Acquisition Timing in Merger Waves:
Learning from Others

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Abstract:
Existing research on merger waves has predominantly focused on predicting the advent of the waves themselves and provides little empirical information about the relative timing decisions of acquirers within waves. In this paper I treat the acquisition decision like an innovation that is spreading among firms and show that the timing of these major investment decisions within waves is explained by the market reaction to other firms' recent acquisitions as well as by CEO and firm characteristics associated with inter-organizational learning.

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1. Introduction

Previous research has investigated why merger activity clusters in time and industry during economic expansions and has provided the following insights: waves of merger activity occur after industry-level technological, economic, or regulatory shocks (Mitchell and Mulherin 1996, Andrade, Mitchell, and Stafford 2001, Harford 2005); merger activity is related to valuation errors at the firm and industry levels (Rhodes-Kropf and Viswanathan 2004, Shleifer and Vishny 2003); and merger waves occur when macro-level liquidity constraints are relaxed (Harford 2005). Although these papers provide understanding for when merger waves occur, they do not explain which firms engage in the reallocation of assets early or late within these multiple year wave periods, or even if both the early and late movers are reacting to the same underlying forces. Given that acquisitions are some of the largest and most controversial investment decisions made by managers, understanding the relative timing and forces leading to these events within waves is important.

Our lack of knowledge about the timing of these decisions within waves is an example of our more general lack of understanding of factors that systematically influence not only the CEO's discovery process of new market opportunities but also his formation of opinions about the expected costs and benefits of new investments. In fact the finance literature has not answered the question of how information that facilitates the identification of new positive NPV investments is initially transmitted for any new major investment. In this paper, I examine one example of the transmission of information among firms by testing for evidence of inter-organizational learning as a factor in the development and timing of acquisition decisions during merger waves.

An acquisition, like other large investments, is undertaken by the CEO only after he becomes aware of the opportunity and forms the opinion that the expected benefits outweigh the expected costs in terms of personal reputation and firm performance. In this paper, I hypothesize that a CEO's current perspective on mergers is influenced by his observation of the market's reaction to other firms' recent acquisition announcements. Although I focus specifically on the stock market reaction to these announcements, these events are accompanied by related signals tied to increased media and analyst attention as well as claims by acquiring CEOs' of cost cutting or synergy creation. If the CEO's discovery process or his formation of opinions is systematically affected by this type of information then the timing of the acquisition decisions should be related to these observable signals.

Indeed, although it is impossible to directly observe the CEO's thoughts, or the managers' private analysis that certainly goes into any large investment decision, it is possible to test for evidence of inter-organizational influence and learning via at least three mechanisms: (1) testing whether recent acquisition announcement returns affect the timing of CEO's future acquisition decisions, (2) testing whether specific firm and CEO characteristics known to affect the speed and ease of the adoption of new corporate practices also explain the timing of acquisition decisions, and (3) testing for trends in performance during the merger waves. Focusing on the timing of these decisions is interesting inasmuch as it provides understanding not only of the specific factors that lead to acquisitions but also the factors that may affect the CEO's decision process for any major investment decision.

In this paper I motivate tests and predictions consistent with the three approaches noted above and find that the timing of acquisition decisions in merger waves is explained by the market's reaction to recent merger announcements as well as both firm and CEO characteristics consistent with inter-organizational learning. Specifically, I find that large firms, young firms, and firms that have recently underperformed relative to their industries are more likely to acquire early in the merger wave. Similarly I find that young CEOs, CEOs with less tenure, and CEOs that are also board chairmen are significantly more likely to make an acquisition early in the wave. Many of these same characteristics have been shown to affect the spread of other innovations among firms (e.g., see Greve 2005) and support the idea that the decision to make an acquisition is similar to the decision to adopt a new corporate practice. I also find some evidence to suggest that later acquisitions are associated with larger improvements in the ROA suggesting that later decision makers are learning from earlier acquisitions and not simply mimicking or herding.

Treating the decision to make an acquisition similar to the decision to adopt a new corporate practice is supported by the following observations: merger waves occur after major shocks have recently changed the competitive nature of the industry, merger waves within the same industry tend to be years apart, and many of the CEOs in the current wave are not likely to have been the CEOs during earlier waves. Hence, the setup becomes analogous to having new decision makers considering an unproven investment in a new environment where the information set and constraints are changing. In this environment CEOs are likely to be influenced by other CEOs' acquisition decisions.

This view of merger activity is related to the herding and information cascade literature which points to the inter-temporal patterns observed in mergers as potential evidence of herding by managers. In this literature managers mimic earlier mangers' investment decisions for reputational or other reasons (e.g., Scharfstein and Stein 1990, Bikhchandani, Hirshleifer, Welch 1992). The idea that CEOs are learning from earlier acquirers is also consistent with the literature that looks at the diffusion of innovations (e.g., see Jensen 1982, and Persons and Warther 1997). In this literature, managers decide each period whether to adopt a new innovation or delay the decision to gather more information. Their decision is influenced by information in the market about the expected profitability of the innovation which comes from earlier adopters of the innovation. My paper complements these literatures and provides empirical evidence of the influence that earlier acquisitions have on later merger events.

This study makes several contributions to the literature. First, on a general level this paper adds to the merger literature by providing additional understanding of factors that affect the timing of acquisitions within merger waves. Second, this paper provides evidence of inter-organizational learning in the acquisition decision using both acquisition timing and performance tests. By emphasizing the similarities between the decision to engage in acquisition activity and the adoption of new corporate practices, this paper also provides insight into the CEO's discovery process for large new investments and/or the formation of his opinions about the associated costs and benefits. And finally, given that the decision of when to engage in merger activity is not independent from the reasons why a firm engages in this activity, this paper draws attention to the idea that there is information embedded in the relative timing decisions within merger waves that can be used to assess the completeness of existing merger explanations.

The paper develops as follows: Section 2 discusses related research and develops the empirical predictions for both the timing and performance of the acquisitions during the merger waves. Section 3 describes the data and my approach in making industry, shock, and wave assignments. Section 4 describes the survival analysis methodology and the results associated with the timing of the acquisition decisions. Section 5 describes the performance tests and results. Section 6 discusses the survival and performance results in relation to existing merger explanations and then Section 7 concludes.

2. Literature review and empirical predictions

I first discuss the finance merger literature with an emphasis on papers related to merger waves. This literature supports the industry- and shock-based setup used in the analysis as well as the control variables described in Section 3. I then briefly review several related areas of literature involving the spread of corporate practices among firms, inter-organizational learning, and herding. I use the discussion of this literature to motivate several empirical predictions consistent with inter-organizational learning explaining the timing of acquisitions within waves. And last, I discuss the performance related empirical predictions related to inter-organizational learning and herding.

2.1. Acquisition activity and waves

Acquisitions are important managerial investment decisions that have significant effects on shareholder wealth. Mergers are widespread with more than 5% of CRSP firms being acquired in some years and large percentages of firms receiving takeover attempts through time (Andrade, Mitchell, and Stafford, 2001, Mitchell and Mulherin 1996). Acquisitions strongly affect shareholder wealth with, for example, the value of aggregate takeover activity exceeding 12% of the GDP in some years (Holmstrom and

Kaplan 2001) and aggregate shareholder dollar losses exceeding $140 billion in 2000 alone (Moeller, Schlingemann, and Stulz 2005). Given the importance of mergers to the firm's financial performance and the discrete nature of these managerial decisions it is important to better understand the factors that affect them.

One of the areas investigated by researchers involves the observed inter-temporal pattern of acquisition activity where relatively short periods of heightened merger activity are followed by periods of reduced activity. These clusters of acquisitions are referred to as merger waves and have been observed multiple times over the last century including several times over recent decades. The merger waves tend to be procyclical (Nelson 1959, Melicher, Ledolter, and D'Antonio 1983, Becketti 1986) and investors clearly anticipate some of the later deals within the clusters as evidenced by the price reaction of rival firms to initial bid activity (Eckbo 1983, Song and Walkling 2000, 2009).

Shleifer and Vishny (1992) suggest that the connection between takeover waves and economic booms is driven by the link between asset liquidation values and debt capacity. Eisfeldt and Rampini (2006) argue that capital reallocation between firms is procyclical due to countercyclical costs of capital reallocation. Consistent with this explanation, Harford (2005) shows that a measure of capital liquidity helps predict the advent of merger waves. Shleifer and Vishny (2003) provide an additional explanation for the association between periods of high market valuation and merger waves by arguing that rational managers take advantage of inefficient markets by using temporarily overvalued equity as a means to purchase less overvalued targets. In related papers Rhodes-Kropf and Viswanathan (2004) and Rhodes-Kropf, Robinson, and Viswanathan (2005) suggest that the correlation between merger activity and market valuation stems from a correlation between takeover synergy estimates and valuation errors at the firm and sector levels.

Other papers have focused on the industry-level determinants of merger activity. For example, Mitchell and Mulherin (1996) built on earlier work by Gort (1969) and others to show that the observed takeover activity in the 1980s strongly clustered during a few years within industries that were affected by deregulation and financing shocks. Other authors, including Andrade, Mitchell, and Stafford (2001), Andrade and Stafford (2004), Harford (2005), and Mulherin and Boone (2000), provide additional evidence of the clustering of acquisition and divesting activity within industries after shocks using various shock definitions, samples, and different time periods. The evidence from these papers collectively supports the idea that waves of acquisition activity occur at the industry level following industry-level events that change the efficient allocation of resources across the industry. These events are broadly described as regulatory, economic, or technological shocks.

Lambrecht (2004), Morellec and Zhdanov (2005), and Toxvaerd (2008), model acquisition activity focusing, respectively, on acquisitions motivated by economies of scale, in the presence of competition, and with a limited number of available targets. The decision of when to acquire is balanced between the threat of being preempted by rival firms seeking the same targets and the value of waiting to obtain either more information or better market conditions. In several of these models, increased competition for targets hastens acquisition activity. In a related paper, Gorton, Kahl, and Rosen (2009) show that the distribution of firm sizes within industries can create scenarios where managers at small or medium firms have motivation to engage in preemptive acquisition activity following an industry regime shift.

Taken together, the above cited papers suggest that the advent of merger waves is procyclical and is a function of industry shocks, firm and industry valuations, capital liquidity, firm size, and is affected by competition. If the assumption is made that within-wave merger timing decisions are a function of the same factors that explain the occurrence of the waves themselves, then variables related to these factors would be important controls in the time-until-acquisition analysis within merger waves. Accordingly, as explained in detail in Section 3, I incorporate measures of these variables in my analysis. I focus on post-shock time periods at the industry level and define the time-until-event as the time between the industry shock and the acquisition announcement.

2.2. Inter-organizational learning and acquisitions

Acquisitions have been viewed as vehicles for market discipline (Martin and McConnell 1991, Dahya and Powell 1998), examples of agency issues and empire building (Jensen 1986, 1988), the result of managerial hubris (Roll 1986, Malmendier and Tate 2008), a method to eliminate excess capacity within an industry (Andrade and Stafford 2004), as bids for monopoly power, as examples of attempts by managers to use over-valued assets (Shleifer and Vishny 2003), as ways to increase efficiency and productivity through synergies or economies of scale or scope (Healy, Palepu, and Ruback 1992, Maksimovic and Phillips 2001), and as competitive responses to shocks to the industry environment (Mitchell and Mulherin 1996, Andrade and Stafford 2001, Harford 2005). Given the wide range of CEO and firm characteristics involved in the various deals across time it is likely that each of the above mentioned motivations has application to specific deals. One question that has not been addressed in detail in this literature is whether the acquisition decision is affected by learning from other firms' experience.

This study addresses this issue and specifically tests whether there is evidence of inter-organizational learning in the timing of acquisition decisions within waves. Although the decision to acquire is ultimately justified by motivations similar to the ones cited above, and only consummated after formal economic analysis, if there is learning involved then the timing of the decision could be sensitive to factors known to affect the speed with which ideas and corporate practices spread among firms. In this paper I emphasize the similarity between the CEO's decision to consider an acquisition and the decision to adopt a new corporate practice.

2.2.1. Acquisitions and the spread new corporate practices

Acquisitions are not done in private. Media and analyst coverage makes the acquisition process a very public process. A Factiva news search for US firms making acquisition announcements during the sample period reveals thousands of news articles that not only announce the acquisitions but also comment on how the share price reacts on the day of the announcement. This type of coverage with an emphasis on how the stock price reacts combined with motivations associated with inter-firm competition ensures that industry participants are aware of each other's acquisitions and are aware of the market sentiment towards the acquisitions.

The CEO's decision to make an acquisition—particularly for firms that are not serial acquirers—is an example of a decision to adopt a new and possibly controversial corporate practice after having observed other CEOs' adoption of the same practice. The decision to make an acquisition in the post-shock environment is new in the sense that competition within the industry, firm leadership, and even the laws and rules related to merger considerations[1] have all possibly changed in recent years since the last merger wave if not since the shock itself. Like the adoption of any new innovation, the cost and payoff from an acquisition are uncertain ex ante. However, to make a decision the CEO uses whatever information available in the market to form an opinion about the costs and benefits of the new practice.

In this paper I argue that the CEO's opinion about the expected benefits from engaging in acquisition activity in the post-shock period is partially informed by other CEOs' recent acquisition decisions and the market's reaction to them. Consistent with the discussion in Jensen (1982) and Persons and Warther (1997), CEOs with more uncertainty about the profitability of making an acquisition in the current period rationally decide to wait and to observe early adopters of the innovation in order to refine their information concerning the new corporate practice.

2.2.2. The spread of new corporate practices and firm characteristics

The idea that practices or ideas spread between firms is not new to this paper. For example, Davis and Greve (1997) and Bizjak, Lemmon, and Whitby (2009) show that the adoption of poison pills and the practice of backdating options spread over time from firm-to-firm via directors affiliated with firms already involved in these practices. Unlike the papers that focus solely on information transfer over directors with multiple board seats, my focus is on how public information related to acquisitions affects the spread of acquisitions within an industry.

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[1] Historical examples of merger considerations that changed and affected subsequent acquisition decisions include new anti-takeover practices in the 1980s and 1990s, new regulatory laws, and new financing alternatives such as the junk bonds in the 1980s.

What affects the spread of new corporate practices among firms? The inter-organizational learning literature has examined this question in detail. Rather than try to cite all the related papers from this well-developed area here, I refer the reader to Greve's (2005) survey of this literature and simply summarize from his survey which characteristics tend to make firms more susceptible to adopting new practices. Past research in this area has shown that firm susceptibility to new innovations increases with poor past economic performance, firm size, and financial resources. Firm susceptibility decreases with firm age. If the decision to acquire spreads like an innovation through an industry, then this research suggests that relatively large but young firms that are profitable despite recent poor relative performance are more likely to acquire early in the wave.

Past research, as cited in Greve (2005), has also shown that an innovation is more likely to spread (i.e. its more infectious) if early adopters of the innovation are viewed as "success stories" and if other potential adopting firms are "close" in some sense to the earlier adopter. This proximity can be based on geography, competing in the same industry, or sharing a director that facilitates information transfer between firms. To apply these ideas within the context of acquisitions, I create several "influence" measures that deal with the idea of infectiousness and proximity together. To do this I assume that management learns how the market judges other firms' acquisitions based on the stock price reaction to their announcements. Firms with large positive price reactions to their acquisition announcements are considered infectious in influencing other CEOs to also consider acquisition activity. As described in detail in Section 3.2, I try various approaches to incorporate the idea of proximity by calculating the influence measures over different subsets of firms.

In summary, if the decision to make an acquisition spreads through an industry like an innovation then based on the above cited research the following empirical predications follow:

E1: Firms that have recently underperformed relative to their industries will acquire earlier in the merger wave.
E2: Larger firms will acquire earlier within the merger waves.
E3: More profitable firms will make acquisitions earlier in the merger wave.
E4: Younger firms will acquire earlier within the merger wave.
E5: Firms make acquisitions earlier in the wave if other firms that are close to them have experienced positive market reactions to their recent acquisition announcements.

2.2.3. Acquisitions and CEO characteristics

In addition to the firm characteristics mentioned above, there are several personal characteristics of the CEO that can also affect inter-organizational learning. Given that acquisitions represent discrete decisions made by individuals, they are affected by the decision makers' personal characteristics, information set, and biases. Indeed, the CEO is in a position to dictate whether and when a firm makes an acquisition. In fact many of the non-neoclassical reasons cited for mergers in some way relate to CEO characteristics. For example, in the empire building story it is the CEO's empire being built (Jensen 1986, 1988), in the hubris story it is the CEO's hubris that affects the final decision (Roll 1986), in other agency stories it is the CEO making the decisions, and it is the CEO's compensation that is documented to grow around acquisitions (Grinstein and Hribar 2004, Harford and Li 2007).

Other CEO characteristics such as age and tenure have implications for the risk taking preferences of management and the likelihood of early adoption of new corporate practices. Vroom and Bernd (1971) document a negative relationship between risk taking and age for top management. Bantel and Jackson (1989) find that innovation at banks is negatively correlated with the average age and tenure of the top management team. Wiersema and Bantel (1992) find that the firms most likely to undergo strategic changes have younger management teams both in terms of average age and tenure. Given that younger CEOs with less tenure are likely to have more risk tolerance and be more accepting of change and new corporate practices, it follows that:

E6: Younger CEOs will make acquisitions earlier in the merger wave.
E7: CEOs with less tenure will make acquisitions earlier in the merger wave.

Alternatively, these same empirical predictions could be motivated using other papers. For example, Bertrand and Mullainathan (2003) find that managers prefer the 'quiet life' which in their analysis is related to less reallocation of assets at the plant level over time. By extension, these same CEOs would likely not be the early acquirers within the wave. Similarly, past research has argued that executives may have different motivations with regard to investments in the years immediately before retirement (e.g., see Butler and Newman (1989), Dechow and Sloan (1991), and Gibbons and Murphy (1992)). To the extent that older CEOs close to retirement age are those seeking the quiet life, or are not as interested in new innovations that might take years to benefit from, the same empirical predictions as listed above would follow.

2.3. Herding and acquisitions

The idea that the observed actions of earlier decision makers might affect the actions of later decision makers is also closely related to the herding and information cascade literatures. For example, Scharfstein and Stein's (1990) model suggests that decision makers have incentive to mimic the actions of earlier decision makers to preserve their reputation. Bikhchandani, Hirshleifer, and Welch (1992) present a model for information cascades where under certain conditions decision makers have incentive to mimic earlier decision makers' behavior even if it means acting against their own private information. They explain fads and fashions using this approach and specifically list merger waves as a possible example of this phenomenon. Strang and Macy (2001) argue that herd behavior and fads in business stem from a strong emphasis on firm performance leading the management of poorly performing firms to mimic the practices of others they perceive to be successful.

For a few examples of other applications of herding and cascades in finance: Anderson and Holt (1997) provide evidence of information cascades in laboratory experiments, while Graham (1999), Welch (2000), and Sias (2004) investigate herding in investment newsletters, analyst recommendations, and institutional holdings, respectively. For a review of the herding literature with a discussion of many other models and papers see Hirshleifer and Teoh (2001).

Several of the papers cited above mention merger waves as potential examples of herding or information cascades. This connection is based on the obvious clustering of acquisition decisions through time and the intuitive application of the herding and information cascade logic in this context where CEOs, to preserve reputation or to act rationally based on the signals coming from the actions of other firms, have motive to engage in acquisitions if a lot of other firms are also making acquisitions. Despite the frequent references to merger waves in this literature the empirical studies are lacking to confirm this view. In fact, to my knowledge the only empirical evidence for this connection is from Bouwman, Fuller, and Nain (2009) who find that the underperformance of acquirers during periods of high-market valuation is concentrated in the late acquirers within these periods. They interpret the differential performance of early and late acquirers within periods of high-market valuation as consistent with managerial herding.

My paper complements this literature by providing empirical evidence of the influence that earlier acquisitions have on the timing of later acquisitions. I empirically link the public signal associated with the announcement returns of earlier acquirers to later decision makers' behavior and provide evidence that the firm and CEO characteristics known to relate to the speed and ease of the spread of new corporate practices between firms (i.e., inter-organizational learning) are also related to timing of the acquisitions within merger waves.

2.4. Performance implications

In the previous sections I motivate empirical predictions related to the timing of acquisition decisions within waves. In this section, rather than focus on the timing of the decisions, I focus instead on the performance implications of these predictions through time. Consider that the papers cited above that model acquisition activity, that relate to herding and information cascades, and that relate to the spread of innovations or practices between firms all share the central idea that CEOs are not only aware of the decisions made at other firms but are also influenced by them. In this section I highlight the performance implications of this awareness and outline tests that allow me to distinguish whether this influence is best characterized as learning from, herding with, or reacting to other CEOs' acquisition decisions.

The idea that merger decisions are influenced by other CEOs' recent acquisition decisions does not by itself imply that the later decisions are better or worse for shareholder wealth than the earlier decisions. For example if the industry is transforming itself given a recent industry-level shock, a late mover might benefit from getting a better idea of what the newly transformed industry will be like before committing to a large investment. Similarly, if later acting CEOs learn from the best practices and mistakes of early movers then they could benefit from delaying their acquisition activity and moving later in the wave (Learning Hypothesis). Although not applied within a wave setting, Delong and DeYoung (2007) make related arguments about information spillover in the execution and valuation of large bank mergers through time.[2] Per the Learning Hypothesis the performance of each successive acquisition in an industry would potentially benefit from recent past acquisitions regardless of whether they were examples of good or bad acquisitions. Hence, acquisition performance would be an increasing function of the number of previous acquisitions in the industry during the wave.

Alternatively, if there are a limited number of attractive target firms, then waiting to acquire within the wave could result in an inferior choice of target (Target Race Hypothesis). Based on this hypothesis, the acquisition performance would be a decreasing function of the number of preceding acquisitions in the industry. Also, consistent with the discussion in Bouwman, Fuller, and Nain (2009) to the extent that later acquirers include managers who are acting more for herding rather than economic reasons, lesser quality deals would be expected to occur late in the wave (Herding

[2] Delong and DeYoung (2007) note that given deregulation and various other shocks in the banking industry that the mergers seen between large banks in the late 1980s were a new phenomenon. Hence information spillover in the banking industry regarding these types of mergers represented new information for managers and investors alike. In my paper, although not all waves follow deregulation events, to the extent that recent industry shocks and new technology have altered the competition in an industry I also argue that there is new information available to managers and investors about current mergers in the post-shock environment.

Hypothesis). Unlike the earlier two performance hypotheses, the Herding Hypothesis isn't necessarily sensitive to just the number of previous acquisitions but instead is also affected by the market reaction to them; whereas firms can learn from both bad and good acquisitions, firms may not be as likely to mimic acquisition behavior if the market reacts negatively to recent acquisition announcements.

Using an approach similar to Delong and DeYoung's (2007) test for the presence of information spillover in bank mergers, I model the change in firm performance around the acquisition as a function of the number of past acquisitions in the wave (number), the market reaction to recent acquisitions (influence), as well as other control variables (controls) used in the merger literature to explain merger performance. The influence variable is described in detail Section 3.2. To the extent that managers are more inclined to herd and mimic earlier decisions if the market reacts positively to them I expect the coefficient on the influence variable to be negative. I include an interaction between the number of past acquisitions and the market reaction to them to account for the possibility that the market reaction could have stronger or weaker effects on herding depending on the number of recent acquisitions. The model is shown below in equation (1). Table 1 summarizes the performance-related empirical predications for each of the three hypotheses.

$$\begin{aligned} \mathit{Performance} = {} & \mathrm{a} + \mathrm{b}\cdot \mathit{Number} + \mathrm{c}\cdot \mathit{Influence} + \mathrm{d}\cdot \mathit{Number}\cdot \mathit{Influence} \\ & + \mathrm{e}\cdot \mathit{Controls} + \mathit{error} \end{aligned} \tag{1}$$

[Insert Table 1]

The firm performance around acquisitions is approximated using short- and long-term measures including 3-day cumulative abnormal returns (CARs) around the acquisition announcement, post-merger buy-and-hold abnormal returns (BHARs), and the change in industry-adjusted ROA around the acquisition. Detailed descriptions of the performance measures and the control variables used in these tests are discussed in Section 5.

3. Data and shock and wave setup

In this paper the financial information comes from Compustat, the stock information from CRSP, and the board and CEO information from Compact Disclosure. The final data sample used in the analysis is based on the intersection of these data sources. To this sample is added acquisition information from SDC and credit spread information from the Federal Reserve Survey of Terms of Business Lending. The specific variables used in the tests based on the above data sources are described in detail in Section 3.2.

The analysis involves modeling the time-until-acquisition following industry-level shocks in a survival model framework with factors related to inter-organizational learning as the main explanatory variables. Given that acquisitions and other important firm, industry, and macro events occur through out the year, the analysis is done at the monthly level rather than at the annual level. If daily financial data were available, the analysis would be conducted at the daily level. Even at the monthly level, some of the monthly data points are extrapolated from annual data. For example, monthly accounting information is estimated by linearly extrapolating annual Compustat data. Hence if a given firm's total assets were reported at the end of years 1994 and 1995 to be $100 and $112 million, respectively, I assume that the assets grew linearly during the year by $1 million dollars each month. The CEO and board variables are left constant across the months of each year. The credit spread data from the Federal Reserve is extrapolated from the quarterly level to the monthly level. The SDC and CRSP data are not extrapolated.

The firms in the sample are required to have a market value of equity of at least $75 million and to have CRSP share codes not associated with funds, REITs, or ADRs.[3] The SDC deals added to this sample involve completed acquisitions by US public acquirers where the reported transaction value is greater than $1 million, the size of the deal is greater than 1% of the acquirer's previous year's market value of equity, and the form of the deal is coded as AA, AM, or M in SDC. Of these deals, only the ones that occur within the industry merger wave periods subsequent to the identified shocks directly enter the survival model. Hence, which deals are included in the analysis depends directly on how the shocks and subsequent waves are defined.

3.1. Shock and wave definitions

To ensure that the results are not driven by my specific choice of shock, wave or industry definitions, I estimate the survival model using two industry classifications and three different shock and wave definitions. The shocks determine the start of the waves, the wave definition affects the total time duration of the waves, and the industry definition affects which firms are grouped together for a given wave. The results are generally consistent across the various specifications. Due to space constraints, I tabulate only the results using one of the shock definitions in Section 4 and place all supporting tables and explanations associated with the other two shock and wave definitions in an

[3] The firm size requirement is related to the SDC deal size requirement. Because I require the SDC transaction value to be at least $1 million and the relative size of the target to the acquirer to be at least 1%, smaller firms like those with market values less than $75 million would appear in the sample not to be making acquisitions when in fact they are making smaller acquisitions. The relative size requirement is meant to ensure that the deal is large enough to require careful managerial consideration in making the acquisition decision. To avoid eliminating firms mid-wave due to size requirements, firms are included in the sample during a given wave period if they meet the $75 million requirement at any time during that wave period.

appendix that is available upon request.

For the first industry classification method, I use Fama and French's 48 (FF48) industries (Fama and French 1997). This method is based on SIC codes and has been used in previous merger research. For the second industry classification method, I use Standard & Poor's and Morgan Stanley's global classification standard (GICs) industry groups. For a comparison of the industry definitions see Bhojraj, Lee, and Oler (2003).

To identify shock periods, I look for months with relatively high amounts of assets being purchased by firms within an industry. Specifically, any 2-month period where the total dollar value of all acquisitions in an industry exceeds 5% of the industry's previous year's equity market value is considered a potential shock with the 2nd month coded as the "buy-shock". After identifying all the buy-shock months from 1990-2006 I then utilize the following process to identify wave periods:

(1) Starting in January 1990 and moving forward in time in each industry identify the first shock month. The first buy-shock marks the start of the first wave. No other shocks are considered to start new waves for the next 24 months[4]
(2) The wave ends sometime after 23 months following a 6 month quiet period without another buy-shock. The next chronological buy-shock after the wave ends is considered to start the next wave and the process is repeated through 2006.

Using the assets purchased in a given month as the shock allows me to identify approximate beginnings of clusters of merger activity using historical information without needing to identify the underlying shock event(s). Figure 1 provides an example of the wave-identification process.

[Insert Figure 1]

[Insert Figure 2]

Figure 2 shows the number of acquisitions in the sample using FF48 and GIC

[4] Mitchell and Mulherin (1996) and Harford (2005) also use 24 month wave durations.

industry assignments across event time. Table 2 shows the number of firms and acquisitions in the sample across calendar time. The number of firms and deals shown in the table columns are only those that appear within the identified merger wave periods using the process described above and illustrated in Figures 3a and 3b using FF48 and GIC industries, respectively. As shown in the figures, this approach identifies 1-3 wave periods for most industries during the 1990-2006 period.

[Insert Table 2]

[Insert Figures 3a and 3b]

3.2. Description of variables

As discussed in Section 2, the variables associated with inter-organizational learning include the influence variables formulated using recent acquisition announcement returns as well as several firm and CEO characteristics associated with the ease of adoption of innovations. Each of these variables is described below.

3.2.1. Influence measures

The influence variable is calculated in several ways. It is an open question whether all firms', or just a subset of firms', past acquisition experience affects the current decision. For this reason I create separate influence measures for each firm based alternatively on all acquisitions, acquisitions in the same industry, acquisitions by firms within a certain geographic distance, and firms close to each firm within the board network. The market measure assumes that all firms' recent acquisition experience is noted and influential to the current decision. The other influence measures each make different assumptions about which subset of these firms' recent past experience is influential based respectively on which firms compete in the same industry, which firms have headquarters in the same geographic area, and which firms have directors with connections to these firms. All influence measures are calculated for each firm each month during the sample period based on deals that were announced within the prior nine months.

To create the market-based influence measure in a given month, the announcement returns are summed for all deals within the prior nine months. For example, the market-based influence on all firms in October 1993 is the weighted sum of acquisition announcement returns for all deals announced from January 1993 through September 1993. Each deal's contribution to the sum is just its announcement return multiplied by a weight which down-weights the returns of deals further in the past. Hence the market influence during month τ for all firms would be calculated as follows:

$$MarketInfluence_{\tau} = \sum_{i=1}^{n} \sum_{t=\tau-10}^{\tau-1} \left(1 - \frac{(\tau - t)}{10}\right)\left(R_{i,t}\right) \tag{2}$$

where $R_{i,t}$ is the (-1,1) acquisition announcement return, τ is the month in which the influence measure is being calculated, and *n* is the number of firms in the full sample. Only firms that made acquisitions affect this measure.[5] To measure the acquisition announcement return I calculate the difference between the announcing firm's daily return and the market return each day over the (-1,1) period. I then sum these returns over the three days.

For both the industry and geographic distance formulations, I create similar measures for each firm using only those deals that occur either within the same industry, or within 150 miles, respectively. For example, the industry influence measure in

[5] Given the noise involved in this approach, in calculating the influence measures I only include deals that are at least \$10 million where the deal value is at least 5% of the bidder's previous year's market value of equity. This limits the sample of potentially influential deals but ensures that the acquisition announcement obtained press coverage and created a noticeable change in the stock price of the bidder's stock. This is important given the learning literature's findings that an origin firm is more infectious if it is large and if its practices are known.

October 1993 for all firms in the retail industry would be the weighted sum of acquisition announcement returns for all acquisitions announced within the retail industry during the prior nine months. Unlike the industry influence measure which is identical in a given month for all firms in the same industry, the geographic influence measure is the same only for firms in a given month that have headquarters within the same zip code. For example the geographic influence measure in October 1993 for all firms that have the same zip code for their headquarters is based on the weighted sum of acquisition announcement returns of firms with zip codes within 150 miles of the reference zip code. The announcement returns for the geographic measure are weighted both using the time-based weight shown above as well as a distance-based weight calculated as one divided by the distance (measured in 10 mile increments) between the reference zip code and the acquirer's zip code. The logic for this distance-based weight is that whatever awareness spills over because of geographical proximity decreases with distance. Hence,

$$IndustryInfluence_{\tau,Z} = \sum_{i=1}^{n_Z} \sum_{t=\tau-10}^{\tau-1} \left(1 - \frac{(\tau - t)}{10}\right)\left(R_{i,t}\right) \quad (3)$$

$$GeographicInfluence_{\tau,G} = \sum_{i=1}^{n_G} \sum_{t=\tau-10}^{\tau-1} \left(1 - \frac{(\tau - t)}{10}\right)\left(\frac{1}{d_i}\right)\left(R_{i,t}\right) \quad (4)$$

where $R_{i,t}$ is the (-1,1) acquisition announcement return, τ is the month in which the influence measure is being calculated, n_Z represents the number of firms in industry Z, and n_G and d_i are the number firms and the number of miles (in 10 mile increments), respectively, between zip code G and the firms announcing acquisitions within 150 miles.

The last influence measure is based on board network proximity. Directors that sit on multiple boards create ties between firms that facilitate information spillover between boards.[6] Tracing the connections made by directors sitting on multiple boards and counting the number of steps that lie between two boards provides a measure of how close two boards are within the network. The number of steps along the shortest connected path between two boards is the geodesic distance between those firms. For example if Firm A shares a director with Firm B which in turn shares a different director with Firm C, then Firm A and B would have a geodesic distance of 1, and Firm A and Firm C would have a geodesic distance of 2 within the board network. The network influence measure is formed like the geographic influence measure above but substitutes the geodesic distance for the geographic distance in the formula. Only firms within a four geodesic distance radius are considered influential for any given firm.

The decision to use nine months of returns to create the influence measure is based on the conflicting ideas that the influence period needs to be long enough to be able to influence the search and research of other firms but not so long that later events have rendered earlier acquisitions non-influential to current decisions. To ensure my results are not dependent on the 9 month period, in untabulated tests I estimate the models discussed in Section 4 using a twelve month period and obtain qualitatively similar results. For robustness, rather than use the (-1,1) announcement period, I also calculate the influence measures using returns from the (-1, 45) period around the announcement dates.

3.2.2. CEO and firm characteristics related to inter-organizational learning

As motivated in Section 2, CEO age and tenure can affect inter-organizational

[6] Several papers have shown that information and corporate practices spread via board ties. For a few examples of corporate practices spreading across board ties see Davis and Greve (1997) and Bizjak, Lemmon, and Whitby (2009). See Schonlau and Singh (2009) and Haunschild (1993) for an example of merger information spreading across board ties.

learning. Both variables are constructed using information from Compact Disclosure. Given data limitations I have an imperfect measure of tenure because I only have information on CEOs back through 1990. Hence my tenure measure is more accurate for the later portion of my sample and is biased for the beginning years of the sample period.

For the firm characteristics associated with the timing-based empirical predictions 1-4, I use the 3 year mean industry-adjusted ROA over years t-1 to t-3 as a measure of relative past firm performance, book assets as a measure of firm size, and the number of years since IPO as the firm age. For the firms in my sample without IPO dates, I use the number of years since the firm appeared in Compustat as the firm age. For a measure of the firm's financial resources I use the firm's current ROA.

3.2.3. Control variables

In addition to the variables described above related to inter-organizational learning, there are several other factors that may be important for the acquisition timing decision based on the merger wave literature. Building on the discussion in Section 2.1, I also account for industry, leverage, and macro level liquidity, respectively, using industry indicators, book leverage, and the 4-month moving average of the spread between the rate on commercial and industrial loans greater than $1 million and the intended federal funds rate as used in Harford (2005). The spread information comes from the Federal Reserve Survey of Terms of Business Lending and is extrapolated from the quarterly to the monthly level.

To account for valuation effects I include firm- and sector-level valuation measures calculated according to Rhodes-Kropf, Robinson, and Viswanathan (2005) model 3. Consistent with the language used in their paper, I call these model-based pricing deviations "errors". The firm error represents the difference at time t between a firm's observed ln(MB) and the predicted ln(MB) based on sector-level information from that year. The sector error represents the difference at time t between the predicted ln(MB) based on sector-level information that year and the predicted ln(MB) based on long-run sector information. Firms with large positive errors are considered to have temporarily over-valued equity.

Other variables related to corporate governance also used in the analysis include an indicator variable for CEO-chair duality, board size, and the percent of board members that are insiders. CEOs that are also chairman have more consolidated control and would likely be able to act on an acquisition sooner than other CEOs that are not in control of their boards. Board size and percent of insiders could also relate to the ease with which a new decision is taken. Table 3 describes the variables used in the survival analysis.

[Insert Table 3]

[Insert Table 4]

Table 4 shows the correlations among the non-indicator variables used in the analysis. Table 5 provides summary information about the variables after dividing the firms into acquiring and non-acquiring groups. To create Table 5, each year each firm is placed in either the acquiring or non-acquiring group. These statistics are then calculated across years on these groups.

[Insert Table 5]

4. Survival analysis results

To model the time-until-acquisition, I use Cox's semi-parametric proportional hazard survival model (Cox 1972). This is a commonly used technique when the dependent variable is the time-until-an-event and has been used extensively in the biostatistics and engineering literatures where the time-until-death and the time-until-failure is of interest to researchers. Much of the terminology associated with survival analysis (i.e., "survival", "hazard", "failure") stems from its development and application within these fields where researchers were interested in the literal survival or failure of the subject subsequent to diagnosis or treatment. Some of the recent applications of survival analysis in finance include the analysis of limit-order execution times (Lo, MacKinlay, and Zhang (2002)), the factors that hasten bank failures (Wheelock and Wilson (1995)), and the default behavior of high-yield bonds (Moeller and Molina (2003)). In the current application, I am interested in modeling the time-until-acquisition following industry shocks with the acquisition being the "failure" or "death" event.

Survival analysis appropriately accounts for the non-negative non-normal distribution of event times and efficiently incorporates information associated with the large portion of censored observations where firms do not make acquisitions during the analysis period. In this kind of approach the time-until-acquisition is treated as a non-negative random number (T) drawn from a distribution of survival times where survival time is defined as the time subsequent to the industry-level shock before a firm makes an acquisition. The probability density (pdf) and cumulative distribution functions (cdf) of the survival times are denoted $f(t)$ and F(t), respectively. By convention, in survival analysis the time-until-event is discussed using transformations of these distributions that allow the focus to be on the probability of surviving beyond a certain time (survival function S(t)), and on the instantaneous rate of failure (hazard rate). The hazard rate (h(t)) is modeled at time t conditional on having survived at least until time t. Formulas relating the pdf, cdf, hazard and survival functions are shown below.

$$S(t) = 1 - F(t) = \Pr(T > t) \tag{5}$$

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t + \Delta t > T > t \mid T > t)}{\Delta t} = \frac{f(t)}{S(t)} \tag{6}$$

To include the effects of covariates on the hazard, the hazard rate is modeled as the product of a baseline hazard (h_0) and a second function that incorporates the explanatory variables (X). Hence, incorporating time, explanatory variables and parameters in the notation the hazard becomes $h(t, X, \beta) = h_0(t) g(X, \beta)$ where the baseline hazard function accounts for the relation between the hazard rate and survival time in the absence of other explanatory variables and the second function characterizes the relation between the hazard rate and the explanatory variables. Following Cox (1972) and the bulk of the survival literature I make $g(X, \beta) = \exp(XB)$.

In parametric models the distribution of survival time is modeled using distributions like the exponential, Weibull, lognormal, or gamma. Each distribution implies a different hazard function which may be constant, decreasing, or both increasing and then decreasing across event time. The choice of distribution and its associated hazard function should be consistent with the observed failure patterns observed in the data across event time. Given the setup in this paper where clusters of merger activity follow industry-level shocks, the number of acquisitions per month could potentially remain constant, increase, or decrease as the wave period progresses before finally decreasing at the end of the wave.

In the semi-parametric approach the exact distribution of survival time, and hence the baseline hazard, is not specified as it drops out in the estimation procedure. This avoids the possibility of applying the incorrect distribution to survival time but is slightly less efficient in parameter estimation than a (correctly specified) parametric model (Allison (1995)). An advantage of using the semi-parametric approach in the current application is its focus on the ordering of the events rather then the exact time process subsequent to the initialization of the wave; even if I slightly misidentify the specific time for the onset of risk (i.e. the precise shock initiating the wave) the semi-parametric estimation uses the information in the ordering of the events rather than my identification of the exact shock date. The semi-parametric approach maximizes a partial likelihood function as described in Cox (1972) while the parametric approach maximizes the full likelihood function which itself is a function of the assumed distribution of survival time. For a more detailed review of survival analysis see Cox and Oakes (1984), Hosmer, Lemeshow, and May (2008), chapter 20 of Woolridge (2001), as well as Allison (1995) and Cleves, Gould, and Gutierrez (2004).

Although the Cox model is often applied to data measured at discrete intervals, it is designed for continuously measured data. To ensure the results shown in this paper are not sensitive to the use of the Cox model on discretely measured data, in untabulated tests I re-estimate the models shown in Table 8 using a discrete time proportional hazard model and obtain qualitatively similar results.

4.1. Univariate results

A common univariate descriptive data approach for survival analysis involves the plotting of survival curves. This allows a visual examination of the time-until-acquisition across specific groups over the entire merger wave period. Figures 4a and 4b show survival curves generated using Kaplan and Meier's (1958) product limit estimator for the survival function. In each of the plots the y-axis represents the proportion of each of the sample groups that has not yet made an acquisition subsequent to the industry-level shock. The x-axis shows the event time in months since the start of the wave.

The proportion of firms that have not made an acquisition decreases as the months progress after the industry shock. In untabulated log-rank tests, I test whether the survival curves are different within each plot for the variables groups shown in Figures 4a and 4b and find that they are all significantly different at the 5% level with the exception of the one based on the geographic distance influence measure. The plots in Figure 4a are based on the influence measures described in Section 3 and the plots in Figure 4b are based on the firm and CEO characteristics associated with inter-organizational learning. To create the plots I form tercile groups for each of the variables and then create Kaplan Meier survival plots for each of the terciles.

[Insert Figures 4a and 4b]

Consistent with inter-organizational learning, the monotonic patterns observed for the board network and market influence plots in Figure 4a show that larger influence is associated with earlier acquisitions within the wave. The plot using industry influence terciles suggests that the firms with the strongest industry influence tend to acquire earlier within the wave. The plot using the geographic influence measure suggests that there is no relation between this influence measure and acquisition timing. The survival plots in Figure 4b suggest that larger firms, younger CEOs, and less-tenured CEOs are all more likely to make acquisitions early in the wave. To better understand the relation between these variables and the time-until-acquisition a multivariate approach is necessary.

4.2 Multivariate results using Cox proportional hazard model

4.2.1. Influence measures

Table 6 shows the hazard ratios from a Cox proportional hazard model controlling for the influence measures and industry and year effects.[7] Using either industry classification method, a one standard deviation increase in the board influence measure is associated with a 9-10% increase in the hazard of making an acquisition. Similarly a one standard deviation increase in either the industry or the market influence measure is associated with approximately a 7-15% and a 15-26% increase, respectively, in the hazard of making an acquisition. The geographical distance-based influence measure is not systematically related to the hazard of making an acquisition.

[Insert Table 6]

4.2.2. Firm and CEO characteristics

Table 7 shows the hazard ratios and z-statistics from a Cox proportional hazard model which controls for the firm and CEO characteristics discussed in Section 2 as being related to inter-organizational learning with the spread of corporate practices between firms. Consistent with the idea that the decision to make an acquisition is similar to the decision to adopt a new corporate practice, higher past performance and greater CEO and firm age are all associated with smaller acquisition hazards corresponding with longer expected time-until-acquisition. Similarly, higher current ROA and larger firm size are associated with higher hazards which correspond with shorter expected time-until-acquisition. These results are significant at the 1% level and are robust to the different industry definitions. Inconsistent with inter-organizational learning, CEO tenure does not explain the time-until-acquisition. Given the transformations mentioned in Table 3, the past performance, firm size, and ROA variables are all standardized such that a one unit increase is associated with a standard

[7] The Breslow method for tied failure times is used for all the Cox models in this paper.

deviation increase in the underlying variable. Both CEO and firm age are in years.

[Insert Table 7]

4.2.3. Influence measures, firm and CEO characteristics, and controls

Given the lack of significance for the geographic distance-based influence measure in the simple model shown in Table 6, I use only the market, industry, and board influence measures in the full models shown in Table 8. I estimate these models both using influence measures based on the (-1,1) announcement returns as well as the (-1,45) announcement returns. In both cases I use the same control variables but given space constraints I only tabulate the influence measures' hazard ratios at the top of the table for the (-1,45) results.

Using the (-1,1) returns the market and industry influence measures remain significant in explaining the time-until-acquisition even after controlling for firm and CEO characteristics as well as the other control variables mentioned in Section 2. Using the (-1,45) returns the market measure remains important in explaining the time-until-acquisition but the industry and board measures are significant in only one of the industry classifications. With regard to the influence measures' hazard ratios, the results in Table 8 are similar to those using the alternative shock and wave definitions in that all the influence measures are significant in some but not all of the specifications. The results using the alternative shock and wave definitions are available upon request.

[Insert Tables 8]

As shown in the table, the firm and CEO characteristic variables remain significant in explaining the time-until-acquisition even after controlling for the influence and the control variables. As predicted in Section 2, large firms, young firms, firms that have recently underperformed relative to their industries, firms that are currently more profitable, and firms led by young CEOs are all more likely to make an acquisition earlier in the wave. For example, a one standard deviation increase in the underlying relative past performance variable is associated with a 32-55% smaller hazard of making an acquisition. A one standard deviation increase in firm size is associated with a 20-40% increase in the hazard. Each additional year of firm or CEO age is associated with a decrease in the acquisition hazard of 1-2%. Although CEO tenure is not found to significantly predict the time-until-acquisition in Table 8, it is worth noting that the point estimates are smaller than 1 as predicted and that using the alternative shock and wave definitions (in the appendix) that CEO tenure is found to be significant. Taken together, the Table 8 results support the idea that the decision to make an acquisition is influenced by inter-organizational learning in ways that are similar to how managers are influenced to adopt new practices or innovations from other firms.

Of the other control variables, several are found to be important in explaining the time-until-acquisition. Pricing deviations at the firm-level explain time-until-acquisition with a one standard deviation increase in firm error associated with a 10-20% increase in the acquisition hazard. As expected, larger credit spreads are associated with smaller hazards. Having a CEO that is also chairman increases the acquisition hazard by 20-30% and larger boards are associated with higher hazards.

4.2.4. Robustness

My results and conclusions regarding the timing of acquisitions are robust to using three different wave definitions (appendix available upon request) and two different industry classification methods. I have controlled for industry and time effects as well as variables known to be associated with the advent of merger waves. Although not discussed above, in untabulated tests I check the proportional hazard assumption for the models in Table 8 using Schoenfeld residuals as discussed in Cleves, Gould, and Gutierrez (2004) and find no evidence that my specifications violate the proportional hazard assumption. As mentioned early, these results are also robust to using a discrete time proportional hazard model. In this section I discuss four additional possible concerns related to my sample construction, the inclusion of serial acquirers in the analysis, the choice of single versus multiple failure events, and the possibility of competing failure events in the survival analysis.

One concern with my sample construction involves whether the extrapolation of the data leads mechanically to the firm size or ROA results. For example, given a merger event that occurs between two year-end dates, the firm size increase from the acquisition would be part of the asset measure at the end of the year and hence mechanically built into the extrapolated firm size values during the year. To ensure that this is not affecting my conclusions, in untabulated results I re-estimate the models in Table 8 using 6 month lagged firm size and ROA values based on Compustat quarterly data extrapolated to the monthly level and obtain qualitatively similar results.

Another question involves serial acquirers and to what extent they affect the results. It is possible that given serial acquirers' strategy for making frequent acquisitions that they are not influenced in the same way as other firms during merger waves. To ensure that my conclusions are not driven by their inclusion in the sample, I re-estimate the models shown in Table 8 but without serial acquirers. I define a firm to be a serial acquirer if they make 3 or more acquisitions within a 3 year period. Table 9 shows the results after removing serial acquirers from the sample. As shown in the table, the same qualitative conclusions hold with or without serial acquirers. However, one difference without serial acquirers is that CEO tenure becomes very significant in explaining the time-until-acquisition in a manner consistent with inter-organizational learning. Specifically a 1 year increase in tenure is associated with a 4-6% decrease in the hazard rate implying more tenured CEOs are associated with longer expected time-until-acquisition.

[Insert Table 9]

A related concern deals with whether to perform the analysis using single or multiple failure events per firm. In other words, there is a question of whether to only measure the time until the first acquisition by any firm following an industry shock, or to measure the time until all acquisitions made by that firm within a given wave. Making one acquisition does not preclude a company from making another acquisition several months, or even years, later within the same wave. For this reason all of the results shown in the paper up to this point have allowed for multiple acquisitions per firm per wave. However, to ensure that this treatment is not driving the results, I re-estimate the models in Table 8 focusing only on the time until the first acquisition and find qualitatively similar results.

The last robustness concern discussed in this section involves the question of whether there are competing processes leading to the reallocation of assets subsequent to the industry shock. Specifically, following an industry shock a firm could reallocate assets by making an acquisition or by being acquired. The analysis up to this point has only considered the possibility of making an acquisition, but to be acquired is an important alternative given that a firm that is acquired doesn't make any subsequent acquisitions. Hence, after industry shocks we really have two major competing risk processes leading to the reallocation of assets – one through a firm making an acquisition and the other through the firm being acquired. In order to ensure that my earlier conclusions regarding the factors that explain the time-until-acquisition are not biased[8] because of the competing risk of being acquired, I re-estimate the models in Table 8 within a competing risk framework based on the method explained in Fine and Gray (1999) and StataCorp (2009). For more information on competing risks see Pintile (2006). Even after controlling for the competing risk of being acquired, I find qualitatively similar results for the firm and CEO characteristics but for the influence measures only the industry influence measure remains significant.

4.2.5 Model prediction

The above tests show that the assumptions necessary to use the Cox proportional hazard model are met but do not provide information on the ability of the model to predict acquisition activity out-of-sample. To assess the strength of the model in this area I use an approach loosely based on the one used in Nam, Kim, Park, and Lee (2008) for assessing the ability of their model to predict failure events out-of-the-sample period. I do the following (using 1997 as an example) with GIC industry assignments:

1. I estimate the Cox proportional hazard model shown in Table 8 using data from 1990-1996. Within these calendar years, I use only the firms' information within the identified merger wave periods.
2. I then identify the industries that have GIC merger waves starting in 1997 and use the estimated coefficients from the earlier period to predict the relative hazards for all firms in these industries as of the start of the new waves in 1997.

[8] In the analysis up through Table 9, the Cox model treats the firms that were acquired as being censored and doesn't explicitly account for the fact that an acquired firm might have made an acquisition if not for being acquired.

3. Based on the estimated relative hazards as of the start of the waves in 1997, I then rank firms into quintiles. These quintiles are only assigned as of the first month of each wave.

I follow the above steps each year from 1997-2005. I start with 1997 to allow the first estimation period referred to in step 1 to include multiple waves (see Figure 3b). In each year as I repeat step 1 from 1997-2005, the estimation period incorporates data up through the previous calendar year to estimate the Cox model and then uses these estimates in step 2 to predict the relative hazards for the firms in the industries that have merger waves starting the following calendar year. Given that the baseline hazard would be identical for all firms as of the first month of the wave, I create the hazard quintiles based solely on the relative hazard. This approach underestimates my model's ability to predict acquisition activity inasmuch as the rankings are only done in the first month of each wave and do not incorporate changes to the explanatory variables that occur during the waves.

Using this approach I then calculate the percentage of acquiring firms that make acquisitions within the first 12, 18, and 24 months of the wave as a function of the relative hazard quintiles calculated as of the start of each wave. The percent of acquisitions associated with each quintile is shown in Table 10. The results show that approximately 12-15% of the acquirers come from each of the lowest ranked quintiles and that 25-26% of acquirers come from each of the highest quintiles.

[Insert Table 10]

5. Performance Tests

The results discussed in the previous sections relate to tests of whether the time-until-acquisition is a function of variables related to inter-organizational influence and learning. Although the variables used in the analysis were motivated from the inter-organizational learning literature, they could also be related to herding. In this section I highlight the performance implications of learning versus herding and present results that suggest that both learning and herding are occurring during the waves.

In Section 2.4 I motivate 3 hypotheses that could explain performance trends through wave time related to learning, herding, and competition. According to the Learning Hypothesis if firms are learning from past acquisitions then later acquisitions within the wave should exhibit better performance and the number of previous acquisitions during the wave should positively explain measures of acquisition performance. According to the Target Race Hypothesis, if firms are competing for a limited number of good targets then those acquisitions late in the wave should represent acquisitions of left-over less-optimal targets and hence later acquisitions within the wave should be related to worse performance. Consistent with this story the number of previous acquisitions during the wave should negatively relate to measures of acquisition performance. According to the Herding Hypothesis, late acquirers are mimicking earlier decisions by other managers and hence are associated with lesser performing acquisitions. Based on this hypothesis, greater numbers of acquisitions with positive market reactions will lead to more herding. The performance predictions associated with each of these hypotheses are summarized in Table 1.

5.1. Performance measures

For the short-term acquisition performance measure I use 3-day (-1,+1) cumulative abnormal returns (CARs) calculated using the market model (Brown and Warner (1985)) with parameter estimates based on data from 200 to 60 trading days before the acquisition announcement. Given that firms' stock prices are affected by market expectations for merger activity (Song and Walkling 2000, 2009) and that announcement returns reveal information not just about the bid but also about the probability of completion and the stand alone value of the bidder (Bhagat, Dong, Hirshleifer and Noah (2005)) short-term announcement returns represent noisy and imperfect signals of the wealth effects from acquisitions. For this reason I also use three other performance measures.

The first additional measure is the 2-year buy-and-hold abnormal return (BHAR) defined relative to a reference portfolio of firms as explained in Barber, Lyon, and Tsai (1999). In this approach the 2-year buy-and-hold return is calculated both for the acquiring firm following the acquisition and for an equal weighted portfolio of 5 firms matched in the year prior to the acquisition using size, book-to-market, and stock performance dimensions. The 2-year BHAR is then calculated as the difference between the event firm's and the portfolio's 2-year buy-and-hold returns. As in the CAR measure, the BHAR is affected by market expectations and is a noisy measure of the wealth impact of an acquisition. For example, to the extent that the market correctly anticipates an acquisition and its future wealth effects prior to the announcement date both the CAR and BHAR measures would not capture the wealth effects of the acquisition.

To avoid the issues associated with market-based measures of performance I also use the change in average annual ROA as a measure of acquisition-related firm performance. To calculate this measure I define ROA as the operating income before depreciation divided by book assets. In each year I then subtract the industry median ROA. For each acquisition the change in ROA (ΔROA) is then calculated as the difference between the mean annual industry-adjusted ROA for years (t+1, t+3) and the mean annual industry-adjusted ROA for years (t-1,t-3) where t is the year of the acquisition. This measure is not affected by market expectations but given that annual ROA is a gross measure of firm performance it may not easily reflect changes in firm performance specific to smaller acquisitions. As an alternative measure of abnormal ROA, I follow Chen, Harford, and Li (2007) in using the residual from the regression of post-merger mean annual industry-adjusted ROA on the pre-merger mean annual industry-adjusted ROA. This measure captures the change in ROA not predicted by pre-merger industry-adjusted ROA.

5.2. Comparison of early and late acquisitions

Despite the issues associated with the performance measures noted above, they provide information about the wealth effects from an acquisition and provide a way to look for evidence of learning, competition, or herding in acquisitions across wave time. To compare the performance of early and late acquisitions I define the first 12 months of wave time as the "early" period and the subsequent months as the "late" period. I then calculate the mean CAR, BHAR, ΔROA, and ROA residuals for the early and late acquirers. This information is shown in Table 11. Column d shows the difference in means for the early and late groups. The GIC results suggest that the late acquirers are associated with better performing acquisitions but the FF48 results do not support this interpretation and even provide some evidence to suggest that early acquirers may have outperformed late acquirers. The difference in results based on the different industry classifications could suggest that one of them is better at grouping similar firms together. This idea is supported by Bhojraj, Lee, and Oler's (2003) finding that the GIC groupings in general do a much better job than the FF48 classifications in identifying stocks that move together through time and which exhibit similar growth and valuation multiples. This conclusion is also consistent with the discrepancies noted by Kahle and Walkling (1996) in the SIC code assignments even between CRSP and Compustat which affects the FF48 industry assignments.

[Insert Table 11]

5.3. Acquisition performance as a function of prior acquisitions

As an alternative approach to investigating acquisition performance through wave time, following equation (1), I model the performance measures as a function of the number of previous acquisitions, the weighted sum of recent acquisition announcements as well as control variables. The specific empirical predictions associated with the key variables are summarized in Table 1. The focus is on whether the number of past acquisitions and the measures of market reactions to past acquisitions are positively or negatively related to firm performance around subsequent acquisitions.

As motivated in Section 2.4, if the number of previous acquisitions is positively associated with merger performance then this is indicative of learning and information spillover benefiting later acquirers within the wave. If the number of previous acquisitions is negatively associated with merger performance then this is indicative of either competition for limited targets or herding. To differentiate between these outcomes I also look at the relation between the performance measures and the influence variables created using the market reaction to recent acquisition announcements. To the extent that herding is more likely to occur following positive market reactions to earlier managers' actions I expect the performance to be negative related to the influence measures.

In testing for the presence of learning or herding it is important to control for other factors that could affect the firm's performance. Accordingly I include industry and year indicators as well as deal, firm, and other industry related variables. At the deal level I control for the relative size of the deal, the public status of the target, whether the deal is diversifying, and the method of payment. All of these variables have been shown to relate to announcement returns and have been used in previous merger research (e.g., Travlos (1987), Fuller, Netter, and Stegemoller (2002)). At the firm level I control for the firm size, leverage, profitability, and M/B measured as of the end of the fiscal year prior to the acquisition announcement. Given that firms also learn from their own experience with acquisitions, I include the number of past acquisitions done by each firm since the start of the wave as a proxy for this kind of learning. I also control for the number of firms in the industry to account for the possibility that competition is a function of the size of the industry. The regression coefficients and t-statistics are shown in Table 12 using the GIC industry assignments.

[Insert Table 12]

The positive coefficients shown in the first row in the last 4 columns provide some evidence consistent with the idea that firms are learning from past acquisitions and that the number of past deals within the industry is positively associated with merger performance. However these results are not robust to using FF48 industry definitions and are only significant at the 10% level in the GIC results.[9] The industry influence variable is not found to consistently predict firm performance. Taken together, the results in

[9] In untabulated results using the FF48 industry classifications I don't find that the number of past acquisitions or the market influence variables relate to merger performance.

Tables 11 and 12 provide some evidence of learning as opposed to herding but the results are weak and not robust to across industry definitions.

6. Discussion

In the multivariate analysis from Section 4 I find two types of evidence supporting the idea that there is inter-organizational learning or influence affecting the acquisition decision. First, I find that influence measures created from recent acquisition announcement returns explain the acquisition timing decision. This finding suggests that later acquirers are learning from the market's reaction to earlier acquisition announcements. The second type of evidence I find is that the timing of acquisition decisions is sensitive to the same firm and CEO characteristics associated with inter-organizational learning and the spread of innovations among firms. Specifically, I find that large firms, young firms, firms that have financial resources, firms that have recently underperformed their industries, and firms lead by young CEOs with less tenure that are also chairmen are all significantly more likely to make an acquisition early in the wave.

6.1. Alternative explanations

In this section I discuss other possible explanations for these findings. With regard to the first type of evidence, it is hard to articulate a non-learning story that easily links recent announcement returns to the timing of current acquisition decisions and which allows for influence across the market, within industries, and across board connections. For example, after an industry shock if new information or new synergies become available at the industry level then it is conceivable that many firms within the same industry would react similarly and pursue acquisitions to take advantage of the changes. However, in this scenario without inter-organizational learning then all the firms in the industry would be expected to act as soon as possible after becoming aware of the opportunity in order to sooner benefit from the new synergies and to ensure they obtained the best targets out of the limited number of possible targets. In this scenario there would be no expected relation between earlier mover's announcement market returns and the timing of later acquisition decisions. However, the relation between the announcement returns and the timing of later acquisitions suggests that later acquirers within the industry are either learning of the synergies' existence from earlier acquisitions or updating their opinions about the benefits of making an acquisition based on the market's reaction to earlier acquisitions.

Depending on what is being learned from the announcement returns, this influence could be consistent with a herding story where later managers want to preserve their reputation by appearing to be part of the merger wave and hence are motivated to mimic earlier acquirers. Or, this could be an example of the influence of recent acquisition announcements on the CEO's discovery process of new acquisition-related positive NPV projects and/or the CEO's formation of opinions about the expected costs and benefits of merger activity in the current period. In both these explanations, CEOs are learning from past acquisitions.

Given that I find that this influence is not limited to previous acquisitions within the same industry, but rather also reaches across the market and across board networks the explanation is broader than a simple discovery process within an industry of new synergies made available within an industry after an industry shock. Rosen (2006) documents momentum in merger announcement returns and notes that investor sentiment towards mergers in the current period is an important factor in the current market reaction to acquisition announcements. If investors are overoptimistic about merger-related synergies then clusters of positive market reactions to acquisition announcements are followed by reversals in the long-term stock performance of acquiring firms. As noted by Rosen, it is possible that managers are also caught up in the temporary optimism and are thus motivated to aggressively pursue these synergies during merger waves. My results suggest that CEOs' opinions about mergers are affected by the market's reaction to earlier acquisitions.

Interpreting this finding as evidence of learning is supported by the second set of findings centering on the relation between acquisition timing and the firm and CEO characteristics discussed in the inter-organizational learning literature. What other explanations easily link acquisition decisions with firm age, firm size, past performance, current resources, CEO age, and CEO tenure? Firms are known to have life cycles and to grow—sometimes via acquisitions—across time. Indeed, young firms are expected to grow but this does not explain why a younger firm would tend to acquire earlier in a merger wave. Alternatively, large firms may have more resources for acquisitions across time possibly leading to more acquisitions throughout the waves and hence more acquisitions early in the wave. I account for this possibility in the robustness tests by both eliminating serial acquirers from the analysis and by estimating the results using both single and multiple failure event analysis. Also, given that the firm's past performance over the prior three years is found to negatively correlate with expected time-until-acquisition this suggests that the accumulation of resources, which might be expected after superior past performance, in fact delays acquisitions within waves.

Unlike past performance, current profitability does lead to shorter expected time-until-acquisition. The opposite effects of the past and current performance variables on the time-until-acquisition support the notion that the decision to make an acquisition is similar to the decision to adopt a new corporate practice or innovation seen at other firms. If it was simply the case of firms with resources being enabled to act sooner in the waves to pre-empt other firms or to ensure the acquisition of the best targets, then past performance would be expected to also lead to earlier acquisitions. Rather, consistent with the learning literature, the firms that have recently underperformed relative to their peers are the ones looking for new ways to compete and that more easily adopt new ideas like acquisitions in the post-shock environment.

The CEO's age and tenure are also found to relate to the acquisition timing decision. This finding can be explained by younger CEOs being less risk averse or being more accepting of change in the organization. Both explanations are part of the learning hypothesis. Or, alternatively, CEO age and tenure might be linked to CEO hubris and hence to acquisition behavior. However, for this to be true we would expect age and tenure to be correlated with hubris which has not been shown in the literature.[10]

6.2. Existing acquisition literature

Indeed, the only explanation that easily explains all of the above findings is based on inter-organizational learning which links the influence measures as well as the firm and CEO characteristics to the ease of adopting a new corporate practice like an acquisition in the post-shock environment. One of the benefits of examining the relative timing of acquisition decisions within waves is that it provides a new angle from which to assess the reasons stated for why acquisitions occur. Based on the intuition that the

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[10] For example, note the very small correlations between age and hubris as reported in Malmendier and Tate 2008 using their hubris measure.

decision of when to engage in merger activity is not independent from the reasons why a firm engages in this activity, the factors found to explain the relative timing can provide a new lens through which to assess the completeness of existing explanations for mergers.

For example, the hypothesis that acquisitions are done to increase operational efficiency, cut costs, or in some other way create additional shareholder wealth has been tested in many studies by focusing on the firm's short- and long-term stock market performance as well as changes in accounting fundamentals around acquisition events (e.g. see Bruner's 2002 survey). This view of acquisition activity does not encompass my findings that younger CEOs, CEOs with less tenure, or CEOs that are also chairmen, tend to make acquisitions sooner after industry shocks. If the decision of when to engage in acquisition activity is not independent from the reasons why a firm engages in acquisition activity then my results point to areas where this theory for acquisitions is unable to provide understanding.

Agency hypotheses for acquisitions such as those describing the building of empires for power or wealth, or those that point to the CEO's hubris could relate to my findings involving the CEO's age and tenure. But, as noted above, this relation is not established in the literature and warrants further investigation. Also, even if these CEO characteristics are linked to existing agency stories, this approach does not easily also explain the relation between acquisition timing and such firm characteristics as firm age, firm size, and relative past firm performance.

7. Conclusion

In this paper I find that the timing of acquisitions within merger waves is explained by the market reaction to recent acquisition announcements as well as by specific firm and CEO characteristics associated with inter-organizational learning. I show that large firms, young firms, and firms that are currently profitable but have recently underperformed relative to their industries are all more likely to engage in acquisitions earlier in the merger waves. Similarly, I show that young CEOs, CEOs with less tenure, and CEOs that are also chairmen are all more likely to engage in acquisitions earlier within the merger waves. These findings are consistent with the empirical predictions motivated in Section 2. Given that the CEO's decision of when to engage in acquisition activity is not independent from his reasons for making an acquisition, my results suggest that inter-organizational learning explains the relative timing of acquisitions within merger waves and is important in the acquisition decision.

By documenting the link between the market's reaction to recent acquisitions and the timing of future acquisition decisions, this paper provides an example of one source of influence for the CEO's discovery process of new projects and/or his formation of opinions about the expected costs and benefits of major investment decisions. These results provide empirical evidence related to the herding and information cascade literature with regard to merger waves as well as contribute to the existing merger literature by providing information about factors that explain within wave timing of acquisitions. Additionally, my CEO age and tenure findings demonstrate that other CEO characteristics in addition to hubris relate to the acquisition decision.

The results in this paper suggest several possible related research questions. For example, the specific firm and CEO characteristics used in this paper which relate to the time of acquisition likely also affect the ease of adoption of other innovations or investment ideas. If this is the case, and hence certain firms and CEOs by their nature are more accepting of new corporate practices, then this leads to the question of whether being susceptible to new practices is good for firm performance. Additionally, given the observed link between acquisition timing and CEO age and tenure, this begs the question to what extent CEO characteristics might affect investment decisions in general.

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Figure 1: Wave assignments

As explained in Section 3.1, shocks are identified as two-month periods where the percent of assets being acquired in an industry exceeds 5% of the industry's previous years' total equity market value. The second month in these shock periods is shown in the figure below as an "x" above the time line. The number below the line indicates the number of months since the start of the sample period in January 1990. All waves are considered to be at least 24 months long. The 1st wave period shown below takes 24 months to end. In this example the wave starts with the first shock shown in the 3rd month and ends 24 months later. The wave's duration does not extend past 24 months because there are no additional shock months within 6 months of the end of the wave. The duration of the 2nd wave shown below extends beyond 24 months to 37 months given the series of shock months around the wave's 24th month. The 2nd wave ends after a 6 month period without additional shocks.

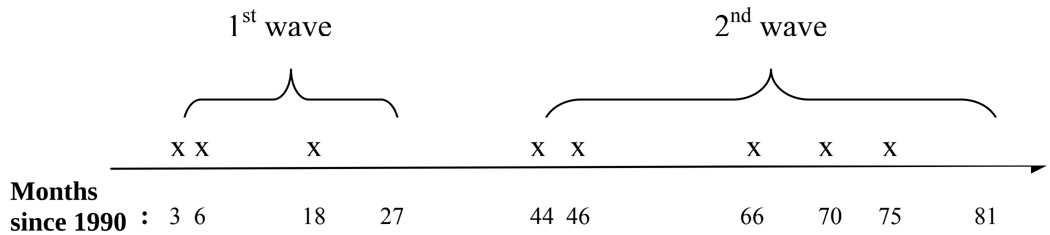

Figure 2: Number of acquisitions within waves across event time

The number of acquisitions in the sample that occur during the industry merger waves is shown below using two different industry definitions. "FF48" and "GICs" indicate, respectively, that Fama and French's (1997) 48 industry classification and Standard & Poor's and Morgan Stanley's global classification standard industry groups were used to make industry assignments. The x-axis shows the relative months after the initial shocks signal the start of the industry merger waves. "Buy-shock" indicates the wave period was identified using the percent of assets acquired in an industry in a given month as explained in Section 3.1.

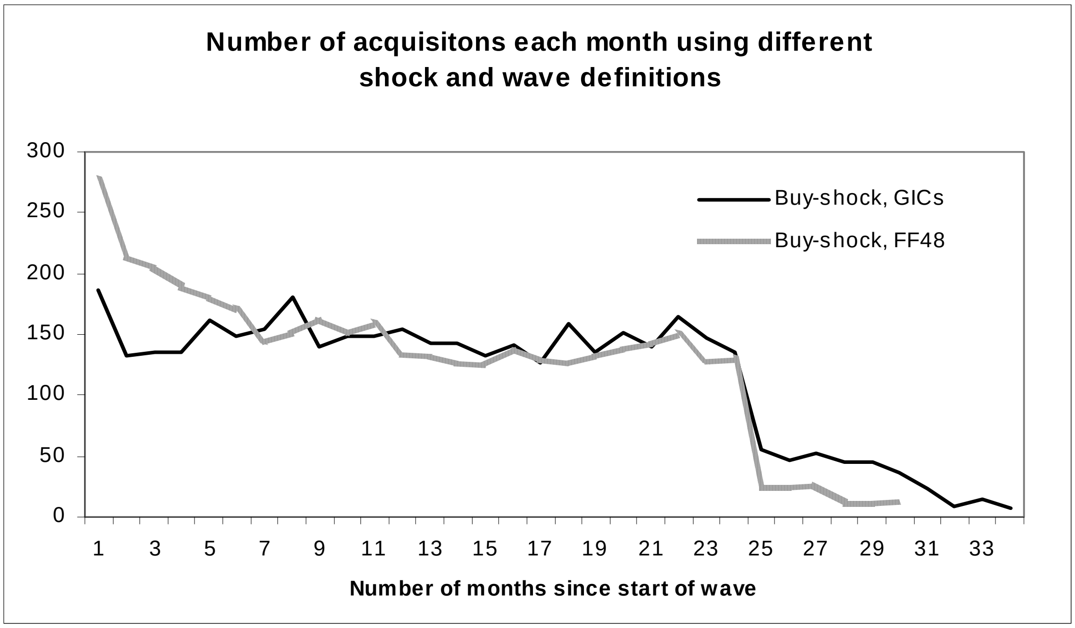

Figure 3a: FF48 wave periods

The industries shown along the y-axis are based on Fama and French's (1997) 48 industry classification. Wave periods are shown by the horizontal bars for each industry. Calendar years are shown along the x-axis. Wave periods are at least 24 months long and are initiated with buy-shocks as illustrated in Figure 1. The wave periods stop after a period of 6 months without additional shocks. The white sections shown at the right-end of the waves mark the 6-month quiet period without additional shocks at the end of the waves.

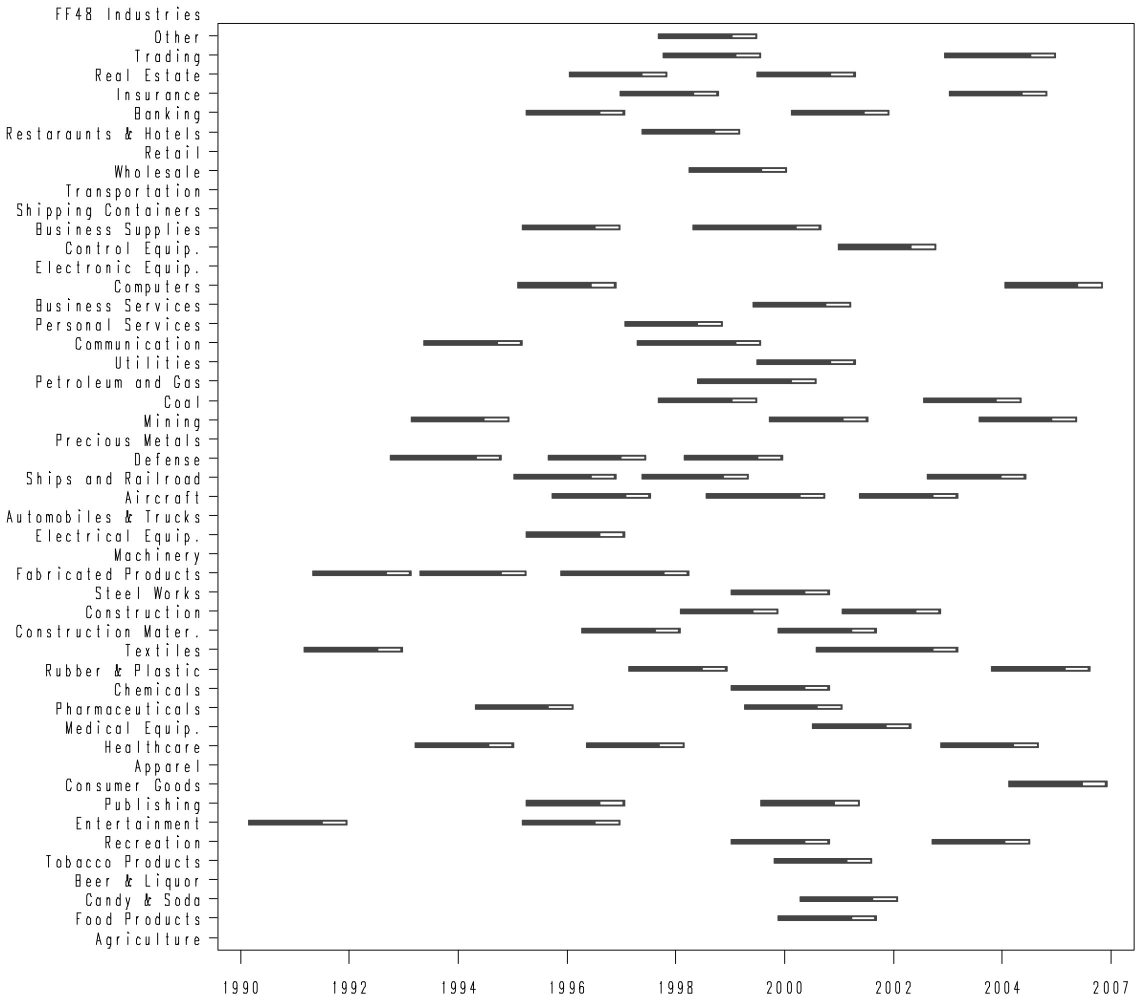

Figure 3b: GIC wave periods

The industries shown along the y-axis are based on Standard & Poor's and Morgan Stanley's global classification standard industry groups. Wave periods are shown by the horizontal bars for each industry. Calendar years are shown along the x-axis. Wave periods are at least 24 months in duration and are initiated with buy-shocks as illustrated in Figure 1. The waves stop after a period of 6 months without additional shocks. The white sections shown at the right-end of the waves mark the 6-month quiet period without additional shocks at the end of the waves.

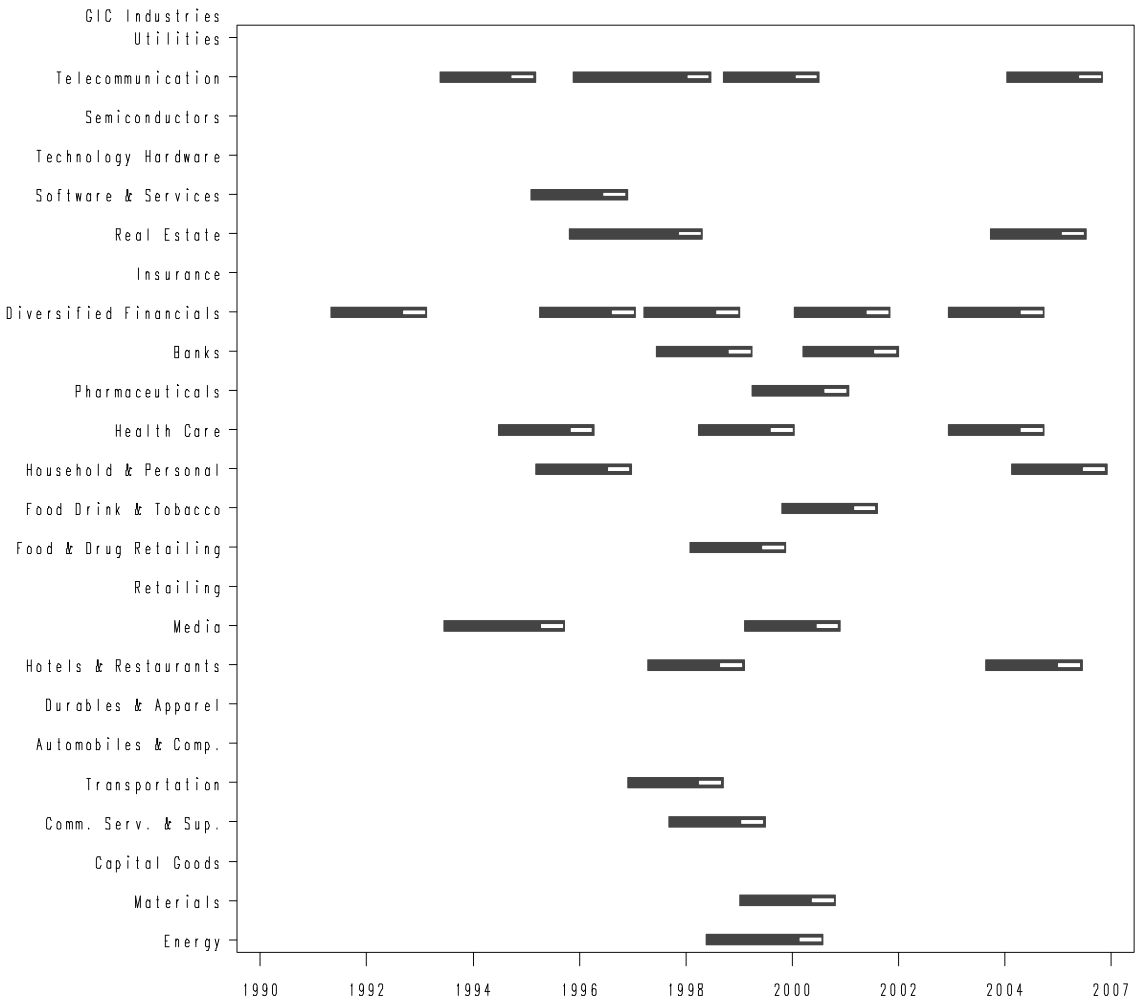

Figure 4a: Kaplan Meier survival plots for influence measures

The Kaplan Meier (1958) survival plots shown below are created using tercile groups formed using the monthly board network, industry, market, and geographical influence measures described in detail in Section 3. Each influence measure is calculated in a given month as the weighted sum of the acquisition announcement returns from the prior nine months. The board, industry and geographic distance measures differ from the market measure in that each is calculated using a different subset of recent acquirers based, respectively, on network connections, industry membership, or geographical location of headquarters rather than all firms in the market. All plots are based on the 1990-2006 sample period.

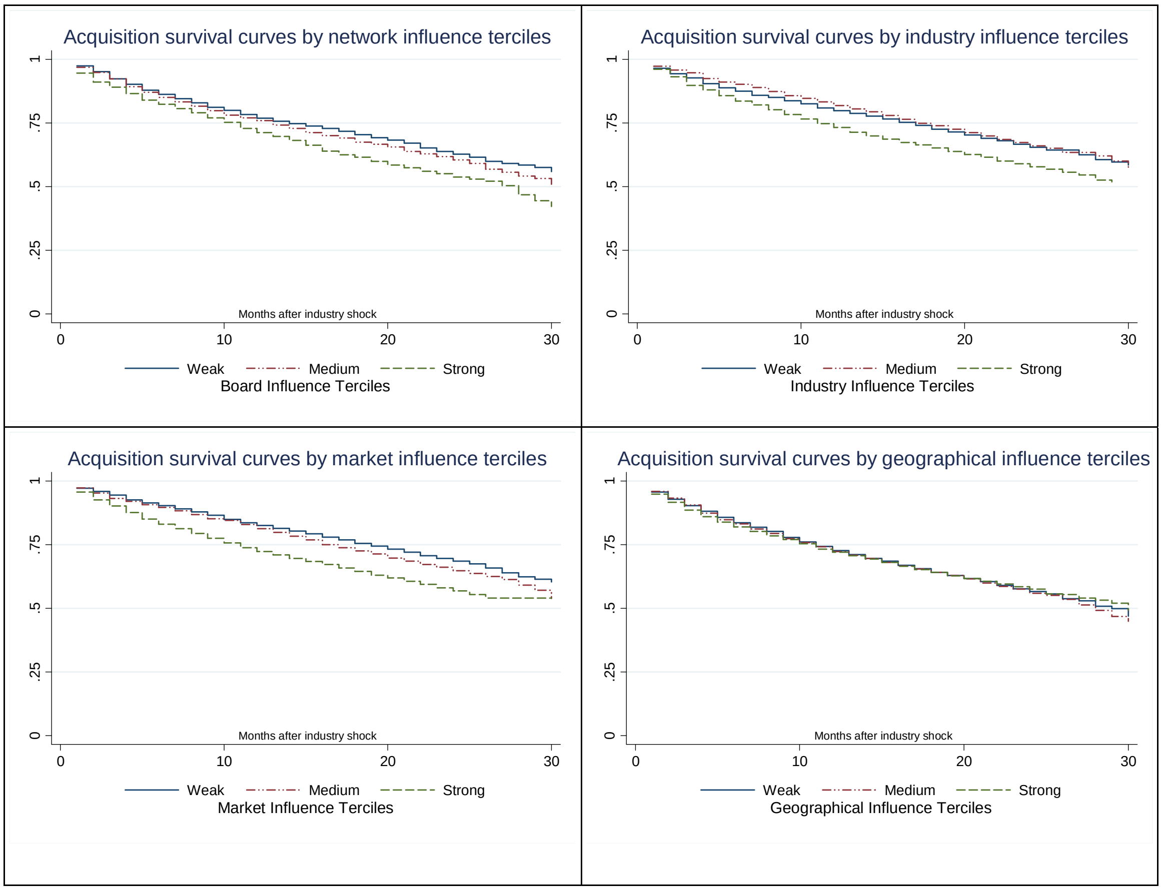

Figure 4b: Kaplan Meier survival plots for firm and CEO characteristics

The Kaplan Meier (1958) survival plots shown below are created using tercile or age groups formed using firm and CEO characteristics identified in Section 2 as being related to the ease of adopting new corporate practices and hence related to inter-organizational learning. With the exception of CEO tenure, all the plots are based on the 1990-2006 sample period. Given the limitations on my measure of CEO tenure, the tenure plot is based on data from 1995-2005. The plots are based on terciles formed using the firm's past performance over years t-1 to t-3, book assets, ROA, firm age, CEO age and tenure as described in Section 3. Firm age, CEO age, and CEO tenure are in years.

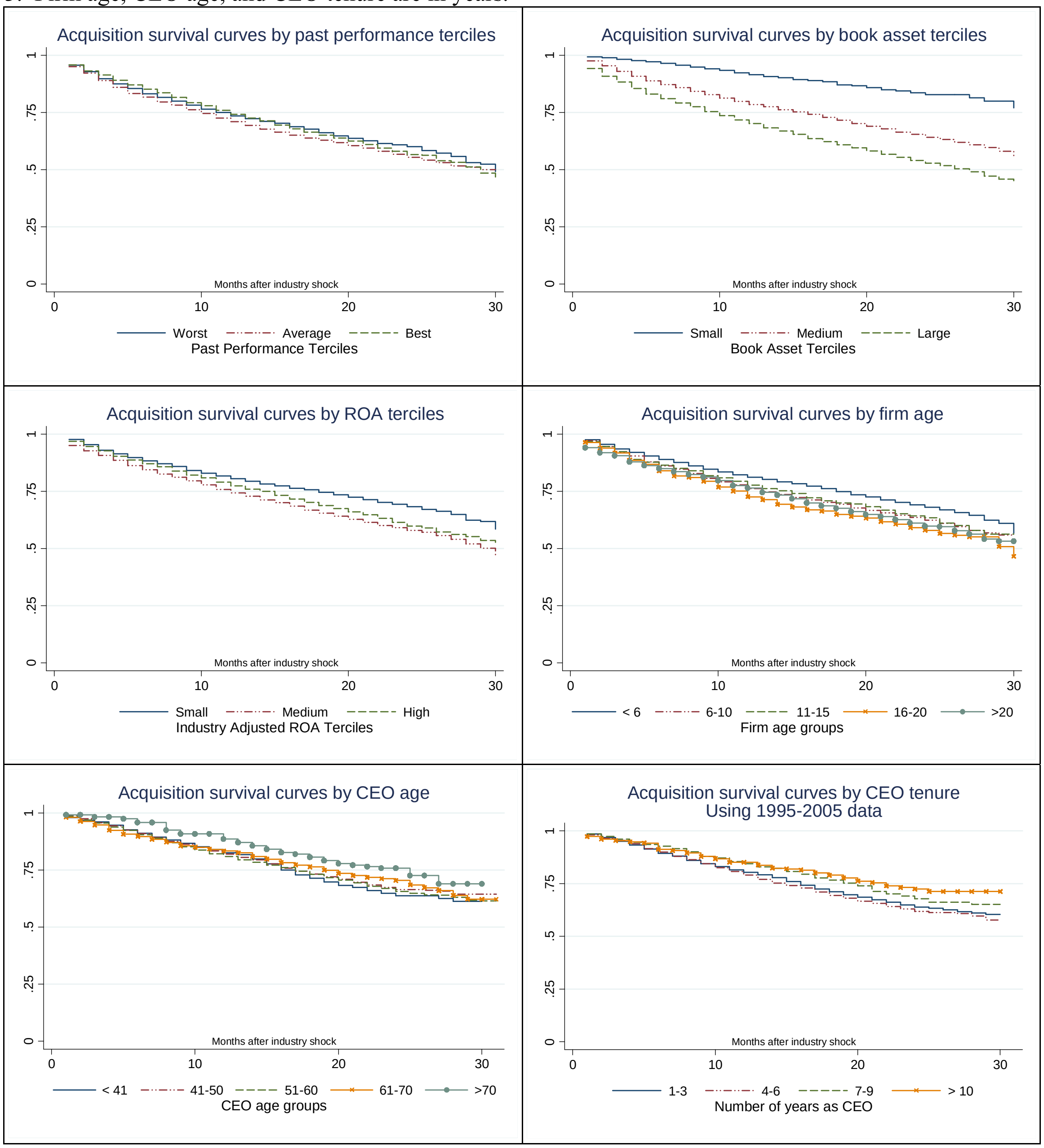

Table 1: Summary of acquisition performance related empirical predications

To distinguish between different types of inter-organizational influence within merger waves three performance hypotheses were motivated in Section 2.4. Per the Learning Hypothesis each successive acquirer learns and benefits from all previous acquisitions in the wave. Per the Target Race Hypothesis there are a limited number of good targets so each additional acquisition within the wave results in lesser quality targets being available for subsequent acquisition. Per the Herding Hypothesis managers mimic earlier managers actions resulting in lesser quality deals at the end of the wave. In the center column the predictions are based on simple comparisons of early and late performance measures. In the third column the predictions are based on equation (1) also shown below.

$$\begin{aligned} \textit{Performance} = {} & \mathrm{a} + \mathrm{b} \cdot \textit{Number} + \mathrm{c} \cdot \textit{Influence} + \mathrm{d} \cdot \textit{Number} \cdot \textit{Influence} \\ & + \mathrm{e} \cdot \textit{Controls} + \textit{error} \end{aligned} \quad (1)$$

	Late acquirers' performance is predicted to be ________ than early acquirers' performance	**Predictions based on equation (1)**
Learning Hypothesis	Greater	b>0
Target Race Hypothesis	Less	b<0
Herding Hypothesis	Less	b<0 c<0 d<0

Table 2: Firm and deal distribution by calendar year

The number of firms and deals shown below include only those that occur within the wave periods identified using the approach explained in Section 3. These wave periods are shown in Figures 3a and 3b. "FF48" and "GICs" indicate, respectively, that Fama and French's (1997) 48 industry classification and Standard & Poor's and Morgan Stanley's global classification standard industry groups were used to make industry assignments.

	FF48 Industries		GIC Industries	
Years	Number of Firms	Number of Deals	Number of Firms	Number of Deals
1990	88	9	0	0
1991	152	8	149	6
1992	167	10	167	14
1993	439	73	504	47
1994	706	171	861	128
1995	1929	223	1599	323
1996	2093	266	2143	421
1997	2536	363	2457	461
1998	2646	641	3042	789
1999	2738	472	3653	479
2000	4497	558	3401	321
2001	3364	380	2424	234
2002	1444	114	992	84
2003	1148	79	524	33
2004	1066	168	1103	142
2005	1097	247	1141	278
2006	603	69	567	119

Table 3: Variable descriptions

Variable	Description
Influence (E5)	This variable is formed each month for each firm as the weighted sum of acquisition announcement returns over the prior 9 months. It is calculated for each firm alternatively using all firms, using firms in the same industry, using firms within 150 miles, and using firms close to a given firm within the board network that made acquisitions during the same 9 month period. It is mean centered and standardized.
CEO age (E6)	This variable is the age of the CEO in years.
CEO tenure (E7)	This variable is the number of years since 1990 that the CEO has been CEO.
Past Performance (E1)	At the annual level, this is the average industry-adjusted ROA for years t-1, t-2, and t-3. To adjust the ROA the median industry ROA is subtracted each year. This variable is extrapolated to the monthly level, winsorized at the 1% level, mean centered, and standardized.
ROA (E3)	At the annual level this variable is operating income before depreciation divided by total book assets. This variable is extrapolated to the monthly level, winsorized at the 1% level, mean centered, and standardized.
Firm Size (E2)	At the annual level this variable is the total book assets. It is extrapolated from the annual to the monthly level. Due to the strong right skew, the natural log of this variable is used. It is then mean centered and standardized.
Firm age (E4)	This variable is the number years since the firm's IPO, or the number of years since the firm was listed in Compustat.
Firm and Sector Errors (Control)	At the annual level these are the firm-specific and the time-series sector errors described for model 3 in Rhodes-Kropf, Robinson, and Viswanathan (2005). The firm error represents the difference at time t between a firm's observed ln(MB) and the predicted ln(MB) based on sector-level information that year. The sector error represents the difference at time t between the predicted ln(MB) based on sector-level information that year and the predicted ln(MB) based on long-run sector information. In both cases the pricing deviations are extrapolated to the monthly level. Both variables are mean centered and standardized for the analysis.
Spread (Control)	This variable is the 4-month moving average of the spread between the rate on commercial and industrial loans greater than $1 million and the intended federal funds rate as used in Harford (2005). The information comes from the Federal Reserve Survey of Terms of Business Lending and is extrapolated from the quarterly to monthly level.
Leverage (Control)	At the annual level this variable is calculated as (debt in current liabilities + long-term debt)/ total book assets. This variable is extrapolated to the monthly level, winsorized at the 1% level, mean centered, and standardized.
%Insiders (Control)	This variable is the percent of the board that are insiders. Directors are categorized as insiders if they are officers at the firm while being on the board, or if they were officers at the firm prior to becoming a director. This variable is mean centered and standardized.
CEO chair (Control)	This is an indicator variable for CEOs that are also chairman of the board.
Board size (Control)	This variable is the number of directors on the board.
Industry and Year (Control)	Industry and calendar year indicators are included in the analysis. If the waves were based on FF48 (GICs) industries then FF48 (GICs) controls are included.
Herfindahl (Control)	This variable is Herfindahl index for each industry each month based on sales.

Table 4: Correlation table

The pairwise correlations shown below are based on the variables described in Table 3 for the FF48 sample. Items 1-4 refer to market, industry, geographic, and board network influence measures as explained in Section 3. Firm error and Sector error are based on the firm and sector level pricing deviations as explained in Rhodes-Kropf, Robinson, and Viswanathan (2005). The Credit spread is the 4-month moving average of the spread between the rate on commercial and industrial loans greater than $1 million and the intended Federal Funds rate using information from the Federal Reserve Survey of Terms of Business Lending. Past performance is the mean industry-adjusted ROA over years t-1 to t-3.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1 Market	1																	
2 Industry	0.20	1																
3 Geographical	0.01	0.01	1															
4 Board	0.37	0.08	0.02	1														
5 CEO age	-0.02	-0.13	-0.01	0.07	1													
6 CEO tenure	-0.10	-0.11	0.00	-0.02	0.37	1												
7 Firm error	0.00	0.01	0.01	0.14	0.04	0.07	1											
8 Sector error	-0.06	-0.04	0.01	-0.02	-0.01	-0.01	0.01	1										
9 Credit spread	-0.65	0.05	0.01	-0.24	0.04	0.18	0.01	0.04	1									
10 Past perf.	0.02	-0.10	0.00	0.07	0.16	0.15	0.04	-0.09	-0.01	1								
11 Firm size	-0.09	-0.09	0.00	0.26	0.18	0.16	0.15	0.05	0.17	0.32	1							
12 Firm age	-0.08	-0.13	0.00	0.20	0.28	0.31	0.13	0.16	0.14	0.18	0.34	1						
13 ROA	0.05	-0.10	0.00	0.10	0.18	0.16	0.07	-0.16	-0.03	0.73	0.37	0.23	1					
14 Leverage	0.04	-0.06	0.01	0.06	0.01	0.00	0.28	0.05	-0.01	0.06	0.20	0.06	0.12	1				
15 ROA	0.05	-0.10	0.00	0.10	0.18	0.16	0.07	-0.16	-0.03	0.73	0.37	0.23	1.00	0.12	1			
16 %insider	0.00	0.02	0.00	-0.14	-0.03	-0.03	-0.06	-0.07	-0.02	-0.03	-0.21	-0.15	-0.05	0.00	-0.05	1		
17 CEO chair	0.02	-0.01	-0.01	0.10	0.22	0.25	0.12	0.02	-0.01	0.04	0.08	0.12	0.06	0.07	0.06	-0.08	1	
18 Board size	-0.02	-0.10	0.00	0.20	0.15	0.08	0.07	0.02	0.06	0.15	0.56	0.26	0.15	0.03	0.15	-0.31	0.00	1

Table 5: Descriptive statistics for acquiring and non-acquiring firms

Each year each firm in the sample is placed in either the acquiring or non-acquiring groups. The statistics shown below are estimated across years on these groups using Fama and French (1997) 48 industries. The market value of equity is in millions. CEO age, CEO tenure, and firm age are all in years. Firm error and Sector error are based on the firm and sector level pricing deviations as explained in Rhodes-Kropf, Robinson, and Viswanathan (2005). Past performance is the mean industry-adjusted ROA over years t-1 to t-3.

	Non-acquiring			Acquiring		
Variables	Number of firm-years	Mean	Median	Number of firm-years	Mean	Median
Market value of equity	22,786	1,756.41	117.60	1,813	3,817.73	479.02
CEO age	19,049	52.85	53.00	1,644	52.24	52.00
CEO tenure	19,474	4.40	4.00	1,662	4.23	3.00
Board size	20,807	8.15	7.00	1,720	9.06	8.00
Book leverage	24,749	0.25	0.18	1,795	0.23	0.20
Number of insiders	24,900	2.08	2.00	1,813	2.36	2.00
ROA	23,680	0.02	0.06	1,798	0.06	0.09
Firm error	22,380	-0.02	0.03	1,737	0.31	0.30
Sector error	22,380	1.94	0.56	1,737	1.80	0.58
%Insider	20,807	0.34	0.29	1,720	0.30	0.27
Past performance	22,603	-0.04	0.00	1,772	-0.02	0.01
Firm age	24,900	11.56	7.00	1,813	12.75	7.00

Table 6: Cox proportional hazard model with influence measures

In each of these models, the time-until-acquisition measured since the start of the merger waves shown in Figures 3a and 3b is modeled as a function of the respective influence variables in addition to year and industry controls. Each influence measure is calculated in a given month as the weighted sum of the acquisition announcement returns from the prior nine months. The board, industry and geographic distance measures differ from the market measure in that each is calculated using a different subset of recent acquirers based, respectively, on network connections, industry membership, or geographical location of headquarters rather than all firms in the market as explained in Section 3.2. "FF48" and "GICs" indicate, respectively, that Fama and French's (1997) 48 industry classification and Standard & Poor's and Morgan Stanley's global classification standard industry groups were used to make industry assignments. Z-statistics are shown below the hazard ratios. Significance shown at the 10%, 5%, and 1% with *, **, and ***, respectively.

	GIC				FF48			
Market Influence	1.258***				1.146***			
	(7.94)				(4.61)			
Industry Influence		1.153***				1.066***		
		(5.94)				(4.64)		
Geographical Influence			1.006				0.988	
			(0.46)				(-0.58)	
Board Influence				1.095***				1.098***
				(4.90)				(5.28)
Industry and Year Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-22139	-22154	-21309	-17999	-24470	-24470	-23582	-19724
Chi2	357.7	328.4	372.7	312.0	457.3	456.5	533.2	464.9
df	31	31	31	30	55	55	54	53
Firm-year-months	118900	118900	104139	93026	134131	134131	120585	106903
Firms	5896	5896	5292	4957	6646	6646	6127	5593
Acquisitions	2628	2628	2611	2228	2859	2859	2827	2394

Table 7: Cox proportional hazard model with firm and CEO characteristics

In each of these models, the time-until-acquisition measured since the start of the merger waves shown in Figures 3a and 3b is modeled as a function of the firm and CEO characteristics noted below in addition to year and industry controls. "FF48" and "GICs" indicate, respectively, that Fama and French's (1997) 48 industry classification and Standard & Poor's and Morgan Stanley's global classification standard industry groups were used to make industry assignments. Z-statistics are shown below the hazard ratios. Significance shown at the 10%, 5%, and 1% with *, **, and ***, respectively.

	FF48	GIC
Past performance	0.556***	0.591**
	(-4.19)	(-2.98)
Firm size	1.716***	1.689***
	(17.69)	(16.89)
ROA	2.338***	3.809***
	(4.36)	(5.56)
Firm age	0.989***	0.985***
	(-5.70)	(-7.23)
CEO age	0.982***	0.979***
	(-6.48)	(-7.42)
CEO tenure	1.000	1.001
	(0.06)	(0.13)
Industry controls	Yes	Yes
Year controls	Yes	Yes
Log-likelihood	-20044.6	-18104.2
Chi2	878.8	717.5
df	59	35
Firm-year-months	105420	91329
Firms	5518	4851
Acquisitions	2466	2276

Table 8: Cox proportional hazard model with influence measures, firm and CEO characteristics, and control variables

In each of these models, the time-until-acquisition measured since the start of the merger waves shown in Figures 3a and 3b is modeled as a function of the respective influence variables, firm and CEO characteristics, and other controls. Each influence measure is calculated in a given month as the weighted sum of the acquisition announcement returns from the prior nine months. The board, industry and geographic distance measures differ from the market measure in that each is calculated using a different subset of recent acquirers based, respectively, on network connections, industry membership, or geographical location of headquarters rather than all firms in the market as explained in Section 3.2. "FF48" and "GICs" indicate, respectively, that Fama and French's (1997) 48 industry classification and Standard & Poor's and Morgan Stanley's global classification standard industry groups were used to make industry assignments. Each specification was estimated two times either using influence measures calculated with announcement returns from the (-1,1) trading days, or from the (-1,45) trading days around the recent acquisition announcements. In both cases the same control variables were used, but for the model using the (-1,45) returns only the influence hazard ratios are tabulated below. The non-influence variables are described in detail in Table 3. Z-statistics are shown below the hazard ratios. Significance shown at the 10%, 5%, and 1% with *, **, and ***, respectively.

	FF48			GIC		
Market Influence (-1,45)	1.050*			1.086***		
	(2.19)			(3.60)		
Industry Influence (-1,45)		1.016			1.072**	
		(1.31)			(2.83)	
Board Influence (-1,45)			1.037*			1.006
			(2.07)			(0.33)
Market Influence (-1,1)	1.085*			1.109**		
	(2.47)			(3.14)		
Industry Influence (-1,1)		1.049**			1.061*	
		(2.95)			(2.31)	
Board Influence (-1,1)			0.97			0.962
			(-1.42)			(-1.63)
Past performance	0.551***	0.562***	0.532***	0.683*	0.681*	0.799
	(-4.08)	(-3.94)	(-3.65)	(-1.96)	(-1.98)	(-0.98)
Firm size	1.327***	1.331***	1.400***	1.226***	1.228***	1.290***
	(7.95)	(8.02)	(8.50)	(5.53)	(5.58)	(6.16)
ROA	2.373***	2.308***	2.288***	4.364***	4.379***	3.991***
	(4.26)	(4.12)	(3.68)	(5.55)	(5.57)	(4.74)
Firm age	0.992***	0.992***	0.993***	0.987***	0.987***	0.987***
	(-3.88)	(-3.89)	(-3.32)	(-5.89)	(-5.87)	(-5.33)
CEO age	0.982***	0.982***	0.981***	0.977***	0.977***	0.977***
	(-6.21)	(-6.22)	(-6.24)	(-7.50)	(-7.49)	(-7.15)

CEO tenure	0.99	0.99	0.996	0.987	0.987	0.987
	(-1.35)	(-1.34)	(-0.52)	(-1.65)	(-1.63)	(-1.59)
Firm error	1.218***	1.214***	1.251***	1.244***	1.240***	1.228***
	(5.15)	(5.07)	(5.41)	(5.35)	(5.28)	(4.69)
Sector error	0.984**	0.983**	0.984*	0.998	0.998	1.001
	(-2.70)	(-2.75)	(-2.49)	(-0.33)	(-0.34)	(0.17)
Credit spread	0.514	0.5	0.518	0.348*	0.321*	0.299*
	(-1.34)	(-1.41)	(-1.27)	(-2.13)	(-2.33)	(-2.35)
Leverage	0.972	0.973	0.953	1.061*	1.061*	1.070*
	(-0.98)	(-0.97)	(-1.57)	(2.10)	(2.11)	(2.27)
%Insider	0.96	0.96	0.97	0.971	0.971	0.986
	(-1.63)	(-1.64)	(-1.15)	(-1.18)	(-1.19)	(-0.55)
CEO chair	1.212***	1.211***	1.217***	1.369***	1.367***	1.384***
	(4.15)	(4.14)	(3.97)	(6.56)	(6.53)	(6.35)
Board size	1.017*	1.017*	1.016*	1.032***	1.032***	1.030***
	(2.49)	(2.50)	(2.19)	(5.01)	(5.01)	(4.57)
Herfindahl Index	1.000	1.000	1.000	1.000	1.000	1.000
	(1.52)	(1.62)	(0.82)	(1.21)	(1.08)	(0.18)
Industry controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-18707.6	-18706.4	-16541.1	-16986.3	-16986.3	-15087.2
Chi2	721.2	723.6	662.1	676.7	676.7	602.7
df	68	68	67	44	44	44
Firm-year-months	97382	97382	89849	83960	83960	77287
Firms	5184	5184	4912	4535	4535	4294
Acquisitions	2316	2316	2068	2156	2156	1935

Table 9: Cox proportional hazard model without serial acquirers.

These specifications are like those shown in Table 7 but without the serial acquirers. I define a serial acquirer to be a firm that makes 3 acquisitions within 3 years. In each of these models, the time-until-acquisition measured since the start of the merger waves shown in Figures 3a and 3b is modeled as a function of the respective influence variables, firm and CEO characteristics, and other controls. Each influence measure is calculated in a given month as the weighted sum of the acquisition announcement returns from the prior nine months. The board, industry and geographic distance measures differ from the market measure in that each is calculated using a different subset of recent acquirers based, respectively, on network connections, industry membership, or geographical location of headquarters rather than all firms in the market as explained in Section 3.2. "FF48" and "GICs" indicate, respectively, that Fama and French's (1997) 48 industry classification and Standard & Poor's and Morgan Stanley's global classification standard industry groups were used to make industry assignments. Each specification was estimated two times either using influence measures calculated with announcement returns from the (-1,1) trading days, or (-1,45) trading days around the recent acquisition announcements. In both cases the same control variables were used, but for the model using the (-1,45) returns only the influence hazard ratios are tabulated below. The non-influence variables are described in detail in Table 3. Z-statistics are shown below the hazard ratios. Significance shown at the 10%, 5%, and 1% with *, **, and ***, respectively.

	FF48			GIC		
Market Influence (-1,45)	1.031			1.096***		
	(1.12)			(3.31)		
Industry Influence (-1,45)		1.012			1.074*	
		(0.83)			(2.36)	
Board Influence (-1,45)			1.046*			0.998
			(2.01)			(-0.06)
Market Influence (-1,1)	1.088*			1.120**		
	(2.12)			(2.89)		
Industry Influence (-1,1)		1.065***			1.038	
		(3.36)			(1.22)	
Board Influence (-1,1)			1.006			0.989
			(0.23)			(-0.37)
Past performance	0.492***	0.503***	0.448***	0.683	0.683	0.786
	(-4.69)	(-4.53)	(-4.43)	(-1.90)	(-1.90)	(-1.01)
Firm size	1.237***	1.243***	1.296***	1.096*	1.099*	1.127*
	(4.83)	(4.93)	(5.19)	(2.03)	(2.10)	(2.33)
ROA	2.499***	2.409***	2.436***	5.622***	5.614***	5.427***
	(4.16)	(3.98)	(3.62)	(5.99)	(5.99)	(5.30)

Firm age	0.985***	0.985***	0.986***	0.979***	0.979***	0.980***
	(-5.52)	(-5.53)	(-4.97)	(-7.04)	(-7.04)	(-6.44)
CEO age	0.983***	0.983***	0.981***	0.976***	0.976***	0.976***
	(-4.97)	(-4.99)	(-5.10)	(-6.59)	(-6.58)	(-6.33)
CEO tenure	0.954***	0.954***	0.965**	0.944***	0.944***	0.943***
	(-4.39)	(-4.38)	(-3.15)	(-5.13)	(-5.11)	(-4.95)
Firm error	1.227***	1.220***	1.269***	1.272***	1.268***	1.262***
	(4.62)	(4.49)	(4.92)	(5.08)	(5.01)	(4.52)
Sector error	0.980**	0.980**	0.980*	1.012	1.012	1.016
	(-2.59)	(-2.65)	(-2.33)	(1.40)	(1.40)	(1.70)
Credit spread	0.816	0.792	0.888	0.47	0.421	0.361
	(-0.32)	(-0.37)	(-0.18)	(-1.23)	(-1.43)	(-1.60)
Leverage	0.978	0.978	0.957	1.079*	1.079*	1.102**
	(-0.67)	(-0.65)	(-1.20)	(2.33)	(2.33)	(2.77)
%Insider	0.961	0.961	0.982	0.967	0.967	0.995
	(-1.30)	(-1.32)	(-0.57)	(-1.12)	(-1.13)	(-0.17)
CEO chair	1.236***	1.235***	1.254***	1.429***	1.426***	1.472***
	(3.87)	(3.85)	(3.80)	(6.27)	(6.24)	(6.29)
Board size	1.022*	1.022*	1.020*	1.036***	1.036***	1.034***
	(2.50)	(2.49)	(2.07)	(4.21)	(4.20)	(3.84)
Herfindahl Index	1	1	1	1	1	1
	(0.01)	(0.22)	(-0.71)	(0.91)	(0.76)	(-0.17)
Industry controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-12482.5	-12479.3	-10685.3	-11331.8	-11335.2	-9821
Chi2	693.7	700.2	607.9	662.2	655.3	560.8
df	68	68	67	44	44	44
Firm-year-months	85495	85495	78441	72924	72924	66769
Firms	4643	4643	4373	4031	4031	3792
Acquisitions	1581	1581	1368	1479	1479	1296

Table 10: Percent of acquiring firms ranked by predicted hazard

Beginning in 1997, the relative hazards of all firms in each industry merger wave were predicted using coefficients estimated using data from an earlier sample period. For example, the predicted relative hazards as of the start of waves beginning in 1997 (1998, 1999, etc.) were estimated using coefficients obtained from estimating the Cox model shown in Table 7 using data from 1990-1996 (1990-1997, 1990-1998, etc). In each year, data for the estimation period went up through the previous calendar year. As of the first month in each of the merger waves all the firms were then ranked into quintiles based on their predicted relative hazards. The information below shows the percent of acquiring firms that then made acquisitions within the first 12, 18, and 24 months of the waves as a function of their predicted relative hazard quintiles.

	Percent of acquisitions within		
Hazard Quintiles	**12 months**	**18 months**	**24 months**
Large	0.25	0.25	0.26
2	0.26	0.26	0.25
3	0.21	0.21	0.21
4	0.16	0.15	0.16
Small	0.12	0.13	0.12

Table 11: Acquisition performance measures early and late within waves

Acquisitions within the first 12 months of each merger wave are considered to be part of the early sample while acquisitions after the first year in the wave are considered to be part of the late sample. The 3-day cumulative abnormal return (CAR) around acquisition announcements is calculated using the market model. The 2-year buy-and-hold abnormal returns (BHAR) following acquisitions are calculated using a reference portfolio of firms matched before the acquisition on size, book-to-market, and recent stock performance as explained in Barber, Lyon, and Tsai (1999). ROA is defined as the operating income before depreciation divided by book assets. Each year the ROA for each firm is industry-adjusted by subtracting the median industry ROA. The change in annual mean industry-adjusted ROA is then calculated by subtracting the annual mean industry-adjusted ROA for years (t-1, t-3) from the annual mean industry-adjusted ROA for years (t+1, t+3) where t is the year of the acquisition. ROA residual is the residual from regressing the mean annual industry-adjusted ROA for years (t+1,t+3) on the mean annual industry-adjusted ROA for years (t-1,t-3). "FF48" and "GICs" indicate, respectively, that Fama and French's (1997) 48 industry classification and Standard & Poor's and Morgan Stanley's global classification standard industry groups were used to make industry assignments. The means for each variable for each respective sample are shown with standard deviations listed below in parenthesis. Significance shown at the 10%, 5%, and 1% with *, **, and ***, respectively.

	(a) Full Sample	(b) Early Sample	(c) Late Sample	(c)-(b) Late - Early
Panel A: GIC Industry Assignments				
CAR	0.004 **	0.005 *	0.004	-0.001
	(0.081)	(0.085)	(0.077)	
BHAR	-0.123 ***	-0.183 ***	-0.057 *	0.127 **
	(1.089)	(1.173)	(0.984)	
ΔROA	-0.008 ***	-0.012 ***	-0.003	0.009 *
	(0.101)	(0.103)	(0.099)	
ROA residual	0.013 ***	0.008 ***	0.018 ***	0.010 **
	(0.098)	(0.099)	(0.097)	
N	1904	1002	902	
Panel B: FF48 Industry Assignments				
CAR	0.005 ***	0.006 *	0.005 **	0.000
	(0.091)	(0.099)	(0.082)	
BHAR	-0.108 ***	-0.112 ***	-0.102 ***	0.010
	(1.141)	(1.094)	(1.194)	
ΔROA	-0.004	0.001	-0.009 ***	-0.010 *
	(0.132)	(0.152)	(0.104)	
ROA residual	0.013 ***	0.016 ***	0.010 **	-0.006
	(0.133)	(0.133)	(0.132)	
N	2041	1095	946	

Table 12: Merger performance as a function of past acquisitions

The regression coefficients shown below are from equation (1) in Section 2.4. The dependent variable is shown at the top of each column. CAR is the 3-day (-1,+1) announcement cumulative abnormal return. BHAR is the 2-year buy-and-hold abnormal returns following acquisitions calculated using a reference portfolio of firms matched before the acquisition on size, book-to-market, and recent stock performance as explained in Barber, Lyon, and Tsai (1999). ROA is defined as the operating income before depreciation divided by book assets. The change in mean annual industry-adjusted ROA (ΔROA) is calculated by subtracting the mean annual industry-adjusted ROA for years (t-1, t-3) from the mean annual industry-adjusted ROA for years (t+1, t+3) where t is the year of the acquisition. Res is the residual from regressing the mean annual industry ROA for years (t+1,t+3) on the mean annual industry-adjsuted ROA for years (t-1,t-3). Number represents the number of acquisitions since the start of the wave. Industry influence is the weighted sum of announcement returns (-1,+1) for all acquisitions within the same industry over the last 9 months. Firm size is the natural log of total book assets, leverage is the (debt in current liabilities + long-term debt)/ total book assets, and M/B is the (market value of equity + book debt)/total book assets. The firm size, leverage, and M/B variables are measured as of the end of the fiscal year prior to the acquisition announcement. Past experience is the number of past acquisitions the firm has made since the start of the wave, industry size is the number of firms in the industry, relative size is the acquisition transaction value divided by the acquirer's market capitalization as of the end of the previous calendar year. White's heteroskedastic consistent standard errors clustered by firm are used. Significance shown at the 10%, 5%, and 1% with *, **, and ***, respectively.

	CAR (1)	CAR (2)	BHAR (3)	BHAR (4)	ΔROA (5)	ΔROA (6)	Res (7)	Res (8)
Number	-0.001**	-0.001	0.006	0.013	0.002*	0.002**	0.001*	0.002*
	(-2.47)	(-1.57)	(0.71)	(1.28)	(1.84)	(2.07)	(1.68)	(1.79)
Industry influence	-0.011***	-0.013***	-0.064**	-0.098***	0.007**	0.004	0.007**	0.005
	(-3.97)	(-3.57)	(-2.33)	(-3.38)	(2.49)	(1.50)	(2.33)	(1.60)
Number* Industry influence		0.000		0.004		0.000		0.000
		(0.81)		(1.55)		(1.59)		(1.18)
Firm size	-0.003***	-0.003***	0.032	0.032	0.004*	0.004*	0.004*	0.004*
	(-2.66)	(-2.67)	(1.60)	(1.57)	(1.93)	(1.92)	(1.96)	(1.95)
Leverage	-0.012	-0.011	-0.063	-0.060	-0.003	-0.003	-0.003	-0.002
	(-0.86)	(-0.85)	(-0.28)	(-0.27)	(-0.15)	(-0.14)	(-0.13)	(-0.13)
ROA	0.020	0.020	0.482	0.468	-0.208***	-0.209***	0.037	0.036
	(0.91)	(0.88)	(1.23)	(1.20)	(-2.66)	(-2.68)	(0.46)	(0.45)
M/B	-0.011***	-0.011***	-0.016	-0.012	-0.003	-0.003	-0.001	-0.001
	(-3.16)	(-3.11)	(-0.27)	(-0.21)	(-0.54)	(-0.49)	(-0.20)	(-0.16)

Past experience	0.000	0.000	-0.015	-0.014	-0.000	-0.000	-0.000	-0.000
	(0.25)	(0.26)	(-0.94)	(-0.92)	(-0.35)	(-0.34)	(-0.31)	(-0.29)
Industry size	0.000	0.000	-0.000	-0.000	0.000	0.000	0.000	0.000
	(1.61)	(1.46)	(-0.10)	(-0.30)	(1.58)	(1.49)	(1.39)	(1.32)
Relative size	-0.004	-0.004	0.331	0.332	0.001	0.001	0.002	0.002
	(-0.71)	(-0.70)	(1.23)	(1.24)	(0.25)	(0.28)	(0.42)	(0.44)
Private target	0.006	0.006	-0.054	-0.056	0.007	0.007	0.008	0.008
	(1.32)	(1.30)	(-0.80)	(-0.83)	(1.30)	(1.28)	(1.56)	(1.54)
Diversifying	0.003	0.003	0.023	0.026	0.005	0.005	0.002	0.002
	(0.64)	(0.67)	(0.46)	(0.51)	(0.85)	(0.89)	(0.31)	(0.34)
100% Cash	0.003	0.003	0.067	0.068	0.003	0.003	0.007	0.007
	(0.70)	(0.71)	(1.19)	(1.21)	(0.60)	(0.62)	(1.40)	(1.42)
100% Equity	-0.006	-0.006	-0.084	-0.089	-0.009	-0.010	-0.010	-0.010
	(-1.11)	(-1.15)	(-1.07)	(-1.14)	(-1.11)	(-1.16)	(-1.25)	(-1.29)
Constant	0.090**	0.090**	-0.526	-0.536	-0.163***	-0.164***	-0.190***	-0.191***
	(2.38)	(2.36)	(-0.66)	(-0.67)	(-3.10)	(-3.12)	(-3.65)	(-3.66)
Year Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R2	0.038	0.038	0.059	0.059	0.127	0.128	0.120	0.120
Obs	1888	1888	1888	1888	1888	1888	1888	1888