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Stock merger activity and industry performance[☆]

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ABSTRACT

We propose a merger activity variable (*MAV*) as an alternative to industry merger waves. Unlike discrete merger waves that separate periods of extreme activity from the rest, our continuous *MAV* utilizes information in the full range of stock merger activity. We rank Fama-French 12 industries by *MAV* each quarter and arrange them into 12 bucket portfolios. We examine their prior and subsequent three-year excess returns using calendar-time portfolio method. The prior returns are positively related to *MAV* ranks while the subsequent returns are negatively related to *MAV* ranks. This evidence suggests a build-up of misvaluation (undervaluation of relatively less stock merger active industries and overvaluation of relatively more active industries) followed by a correction. On average, the most active industry outperforms the least active industry by 13.46% during the prior period, but underperforms by 10.30% during the subsequent period. Industry operating performance results further support the industry misvaluation theory of stock merger activity.

1. Introduction

Merger waves connote sharp increases in industry-specific or market-wide merger activity over short periods. A large segment of finance literature investigates the causes and consequences of industry merger waves. The neoclassical theory advanced by Gort (1969), Mitchell and Mulherin (1996), Maksimovic and Phillips (2001), Harford (2005), and others argues that the increased merger activity is an efficient response to economic, regulatory, and technological shocks to an industry. These authors report many empirical results in support of their theory. The alternate overvaluation theory advanced by Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004) (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. While these two papers have been published for a long time, there is no documented empirical evidence in support of their industry overvaluation theory of merger waves (more generally, the industry *misvaluation* theory of merger *activity*) based primarily on the before and after long-term excess returns or operating performance of entire industries.[1] This paper fills this gap in the literature.

Several papers in the existing literature have shown that individual stock acquirers are overvalued as measured by their negative post-acquisition long-term excess returns (Loughran and Vijh, 1997; Rau and Vermaelen, 1998; Dong et al., 2006; Savor and Lu, 2009; and others). Therefore, one may ask what motivates further examination of the overvaluation (or misvaluation) of industries in this paper. We mention several reasons for this examination as follows. First, because only a few firms in an industry make stock acquisitions over a relatively short measurement period such as one year, the overvaluation of individual stock acquirers does not necessarily imply overvaluation of their industries. Their contribution to industry returns may be small, and it is even possible that their overvaluation is diminished by undervaluation of non-acquiring firms in the industry. Thus, papers that

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[1] Rhodes-Kropf, Robinson, and Viswanathan (2005) show that industry overvaluation is associated with stock merger activity using a model that decomposes market-to-book ratios of individual firms. However, as recognized by them and by Harford (2005) and Savor and Lu (2009), their evidence is also consistent with emerging growth opportunities in an industry as implied by the neoclassical theory. We further discuss this issue in Section 2.3.

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show overvaluation of individual stock acquirers do not provide acceptable evidence on the industry misvaluation theory of stock mergers. Ultimately, that theory still needs to be tested.[2] Second, in a similar spirit, it is difficult to be sure that the negative long-term excess returns of individual stock acquirers are caused by their prior overvaluation and not by the poor performance of their acquisitions. Several authors have argued that personal objectives and overconfidence of managers lead to non-synergistic acquisitions that destroy shareholder wealth in the long term (Roll 1986; Morck, Shleifer, and Vishny, 1990; Malmendier and Tate, 2008; Duchin and Schmidt, 2013; and others). Once again, because only a few firms in an industry make acquisitions over a short measurement period, the industry returns are likely to be driven in large part by firms that are not involved in mergers. Thus, long-term negative industry returns may provide more reliable evidence of overvaluation than long-term negative returns of individual stock acquirers. Third, from a practitioner's point of view, recent proliferation of industry ETFs (exchange-traded funds) has made it possible to capture industry-wide misvaluation with a long or short position in chosen ETFs. In fact, a strategy with industry ETFs may be easier to implement than a strategy with individual stocks due to a greater number of dispersed transactions and less effective diversification in the latter case. The availability of these new trading opportunities also increases the interest in studying indicators of misvaluation such as industry-wide stock merger activity quite apart from the misvaluation of individual stock acquirers.

Considering the obvious importance of the theory linking industry valuation and merger activity, it is surprising that there is no returns-based evidence on it. We believe that is because of two reasons. First, the merger-wave literature typically divides an aggregate period into a short period of an intense merger wave vs. the remaining period as one non-wave. Researchers typically use variations on a measure proposed by Harford (2005), who classifies a 24-month subperiod with the highest industry merger activity during an aggregate period as a merger wave if that activity exceeds a threshold that is crossed 5% of the times in a simulation experiment. This classifies around 7% of industry-years as wave years and the rest as non-wave years, with no further gradation in either category. We refer to this issue as the discreteness problem, and it limits the information drawn from the full range of merger activity. Second, most industry merger waves so identified occur within a short calendar period due to market-wide trends in merger activity, which further makes it difficult to find evidence in support of the industry misvaluation theory. That difficulty arises because excess return for any industry during the wave years is calculated by including market return as one of the factors in an expected return model. The market consists of all other industries, and if many of them are misvalued because they are undergoing a merger wave at the same time, then there may be a washout of evidence. We refer to this second issue as the clustering problem.

Besides testing the industry misvaluation theory of merger activity, a key contribution of this paper is to propose a continuous **merger activity variable** (*MAV*) rank as an alternative to the traditional measures of merger waves. This measure overcomes the discreteness and clustering problems mentioned above. We describe this measure fully in Section 3, but briefly outline it here. First, starting with Fama-French 12 industries, for each industry we define its *MAV* for quarter t as the number of stock merger offers made per firm quarter over a four-quarter period spanning $(t-3, t)$ divided by a similar number computed over the aggregate period. That measures the abnormal stock merger activity in an industry relative to its long-term average. Second, each quarter we rank all industries by their *MAV*s. The resulting *MAV* rank for any industry is an ordinal measure of the abnormal stock merger activity of that industry relative to all other industries during that quarter. Thus, *MAV* rank adjusts for market-wide changes in stock merger activity. In times of market-wide downturn in stock merger activity, the industry with the biggest (smallest) downturn ends up with *MAV* rank of one (twelve). Conversely, in times of market-wide upturn in stock merger activity, the industry with the smallest (biggest) upturn ends up with *MAV* rank of one (twelve). In any market or any quarter, each rank between 1 and 12 is assigned to one industry, showing how that industry ranks on the abnormal stock merger activity across all industries. There is always a full dispersion of *MAV* ranks at any time, and no clustering that occurs with a binary wave vs. non-wave measure.

We next form 12 post-*MAV* bucket portfolios, numbered 1 to 12. In the beginning of each quarter $t+1$, we drop each industry in a bucket with the same number as its *MAV* rank calculated at the end of quarter t and keep it there for three years. In equilibrium, there are 12 industries in each bucket at all times, one entering and one exiting each quarter. That is the calendar-time portfolio strategy suggested by Fama and French (1993), but implemented with industry portfolios (ETFs) instead of stocks. We similarly form 12 pre-*MAV* bucket portfolios based on the same *MAV* ranks of industries calculated during quarter t, but include them in bucket portfolios over a three-year period ending in quarter $t-4$.

Section 4 develops testable implications of the industry misvaluation theory of stock merger activity in our setting. We make three predictions concerning returns: 1. Pre-*MAV* alphas of bucket portfolios should be positively related to bucket numbers, consistent with a buildup of overvaluation (undervaluation) before increased (decreased) stock merger activity. 2. Post-*MAV* alphas should be negatively related to bucket numbers as misvaluation is corrected. 3. The difference between post-*MAV* and pre-*MAV* alphas should be positive for lower-numbered buckets, negative for higher-numbered buckets, and overall negatively correlated with bucket numbers.

We test these predictions with returns of the 12 bucket portfolios from 1989 to 2018 (360 months) using the Fama-French three-factor model. Regression analysis shows that post-*MAV* alphas decrease by -0.026% per month per bucket number. This decrease translates into a difference of -0.026 $\times$ 11 $\times$ 36 = -10.30% between the post-*MAV* three-year excess returns of buckets 12 and 1. That is a large difference in economic terms, because we are talking about industry returns that are driven by a few stock acquirers but many more firms that are not involved in mergers.

We next analyze the pre-*MAV* bucket excess returns. The pre-*MAV* alphas increase by 0.034% per month per bucket number, following an opposite pattern to the post-*MAV* alphas. That translates into a difference of 0.034 $\times$ 11 $\times$ 36 = 13.46% between the pre-*MAV* three-year excess returns of buckets 12 and 1. Furthermore, the difference between post-*MAV* and pre-*MAV* alphas is positive for all six lower-numbered buckets (below median abnormal merger activity) and negative for all six higher-numbered buckets (above median abnormal merger activity). This result has 1 in $2^{12} = 4{,}096$ probability of occurrence under the null hypothesis that the differences are unrelated to merger activity and are equally likely to be positive or negative. The Pearson and Spearman correlations between differences in alphas and bucket numbers equal -0.92 and -0.96 (p-values < 0.0001). Overall, that is

[2] Surprising though it may seem, in some contexts the excess returns of individual stocks related to certain corporate events are in the opposite direction of the excess returns at the aggregate level. For example, Kothari, Lewellen, and Warner (2006) show that aggregate returns and aggregate earnings growth are negatively related, even though at the individual stock level they are positively correlated. Similarly, Hirshleifer, Hou, and Teoh (2009) show that, in sharp contrast with the well-known firm-level findings (Sloan 1996), the level of aggregate accruals is a strong positive predictor of aggregate stock returns while the level of aggregate cash flows is a strong negative predictor. This contrast further suggests that individual stock acquirer returns cannot be taken as evidence in support of the industry misvaluation theory of stock mergers.

strong evidence of reversals in returns. Industries experiencing the largest upturn in stock merger activity have strong prior returns and weak subsequent returns, while the opposite is true for industries experiencing the largest downturn in stock merger activity.

Lastly, we investigate the operating performance of industries during three-year periods before and after year y of calculating *MAV* and assigning to bucket portfolios. The annual operating income before depreciation normalized by assets changes from year y to $y+3$ by 0.29% for bucket number 1 and -1.01% for bucket number 12. The difference of 1.30% is significant compared to the average operating income of 13.0% for all industries. Thus, on average, industries with higher (lower) than usual stock merger activity have decreasing (increasing) operating income during subsequent years, which is similar to the evidence on post-*MAV* returns. Interestingly, we find that the trend in post-*MAV* operating performance starts in year $y-1$ itself, but there is no discernible trend in the years before then. Positive excess returns simultaneous with flat or decreasing operating income before base year y for industries with higher than usual stock merger activity are further consistent with their overvaluation (and the converse with undervaluation).

In summary, our evidence supports the industry misvaluation theory, which says that currently high (low) industry valuations increase (decrease) stock merger activity. We raise this theory as an alternative to the neoclassical theory, which cannot explain our evidence on returns. These results are made possible by our innovative methodology of measuring stock merger activity of an industry relative to its own historical average and then relative to other industries. We report many additional tests of our main hypotheses, some of which are as follows. First, we show that our results are similar irrespective of whether we include all announced stock merger offers or only completed offers. Second, our results remain significant regardless of the minimum required percent stock payment in defining a stock merger. Third, we repeat our main tests with buckets formed by cash-*MAV* ranks and obtain expected results that are different from those for stock-*MAV*. We defer further discussion of these additional tests to later sections.

In the remaining paper, Section 2 discusses previous literature. Section 3 describes data and methods. Section 4 develops testable predictions. Section 5 presents the main results. Section 6 presents additional results. Section 7 concludes.

2. Literature survey

2.1. The industry misvaluation theory of stock merger activity

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

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

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

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

2.2. Other theories of changes in merger activity

2.2.1. The neoclassical theory

The neoclassical theory 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 increase in variance 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) 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 and with an intensity that is expected with a probability of less than 5%. Hartford finds significant clustering of industry merger waves 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. Harford tests the implications of the neoclassical theory and the misvaluation theory (which he refers to as the behavioral theory). He finds support for the former but not the latter. He lists several implications of the misvaluation theory. Most significantly, he observes that merger waves should be preceded by high industry returns and followed by low industry returns. As we explain in the introduction, the clustering of industry merger waves in calendar time 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 others. Clearly, this is a key theory that explains the time variation in merger activity. Therefore, we discuss its implications at a few places in our paper. However, we do not run a 'horse race' between the misvaluation and the neoclassical theories. That would be difficult within our framework that relies on continuous variation in merger activity suited to testing the misvaluation theory rather than a few discrete shocks that lead to discrete merger waves suited to testing the neoclassical theory.

2.2.2. The q-theory

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 says that after industry shocks, some managers emerge as leaders who are more capable of dealing with change than others. If these more efficient managers initiate many mergers, then the q-theory may explain some of the increased merger activity. Empirically, there is some overlap between the implications of the q-theory and the misvaluation theory because there is a positive correlation between firm overvaluation and a higher q ratio. However, the two theories have different implications for subsequent performance. The q-theory predicts a higher post-merger operating performance of acquirer firms, although the proportion of acquiring firms may not be large enough to imply a measurable increase in industry performance. The misvaluation theory predicts lower industry performance after periods of intense merger activity.

2.3. The prior empirical evidence

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

We raise some concern about RKRV's measures of misvaluation and argue that our measures based on prior and subsequent excess returns and operating performance are superior. Notice their model of firm valuation does not account for cross-sectional differences in growth opportunities. Thus, their firm-specific error could be a proxy for firm-specific growth opportunities, and their time-series sector error could be a proxy for sector-wide growth opportunities.[3] Since the financial crisis of 2008, firms and industries with high valuation ratios (market-to-book, price-to-earnings) have turned in much stronger performance than firms and industries with low valuation ratios.[4] That raises a question about interpreting high market-to-book ratios or their components as indicators of overvaluation. Thus, *in expectation*, higher industry multiples during their study period could have represented higher growth opportunities or overvaluation. While higher growth opportunities do not appear in models of industry misvaluation as a driver of merger activity, those are a prime driver of merger activity in the neoclassical theory. For this reason, in the next section we argue that stronger returns before periods of increased merger activity combined with weaker returns afterwards in a reversing manner are a better indicator of overvaluation (and the converse is true for undervaluation). This is more so because our return model controls for cross-sectional variation in market-to-book ratios. Further review of finance literature shows that studies on whether firms involved in various corporate actions are overvalued or undervalued often examine long-term returns and, occasionally, long-term operating performance.

3. Data and methodology

3.1. Sample of mergers

We retrieve our sample of mergers announced during 1985-2018 from the Securities Data Company (SDC) files. We often use the simpler term 'merger' to connote all types of acquisitions in this paper. We start our sample in 1985 because the SDC mergers data on payment terms is less complete before then. The exact steps used to identify the sample are listed in Panel A of Table 1. The main features of our sample are summarized as follows: U.S. acquirers and targets; acquirers are public firms while targets may be public, private, or subsidiary firms; and deal value is at least $10 million in 2018 dollars. This procedure gives us a sample of 34,792 mergers, including all announced offers, both completed and incomplete.

The top panel of Fig. 1 shows the sample distribution over time. Over the 34-year period of our study, there are an average of 34,792/34 = 1,023 mergers per year. The merger activity peaks during the late 1990s, reaching 2,570 mergers in 1998. However, even during the market recession there are 516 mergers in 2009. Similar to Netter, Stegemoller, and Wintoki (2011), we find that the aggregate merger activity is a continuous variable that fluctuates but never totally busts during any year.

Inclusion of all announced merger offers (i.e., both completed and incomplete) in our sample is similar to the choice made by RKRV. The main reason behind this choice is that on the offer announcement date we do not know whether the offer will be completed, in other words successful. An estimated 13% of stock offers (and a comparable number of cash offers) are incomplete (or unsuccessful), but that outcome is not known until much later (median 148 days later). More importantly, Savor and Lu (2009) show that firms that make unsuccessful stock offers earn significantly more negative long-term returns than firms that make successful stock offers. Thus, potentially all stock offers can provide evidence on the industry misvaluation theory. We further address this issue (along with terminologies) in Section 6.1 and show that our

[3] In this regard, Savor and Lu (2009) state: "Accounting ratios might signal a firm's future growth rate or the riskiness of its cash flow rather than any mispricing."

[4] During 2009-2020, Vanguard Growth Index Fund Admiral (ticker VIGAX) earned a geometric average annual return of 18.24%, compared to 12.18% earned by Vanguard Value Index Fund Admiral (ticker VVIAX).

Table 1
Sample of mergers. Our sample period spans 1985-2018. 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 mergers are those for which at least 50% of total payment is in the form of acquirer stock, and majority cash mergers 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 of merger is the year of announcement date.

Panel A: Sample retrieval

No.	Description	No of mergers
1	All merger offers from U.S. public firms (acquirers) to U.S. targets during 1985-2018	134,338
2	Target firm is a public, private, or subsidiary firm	133,167
3	Deal form is 'Merger', 'Acquisition of Assets', or 'Acq. Maj. Int.'	96,660
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	96,627
5	In case of multiple offers for target within a 2-month window, include only the completed offer	95,958
6	Deal value is at least $10 million in 2018 dollars	36,983
7	Payment method is available	34,792

Panel B: Sample distribution by payment method and target type

Target type →	Public	Private	Subsidiary	All targets
Payment method ↓				
Majority stock payment	4,169	4,990	959	10,118
Majority cash payment	3,604	11,330	9,740	24,674
All payment methods	7,773	16,320	10,699	34,792

results are about the same regardless of whether we include all announced merger offers or only completed offers.

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. Unlike previous studies that analyze data from earlier years, we cannot restrict our sample to all-stock deals in our study for the following reason. Boone, Lie, and Liu (2014) and de Bodt, Cousin, and Roll (2018) document that there has been a sharp decrease in the number of all-stock deals and a concurrent increase in the number of mixed-payment deals in the 21st century. De Bodt et al. attribute this change to the abolishment of pooling method of accounting and amortization of goodwill by the Financial Accounting Standards Board (FASB) in 2001. Consistent with their findings, the lower panel of Fig. 1 shows a sharp decrease in the proportion of all-stock deals since 2002 in our sample. We conjecture that this decrease may have occurred because overpriced acquirers use some cash payment to win over the more skeptical individuals among the target shareholders, especially since there is no longer a clear reason for using all stock payment. Dropping such cases from our sample would overlook the information conveyed by them. In addition, we later explain that the lower number of observations that results from requiring all stock payment decreases the stability of bucket portfolios and weakens the results. The final choice of what constitutes a stock merger thus takes into account an overpriced acquirer's incentives to use sufficient, *but not all*, stock payment and the desire for a larger sample of mergers. We require majority stock payment for our base sample. However, in Section 6.2 we show that our results remain significant if we change the required stock payment to at least 60, 70, 80, 90, 95, or 99 percent of total payment.

Panel B of Table 1 shows that 54% of the 7,773 public targets, 31% of the 16,320 private targets, and 9% of the 10,699 subsidiary targets receive majority stock payment, a total 10,118 cases, or 29% of all mergers (henceforth, stock mergers). 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. A finer industry classification again decreases the stability of quarterly merger activity variable *MAV* (defined below) because it means fewer firms and mergers in any one industry-quarter. Later we show 48-industry classification as part of robustness tests.

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. 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 nondurables and durables industries at one end and 38% for business equipment industry at the other end. The last column of Table 2 shows that the mean number of stock mergers per firm quarter equals 0.0154 in the combined sample. However, it varies considerably from 0.0047 in durables industry to 0.0289 in telecommunications industry. It therefore becomes necessary to use this mean number of stock mergers per firm quarter as a scaling factor in defining *MAV* below.

3.2. Stock merger activity variable (MAV)

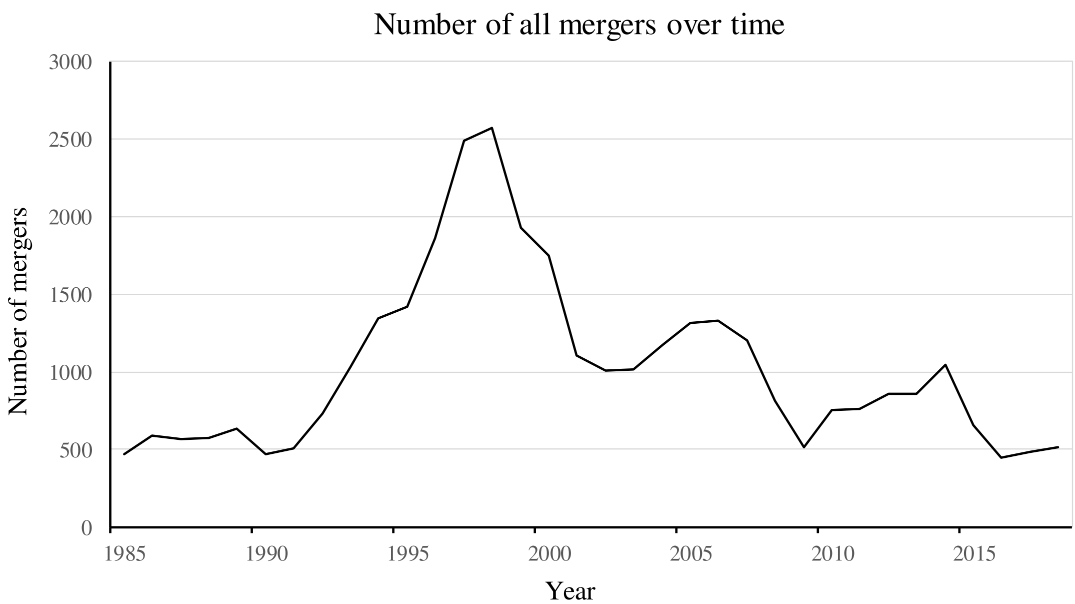
We propose a continuous stock merger activity variable as an alternative to discrete industry merger waves due to reasons outlined in the introduction and revisited below. Each quarter t, starting in 1985-Q4 and ending in 2018-Q3, we compute stock **merger activity variable** $MAV_{jt,stk}$ for industry j 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 τ, $n_{j\tau}$ denotes the number of firms in that quarter, and T denotes the total number of calendar quarters. In our case, the aggregate sample period extends from 1985 to 2018, or $T = 136$ quarters.

A few aspects of this stock merger activity variable require 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. Such procedure is often used in other financial analyses. 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.

Second, the denominator of *MAV* is the long-term average merger activity for industry j, which is the natural benchmark for scaling its current merger activity in the numerator. This denominator is the variable reported in the last column of Table 2, and it



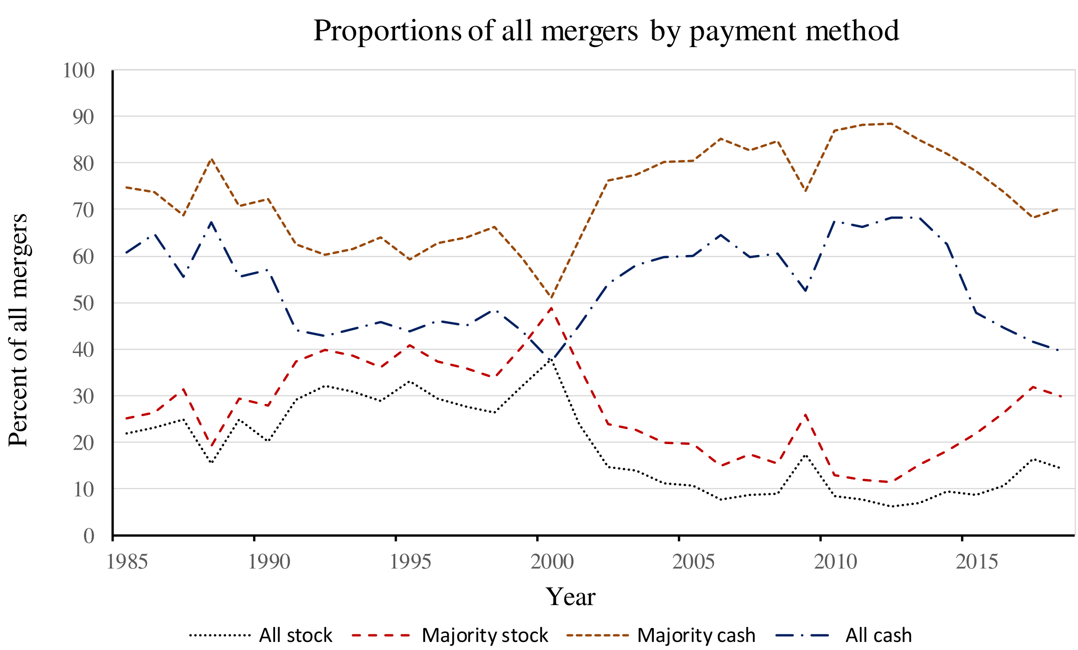


Fig. 1. Merger activity over time and by payment method. The sample of 34,792 acquisitions made by U.S. public firms during 1985-2018 is retrieved from the SDC database following criteria listed in Table 1. The top panel shows number of all mergers over time and the bottom panel shows percent breakdown by payment method. All-stock mergers involve at least 99% payment using the acquirer's common stock, and all-cash mergers involve at most 1% payment using the acquirer's stock. Majority stock (majority cash) mergers require at least (at most) 50% payment using the acquirer's stock. The proportions of all stock mergers as well as majority stock mergers have declined over time.

makes the average value of *MAV* calculated over all quarters for an industry equal to one. When standing in quarter t, this variable also includes some look-ahead information. That follows a common practice in the related literature since merger waves are *always* identified by setting a cutoff value that equals some multiple of the average merger activity over an aggregate period. Following similar practice, RKRV use the aggregate time-series of sector multiples to calculate the current sector misvaluation, which involves look-ahead information. Later, we show that our test results hold even if we use only backward-looking information in constructing *MAV*.

3.3. Bucket assignment procedure for assessing subsequent (post-MAV) performance

$MAV_{jt,stk}$ is our measure of stock merger activity of industry j during quarter t, calculated by adjusting for that industry's long-term average stock merger activity. This raw *MAV* is a cardinal measure of abnormal stock merger activity. We rank all industries by this *MAV* value. The resulting *MAV* rank is an ordinal measure of abnormal stock merger activity across industries at a given point in time. This ordinal measure is very useful as it always takes the value between 1 and 12, so we can form 12 bucket portfolios in

Table 2
Merger activity by industry. The sample of all mergers is described in Table 1. We identify which of the Fama-French 12 industries an acquirer belongs to using the Compustat historic SIC codes after 1987 and CRSP historic SIC codes before 1987. The second column below reports the mean number of firms by industry. The third and fourth columns show the number of all mergers during the aggregate period 1985-2018 and the number of mergers that use majority stock payment. The last column reports the mean number of mergers that use majority stock payment per firm quarter. To understand the calculation, notice that, for the nondurables industry, there are a total of 170 majority stock mergers over 136 quarters from 1985-Q1 to 2018-Q4. The mean number of firms at any time is 256, so there are a total of 136 × 256 = 34,816 firm quarters. Thus, the mean number of majority stock mergers per firm quarter is 170/34,816 = 0.0049 as shown in the last column.

Industry	Mean number of firms at year-end	Number of mergers during 1985-2018: All mergers	Number of mergers during 1985-2018: Mergers that use majority stock payment (% of all mergers)	Mean number of majority stock payment mergers per firm quarter
1. Nondurables	256	1,198	170 (14)	0.0049
2. Durables	121	541	78 (14)	0.0047
3. Manufacturing	501	2,592	380 (15)	0.0056
4. Energy	168	1,936	373 (19)	0.0163
5. Chemicals	105	484	74 (15)	0.0052
6. Business Equipment	823	6,443	2,426 (38)	0.0217
7. Telecommunications	120	1,982	471 (24)	0.0289
8. Utilities	139	837	200 (24)	0.0106
9. Shops	485	2,143	520 (24)	0.0079
10. Healthcare	495	2,764	790 (29)	0.0117
11. Money	1,002	9,787	3,617 (37)	0.0265
12. Other	625	4,085	1,019 (25)	0.0120
All industries	4,841	34,792	10,118 (29)	0.0154

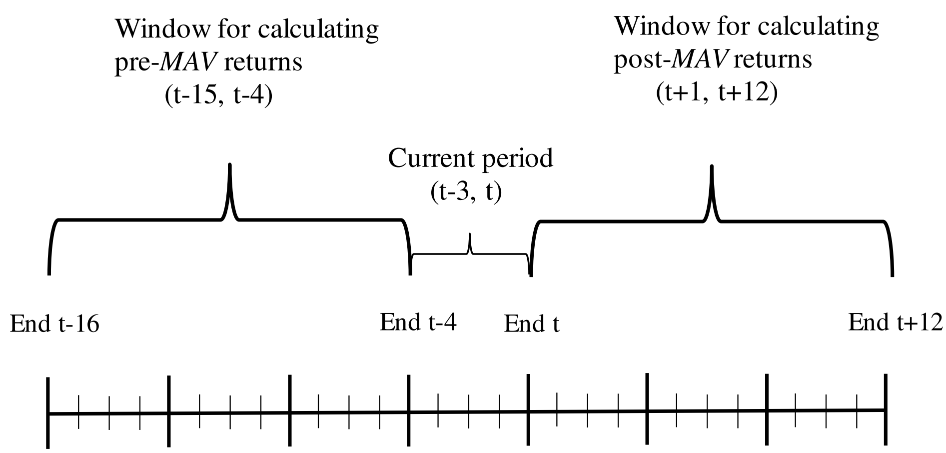


Fig. 2. Timeline. $MAV_{jt,stk}$ for industry j during quarter t is calculated using majority stock mergers announced over the period from the beginning of quarter $t-3$ to the end of quarter t. See Sections 3.2 and 3.3 and Equation (1) for further methodological details. The twelve industries $j = 1$ 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 a three-year 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 a three-year period from the beginning of quarter $t-15$ to the end of quarter $t-4$. Thus, pre-*MAV* bucket portfolios have the same composition as post-*MAV* bucket portfolios, but with a four-year lag.

calendar time. Next, each quarter $t+1$, we add each industry to a bucket with the same number as that industry's *MAV* rank during quarter t. Thus, bucket 12 always collects an industry with currently the highest abnormal stock merger activity, which may be the industry with the lowest downturn in activity during periods of downturn in market-wide activity, or the industry with the highest upturn in activity during periods of upturn in market-wide activity. Bucket 1 is at the opposite end of the spectrum compared to bucket 12, and the in-between buckets collect industries with in-between ranks on abnormal stock merger activity. Looking at it another way, *MAV* rank takes out the effect of market-wide change in activity and focuses on the effects of industry-specific change in activity.

To complete description of the bucket assignment procedure for assessing subsequent or post-*MAV* long-term excess returns, each industry added to a bucket is kept there for a period of three years, or 12 quarters. Every quarter, one industry that was included 12 quarters back is dropped and a new industry is added. Every bucket has exactly 12 entries during every quarter, from 1989-Q1 to 2018-Q4, although these entries may not be distinct. Fig. 2 shows the procedure graphically using a timeline.

Table 3 shows summary information for industries included in every bucket from 1 to 12, calculated at the time of entry and then averaged over all quarters. Recall that by construction, the average *MAV* value for any industry over time equals one. In addition, we find that every industry spends about half the time in lower bucket numbers and half the time in higher bucket numbers. As a result, the first two columns of Table 3 show that there is no significant correlation between bucket number and mean ratio of industry value to total market value or mean book-to-market ratio of industries at the time of inclusion. The next two columns show that, as expected, there is a highly significant correlation of 0.96 between bucket number and either of mean *MAV* or mean number of stock mergers per firm quarter of industries at the time of inclusion. Finally, the last column of Table 3 shows that the distinct number of industries over time in a bucket portfolio ranges between 3.70 and 6.98. That is because *MAV* for any industry changes gradually over time, partly the result of our moving-average calculation procedure underlying Equation (1). So, the same industry may enter a bucket during adjacent quarters.

We calculate monthly return for a bucket portfolio as the equally weighted average of monthly returns for each of the 12 in-

Table 3
Buckets formed by relative stock merger activity of industries. Each quarter t, starting in 1985-Q4 and ending in 2018-Q3, we calculate stock merger activity variable $MAV_{jt,stk}$ for industry j during quarter t as follows: $MAV_{jt,stk} = \frac{\sum_{\tau=t-3}^{t} m_{j\tau,stk} / \sum_{\tau=t-3}^{t} n_{j\tau}}{\sum_{\tau=1}^{T} m_{j\tau,stk} / \sum_{\tau=1}^{T} n_{j\tau}}$ Here, $m_{j\tau,stk}$ denotes the number of stock mergers announced by all acquiring firms in industry j during quarter τ, $n_{j\tau}$ denotes the number of firm-quarters, and T denotes the total number of calendar quarters. The sample period is 1985 to 2018, thus $T = 136$ quarters. At the end of each quarter, we rank the Fama-French 12 industries from lowest to highest values of $MAV_{jt,stk}$ and assign them into 12 buckets with the same numbers as the *MAV* ranks. Thus, bucket 1 always collects the least stock merger active industry and bucket 12 always collects the most stock merger active industry. The first quarter of bucket formation is 1986-Q1 (given the calculation of *MAV* over a rolling four-quarter window), and the last quarter is 2018-Q4. Each industry assigned to a bucket is kept there for 12 quarters, starting with quarter $t+1$ and ending with quarter $t+12$. The first five columns of this table show each bucket's mean ratio of industry value to total market value, mean book-to-market ratio, mean $MAV_{jt,stk}$, and mean number of stock mergers per firm quarter. Each variable is calculated each quarter for the industry just added to the bucket, and then averaged over all quarters. Industry book-to-market is calculated as the aggregate book value of all firms included in an industry divided by the aggregate market value. In calculating this variable, we ignore firms whose book-to-market value lies outside 1 and 99 percentile of the distribution of book-to-market values. The last column of table shows the mean number of distinct industries in a bucket, starting in 1989-Q1, when the return measurement for all post-*MAV* tests starts. The reason is that 1989-Q1 is the first quarter when we have exactly 12 entries in each bucket for an entire year. 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 ratio	Mean $MAV_{jt,stk}$	Mean number of stock mergers per firm-quarter	Mean number of distinct industries over time
	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	0.550	0.333	0.0038	4.79
2	0.078	0.468	0.473	0.0060	5.98
3	0.093	0.505	0.581	0.0087	6.13
4	0.082	0.516	0.651	0.0103	6.67
5	0.083	0.524	0.722	0.0095	6.36
6	0.085	0.524	0.804	0.0119	6.42
7	0.090	0.497	0.896	0.0121	6.98
8	0.098	0.503	0.993	0.0130	6.59
9	0.092	0.527	1.111	0.0158	6.43
10	0.085	0.566	1.247	0.0142	6.07
11	0.075	0.483	1.458	0.0170	4.75
12 (most merger active)	0.082	0.454	1.885	0.0196	3.70
Correlation between bucket number and variable	0.34	-0.21	0.96***	0.96***	-0.30

dustries included in that month. The industry returns themselves are calculated for value-weighted portfolios of all industry stocks and made available on Professor Ken French's website.[5] It helps to think of industries as ETFs. Viewed that way, our bucket portfolio formation procedure is the same as calendar-time portfolio formation procedure for individual stocks used in many studies.

We use the calendar-time portfolio method because it is recommended as a conservative procedure of testing for excess returns by Fama and French (2003). Following this method, we will estimate just one alpha for each bucket portfolio (or *MAV* rank) using 360 monthly returns. An alternative technique based on event-time methods would be as follows. First, every quarter assign the 12 industries to 12 buckets. Then, for each bucket number, calculate the corresponding alpha using 36 months of industry returns. Do this for each of 120 quarters and calculate the final mean alphas for each bucket using the time-series of quarterly alphas. We do follow a somewhat similar approach as a robustness check in Section 6.6. However, it is not a recommended approach because it overstates the statistical significance of results relative to calendar-time methods because the 120 estimates use overlapping series of monthly industry returns and therefore cannot be independent.

3.4. Bucket assignment procedure for assessing prior (pre-MAV) performance

Fig. 2 also shows the procedure of forming bucket portfolios for calculating prior or pre-*MAV* excess returns leading to changes in current stock merger activity (calculated over the quarters $t-3$ to t). We use a parallel procedure to that for assessing post-*MAV* excess returns, but instead of dropping an industry into a bucket portfolio over quarters $t+1$ to $t+12$, we do so over quarters $t-15$ to $t-4$. Thus, the pre-*MAV* bucket portfolio returns aggregate the returns of included industries over a three-year period ending before the period over which we calculate the current stock merger activity.

3.5. Extended applications of MAV measure

We believe that our *MAV* measure can be adopted to many situations beyond the current study. With a change of input variable, it can be adopted to measuring industry cash merger activity (done later in this paper), industry all merger activity, or market-wide stock, cash, or all merger activity. It can also be extended to other corporate events, such as IPOs (initial public offerings), SEOs (seasoned equity offerings), and stock repurchases. This measure has the advantage of being a continuous variable compared to a binary wave vs. non-wave variable, which captures information from the full range of activity.

4. Empirical predictions

In this section, we develop testable predictions of the industry misvaluation theory of stock merger activity. We start with predictions of excess returns.

Prediction 1 (in terms of industry returns): The prior excess return of an industry calculated over a three-year period ending just before the period of calculating merger activity will be positively related to its MAV rank (which is a measure of that industry's abnormal stock merger activity after adjusting for its own long-term average activity and also the abnormal stock merger activity of other industries).

(Equivalently, in terms of bucket portfolio returns): The excess returns of pre-MAV bucket portfolios (more simply, pre-MAV alphas) calculated over the aggregate period will be positively related to bucket numbers.

Both SV and RKV theories suggest that industry overvaluation increases stock merger activity and industry undervaluation decreases it. Overvaluation or undervaluation builds up over time. The length of this time-period is unknown and may vary across

[5] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

the sample. Somewhat arbitrarily, we assume that it equals three years. Three years is a common length of time-period in studies of long-term returns. If the actual length is shorter, we will still capture the entire excess return, but with added noise. If the actual length is longer, we will miss some of the excess return, but we hope that we will capture most of it.

Correctly measuring an industry's abnormal stock merger activity is critical. It needs no explaining that it must adjust for that industry's own long-term activity as in all models of merger waves. Further adjustment for market-wide increase in activity (i.e., for all other industries) is less obvious, but necessary because all models of excess return include market return as one factor. Suppose a subject industry has become overvalued by 10%, which has led to a 15% increase in its activity relative to its own long-term average. Suppose further that all other industries (i.e., the market) have become overvalued by 16%, which has led to an average 24% increase in their activity relative to their long-term average. The subject industry in this case would have earned a pre-*MAV* excess return of 10-16 = -6%. That pre-*MAV* excess return is consistent with its current abnormal activity of 15-24 = -9% *after adjusting* for activity of other industries. It is not consistent with abnormal activity of +15% *without adjusting* for activity of other industries. Our *MAV* rank makes these adjustments by comparing industries with each other. (Numbers are chosen to illustrate a concept and are not based on any model of prices versus merger activity.)

Our bucket portfolios include industries with the same *MAV* rank at the time of their inclusion as the bucket number, which explains the leap from prediction in terms of industry returns to bucket returns. As clarified in Section 3.3, testing with bucket returns over the aggregate period follows the Fama-French calendar-time portfolio method designed for conservative inference. In the following excess return predictions, we skip the mention of industry returns and stick to bucket returns.

<u>Prediction 2</u>*: The excess returns of post-MAV bucket portfolios (more simply, post-MAV alphas) calculated over the aggregate period will be* <u>*negatively*</u> *related to bucket numbers.*

The logic for this prediction starts with the last prediction. Overvaluation must dissipate over some time-period, which we again assume to be three years. Empirically, most studies of misvaluation of individual stocks around different corporate events start with Prediction 2. That is because post-event excess returns are inconsistent with market efficiency and can be captured with a trading strategy. Pre-event excess returns of the opposite sign reinforce post-event results, but by themselves do not violate market efficiency. In our context, pre-event excess returns alone can also be explained by the neoclassical theory (emerging growth opportunities), which is not rooted in market inefficiency.

<u>Prediction 3</u>*: The difference between excess returns (or alphas) of post-MAV and pre-MAV bucket portfolios of the same number will be positive for lower bucket numbers; negative for higher bucket numbers; and overall negatively related to bucket numbers.*

This prediction follows by combining Predictions 1 and 2. What goes up abnormally must come down eventually, and the converse is also true. The greater the abnormal rise, the greater the abnormal fall, which explains the correlation. Lower bucket numbers include industries with negative abnormal stock merger activity. That is consistent with their negative pre-*MAV* excess returns, positive post-*MAV* excess returns, and the positive difference between post-*MAV* and pre-*MAV* excess returns under the industry misvaluation theory. The opposite is true for higher bucket numbers.

We now start with predictions of operating performance. Tests of operating performance are more challenging than tests of excess returns for two reasons. First, operating performance is measured using annual accounting data. Quarterly accounting data suffers from seasonality effects that are different for different industries. Second, there are no obvious calendar-time portfolio methods similar to those for excess returns. We explain our procedures of testing for changes in operating performance later along with the results. The following two predictions are stated in terms of industry performance.

<u>Prediction 4</u>*: During the prior (or pre-MAV) three-year period, operating performance will not improve commensurate with positive excess returns for industries with high MAV rank, and it will not deteriorate commensurate with negative excess returns for industries with low MAV rank.*

The main idea behind this prediction is that if prior operating performance improves or deteriorates 'commensurate' with excess returns, then there may be no overvaluation or undervaluation. Unfortunately, there is no model of what is 'commensurate', so testing this prediction will be hard. However, if prior excess returns for an industry with high *MAV* rank are positive and prior operating performance is flat or declining, and the opposite is true for an industry with low *MAV* rank, then we will have shown evidence consistent with this prediction. Alternately, if increase in operating performance has an opposite correlation with *MAV* rank to that observed for excess return, or no correlation, that will serve the same purpose.

<u>Prediction 5</u>*: During the subsequent (or post-MAV) three-year period, changes in operating performance of industries will be* <u>*negatively*</u> *related to their MAV ranks (i.e., in the same direction as* <u>*excess returns*</u>*).*

The idea behind this prediction is that, during the subsequent period, the excess returns will track the correction of unreasonably high or low expectations of investors regarding an industry's operating performance. Previous literature documents such deterioration in subsequent operating performance consistent with negative excess returns of individual firms that make seasoned equity offerings or stock acquisitions (Loughran and Ritter, 1997; Akbulut, 2013). If there is an industry-wide component to changes in their operating performance, we should expect the same result for entire industries.

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

5.1. Post-MAV raw returns and risk

As explained in Section 4, we start our testing of the industry misvaluation theory of stock merger activity by analyzing the post-*MAV* returns of bucket portfolios. Section 3.3 and Fig. 2 describe the construction of these bucket portfolios. We start with raw returns. The first data column in Panel A of Table 4 shows the average annual (raw) returns of bucket portfolios calculated over the period 1989 to 2018. Annual bucket returns are calculated by compounding the monthly bucket returns, and the monthly bucket returns are calculated by averaging the monthly industry returns. We find that the average annual return declines steadily from 13.18% for bucket 1 (containing industries with the lowest abnormal stock merger activity) to 9.01% for bucket 12 (highest abnormal stock merger activity). In the bottom rows of this and many other tables that follow, we show the correlation between the column variable and the bucket number as well as the results from a univariate regression of the column variable on the bucket number. With raw returns, the correlation equals -0.88, and the slope coefficient shows that the average annual return decreases by -0.31% per bucket number, significant at 1% level.

The next column of Panel A shows that the standard deviation of annual returns follows the opposite pattern as above and increases with increasing bucket number. The double impact of lower average return and higher standard deviation leads to a lower Sharpe ratio for higher bucket numbers than for lower

Table 4

Stock merger activity of industries and their subsequent three-year returns (i.e., 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 2018-Q4, at any time every bucket has 12 entries (industries). 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. Fig. 2 shows other timeline details. Monthly returns for buckets are calculated as the arithmetic average of value-weighted industry returns retrieved from Professor Ken French's data library. The entire procedure is similar 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 (ETFs). Panel A starts with the post-merger activity raw returns for each bucket and calculates average annual return, standard deviation of annual returns, and Sharpe ratios, and cumulative returns from January 1989 to December 2018 (30 years). Panel B reports the Fama-French 3-factor alphas and other model outputs using monthly bucket returns. 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. Each regression has 360 monthly return observations. The third row from the bottom of Panel A and the second row from the bottom of Panel 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. Another benchmark is an equally weighted portfolio of all 12 industries over time. Panel C reports one consolidated regression that replaces the multiple regressions of Panel B. Figures in parentheses are t-statistics. For alphas in Panel B and coefficient of bucket number in Panel C, we report both OLS and wild bootstrapping t-statistics in parentheses followed by their significance levels outside parentheses. For remaining coefficients of factors, we report only OLS t-statistics in Panel C and omit them in Panel B. 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, 1989-2018*

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 2018
1 (least merger active)	13.18%	18.00%	0.568	$27.31
2	12.96	15.39	0.651	28.65
3	12.92	16.60	0.601	26.77
4	12.71	15.76	0.619	26.27
5	12.98	17.43	0.576	26.24
6	12.01	17.95	0.505	19.78
7	11.67	18.06	0.483	17.81
8	11.55	16.26	0.529	18.79
9	11.66	18.08	0.482	17.81
10	12.05	18.06	0.504	19.55
11	10.07	18.28	0.390	11.50
12 (most merger active)	9.01	19.17	0.316	8.22
Correlation between variable and bucket number	**-0.88*****	0.63**	-0.88***	-0.93***
Slope of variable regressed on bucket number,	-0.31%	0.20%	-0.023	-$1.68
t-statistic in round brackets, and adj-R^2 in square	(-5.72)***	(2.55)**	(-5.72)***	(-8.02)***
brackets	[0.74]	[0.33]	[0.84]	[0.85]
Value-weighted market returns	11.89	17.87	0.500	17.24
Equally-weighted portfolio of all 12 industries	11.87	16.55	0.539	20.22

***Panel B**: **Fama-French 3-factor alphas** for buckets containing industries ranked by their stock merger activity, 1989-2018*

Bucket number	**Alpha** (OLS t-statistic, wild bootstrap t-statistic)	Coefficients of			Adjusted-R^2
		RMRF	*SMB*	*HML*	
1 (least merger active)	**0.116** (1.09, 2.15) ,**	0.926	-0.004	0.391	0.79
2	**0.199** (2.34, 3.69)**,***	0.826	-0.018	0.226	0.82
3	**0.140** (1.72, 2.59)*,***	0.913	-0.030	0.205	0.86
4	**0.137** (2.24, 2.54)**,**	0.920	-0.003	0.124	0.92
5	**0.125** (2.01, 2.32)**,**	0.920	0.030	0.176	0.92
6	**0.016** (0.26, 0.30)	0.978	-0.015	0.214	0.92
7	**-0.028** (-0.54,-0.53)	1.004	0.039	0.187	0.95
8	**0.021** (0.41, 0.38)	0.955	-0.076	0.187	0.95
9	**-0.036** (-0.49,-0.66)	0.998	0.033	0.283	0.91
10	**0.000** (0.00, 0.01)	0.976	-0.017	0.318	0.90
11	**-0.056** (-0.48,-1.04)	0.942	-0.184	0.034	0.76
12 (most merger active)	**-0.156** (-1.59,-2.89) ,***	0.963	-0.124	-0.061	0.83
Correlation between bucket number and variable	**-0.91*****	0.63**	-0.53*	-0.53*	
Slope of variable regressed on bucket number, OLS	-0.026%	0.008	-0.010	-0.018	
t-statistic in round brackets, and adj-R^2 in square brackets	(-6.96)***	(2.57)**	(-1.99)*	(-2.00)*	
	[0.81]	[0.34]	[0.21]	[0.21]	
Equally-weighted portfolio of all 12 industries at all times	0.041 (1.07, 0.75)	0.945	-0.043	0.182	0.97

***Panel C**: **Consolidated regression of excess returns** from all 12 buckets in Panel A pooled together*

$$
\begin{aligned}
\textit{bucket return} - \textit{riskfree return} = {} & \underset{(4.20)^{***}}{0.210} \; \mathbf{-} \; \underset{(\mathbf{-3.85,-5.91})^{***,***}}{\mathbf{0.026}} \times \textbf{\textit{bucket number}} + \underset{(73.45)^{***}}{0.888} \times \textit{RMRF} + \underset{(5.14)^{***}}{0.008} \times \textit{RMRF} \times \textit{bucket number} \\
& + \underset{(1.99)^{**}}{0.033} \times \textit{SMB} - \underset{(-4.34)^{***}}{0.010} \times \textit{SMB} \times \textit{bucket number} + \underset{(17.90)^{***}}{0.306} \times \textit{HML} - \underset{(-7.69)^{***}}{0.018} \times \textit{HML} \times \textit{bucket number}
\end{aligned}
$$

N = 4,320, Adjusted-R^2 = 0.87

bucket numbers. Specifically, the Sharpe ratio decreases by -0.023 per bucket number, significant at 1% level. That implies a fitted difference of $0.023 \times 11 = 0.253$ between Sharpe ratios of buckets containing the least merger active and the most merger active industries, a big number compared to Sharpe ratio of 0.500 for the CRSP value-weighted market portfolio during this period.

In economic terms, the investor experience is better captured by cumulative returns shown in the last column of Panel A of Table 4. $1 invested in bucket number 1 in the beginning of 1989 would have grown to $27.31 by the end of 2018 (a period of 30 years) compared to $8.22 in bucket number 12. Those cumulative amounts stand in a ratio of 3.32 to 1. The cumulative value of $1 has a correlation of -0.93 with bucket number, and it decreases by -$1.68 per bucket number. We include two benchmarks for further comparison: first, the returns on the CRSP value-weighted market portfolio (VWRETD), and, second, the returns on an equally weighted portfolio of the 12 industries. Recall that the industry returns themselves are returns on value-weighted portfolios of industry stocks. The second benchmark seems more relevant in the context, but the return statistics for both benchmark portfolios are shown in Table 4. $1 invested in the market index in the beginning of 1989 would have grown to $17.24 by the end of 2018, and the same dollar invested in the equally weighted portfolio of all industries would have grown to $20.22. The latter value is somewhere in the middle of the cumulative wealth for the 12 buckets portfolios.

5.2. Post-MAV alphas and t-statistics

Panel B of Table 4 shows the Fama-French 3-factor alpha calculated using 360 monthly returns for each post-*MAV* bucket portfolio during 1989-2018. The three factors are *RMRF, SMB*, and *HML*, defined as the returns on zero-investment portfolios of market minus riskfree, small minus big, and high minus low book-to-market stocks (Fama and French 1993). *Prediction 2* says that post-*MAV* alphas should be negatively related to bucket numbers. This prediction is best tested by whether a trend line fitted through alphas relative to bucket numbers has a significantly negative slope. In addition, one would expect post-*MAV* alphas to change from positive for low bucket numbers to around zero for middle bucket numbers and further to negative for high bucket numbers.

Before discussing alphas and trends, we need to explain our procedure of calculating the associated *t*-statistics. In all our tests, we first show ordinary-least-squares (OLS) *t*-statistics. However, an extensive literature shows that in the presence of heteroscedasticity (i.e., violation of the assumption that error terms have a constant variance over the entire sample), the OLS *t*-statistics are biased. In Appendix A, we discuss that our portfolio returns suffer from significant heteroscedasticity and that this problem is more acute in extreme buckets characterized by large positive or large negative returns in both the pre-*MAV* and post-*MAV* periods. Heteroscedasticity leads to biased *t*-statistics and inference. Appendix A further describes wild bootstrap techniques following classical papers by Wu (1986) and Liu (1988), which provide the best correction for heteroscedasticity and have been used in many finance studies. Thus, for accurate inference of the statistical significance of key coefficients in this paper, we report wild bootstrap *t*-statistics next to OLS *t*-statistics. This statistic becomes necessary since the individual alphas of the 12 portfolios of industry ETFs are expected to be of a smaller magnitude than the alphas of portfolios of stock acquirers that are often tested in the finance literature. For less important coefficients of market, size, and book-to-market factors in regressions, we report only the OLS *t*-statistics (or no *t*-statistics) to reduce clutter.

The alphas for the 12 bucket portfolios presented in Panel B support *Prediction 2*. First, all six alphas of buckets numbered 1 to 6 are positive, four of them have significant OLS *t*-statistics, and five of them have significant wild bootstrap *t*-statistics. Second, four out of six alphas of buckets numbered 7 to 12 are negative, although only the alpha of bucket numbered 12 has a significantly negative wild bootstrap *t*-statistic. These asymmetric results arise from a statistical limitation of Fama-French tests. To understand that, notice the simple average of the 12 bucket alphas is positive, even though collectively the industries included in this paper form the market. That occurs because of the weighting procedure. A monthly return for any bucket portfolio is calculated as an equally weighted average of the included value-weighted industry returns of very different-size industries. The last row of Panel B shows that an equally weighted portfolio of all 12 value-weighted industry ETFs over the entire study period has a small positive but statistically insignificant alpha of 0.041% per month. This finding suggests that, on average, the alphas of bucket portfolios can also be positive, by an unknown amount depending on the composition of portfolios. Because *t*-statistics are calculated by comparing measured alphas against the benchmark of zero return, the number of significantly positive alphas in lower numbered buckets 1 to 6 can be greater than the number of significantly negative alphas in higher numbered buckets 7 to 12.

For these reasons, even though the alphas of individual buckets are broadly supportive of the misvaluation hypothesis, a more meaningful inference requires fitting a trend line through the individual alphas. Along these lines, we first note that the correlation between bucket alphas and bucket numbers is a high -0.91 (p-value = 0.00004). The corresponding rank correlation (not reported in the table) is a similarly high -0.88. A trend line fitted through alphas plotted against bucket numbers has a highly significant slope of -0.026% per month per bucket number. That translates into a decrease of $-0.026 \times 12 = -0.312\%$ per year per bucket number, which is about the same as a decrease of -0.31% per bucket number for raw annual returns reported in Panel A. Risk adjustment does not alter our results concerning the differences between raw bucket returns. This consistency holds true despite the fact that, as inferred from the coefficients of *RMRF, SMB*, and *HML* risk factors, the market beta increases, average firm size increases, and average book-to-market ratio decreases with increasing bucket number. The effects of changes in different firm characteristics with increasing bucket numbers approximately cancel out in our sample.

The above tests provide economically and statistically significant evidence in favor of a decreasing trend in post-*MAV* alphas with increasing stock merger activity. There is an effective way to answer the same question with one consolidated regression of all $360 \times 12 = 4{,}320$ monthly returns (net of riskfree rate) for 12 buckets over 30 years that is shown in Panel C of Table 4. The regressors include the original terms of intercept, *RMRF, SMB*, and *HML* in the Fama-French model, plus the bucket number and the interaction of *RMRF, SMB*, and *HML* with the bucket number. We find that the intercept equals 0.210% and the (slope) coefficient of bucket number equals -0.026%. This critical slope coefficient of bucket number has OLS and wild bootstrap *t*-statistics of -3.85 and -5.91, significant at 1% level. Thus, the fitted post-*MAV* alpha equals $0.210-0.026 \times 1 = 0.184\%$ for bucket number 1, $0.210-0.026 \times 2 = 0.158\%$ for bucket number 2, and so on, until $0.210-0.026 \times 12 = -0.102\%$ for bucket number 12. The fitted slope of the bucket number used as a key variable for inference is about the same in both Panels B and C of Table 4.

5.3. Pre-MAV alphas

Prediction 1 regarding pre-*MAV* alphas is stated first in the order it appears in event time, but tested next for reasons ex-

Table 5
Stock merger activity of industries and their prior three-year returns (Pre-*MAV* alphas). This table analyzes the relation between stock merger activity of industries and their **preceding** three-year excess returns. For each calendar quarter t, starting with 1985-Q4 and ending with 2018-Q3, we compute stock merger activity variable $MAV_{jt,stk}$ for $j = 1$ to 12 industries as described in Sections 3.2 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 $MAV_{jt,stk}$. Fig. 2 shows other timeline details. We calculate monthly bucket returns from 1985-Q1 to 2014-Q4, a period during which each bucket has exactly 12 entries. Monthly returns for buckets are calculated as the arithmetic average of value-weighted industry returns retrieved from Professor Ken French's data library. Panel A reports the Fama-French 3-factor alphas and other model outputs for each bucket portfolio. Alpha values are in percent per month. The second from bottom row of this table reports results of a univariate regression of the corresponding column variable on the bucket number. Panel B pools all monthly returns for all buckets and reports one regression that includes the intercept and the three Fama-French factors, plus the bucket number and interaction terms between each Fama-French factor and the bucket number. Figures in parentheses are t-statistics. For alphas in Panel B and coefficient of bucket number in Panel C, we report both OLS and wild bootstrapping t-statistics in parentheses followed by their significance levels (if under 10 percent) outside parentheses. For remaining coefficients of factors, we report only OLS t-statistics in Panel B and omit them in Panel A. Notations *, **, and *** represent statistical significance at 10, 5, and 1 percent levels.

***Panel A**: **Fama-French 3-factor alphas** for buckets containing industries ranked by their stock merger activity, 1989-2018*

Bucket number	**Alpha** (OLS t-statistic, wild bootstrap t-statistic)	Coefficients of *RMRF*	*SMB*	*HML*	Adjusted-R^2
1 (least merger active)	**-0.112** (-1.15,-2.08) ,**	0.986	-0.023	0.350	0.85
2	**-0.072** (-0.83,-1.34)	0.930	-0.073	0.313	0.86
3	**-0.001** (-0.02,-0.03)	0.967	-0.049	0.105	0.88
4	**-0.011** (-0.14,-0.20)	0.971	-0.018	0.291	0.90
5	**-0.048** (-0.76,-0.86)	0.964	-0.055	0.187	0.93
6	**-0.004** (-0.07,-0.08)	0.997	-0.079	0.186	0.93
7	**-0.028** (-0.51,-0.52)	1.050	-0.005	0.167	0.95
8	**0.081** (1.57, 1.50)	0.980	-0.016	0.185	0.95
9	**0.005** (0.06, 0.10)	0.984	-0.021	0.332	0.88
10	**0.090** (1.20, 1.67) ,*	0.932	0.046	0.214	0.90
11	**0.282** (2.69, 5.30)***,***	0.917	-0.053	-0.107	0.82
12 (most merger active)	**0.379** (3.62, 7.05)***,***	0.834	-0.076	-0.096	0.79
Correlation between bucket number and variable	**0.84***	-0.45	-0.02	-0.71***	
Slope of variable regressed on bucket number, OLS t-statistic in round brackets, and adj-R^2 in square brackets	0.034% (4.87)*** [0.67]	-0.007 (-1.58) [0.12]	0.000 (-0.06) [-0.10]	-0.029 (-3.18)*** [0.45]	
Equally-weighted portfolio of all 12 industries	0.048 (1.27, 0.89)	0.961	-0.046	0.175	0.97

***Panel B**: Consolidated regression of excess returns from all 12 buckets in Panel A pooled together*

bucket return − riskfree return = − 0.173 **+ 0.034** × ***bucket number*** + 1.002 × *RMRF* − 0.007 × *RMRF* × *bucket number*
(−3.41)*** (**4.90, 7.55**)***,*** (86.24)*** (−4.16)***
− 0.029 × *SMB* − 0.000 × *SMB* × *bucket number* + 0.374 × *HML* − 0.029 × *HML* × *bucket number*
(−1.72)* (-0.08) (21.05)*** (−12.08)***
N = 4,320, Adjusted-R^2 = 0.88

plained in Section 4. Section 3.4 and Fig. 2 show that pre-*MAV* bucket portfolios have the same composition as post-*MAV* portfolios, but lagged by four years. Thus, we analyze monthly returns for the 12 pre-*MAV* bucket portfolios from 1985-Q1 to 2014-Q4, a 360-month period during which each bucket has 12 entries at all times.

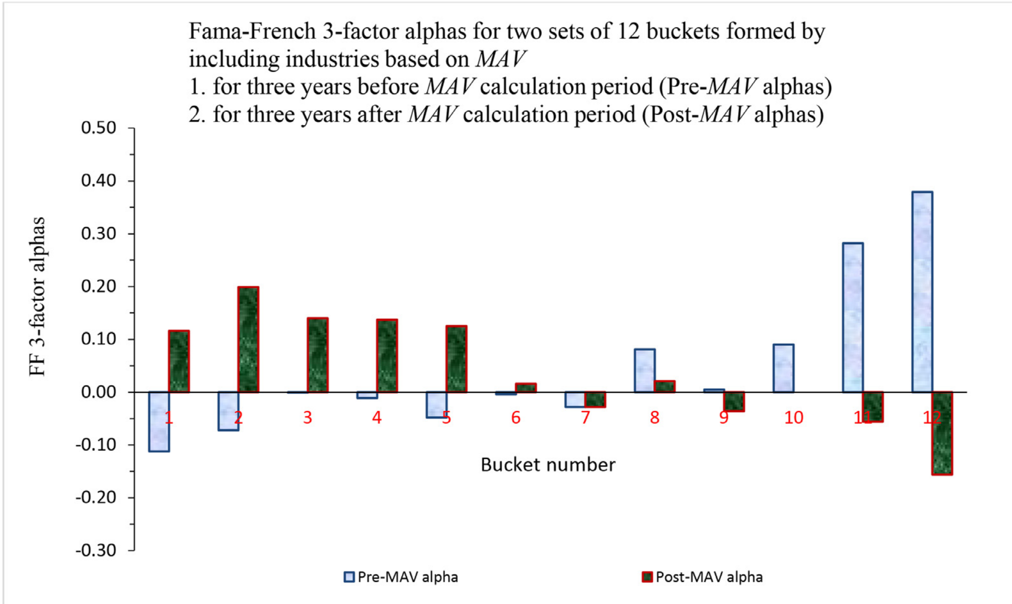
Panel A of Table 5 shows that the pre-*MAV* alphas of buckets numbered 1 to 7 are all negative while alphas of buckets numbered 8 to 12 are all positive. Four out of 12 alphas, all for extreme bucket numbers, have significant wild bootstrap t-statistics. More importantly, the correlation between bucket numbers and alphas is a highly significant 0.84, and the fitted trend line shows that the pre-*MAV* alpha increases by 0.034% per month per bucket number (or $0.034 \times 12 = 0.408\%$ per year per bucket number). That compares with -0.026% per month per bucket number for post-*MAV* alpha. The consolidated regression approach followed in Panel B of Table 5 shows the same evidence that is highly significant with OLS and wild bootstrap t-statistics of 4.90 and 7.55.

Fig. 3 plots the pre-*MAV* and post-*MAV* alphas of the 12 bucket portfolios. It shows three trends consistent with the misvaluation theory of stock merger activity: (i) Post-*MAV* alphas are decreasing with bucket number (correlation -0.91, rank correlation -0.88), (ii) Pre-*MAV* alphas are increasing with bucket numbers (correlation 0.84, rank correlation 0.89), and (iii) Pre-*MAV* and post-*MAV* alphas are negatively correlated with each other (correlation -0.78, rank correlation -0.69). All correlations except the last are significant at 1% level, while the last correlation of -0.69 has a p-value of 0.014.[6] These results support *Predictions 1* and *2*.

5.4. Reversals between pre-MAV and post-MAV excess returns

Table 6 shows pre-*MAV* alphas, post-*MAV* alphas, and the difference between the two (post minus pre). We notice several aspects of the relation between differences in alphas and bucket numbers that are highly significant in statistical and economic terms and provide key evidence in favor of *Prediction 3*. First, all six differences of lower-numbered buckets with below average merger activity are positive while all six differences of higher-numbered

[6] Our evidence on opposite trends in post-*MAV* and pre-*MAV* alphas is clearly consistent with the industry misvaluation theory of stock mergers. However, in a somewhat related context, Carlson, Fisher, and Giammarino (2006, 2010) argue that prior positive and subsequent negative excess returns of SEO (seasoned equity offering) firms can be explained by an alternate real options theory. According to this theory, SEO firms have emerging growth options before issuance that are cashed out after issuance. Consistent with their theory, Carlson, Fisher, and Giammarino show that the market betas of SEO firms increase before issuance and decrease after issuance. If mergers are a result of growth options exercised by acquirers, then one may expect some such effect in our sample. To test this possibility, we calculate the difference between post-*MAV* beta and pre-*MAV* beta for the 12 buckets that are reported in Tables 4 and 5. These differences are strongly *positively* related to bucket numbers (i.e., stock merger activity), with a correlation of 0.88, significant at 1% level. This evidence is in the opposite direction to the predictions of real options theory and suggests that our excess return results cannot be explained by that theory.



Predicted trend in Post-*MAV* alphas (opposite for Pre-*MAV* alphas)

Positive ……………………………..…….. Zero ……………………..…………. Negative

Fig. 3. Pre-*MAV* and post-*MAV* alphas. This figure graphically shows the pre-*MAV* alphas for the 12 bucket portfolios from Table 5, Panel A, and post-*MAV* alphas for the same portfolios from Table 4, Panel B. Please see those tables and Sections 3.2 and 3.3 for details of bucket portfolio formation. The correlation between pre-*MAV* and post-*MAV* alphas equals -0.78, significant at the 1% level.

Table 6

Reversals between pre-*MAV* and post-*MAV* excess returns related to stock merger activity. This table further examines data presented in Tables 4 and 5 for evidence on return reversals. Those tables show the definition and calculation of pre-*MAV* and post-*MAV* alphas and report the associated *t*-statistics. This table focuses on the differences between post-*MAV* and pre-*MAV* alphas and the associated *t*-statistics assuming their independence. We thus calculate the standard error of the difference in alphas as the square root of the sum of standard errors of pre-*MAV* and post-*MAV* alphas. We do this calculation for both OLS and wild bootstrapping estimates and report the associated *t*-statistics of difference in alphas in parentheses followed by their significance levels (if under 10 percent) outside parentheses. For expositional convenience, we do not show the *t*-statistics of pre-*MAV* and post-*MAV* alphas that are shown in Tables 4 and 5. Notations *, **, and *** represent statistical significance at 10, 5, and 1 percent levels.

Bucket number	Pre-*MAV* alpha (see Table 4, Panel B, for *t*-statistics)	Post-*MAV* alpha (see Table 5, Panel A, for *t*-statistics)	Difference in alphas (OLS *t*-statistic, wild bootstrap *t*-statistic)[1]
1 (least merger active)	-0.112	0.116	**0.228** (1.58, 2.99) ,***
2	-0.072	0.199	**0.271** (2.23, 3.56)**,***
3	-0.001	0.140	**0.141** (1.22, 1.85) ,*
4	-0.011	0.137	**0.148** (1.52, 1.94) ,*
5	-0.048	0.125	**0.173** (1.95, 2.24) *,**
6	-0.004	0.016	**0.021** (0.23, 0.27)
7	-0.028	-0.028	**-0.000** (-0.00,-0.00)[2]
8	0.081	0.021	**-0.060** (-0.84,-0.79)
9	0.005	-0.036	**-0.041** (-0.37,-0.54)
10	0.090	0.000	**-0.090** (-0.87,-1.17)
11	0.282	-0.056	**-0.338** (-2.17,-4.47)**,***
12 (most merger active)	0.379	-0.156	**-0.534** (-3.73,-7.03)***,***
Correlation between bucket number and variable	**0.84*****	**-0.91*****	**-0.92*****
Rank correlation between bucket number and variable	**0.89*****	**-0.88*****	**-0.96*****
Slope of variable regressed on bucket number, OLS *t*-statistic in round brackets, and adj-R^2 in square brackets	0.034% (4.87)*** [0.67]	-0.026% (-6.96)*** [0.81]	-0.060% (-7.31)*** [0.83]

Notes:

[1] The probability of the first six differences (below average merger activity) all being positive and the next six differences (above average merger activity) all being negative is 1 in $2^{12} = 4{,}096$, under the null hypothesis that there is no relation between difference in alphas and merger activity.

[2] The difference and *t*-statistics are slightly negative, but round off to zero.

buckets with above average merger activity are negative. That has a one-tail probability of 1 in $2^{12} = 4{,}096$ under the null hypothesis of equally likely positive and negative differences for all buckets versus the alternate hypothesis that the differences for the six lower numbered buckets are positive and for the six higher numbered buckets are negative. The wild bootstrap *t*-statistics of differences in alphas are significant in the predicted direction in seven out of 12 cases (leaving out the middle bucket numbers where the magnitudes are expectedly small), and the OLS *t*-statistics are significant in four out of 12 cases. Second, the correlation and rank correlation between differences in alphas and bucket numbers equal -0.92 and -0.96 (p-values < 0.0001). Third, the difference in monthly alphas for bucket number 1 exceeds that for bucket number 12 by a large 0.228-(-0.534) = 0.762% using raw values and

Table 7

Stock merger activity of industries and their prior and subsequent three-year operating performance. This table analyzes the relation between the stock merger activity of industries and their preceding and following three-year operating performance. We use annual operating income data from Compustat 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 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). 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 2017. 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, later year minus earlier year). 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.

MAV rank (or bucket number)	Mean value of base year operating income minus preceding year operating income (i.e., improvement during pre-*MAV* period)			Mean operating income for base year of stock merger activity	Mean value of following year operating income minus base year operating income (i.e., improvement during post-*MAV* period)		
	$y - 3$	$y - 2$	$y - 1$	Year y	$y + 1$	$y + 2$	$y + 3$
1 (least merger active)	-0.41%	-0.18%	0.07%	13.54%	0.23%	0.34%	0.29%
2	0.07	0.17	0.12	14.14	0.24	0.52	0.38
3	0.42	0.34	0.24	13.29	0.10	0.13	0.18
4	0.12	0.06	0.14	12.95	0.25	0.41	0.06
5	0.03	-0.02	0.06	12.61	0.32	0.41	0.55
6	-0.26	-0.07	-0.09	12.64	0.08	0.19	0.10
7	0.02	0.16	0.12	12.28	-0.15	-0.19	-0.16
8	-0.24	0.01	0.00	12.23	0.07	0.05	0.10
9	-0.05	-0.19	-0.15	12.16	-0.09	0.02	0.11
10	-0.16	-0.13	-0.18	11.52	-0.45	-0.53	-0.39
11	0.25	-0.07	-0.10	14.57	-0.02	-0.65	-1.08
12 (most merger active)	-0.66	-0.10	-0.05	14.93	-0.39	-0.73	-1.01
Average	-0.07	0.00	0.02	13.07	0.02	0.00	-0.07
Correlation between *MAV* rank and variable	-0.28	-0.44	**-0.74*****		-0.79***	-0.89***	**-0.80*****
Slope of variable regressed on *MAV* rank, *t*-statistic in round brackets, and adj-R^2 in square brackets	-0.023%	-0.019%	-0.027%		-0.055%	-0.106%	-0.115%
	(-0.93)	(-1.54)	(-3.50)***		(-4.13)***	(-6.04)***	(-4.27)***
	[-0.01]	[0.11]	[0.51]		[0.59]	[0.76]	[0.61]

$0.060 \times 11 = 0.660\%$ using fitted values from regression reported in the last row. The corresponding raw and fitted values for bucket numbers 2 and 11 equal 0.609% and 0.540% per month. Those are highly significant effects in economic terms. At the high bucket number end of the spectrum, a three-year pattern of strong industry returns before high stock merger activity is broken and reversed during the next three years, and at the low bucket number end of the spectrum the opposite happens.

5.5. Post-MAV and pre-MAV operating performance

We now examine the trends in industry operating performance related to stock 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 we employ that measure. They further recommend an industry and performance matching firm approach to calculate the abnormal performance of a sample of individual firms. However, we cannot follow that approach because our sample consists of 12 industries that differ by their *MAV* rank, and we predict that *MAV* rank is related to the changes in operating performance. Therefore, we follow a different methodology described in Table 7 and briefly outlined below. This methodology is well suited to testing *Predictions 4* and *5*.

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 from 1989 to 2017. Thus, each year we have four industry ETF entries in each bucket, although these entries may not 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 7 shows the mean operating income for the base year calculated from $29 \times 4 = 116$ entries in each bucket. The columns to the right show the mean difference between the operating incomes for the following years $y + 1$, $y + 2$, and $y + 3$ and base year y (later minus earlier). These columns show the post-*MAV* improvement in operating performance over one, two, and three year periods. The columns to the left show the mean difference between the operating incomes for the base year y and the preceding years $y - 3$, $y - 2$, and $y - 1$ (still, later minus earlier). These latter columns show the pre-*MAV* improvement in operating performance over three, two, and one year periods.

Consider first the post-*MAV* changes in mean operating income from year y to year $y + 3$. These changes are significantly negatively related to the *MAV* rank (or bucket number), similar to post-*MAV* excess returns in Table 4. The correlation equals -0.80, and the regression shows that operating income changes at a rate of -0.115% per rank, both significant at 1% level. Further, from year y to $y + 3$, mean operating income increases for all six lower ranks and decreases for four out of six higher ranks as predicted. In economic terms, operating income increases by 0.29% for rank 1 and decreases by 1.01% for rank 12. The difference of 1.30% is economically significant relative to the average operating income of 13% for all industries over the study period. These results support *Prediction 5*. The evidence is quite similar if we examine the alternate windows y to y+1, or y to y+2. It appears that the changes in operating performance occur soon after the year of abnormally high or low stock merger activity.

Before moving further, we address a potential concern that the post-*MAV* operating performance of acquiring firms may be understated due to step-up of target assets after merger, which may in turn understate the performance of higher numbered buckets that contain a greater number of acquiring firms. At the outset, this should be a much smaller concern with operating performance of entire industries than with individual acquirers since most firms in any industry are not involved in merger activity in any one year. In addition, before 2001 (approximately the midpoint of our sample) acquiring firms could avoid step-up of target assets by choosing the pooling method of merger accounting, which they did when the alternate purchase method would have resulted in a substantial step-up (Aboody, Kasznik, and Williams 2000). Consistent with these conjectures, we estimate that the difference in step-up of target assets across buckets 1 to 12 is likely to be small and cannot explain the difference between changes in their post-*MAV* operating performance reported in Table 7. [7]

Last, we test the less obvious but quite relevant *Prediction 4* which says that operating performance of industries in high (low) bucket numbers will not improve (deteriorate) commensurate with their positive (negative) pre-*MAV* excess returns. We first look at changes in operating income over a shorter pre-*MAV* window from $y-1$ to y in Table 7. During this window, increases in operating income are negatively related to *MAV* ranks with a correlation coefficient of -0.74, significant at 1% level. That contrasts remarkably with a positive correlation of 0.84 between pre-*MAV* excess returns and *MAV* ranks (or bucket numbers) in Table 5 (although over a three-year period). More simply, for industries with high *MAV* ranks the operating performance is decreasing while excess returns are positive, and the opposite is true for industries with low *MAV* ranks. Notice further that operating income during this window increases for industries with the four lowest *MAV* ranks and decreases for industries with the four highest *MAV* ranks, while their excess returns are moving in the opposite direction. This result shows that misvaluation builds up and leads to the noted changes in stock merger trading activity. Finally, the evidence over pre-*MAV* two-year and three-year windows is of the same sign as over one-year window, but statistically insignificant. Overall, these tests support *Prediction 4*.

5.6. Interpreting the evidence on excess returns and operating performance

Our evidence supports the industry misvaluation theory of stock merger activity proposed by Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004). First, we find that preceding excess returns over a three-year period are positive for industries with higher *MAV* ranks and negative for industries with lower *MAV* ranks. However, there is no parallel trend in their operating performance. In fact, during the preceding one year there is an opposite trend, with decreasing (increasing) operating incomes in industries with higher (lower) *MAV* ranks. That implies overvaluation (undervaluation) of industries with higher (lower) *MAV* ranks. Second, the misvaluation reverses during subsequent three 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 change in the level of stock merger activity, followed by a correction of misvaluation. In summary, the evidence is consistent with all five of our predictions.

The negative post-*MAV* excess returns and changes in operating performance of more merger-active industries in our study cannot be explained by the neoclassical theory. According to this theory, in cases where the increased merger activity occurs in response to emerging growth opportunities, one may even expect improvements in operating performance and positive excess returns. However, Mitchell and Mulherin (1996) and Harford (2005) argue that this improvement may not occur if the increased merger activity occurs in distressed industries, only that the subsequent performance may not be as bad as it would have been in the absence of merger activity. Undoubtedly, some merger waves (or periods of increased stock merger activity) occur in distressed industries, but we find that is not the norm. In unreported tests, we find that the average Standard and Poor's long-term issuer credit ratings for industries, a contrary measure of distress, are positively but insignificantly correlated with their bucket numbers (correlation 0.45, p-value 0.14, higher ratings are better ratings). Furthermore, the strong pre-*MAV* excess returns of industries with higher bucket numbers are inconsistent with their financial distress. Only the industry misvaluation theory of mergers can explain the totality of our evidence, including the negative correlations between pre-*MAV* and post-*MAV* excess returns.

6. Additional tests of misvaluation theory

The results of Section 5 are broadly consistent with the industry misvaluation theory of stock merger activity. In this section, we report several additional tests that change one feature of our methodology at a time. In all these tests, we focus on the relation between the bucket number and the pre-*MAV* and post-*MAV* bucket returns using the consolidated regression approach. We end the section by replicating the tests of Tables 4 to 7 with cash merger activity.

6.1. Calculating MAV using all announced merger offers vs. only completed offers

Section 3.1 mentions that, like Rhodes-Kropf, Robinson, and Viswanathan (2005), our base sample analyzed so far includes all announced stock offers including both completed and incomplete offers. We now dig deeper into this issue, initially by examining the reasons given by SDC for why 13.2% of announced stock offers are incomplete. The reasons are inferred from deal status, which is coded as 'withdrawn' in 61% cases, 'pending' in 29% cases, and 'status unknown' in most of the remaining 10% cases. For withdrawn offers, we have the withdrawal date, which occurs a median 148 days after the announcement date. For pending or status unknown offers, we do not have a similar outcome date. One reason why we include both completed and incomplete offers is that the actual outcome is known only after a long delay and we want to avoid the associated look-ahead bias.

Ultimately, all announced offers must be either successful or unsuccessful. Withdrawn offers are unsuccessful, and they constitute the majority of incomplete offers. Pending or status-unknown offers may have been successful or unsuccessful, which remains unknown. The three status codes applicable to incomplete offers are well distributed over the sample period, with many offers that were initiated during the 1990s but are coded as pending. It is unlikely that those offers are still open. Overall, given the code frequencies, it appears that the large majority of incomplete offers are unsuccessful offers. Therefore, with some approximation, we rephrase the question 'should we include both completed and incomplete offers or only completed offers?' as 'should we include both successful and unsuccessful offers or only successful offers?' This transformation helps a lot, because Savor and Lu (2009) provide a thorough investigation of successful versus unsuccessful

[7] Specifically, we estimate the total target assets before merger normalized by the total industry assets in the year of merger. Averaged over the years, this proportion has the following values (in percent) for buckets 1 to 12: 0.39, 1.01, 1.03, 0.77, 1.40, 1.61, 1.66, 1.35, 1.64, 1.30, 1.30, and 1.91. The difference in target assets scaled by industry assets between buckets 1 and 12 equals 1.52%. Based on numbers provided in Table 2 of Aboody, Kasznik, and Williams, we estimate that the mean step-up of target assets may be between 0.35 and 0.49 times the pre-merger target assets in cases where the purchase method of accounting was chosen. This estimation implies a difference in step-up of industry assets between buckets 1 and 12 of the order of $1.52\times(0.35+0.49)/2 = 0.64\%$ of industry assets post-2001 (when only purchase method was available) and much less pre-2001 (when both pooling and purchase methods were available). This effect cannot explain the difference in operating performance of the order of $(0.29-(-1.01))/((13.54+14.93)/2) = 9.13\%$ of prior industry operating performance between buckets 1 and 12 (see our Table 7).

Table 8
Additional tests of pre-*MAV* and post-*MAV* returns of buckets formed by stock *MAV* rank: Comparing results for both completed and incomplete stock offers vs. only completed stock offers. Tables 8, 9, and 10 report several additional tests of the market misvaluation theory of stock mergers using variations on the base sample or techniques. We use a consolidated regression approach applied to pre-*MAV* and post-*MAV* bucket returns. This approach tests an enhanced version of the Fama-French 3-factor model that includes the bucket number and the interaction of bucket number with each of *RMRF, SMB*, and *HML* factors in addition to the intercept and the factors themselves. The dependent variable is the monthly excess return on a bucket portfolio. The key inference is derived from the coefficient of the bucket number, which should be significantly positive for pre-*MAV* tests (indicating higher prior excess returns of industries with higher abnormal stock merger activity) and significantly negative for post-*MAV* tests (indicating lower subsequent excess returns of industries with higher abnormal stock merger activity). Row 1 reports tests of the base sample that includes both *completed* and *incomplete* (i.e., all announced) merger offers, and Row 2 reports tests of only the subset of *completed* offers. All post-*MAV* (pre-*MAV*) regressions include 360 monthly returns from 1989-Q1 to 2018-Q4 (1985-Q1 to 2014-Q4) for each of the 12 bucket portfolios, for a total 4,320 observations. Figures in parentheses are *t*-statistics. For the key coefficient of bucket number, we report both OLS and wild bootstrapping *t*-statistics in parentheses (see Appendix A) followed by their significance levels outside parentheses. For remaining coefficients, we report only OLS *t*-statistics. Notations *, **, and *** represent statistical significance at 10, 5, and 1 percent levels (shown only for the coefficient of bucket number to avoid clutter).

MAV calculated using the sample of ...	Pre- or post-*MAV*	Intercept	Bucket number (OLS *t*-stat, wild bootstrap *t*-stat)	*RMRF*	*RMRF* × bucket number	*SMB*	*SMB* × bucket number	*HML*	*HML* × bucket number	Adjusted-R^2
1. All announced stock offers	Pre-	-0.173	**0.034**	1.002	-0.007	-0.029	-0.000	0.374	-0.029	0.88
		(-3.41)	(4.90, 7.55)***,***	(86.24)	(-4.16)	(-1.72)	(-0.08)	(21.05)	(-12.08)	
	Post-	0.210	**-0.026**	0.888	0.008	0.033	-0.010	0.306	-0.018	0.87
		(4.20)	(-3.85,-5.91)***,***	(73.45)	(5.14)	(1.99)	(-4.34)	(17.90)	(-7.69)	
2. Only completed stock offers	Pre-	-0.162	**0.032**	0.990	-0.005	-0.036	0.001	0.343	-0.024	0.88
		(-3.23)	(4.72, 7.18)***,***	(86.48)	(-3.02)	(-2.14)	(0.36)	(19.58)	(-10.24)	
	Post-	0.226	**-0.029**	0.893	0.008	0.031	-0.009	0.292	-0.016	0.87
		(4.51)	(-4.21,-6.43)***,***	(73.47)	(4.66)	(1.82)	(-4.14)	(16.98)	(-6.71)	

merger offers. We are not aware of a similar investigation of completed versus incomplete offers in the literature.

Savor and Lu (2009) set out to test the Shleifer and Vishny (2003) theory that overvalued stock acquirers reduce their overvaluation by merging with better-valued targets. Consistent with that theory, they find that firms that make unsuccessful stock offers earn significantly more negative long-terms excess returns than firms that make successful stock offers. A long-short strategy that buys stocks of firms that make successful stock offers and sells stocks of firms that make unsuccessful stock offers using the calendar-time method earns 25.2% excess return over a three-year period starting with the announcement date of stock offers. For us, that means excluding unsuccessful stock offers from the base sample would amount to ignoring relevant information concerning industry misvaluation. This is primarily why we include all announced stock merger offers in our base sample.

We now consider whether our results change by restricting attention to only completed stock offers. We start by looking at the distribution of incomplete offers across industries. A chi-square test cannot reject the null hypothesis that the percent frequency of unsuccessful offers is equal across the 12 industries. We examine how the sample choice affects the formation of bucket portfolios. Each quarter we assign *MAV* ranks to all industries two different ways: first, using all announced offers (i.e., both completed and incomplete), and second, using only completed offers. We calculate the correlation between the two time-series of quarterly *MAV* ranks for each industry. The correlations lie between 0.82 and 0.95, with an average value of 0.91. Thus, the composition of our bucket portfolios is not so sensitive to the inclusion of all announced offers or only completed offers.

Finally, we examine the behavior of pre-*MAV* and post-*MAV* alphas across bucket portfolios. Table 8 shows that with only completed stock offers the pre-*MAV* alphas increase at a rate of 0.032% and post-*MAV* alphas decrease at a rate of -0.029% per month per bucket number, both of which are highly significant. That compares with corresponding rates of 0.034% and -0.026% using all announced stock offers, which are also highly significant. The difference between the two sets of numbers is quite small. Further, in untabulated results, we find that the operating performance results with sample of completed offers are a little stronger over post-*MAV* windows, but a little weaker over pre-*MAV* window from year $y-1$ to y. Overall, we reach the same conclusion for all our predictions using either the sample of both completed and incomplete stock offers or the sample of only completed stock offers.

6.2. Changing minimum required percent stock payment in defining the sample of stock mergers

In Section 3.1, we explained why our base sample includes all mergers for which at least 50% of payment is in the form of acquirer stock. Since 2002, there has been a steep decline in the number of all-stock merger offers (defined in this study as those involving at least 99% stock payment). Previous literature attributes this decline to the abolishment of pooling method of accounting for all-stock mergers in 2001 (de Bodt et al., 2018). Additionally, there is the desire for flexible payment terms by target shareholders (Boone et al., 2014). All-stock mergers comprise 28.6% of sample during 1985-2001, but only 10.3% of sample during 2002-2018 (see Fig. 1). If we exclude the Money industry, for the remaining 11 industries that proportion falls to 8.8% during 2002-2018 and 6.9% during 2011-2018. As an extreme case, during 2016 there are only 17 all-stock mergers for these 11 industries. A relatively small number of mergers decreases the stability of bucket assignments because even one or two mergers in an industry can change its *MAV* rank relative to other industries, from one quarter to another. Lower stability weakens our results, because overlapping time series of monthly returns for that industry may be added to a higher numbered and a lower numbered bucket portfolio in near quarters, which reduces the difference between their alphas.

More importantly, we argue that the abolishment of pooling method of accounting during the latter half of our sample period creates incentives for overpriced acquirers to use some cash payment if that wins over some of the reluctant target shareholders and clinches the deal.[8] The acquirers may prefer this alternative to insisting on all stock payment and losing the deal. We conjecture that this may be the reason why there has been such an increase in the number of mixed payment mergers and a decrease in the number of all stock mergers during 2002-2018. Of course, too little stock payment may also prove unattractive to an acquirer who

[8] Boone et al. (2014) estimate that about half of the acquisitions involving a mix of stock and cash payment give target shareholders a choice of payment.

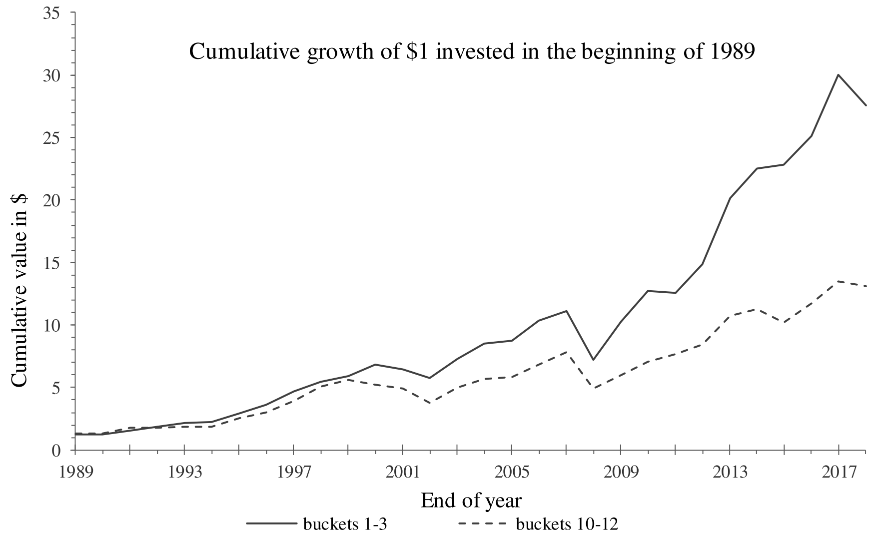


Fig. 4. Cumulative growth over time of $1 invested in the beginning of 1989 by bucket number. For parsimony of presentation and to reduce noise, we show only two lines in this graph. First, the solid line is the average of cumulative growth over time for buckets numbered 1, 2, and 3. Second, the broken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

Table 9
Additional tests of pre-*MAV* and post-*MAV* returns of buckets formed by stock *MAV* rank: The role of minimum required percent stock payment. This table employs the same techniques as Table 8. It addresses the question of how the pre-*MAV* and post-*MAV* tests are affected by whether we include majority stock mergers (at least 50% stock payment), all stock mergers (at least 99% stock payment), or somewhere in-between. Fig. 1 shows that the number of all stock mergers (and, to a lesser extent, majority stock mergers) has declined since 2002. The number of all stock mergers in many industries is low and an increment of one or two stock mergers in a year can make a significant difference to calculated *MAV* ranks. This decreases stability of bucket portfolios and reduces coefficient of bucket number in post-*MAV* tests as we transition from majority stock payment to all stock payment. Section 6.2 reports how many mergers are in each category. Please see Table 8 for further details.

MAV calculated using the sample of stock merger offers defined as ...	Pre- or post-*MAV*	Intercept	Bucket number (OLS *t*-stat, wild bootstrap *t*-stat)	*RMRF*	*RMRF* × bucket number	*SMB*	*SMB* × bucket number	*HML*	*HML* × bucket number	Adjusted-R^2
1. At least **50%** stock	Pre-	-0.173	**0.034**	1.002	-0.007	-0.029	-0.000	0.374	-0.029	0.88
		(-3.41)	(4.90, 7.55)***,***	(86.24)	(-4.16)	(-1.72)	(-0.08)	(21.05)	(-12.08)	
	Post-	0.210	**-0.026**	0.888	0.008	0.033	-0.010	0.306	-0.018	0.87
		(4.20)	(-3.85,-5.91)***,***	(73.45)	(5.14)	(1.99)	(-4.34)	(17.90)	(-7.69)	
2. At least **60%** stock	Pre-	-0.172	**0.034**	1.003	-0.007	-0.018	-0.002	0.367	-0.028	0.89
		(-3.46)	(4.98, 7.49)***,***	(88.38)	(-4.33)	(-1.11)	(-0.83)	(21.17)	(-11.94)	
	Post-	0.189	**-0.023**	0.894	0.008	0.034	-0.010	0.311	-0.019	0.87
		(3.88)	(-3.47,-5.14)***,***	(75.59)	(4.71)	(2.08)	(-4.49)	(18.55)	(-8.14)	
3. At least **70%** stock	Pre-	-0.173	**0.034**	0.992	-0.005	-0.028	-0.000	0.367	-0.028	0.88
		(-3.46)	(4.97, 7.57)***,***	(86.67)	(-3.24)	(-1.69)	(-0.15)	(20.95)	(-11.79)	
	Post-	0.184	**-0.022**	0.883	0.009	0.039	-0.011	0.351	-0.025	0.87
		(3.67)	(-3.25,-4.96)***,***	(72.42)	(5.59)	(2.31)	(-4.69)	(20.37)	(-10.58)	
4. At least **80%** stock	Pre-	-0.181	**0.035**	0.994	-0.005	-0.028	0.000	0.378	-0.030	0.89
		(-3.64)	(5.19, 7.83)***,***	(87.57)	(-3.45)	(-1.69)	(-0.17)	(21.79)	(-12.65)	
	Post-	0.164	**-0.019**	0.891	0.008	0.041	-0.011	0.359	-0.026	0.87
		(3.25)	(-2.78,-4.26)***,***	(73.04)	(4.85)	(2.42)	(-4.81)	(20.77)	(-10.06)	
5. At least **90%** stock	Pre-	-0.186	**0.036**	0.998	-0.006	-0.031	0.000	0.347	-0.025	0.89
		(-3.80)	(5.38, 8.01)***,***	(89.16)	(-3.91)	(-1.88)	(0.01)	(20.25)	(-10.73)	
	Post-	0.143	**-0.016**	0.884	0.009	0.035	-0.010	0.341	-0.023	0.87
		(2.89)	(-2.36,-3.52)**,***	(73.78)	(5.57)	(2.09)	(-4.48)	(20.09)	(-10.06)	
6. At least **95%** stock	Pre-	-0.196	**0.037**	0.998	-0.006	-0.032	0.000	0.345	-0.025	0.89
		(-3.93)	(5.51, 8.34)***,***	(87.35)	(-3.83)	(-1.94)	(0.12)	(19.77)	(-10.43)	
	Post-	0.139	**-0.015**	0.887	0.009	0.034	-0.010	0.349	-0.024	0.87
		(2.80)	(-2.26,-3.40)**,***	(73.65)	(5.30)	(2.02)	(-4.39)	(20.48)	(-10.56)	
7. At least **99%** stock	Pre-	-0.202	**0.038**	1.000	-0.006	-0.034	0.001	0.355	-0.026	0.89
		(-4.11)	(5.73, 8.54)***,***	(88.84)	(-4.04)	(-2.07)	(0.25)	(20.62)	(-11.21)	
	Post-	0.131	**-0.014**	0.895	0.007	0.040	-0.011	0.365	-0.027	0.87
		(2.64)	(-2.07,-3.11)**,***	(74.47)	(4.58)	(2.40)	(-4.82)	(21.48)	(-11.65)	

wants to use its overpriced stock currency. As a compromise, we require majority stock payment in the base sample. That requirement approximately doubles the number of observations during the latter half of our sample period, which increases the stability of bucket assignments and preserves cases with sufficient incentive for wealth transfer from target to acquirer shareholders.

Table 9 further shows how our results change with minimum required stock payment. Pre-*MAV* alphas increase at a rate of 0.034, 0.034, 0.034, 0.035, 0.036, 0.037, and 0.038 percent per month per bucket number for required minimum stock payment of 50, 60, 70, 80, 90, 95, and 99 percent. (The corresponding number of mergers that enter bucket formation equals 2801, 2455, 2137, 1851,

Table 10
Additional robustness tests of pre-*MAV* and post-*MAV* returns of buckets formed by stock *MAV* rank. This table reports several robustness tests of the base model of Tables 4 and 5 (also reproduced in the first row). It employs the same techniques as in Table 8. Sections 6.3 to 6.6 explain each robustness test. The time series for each post-*MAV* (pre-*MAV*) regression in Rows 1, 2, 4, and 5 below includes 360 monthly returns from 1989-Q1 to 2018-Q4 (1985-Q1 to 2014-Q4) for each of 12 bucket portfolios, for a total 4,320 observations. However, Row 3 (no look-ahead bias tests), requires initial 10 years of data to calculate the first *MAV* values based on historical data. Therefore, this row includes only 252 monthly returns for each of the 12 bucket portfolios, for a total 3,024 observations. Please see Table 8 for further details.

Description	Pre- or post-*MAV*	Intercept	Bucket number (OLS *t*-stat, wild bootstrap *t*-stat)	*RMRF*	*RMRF* × bucket number	*SMB*	*SMB* × bucket number	*HML*	*HML* × bucket number	Adjusted-R^2
1. Base model tests	Pre-	-0.173	**0.034**	1.002	-0.007	-0.029	-0.000	0.374	-0.029	0.88
		(-3.41)	(4.90, 7.55)***,***	(86.24)	(-4.16)	(-1.72)	(-0.08)	(21.05)	(-12.08)	
	Post-	0.210	**-0.026**	0.888	0.008	0.033	-0.010	0.306	-0.018	0.87
		(4.20)	(-3.85,-5.91)***,***	(73.45)	(5.14)	(1.99)	(-4.34)	(17.90)	(-7.69)	
2. FF 48 industries instead of 12 industries	Pre-	-0.028	**0.023**	0.934	0.012	0.144	0.003	0.428	-0.025	0.88
		(-0.44)	(2.60, 4.89)***,***	(63.76)	(6.19)	(6.73)	(1.02)	(19.10)	(-8.10)	
	Post-	0.142	**-0.022**	0.911	0.013	0.159	-0.006	0.364	-0.011	0.83
		(2.23)	(-2.55,-4.96)**,***	(59.38)	(6.41)	(7.66)	(-2.16)	(16.34)	(-3.62)	
3. No look-ahead bias	Pre-	-0.172	**0.034**	1.022	-0.010	-0.063	0.005	0.282	-0.015	0.88
		(-3.52)	(5.07, 7.52)***,***	(91.60)	(-6.37)	(-3.89)	(2.28)	(16.49)	(-6.44)	
	Post-	0.200	**-0.019**	0.874	0.009	-0.059	0.000	0.325	-0.018	0.86
		(3.14)	(-2.21,-3.60)**,***	(59.47)	(4.71)	(-2.93)	(0.00)	(15.68)	(-6.40)	
4. Current quarter instead of moving-average four-quarter *MAV*	Pre-	-0.085	**0.020**	0.993	-0.005	-0.020	-0.002	0.356	-0.026	0.88
		(-1.77)	(3.10, 4.54)***,***	(90.62)	(-3.45)	(-1.26)	(-0.73)	(21.23)	(-11.58)	
	Post-	0.145	**-0.016**	0.908	0.005	0.024	-0.008	0.333	-0.022	0.86
		(3.15)	(-2.59,-3.71)***,***	(81.55)	(3.57)	(1.56)	(-4.03)	(21.13)	(-10.26)	
5. Event time instead of calendar time	Pre-	-0.183	**0.034**	1.006	-0.007	-0.063	0.002	0.316	-0.024	0.62
		(-6.25)	(8.63, 7.89)***,***	(147.62)	(-7.20)	(-6.43)	(1.80)	(30.07)	(-16.90)	
	Post-	0.192	**-0.024**	0.902	0.008	0.013	-0.009	0.294	-0.018	0.61
		(6.41)	(-5.94,-5.47)***,***	(126.64)	(8.03)	(1.35)	(-6.49)	(27.50)	(-12.62)	

1640, 1566, and 1516 during 2002-2018, and 7317, 6941, 6599, 6290, 5988, 5835, and 5729 during 1985-2001.) All estimates are highly significant. Thus, there seems to be a slight strengthening of evidence in favor of *Prediction 1* with increasing stock payment. Table 9 further shows that post-*MAV* alphas decrease at a rate of -0.026, -0.023, -0.022, -0.019, -0.016, -0.015, and -0.014 percent per month per bucket number for the same stock payment levels. All estimates are significant at 1% level using wild bootstrapping *t*-statistics (and at 1% or 5% level using OLS *t*-statistics), which supports *Prediction 2*. Further, in untabulated results we find that operating performance results are significant at 1% level over all post-*MAV* windows with the reduced sample (which supports *Prediction 5*), but insignificant over pre-*MAV* windows (which still supports *Prediction 4*).

6.3. Fama-French 12 industries vs. 48 industries

We choose 12 industries for our main illustration because for most industries during most periods this classification gives a continuous *MAV* distribution. Using a finer industry classification leaves very few stock mergers in many industries. 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. Row 2 of Table 10 shows that with this variation the pre-*MAV* returns still increase at a rate of 0.023% per month per bucket number while the post-*MAV* returns decrease at a rate of -0.022% per month per bucket number, both significant at 1% level using wild bootstrapping *t*-statistics.

6.4. Using only historical information to calculate MAV

In Section 3.2 we pointed out that $MAV_{jt,stk}$ defined by Equation (1) has some forward-looking information similar to any other study of merger waves. In this subsection, we redefine the 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 subsection, it is from quarter 1 to quarter t. Because our post-*MAV* return computation starts from quarter $t+1$, there is no look-ahead bias with this measure. We require the first 10 years of historical information to start the *MAV* calculation. Since our mergers sample starts in 1985, the first calculation of *MAV* and the corresponding assignment of industries to buckets occurs in 1995-Q1. All buckets have 12 industries in steady state from 1997-Q4 onwards, so we begin our post-*MAV* returns experiment in 1998-Q1. That gives us a period of 21 years until 2018-Q4. Row 3 of Table 10 shows that with this variation the pre-*MAV* returns increase at a rate of 0.034% per month per bucket while the post-*MAV* returns decrease at a rate of -0.019% per month per bucket number, both significant at 1% level using wild bootstrapping *t*-statistics.

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

A moving-average 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 in Equation (1). The only difference between *MAV* definitions in Equations (1) and (3) is

Table 11
Stock merger activity of industries and their prior and subsequent three-year asset turnover. The bucket assignment and all other procedures in this table are identical to those in Table 7. 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.

MAV rank (or bucket number)	Mean value of base year asset turnover minus preceding year asset turnover (i.e., improvement during pre-*MAV* period)			Mean asset turnover for base year of stock merger activity	Mean value of following year asset turnover minus base year asset turnover (i.e., improvement during post-*MAV* period)		
	$y-3$	$y-2$	$y-1$	Year y	$y+1$	$y+2$	$y+3$
1 (least merger active)	-2.70%	-1.18%	0.45%	87.81%	0.44%	0.92%	2.26%
2	2.06	2.05	0.77	93.53	0.64	3.58	2.98
3	3.12	2.62	1.20	82.83	0.43	1.04	1.74
4	1.10	0.39	0.41	86.17	0.72	1.08	1.89
5	1.86	1.06	1.10	87.91	1.43	2.30	3.49
6	1.22	1.18	0.17	82.02	0.60	0.64	1.27
7	3.52	2.28	0.53	81.11	0.02	-0.16	0.54
8	-0.44	0.23	0.18	76.30	0.32	0.63	1.42
9	1.76	0.15	-0.23	76.00	0.14	1.59	1.78
10	0.83	-0.02	-0.15	74.86	-0.47	-0.11	0.25
11	0.89	-1.12	-1.54	91.74	-0.88	-2.23	-2.60
12 (most merger active)	-3.17	-1.67	-0.31	87.66	-0.83	-3.33	-4.97
Average	0.84	0.50	0.21	84.00	0.21	0.50	0.84
Correlation between bucket number and variable	-0.20	-0.50	-0.76***		-0.76***	-0.75***	-0.78***
Slope of variable regressed on bucket number, *t*-statistic in round brackets, and adj-R^2 in square brackets	-0.12% (-0.66) [-0.05]	-0.19% (-1.81) [0.17]	-0.15% (-3.68)*** [0.53]		-0.14% (-3.74)*** [0.54]	-0.39% (-3.61)*** [0.52]	-0.52% (-3.92)*** [0.57]

that in the latter case the current stock merger activity in the numerator is calculated for quarter t alone. Row 4 of Table 10 shows that with this variation the pre-*MAV* returns increase at a rate of 0.020% per month per bucket number while the post-*MAV* returns decrease at a rate of -0.016% per month per bucket number, both significant at 1% level.

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

All our inferences concerning pre-*MAV* and post-*MAV* excess returns of industries in this paper are based on the conservative calendar-time portfolio method. As a robustness check, we now calculate alphas using the alternate event-time method as follows. First, we calculate the *MAV* rank or bucket number for every industry during a quarter t as before. Second, we use 36 months of data over the subsequent (prior) 12 quarters for every industry and apply the consolidated regression approach to $12 \times 36 = 432$ monthly returns. Repeating this process gives us a time-series of post-*MAV* (pre-*MAV*) coefficient estimates from 120 quarterly consolidated regressions. Third, we calculate the mean and standard error for each coefficient using its time-series of 120 quarterly estimates. The final numbers are shown in Row 5 of Table 10. We find that using this procedure the pre-*MAV* alphas increase at a rate of 0.034% per month per bucket number while the post-*MAV* alphas decrease at a rate of -0.024% per month per bucket number, with large t-statistics. The t-statistics are overstated from overlapping returns as explained in Section 3.3. However, the important point is that the event-time alphas are comparable to the calendar-time alphas in magnitude.

6.7. Operating performance results based on top-line revenue vs. bottom-line earnings

The tests of pre-*MAV* and post-*MAV* operating performance in Table 7 use operating income as the primary measure as recommended by Barber and Lyon (1996). Operating income is related to the bottom-line earnings. An extensive accounting literature highlights the additional role of top-line sales revenue. We therefore analyze industry asset turnover, calculated as the aggregate sales revenue of all firms in the industry divided by the aggregate assets. Changes in asset turnover may be thought of as sales growth. Table 11 shows that the results with industry asset turnover as an alternate measure of operating performance are similar to the results with OIBDP as the primary measure.

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

Using the base methodology of Table 4, Fig. 4 shows that the difference between annual returns of low and high bucket portfolios is spread out over the years, and therefore the difference between cumulative returns grows over time. Averaged across buckets numbered 1, 2, and 3, $1 invested in the beginning of 1989 grows to $5.49 by the end of 1998, $7.22 by the end of 2008, and $27.58 by the end of 2018. In comparison, averaged across buckets numbered 10, 11, and 12, the same $1 invested in the beginning of 1989 grows to $5.04 by the end of 1998, $4.89 by the end of 2008, and $13.09 by the end of 2018. The difference between geometric average annual returns equals 1.01%, 3.08%, and 3.99% in the three subperiods (highest most recently).

6.9. Cash merger activity and industry performance

Based on theory and empirical evidence, we conclude that stock merger activity is higher during periods of industry overvaluation and lower during periods of industry undervaluation. However, there is no theory to suggest that the opposite is true for cash merger activity. Consider Theorem 4 of RKV that is stated in Section 2.1. It says that mergers are more likely in overvalued markets than in undervalued markets, and that the method of payment includes a greater fraction of stock deals in overvalued markets than in undervalued markets. Suppose there are a total of N_1 mergers in an overvalued market and N_2 mergers in an undervalued market, and the fraction of stock deals is f_1 in the overvalued market and f_2 in the undervalued market. Thus, the number of stock mergers equals $N_1 f_1$ in the overvalued market and $N_2 f_2$ in

Table 12

Cash merger activity of industries and their prior and subsequent returns and operating performance. The sample for investigation in this table begins with 24,674 majority cash acquisitions of all public, private, and subsidiary targets during 1985-2018 as described in Table 1. The bucket assignment procedure is described in Sections 3.2 and 3.3. We calculate $MAV_{jt,cash}$ using a procedure similar to that for $MAV_{jt,stock}$ described by Equation (1). We next regress the time-series of $MAV_{jt,cash}$ values for industry j on $MAV_{jt,stock}$ values for the same industry and take residuals. Using the cross-section of residual $MAV_{jt,cash}$ values for 12 industries within each quarter, we assign ranks and form bucket portfolios the same way as we did for stock merger activity. Panel A reports results of main tests similar to those in Tables 4 to 7. This panel includes the base sample of all announced (both completed and incomplete) majority cash merger offers. Panel B presents results using the enhanced Fama-French 3-factor model similar to Tables 8 and 9. The dependent variable is the monthly excess return on a bucket portfolio. This panel reports the tests for the base sample and two variations as described. All regressions in Panel B have 360 monthly returns for the 12 bucket portfolios, for a total 4,320 observations. For the coefficient of bucket number in this panel, we report both OLS and wild bootstrapping t-statistics in parentheses followed by their significance levels outside parentheses. For the remaining coefficients, we report only OLS t-statistics. Notations *, **, and *** represent statistical significance at 10, 5, and 1 percent levels (shown only for coefficient of bucket number).

***Panel A**: Post-MAV and pre-MAV excess returns and operating performance for bucket portfolios formed by majority cash merger activity*

	Returns (or alphas, three columns)			Operating performance (last two columns)	
Bucket number	Post-*MAV* alpha (wild bootstrap t-statistic)	Pre-*MAV* alpha (wild bootstrap t-statistic)	Difference (wild bootstrap t-statistic)	Base year y minus prior year y-1 operating income	Subsequent year y+3 minus base year y operating income
Compare to →	Table 4, Panel A	Table 5, Panel A	Table 6	Table 7	Table 7
1 (least cash merger active)	-0.065 (-1.21)	0.038 (0.71)	-0.103 (-1.35)	0.39%	0.51%
2	0.104 (1.94)*	0.014 (0.26)	0.091 (1.19)	-0.35	0.91
3	-0.034 (-0.64)	-0.030 (-0.55)	-0.005 (-0.06)	0.17	-0.55
4	0.006 (0.12)	0.022 (0.40)	-0.015 (-0.20)	0.00	-0.36
5	0.070 (1.30)	-0.007 (-0.12)	0.077 (1.01)	-0.03	0.31
6	0.084 (1.56)	-0.009 (-0.17)	0.093 (1.22)	0.06	0.04
7	-0.025 (-0.46)	0.071 (1.32)	-0.096 (-1.26)	0.01	-0.07
8	0.049 (0.90)	0.020 (0.36)	0.029 (0.38)	-0.13	-0.11
9	0.049 (0.90)	0.076 (1.40)	-0.027 (-0.36)	-0.05	0.27
10	0.054 (1.00)	0.049 (0.91)	0.005 (0.07)	-0.02	-0.32
11	0.031 (0.58)	0.093 (1.73)*	-0.062 (-0.81)	-0.09	-0.18
12 (most cash merger active)	0.155 (2.89)***	0.224 (4.18)***	-0.069 (-0.91)	-0.15	-1.31
Correlation between variable and bucket number	0.49	0.70**	-0.24	-0.39	-0.59**
Slope of variable regressed on bucket number, OLS t-statistic in round brackets, and adj-R^2 in square brackets	0.008 (1.78)* [0.16]	0.013 (3.13)** [0.44]	-0.005 (-0.78) [-0.04]	-0.000 (-1.33) [0.07]	-0.092 (-2.31)** [0.28]

Panel B: Enhanced Fama-French 3-factor model tests of base sample and variations

Description	Pre- or post-*MAV*	Intercept	Bucket number (OLS t-stat, wild bootstrap t-stat)	*RMRF*	*RMRF* × bucket number	*SMB*	*SMB* × bucket number	*HML*	*HML* × bucket number	Adjusted-R^2
1. Both completed and incompletemajority cash merger offers	Pre-	-0.038	**0.013**	0.966	-0.001	-0.034	0.001	0.227	-0.006	0.88
		(-0.75)	(1.88, 2.93)*,***	(82.54)	(-0.67)	(-1.99)	(0.23)	(12.66)	(-2.67)	
	Post-	-0.015	**0.008**	0.921	0.003	0.025	-0.009	0.187	0.001	0.86
		(-0.30)	(1.22, 1.86) ,*	(74.82)	(2.02)	(1.49)	(-3.74)	(10.73)	(0.21)	
2. Only completed majority cash offers	Pre-	-0.029	**0.012**	0.957	0.000	-0.038	0.001	0.179	0.001	0.88
		(-0.56)	(1.66, 2.67)*,***	(81.00)	(0.26)	(-2.23)	(0.52)	(9.88)	(0.37)	
	Post-	0.000	**0.006**	0.937	0.001	0.024	-0.008	0.192	0.000	0.86
		(0.01)	(0.88, 1.38)	(75.94)	(0.59)	(1.43)	(-3.67)	(11.00)	(-0.12)	
3. Both completed and incomplete, but only all cash offers	Pre-	-0.008	**0.008**	0.943	0.003	-0.030	-0.000	0.277	-0.014	0.89
		(-0.16)	(1.24, 1.95) ,*	(82.61)	(1.63)	(-1.78)	(-0.06)	(15.89)	(-6.02)	
	Post-	0.000	**0.006**	0.927	0.003	0.023	-0.008	0.195	-0.001	0.88
		(0.00)	(0.96, 1.42)	(81.72)	(1.65)	(1.44)	(-3.86)	(12.13)	(-0.32)	

the undervalued market, while the corresponding number of cash mergers equals $N_1(1-f_1)$ and $N_2(1-f_2)$. From Theorem 4 of RKV, we infer that $N_1 > N_2$, $f_1 > f_2$, and $N_1 f_1 > N_2 f_2$. However, we cannot say whether $N_1(1-f_1)$ is greater than or less than $N_2(1-f_2)$. This highlights the difficulty of associating the variation in cash merger activity with the variation in industry valuation. In addition, the alternate theories of merger activity (the neoclassical theory, the q theory, and the agency theory) do not suggest any particular role for the payment method. Previous literature shows evidence in favor of these theories, which would explain parts of the merger activity.

It is also difficult to separate cash mergers from stock mergers because the SDC does not list the source of financing for cash deals. Vladimirov (2015) documents that 20% of cash bids are financed by a common stock issue and 5% are financed by a rights issue or a preferred stock issue. Thus, unsurprisingly, we find that the stock merger activity and cash merger activity are positively related. The correlation between the time series of $MAV_{jt,stk}$ and $MAV_{jt,cash}$ calculated for each industry and then averaged across the 12 industries equals 0.35. Keeping in view all these considerations, we can only predict that cash merger results should be weaker than stock merger results.

Our sample for the following investigation includes 24,674 majority cash acquisitions of public, private, and subsidiary targets during 1985-2018 described in Panel B of Table 1. For this sample, we calculate $MAV_{jt,cash}$ values for each industry j and quarter t following a procedure similar to that described by Equation (1), but using numbers of majority cash mergers in place of majority stock mergers. We regress $MAV_{jt,cash}$ values on $MAV_{jt,stock}$ values to calculate the residual $MAV_{jt,cash}$ values. This calculation should exclude some part of the cash merger activity that is financed by stock issues or explained by other theories that do not suggest any particular role for the payment method. Using the cross-section of residual $MAV_{jt,cash}$ values (which we also call cash-*MAV* values) for 12 industries within each quarter, we assign ranks and form bucket portfolios the same way as we did for stock merger activity. We repeat the tests of Tables 4, 5, and 6 with these bucket portfolios and report the results in Table 12.

Panel A of Table 12 shows that the correlation between post-cash-*MAV* alphas and bucket numbers is an insignificant 0.49 (although bordering on significant, *p*-value 0.106). This correlation is in the opposite direction to that between post-stock-*MAV* alphas and bucket numbers that equals -0.91 as shown in Panel B of Table 4. Thus, based on subsequent returns, higher cash merger activity does not occur when industries are overvalued. The next column shows that the correlation between pre-cash-*MAV* alphas and bucket numbers is significantly positive, although the associated slope coefficient is smaller than for pre-stock-*MAV* reported earlier (0.013% vs. 0.034% per month per bucket number). The final column under returns shows that the difference between post-*MAV* and pre-*MAV* alphas is unrelated to bucket numbers. Thus, there is no evidence of reversals of pre-*MAV* returns during the post-*MAV* period for cash merger activity. Moving to operating performance, the evidence is partly similar between the two payment types. For cash mergers, the change in operating performance from year y-1 to y is unrelated to bucket number (not similar), but the change from year y to $y+3$ is negatively related to it (similar).

Panel B of Table 12 shows the results using the consolidated regression approach, first for the base sample of all announced majority cash offers used in Panel A. For completeness, we present two robustness tests: first, with the sample of only completed majority cash offers, and second, with the sample of all announced all cash offers. The key coefficients are marginally lower in these tests relative to the base sample tests. Overall, unlike *stock* merger activity, there is no clear relation between variations in *cash* merger activity and subsequent industry excess returns. This evidence is consistent with misvaluation theory that predicts weak or insignificant results for cash merger activity.

7. Conclusion

The overvaluation hypothesis is an important part of the mergers and acquisitions literature. Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004) theoretically model industry-wide overvaluation as the reason for increased stock merger activity, such as 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 their increased stock merger activity has been lacking. This paper provides that evidence.

We argue that traditionally defined merger waves are not suited to testing the implications of the industry misvaluation theory for two reasons. First, this measure divides all industry-years into discrete wave and non-wave years and ignores further information in the full range of merger activity. Second, industry merger waves cluster in time, so one needs to take out the common component. Otherwise, each industry undergoing a merger wave is benchmarked against the market consisting of other industries also undergoing a merger wave, which washes out the returns evidence. To overcome these limitations, we propose a continuous stock merger activity variable, *MAV*, which first adjusts an industry's current merger activity by its own long-term activity. Further ranking industries by their *MAV* value takes out the common component. We show that *MAV* rank is a better measure than traditionally defined industry merger waves in capturing industry misvaluation. It is a simple concept that can be adopted to studying variations in other types of corporate activity.

We predict three patterns for excess returns and two patterns for operating performance based on the industry misvaluation theory. Using bucket portfolios that aggregate industries by their *MAV* rank over time, we find evidence in support of all five predictions. During a three-year period prior to measuring the current merger activity, the excess returns are positively related to bucket numbers (i.e., *MAV* ranks of included industries) while changes in operating income are negatively related to bucket numbers. That shows build-up of overvaluation for industries ranked higher on abnormal activity and undervaluation for industries ranked lower on abnormal activity. Furthermore, during the subsequent three-year period, both the excess returns and changes in operating income are negatively related to bucket numbers, consistent with the correction of misvaluation. The prior and subsequent excess returns are negatively related to each other, which reinforces this evidence. In summary, our combined evidence provides strong support for the industry misvaluation theory of stock merger activity.

Credit author statement

Bo Meng and Anand M. Vijh are equal coauthors of the above referenced manuscript. The names are stated in alphabetical order of last names following the convention in our field. Anand M. Vijh is the corresponding author.

Declaration of Competing Interest

No.

Appendix A. Wild bootstrap t-statistics

Casual observation of alphas and OLS *t*-statistics in Panel B of Table 4 suggests that the assumption of homoscedasticity may be violated because the underlying standard errors of alphas for buckets 1 to 12 equal 0.1068, 0.0847, 0.0810, 0.0609, 0.0622, 0.0641, 0.0526, 0.0505, 0.0720, 0.0711, 0.1151, and 0.0978 percent. (The standard errors are not reported in the table, but can be inferred by dividing the coefficients by OLS *t*-statistics.) That observation is remarkable since it is the same 12 industries entering all the buckets at different times. The reason is that standard errors of extreme bucket numbers are influenced by extreme returns, likely because industries enter these buckets after periods of sharp price decreases and increases and subsequently experience reversals as suggested by the misvaluation theory. Formally, the White test rejects homoscedasticity in favor of heteroscedasticity in ten buckets with a confidence level of 1% and in two buckets with a confidence level of 5%. Heteroscedasticity leads to biased *t*-statistics and inference of significant alphas.

Wu (1986) and Liu (1988) proposed a wild bootstrap technique to correct for heteroscedasticity that has attracted considerable attention in economics literature. Their papers are extensively cited and their insights have led to many variations of wild bootstrap methods. Many finance studies use wild bootstrap methods to calculate statistical significance of key variables (for example, Paya and Peel 2006, Khan 2008, Li and Zhao 2009, Christensen, Nielsen, and Zhu 2010, Polkovnichenko and Zhao 2013, Rapach, Strauss, and Zhou 2013, Goncalves, Hounyo, and Meddahi 2014, Cowan and Salotti 2015, Huang, Jiang, Tu, and Zhou 2015, Harvey, Leybourne, Sollis, and Taylor 2016, Jiang, Lee, Martin, and Zhou 2019, and many others). For accurate inference of the statistical significance of key coefficients in this paper in view of heteroscedasticity, we employ the wild bootstrap technique as outlined on Page 1282 of Wu's paper and reproduced below.

1. Denote dependent variable $y = (y_1, \ldots, y_n)^T$, independent variables $X = (x_1, \ldots, x_n)^T$, and error term $e = (e_1, \ldots, e_n)^T$.
2. Estimate the linear model $y = X\beta + e$ by the OLS method, and obtain $\hat{\beta} = (X^TX)^{-1}X^Ty$.
3. Compute the OLS residuals $\{r_i\}_1^n$, where $r_i = y_i - x_i^T\hat{\beta}$ is the ith residual.

4 Draw a random sample $\{t_i^*\}_1^n$ from a bootstrap sample $\{a_i\}_1^n$, where $a_i = (r_i - \bar{r})/[(\frac{1}{n})\Sigma_1^n(r_i - \bar{r})^2]^{1/2}$, $\bar{r} = \frac{1}{n}\sum_1^n r_i$, and $i = 1, \ldots, n$, with replacement, and attach it to $\hat{y}_i$ to obtain *wild bootstrap* observation $y_i^* = x_i^T\hat{\beta} + \frac{r_i}{\sqrt{1-w_i}}t_i^*$, where $w_i = x_i^T(X^TX)^{-1}x_i$. Denote further $y^* = (y_1^*, \ldots, y_n^*)^T$.
5 Estimate the linear model $y^* = X\beta + \epsilon$ by the OLS method, and get $\hat{\beta}^* = (X^TX)^{-1}X^Ty^*$ and standard errors $s.e.(\hat{\beta}^*)$.
6 Repeat steps 4 and 5, say, 1,000 times, and obtain $\{\hat{\beta}_b^*\}_1^{1000}$, and $\{s.e.(\hat{\beta}_b^*)\}_1^{1000}$.
7 Calculate wild bootstrap t-statistics as $t_{\hat{\beta}^*} = \frac{\Sigma_1^{1000}\hat{\beta}_b^*}{\Sigma_1^{1000}s.e.(\hat{\beta}_b^*)}$ (i.e., average bootstrap coefficient of any variable divided by the average bootstrap standard error).

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