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Journal of Financial Economics 77 (2005) 529–560

JOURNAL OF Financial ECONOMICS

www.elsevier.com/locate/jfec

What drives merger waves?☆

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Received 5 December 2003; accepted 24 May 2004
Available online 4 January 2005

Abstract

Aggregate merger waves could be due to market timing or to clustering of industry shocks for which mergers facilitate change to the new environment. This study finds that economic, regulatory and technological shocks drive industry merger waves. Whether the shock leads to a wave of mergers, however, depends on whether there is sufficient overall capital liquidity. This macro-level liquidity component causes industry merger waves to cluster in time even if industry shocks do not. Market-timing variables have little explanatory power relative to an economic model including this liquidity component. The contemporaneous peak in divisional acquisitions for cash also suggests an economic motivation for the merger activity.

JEL classification: G34

Keywords: Mergers and acquisitions; Takeover; Merger waves; Behavioral; Capital liquidity

☆I thank John Chalmers, Larry Dann, Harry DeAngelo, Vidhan Goyal, Alan Hess, Jon Karpoff, Paul Malatesta, Wayne Mikkelson, Harold Mulherin, Ed Rice, Husayn Shahrur, an anonymous referee, and seminar participants at Babson College, Penn State, Purdue, Vanderbilt, Duke, the Universities of Arkansas, Southern California, and Utah, the University of Oregon research roundup, the 2001 Pacific Northwest Finance Conference, and the 2004 AFA meetings for comments. Sandy Klasa provided excellent research assistance. I gratefully acknowledge the contribution of Thomson Financial for providing earnings per share forecast data, available through I/B/E/S. This paper is partially derived from an earlier paper that circulated under the title, ''Efficient and distortional components to industry merger waves.''

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doi:10.1016/j.jfineco.2004.05.004

1. Introduction

Recent debate about the cause of merger waves has highlighted the fact that merger waves are correlated with high stock market valuations. Authors such as Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004) develop models in which merger waves result from managerial timing of market overvaluations of their firms. More neoclassical explanations of merger waves, dating at least to Gort (1969) and more recently examined by Mitchell and Mulherin (1996), argue that merger waves result from shocks to an industry's economic, technological, or regulatory environment. This study asks whether a clustering of mergers at the aggregate level is due to a combination of industry shocks for which mergers facilitate change to the new environment, or whether such clustering is due to market timing.

The results presented here support a neoclassical explanation of merger waves: merger waves occur in response to specific industry shocks that require large scale reallocation of assets. However, these shocks are not enough on their own. There must be sufficient capital liquidity to accommodate the asset reallocation. The increase in capital liquidity and reduction in financing constraints that is correlated with high asset values must be present for the shock to propagate a wave. Variables that separately measure capital liquidity and market valuations suggest that the observed relation between high stock market valuations and merger waves has been misattributed to behavioral misvaluation factors. Rather, the relation is actually driven by the higher capital liquidity (lower transaction costs) that accompany an economic expansion.

Thus, the explanation for merger waves is intuitive: merger waves require both an economic motivation for transactions and relatively low transaction costs to generate a large volume of transactions. The influence of this macro-level liquidity factor causes industry merger waves to cluster in time even if industry shocks do not.

This study proceeds by using a sample of industry-level merger waves in the 1980s and 1990s to test the behavioral and neoclassical hypotheses about the causes of merger waves. The first test examines the characteristics of the industries before merger waves. The set of characteristics is designed to capture economic shocks to an industry's operating environment. One potential economic characteristic, the market-to-book ratio, is ambiguous because it is also claimed by the behavioral hypothesis. However, the behavioral models rely on both high valuations and dispersion in valuations, so I include the cross-sectional standard deviation of the market-to-book ratio, the average one- and three-year stock returns, and the cross-sectional standard deviation of those returns.

Since economic shocks could have different effects across firms and, further, since different shocks across industries could have different average directional implications, I use the median absolute change in the economic characteristics to measure economic shocks. I find that waves are directly preceded by abnormally large absolute changes in most of the economic characteristics studied. As for the behavioral variables, market-to-book ratios are also abnormally high and the one- and three-year returns are marginally high, but the standard deviations of these measures are not.

Building on this first set of tests, I employ successive logit models to predict the start of an industry merger wave. Industry median market-to-book alone has some predictive power. However, once it is included with the economic variables, it becomes insignificant. The industry-specific economic shock measures predict waves, but only when capital liquidity is also high. An index of major deregulatory events and a measure of capital liquidity adds sharply to the predictive power of the model. Finally, on their own, the behavioral variables (prior industry return, the standard deviation of this return, and including market-to-book in this set) have only a fair ability to predict merger waves, and they add only marginally to the predictive power of the neoclassical model, which uses industry-specific shocks, deregulation, and liquidity.

Following the examination of the causes of industry-level merger waves, the next step is to connect the industry-level waves to aggregate merger activity. I show that the vast majority of activity in aggregate merger waves is being driven by the clustering of the industry merger waves identified here. Further, a model of aggregate merger activity that takes into account industry shocks and overall capital liquidity further supports the role of these factors rather than behavioral ones in causing aggregate clustering of merger activity.

One prediction distinguishing between the behavioral and neoclassical hypotheses of merger waves centers on acquisitions of firms' divisions for cash. Since the neoclassical hypothesis predicts that capital will be reallocated as quickly and efficiently as possible, it follows that not all transactions will be for whole firms and that not all transactions will use stock as the method of payment. Under the behavioral hypothesis, there is no underlying reason for a merger wave other than the desire by managers to use overvalued stock to acquire the assets of less overvalued firms. Thus, while stock swap mergers are predicted by the behavioral hypothesis, cash-financed partial-firm (divisional) acquisitions are not. Consequently, in the next set of tests, I examine the relation between firm-level and partial-firm level acquisition activity. There is a strong time-series correlation between the proportion of an industry involved in firm-level mergers and the proportion involved in partial-firm acquisitions. This correlation holds even when only stock swap mergers are compared to cash partial-firm acquisitions. Further, at the firm level, being a bidder (even a stock bidder) strongly predicts being a partial-firm acquirer (even for cash). These results are directly implied by the neoclassical explanation of merger waves, but are inconsistent with the behavioral explanation.

The focus of the behavioral hypothesis on asset misvaluation warrants a further examination of the returns surrounding merger waves. Using the Fama (1998) calendar-time approach, I examine the returns of the portfolios of firms in each industry over the 20-year sample period. Fama-French Three-Factor adjusted returns in the period immediately before, during, or following a wave are not significantly different from the returns of non-wave periods. Only unadjusted value-weighted returns show the typically observed pattern of relatively high returns before and during a wave followed by relatively low returns after the wave. This finding is not robust to equal weighting, suggesting that if anything, it is large firms that experience poor post-wave performance. The evidence does not suggest that managers in these industries are taking advantage of temporary mispricing of their industries, but rather, that the capital liquidity that a business expansion and accompanying bull market provide allows industry-level merger waves to occur. Examining only the returns of bidders, I find that there is some evidence in the value-weighted returns of post-bid underperformance by bidders in waves using stock. This finding is also not robust to equal weighting.

The tests conclude with an examination of changes in operating performance, a valuation measure, and analyst forecasts following mergers. I argue that augmenting traditional operating performance tests with changes in analyst forecasts mitigates the benchmarking problem typical of these tests, specifically, that the empiricist cannot observe the expected performance absent a merger to compare it to post-merger performance. I present evidence that changes in both forecasts and actual operating performance following mergers in waves are not worse than (and by some measures are better than) changes following non-wave mergers.

The next section briefly reviews the literature and establishes the framework for testing the hypotheses. Section 3 describes the data and identification of merger waves. Section 4 presents the empirical tests and results, and Section 5 concludes.

2. Literature review and hypothesis development

It is well known that merger waves exist (see, e.g., Brealey and Myers, 2003). Mitchell and Mulherin (1996) document clear clustering of waves within industries and tie that clustering to various technological, economic, or regulatory shocks to those industries. They suggest that a systematic analysis of industry shocks and merger activity may shed light on understanding merger waves. The industry-level clustering of mergers is confirmed for the 1990s in Mulherin and Boone (2000) and Andrade, Mitchell, and Stafford (2001). Nonetheless, there is no consensus as to why merger waves occur. The competing explanations can be broadly categorized into two groups: neoclassical and behavioral.

2.1. Neoclassical hypothesis

Neoclassical explanations of rational merger waves (see, e.g., Gort, 1969) are based on an economic disturbance that leads to industry reorganization. Coase (1937) is one of the earliest to argue that technological change leads to mergers. More recently, Jovanovic and Rousseau (2001, 2002) put forth models under which technological change and subsequent increased dispersion in q ratios lead to high-q firms taking over low-q firms in waves. Maksimovic and Phillips (2001) use performance improvements at the plant-level to support a neoclassical theory of merger waves.

Building on recent work on capital liquidity, this paper suggests a role for capital liquidity in a neoclassical hypothesis of merger waves. Eisfeldt and Rampini (2003) show that variation in capital liquidity strongly impacts the degree of total (industrial, household, and labor) capital reallocation in the economy and further that the degree of capital liquidity is cyclical. While they do not explicitly study market valuations, I argue that because higher market valuations relax financing constraints, market valuations are an important component of capital liquidity. Shleifer and Vishny (1992) make a similar argument in a study of asset liquidity, showing that in order for transactions to occur, buyers who intend to employ the asset in its first-best use must be relatively unconstrained. This allows prices offered to be close to fundamental values. Shleifer and Vishny hypothesize that the reason merger waves always occur in booms is because increases in cash flows simultaneously increase fundamental values and relax financial constraints, bringing prices closer to fundamental values. Empirical evidence by Harford (1999) supports this argument by showing that firms that have built up large cash reserves are more active in the acquisition market. Recently, Schlingemann et al. (2002) show that industry-specific asset liquidity is important in determining which assets will be divested.

To summarize, under the neoclassical hypothesis, once a technological, regulatory, or economic shock to an industry's environment occurs, the collective reaction of firms inside and outside the industry is such that industry assets are reallocated through mergers and partial-firm acquisitions. This activity clusters in time as managers simultaneously react and then compete for the best combinations of assets. The capital liquidity argument modifies the neoclassical hypothesis of waves to predict that only when sufficient capital liquidity exists to accommodate the reallocation of assets, will an industry shock generate a merger wave. Thus, even if industry shocks do not cluster in time, the importance of capital liquidity means that industry merger waves as reactions to shocks will cluster in time to create aggregate merger waves.

2.2. Behavioral hypothesis

Recent theoretical work has addressed the observed positive correlation between stock valuations and merger activity, which has been noted by Golbe and White (1988), among others. Shleifer and Vishny (2003) argue that we observe clustering in merger activity because a substantial portion of merger activity is driven by stock market valuations. They posit that bull markets lead groups of bidders with overvalued stock to use the stock to buy real assets of undervalued targets through mergers. Coupled with sufficiently high misperceived merger synergies in the marketplace, Shleifer and Vishny's model allows for (less) overvalued targets as well, relying mainly on dispersion in valuations. Target managers with short time horizons are willing to accept the bidder's temporarily overvalued equity. Overvaluation in the aggregate or in certain industries would lead to wave-like clustering in time. Contemporaneously, Rhodes-Kropf and Viswanathan (2004) develop a model of rational managerial behavior and uncertainty about sources of misvaluation that also would lead to a correlation between market performance and merger waves. In their model, rational targets without perfect information will accept more bids from overvalued bidders during market valuation peaks because they overestimate synergies during these periods. The greater transaction flow produces a merger wave.

Their model differs from that of Shleifer and Vishny in that target managers rationally accept overvalued equity because of imperfect information about the degree of synergies rather than shorter time horizons. Nonetheless, because both explanations rely at least partly on bidders taking advantage of temporary misvaluations and also on dispersion in misvaluations in the market, they can be grouped as behavioral hypotheses.

In a follow-up empirical study, Rhodes-Kropf et al. (2004) show that aggregate merger waves occur when market valuations, measured as market-to-book ratios, are high relative to true valuations, estimated using residual income models or industry multiples. However, they note that their results are consistent with both the behavioral mispricing stories and the interpretation that merger activity spikes when growth opportunities are high or when firm-specific discount rates are low. This latter interpretation is similar to a neoclassical hypothesis with a capital liquidity component. Nonetheless, further tests lead them to favor a mispricing explanation. Dong et al. (2003) and Ang and Cheng (2003) also use accounting numbers to estimate a fundamental value and find evidence consistent with the behavioral explanation of merger activity. Verter (2002) confirms that the level and dispersion of stock market valuations are correlated with merger activity, especially mergers for stock. While Rhodes-Kropf et al. (2004) recognize alternative interpretations of their evidence and try to distinguish between competing explanations, the other studies that examine the behavioral hypothesis tend to only provide evidence consistent with behavioral explanations, rather than considering both neoclassical and behavioral hypotheses and then formally rejecting the neoclassical.

2.3. *Specific predictions*

The behavioral hypothesis asserts that mergers happen when managers use overvalued stock to buy the assets of lower-valued firms. To generate a merger wave, this requires waves of high valuations for enough firms. Consequently, the behavioral hypothesis makes the following predictions: (1) Merger waves will occur following periods of abnormally high stock returns or market-to-book ratios, especially when dispersion in those returns or ratios is large; (2) Industries undergoing waves will experience abnormally poor returns following the height of the wave; (3) As there is no economic driver to the wave, identifiable economic or regulatory shocks will not systematically precede the wave; (4) The method of payment in a wave should be overwhelmingly that of stock, such that cash mergers should not increase in frequency during waves; and, as a corollary, (5) Because the wave is being driven by the acquisition of real assets with overvalued stock, partial-firm (divisional) transactions for cash should not be common and they should be especially rare by firms that are bidding for other firms with stock.

Alternatively, the neoclassical hypothesis asserts that merger waves occur when industries react to shocks to their operating environment. If the efficient response to a shock requires a reallocation of assets, then some firms acquire either all or part of the assets of other firms through mergers and partial-firm transactions. Observable economic or regulatory shocks will precede waves. The method of payment will be either stock or cash, and partial-firm transactions for cash will be observed. The same firm might engage in both a stock swap merger and a cash partial-firm transaction. The capital liquidity component of this explanation predicts that credit constraints will be low and/or asset values will be high.

One can also use post-merger operating performance to distinguish between the neoclassical and behavioral explanations. Some authors, such as Shleifer and Vishny (2003), argue that the neoclassical hypothesis is lacking because it predicts performance improvements following a merger and the extant evidence on this is mixed at best (see Agrawal and Jaffe, 2003, for a review of the evidence). However, when the neoclassical hypothesis is applied to merger waves, it does not necessarily predict that raw performance will improve following mergers in a wave. The neoclassical hypothesis predicts that performance of the combined firms will be better than it would have been without the merger. In many circumstances, prior performance is a reasonable proxy for performance without the merger. In a merger wave, however, this proxy is much worse than usual because in a wave, the firms are responding to an industry shock.

Due to the changes the industry is undergoing and the endogeneity of the choice to merge, the contemporaneous performance of the industry also is a problematic proxy. All firms are likely to restructure in some way (either externally or internally) in response to the industry shock, and thus there is no reason to expect that the performance of the merging parties should outperform the benchmark. One could observe a performance decline following a merger, but relative to what would have happened in the absence of the merger, this result may be the better outcome. Thus, the neoclassical hypothesis predicts that performance will improve relative to the unobservable unmerged performance. Any empirical test of this hypothesis implicitly tests the joint hypothesis that the empirical benchmark is a good proxy for the unobservable benchmark and that performance improves relative to this benchmark. I argue that using traditional proxies for the unobservable benchmark is likely to lead to the rejection of the first part of the joint hypothesis.

Although I believe that the joint hypothesis problem makes examination of operating performance changes inherently problematic, in the interest of completeness I report the results of such tests. To mitigate the joint hypothesis problem, I use both traditional industry benchmarks and analyst forecasts. Using I/B/E/S data, I compare analyst forecasts of the sample firms' long-term performance before the announcement of the merger to forecasts made after the completion of the merger. Under the assumption that analysts have already incorporated the expected impact of the industry shock into their forecasts prior to the merger, the pre-merger forecast should be a good proxy for the unobservable unmerged performance.

The neoclassical hypothesis predicts that analyst performance forecasts will increase post-merger. One can also derive a prediction under the behavioral hypothesis. Because in the behavioral framework mergers in waves have no underlying economic rationale and no real synergies, there are no benefits to offset the costs of integration. Thus, the merged firm should endure especially poor post-merger operating performance. Under the null of the behavioral hypothesis, performance forecasts following mergers in waves should be worse than average.

Table 1
Predictions of the neoclassical and behavioral hypotheses for merger waves

	Neoclassical	Behavioral	Finding
Cause of industry wave	Regulatory or economic shock accompanied by capital liquidity	Overvaluation and dispersion of valuation within industry	Regulatory and economic shocks accompanied by capital liquidity
Cause of aggregate wave	Multiple simultaneous industry waves clustering because of macro liquidity factor	Overvaluation and dispersion in the aggregate	Multiple simultaneous industry waves clustering because of macro liquidity factor
Cash partial-firm acquisitions	Increase during wave; could be made by stock bidders	Do not increase during wave; are not made by stock bidders	Increase during waves and are made by stock bidders
Pre-wave returns and market-to-book ratios	High if capital liquidity is tied to asset valuation	High	High
Dispersion in pre-wave returns	No prediction	High	Normal
Post-wave returns	No prediction	Low	Normal
Measures of tight credit	Low if capital liquidity is important	No prediction	Low
Post-merger operating performance	Better than without a merger	Worse in waves	Similar/better in waves

Table 1 summarizes the predictions of the behavioral and neoclassical hypotheses of merger waves. The table also previews the empirical findings of Section 4.

3. Data and merger wave identification

I start with all merger or tender-offer bids recorded by Thomson Financial's Securities Data Company (SDC) between 1981 and 2000 with a transaction value of at least \$50 million. I assign each bidder and target to one of 48 industry groups based on their SIC code recorded by SDC at the time of the announcement.[1] Because the 1980s and 1990s were characterized by two distinct aggregate merger waves, with a substantial trough surrounding the 1990 to 1991 recession, I split the sample into the 1980s and 1990s. Based on Mitchell and Mulherin (1996)'s study of two-year

[1]These industry groupings are the same 48 groups used in Fama and French (1997), and are detailed in the appendix of that paper.

wave periods, waves in this paper will be 24-months. Thus, for each industry, I calculate the highest 24-month concentration of merger bids involving firms in that industry in each decade.[2] This 24-month period is identified as a potential wave. Taking the total number of bids over the entire decade for a given industry, I simulate 1000 distributions of that number of occurrences of industry member involvement in a bid over a 120-month period by randomly assigning each occurrence to a month where the probability of assignment is 1/120 for each month. I then calculate the highest 24-month concentration of activity from each of the 1000 draws. Finally, I compare the actual concentration of activity from the potential wave to the empirical distribution of 1000 peak 24-month concentrations. If the actual peak concentration exceeds the 95th percentile from that empirical distribution, that period is coded as a wave. For example, 36% of the 161 bids in the health care industry in the 1990s occurred within one 24-month period starting in May of 1996. Out of 1000 simulated distributions of 161 bids across a 10-year period, the 95th percentile of maximum concentration within any 24-month period is 27%. Thus, the cluster of bids in the health care industry starting in May of 1996 is coded as a wave.

The end result is 35 waves from 28 industries (seven of which have two distinct waves, one in the 1980s and one in the 1990s). The industries and their waves are described in Table 2. Over the 20-year sampling period, the average number of bids any one of these 28 industries sees in a 24-month non-wave period is 7.8 while the average number of bids it sees during a 24-month wave is 34.3.

4. Results

I start with an examination of the two sets of factors predicted by the behavioral and neoclassical hypotheses to be associated with merger waves. One set of factors captures economic shocks to an industry's operating environment. These factors are: cash flow margin on sales (cash flow scaled by sales), asset turnover (sales divided by beginning-of-period assets), research and development (scaled by beginning-of-period assets), capital expenditures (scaled by beginning-of-period assets), employee growth, return on assets (ROA), and sales growth. These variables are motivated by papers such as Healy et al. (1992), who look at efficiency measures affecting performance around mergers and Mitchell and Mulherin (1996), who examine sales, employment, and regulatory shocks and industry merger activity in the 1980s. One other potential economic characteristic, the market-to-book ratio, is ambiguous because it is also claimed by the behavioral hypothesis. The set of factors chosen to more directly examine the behavioral hypothesis' reliance on market timing includes

[2] If the bidder is in industry X and the target is in industry Y, then the bid will count toward merger activity in that month for both industry X and Y. If the bidder and target are both in industry X, then the bid will count once toward the merger activity for industry X for that month (it will not be double counted). Multiple bids for a single target within a two-month period only count as one contest when calculating merger activity in that industry.

Table 2
Industries with merger waves
The industries and starting dates of the merger waves comes from the procedure described in Section 3. The reasons for the wave come from Lexis–Nexis searches of news reports analyzing the merger activity at the time of the wave.

Industry	Date wave started and reason given
Aircraft	Jan, 1999 Big, older fleets require increased maintenance, repair and overhaul Increasingly outsourced from carriers, who want "one-stop shops"
Banking	Aug, 1985 Deregulation allows interstate banking, particularly in California Oct, 1996 Deregulation and Information Technology (IT)
Business Services	Oct, 1986 Partially IT-driven mergers as IT becomes important Sep, 1998 Fragmented, smaller players combine, share cost structures, offer more complete line of services to customers—industry grows as outsourcing takes off
Business Supplies	Jan, 1997 Paper and pulp industry consolidates from fragmented price takers to gain market power and avoid costly duplication of capital intensive production facilities
Candy & Soda	Apr, 1992 Snapple and other non-carbonated beverages make strides, leading to activity to beat or buy them
Chemicals	Mar, 1995 Large cash flows, over capacity in production, need to consolidate research
Communication	Nov, 1987 Deregulation: Break-up of AT&T in 1984 followed by entry into long distance, investment in fiber optic capacity, etc. July, 1997 Deregulation: Telecommunications Act in 1996, consolidation, technological changes
Computers	July, 1998 Internet
Consumer Goods	Aug, 1986 Mature market and the need to offer full line leads to consolidation
Electrical Equipment	June, 1986 Several companies seek growth through acquisition to compete better with industry leaders Westinghouse and General Electric
Electronic Equipment	Jan, 1999 OEM's growth leads to demand for electronic equipment manufacturers to shift from small regional players to larger global players capable of infrastructure, IT, etc. to grow with their customers

Table 2 (*continued*)

Industry	Date wave started and reason given
Entertainment	Oct, 1987 Deregulation allows firms to own many stations Mar, 1998 Studios seek diversified production sources and strong libraries; Telecom act of 1996 relaxes media ownership limits
Food Products	Jan, 1999 Retail consolidation pushes distribution consolidation and/or sale of distributors to bigger retailers who want to buy rather than build distribution channels
Healthcare	May, 1996 Service providers consolidate to have bargaining power with HMOs
Insurance	Nov, 1998 Bigger is safer, leading to consolidation, especially in reinsurers
Machinery	May, 1996 Large manufacturers decreased number of suppliers they were willing to deal with in bid to improve efficiency. This forced consolidation in a number of capital goods industries—many smaller players were bought in "roll-up" deals
Measuring and Control Equip	Nov, 1998 Depression in semi-conductor industry (big customer)
Medical Equipment	Nov, 1998 Two motives: first, acquisitions in core areas to grow, then acquisitions outside core areas to offer broad products to increasingly consolidated customer base (hospitals)
Personal Services	Feb, 1996 Consolidation in legal and funeral services industries
Petroleum and Natural Gas	June, 1997 Increasing prices, record drilling, increasing costs lead drive to increase size to be more efficient
Pharmaceutical Products	Oct, 1998 Mid-sized companies merge to garner size necessary to fund increasingly large costs of development
Restaurants, Hotels, Motels	Mar, 1985 Saturation and similarity, trends toward take-out, competition from supermarket delis Dec, 1996 Operators such as Starwood have buying sprees. Others buy properties to gain sufficient bulk to compete in corporate account business market
Retail	Oct, 1986 Shift to specialty stores as aging department stores consolidated; value of land & buildings in revitalized urban centers Aug, 1996 Strong growth and impact of internet

Table 2 (*continued*)

Industry	Date wave started and reason given
Shipbuilding, Railroad Equip	Aug, 1998 Shrinking defense budgets finally forced the issue of overcapacity in the industry
Steel Works	Sep, 1997 Collapse in demand from Asia leads to falling prices forcing consolidation
Transportation	Aug, 1986 Mostly still working out issues following deregulation July, 1997 End of Interstate Commerce Commission, overcapacity in shipping, open-skies agreements, railroad consolidation started with a few big mergers and then forced responses to balance
Utilities	Nov, 1997 Deregulation in some markets plus elimination of a law prohibiting mergers between non-contiguous providers
Wholesale	June, 1996 Simultaneous consolidation in several wholesale sectors as growth slows and firms move to add breadth, take advantage of new IT ability, grow by acquisition

the cross-sectional standard deviation of the market-to-book ratio and the average one- and three-year stock returns and cross-sectional standard deviation of those returns.

4.1. *Univariate evidence*

The tests examine the above two sets of industry characteristics before merger waves. All variables are examined in the year prior to the start of an industry's merger wave. Thus, out of 28 industries each with a 20-year history, there are 35 industry-years preceding the start of a merger wave. The results are summarized in Table 3. Since economic shocks could have different effects across firms, and further, since different shocks across industries could have different average directional implications, I use the median absolute change in each of the above variables to measure economic shocks. The number presented in the table is the mean, across all industries, of this industry-specific median in the year immediately preceding the start of the merger wave. For each industry, I also rank the time-series of 20 shock observations into quartiles and present the cross-industry mean rank of the shock in the pre-wave year. The table shows that changes to profitability, asset turnover, R&D, capital expenditures, employee growth, ROA, and sales growth are all abnormally high prior to waves. The time-series ranks show that the pre-wave changes were high for the average industry, and the (untabulated) medians establish that the changes were at least in the third quartile of the industry's own history of changes.

Turning to the variables that are related to both the behavioral and neoclassical hypotheses, one sees that market-to-book (M/B), the change in M/B, and the intra-industry dispersion of M/B are all abnormally high in the year preceding a wave. The stock return variables motivated by behavioral hypothesis are less conclusive. While all are relatively high before the start of a wave, they are not significantly abnormally high relative to each industry's history of returns. I examined the pattern of returns further and found that while returns are higher than average before an industry merger wave, the relation is weak because the highest returns for most industries do

Table 3

(Panel A) Measures of economic shocks and stock valuation

The state of the industry in the year before a merger wave is summarized. Several variables are used to measure economic shocks to the industry: net income/sales (profitability), asset turnover, R&D, capital expenditures, employee growth, ROA, and sales growth. The median absolute change in each of above variables is computed for each industry-year. Market-to-book and dispersion in market-to-book are either economic variables or misvaluation proxies. Stock valuation is also addressed by the median prior one- and three-year compounded return for firms in the industry along with the intra-industry dispersion of that return. For all variables, the number presented in the table is the mean, across all industries, of this industry-specific median in the year immediately preceding the start of the merger wave (there are 35 industry-year observations for this pre-wave year). For each industry, the 20-year time series of shock observations is ranked into quartiles and the cross-industry mean rank of the shock in the pre-wave year is presented. A test is performed on the average difference between a rank of 2.5 (middle) and the ranking of the pre-wave year within its own industry time series. The *p*-value for the hypothesis that this difference is zero is presented in brackets.

Economic shocks (Variables related to the neoclassical hyp.)	Mean	Rank	Stock valuation (Variables related to the behavioral hyp.)	Mean	Rank
Net income/sales	0.030	2.83	3yr-Return	0.638	2.66
H_0: Rank = 2.5		[0.100]	H_0: Rank = 2.5		[0.372]
Asset turnover	0.096	2.77	σ (3yr-Return)	1.317	2.60
H_0: Rank = 2.5		[0.076]	H_0: Rank = 2.5		[0.372]
R&D	0.004	2.86	1yr-Return	0.132	2.66
H_0: Rank = 2.5		[0.007]	H_0: Rank = 2.5		[0.328]
Capital expenditures	0.023	2.80	σ (1-yr Return)	0.566	2.74
H_0: Rank = 2.5		[0.109]	H_0: Rank = 2.5		[0.152]
Employee growth	0.128	2.97	Market-to-Book variables (related to both hypotheses)		
H_0: Rank = 2.5		[0.008]			
			Market to book	1.563	3.14
ROA	0.040	2.80	H_0: Rank = 2.5		[0.001]
H_0: Rank = 2.5		[0.066]			
			Industry σ(market to book)	1.201	3.11
Sales growth	0.128	3.03	H_0: Rank = 2.5		[0.001]
H_0: Rank = 2.5		[0.003]			
			Change in market to book	0.022	2.86
			H_0: Rank = 2.5		[0.055]

Table 3 (*Continued*)

(Panel B) This table lists the major deregulatory initiatives during the sample period and is constructed from Viscusi et al. (2000), Economics of Regulation and Antitrust, Tables 10.2 and 10.3.

Year	Deregulatory event	Industry affected
1981	Decontrol of crude oil and refined petroleum products (executive order)	Petrol and Natural Gas
	Deregulation of radio (FCC)	Entertainment
1982	Garn-St. Germain Depository Institutions Act	Banking
	AT&T settlement	Communications
1984	Cable Television Deregulation Act	Entertainment
	Shipping Act	Transportation
1987	Elimination of fairness doctrine (FCC)	Entertainment
1989	Natural Gas Wellhead Decontrol Act of 1989	Petrol and Natural Gas
1991	Federal Deposit Insurance Corporation Improvement Act	Banking
1992	Cable Television Consumer Protection and Competition Act	Entertainment
	Energy Policy Act	Petrol and Natural Gas
	FERC Order 636	Utilities
1993	Elimination of state regulation of cellular telephone rates	Communications
	Negotiated Rates Act	Transportation
1994	Trucking Industry and Regulatory Reform Act	Transportation
	Interstate Banking and Branching Efficiency Act	Banking
1995	Interstate Commerce Commission Termination Act	Transportation
1996	Telecommunications Act	Communications
	FERC Order 888	Utilities

not precede their waves. Thus, the strongest relation between a measure of valuation and waves found here is for market-to-book rather than returns.

Shocks to an industry environment can also come from major regulatory changes. Panel B of Table 3 documents major deregulatory events over the sample period and identifies which industries were affected by those events. A comparison of the panel and the starts of the waves suggests a relation which will be explored further in the next section.

Applying the capital liquidity arguments advanced by Shleifer and Vishny (1992) and Eisfeldt and Rampini (2003) to merger waves suggests that a macro component which proxies for capital liquidity should help explain waves. One proxy is provided by the Federal Reserve Senior Loan Officer (SLO) survey. The Federal Reserve surveys senior loan officers across the nation on a quarterly basis, asking them whether over the previous quarter they had tightened or eased credit standards for commercial lending. Lown et al. (2000) show that the SLO Survey forecasts not only commercial loan growth, but also overall economic activity and narrower measures such as inventory investment and industrial production. They find evidence of a series of events characteristic of a credit crunch—credit standards tighten, commercial loans contract sharply, and output falls. Unfortunately, the Federal Reserve did not ask the question between 1984 and 1990. Nonetheless, Lown et al. (2000) find that the degree to which the SLO survey reports tightening is strongly correlated with the spread between the average interest rate on commercial and industrial loans and the Federal Funds rate. This spread has been collected consistently over the entire sample period. I do not argue that the availability of commercial and industrial credit has a direct causal effect for merger activity. Indeed, equity mergers do not require access to the credit markets. Instead, I assert that, based on the results of the Lown et al. paper, the rate spread may be used as a proxy for overall liquidity or ease of financing (in whatever form) in the economy. In the neoclassical model with transaction costs, the rate spread will be correlated with transaction costs. Based on the argument that higher asset values accommodate capital liquidity in an industry, the empirical specifications to test the model will also include an industry-specific interaction variable that accounts for the valuation levels in the industry.

The four-quarter moving average of the rate spread is plotted against aggregate merger activity in Fig. 1. The figure displays an inverse relation (with a slight lag) between the rate spread and aggregate merger activity. A decrease in the rate spread precedes an increase in merger activity and an increase in the rate spread signals the end of a merger wave. Fig. 1 also contains bars showing the timing of individual industry merger waves. Industry merger waves tend to cluster when the rate spread is relatively low, creating aggregate merger waves.

One might expect the transaction costs proxy, the rate spread, to be correlated with some of the key variables in the behavioral models. Fig. 2 shows that the level of the rate spread is correlated with both overall median market-to-book and the three-year compounded return on the S&P 500 index. However, as suggested by Fig. 2, the rate spread leads the market-to-book ratio. Decreases in the rate spread lead to increases in the market-to-book ratio; the correlation between lagged changes in the rate spread and current changes in the market-to-book ratio is a significant -0.38. The reverse is not true; the correlation between lagged changes in the market-to-book ratio and current changes in the rate spread is an insignificant -0.03. This is consistent with the evidence presented in Lown et al. (2000) on the effects of changes in the ease of credit on overall economic growth. A decrease in the rate spread leads to increased economic growth, potentially lower risk-premiums, and as shown later, greater merger and acquisition activity. All of these would have the effect of causing an increase in market-to-book ratios.

The only correlation between changes in the rate spread and the S&P500 return is a marginally significant lagged positive relation, which is opposite of what would need to be present for the rate spread to simply be capturing the stock return effects of a market-timing explanation. The correlation between lagged S&P500 returns and current changes in the rate spread is 0.39. Thus, after periods of strong growth, the rate spread starts to rise. While these results should mitigate concerns about the relation between the liquidity variable and traditional behavioral variables, one might still harbor doubts. In the multivariate tests, I attempt to control for the behavioral variables in testing the explanatory power of the liquidity variable.

The results thus far present definite indications that economic factors drive merger waves. Observable economic and deregulatory shocks precede industry merger waves

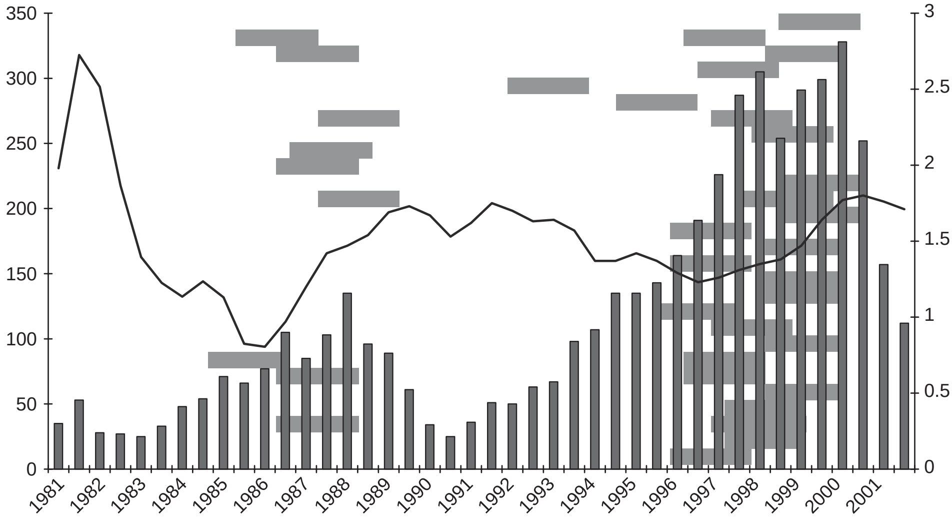

Fig. 1. Capital liquidity, industry merger waves and aggregate merger activity. The line is the spread between the average rate charged for commercial and industrial loans and the fed funds rate, reported in the Federal Reserve's Survey of Terms of Business Lending (right axis). This spread is measured in percentage points and proxies for low capital liquidity. The horizontal bars mark the timing of the industry-level merger wave periods in this study (e.g. the top-most bar represents an industry-level merger wave starting in the latter half of 1998 and ending in the first half of 2000. The vertical bars represent the total number of merger bids with a transaction value of at least $50 million in 2002 dollars (left axis).

and those merger waves cluster when transaction costs are low enough so that capital liquidity is relatively high. Nonetheless, if one counts the level and dispersion of market-to-book as behavioral hypothesis variables, then the evidence on them is still consistent with a role for the behavioral explanation. In the next test, I distinguish between these two interpretations by employing successive logit models to predict merger waves. The successive logits will also bear on the interpretation of the relation between the rate spread and the behavioral variables. Since the behavioral variables will be included in the regression, if the rate spread is actually a proxy for those variables, it will be insignificant. If, instead, the behavioral variables are simply capturing effects correlated with the rate spread, then they will be insignificant.

4.2. Logit models

Table 4 presents the results of estimating logit models of merger wave starts. The sample is all 48 industries for the 20-year sample period. The explanatory variables come from those analyzed in Table 3. One problem with the industry-specific economic shock variables is that they are highly correlated within an industry and cause multicollinearity if simultaneously included in a regression model. To address this problem, I extract the first principal component from the seven economic shock variables (profitability, asset turnover, R&D, capital expenditures, employee growth, ROA, and sales growth). The

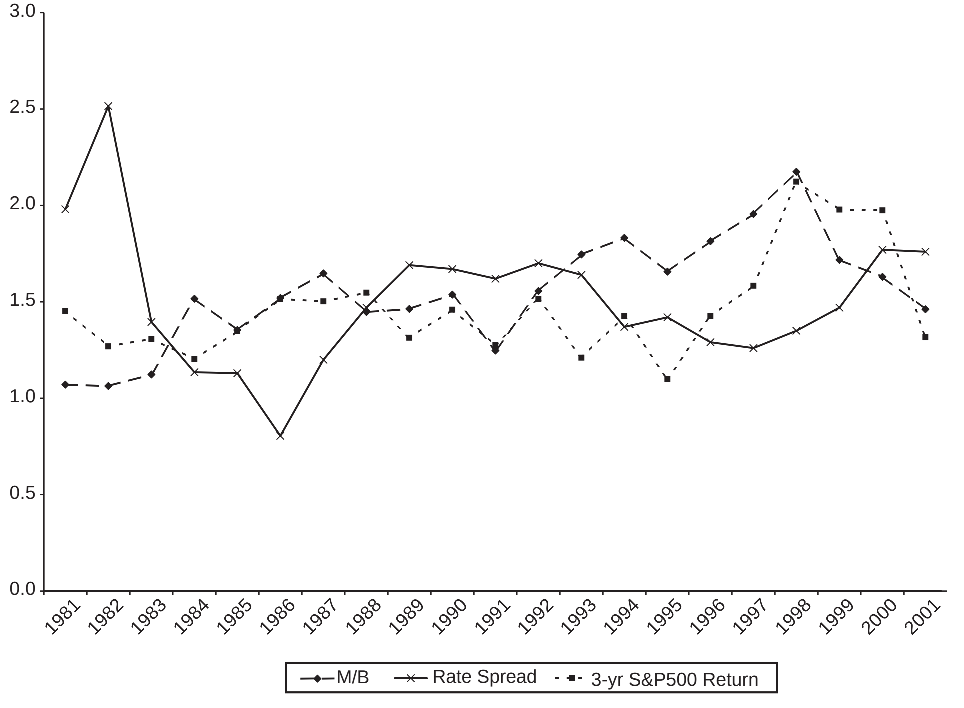

Fig. 2. Time-series relation between the rate spread variable and variables commonly used in behavioral explanations of merger waves. The rate spread is the spread between the average commercial and industrial loan rate and the Fed Funds rate, as collected by the Federal Reserve in its Survey of Terms of Business Lending. This spread is measured in percentage points and proxies for low capital liquidity. The M/B time series is the median market-to-book ratio of all firms on Compustat each year. Finally, 3-yr S&P500 Return is one plus the compounded prior three-year return on the S&P500 index. All series are scaled to use the left axis (e.g. 1.5 represents a rate spread of 1.5 percentage points, a median market-to-book ratio of 1.5, and 50% compound return on the S&P500 index).

capital liquidity part of the neoclassical hypothesis predicts that these shocks will be less likely to propagate a wave when liquidity is low. High liquidity years would be years in which the rate spread is below its time-series median and the industry's M/B ratio is simultaneously above its time-series median. Thus, low liquidity years would be all other years. The economic shock principal component will enter the logit models both on its own and interacted with a dummy identifying low liquidity years.

The first column of Table 4 shows that industry M/B by itself has some ability to predict merger waves.[3] The second column adds the industry three-year return and

[3]The intra-industry standard deviation of market-to-book is too highly correlated with the industry median level of market-to-book for both to enter the specification at the same time. When the specifications are estimated replacing the level of market-to-book with the standard deviation, the results for the standard deviation are qualitatively the same, but with marginally higher p-values than the results tabulated for the level. The other results are unaffected.

Table 4
Predicting merger waves
Logit models are used to predict when an industry will have a merger wave. The sample is 48 industries, each over 20 years (1981–2000). The dependent variable in the first four columns is equal to one if the industry-year is the beginning of a merger wave in that industry. The explanatory variables are measured at the end of year $t-1$. Market-to-book is the industry median market-to-book ratio, 3-year return and σ(3-year Return) are the median return in the industry for the three years ending at the end of year $t-1$ and the intra-industry standard deviation of that return, and the commercial and industrial (C&I) loan rate spread (spread above the fed funds rate) proxies for low capital liquidity. There is also a dummy variable selecting years that were preceded by a major deregulatory event. The economic shock index is the first principal component of the seven economic shock variables in the first column of Table 3. The shock index is also interacted with a dummy variable selecting years when market-to-book ratios are below their industry-specific time-series median or the C&I rate spread is above its time-series median (years of low capital liquidity).

The last three columns regress an indicator for aggregate merger activity on aggregate versions of the independent variables. There are 20 observations, one for each year from 1981–2000. The dependent variable identifies whether aggregate merger activity is in the top, middle, or bottom third of the time-series of merger activity over the sample period. Aggregate merger activity is defined as the fraction of firms in the population involved in merger activity (as a target or bidder) in a given year. Years in the top third can be thought of as merger wave years (the years are 1986–1988 and 1996–1999). The independent variables are weighted averages of the industry-level variables for that year, where the weights are the number of firms in the industry. For example, the economic shock index is the average economic shock index across all industries, weighted by the number of firms in each industry.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	**−4.445**	**−4.450**	**−2.980**	**−3.320**	**−0.713**	**3.499**	2.306
	[<.0001]	**[<.0001]**	**[<.0001]**	**[<.0001]**	**[0.074]**	**[0.001]**	[0.173]
M/B_{t-1}[a]	**0.847**	**0.840**		0.165	**2.172**		0.520
	[0.017]	**[0.031]**		[0.745]	**[0.002]**		[0.297]
3-year Return_{t-1}		0.152		−0.109	1.027		0.426
		[0.736]		[0.850]	[0.216]		[0.463]
σ(3-year $\text{Return})_{t-1}$		−0.059		0.250	−0.790		0.015
		[0.846]		[0.492]	[0.203]		[0.973]
C&I Rate Spread_{t-1}			**−0.521**	**−0.567**		**−1.079**	**−0.998**
			[0.032]	**[0.026]**		**[0.004]**	**[0.011]**
Deregulatory Event_{t-1}			**1.872**	**1.930**		3.313	2.166
			[0.025]	**[0.023]**		[0.291]	[0.488]
Econ Shock Index_{t-1}			**0.452**	**0.369**		**1.137**	**1.000**
			[0.007]	**[0.091]**		**[0.001]**	**[0.003]**
Econ Shock Index_{t-1}			**−0.917**	**−0.881**		**−0.290**	−0.205
* (Tight Capital)			**[0.001]**	**[0.002]**		**[0.083]**	[0.268]
Adj R^2					0.356	0.774	0.786
Pseudo-R^2	0.016	0.017	0.151	0.154			
Correlation of prediction with waves	0.079	0.075	0.240	0.248			

intra-industry standard deviation of this return for the full set of variables motivated by behavioral explanations.[4] For each model, one can correlate the actual occurrence of a wave in a given industry-year with the probability of a wave generated by the model. These correlations are tabulated in the last row of the table. Column 2 reports that the correlation between the behavioral-predicted probability of a merger wave and the actual occurrence of a merger wave is 0.08, significant at the 4% level.

In column 3, the model is estimated using only the economic variables. Notably, the shock variable is positive and significant, but the shock variable interacted with the dummy variable for low liquidity is negative and significant (and the sum of the two is insignificant). Both the deregulation indicator variable and the rate spread variable are strongly significant. The deregulatory variable is consistent with similar findings in Mitchell and Mulherin (1996) for the 1980s. These results confirm the univariate results supporting the neoclassical hypothesis. The correlation between the predicted probabilities of this model and the actual occurrence of a wave is 0.24, significant at less than the 1% level.

Finally, the full model is estimated in column 4. The stock return and standard deviation of stock return remain insignificant and market-to-book becomes insignificant. The fact that M/B predicts merger waves is generally cited as evidence in favor of the behavioral hypothesis. However, column 5 shows that the market-to-book variable is subsumed by the shock and rate spread variables. This suggests that the market-to-book variable is in fact proxying for lower transaction costs that come with greater capital liquidity. The results for the neoclassical variables are qualitatively unchanged. The correlation between the predicted probabilities of the full model and the actual waves is 0.25, significant at better than the 1% level. The addition of the behavioral variables (even counting M/B as a behavioral variable) to the neoclassical variables increases the correlation between the probabilities and actual waves by only 0.01, from 0.24 to 0.25. The results of the full model support the neoclassical hypothesis over the behavioral one. They further suggest that variables associated with behavioral explanations are actually proxying for an important economic condition that is necessary, but not sufficient, for merger waves: capital liquidity.

4.3. Relation between industry merger waves and aggregate merger activity

The next question is whether clustering of merger activity at the aggregate level is caused by clustering of industry-level merger waves. Fig. 3 shows the relation between aggregate merger activity and the timing and fraction of bids occurring in the industry-level merger waves identified here. It is clear from the figure that aggregate merger waves occur when industry-level merger waves cluster in time and that the total merger activity in these waves is driven by bids in the industries undergoing waves. As a formal test of this observation, the correlation between the

[4] In separate regressions, I substitute the one-year return level and standard deviation for the three-year return variables. The coefficients are not significant.

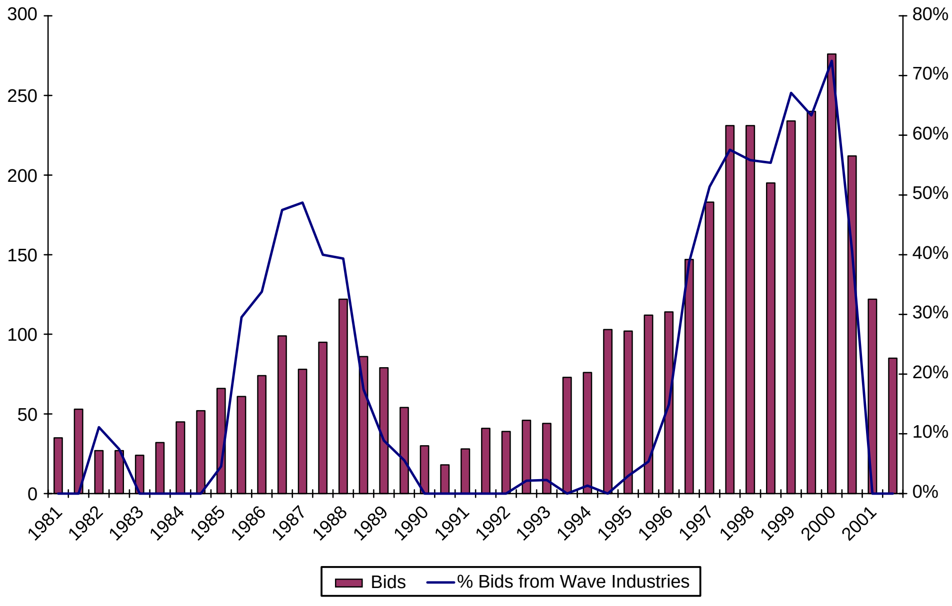

Fig. 3. Relation between industry merger waves and aggregate merger activity. The height of each bar represents the number of bids, shown on the left axis, with a deal value of at least $50 million (2002 dollars) across all industries in that year. The line indicates the percent of all bids, shown on the right axis, in each year that involved one of the industries undergoing a merger wave in that year.

fraction of bids in industries undergoing industry-specific waves and the total number of merger transactions in the economy is computed to be a highly significant 0.85. This strongly suggests that industry-level merger waves explain aggregate clustering of merger activity.

As a further test of the relation between the neoclassical explanation of industry level merger waves and overall aggregate merger activity, I try to predict aggregate merger waves using a specification analogous to those used to predict industry merger waves. In the aggregate merger waves specification, the dependent variable identifies whether aggregate merger activity is in the top, middle, or bottom third of the time-series of merger activity over the sample period. Aggregate merger activity is defined as the fraction of firms in the population involved in merger activity (as a target or bidder) in a given year. Years in the top third can be thought of as merger wave years (the years are 1986–1988 and 1996–1999). The independent variables are industry-weighted analogs of the independent variables in the logit models of Table 4. Thus, the median market-to-book ratio is the weighted average of the 48 industry median market-to-book ratios, where the weights are the fraction of the total population of firms in an industry. Similarly, the industry shock variable is the weighted average of the shock index across industries. Thus, a large realization of this variable corresponds to a large fraction of the total population of firms being exposed to industry-level shocks. The results are presented in columns 5–7 of Table 4.

There are only 20 observations, so the significance levels are reduced. Nonetheless, the results confirm at the aggregate level the primary inferences from the industry wave regressions. When only behavioral variables are included, the market-to-book ratio is significantly positively related to industry merger activity. The three-year stock return is positive, but insignificant, and the standard deviation of that return is insignificantly negative. Column 6 presents the results for the neoclassical variables. The shock variable shows that when a larger proportion of firms are exposed to industry-level shocks, an aggregate merger wave occurs. The variable interacting industry-level shocks with periods of low capital liquidity is negative and significant. Also, a high rate spread reduces aggregate merger activity. Notably, deregulation is positive, but not significant in the aggregate model. Column 7 shows that once the neoclassical and behavioral variables are included together, the magnitude of the market-to-book ratio drops substantially, and it becomes insignificant, but the industry shock variable and the rate spread variable remain significant.[5]

Based on Fig. 3, the correlation between industry merger waves and aggregate merger activity, and the results of Table 4, I conclude that aggregate merger waves can be understood as a clustering of industry merger waves. When a large portion of the population of firms is exposed to shocks at an industry level during a time of low transaction costs brought about by relatively high capital liquidity, an aggregate merger wave occurs. In the following subsections, I examine further tests that attempt to distinguish between behavioral and neoclassical explanations for industry merger waves.

4.4. Partial-firm acquisitions

One distinguishing prediction of the two hypotheses centers around partial-firm acquisitions. Because the efficient response to an economic shock is likely to involve not only firm-level transactions, but also divisional-level transactions, the neoclassical hypothesis predicts that partial-firm acquisitions will spike during merger waves. Many of these transactions occur via cash payments. It is harder to produce such a prediction from the behavioral hypothesis, which relies on managers taking advantage of stock price errors to acquire other firms using overvalued stock. Partial-firm acquisitions for stock could fit into these models, but not those for cash.

Fig. 4 summarizes the firm-level and partial-firm level acquisition activity prior, during, and after a merger wave in the sample of 28 industries with merger waves. It is clear that, as implied by the neoclassical hypothesis, partial-firm acquisition activity, even that for cash, follows the pattern of firm-level acquisition activity. Panel A of Table 5 shows the average across all 48 industries of the time-series correlations between merger activity and partial-firm acquisition activity in a given year, defined as the proportion of an industry involved in merger activity and

[5]With aggregated variables, one might be concerned about multicollinearity between the market-to-book ratio and the variable interacting economic shocks with tight liquidity. When I remove the interaction variable, the significance of the market-to-book ratio increases marginally, but remains insignificant.

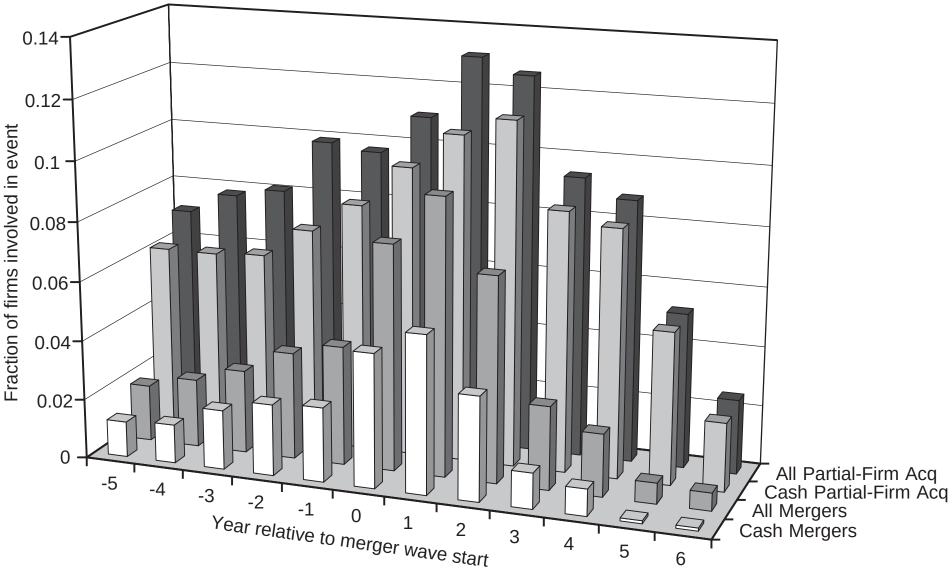

Fig. 4. Merger and partial-firm acquisition activity around an industry merger wave. The fractions of firms in an industry that are involved in a merger or partial-firm acquisition (e.g. acquisition of a division) during the industry merger wave (years 0 and 1) and for 5 years on either side of the merger wave are presented. The first contains only mergers where cash is the method of payment, while the second row presents the data for all mergers. The third row presents only partial-firm acquisitions paid for with cash and the last row has all partial-firm acquisitions.

Table 5
(Panel A) The relation between merger activity and partial-firm acquisitions
The simple correlations between the fraction of firms in an industry that bid in a firm-level merger and are buyers in a partial-firm level acquisition over any 12-month period are presented. Partial-firm does not mean transactions for less than 100% of a selling firm's outstanding equity. Rather, it refers to divisional transactions (outright purchases of an operational piece of the selling firm). The merger and partial-firm transactions are also split according to whether the method of payment was cash or stock. The correlations are calculated separately for all 48 industries and the cross-industry mean correlation is presented here along with its *p*-value, in brackets.

	Stock mergers	Cash mergers	Total partial-firm	Stock partial-firm	Cash partial-firm
Total mergers	0.728	0.902	0.369	0.179	0.341
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Stock mergers		0.535	0.176	0.218	0.109
		[0.000]	[0.000]	[0.000]	[0.019]
Cash mergers			0.331	0.124	0.273
			[0.000]	[0.008]	[0.000]
Total partial-firm				0.312	0.890
				[0.000]	[0.000]
Stock partial-firm					0.159
					[0.000]

Table 5 (*continued*)

(Panel B) Logit models to predict which firms will be buyers in partial-firm acquisitions
The dependent variable takes a value of one in years in which the firm is a buyer in at least one partial-firm transaction, and is zero otherwise. In the first column, this variable is one for buyers in any partial-firm acquisition and in the final two columns it is one only for buyers in cash partial-firm acquisitions. The independent variables include three dummy variables indicating whether the firm was a bidder in a merger in that year, a cash bidder, or a stock bidder. The C&I rate spread for the year and a dummy variable set to one if the year is during the industry's merger wave are included in the specification. The remaining control variables are all measured in the prior year and are: cash to total assets, asset turnover, size (the log of sales), market-to-book of assets, cash flow scaled by beginning-of-period assets, leverage (total debt scaled by assets), and the one-year stock return.

	All partial acquisitions	Cash partial acquisitions	
Intercept	**−2.811**	**−3.429**	**−4.299**
	[<.0001]	**[<.0001]**	**[<.0001]**
Bidder_t	**0.863**	**0.906**	
	[<.0001]	**[<.0001]**	
Cash bidder_t			**0.874**
			[0.009]
Stock bidder_t			**1.743**
			[<.0001]
$\text{C\&I rate spread}_t$	**−0.637**	**−0.492**	**−0.503**
	[<.0001]	**[<.0001]**	**[<.0001]**
In-wave dummy_t	**9.128**	**3.378**	**3.378**
	[<.0001]	**[<.0001]**	**[<.0001]**
Cash_{t-1}	**−0.196**	−0.046	−0.036
	[0.017]	[0.651]	[0.727]
$\text{Asset turnover}_{t-1}$	**−0.257**	**−0.425**	**−0.427**
	[<.0001]	**[<.0001]**	**[<.0001]**
Size_{t-1}	**0.336**	**0.303**	**0.307**
	[<.0001]	**[<.0001]**	**[<.0001]**
$\text{Market-to-book}_{t-1}$	**0.017**	**0.015**	**0.015**
	[0.000]	**[0.012]**	**[0.010]**
Cash flows_{t-1}	**0.117**	**0.360**	**0.359**
	[0.067]	**[<.0001]**	**[<.0001]**
Leverage_{t-1}	0.069	**0.149**	**0.147**
	[0.174]	**[0.010]**	**[0.011]**
$\text{Stock return}_{t-1}$	**0.079**	**0.076**	**0.076**
	[<.0001]	**[<.0001]**	**[<.0001]**
Pseudo-R^2	0.132	0.106	0.105
Firm-years	108183	108183	108183

partial-firm acquisition activity, respectively. Not only is total firm-level merger activity correlated with total partial-firm level activity, but also the stock swap only merger activity is correlated with the cash partial-firm level activity. While both the neoclassical and behavioral hypotheses can explain an increase in stock swap merger activity constituting a wave, only the neoclassical one explains the accompanying increase in cash mergers and cash partial-firm transactions.

It is possible that there is a behavioral set of firms engaging in stock swap mergers and a different set of firms making partial-firm transactions. Therefore, Panel B of Table 5 presents a specification designed to test whether bidders in mergers are also buyers in partial-firm transactions. The sample is all firms in the 48 industries, although the results are the same if the sample is restricted to the 28 industries with merger waves. The table presents logit models for partial-firm buying activity. All three columns show that, like mergers, partial-firm transactions are also more common when the rate spread is lower. Further, as predicted by the neoclassical hypothesis, partial-firm transactions are more likely during merger waves. The first column shows that bidding in a given year predicts that the same firm will also be a buyer in a partial-firm transaction. The second column shows that bidding also predicts being a cash buyer in a partial-firm transaction. Finally, the last column shows that being a bidder in a stock swap merger strongly predicts being a cash buyer in a partial-firm acquisition. These results, while directly implied by the neoclassical hypothesis, are at odds with the behavioral hypothesis.

4.5. Long-run returns

One of the implications of the behavioral hypothesis is that long-run returns should be poor following merger waves. Previous studies of long-run returns following mergers have found evidence of significant underperformance for subsets of bidders. Rau and Vermaelen (1998) find that low book-to-market "glamour" firms underperform following acquisitions and Loughran and Vijh (1997) find that firms that use stock as the method of payment experience long-run underperformance. However, a recent paper by Mitchell and Stafford (2000) which reviews the long-run return literature questions the common methodology of calculating buy-and-hold returns and forming event-time portfolios. They show that positive cross-correlations for event firms, especially in dealing with events that cluster in time and industry such as mergers, invalidates the bootstrapping approach used for statistical inference in this methodology. Instead, they implement a calendar portfolio approach advocated by Fama (1998). This approach does not suffer from the above problems. The method can be summarized as follows. First, each month, form a portfolio consisting of all firms in the treatment sample. Calculate the one-month value-weighted and equally weighted returns for that portfolio. Repeat this each month. Finally, regress each vector of one-month returns on the monthly Fama-French factor realizations and examine the intercept. A significant intercept is evidence of abnormal performance. Loughran and Ritter (2000) argue that one should weight the monthly observations by the number of firms in the monthly portfolio, and that equally weighted returns are more likely to pick up abnormal performance than are value-weighted returns. I use weighted least squares estimation and present both value-weighted and equally weighted return results. The sample is the 28 wave industries.

In Table 6, I examine the returns both of the overall industry and of the bidders specifically. The behavioral hypothesis predicts that waves will occur during times of high valuation for the industry, so we would expect to see abnormally high returns prior to and possibly during a wave and abnormally low returns following a wave. The first four columns examine the returns for the whole industry. Applying the Fama (1998) methodology, each month a portfolio of all firms in the industry is formed and the one-month return for that portfolio is calculated. The time series of monthly returns for each industry is regressed separately and the cross-industry median coefficients are presented along with their p-values. The first two columns show that, relative to the Fama-French three-factor portfolios, the industries do not exhibit abnormal performance around merger waves. Column 3 shows that the unadjusted returns are relatively high before and during a wave and relatively low following a wave. Since the pattern of high then low returns is not abnormal relative

Table 6

(Panel A) Calendar time-based regressions of long-run stock return performance for the 28 industries

The dependent variables in the VW and EW columns are the value-weighted and equally weighted returns, respectively, for month t of the portfolio of merged companies. Market, small minus big, and high minus low are the monthly factor realizations of the Fama and French (1993) factors. The estimation procedure is described in Section 4. Abnormal performance is detected in the intercept or dummy variable. The regressions are estimated separately for the time series of each of the 28 industries over the entire sample period. The median coefficient estimates from those 28 regressions and the p-values for a test of whether the median is different from zero are presented here. Pre-wave is a dummy variable identifying the 12 months immediately prior to a merger wave, In-wave is a dummy variable identifying the 24-month wave period, and post-wave is a dummy variable identifying the 36 months following the end of the wave.

	VW	EW	VW	EW
Intercept	0.139	−0.016	**0.751**	**0.787**
	[0.459]	[0.845]	**[0.001]**	**[0.001]**
Pre-wave	0.155	0.069	**0.895**	−0.159
	[0.447]	[0.665]	**[0.001]**	[0.627]
In-wave	−0.149	−0.134	**1.195**	0.415
	[0.998]	[0.511]	**[0.001]**	[0.150]
Post-wave	0.185	0.351	**−0.865**	−0.610
	[0.669]	[0.260]	**[0.072]**	[0.103]
Market	**1.024**	**0.994**		
	[0.001]	**[0.001]**		
Small minus big	0.052	**0.892**		
	[0.275]	**[0.001]**		
High minus low	−0.065	**0.196**		
	[0.301]	**[0.001]**		

Table 6 (*continued*)

(Panel B) Calendar time-based regressions of long-run stock return performance following a completed merger

The calendar time estimation is described in Section 4. Stock is a dummy variable taking the value of one for mergers in which stock was the method of payment and zero otherwise. In wave stock and non-wave stock dummies identify stock-payment mergers taking place inside or outside and industry merger wave. Market, small minus big, and high minus low are the monthly factor realizations of the Fama and French (1993) factors. The observations are monthly returns for time series of portfolios containing bidders in different categories. The number of observations varies depending on the number of different samples considered and the number of calendar months in the estimation. In columns 1 and 2, there are 237 total months in the time series of returns for the portfolio of cash bidders and 248 for the portfolio of stock bidders. In columns 3 and 4, there are 248 months of data for portfolios of non-wave stock bidders, 215 months of data for portfolios of wave stock bidders, and the remaining 237 observations are the time series of months for the cash bidders. Columns headed VW use value-weighted returns and those headed EW use equally weighted returns as the dependent variables. *P*-values from heteroskedasticity-consistent tests of the coefficients are presented.

	VW	EW	VW	EW
Intercept	0.254	−0.213	0.233	−0.223
	[0.132]	[0.280]	[0.166]	[0.254]
Stock	**−0.396**	−0.179		
	[0.057]	[0.567]		
In-wave stock			**−0.667**	−0.458
			[0.021]	[0.352]
Non-wave stock			−0.258	−0.074
			[0.230]	[0.783]
Market	**1.044**	**1.239**	**1.057**	**1.252**
	[<.001]	**[<.001]**	**[<.001]**	**[<.001]**
Small minus big	**−0.179**	**0.341**	**−0.180**	**0.336**
	[<.001]	**[<.001]**	**[<.001]**	**[<.001]**
High minus low	−0.047	**0.372**	−0.004	**0.382**
	[0.323]	**[<.001]**	[0.922]	**[<.001]**
Adj R^2	0.904	0.844	0.878	0.824
N	485	485	700	700

to market conditions, this evidence suggests that managers in these industries are not taking advantage of temporary mispricing of their industries. Rather, the capital liquidity that a business expansion and overall bull market provide allows industry-level merger waves to occur. Regardless, column 4 shows that this result is not robust to equally weighted portfolio returns.

Panel B presents results for bidders only. The sample is all bidders in the 28 wave industries, whether their bids took place during a wave or not. Implementing the calendar time approach to test for post-event long-run returns requires that each month, one form a portfolio of all firms that have made a bid in the prior 36 months. Using these monthly portfolios, one proceeds as before, calculating a vector of monthly returns and regressing that vector on explanatory variables. Columns 1 and 2 examine the general result from the extant literature that bidders in stock-financed mergers underperform in the three years following the merger. The results are mixed. In the value-weighted specification, the stock bidders significantly underperform the cash bidders (who are represented by the intercept), but because the cash bidders have a positive point estimate, a test of the net abnormal performance ($+0.25-0.40 = -0.15$) of the stock bidders reveals it to be insignificantly different from zero. In the equally weighted specification, the net abnormal performance of the stock bidders ($-0.21-0.18 = -0.39$) is also insignificantly different from zero.

The next two columns split the stock bidders into those whose bids took place in a wave and those whose did not. Again, the results are mixed for the equally and value-weighted portfolios. The value-weighted approach reveals evidence of underperformance and that it is concentrated in the wave bidders. The total underperformance for stock bidders in waves ($0.23-0.67 = -0.44$) is significant, but is not significantly different from that for non-wave stock bidders ($0.23-0.26 = -0.03$). The equally weighted approach finds no underperformance for either wave or non-wave stock bidders. The mixed results for the two weighting approaches suggest that only large bidders experience poor post-merger performance. This is consistent with the findings of Moeller, Schlingemann, and Stulz (2004), who, in a comprehensive look at the 1980–2001 period find that large acquirers destroy billions in value while small acquirers actually create value in mergers. The findings for large wave bidders can be interpreted as consistent with Rosen (2004), who finds that bidders in "hot" merger markets have lower long-run performance.

The results provide only weak support for the behavioral hypothesis, especially given that the behavioral models were designed to explain the previously observed rise and fall pattern in the bidder's stock price. The only evidence of underperformance for wave bidders comes in the value-weighted specification, and even in that specification, the performance of wave bidders is not significantly different from that of non-wave bidders. Further, the finding is not robust to changing to equally weighted portfolios.

4.6. Operating performance

As noted before, because benchmark performance is inherently unobservable in merger waves, tests of the neoclassical hypothesis using operating performance face the problem of actually testing a joint hypothesis that performance improves relative to what it would have been and that the empirical proxy for that unobservable benchmark is valid.[6] None of the behavioral papers explicitly make predictions regarding operating performance, but one can derive a prediction that the costs of integrating two firms with no real combined synergies (and hence no operational

[6] Maksimovic and Phillips (2001) find efficiency gains following mergers and interpret the evidence as supportive of a neoclassical model of resource allocation. They use plant-level data, which is arguably less susceptible to the benchmarking problem.

motive to merge) would produce particularly poor post-merger operating performance for mergers in waves.

Despite the inherent noisiness of operating performance tests, in the interest of completeness, Table 7 presents results of operating performance regressions. The model regresses post-merger industry-adjusted operating performance on pre-merger industry-adjusted operating performance and a dummy variable set to one if the merger occurred in a wave and zero otherwise. This test is based on Healy et al. (1992). As in that study, the intercept in this regression will capture the average post-merger change in the performance measure. The dummy variable will indicate whether waves are different from other periods. The slope coefficient is expected to be less than one because of mean-reversion in industry-adjusted operating performance (see Barber and Lyon, 1996). Because of the clustering of merger activity at the industry level, the observations in these regressions are not independent. Thus, I report the results of grouped-mean (the between estimator, described in Greene, 1993, p. 472) regressions as well as those for the full data set.

The results in the table show no evidence that changes in actual performance following mergers in waves are worse than during other periods. The only significant coefficients on the wave dummy is for sales growth, which is positive. The grouped-means results do not change the overall inferences; there are no cases in which mergers in waves perform significantly worse than those outside waves. Instead, post-merger changes in sales growth remains significantly greater inside waves.

I make two attempts to control for the unobservable benchmark problem in operating performance tests. First, I attempt to identify waves in which the benchmark performance is likely to be particularly poor. To do so, I create a subsample of waves that respond to contractionary shocks, defined as shocks such that the pre-wave change in sales growth and ROA are both negative and below their medians. I reestimate the operating performance regressions including a dummy for contractionary waves. The results on asset turnover are affected by the benchmarking problem. Controlling for contractionary waves, the coefficient on the wave dummy is positive and significant. None of the other inferences are changed by the inclusion of the contraction dummy.

Second, I use I/B/E/S data on analyst forecasts of long-term growth as a proxy for expected performance absent the merger. I collect the last forecasts for both the bidder and target prior to the announcement of the bid. Even if the industry has undergone a shock that changes expected performance, this change in expectations should be incorporated into analyst projections at the time. I compare the average of the bidder and target pre-bid forecasts, weighted by their market values, to the first forecast made for long-term growth of the combined firm following consummation of the merger. I report the results of this regression in columns 6 and 12 of Table 7.

The results show that analyst forecast revisions following mergers in waves are significantly greater than those outside of waves; columns 6 and 12 show that the revisions in the long-term growth rate forecast are almost 40 basis points higher inside a wave than outside. The positive coefficient remains significant even after a correction for the independence problem using group means. In the specifications that include the contraction dummy, the contraction dummy is not significant, and

Table 7
Operating performance and analyst forecast changes following mergers
This table presents the results of regressions where the dependent variable is a measure of post-merger industry-adjusted operating performance or valuation (average of years +1 to +3 relative to merger completion) and the independent variables are the corresponding pre-merger (average of years −3 to −1 relative to the announcement) industry-adjusted performance or valuation measure and a dummy variable taking the value of one for mergers taking place during a wave and zero otherwise. LTG forecast is the forecast long-term earnings growth (in percent) and it comes from the I/B/E/S summary analyst forecast measure of long-term growth immediately before announcement and after completion of the merger. The bottom panel also contains a dummy variable taking the value of one when the wave is classified as contractionary, meaning that the pre-wave shock to sales growth and ROA for the industry were both negative and below their respective medians. OLS regressions based on all observations and on group means are presented. *P*-values are in brackets.

	Individual observations						Group means					
	Profitability	Asset turnover	ROA	Sales growth	M/B	LTG forecast	Profitability	Asset turnover	ROA	Sales growth	M/B	LTG forecast
Intercept	**−0.016**	**0.017**	**−0.015**	−0.003	−0.035	**0.410**	−0.008	0.025	**−0.014**	0.004	−0.020	0.548
	[0.073]	**[0.094]**	**[<.0001]**	[0.683]	[0.289]	**[0.067]**	0.503	[0.106]	**[0.004]**	[0.718]	[0.686]	[0.114]
Pre-merger	**0.590**	**0.608**	**0.449**	**0.159**	**0.362**	**0.986**	**0.970**	**0.482**	**0.243**	0.029	**0.319**	**0.975**
Measure	**[<.0001]**	**[<.0001]**	**[<.0001]**	**[<.0001]**	**[<.0001]**	**[<.0001]**	**[<.0001]**	**[<.0001]**	**[0.070]**	[0.814]	**[0.001]**	**[<.0001]**
In wave	−0.010	0.024	0.004	**0.024**	0.069	**0.372**	−0.005	0.021	0.003	**0.027**	0.073	**0.390**
	[0.522]	[0.148]	[0.424]	**[0.043]**	[0.194]	**[0.059]**	[0.804]	[0.396]	[0.657]	**[0.092]**	[0.272]	**[0.084]**
Adj R^2	0.330	0.517	0.296	0.032	0.204	0.895	0.479	0.450	0.028	0.022	0.220	0.972
Obs	1323	1323	1323	1323	1323	613	56	56	56	56	56	55
Intercept	**−0.016**	**0.017**	**−0.015**	−0.003	−0.035	**0.433**	−0.008	0.025	**−0.014**	0.006	−0.016	**0.631**
	[0.073]	**[0.095]**	**[<.0001]**	[0.691]	[0.289]	**[0.054]**	[0.513]	[0.107]	**[0.003]**	[0.618]	[0.732]	**[0.070]**
Pre-merger	**0.590**	**0.609**	**0.449**	**0.157**	**0.362**	**0.984**	**0.988**	**0.487**	**0.254**	0.004	**0.309**	**0.969**
Measure	**[<.0001]**	**[<.0001]**	**[<.0001]**	**[<.0001]**	**[<.0001]**	**[<.0001]**	**[<.0001]**	**[<.0001]**	**[0.048]**	[0.976]	**[0.001]**	**[<.0001]**
In wave	−0.004	**0.031**	0.006	**0.035**	0.065	0.292	0.003	0.026	0.005	**0.039**	0.070	0.306
	[0.813]	**[0.081]**	[0.294]	**[0.007]**	[0.266]	[0.169]	[0.880]	[0.324]	[0.558]	**[0.021]**	[0.330]	[0.198]
Contraction	−0.025	−0.033	−0.007	**−0.048**	0.020	0.346	−0.035	−0.023	−0.006	**−0.052**	0.019	0.396
	[0.383]	[0.296]	[0.428]	**[0.033]**	[0.846]	[0.329]	[0.351]	[0.616]	[0.675]	**[0.071]**	[0.876]	[0.320]
Adj R^2	0.330	0.517	0.296	0.035	0.204	0.895	0.489	0.438	0.022	0.062	0.207	0.969
Obs	1323	1323	1323	1323	1323	613	59	59	59	59	59	57

the significance of the wave coefficient drops, but the intercepts are positive, indicating a general expectation of performance improvement following mergers that is no different for mergers in waves.

Overall, the operating performance results show that mergers inside waves produce no worse, and by some measures better, post-merger operating performance. Further, when I control for the benchmarking problem, the results either show that mergers in general are seen to have performance improvements or that wave mergers have either better or no different performance from mergers outside waves. These results, while consistent with the neoclassical explanation, cannot be reconciled with the behavioral explanations of merger waves.

4.7. Contractionary waves

In the previous subsection, I separate waves preceded by contractionary shocks from all others. In untabulated tests, I examine whether more can be learned from using such a separation in the other tests. For example, contractionary shocks requiring consolidation in the industry can be met only through merger, but those that do not can be met either through internal expansion or reorganization through merger (the classic buy vs. build decision). Expansion through merger will only be optimal if the transaction costs of merger are low enough. Thus, under the neoclassical hypothesis, one might expect the ability of contractionary shocks to propagate a wave to be less sensitive to capital liquidity than other shocks would be. I repeat the logit models in Table 4 for industry waves, separating shocks into contractionary vs. non-contractionary categories. The results support the conjecture: the coefficient interacting capital liquidity and contractionary shocks is smaller than that for other shocks, and its p-value is 0.15.

I also examine long-run returns following contractionary and non-contractionary waves and find no difference. One could argue that the behavioral explanation would predict that waves preceded by expansionary shocks should produce worse long-run returns if those waves are driven by market valuations that have overreacted to positive shocks. The fact that the long-run post-merger returns are equivalent in contractionary vs. non-contractionary waves is consistent with bidders having similar motivations to merge in each type of wave. The neoclassical hypothesis predicts such similar motivation while the behavioral hypothesis does not.

5. Conclusion

Recent explanations of merger waves as the outcome of attempts to time market misvaluations have refocused the literature on an old question: what causes merger waves? In this paper, I examine two general classes of explanations: the neoclassical model, in which industries responding to shocks reorganize through mergers and acquisitions, and thereby create a clustering of merger activity; and, the behavioral model, in which rational managers take advantage of consistent pricing errors in the market to buy real assets with overvalued stock. While there has been some evidence in the extant literature supporting each of the above explanations, most prior work tests the implications of only one of the explanations, rather than directly attempting to distinguish between the two. The tests in this paper directly compare the two explanations and support the neoclassical model, as modified to include a role for capital liquidity. It is the importance of capital liquidity that causes individual industry-level merger waves to cluster in time to create aggregate-level merger waves. Further, the relation between asset values and merger activity that is the motivation of the behavioral hypothesis reflects the capital liquidity effect rather than any misvaluation effect.

Overall, the view supported here is that shocks, be they economic, regulatory, or technological, cause industry merger waves. Not all shocks will propagate a wave; sufficient capital liquidity must be present to accommodate the necessary transactions. This macro-level liquidity component causes industry merger waves to cluster even if industry shocks do not. While it would be disingenuous to claim that there are no mergers driven by managers timing the market, such mergers are not the cause of waves. Rather, aggregate merger waves are caused by the clustering of shock-driven industry merger waves, not by attempts to time the market.

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