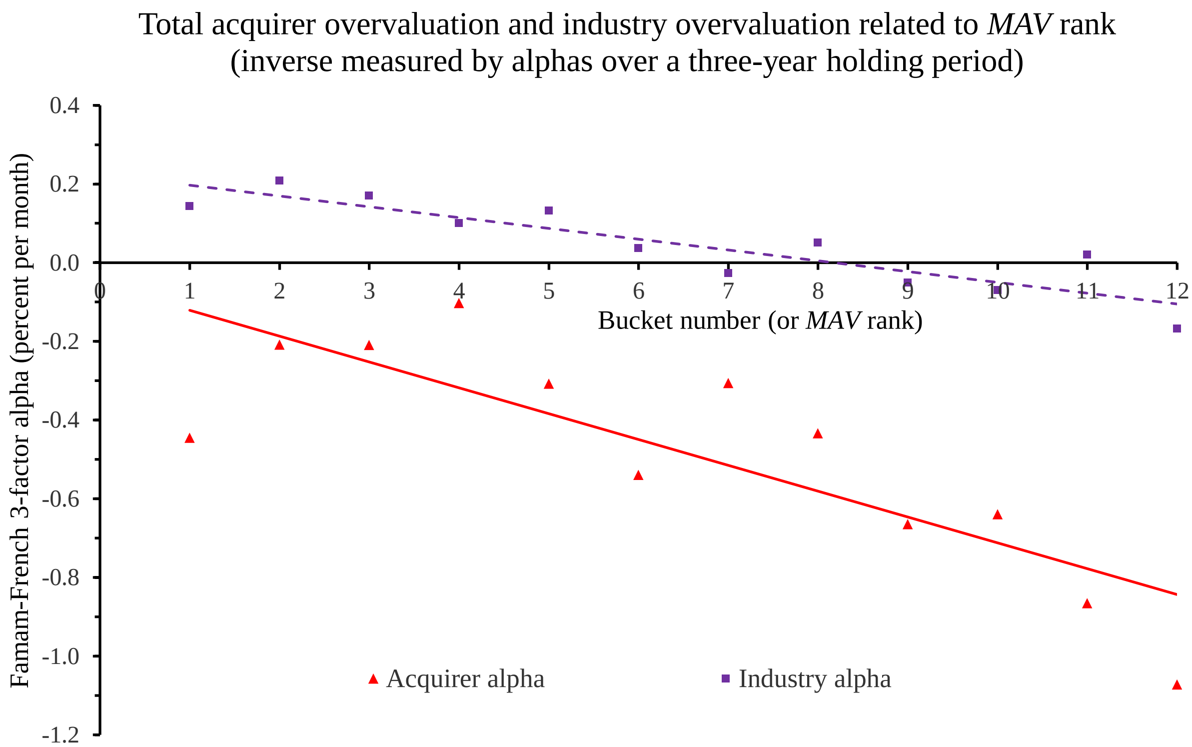



**Figure 7: Components of total acquirer overvaluation related to bucket number (or *MAV* rank).** The horizontal axis shows the bucket number, and the vertical axis shows the Fama-French 3-factor alphas. The solid line shows the acquirer alpha, which is calculated as described in Table 10 and is an 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 → <br> 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 $\tau$, $n_{j\tau}$ 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 $MAV_{jt,stk}$, mean $MAVresid_{jt,stk}$, and number of mergers for industries added to a bucket, each variable calculated at the time of entry and then averaged over time. $MAVresid_{jt,stk}$ is the residual from a regression of $MAV_{jt,stk}$ on year dummies, and it is another measure of industry stock merger activity that abstracts from market-wide activity (besides bucket number). 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 $MAVresid_{jt,stk}$ 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 | -0.590 | 0.0039 | 4.94 |
| 2 | 0.079 | 0.462 | 0.495 | -0.442 | 0.0063 | 5.99 |
| 3 | 0.088 | 0.508 | 0.598 | -0.339 | 0.0093 | 6.35 |
| 4 | 0.088 | 0.512 | 0.667 | -0.270 | 0.0104 | 6.06 |
| 5 | 0.078 | 0.515 | 0.742 | -0.196 | 0.0094 | 6.54 |
| 6 | 0.087 | 0.516 | 0.823 | -0.115 | 0.0134 | 6.54 |
| 7 | 0.092 | 0.499 | 0.915 | -0.023 | 0.0122 | 7.25 |
| 8 | 0.094 | 0.522 | 1.007 | 0.070 | 0.0131 | 6.27 |
| 9 | 0.093 | 0.535 | 1.123 | 0.186 | 0.0155 | 6.44 |
| 10 | 0.083 | 0.550 | 1.246 | 0.309 | 0.0148 | 6.76 |
| 11 | 0.080 | 0.498 | 1.444 | 0.506 | 0.0160 | 4.97 |
| 12 (most merger active) | 0.081 | 0.471 | 1.841 | 0.904 | 0.0204 | 3.99 |
| Correlation between bucket number and variable | 0.41 | 0.04 | 0.97$^{***}$ | 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 2 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%<br>$(-7.97)^{***}$<br>[0.85] | 0.19%<br>$(2.81)^{**}$<br>[0.39] | -0.024<br>$(-7.63)^{***}$<br>[0.84] | -$1.38<br>$(-13.16)^{***}$<br>[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*

| | | Coefficients of | | | |
|---|---|---|---|---|---|
| Bucket number | Alpha (t-statistic) | *RMRF* | *SMB* | *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 2 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 *RMRF* | *SMB* | *HML* | Adjusted-$R^2$ |
|---|---|---|---|---|---|
| 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 |
|---|---|---|---|---|---|---|---|---|
| Bucket number | $y-3$ | $y-2$ | $y-1$ | Year $y$ | $y+1$ | $y+2$ | $y+3$ | $y+3$ |
| 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*

| | | Coefficients of | | | |
|---|---|---|---|---|---|
| Bucket number | Alpha (t-statistic) | *RMRF* | *SMB* | *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 $\tau$, $n_{j\tau}$ 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%<br>(5.07)$^{***}$<br>[0.69] | 0.03%<br>(0.17)<br>[-0.10] | -0.014<br>(-3.39)$^{***}$<br>[0.49] | -$0.17<br>(-4.64)$^{***}$<br>[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%<br>(-0.63)<br>[-0.06] | -0.021%<br>(-1.71)<br>[0.15] | -0.019%<br>(-3.69)***<br>[0.53] | | -0.16%<br>(-3.28)***<br>[0.47] | -0.39%<br>(-3.86)***<br>[0.56] | -0.52%<br>(-4.20)***<br>[0.60] | -0.71%<br>(-5.66)***<br>[0.74] |

**Table 10**

**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$^{***}$ | | | | | |

**Table 11**

**Industry stock merger activity and individual stock acquirer excess announcement returns (CAR)**

Our sample starts with 9,426 stock acquisitions announced during 1986-Q1 to 2015-Q3 as described in Table 10. For each deal we identify $MAV_{jt,stk}$, the stock merger activity variable for industry $j$ (of acquirer firm) and quarter $t$, and $MAVresid_{jt,stk}$, the residual from a regression of $MAV_{jt,stk}$ on year dummies, as described in Table 3. In addition, we identify the bucket number of industry $j$ assigned during quarter $t$ as described in Sections 3.2 and 3.3 and Table 3, and $MAV_{t,stk}$, the quarterly stock merger activity variable for the entire market (i.e., all 12 industries). These are our key independent variables. The dependent variable in all tests is the percent acquirer excess announcement return, denoted by CAR, and calculated as the difference between the cumulative three-day stock return centered on the acquisition announcement date and the corresponding value-weighted market return. We restrict the sample to cases where the deal size is less than five times the acquirer size. The acquirer and target size are measured as the market value of equity on AD-21. Conglomerate takes the value of one if the target and the acquirer have different 2-digit SIC codes, and zero otherwise. Tender offer, hostile, and compete take the value of one if identified as such by SDC, and zero otherwise. Leverage equals the book value of debt divided by the market value of assets. Cash flow equals the sum of earnings before extraordinary items and depreciation divided by the total assets. In Panel A we analyze separately the subsets of deals involving public targets, private targets, and subsidiary targets in univariate tests. That is because their CARs are starkly different. In Panel B, we report multivariate tests only for public targets because variables such as target size, tender offer, and hostile are not well defined for private targets and subsidiary targets. Notations $^{*}$, $^{**}$, and $^{***}$ represent statistical significance at 10, 5, and 1 percent levels.

*Panel A: Univariate tests of acquirer excess announcement returns (CAR)*

| | Public targets | | Private targets | | Subsidiary targets | |
|---|---|---|---|---|---|---|
| Bucket number | Mean CAR | N | Mean CAR | N | Mean CAR | N |
| 1 | -1.35% | 76 | 3.90% | 67 | 0.98% | 19 |
| 2 | -0.48 | 126 | 5.05 | 166 | 4.22 | 41 |
| 3 | -2.74 | 265 | 3.16 | 309 | 7.26 | 55 |
| 4 | -1.38 | 337 | 1.79 | 348 | 2.09 | 78 |
| 5 | -2.91 | 210 | 4.72 | 270 | 4.82 | 57 |
| 6 | -1.15 | 439 | 1.89 | 370 | 4.77 | 68 |
| 7 | -1.76 | 377 | 2.81 | 497 | 6.49 | 80 |
| 8 | -2.07 | 352 | 1.60 | 395 | 4.49 | 97 |
| 9 | -1.29 | 493 | 1.84 | 550 | 9.29 | 92 |
| 10 | -2.25 | 396 | 1.80 | 583 | 4.24 | 89 |
| 11 | -1.70 | 368 | 2.70 | 367 | 2.11 | 72 |
| 12 | -3.42 | 365 | 3.12 | 762 | 5.25 | 119 |
| All | -1.91 | 3,784 | 2.59 | 4,684 | 4.98 | 867 |
| Correlation between bucket number and CAR | -0.42 | | $-0.51^{*}$ | | 0.24 | |

Table 11 continued …

*Panel B: Multivariate tests of acquirer excess announcement returns (CAR) for* ***public targets***

| Variable name | (11.1) | (11.2) | (11.3) | (11.4) |
|---|---|---|---|---|
| Intercept | -0.79 | -0.02 | -1.15 | -0.49 |
| | (-1.26) | (-0.02) | (-2.13)*** | (-0.84) |
| Bucket number | -0.05 | | | |
| | (-1.09) | | | |
| $MAV_{jt,stk}$ | | -0.48 | | |
| | | (-1.66)* | | |
| $MAVresid_{jt,stk}$ | | | -0.66 | |
| | | | (-2.40)** | |
| $MAV_{t,stk}$ | | | | -0.61 |
| | | | | (-2.78)*** |
| Log acquirer size | 0.33 | 0.40 | 0.34 | 0.37 |
| | (3.38)*** | (4.02)*** | (3.41)*** | (3.76)*** |
| Log target size | -0.79 | -0.79 | -0.78 | -0.80 |
| | (-7.34)*** | (-7.19)*** | (-7.22)*** | (-7.64)*** |
| Tender offer | -0.63 | 0.01 | -0.50 | -0.57 |
| | (-0.58) | (0.01) | (-0.47) | (-0.57) |
| Hostile | -0.15 | -0.52 | -0.22 | -0.17 |
| | (-0.12) | (-0.40) | (-0.17) | (-0.13) |
| Conglomerate | 0.07 | 0.17 | 0.10 | 0.09 |
| | (0.21) | (0.54) | (0.31) | (0.30) |
| Compete | -0.11 | -0.05 | -0.14 | -0.10 |
| | (-0.15) | (-0.07) | (-0.19) | (-0.15) |
| Acquirer leverage | 5.19 | 4.80 | 5.03 | 4.73 |
| | (4.95)*** | (4.59)*** | (4.79)*** | (4.59)*** |
| Cash flow | 2.16 | 1.28 | 2.10 | 2.35 |
| | (1.47) | (0.87) | (1.44) | (1.63) |
| Year dummies | No | Yes | No | No |
| N | 3,241 | 3,241 | 3,241 | 3,241 |
| Adjusted-$R^2$ | 0.024 | 0.052 | 0.026 | 0.026 |

**Table 12**

**Industry stock merger activity and acquisition premium**

Our sample starts with 9,426 stock acquisitions announced during 1986-Q1 to 2015-Q3 as described in Table 10. However, acquisition premium is a well-defined concept for public targets only. For each deal we identify $MAV_{jt,stk}$, the stock merger activity variable for industry $j$ (of acquirer firm) and quarter $t$, $MAV_{t,stk}$, the stock merger activity variable for entire market, and $MAVresid_{jt,stk}$, the residual from a regression of $MAV_{jt,stk}$ on year dummies, as described in Table 3. In addition, we identify the bucket number of acquirer industry $j$ assigned during quarter $t$ as described in Table 3. These are our key independent variables. The dependent variable is the acquisition premium, calculated as the ratio of offer price to target stock price on AD-21, where AD is the acquisition announcement date. Depending on data availability, we measure the offer price by the "initial offer price", the "final offer price", or the "aggregated cost to acquire common shares", all reported by the SDC, and in that preferred order. We restrict the sample to cases where the acquisition premium lies between 0 and 200%, and the deal size is less than five times the acquirer size. The acquirer and target size are measured by their market value of equity on AD-21. Toehold takes the value of one if the acquirer holds at least 5% of the target's shares six months before the acquisition announcement date, and zero otherwise. Conglomerate takes the value of one if the target and the acquirer have different 2-digit SIC codes, and zero otherwise. Tender offer, hostile, and compete take the value of one if identified as such by SDC, and zero otherwise. Financial takes the value of one if both the target and the acquirer have SIC codes between 6000 and 6999, and zero otherwise. Notations $^{*}$, $^{**}$, and $^{***}$ represent statistical significance at 10, 5, and 1 percent levels.

*Panel A: Univariate tests*

| Bucket number | Average acquisition premium | N |
|---|---|---|
| 1 | 39.8 | 66 |
| 2 | 40.5 | 104 |
| 3 | 42.2 | 248 |
| 4 | 35.6 | 308 |
| 5 | 41.3 | 189 |
| 6 | 34.7 | 406 |
| 7 | 40.7 | 350 |
| 8 | 39.3 | 323 |
| 9 | 35.7 | 456 |
| 10 | 39.5 | 340 |
| 11 | 32.7 | 341 |
| 12 | 48.0 | 327 |
| All | 39.2 | 3,458 |
| Correlation between bucket no and acquisition premium | 0.00 | |

*Panel B: Multivariate tests of acquisition premium*

| Variable name | (12.1) | (12.2) | (12.3) | (12.4) |
|---|---|---|---|---|
| Intercept | 54.42 | 45.73 | 55.64 | 55.31 |
| | (21.08)$^{***}$ | (7.76)$^{***}$ | (24.97)$^{***}$ | (22.45)$^{***}$ |
| Bucket number | 0.23 | | | |
| | (1.26) | | | |
| $MAV_{jt,stk}$ | | 4.24 | | |
| | | (3.89)$^{***}$ | | |
| $MAVresid_{jt,stk}$ | | | 5.02 | |
| | | | (4.80)$^{***}$ | |
| $MAV_{t,stk}$ | | | | 0.64 |
| | | | | (0.71) |
| Log acquirer size | 3.63 | 3.17 | 3.56 | 3.59 |
| | (9.01)$^{***}$ | (7.88)$^{***}$ | (8.87)$^{***}$ | (8.88)$^{***}$ |
| Log target size | -7.61 | -7.24 | -7.64 | -7.57 |
| | (-17.65)$^{***}$ | (-16.46)$^{***}$ | (-17.81)$^{***}$ | (-17.59)$^{***}$ |
| Toehold | -7.60 | -6.95 | -7.54 | -7.41 |
| | (-2.16)$^{**}$ | (-2.00)$^{**}$ | (-2.15)$^{**}$ | (-2.10)$^{**}$ |
| Tender offer | 1.90 | -0.13 | 0.22 | 2.33 |
| | (0.46) | (-0.03) | (0.60) | (0.57) |
| Hostile | 1.94 | 3.83 | 2.76 | 1.72 |
| | (0.42) | (0.84) | (0.60) | (0.37) |
| Conglomerate | 0.11 | -0.07 | 0.14 | 0.13 |
| | (0.08) | (-0.05) | (0.11) | (0.10) |
| Compete | 0.10 | -0.18 | 0.54 | 0.01 |
| | (0.04) | (-0.07) | (0.20) | (0.00) |
| Financial | -9.43 | -7.91 | -8.46 | -9.40 |
| | (-8.01)$^{***}$ | (-6.61)$^{***}$ | (-7.10)$^{***}$ | (-7.95)$^{***}$ |
| Year dummies | No | Yes | No | No |
| N | 2,629 | 2,629 | 2,629 | 2,629 |
| Adjusted $R^2$ | 0.128 | 0.170 | 0.135 | 0.127 |