

Variability and Synchronization of M&A and Alliance Behavior: An Entrainment View

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We extend the M&A and alliances literature to include a temporal perspective focusing on when and under what conditions firms should accelerate or slow down their M&A and alliance initiatives. Using a social entrainment model, we explore the relationship between the temporal properties of variability, synchronization and firm performance. We test our model in the context of the U.S specialty pharmaceutical industry. We find a curvilinear relationship between the overall variability of strategic actions and performance. Establishing internal synchronization increases performance while external synchronization of variability with competitors reveals a more complex picture. Our study further opens the window for understanding the creation of competitive advantage by managing rhythm-type strategic actions against time.

Key words: M&A, Alliance, Temporal, Synchronization, Entrainment, Variability, Specialty Pharmaceutical industry

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PREFACE

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1.0 INTRODUCTION

"We're thoughtfully non-rhythmic", Mike Tomlin, Head Coach of the Pittsburgh Steelers¹

While the M&A and alliance literatures have a rich tradition, a temporal perspective exploring rhythm-type activity that focuses on when and under what conditions firms should accelerate or slow down their M&A and alliance initiatives has received scant attention. Our research seeks to advance the temporal lens in the strategic management literature in general and in the M&A and alliance literature in particular. We apply the social entrainment framework (McGrath & Kelly, 1986) and its associated temporal constructs of variability of activity change rate (Laamanen & Keil, 2008; McGrath & Kelly, 1986; Vermeulen & Barkema, 2002) and synchronization or mutual entrainment, defined as the adjustment of one activity to match with that of another (Ancona and Chong, 1996). Focusing on both M&A and alliances allows us to explore the performance impact of firms' overall variability for these two initiatives. Additionally, we examine the performance impact of internally synchronizing M&A and alliance initiatives and the external synchronization of these strategic initiatives with their competitors.

¹ Gene Collier, Pittsburgh Post-Gazette, July 29, 2007. According to Collier, "His (Tomlin's) thoughtfully non-rhythmic remark was crafted to explain that (training) camp schedule is designed to make players uncomfortable and unable to anticipate any pattern to the tasks, the better to sharpen their cognition and adaptability..." In our context, we extend his meaning to reflect a desire to be semi-predictable not only to the players but to the other teams and coaches in the NFL. See the theory development for hypothesis 1.

Our entrainment view suggests that M&A and alliance behaviors are rhythmic and are coordinated through internal and/or external synchronization mechanisms such as pacer, isomorphism, repetitive momentum (i.e., routines) and intentional strategic choice (Ancona and Chong, 1996). Essentially, the entrainment perspective calls for a focus on when activities take place rather than what and how these activities occur and are implemented. Coordination of activity is achieved through an analysis of time rather than information processing requirements or activity. Entrainment highlights the role of a temporal perspective of M&A and alliance initiatives by theoretically and methodologically recognizing the variability of these activities, their interdependence, the interplay between these activities and firms' external environment and performance.

The temporal dimension of strategy is embedded in a wide range of phenomenon , including, but not limited to first mover advantage (Lieberman & Montgomery, 1988), resource based view (Dierickx & Cool, 1989), dynamic capabilities (Teece, Pisano, & Shuen, 1997), decision making under uncertainty (Eisenhardt, 1989), change management (Huy, 2001), and the real option perspective (Kogut, 1991). While these research streams have provided significant practice and process insights, their central focus has not addressed temporal constructs such as tempo, cycles, variability of activity change rate and entrainments (with some exceptions such as time-based competition). A fundamental underpinning of strategic management logic lies in a prevailing focus on substance, i.e. what to do, over temporality, i.e. when, how fast, how often and how frequently to do. Thus, the temporality of strategy is relegated to a peripheral role (Ancona, Goodman, Lawrence, & Tushman, 2001) in that time associated constructs and assumptions are not explicitly developed but implicitly assumed (Butler, 1995)

and often employed as methodological proxies for other constructs of interest. For example, in the top management team literature, tenure is a methodological proxy for firm or industry knowledge, group cohesion, inertia, and harmonious working relationships (Mosakowski & Earley, 2000). In the alliance literature, repeated partnering with the same firm is a proxy for trust and positive working relationships (Gulati, 1995).

There are some notable exceptions with respect to our focus in the M&A and alliance streams. For example, questions related to accelerating or slowing down post-acquisition integration (Homburg & Bucerius, 2006), preemptive acquisition (Carow, Heron, & Saxton, 2004), M&A and alliance experience relationship with performance (Haleblian & Finkelstein, 1999) and M&A and alliances as learning tools and races (Hamel, 1991). While these different thrusts offer unique contributions for enhancing our temporal understanding of M&A and alliance initiatives, two important temporal issues are underdeveloped. First, their focus typically centers on a single M&A or alliance and therefore do not incorporate the nature of multiple strategic initiatives and their interplay (Haspeslagh & Jemison, 1987). However, recent studies suggested that most firms engage in multiple M&As and alliances overtime (Frick & Torres, 2002; Laamanen & Keil, 2008). These M&A and alliances initiatives typically are part of the overall strategic portfolio program (Rovit & Lemire, 2003, Lavie, 2007) or part of firms' core business routines (Ginsberg & Baum, 1994). The notion of serial acquirer (McNamara, Haleblian, & Dykes, 2008; Laamanen & Keil, 2008) and alliance portfolio (Hoffmann, 2007; Lavie, 2007; Parise & Casher, 2003) suggested that firms' multiple M&A and alliance initiatives have become a norm rather than an exception in their overall strategic plan. Second, those scholars that have recognized the interdependent nature among multiple M&A and alliances

(Haleblian & Finkelstein, 1999) have not examined their periodicity, variability of the change rate of these initiatives and the fact that multiple initiatives can occur synchronously at the same level of analysis (e. g., firm) or across levels of analysis (firms and their competitive environment). In other words, through the examination of these temporal properties, we can discern a pattern in the timing of M&A and alliances occurrences conditioned by internal or external pacers.

Drawing on the social entrainment framework and its associated temporal constructs of variability of activity change rate and synchronization we demonstrate one approach for addressing the call to further incorporate a temporal lens into the M&A and alliance literature. Using a sample of small and medium sized biopharmaceutical firms we find a curvilinear relationship between their overall variability of M&A and alliance initiatives change rate with firm performance. In addition, our analysis shows that internal synchronization of variability between M&A and alliance enhances firm performance. As for external synchronization, the results are more complicated. Performance increased when firms synchronized their alliances with competitors' alliance initiatives. However, synchronization of M&As with competitors did not enhance performance. Our research identifies an important venue for corporate managers to rethink the way they design and coordinate repeated cycles of M&A and alliance activities.

2.0 THEORETICAL BACKGROUND

2.1 THE SOCIAL ENTRAINMENT FRAMEWORK AND STRATEGY

The social entrainment model was borrowed from the biological sciences, in which the notion of entrainment refers to one cyclic process being captured by, and setting to oscillate in rhythm (or variability of activity change rate) with, another process. McGrath and Kelly (1986) were among the first to introduce the entrainment model in social science. The social entrainment model specifies that psychological and behavioral cycles can become entrained to other social or environmental processes. For example in universities, the academic calendar and faculty teaching/meetings are entrained. As McGrath and Kelly stated, “the social entrainment model provides a coherent framework for describing the operation of rhythmic process, their coupling to or synchronization with one another and potentially to outsider cues” (McGrath & Kelly, 1986, p 80).

Incorporating strategic activities, such as M&A and alliance within the social entrainment framework allows strategy scholars to leverage a temporal lens in at least four ways. First, studying temporal constructs such as variability of change rate and synchronization addresses the fundamental concerns of strategy, i.e. how firms behave and why firms differ? (Rumelt, Schendel, & Teece, 1994). In particular, a temporal view that emphasizes the role of variability

and synchronization suggests a past-present-future link (when to do) and is in line with the conceptualization of strategy as emergent, dynamic, logically incremental, path dependent and patterns of interaction (Mintzberg, 1990).

Secondly, the entrainment model can address rhythmic-type processes within firms as well as the interaction between firms and their environment. Therefore, it serves as a theoretical foundation for studying multiple activities and multi-level phenomena that are called for in strategy research (Pettigrew, 1992). M&A and alliances can be viewed as two separate activities that have different momentums, variability, and trajectories. Alternatively, viewing M&A and alliances as internally embedded is consistent with the call for an explicit understanding of multiple activities at the same level of analysis (Pettigrew, 1992). Alignment between activities, as Powell (1992) concluded, can become a competitive advantage. In our case, performance difference can also be linked to higher levels of analysis— the competitive environment in that multiple M&A and alliances can be observed at both the firm and industry levels.

There are different ways that M&A and alliance activity can be mapped with time. Ancona and her associates (2001b), identify four types of activity mapping with time². According to their classification, prior studies in the M&A and alliance domain mainly focus on single activity (transformation) mapping where key constructs of interest include duration, endurance, and trust (Inkpen & Currall, 2004). Other categories such as repeated activities mapping is less studied. The repeated activities category reflects the reoccurring nature of M&A

² They are 1) single activity mapping to the continuum; 2) repeated activity mapping of the same activity multiple times on the continuum; 3) single activity transformation mapping of change processes, where one activity changes in character in response to a marker; 4) multiple activity mapping of two or more activities on the continuum; and 5) comparison and meshing of multiple temporal mappings with one another (Ancona, Okhuysen, & Perlow, 2001 p 515).

and alliance initiatives over a firm's history. Two examples are Halebian and Finkelstein's (1999) examination of acquisition frequency and Hayward (2002) study of the interval between repetitions of acquisitions. Our approach explores the meshing activity category, where multiple M&As and alliances are studied simultaneously allowing us to study internal and external synchronization.

Thirdly, an entrainment view that stresses a rhythm-driven M&A and alliance approach complements the conventional opportunity driven approach. A rhythm-driven approach is based on an assumption that managers purposely plan and implement M&A and alliance activities. In large corporations, corporate development offices staffed with analysts often assume this role (Kale, Dyer, & Singh, 2002). In the context of small and medium-sized firms, corporate development offices are not common or economically feasible. However, small and medium-sized firms are likely to adopt a rhythm-type M&A and alliance approach under two often interrelated circumstances. First, for firms whose growth strategies are mostly driven by M&A and alliance initiatives one would expect to see such an approach. Second, firms who lack capability or resources for internal growth development would adopt a rhythm-based approach to M&A and alliances. In our setting, specialty pharmaceutical firms need to develop therapeutic product and relevant skill sets such as protein and gene-based technology. Either as a conscious choice or due to limited resources many small and medium sized firms have not developed capabilities to internally develop new products. As a result, these firms will proactively search for targets and allying partners rather than passively wait for M&A and allying opportunities to emerge. Our approach is consistent with and complements the opportunity-driven approach. We

suggest that corporate managers might develop a mindset to proactively seek partners or targets and infuse a rhythmic-type M&A and alliance initiatives into their routine system.

Lastly, the notion of entrainment provides a fresh perspective for the static vs. dynamic strategic fit debate (Zajac, Kraatz, & Bresser, 2000). The entrainment view asserts that activities are embedded, interdependent and, to some extent, fit should be achieved by matching different activities along the time dimension. This serves two purposes to help clarify the fit debate. On the one hand, incorporating time directly allows for an understanding of the dynamics of why and how outcomes are differentially shaped by multiple ongoing activities. Second, we argue that fit has an inherent temporal characteristic that influences and is influenced by multiple activities within and external to systems.

The social entrainment model employed here focuses on three temporal constructs, namely, the *variability* of M&A and alliance change rate, *internal synchronization*, defined as the variability synchronization between alliances and M&As within firms, and *external synchronization*, defined as variability synchronization between M&A and alliance activities of focal firms and their competitors.

2.2 WHAT DOES VARIABILITY AND SYNCHRONIZATION MEAN IN M&A AND ALLIANCE ACTIVITIES CHANGE RATE?

To organizational theorists, rhythm-type activities refer to the variability of the frequency of organizational activities (Huy, 2001) or the nature of cycles that periodically repeats (Ancona & Chong, 1996). Clearly, variability is a time construct that characterizes repeated activities

mapping. In the M&A and alliance context, variability emphasizes the recurring nature of such frequency, i.e. the pattern of variability in the frequency of M&A and alliance initiatives. To this end, our major focus in discussing the rhythm-type M&A and alliance initiatives is the variability, consistence and regularity of the pattern across a specified time period.

In biology, the study of rhythm-type behaviors has a long history. Many biological processes undergo regularly recurring quantitative and qualitative change. These processes are “repeated with such beat-like regularity that the processes are referred to as being rhythmic” (Brown, Hastings, & Palmer, 1970, p 1). For instance, bean seedlings which raise their leaves in daylight and lower them at night. Biologists are confronted with the question: what is the origin of the rhythmical behaviors? Although there is no rigorous physicochemical explanation, two conjectures of rhythmic-type activity have emerged (Oatley & Goodwin, 1971) and we will draw on them for our synchronization hypotheses. The intrinsic view (cellular biochemical clock hypothesis) suggests that it is an essential dynamical feature of the observed process. The fundamental periodicities in living systems are the cycle of growth and division in cells, which need bear no relation to any environmental periodicity. The extrinsic perspective (Hypothesis of environmental timing of the clock), on the other hand, maintains that such rhythm-type behaviors represent adaptive responses to a periodic environment such as solar or lunar system. For instance, Oatley and Goodwin (1971, p 7) argued “the most intensively studied of these phenomena are the 24-h rhythms relating to the solar day and 12 h tidal rhythms in marine organisms”. Biological scholars tend to agree that complicated periodic organisms can be understood as partly adaptive and partly of internal origin.

The origins of rhythm-type activities in corporate strategic actions can be understood in a similar way since the physiological processes of biologic organisms can be applied reasonably well to psychological processes of individual decision makers or to social-psychological mechanisms at the interacting dyads, groups or even larger organized social units (McGrath & Kelly, 1986). Internally, a rhythmic-type M&A or alliance pattern can be formed through multiple means over time. It can be influenced and shaped consciously by a top management team whose members have some sort of rhythmic-type orientation intended to achieve economic efficiency. Individuals who are more rhythmic will be more likely to reflect such a mindset in their actions. For example, major PC manufacturers release upgraded products at Christmas time each year in order to take advantage of newly released versions of software (i.e. Microsoft: games) or hardware (i.e. Intel: memory chips). Events such as annual strategic planning create ‘repetitive momentum’ providing a time-based routine for managers to reconsider or revise their M&A or alliance behaviors. In the case of small-medium size bio-pharmaceutical firms, M&A and alliance activity is largely driven by sales gaps³. As a result, the overall level of M&A and alliance is not stable over time, with periods of sped-up activity and slowed down activity that is consciously driven.

From an external perspective, the variability of M&A and alliance initiatives may be captured or entrained by external cyclic phenomena often reflected in isomorphic behavior. For instance, Jansen and Kristof-Brown (2005) reported that an individual’s working variability matches their working environment’s variability. Souza and associates (2004) found that the optimal variability of new product introduction is primarily driven by external industry

³ We thank George Lasezkay, a former Corporate Vice President, Business Development at Allergan, for identifying this rationale during our interview.

condition. M&A and alliance initiatives can also be captured by external competitive dynamics such as competitor initiatives or regulatory change (Brown & Eisenhardt, 1997).

Building on the internal and external drivers of rhythm-type activity the main feature of these behaviors is revealed in stability properties as opposed to duration, magnitude, and frequency. The degree of stability or regularity differs across organizations. This can be understood in two extreme examples consistent with the resource based view that resources and capabilities are distributed heterogeneously among firms (Barney, 1991). On one hand, firms may conduct M&As or alliances without deliberate plotting along the temporal dimension, demonstrating a purely random or high variability process. On the other hand, firms may perceive time as a variable that can be purposely designed and effectively managed, making M&A and alliance activity a temporal regularity within which the pattern persists over time. In other words, firms differ in their capability to design their corporate strategy with respect to time. To this end, we suggested to focus directly on time as a theoretical and empirical construct rather than as a proxy for other constructs. Even Dierickx and Cool (1989) also recognized that time itself—not its proxy—may be an important input into capability creation process. Most firms clearly will not fall at the extremes of pure random or pure regularity. The differentiated variability pattern among firms reflects the underlying combination of firms' distinctive capabilities including, but not limited to top management team, strategic planning, environmental scanning systems, history and managerial intent or vision regarding.

Like the concept of variability, the notion of synchronization is largely derived from biological science. The intrinsic and extrinsic view of entrainment suggested that synchronization can occur both internally and externally. Within an organization, multiple

processes are entrained with each other (i.e., synchronized) through conscious decision processes, coordination, repetitive momentum and isomorphic mechanisms (McGrath and Kelly, 1986).

Social behavior can be entrained/synchronized to powerful external pacer event or cycles. However, external pacer events or cycles should be understood from an ontological assumption of co-evolution rather than an assumption of independence of the firm and its environment (Volberda & Lewin, 2003). We cannot understand these external pacers by separating them on their own since these exogenous forces are often endogenized over time.

3.0 HYPOTHESES

3.1 VARIABILITY AND PERFORMANCE

Variability of M&A and alliance rate can affect performance through its ability to coordinate internal events (Goodwin, 1970) or increase the predictability and hence the control of human behaviors. Essentially, variability creates a dominant temporal order and reflects “the underlying dynamic equilibrium processes by which the many aspects of complex social systems” (McGrath & Kelly, 1986, p 89) or a series of repeated activities are coordinated.

As argued above, neither a consistent nor an irregular variability of M&A and alliance rate will influence performance positively. An effective variability of M&A and alliance rate requires organizations to alternate between regularity and irregularity. This suggests that organization can experience a regular variability of M&A and alliance rate for a period of time and then adjust their rate thereafter. From learning point of view, a regular or consistent pattern of corporate strategic actions is an effective strategy to coordinate learning processes across a series of repeated M&A and alliances (Hayward, 2002). Regularity can allow companies to absorb knowledge in a habitual temporal order and over time can facilitate the formation of a routine that is an essential element to managing uncertainty. However, regularity seldom allows companies to modify or revise their existing variability strategy and is prone to generate inertia

(Carroll & Hannan, 1990). With an orderly and consistent pattern of strategic actions, firms fail to recognize whether their current rhythm-type behavior is the most optimal. Minor adjustments can serve as a benchmark against which an existing variability can be compared, revised, and modified. A modification may also serve the purpose of time-brackets associated with learning processes, indicating that it is time to switch attention or to reach an end point of previous learning variability.

From a resource availability perspective, a consistent variability of M&A and alliance rate allows companies to coordinate resource allocation processes in line with M&A and alliance activities. Vermeulen and Barkema (2002) found that organizations with regular expansion patterns can utilize but do not overstretch their absorptive capacity. As they posited, a rhythmical pattern characterized by consistency and predictability may reach a state of ‘flow’, suggested by Brown and Eisenhardt (1997), all of which is not available to firms that follows an unpredictable expansions path. Predictability indeed increases the efficiency and volume of absorptive capacity (Vermeulen & Barkema, 2002). It also makes the resource allocation process more predictable and hence alleviates pressure from unexpected capital investment needs. For instance, Laamanen and Keil (2008) argued that predictability of acquisition rate can contribute to a smoother utilization of managerial capacity—one of the key resources in M&A initiatives. On the contrary, an uneven peak in the volume of M&A—unpredictable variability of M&A rate will push the firms to their capacity limits (Shaver, 2006), particularly considering that M&A and alliance-related managerial capacity cannot be increased or expanded significantly during short period of time, or even may not be possible in the long run (Penrose, 1959). However, a regular or predictable variability of M&A and alliance rate reduces the diversity of absorptive capability.

Regular repetition of similar activities with a fixed variation implies a logic of linearity (Geibler, 2002) and continuity, neither of which is essential building block for creativity. The development of creativity is not released by “a series of points and steps that follow one another in a regular fashion” (Geibler, 2002, p 134). Creative resource allocation processes require freedom, flexibility, and diverse forms of absorptive capability

In addition, unlike many internal initiatives which can be shielded from competitors’ attention, M&A and alliances are corporate actions easily caught by competitors’ radars. M&A and alliances can be interpreted by competitors as a preemptive strategy to occupy a market or to acquire valuable resources. From an action and reaction point of view (Grimm & Smith, 1997), a regular pattern of M&A and alliances reduces within-firm variability (unpredictability) and hence the complexity of a firm’s sequence of competitive actions over time. In contrast, regular patterns coupled or alternated with adjustment and modification can increase the possibility of surprise actions, therefore limiting a competitor’s ability to map action and reaction cycles in an accurate way. Simply put, *semi-predictability* generates the highest level of performance. To illustrate the concept of variability of M&A and alliance rate, we depict two contrasting pictures to demonstrate the difference between low variability (predictable, and consistent) and high variability (random, unpredictable) of M&A and alliance rate from firms in our sample.

Insert Figure 1 about here

Hypothesis 1: Variability of M&A and alliance change rate has an inverted-U relationship with performance. i.e. a moderate level of variability (neither regular nor irregular(random)) of combined M&A and alliances initiatives rate generates the highest level of performance.

The above argument rests on the assumption that our sample of pharmaceutical firms bundle their M&A and alliance initiatives under the guidance of corporate office. An alternative view suggests that M&A and alliance are unbundled (not coordinated). For this reason, we also examine M&A and alliance separately in our empirical setting.

3.2 SYNCHRONIZATION OF VARIABILITY WITH THE EXTERNAL ENVIRONMENT

External rhythm entrainment is defined as the congruence of variability between firms and their external environment. Despite scholars' call for an understanding of rhythmic-type activity compatibility, little research has examined how synchronization of variability impact firm performance. Jansen and Kristof-Brown (2005) found that congruence of variability between individuals and their working environment can significantly influence individuals' job satisfaction and their psychological stressfulness. At the firm level, firms may experience similar effects when they fit/synchronize their variability to the competitive environment.

While variability helps to coordinate internal events (Goodwin, 1970) external rhythmic compatibility can create a coordination interface between focal firms and their environment. Such congruence is more likely to be "satisfying" to firms since it creates order and coordinated interaction patterns out of chaos. It also is a "strain-reducing mechanism because it imposes less of a burden on an individual firm to attend to discordant external stimuli" (Jansen & Kristof-Brown, 2005, p 95). These effects are transformed into a sense of control with respect to the

external environment. Therefore, external synchronous variability reduces focal firms' uncertainty and increases their predictability about the external environment, which will further transform into increased control over key resources from the environment (such as experienced managers with sufficient knowledge in M&As or alliances—assuming these critical resources are in consistently in short supply due to the nature of path-dependency when accumulating or development these resources. In other words, synchronizing firms' variability of M&A and alliance with competitors will, to some extent, alter the dependence relationship between focal firms and their competitors by minimizing their own dependence or by increasing the dependence of their competitors on them (Pfeffer & Salancik, 1978).

Variability compatibility between firms and the external environment also validates behaviors in a mutually reinforcing manner through which firms feel comfortable about “social norms” (Jansen & Kristof-Brown, 2005). For instance, Williamson and Cable (2003: p 350) argued that “when focal firms face strong ambiguity about the environment, they are more likely to be motivated to monitor the actions of other organizations in their field in an effort to find viable solutions to organizational issue”. In particular, the alignment of a firm's variability of M&As and alliances with competitors can influence performance through its impact on the perception of other stakeholders (i.e. major shareholders, Wall Street analysts, etc). Our argument is also slightly different from the logics of institutional theory which predicts that performance will decrease when firms mimic and follow their competitors' actions (DiMaggio & Powell, 1983) due to bandwagon effect—firms are less likely to fully access the targets or partners and act in a rational manner (Song & Walkling, 2000). For serial acquirers or firm with alliance portfolio program (i.e. firms conducted multiple M&A or alliances), the proactive nature

of their acquiring or allying behaviors have been well interweaved into their internal routines. Therefore, these firms will less likely suffer from cost of “irrational” bandwagon effect. For instance, McNamara et al (2008) found that acquisition routines will help generate procedural memory that focuses on general acquisition issues, such as target value assessment and strategic fit rather than on the identification of the emerging opportunities that drive the acquisition bandwagon behavior. ,

Hypothesis 2: Firms that synchronize their variability of combined M&A and alliances initiatives change rate with that of their competitors achieve higher levels of performance.

Again, we also investigate the unbundled initiatives that separate M&A and alliance.

3.3 INTERNAL SYNCHRONIZATION OF VARIABILITY BETWEEN M&A AND ALLIANCE

While external variability compatibility allows firms to better control their environment and increase the accuracy of predicting the future, internal variability congruence can achieve a similar goal, i.e. more control over and predictability of the internal environment. McGrath and Kelly (1986, p 90) argued that internal synchronization of variability will result in a “dynamic equilibrium” in which specific process patterns, that constitute a balanced or steady state, change over time and do so in systematic ways. Such a “dynamic equilibrium”, in our view, can be achieved in two ways in the cases of M&A and alliance initiatives. In Figure 2, we demonstrate synchronization of M&A and alliance graphically.

Insert Figure 2 about here

First, when M&As and alliances initiatives proceed simultaneously within a firm, it can establish a minimum levels of overlap between each activity. Such an overlap establishes a foundation for information exchange between M&As and alliances. For instance, knowledge acquired from experiential learning in M&As can be shared and utilized in experiential learning of alliances if the underlying knowledge structure (such as target/partner selection) of M&As and alliances are similar. Knowledge from each type of activity can cross-fertilize, spillover or reinforce the value of the other (Zollo & Reuer, 2001) creating repetitive momentum. This type of logic has been empirical examined in the product development literature where Lilly and Walters (1997) reported that pairing two new product development efforts can generate numerous benefits such as timely information sharing, building interest and demand for the new product, and obtaining feedback from customers.

Second, Albert (1995) argued that the synchronization of multiple activities can strengthen their cumulative effect. It creates a heightened sense of beginning or of ending for organization members. Our arguments go beyond that. We suggest that such a heightened sense of time can create an institutionalized temporal map for members to adhere to and coordinate with. This will result in advantages over firms who did not synchronize their internal M&As and alliances. On one hand, internal variability compatibility smoothes the resource allocation process through deploying resources to the “right activities at the right time”. The combined effect is far from additive or cumulative, but rather interwoven in a systematic order, which creates complexity for competitors to understand and predict. On the other hand, a synchronized variability of internal activities speaks to the resource based view, i.e. the pattern of

synchronization becomes an integrated element within firms' activity systems that jointly, is hard to imitate, socially complex, and causally ambiguous.

Hypothesis 3: Firms that internally synchronize their variability of M&A change rate with variability of alliances change rate achieve higher levels of performance.

4.0 METHDOLOGY

4.1 INDUSTRY CONTEXT

We define specialty pharmaceuticals as those firms that mainly deal with expensive medications that treat rare, chronic diseases inflicting a small proportion of people (Employee Benefit News. 2005). Those special diseases include but not limited to Heophilia, Hepatitis C, Ocology, HIV/AIDs and transplant, which usually have been classified as an orphan disease⁴. The companies in our sample typically occupy a niche market that was either ignored or neglected by large pharmaceutical firms. In this study, we adopt a broad definition of specialty pharmaceutical firms to also include generic drug firms into our sample. From a market niche perspective, these generic firms have positioned themselves in a niche market where big pharmaceutical firms have either been unable to or not been willing to compete. Our inclusion of generic firms is not without validity. For instance, Banc of American has a specialty pharmaceutical report that includes both specialty firms and generic drug companies.

The specialty pharmaceutical sector is a rapidly growing market with annual increase of 43% from 2002 to 2005, a much faster pace than the 10.2% average increase in drug spending in

⁴ For instance, in United States, if a particular disease has less than 200,000 people with that condition; that is classified by the federal government as an orphan disease. We thank Dick Rylander, former president and founder of biopharmaceutical Strategies, LLC to bring this issue up.

general (Mergers & Acquisitions Report, 2006). The growth of specialty drug is particular strong in U.S. It is estimated, by 2010, specialty drug spending in the U.S. could reach \$99 billion by 2010, nearly double the \$54 billion spent in 2006 (Wall Street Journal, 2008). The fast growing specialty drug industry is largely due to 1) big pharmaceutical firms' lack of interest or ignorance of niche market, 2) the change of patient trend (i.e. from acute therapy to chronic therapy), 3) released resource space in different therapeutic areas due to intense competition among giant generalist pharmaceutical firms, and 4) the development of supporting industries and agencies (i.e. venture capital industry and government regimes), 5) higher profit markup due to high price (usually as much as 250% of its cost).

The competitive arena in the specialty areas is quite different from that in traditional pharmaceutical field. The industry is rather young and firms within this particular industry compete in several ways. For public firms, they are competing for public investor, so their stock prices will go up. They also compete for strategic partners--the big pharmaceutical firms, which is also a form of financing. For instance, they compete for strategic partners for the purpose of funding their clinic three stage testing on large human population⁵. In addition to that, they also compete for large pharmaceutical firms' collaboration for marketing or manufacturing their in-house products. Meanwhile, specialty drug firms also compete for acquisition target in an attempt to generate financial capital to support their other developments. Since the number of partners and targets is limited, a proactive allying or acquiring strategy is highly important for

⁵ Typically, there are four stages in the development of drug, one pre-clinical stage and three phases of clinical trials. Phase 1 is all about safety with a small number of people. Phase 2 is about beginning to show some efficacy. In Phase 3, firms should achieve statistically validity based on large population. The total cost of running phase 1,2,3 is in excess of a hundred million dollars. In particular, phase 1 and 2 may not be a major hurdle for most small specialty firms. It is phase 3 that is most costly and risky. If failed, the company's prospect will be quickly in jeopardy. Small specialty firms usually partner with large pharmaceutical firms to access latter' financial and human capitals to conduct phase 3 clinical trials.

firms to secure valuable, rare assets and resources and to timely access market information. As we discussed above, this also constitute a good setting for examining synchronization of M&A and alliance initiatives since these activities are likely to be captured by external competitive dynamics when an industry is highly competitive due to limited availability of partners or targets.

The motivation for acquisition and alliance is quite different for giant pharmaceutical firms from that of small and young specialty firms. For instance, generic drug firms usually desire to achieve instant economies of scale (i.e. manufacturing and administrative capacity) through acquisition rather than use excessive capacity due to patent expiration to acquire other pharmaceutical firms (which is common for large pharmaceutical firms) (Danzon, Nicholson, & Pereira, 2005). For small and young specialty drug companies, they prefer M&A strategy (purchasing marketed drugs, etc) to generate sufficient revenue in the hope that it can be used to fund their innovative projects. The motivation for alliance is also quite unique to small and young specialty drug firms. Most likely, they prefer to achieve commercial application of their in-house innovative technological capabilities and to engage in new activities (e.g. drug commercialization in global pharmaceutical markets). Since small specialty drug companies usually do not have downstream function, they have to draw on big-pharmaceutical firms to manufacture or market their products, particularly when markets for a specific drug are small due to the nature of the disease. Through this way, small and young specialty drug firms can significantly reduce their cost to search for policy requirements of pricing, reimbursement and promotional efforts in different markets and countries. To this end, it is important for small specialty drug firms to proactively maintain their acquisition and alliance initiatives rather than

wait for these opportunities to emerge. Therefore, the fact that these firms have limited functions along the industry value chain also establish a suitable context for studying temporal features such as variability and synchronization.

Furthermore, small specialty drug firms also cooperate with large pharmaceutical firms to obtain sufficient financial and human resources in an effort to conduct costly phase three clinical trials, which require statistically validity based on large population. To quote a senior pharmaceutical executive: “So you need data that shows that you have a lead chemical compound. And then you need to partner with somebody who’s got the resources to actually conduct that Phase 3 clinical trial. And that’s really been the model that all these companies now use. Get good data and then form a strategic alliance with somebody big, somebody who has deep enough pockets to bring the thing to market”. Recent research also shows that products developed in an alliance between small and large pharmaceutical firms tend to have a higher probability of success (i.e. getting approval eventually), particularly in more complex phase 3 trials (Danzon et al., 2005; DiMasi, 2000; Arora, Gambardella, Pommolli, & Riccaboni, 2000)⁶. In addition, large pharmaceutical firms also prefer cooperating with small specialty firms on developing phase 3 drugs, because the probability of success in phase 3 is usually 73% compare with 7% at pre-clinical stage, 23% at phase 1 and 33 at phase 2 (Fischette, 2004). These numbers also reflect the fact that the pharmaceutical business involves huge risk. The risk is usually much higher for small specialty drug firms than for giant pharmaceutical firms. If product development

⁶ On the contrary, Pisano (1997) argued the opposite, i.e. product co-developed in an alliance are less likely to succeed in clinical trials than drugs that developed by a single small firm. He proposed a “lemons” hypothesis that stressed the information advantages small firms have regarding their drug candidates. Danzon et al (2005: p7) argued that “the positive benefit from collaboration with a more experienced partner appears to dominate any moral hazard effect that might result from the sharing of gains in alliance, and any lemons or adverse selection effects”.

fails, the small specialty drug companies' prospect will be in jeopardy. It is important to develop a temporal strategy that emphasizes variability and synchronization in these industries setting since a well developed temporal routine can smooth out the risks in the long run.

Finally, small specialty firms' motivation to ally with large pharmaceutical firms is also related with transfer of status and signaling effect. Small specialty firms or young biotechnology firms suffer from liability of smallness and/or newness. The strategy literature suggested that they can increase their survival chance and access to external resources by gaining legitimacy via ties with prestigious businesses (Stuart, Hoang, & Hybels, 1999; Gulati & Higgins, 2003). In the competitive arena, small specialty firms compete for finance and investors' attention. Allying with a large pharmaceutical firm allow small specialty drug firms to send signals of their quality to financial markets under the assumption that there is information asymmetry between specialty firms and investors, and pharmaceutical firms can better evaluate the quality of these small specialty drug firms' technological know-how and managerial capabilities. This assumption is quite true particularly when small firms are operate in specialty domains where knowledge are quite specialized and therefore less likely be evaluated accurately by general public investors and venture capitalists. In other words, pharmaceutical firms, in this case, perform a validating function which is usually assumed by financial intermediaries (Nicholson, Danzon, McCullough, 2005).

We selected this industry for several reasons consistent with our theoretical logic. First, for small and young specialty pharmaceutical firms, their growth strategies are largely driven by M&A and alliances activities. As we mentioned above, the M&A and alliance growth-driven strategy provides an ideal context for firms to develop rhythm in these strategic initiatives. An

M&A and alliance growth-driven strategy allows firms to develop skills to facilitate and institutionalize a temporal map for their multiple M&A and alliance activities. Second, specialty pharmaceutical firms often do not possess the requisite complementary resources and knowledge for in-house development activities; they instead rely on partner firms for important resources such as finance, marketing and manufacturing (Lee, Lee, & Pennings, 2001)⁷. The lack of internal capabilities to develop these resources suggests that these firms are more likely to search for targets or partners proactively. Their M&A and alliance initiatives are less likely to be driven opportunistically. Third, small, young and specialized firms are regarded as a driving force for industrial renewal and innovation (Audretsch, 1995). Their survival environment is extremely dynamic and competitive advantage often accrues to those firms that can manage the temporality of their collaborative activities (Barkema, Baum, & Mannix, 2002). In particular, small and young firms have an incentive to adopt a synchronization strategy since these firms usually do not have deeply-rooted organizational inertia and are willing to follow their competitors' variability of M&A and alliance initiatives. In other words, these small firms, compared with giant pharmaceutical firms, have more discretion to organize the rhythm-type behaviors and their synchronization by design.

Finally, we also unpack our data to achieve a better understanding of the overall features of our sample firms' M&A and alliance initiatives. We find that on average, our sample firms conduct 0.32 acquisitions and 0.09 alliances a year, which is quite low compared with giant pharmaceutical firms (For instance, Abbott conduct 10 acquisitions in 2006). The low frequency context is actually important for us to study variability and synchronization strategy. A low

⁷ George Lasezkay, former Corporate Vice President, Business Development at Allergan also pointed this out during our interview.

number of acquisitions and alliances allows firms to more easily keep track of their temporal features such as variability. It also helps them synchronize their variability with competitors since the cognitive ability that is required for rhythm-type activity and synchronization does not pose a significant challenge in this context.

4.2 SAMPLE AND DATA COLLECTION

We developed several criteria to select our sample. These criteria are 1) the firms have value chain activities in the pharmaceutical industry (SIC 2834). 2) Through the search of company websites, annual reports and major pharmaceutical industry journals and proceedings, we identified key words such as special drug, specialty pharmacy, special patients need, niche etc that distinguish the selected firms from traditional pharmaceutical giants. 3) firms listed on either the NYSE or NASDAQ. This ensures that we have complete access to relevant financial data through COMPUSTAT. Our procedure generated 58 listed companies in the global specialty pharmaceutical industry (SIC 2834). There are two types of firms in this industry sector; 1) specialty pharmaceutical firms that produce expensive medications that treat rare, chronic diseases inflicting a small proportion of people, such as Gucher's disease and hemophilia (Employee Benefit News, 2005) and 2) Generic pharmaceutical firms that produce branded medications at a lower cost due to patent expiration, such as Watson and Teva. These two types of firms have a common defining characteristic, i.e. they all have limited product lines, due to either smaller market demand or limited availability of products whose patents are close to expiration. They occupy a special niche in the overall pharmaceutical market and compete in a

very different domain from the traditional pharmaceutical giants⁸. We control for the type of firm. To provide additional validity for our selection procedure, we had two pharmaceutical industry managers provide an assessment of the firms we selected. The correlation was 0.98.

We obtained alliances and acquisitions data from Thomson Financial Security Data Company's (SDC) database. The SDC database has been extensively used in alliance (Carow et al., 2004), and M&A (Oxley & Sampson, 2004) research. The time period for our study spans the years 1985 to the end of 2003 because the SDC dataset has more complete information coverage after the middle 1980s. During this period, two important events occurred in the U.S that shaped the evolution of specialty pharmaceutical industry. The first was the enactment of Orphan Drug Act in 1984 that created incentives to encourage manufacturers to develop products for diseases affecting relatively small numbers of patients. Following the act's passage, many drugs were developed and introduced addressing these relatively rare diseases. The second was the U.S Drug Price Competition and Patent Term Restoration Act, informally known as the "Hatch-Waxman Act", also enacted in 1984, for the purpose of standardizing U.S. procedures for recognition of generic drugs.

Although the SDC database is far from perfect, it nevertheless is the most comprehensive source on alliances and M&A announcements compared with other databases. We used annual reports and (10-Ks) to corroborate data obtained from the SDC database. Therefore, we are confident that our data derived from the SDC accurately reflects the M&A and alliance activity for our sample firms.

⁸ An alternative view would be a dynamic interplay between specialists and generalists during the resource partitioning process (Carroll & Hannan, 1990). Given the fact that most resources partitioning processes often take extremely long periods of time, our 19 years dataset will not reveal such a process.

We established the following criteria to select alliance and M&A deals; 1. Only completed deals are included. We delete cases that were pending, intended or ambiguous (rumor). 2. For M&A, we do not include cases that suggest self tender (stock buyout). 3. The target in an acquisition is either a firm that has legal entity, or a specific product line or division. Finally, we obtained financial data from COMPSTAT industry annual database and information regarding firms' growth stage through interviews with industry experts, industry journals, annual reports and company websites.

One caveat is that we do not include internal development initiatives because firms in our sample are likely to base their growth strategies on M&A and alliance initiatives due to their lack of internal development capabilities and resources. Nevertheless we use R&D intensity as a proxy for the opportunity for internal development to control for its potential impact.

Our final sample consists of 57 listed firms ⁹ with 421¹⁰ observations over the period 1985 to 2003. Since some of our sample firms were established after 1990, not every firm has coverage of nineteen years. Our method accommodates this reality.

⁹ We drop 1 firm because it was obviously a division (subsidiary) of a larger diversified company.

¹⁰ We used 373 observations in regression since we lagged our dependent variable for 1 year.

4.3 VARIABLES AND MEASURES

4.3.1 Independent Variables

Variability of M&A and alliance change rate. We measure variability of M&A and alliance rate in two different ways in to order to establish construct reliability. First, we measure it through the kurtosis of the first derivative of the number of M&As and alliances over time. This measure has been used in international management literature where scholars examine foreign expansion process (Vermeulen & Barkema, 2002). The kurtosis of distribution is as follow:

$$kurtosis = \left\{ \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \left(\frac{x_i - x_m}{s} \right)^4 \right\} - \frac{3(n-1)^2}{(n-2)(n-3)}$$

Where n=number of observation, x_i = number of strategic actions (M&A and alliances) in year i , and s = standard deviation of the number of strategic actions. Higher kurtosis means more of the variance is due to infrequent extreme deviations, as opposed to frequent modestly-sized deviations. Therefore, a very regular and constant variability of strategic actions will result in a relatively flat distribution and therefore a lower kurtosis (called platykurtic, a distribution which has a smaller "peak" around the mean). In contrast, purely random pattern of strategic actions will result in a high value of kurtosis measure (called leptokurtic which has a more acute "peak" around the mean).

Second, we use the number of M&A and alliances as a dependent variable and regress it on time over the period 1985 to 2003. We then divide the standard error of the regression slope coefficient by its mean value (Dess and Beard, 1984). This measure reflects the dispersion about

a trend line when controlling for the absolute number of M&As and alliances of each firm. An advantage of this measure is that it takes the ordering of data points and the trend line of time into consideration, which is theoretically in line with our focus of time as a causal variable.

Internal Synchronization. The concept of internal synchronization methodologically, is similar to the perspective of organizational alignment or strategic fit (Venkatraman, 1989) We adopted the “fit as matching” perspective and choose the corresponding deviation score analysis as an analytic tool for two reasons. First, Powell (1992) argued that when variables are endogenous or when they are subject to managers’ design or control the “fit as matching” perspective is preferable. The variability of two internal processes, namely M&A and alliances, can plausibly be interpreted by managers from a matching perspective. Second, the concept of entrainment implies that different processes adopt similar variability.

The deviation score analysis method is based on a premise that the absolute difference between the scores of two variables indicates a lack of fit and the performance implications of fit is therefore tested by examining the impact of this difference (Venkatraman, 1989, p 431; Venkatraman & Prescott, 1990). A formal equation is as follows:

$$Y = a_0 + a_1X + a_2Z + a_3(|X - Z|) + \varepsilon$$

Where X is the variability of M&A, Z is the variability of alliance. If a_3 is negative and statistically significant, then a “fit as matching” hypothesis is supported.

External Synchronization. Because our measure of competitors’ variability is created by averaging the variability of proximal competitors (in terms of stage of firm development), the reliability of the difference score is reduced because the focal firm’s variability may share some variance with its competitors’ variability. Under this situation, polynomial regression analysis is

a better alternative to difference score analysis (Edwards, 2002). In essence, polynomial regression replaces differences scores with a component measure that constitute the difference and higher-order terms such as the squares and product of these measures (Edwards, 2002, p 2). The polynomial regression takes the following form:

$$P = b_0 + b_1R + b_2C + b_3R^2 + b_4RC + b_5C^2 + \varepsilon$$

in which P represents firm performance, R is firm's variability of acquisitions (alliances), C is the competitors' level of variability of acquisitions (alliances).

Because competitors' variability is a higher level of analysis than the focal firm, we, therefore, incorporated the polynomial regression model within hierarchical linear modeling (HLM) to control for the shared variance in the measures of the competitors' variability—a technique that scholars refer to as cross-level polynomial regression (Jansen & Kristof-Brown, 2005). The resulting set of HLM equations were specified as

$$\text{Level 1 equation: } P_{ij} = \beta_{0ij} + \beta_{1ij}R + \beta_{2ij}R^2 + r_{ijk}$$

$$\text{Level 2 equation: } \beta_{0ij} = \beta_{00j} + \beta_{01j}C + \beta_{02j}C^2 + \mu_{0ij}$$

$$\beta_{1ij} = \beta_{10j} + \beta_{11j}C + \mu_{1ij}$$

$$\beta_{2ij} = \beta_{20j}$$

Level 3 equation:

$$\beta_{00j} = \gamma_{000}, \beta_{01j} = \gamma_{010}, \beta_{02j} = \gamma_{020}, \beta_{10j} = \gamma_{100}, \beta_{11j} = \gamma_{110}, \beta_{20j} = \gamma_{200}$$

The HLM model statement indicates that performance was influenced by focal firms' variability of M&A and alliance rate, their competitors' variability of M&A and alliance rate, their product and their square term respectively. The cross-level equations also suggested that the

data were nested by year (level 3 equation) and stage of firms (level 2 equation), i.e. firm-year observations were nested within year, which were further nested within firm stages.

4.3.2 Dependent Variable

Performance. Researchers investigating firm performance in the pharmaceutical industry have used a variety of measures: ROE, ROS, new product development and patents (Rothaermel, 2001; Nerkar & Roberts, 2004). We use the market-based financial performance measure Tobin's Q, computed as the sum of market value of equity (common shares outstanding x the closing stock price), the liquidating value of preferred stock, and the book value of debt divided by the book value of assets (Chung and Pruitt, 1994) for two reasons. First, many of our sample firms are relatively young (around 20 years) compared with most pharmaceutical giants because specialty pharmaceuticals is a recent phenomenon. In fact, many specialty pharmaceutical firms generate negative return in their early years, which is normal for most young organizations. Therefore, performance measures based on return on sales, equities, or assets do not accurately capture the ability of these organizations to create value. Our interview with pharmaceutical industry experts also lends support to this argument. For instance, George Lasezkay, one of our interviewees, noted that *“many of these companies go public and they don't have commercial infrastructures. They are still conducting largely R&D. So now how did you measure what it is their performance? And to me, about the only way to do that before they become commercially oriented is: has the stock price gone up as a result of it? or are the shareholders happy?”*

Second, the Tobin's Q ratio reflects a firm's ability to create efficiency. It aims to measure a company's strategic performance (Chakravarthy, 1986) which is in line with

investors' and other stakeholders' perceptions of a firm's value creation. To facilitate causal inference, we lagged Tobin's Q by one year¹¹. Tobin's Q tends to be skewed (the normality assumption is violated), we therefore use a log transformation. As a robust check, we include ROA (with one year lead) as a performance measure and expect non-significant results.

4.3.3 Control Variables.

We measure firm size by asset (log)¹² since previous studies have indicated that firm size can influence firm performance (Skaggs & Youndt, 2004). Tobin's Q is strongly influenced by firms' growth potential. Firms with higher growth momentum are perceived by investors as valuable and more profitable in the long run. We therefore use the percentage of asset growth in year i compared with year $i-1$ to capture this effect¹³. We also control for internal development measured by R&D intensity¹⁴. In addition to that, we also use patent as a proxy for internal development in lieu of R&D intensity. Our results do not change significantly. We found patent is highly correlated with R&D intensity ($\gamma_{pr}=0.89$). We, therefore, only include R&D intensity in the final results¹⁵. The life cycle stage of a firm may impact its market value. Firms in the emerging stage are subject to liability of newness and are vulnerable to environment selection. Specialty pharmaceutical firms in the emerging stage may have potential blockbuster products

¹¹ We also use three year forward moving average Tobin's Q (log), results do not change significantly.

¹² We also replace asset with number of employee (log), no significant change was found.

¹³ We also use growth of sales and the number of employee. The results are the quite similar. Since sales and assets are highly correlated, we only report asset in our analysis.

¹⁴ We use 1 year and three year moving average of R&D intensity. Results do not differ. We reported 1 year in the result section.

¹⁵ The results are also in consistent with our interview with George Lasezkay, former Corporate Vice President, Business Development at Allergan. He pointed out that the key is to achieve market exclusivity, while patent is just one way to achieve that and companies can have lots of other way to do it.

that have extremely high market uncertainty. We controlled for inter-temporal trends with year dummy variables. We also control for firm's acquisition and alliance experience. We measure experience by the accumulated number of acquisition and alliance each firm conducts each year. The remaining controls include profitability measured by return on assets (For models that use Tobin's Q only), debt-to-equity ratio as a measure of financial leverage, and product characteristics (whether it produces branded or generic products). We control for industry effects using a dummy variable since some of our sample firms' primary SIC code is not 2834. Finally, to eliminate the alternative hypothesis that Tobin's Q is driven by the overall market, we use the *Dow Jones* index to control for overall stock market movement.

4.4 DATA ANALYSIS

To test hypotheses 1 and 3, we analyze our panel data using feasible generalized least square (FGLS) regression. FGLS regression can deal with autocorrelation within panels (AR1) and heteroskedasticity across panels (Greene, 2000)^{16 17}. We prefer FGLS for two reasons. First, it is only appropriate to use GLS estimator when a sample has a large number of panels relative

¹⁶ In stata, we use the option corr (ar1) force and panel (hetero) to model both autocorrelation and heteroskedasticity effects. We did not model cross-sectional correlation effect since it only makes sense to assume that the error terms of panels are correlated when panels are balanced and when the number of time period is greater than the number of panels.

¹⁷ Since the number of observations for each firm is not the same in our sample, the panel dataset is therefore unbalanced. To take this information into account, we use the xtpcse function and np1 option in Stata. These functions calculate panel-corrected standard error (PCSE) estimates for linear cross-sectional time-series models where the parameters are estimated by Paris-Winsten regression and specify that the panel-specific autocorrelations are weighted by the number of observations in each panel (Greene, 2000). These results differ little from the results of FGLS estimation. We therefore concluded that the unbalanced panel does not pose a major threat to the validity of our results. Only results from FGLS model are reported.

to time periods¹⁸(Stata, 2005). Second, the FGLS estimator addresses more complex heteroskedasticity problems¹⁹ compared with GLS estimator. In particular, when we test different scores between variability of M&A and alliance, each firm may have a different number of M&A and alliances. This results in more complex heteroskedasticity issues which arise from different variances among firms in addition to non-constant variance over time.

To test non-linear relationships, we use the square term of variability. For hypotheses 1 and 3, we test models using Tobin's Q (Model 1-7) and ROA (Model 8-14). To test Hypothesis 2, as stated above, we use cross-level polynomial regression to control for the shared variance in the measures of competitors' variability. We also use three-dimensional surface plot analysis to graphically demonstrate the precise nature of the relationship between variability of focal firms, variability of their competitors and performance.

¹⁸ We have around 40 panels and each has average 10 years time periods, in which case FGLS estimator is better.

¹⁹ GLS estimator only deals with basic heteroskedasticity problem that is relevant to panel data per se, i.e. assuming each firm has different value of mean, but same value of variance, although such a variance is not constant over time.

5.0 RESULTS

Table 1 presents the correlation matrix and descriptive statistics. With the exception of variability of M&A and alliance rate and its square term there are no extremely high correlations. We use the centering solution to reduce multicollinearity among variability of M&A and alliance rate and its square. For all models testing curvilinear relationships between variability of M&A and alliance rate and performance, we subtract the mean from the variability variable value before creating the product terms. The average VIF is 2.84 (Max: 8.23, Min: 1.04), which is lower than the threshold level 10 for the presence of multicollinearity (Chatterjee, Hadi, & Price, 2000). The results of Hypotheses 1 and 3 are presented in Table 2.

Insert TABLE 1, 2 about here

Hypothesis 1: Does variability have an Inverted U-shape Relationship with Performance?

We find support for hypothesis 1. Model 1 is the base model. The variability variable is in model 2 and its coefficient is not statistically significant. However, when we put both variability of M&A and alliance rate and its square term in model 3, the coefficient for variability is positive and the coefficient for the square term is negative. Both coefficients are statistically significant ($\beta_r = 0.097$; $\rho < 0.001$; $\beta_{rs} = -0.011$; $\rho < 0.05$). Figure 3 demonstrates the

inverted U-Shape relationship^{20 21}. In general, the variability of M&A and alliance rate that is characterized by a mixed of regularity and irregularity achieves the highest level of performance. Neither a predictable or consistent variability of M&A and alliance rate nor an unpredictable or inconsistent variability of M&A and alliance rate generates superior performance.

Insert Figure 3 about here

While our theory is based on a curvilinear relationship between the variability of bundled M&As and alliances and performance, these initiatives can be viewed from an unbundled perspective. We, therefore, conducted supplemental analysis of variability of M&A and alliances separately in model 4 and 5.

Results in Table 2 and Figure 3 shows the curvilinear relationship between variability and performance is largely driven by M&A rather than alliances (In model 5: $\beta_{ac} = 0.112, p < 0.001$, $\beta_{acs} = -0.010, p < 0.01$). We discuss the implication of this finding below.

Hypothesis 2: If firms synchronize rhythms of their strategic actions with their competitors, will such an external synchronization increase performance?

We argued that when firms synchronize their rhythms with competitors, an external entrainment effect will enhance performance through uncertainty reduction and legitimacy enhancement. To test this hypothesis we use cross-level polynomial regression. We regress firm

²⁰ From Table 2, model 3, we obtain the following form of the model:

Tobin's $Q_{t+1} = \text{EXP} (1.679 + 0.002 * \# \text{ of acquisition} + 0.021 * \# \text{ of alliances} - 0.208 * \text{asset (log)} - 0.055 * \text{R\&D} - 0.286 * \text{roa} - 0.066 * \text{industry dummy} + 0.033 * \text{stage} + 0.036 * \text{growth} + 0.002 * \text{leverage} - 0.055 * \text{product characteristics} + 0 * \text{stock market index} + 0.097 * \text{variability} - 0.011 * \text{variability}^2)$. When calculating, we substitute the mean value for all variables into this expression except for variable variability and its square term.

²¹ When plotting the data, we use one standard deviation below and above the mean, which represents 95% of the sample [-1.682, 4.982]. However, the lower end of variable rhythm in our dataset is zero. We, therefore, use zero score instead of one standard deviation below the mean.

performance on the set of control variables and the five fit-related variables (Focal firm's variability, competitors' variability, focal firm's variability * competitors' variability, focal firm's variability squared, competitors' variability square). As in hypothesis 1, we examine the variability of both the bundled (Model 15) and unbundled M&A and alliance initiatives (Model 16 and Model 17). Table 3 reports the fixed effects estimates of the fit parameters. The slope and curvature along the lines of fit ($R = C$) and misfit ($R = -C$) were calculated using equations specified in Edwards and Parry (1993) and annotated in Table 3. Statistical significance of these slopes and curvatures was essentially determined by testing their linear combinations within SAS using CONTRAST statements.

To facilitate interpretation, we draw on response surface methodology (Khuri & Cornell, 1996), which permits precise description and evaluation of three dimensional surfaces corresponding to polynomial regression equations (Edwards & Parry, 1993, p 1578). In the graph in Figure 4 and 5 the fit line runs across the floor of the graph from front to back, and the misfit line runs across the floor of the graph from left to right.

Insert Figure 4 and 5 about here

Our hypothesis predicted that performance would be highest along the line of fit and lowest when focal firm's variability and competitors' variability differ. Results in table 3 reveal that the overall bundle of strategic initiatives does not show congruent effect, i.e. performance was not highest along the line of fit between firms' variability of bundled M&A and alliance and that of competitors (This was indicated by the insignificant coefficient of curvature along the misfit line in model 15). However, when we examine the unbundled M&A and alliance separately, we find congruent effect for alliance, but not for M&A. In model 16 (alliance), the

surface along the line of fit ($R = C$), had a downward curvature ($\beta_{\text{Curvature}} = -0.184, p < 0.01$) and its slope at the point $R = 0, C = 0$ did not differ from zero ($\beta_{\text{slope}} = 0.081$). This suggests that performance increased as R and C both increased and leveled off as R and C reach their maximum levels. This is an interesting result since we do not find a curvilinear relationship between focal firm's variability of alliance and performance in hypothesis 1. However, the result indicates that such a curvilinear relationship can be found along the fit line. Along the misfit line, the surface was curved downward ($\beta_{\text{curvature}} = -0.242, p < 0.05$) and essentially flat at the point of fit (based on the insignificant slope coefficient along the $R=-C$ line). Taken together, these results provide evidence for the hypothesized congruence effect for alliance.

In model 17 (M&A), we found similar results along the fit line ($R=C$) for variability of acquisitions. The surface along the line of fit has a significant downward curvature, such that performance increased as focal firm's variability of acquisition and competitors' variability of acquisitions both increase and leveled off as they both reached their maximum levels. However, along the misfit line ($R=-C$), the curvature of the surface does not significantly differ from zero, indicating the surface was not downward. The coefficient of slope along the misfit line is also insignificant. These results fail to provide support for the congruent effect for variability of acquisitions.

Taken together, hypothesis 2 is partially supported. We find support for external synchronization of alliances but not for acquisitions. This shed some interesting light on the boundary condition of the entrainment model, which we will discuss below.

Hypothesis 3: If firms synchronize rhythms of M&A and rhythms of alliances internally, will such an internal synchronization increase performance?

Hypothesis 3 predicts a positive relationship between internal synchronization and performance. We argued that synchronization of M&As and alliances can achieve higher performance through effective resource allocation, knowledge cross-fertilization and increases the complexity of strategic processes, which makes competitor imitation more difficult. Both models 6 and 7 support our hypothesis. In model 6, the coefficient of internal synchronization is negative and significant ($p < 0.05$), suggesting the smaller the difference between the variability of M&A and the rhythm of alliance, the better the performance.

We replace the Tobin's q with ROA and rerun the analysis. Consistent with our expectation, none of the coefficients are significant at 0.01 level.

Most of our control variables show predicted relations with performance. In most models, asset growth shows a positive and significant association with Tobin's Q but not ROA. Assets per se are negatively related to Tobin's Q , suggesting that investors tend to discount large firms due to their inefficiency. However, assets are positively associated with ROA, indicating that assets may be a beneficial factor for short-term profit but hurt performance in the long run. This conclusion can be further inferred from the fact that profitability is negatively related with Tobin's Q , suggesting that investors do not equate short term profitability with long term performance. R&D intensity shows negative relationship with both Tobin's Q and ROA, suggesting investing in internal R&D will not only generate expense that lower short term performance, but also hurt firms' long term performance. Investors do not appreciate the fact that small firms invest heavily internally since drug development is a risky business and the odds of developing a successful or blockbuster drug is very low. The relationship between stages of firm development and performance is not significant probably because most of the sample firms are

young and the distinction of developmental stages among them is not very precise. Industry effects did not impact our findings. Both leverage and product characteristics do not impact performance. Our sample of young firms may not have the capability to profit from financial leverage. Product characteristic (branded versus generic) has no impact on Tobin's Q because investors perceive these two product categories as equally promising in the future. Our results also indicate that neither alliance experience (the number of alliance) nor acquisition experience (the number of acquisition) have significant effects on performance measured by Tobin's Q and ROA. Finally, overall stock market has positive and significant impact on performance.

Finally, our second measure of variability—the instability measure proposed by Dess and Beard (1984) generates very similar results suggesting that our temporal constructs are quite reliable. In addition to using kurtosis as a fourth order measure, we also use standard deviation as a second order (Laamanen & Leil, 2008) and skewness as a third order functions to measure variability. Our results did not change significantly based on these different measurements. The correlation between kurtosis and skewness measures are very high and statistically significant at 0.05 level (bundled M&A and alliance: 0.90, acquisition: 0.95, alliance: 0.91), while the correlation between kurtosis and standard deviation is not very high (bundle: 0.134, acquisition: 0.205, alliance: 0.365). Such a triangulation measurement indicates that our results are quite robust and reliable since replication of established findings through different measurements can be seen as one way of eliminating bias and enable us to ensure that what we have identified as 'cause' actually impacts upon 'effect' (Johnson & Duberley, 2000). Only the results of the kurtosis measure are reported.

6.0 DISCUSSION

We examine and advance the temporal view of M&As and alliances in by adopting the social entrainment model with an emphasis on variability and synchronization. Theoretically, we explore the temporal rationales underlying the variability, synchronization, and entrainment performance effects for M&A and alliance initiatives. Empirically we found that the variability of corporate M&A and alliance activities have a non-linear relationship with performance. Equally important is the finding that internal synchronization enhances firm performance while external synchronization demonstrates a more complex picture.

Our study contributes to the literature along several dimensions. We extend the social entrainment model to the field of strategy research which requires us to view corporate strategy, particularly M&As and alliances from a temporal perspective. Complementing the perspectives that stress the role of target or partners characteristics, learning and post M&A integration processes, an entrainment view is concerned with when and how these actions should proceed over time. Entrainment suggests that variability and synchronizations have a significant impact on the nature and outcome of organization's competitive advantages.

Viewing M&As and alliances as mutually entrained and synchronized allows researchers to shed new light on the historical debate between adaptation and strategic choice. While it is important to note that an entrainment model embraces both the reactive and proactive sides of

competitive actions, what is missing from the debate is the notion that these actions also take place in a temporal order (Ancona & Chong, 1996). Traditional open-system approach (Thompson, 1967) that emphasize the interface between organizations and their environment falls short of developing a theoretical foundation that can reveal the temporal pattern of these actions ranging from high variability to low variability along the time spectrum.

Vermeulen and Barkema (2002) found a negative moderating role of variability in the context of foreign expansion. We complement their research by studying a direct relationship between variability and performance. Although an extreme irregular path may overstretch firm's absorptive capacity as they argued, our reported curvilinear relationship suggests that regularity may harm organization performance as much as irregularity. This happens when a regular variability creates strong inertia and the isolating mechanisms of a firm can be better understood by competitors. Our results further suggested that the curvilinear relationship between variability of M&A and alliance rate and performance is largely driven by M&A rather than alliances. Although further theoretical development is needed to theoretical differentiate these two different, yet related corporate strategies, we provide some possible explanations based on our best knowledge. This could be a result of different characteristics of M&As and alliance, i.e. resource commitment, information transparency, and asset digestibility (Hennart & Reddy, 1997). For instance, for specialty pharmaceutical firms to acquire another pharmaceutical firm for a specific resource, it is usually difficulty to separate that critical resource from other unwanted resource. Therefore, a temporal acquisition strategy that is characterized by variability of acquisition rate might be very susceptible to digestibility nature of the resource. Follow-up

study will extend this line of research and provide more systematic theoretical and empirical examination.

Within the context of our sample, our finding for the performance implications of synchronization also questions the boundary condition of the social entrainment model proposed by McGrath and Kelly (1986) and enriched by Ancona and Chong (1996). While they pinpointed the importance of synchronization of variability both internally and externally, little is known about the impact of each type of synchronization. Our finding suggests that, for small, young and specialty pharmaceutical firms, matching their internal processes and their alliances with their competitors creates more of an impact on performance than matching the variability of their competitors' acquisitions. This finding generates more discussion than affirmation and is a fruitful direction for future research.

We further opened the window for strategic scholars to think about creating competitive advantage: to regulate the variability and synchronization of variability when conducting strategic actions. An important managerial implication is that top managers should explicitly learn how to leverage the timing of strategic activities. To this end, the important issue lies far beyond how fast or quickly firms should conduct M&A and alliances, but rather in when, how and under which condition should firm accelerate or slow down the processes. Speeding up or slowing down certain processes at the wrong time may result in mismatches of synchrony among important internal or external processes. Meanwhile, our analysis also suggests that firms' specific experience in acquisition or alliance may not be a good predictor of their performance. This is an interesting finding since prior studies found that acquisition experience has a positive (Bruton, Oviatt, & White, 1994) or curvilinear relationship with performance (Haleblian, &

Finkelstein, 1999). The acquisition or alliance experience, for our sample firms, is not as important as the temporal structure of these experiences, i.e. the variability of acquisitions or alliances change rate. Given different samples and industry settings used in our study, we suggest take caution when generalizing our findings. However, we believe understanding the variability and synchronization of acquisition and alliance will enhance and clarify our understanding of the relationship between experience and performance debate.

Our analysis of external synchronization indicates that synchronization of alliance but not M&A with external competitors will increase performance significantly. Even when a focal firm's variability of M&A is exceeded by competitors, performance is not negatively affected. Our finding is more consistent with the traditional institutional arguments that emphasize the negative aspect of mimetic M&A behaviors in the absence of an adequate concern for economic rationality. An implication is that for small and medium-sized specialty drug firms, it is important for them to develop and maintain their distinctive variability pattern rather than to follow a trendy variability irrationally produced by a group of firms in the market. However, we do find that performance increase when firms follow their competitors' variability of alliance. One possible explanation is that internal routines that deal with multiple alliances are more fungible and transferable than those that deal with acquisitions. Acquisition routines may be very unique and specific to a particular acquisition, therefore is much more difficult to generate. These findings present a venue to extend interesting but underdeveloped research on strategic temporality.

The "matching as fit" embedded in the entrainment hypothesis can serve as a benchmark for synchronization behaviors against which actual instances of synchronization behaviors can be

evaluated. The role of benchmark is particularly important in testing a theory (Dubin, 1978; Popper 1968). While the benchmark hypothesis implies an efficiency rationale regarding firm's M&A and alliance behaviors, an interesting question that our current study cannot answer, but merits further investigation is why firms do not correct their seemingly misleading asynchrony among multiple processes. We argue that there could be a variety of reasons to cause such deviant behavior. For instance, firms may realize the importance of developing synchronization among multiple processes, however, the lack of coordination skills may limit their capability to accomplish the goal. This issue is particularly salient when M&A and alliance managers insufficiently consider their dynamic interplay and are unable to see how their own actions can affect and be affected by those of others whom they interact (Zajac & Bazerman, 1991). Such suboptimal behavior could also result from the different mindsets of M&A and alliance managers. The clash or conflict between their visions can delay the process of effective adjustment to the efficiency level of synchronization.

We make an important assumption regarding managers' motivation and ability to plan M&A and alliance initiative consistent with our entrainment model. This assumption is plausible under two conditions: 1) firms' overall growth strategies are largely driven by M&A and alliances activities, 2) firms do not have sufficient capabilities to develop drug products and relevant technologies internally. These two important conditions are met in our sample firms. Future research can test our argument to large firm and other industry contexts, where the two conditions may not hold.

Indeed, there are few strategy studies that examine the performance implication of temporal strategy of M&A and alliance. This stream of research is still in the process of

formation. We suggest that drawing normative implication from our study needs to be done with caution. For this reason, our research question is an interesting “academic question” that that should be subject to further theoretical and empirical examination. purpose of our study is, therefore, to stimulate further thoughts and open a new venue for academic scholars and practitioners to think about M&A and alliance from a temporal perspective. Future research that aims to strengthen normative implication of this stream of research by adopting an approach that combine quantitative and qualitative methods will be a very challenging, yet very rewarding endeavor.

Table 1. Descriptive Statistics and Correlations

	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1 Tobin's Q	4.446	5.281	1.000																	
2 Variability of Bundled M&A and Alliance	1.654	1.699	-0.049	1.000																
3 Variability of M&A	1.386	2.161	-0.106*	0.623*	1.000															
4 Variability of Alliance	1.216	1.486	-0.023	0.579*	0.152*	1.000														
5 Internal Synchronization	1.431	1.970	-0.010	0.753*	0.679*	0.359*	1.000													
6 Competitors' Variability of Bundled M&A and Alliance	1.651	0.774	-0.131*	0.459*	0.334*	0.340*	0.345*	1.000												
7 Competitors' Variability of M&A	1.382	0.951	-0.174*	0.345*	0.445*	0.178*	0.279*	0.752*	1.000											
8 Competitors' Variability of Alliance	1.213	0.658	-0.098*	0.350*	0.177*	0.446*	0.185*	0.763*	0.398*	1.000										
9 Number of Acquisitions	2.854	5.044	-0.146*	0.128*	0.236*	0.169*	-0.064	0.261*	0.372*	0.267*	1.000									
10 Number of Alliances	1.446	1.843	0.012	0.177*	0.119*	0.397*	0.082	0.199*	0.228*	0.177*	0.491*	1.000								
11 Asset	572.121	1005.372	-0.155*	0.139*	0.219*	0.108*	-0.014	0.214*	0.398*	0.202*	0.719*	0.470*	1.000							
12 R&D intensity	1.121	2.474	0.116*	-0.081	-0.125*	-0.071	-0.025	-0.145*	-0.220*	-0.162*	-0.174*	-0.092	-0.196*	1.000						
13 Profitability	-0.114	0.344	-0.414*	0.104*	0.196*	0.072	0.021	0.100*	0.274*	0.086	0.199*	0.046	0.227*	-0.470*	1.000					
14 Industry	0.900	0.301	-0.081	0.105*	0.117*	0.091	0.063	0.033	0.033	0.109*	0.147*	0.185*	0.119*	0.020	0.068	1.000				
15 Stage	1.754	0.764	-0.250*	0.056	0.118*	0.136*	-0.100*	0.129*	0.269*	0.314*	0.368*	0.063	0.289*	-0.391*	0.482*	0.258*	1.000			
16 Growth	0.441	1.117	0.058	0.116*	0.127*	-0.052	0.102*	-0.008	0.054	-0.081	-0.053	-0.066	-0.005	-0.008	0.117*	-0.071	-0.088	1.000		
17 Leverage	0.303	6.401	-0.043	0.016	-0.013	0.011	0.013	-0.033	-0.008	0.008	0.004	0.036	0.031	-0.008	0.065	-0.007	0.011	0.132*	1.000	
18 Branded	0.652	0.477	0.102*	0.022	-0.062	-0.032	0.103*	-0.048	-0.129*	-0.154*	-0.201*	0.033	-0.107*	0.273*	-0.319*	-0.127*	-0.631*	0.065	-0.015	1.000
19 Stock Market	6818.538	3098.063	0.012	0.262*	0.292*	0.132*	0.246*	0.570*	0.657*	0.296*	0.269*	0.251*	0.329*	-0.060	0.052	-0.101*	-0.091	0.081	0.003	0.078

Notes: * p<0.05

Table 2. Feasible Generalized Least Square Regression

	Tobin's Q_{t+1} (Log)							ROA $_{t+1}$						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
Main Effect														
Variability (Bundle of M&A and alliance)		0.016	0.097**						0.001	0.008				
Variability Square (Bundle of M&A and alliance)			-0.011*							-0.001				
Variability of M&A				0.024	0.112***		0.023 ^a				0.006	0.015 ^a		0.009 ^a
Variability of Alliance				-0.003	-0.006		-0.008				-0.004	-0.001		-0.003
Variability of M&A Square					-0.010**							-0.001		
Variability of Alliance Square					0.001							-0.001		
Internal Synchronization between M&A and alliance						-0.068*	-0.062*						-0.012	-0.017
Control Variables														
Intercept	1.209**	1.264**	1.679***	1.289**	1.534***	1.722***	1.705***	-0.098	-0.094	-0.072	-0.089	-0.065	-0.091	-0.116
Total Number of Acquisitions	0.001	0.001	0.002	-0.001	-0.006	-0.003	-0.005	-0.001	-0.001	-0.001	-0.001	-0.002	-0.003	-0.004
Total Number of Alliances	0.035	0.032	0.021	0.039	0.044 ^a	0.013	0.022	-0.006	-0.006	-0.008	-0.004	-0.005	-0.009 ^a	-0.009
Asset (log)	-0.234***	-0.231***	-0.208**	-0.238***	-0.267***	-0.223***	-0.240***	0.008	0.008	0.006	0.006	0.001	0.009	0.013
R&D intensity	-0.053 ^a	-0.051 ^a	-0.055**	-0.052 ^a	-0.057*	-0.059 ^a	-0.061 ^a	-0.047***	-0.047***	-0.048***	-0.047***	-0.047***	-0.048***	-0.049***
Profitability	-0.151	-0.159	-0.286*	-0.152	-0.173 ^a	0.006	0.009	0.490***	0.491***	0.492***	0.489***	0.496***	0.472***	0.406***
Industry Dummy	0.033	0.020	-0.066	0.004	-0.064	0.035	0.015	0.018	0.017	0.014	0.013	0.012	0.039	0.034
Stage	0.098	0.089	0.033	0.101	0.129	0.030	0.057	0.016	0.016	0.017	0.019	0.025 ^a	0.033*	0.042*
Asset Growth	0.026*	0.026*	0.036**	0.025*	0.032**	0.013	0.016	0.003	0.003	0.003	0.002	0.002	0.006	0.003
Leverage	0.001	0.001	0.002	0.001	0.001	0.002	0.002	-0.002	-0.002 ^a	-0.002 ^a	-0.002	-0.001	-0.001	-0.001
Branded	0.118	0.111	0.055	0.110	0.077	0.032	0.015	-0.019	-0.019	-0.021	-0.019	-0.019	-0.009	-0.012
Stock market	0.000***	0.000***	0.000*	0.000***	0.000***	0.000**	0.000**							
Year Dummy (1986-2003)	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Num	373	373	373	373	373	373	373	374	374	374	374	374	374	374
Wald Chi2	177.17***	185.21***	196.87***	184.35***	199.62***	169.87***	167.47***	339.61***	339.84***	339.87***	343.14***	345.22***	336.12***	335.72***
Log Likelihood	-345.29	-342.59	-338.74	-342.88	-337.84	-203.64	-204.37	-10.16	-10.09	-10.08	-9.23	-8.69	-10.89	-11.12

Notes: ^a $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

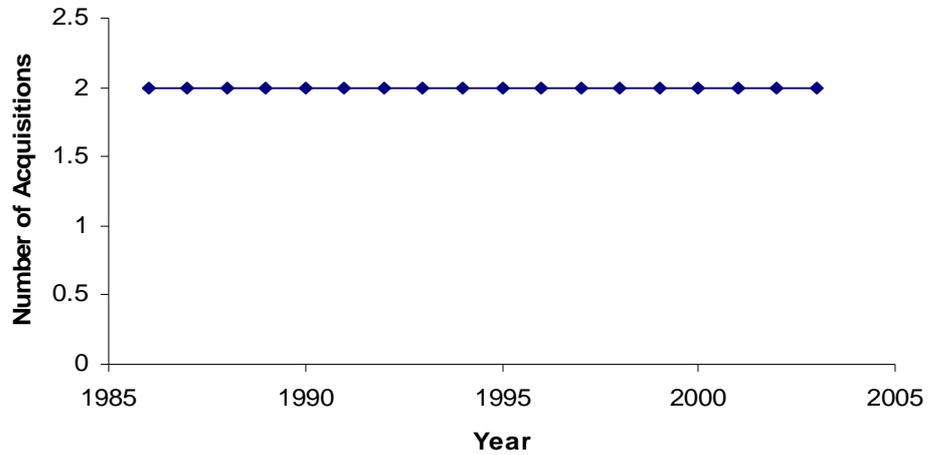
Table 3. Cross-level Polynomial Regression Results of Firm's Performance (Tobin's Q) on Firm's Variability and Competitors' Variability

Fixed Effect Coefficients	Bundle M&A and Alliance	Unbundled M&A and Alliance	
	Model 15	Model 16 (Alliance)	Model 17(M&A)
Controls			
Intercept	1.810*** (0.219)	2.149*** (0.252)	2.146*** (0.246)
Total Number of Acquisitions	0.000 (0.009)	-0.002 (0.010)	-0.003 (0.011)
Total Number of Alliances	0.043 ^a (0.023)	0.034 (0.028)	0.035 (0.027)
Asset	-0.194*** (0.033)	-0.214*** (0.034)	-0.231*** (0.036)
R&D intensity	-0.021 (0.016)	-0.023 (0.016)	-0.019 (0.016)
Profitability	-0.393*** (0.124)	-0.439** (0.126)	-0.453*** (0.125)
Asset growth	0.036 (0.029)	0.035 (0.029)	0.039 (0.029)
Leverage	0.002 (0.005)	0.004 (0.005)	0.004 (0.005)
Branded	-0.035 (0.078)	0.004 (0.079)	0.034 (0.081)
Industry Dummy	-0.022 (0.115)	-0.022 (0.117)	-0.047 (0.116)
Stock market	0.000* (0.000)	0.000 (0.000)	0.000* (0.000)
Variability of acquisition--R		0.076* (0.036)	
Variability of acquisition (squared)		-0.006 (0.004)	
Variability of competitors' acquisition--E		0.079 (0.062)	
Variability of alliance--R			0.104* (0.040)
Variability of alliance (squared)			-0.014* (0.007)
Variability of competitors' alliance--E			-0.053 (0.073)
Fit variables			
R	0.131***	0.099*	0.068 ^a
E	-0.124	-0.018	0.095
R ²	-0.002	-0.018	-0.005
R*E	-0.068*	0.029	0.003
E ²	-0.058	-0.195*	-0.105
Response surface features			
<u>R=E fit line</u>			
Slope (R+E)	0.007	0.081	0.163 ^a
Curvature (R ² +R*E+E ²)	-0.128**	-0.184**	-0.107
<u>R=-E misfit line</u>			
Slope (R-E)	0.255**	0.117	-0.027
Curvature (R ² - R*E+E ²)	0.008	-0.242*	-0.113
Total variance explained ^b	0.308*	0.290*	0.301*

Notes: ^a p<0.1; * p<0.05; ** p<0.01; *** p<0.001, ^b Total variance explained= 1- (residual variance of full model / residual variance of null model), significance was determined by Chi Square difference across models

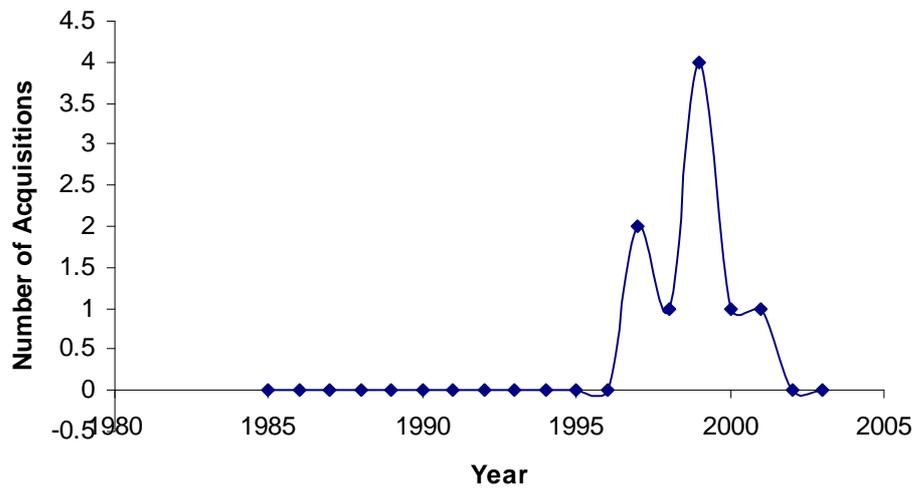
Figure 1. Difference between Low Variability and High Variability of M&A and Alliance Rate

(a). Low Variability



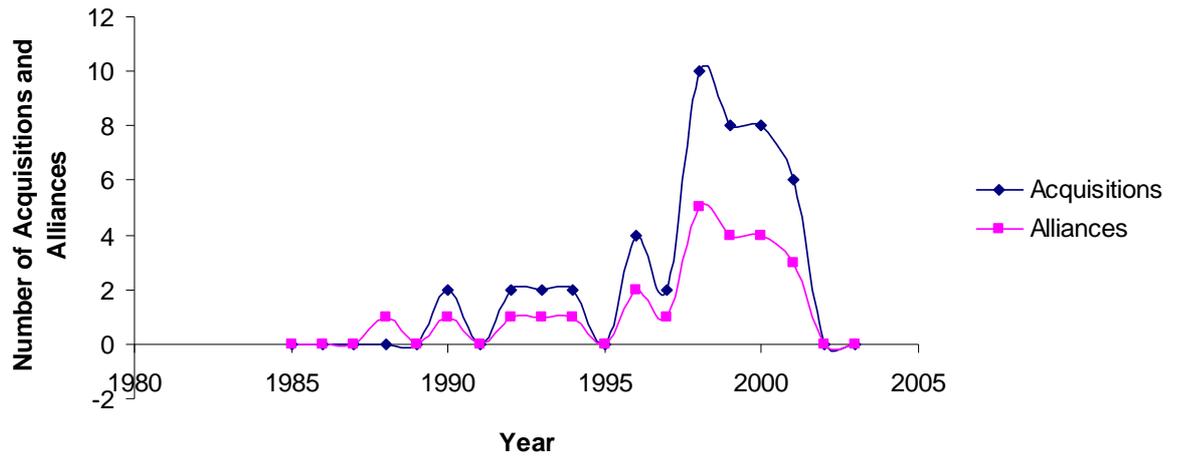
Average variability of acquisition in the sample is 1.59 and the standard deviation is 2.16. The variability above in 2000 is zero, well below the average

(b) High Variability



Average variability of acquisition in the sample is 1.59 and the standard deviation is 2.16. The variability above in 2000 is 5.03, well above the average (about 1.5 times of standard deviation)

Figure 2. Synchronization of M&As and Alliances



The number of acquisitions is synchronized with the number of alliances in a way that increase (decrease) in acquisitions is accompanied by increase (decrease) in alliances.

Figure 3. Hypothesis 1: The Inverted Relationship between Variability of Strategic Initiatives and Performance

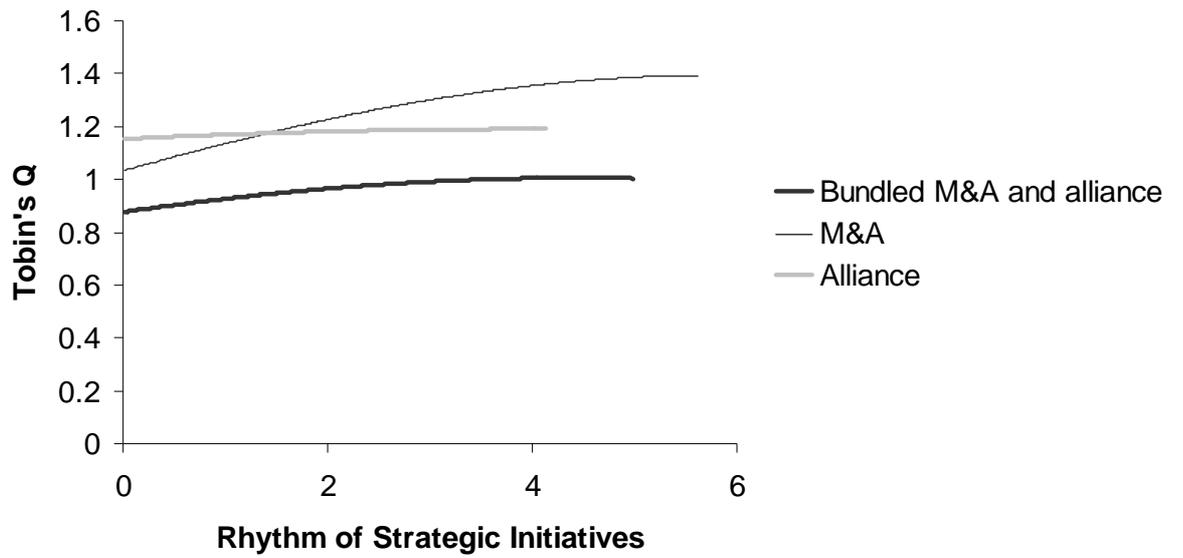


Figure 4. Surface Graph of Fit between Firm's Variability of Alliances and Competitors' Variability of Alliance Predicting Firm's Performance

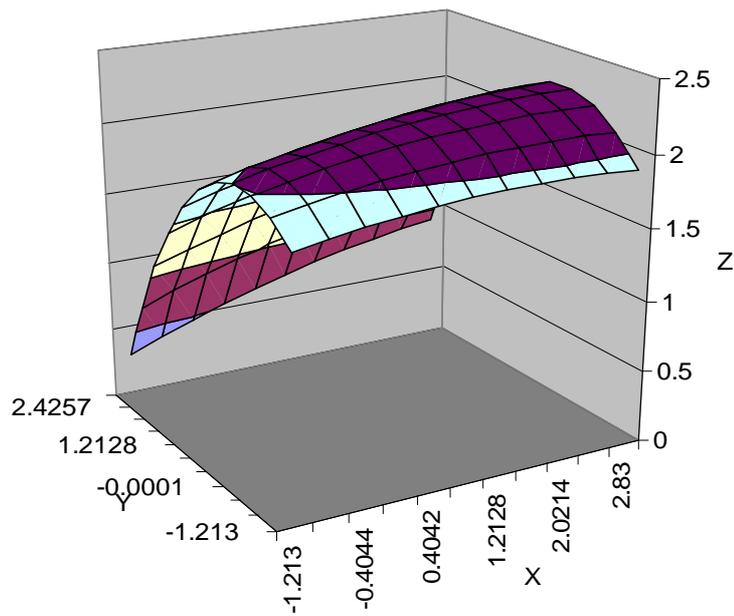
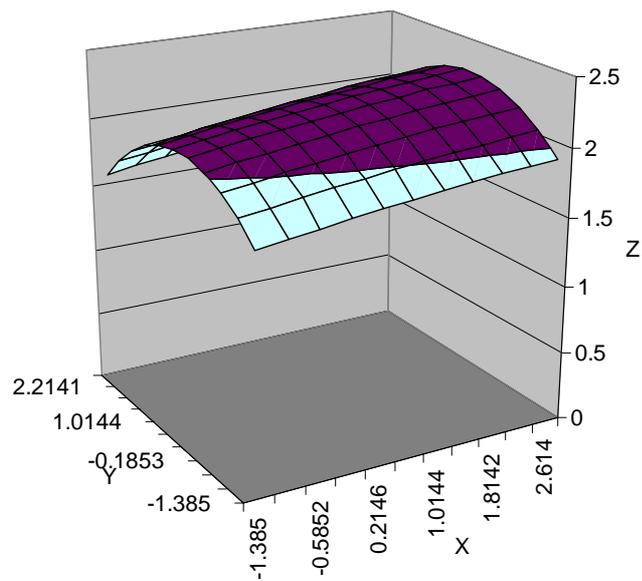


Figure 5. Surface Graph of Fit between Firm's Variability of Acquisitions and Competitors' Variability of Acquisitions Predicting Firm's Performance



APPENDIX A

[TIME IN STRATEGY RESEARCH]

The temporal dimension of strategy is embedded in a wide range of phenomena, including but not limited to first mover advantages (Lieberman & Montgomery, 1988), the resource based view (Dierickx & Cool, 1989), dynamic capabilities (Teece, Pisano, & Shuen, 1997), decision-making under uncertainty (Eisenhardt, 1989), change management (Huy, 2001), and the real options perspective (Kogut, 1991). For instance, Barney (1991) argued that resources that are developed and accumulated over time are less likely to be imitated by competitors—a path dependent notion that is clearly relevant to time. Similarly, based on the law of diminishing returns, Dierickx and Cool suggested that firms cannot possibly accumulate the same stock of knowledge in one year as in two, even if all other inputs are doubled. In the field of real options, scholars stress the value of a “wait and see,” approach implying that time can be an important asset in generating firms’ strategic flexibility (Tong & Reuer, 2007). While these research streams have provided significant practice and process insights, the role of time in these studies has not been explicitly spelled out and therefore time as a theoretical concept and as an object of empirical inquiry remains mostly peripheral (Ancona, Goodman, Lawrence & Tushman, 2001), the lack of which constrains strategy

scholars' enhanced understanding and application of a temporal lens in strategy research. In particular, there are three points in the temporal perspective that deserve strategy scholars' attention.

First, for time to be an important direct causal variable in theories of firm strategy (Mosakowski & Earley, 2000), and therefore to be subject to managerial design and manipulation, time as a strategic construct should take center stage as a construct standing on its own and receiving direct theoretical and empirical inquiry (Ancona et al., 2001). The temporal lens, as Ancona et al. (2001) suggested, should offer its own set of constructs, variables, relationships, laws of interaction, and its own set of parameters to guide managerial action and create new sources of competitive advantage. This has garnered some interest in strategy research, but has not been fully recognized and integrated into prior strategy studies. This inattention can be understood from two separate yet interrelated issues—one is the conceptualization of time and the other is the associated model or framework that incorporates time as a strategic variable.

Prior strategy studies usually consider time as part of the general background of a problem rather than as an important issue in its own right (Albert, 1995). Therefore, the conceptualization of time has become a less important issue and has seldom been identified and clarified. For instance, in studies that have frequently adopted concepts such as first mover advantages, timing, uncertainty, or responsiveness, the notion and concept of time remains implicit, rather than explicit (Bulter, 1995: 925) and the assumptions of time are also seldom or never discussed in studying these strategy dynamics (Mosakowski & Earley, 2000). The conceptualization of time is an important issue because it is time per se that is a critical input in the process of creating competitive advantage. Lack of such

conceptualization will lead strategy scholars to search for other proxy factors of time such as labor, learning, and trust, to mention a few. While we do not deny the importance of these proxies as separate constructs, focus on these constructs alone will, in our view, overshadow the value of a direct examination of temporal constructs. Even Dierickx and Cool (1989) recognized that time itself—not its proxy—may be an important input into asset creation processes. A related consequence is the absence of solid and coherent theoretical frameworks, models or foundations that address the question of how to think about time in strategic management research. As such, although we can see a growing interest in incorporating a temporal lens as an additional component of other traditional lenses in strategy research, we do not see the emergence of corresponding new paradigms, frameworks or models that can incorporate a temporal lens, giving time center stage to stand on its own and to integrate time constructs with other relevant strategy-related variables.

Our temporal approach to examining strategy phenomena resonates with Ancona et al.'s (2000) call for a direct focus on time as a conceptual and empirical construct rather than as a proxy for other constructs. For instance, we focus on rhythm as an important temporal construct that brings time onto center stage. We define rhythm as the variability of M&A and alliance rate and measure it by kurtosis of the first derivative of the number of M&As and alliances over time. This conceptualization and operationalization of rhythm suggest that rhythm is not a proxy measure for other constructs, but is rather a temporal construct that is subjective to managerial design and manipulation against time.

The temporal approach we adopted also has an integrated theoretical framework that can link different temporal constructs cohesively. For instance, our entrainment framework contains several temporal constructs such as rhythm, internal synchronization and external

synchronization that are linked together. We argue that firms' rhythm of M&A and alliance formation will have a profound effect on performance. Meanwhile, different units within an organization (such as M&A and alliance initiatives) maintain different rhythms, and yet they can be integrated and oscillate in sympathy with each other (internal synchronization), which will also impact performance. Furthermore, firms can also match their rhythms with competitors (external synchronization), which will further impact performance.

Our temporal approach, therefore, incorporates several time-related constructs within an integrated theoretical framework that demonstrates significant theoretical complexity. Such complexity reflects our views of organizations as nonlinear and dynamic systems, within which different strategic actions struggle the inherent tension between predictability and unpredictability, are irreversible and highly susceptible to initial conditions (Ofordi-Dankwa & Julian, 2001).

Second, strategy scholars have agreed that strategy is emergent, dynamic, logically incremental, path dependent and express patterns of interaction overtime (Mintzberg, 1990). This clearly demonstrates that we should examine the relevant issue in strategy from a "past-present-future" time perspective. However, current literature, particularly empirical studies in strategy tends to focus on either the "past-future" link or the "present-future" connection (Ofordi-Dankwa & Julian, 2001). For instance, the resource-based view has emphasized how resources accumulated in the path-dependent manner (past) influences sustainability of economic rents and competitive advantage (future) without incorporate a present time orientation (Mosakowski, 1998). The present-future time linkage has been reflected in real options theory, hyper-competition (D'Aveni, 1994), strategic decision making in high-velocity environments (Eisenhardt & Brown, 1998), and the traditional SWOT analysis

(Hamel & Prahalad, 1994). For example, scholars using the real options perspective suggest how current decisions regarding allying with a foreign partner can generate strategic flexibility in the future when uncertainty becomes more clarified.

The “past-present-future” time perspective posits that past strategic actions have profound impact on present results as well as future outcomes. Similarly, future decisions are collections of reflections of not only present behaviors, but also a series of past actions. In our study, we posit that firms’ future performance can be predicted by a series of past and present M&A and alliance initiatives. The present rhythm of these strategic initiatives is somewhat path dependent, irreversible and bounded by initial conditions (Ofordi-Dankwa & Julian, 2001).

Third, previous strategy research that implicitly embodies the temporal view tends to examine a single strategic action, activity or event along the time dimension, with few exceptions (Ferrier, Smith, & Grimm, 1999). For instance, the decision making literature mainly focuses on the speed of making a single strategic decision (Eisenhardt, 1989). Also, change management examines the process of change of a single phenomenon or event, such as a technological breakthrough. In M&A research, scholars are interested in examining how speed of post-integration of a single merger will affect the performance of the acquirer. Such a singular view of strategy is quite restricting given the fact that strategy is consistently defined and perceived as a pattern emerged from a series of actions and decisions (Mintzberg & Water, 1985). A repeated and multiple action perspective of strategy, in our view, enlarges the horizon of time, thus increasing the value of incorporating the temporal view in strategy research and therefore enhancing the possibility to detect patterns in strategic decisions over time.

Our current study is consistent with the multiple action view of strategy. This has been reflected in both our theoretical development and empirical examination. From a theory perspective, our core temporal constructs such as rhythm, and internal and external synchronization are conceptualized based on repeated and multiple M&A and alliance initiatives. Our methodology is also consistent with such a multiple action orientation. We collect information on a longitudinal base that tracks individual firms' multiple M&A and alliance initiatives over their histories.

APPENDIX B

[TIME IN ALLIANCE AND M&A RESEARCH]

A temporal view of alliances and M&As has been advanced in some recent research streams; however, there is no systematic investigation that explicitly adopts a clear temporal perspective based on the criteria developed above. The studies that implicitly relate time with M&As and alliances include, but are not limited to, accelerating or slowing down post-acquisition integration (Homburg & Bucerius, 2006), preemptive acquisition (Carow, Heron, & Saxton, 2004), the relationship between M&A and alliance experience and performance (Haleblian & Finkelstein, 1999) and M&A and alliances as learning tools and races (Hamel, 1991). For instance, Inkpen (2001) argued that learning about alliance partners is highly associated with effective alliance management. The key emphasis in this type of learning is to create new knowledge and capabilities that are jointly developed by both partners (Dussauge, Garrette, & Witchell, 2004), which lead to common benefits (Khanna, Gulati, & Nohria, 1998), those that accrue to each partner in an alliance from the collective application of the learning that both firms go through as a consequence of being part of the alliance. In another study, Hamel, Doz and Prahalad (1989) proposed the notion of learning from an alliance partner, which is different from learning about the partner. Unlike learning about the

partner, which stresses the joint utilization of resources, the argument of learning from partners shifts alliance partners' emphasis on cooperation toward competition. The central issues associated with this type of learning are the bargaining power (Inkpen & Beamish, 1997; Yan, 1998) or dependence argument (Inkpen & Currall, 2004). In these studies, scholars tend to focus on a single alliance rather than multiple alliance initiatives or alliance portfolio. As a result, the key temporal-related concept is duration of an alliance, within which learning is unfolded. Meanwhile, time has neither been conceptualized nor measured directly in the framework. Instead, time has been perceived as a proxy for learning, i.e., the longer time passes during an alliance, the better the learning effect.

In M&A research, one of the most studied topics that are relevant to time is the relationship between acquisition experience and performance, though empirical findings generate conflicting results. For instance, building on the learning curve argument, Lubatkin (1982) failed to find a positive relationship between acquisition experience and performance. Bruton, Oviatt, and White (1994) found that whether firms' acquisition experience can impact their performance depends on their financial condition prior to acquisition. The positive relationship, as they observed, is only clear in a group of distressed firms, defined as those who have two consecutive years of declining net income and return on investment prior to acquisition. Recently, Halebian and Finkelstein (1999) challenged the implicit assumptions in traditional learning research, arguing that an organization's acquisitions may not be similar to each other and therefore past acquisition experience is not readily generalized from one acquisition to another. Research on acquisition experience equals time with experience. Experience increases as time passes by. In other words, time is viewed as a proxy for experience. This stream of research has centered on multiple acquisitions;

however, it does not recognize the nature of interdependence and embeddedness in strategy. For instance, firms' serial acquisitions might well be affected by their alliance initiatives. Several scholars have argued that knowledge gained from alliances might spill over to managing acquisitions (Zollo & Reuer, 2001). Similarly, firms' acquisition momentum can also be influenced by their competitors' serial acquisition initiatives. Essentially, our study recognized that strategy is a multi-level and multi-process phenomenon that involves different activities interacting in a complex and dynamic way.

Another important topic that is time relevant centers on studying the relationship between post-integration process and M&A success. In this research stream, researchers tend to explore different types of fit between the acquirer and target firms (Finkelstein & Halebian, 2002; Harrison & St. John, 1998). For instance, Larsson & Finkelstein's (1999) analysis revealed that organizational integration was the single most important factor in explaining synergy realization, even as the strategic potential of the combination was taken into consideration. Furthermore, Marks and Mirvis (1998) argued that a critical element in successful M&As is to build cooperation between acquirer and target companies. Top managers, as Marks and Mirvis suggested, should create an appropriate climate or culture to understand the mindset of their respective firms. Other scholars stressed the role of resource allocation process between targets and acquirers (Capron, 1999). Capron and Pistre (2002) empirically explored the conditions under which acquirers can earn abnormal returns. They found that positive returns are expected only when acquirers transfer their own resources to the target rather than *vice versa*. This stream of research aims to understand the acquisition process from a single deal perspective. The eventual outcome of acquisitions is either successful integration or failure. The emphasis is on the duration of a single acquisition.

These studies, however, do not provide normative implications in terms of whether a successful integration or a failed deal will pass on to other acquisitions in the future. Our study took a different approach and assumed all acquisitions to have been integrated with an emphasis on temporal distance between different deals rather than on the time span within a single deal.

While these different thrusts offer unique contributions for enhancing our temporal understanding of M&A and alliance initiatives, two important temporal issues remain underdeveloped. First, focus on a single M&A or alliance does not incorporate the nature of multiple strategic initiatives and their interplay. In other words M&A and alliances are not approached from a portfolio perspective (Hoffmann, 2007). Researchers, when describing the post integration process, focus on a single acquisition which occurs on the time continuum. A key emphasis is on how long this post integration lasts, from beginning to endpoint. Clearly, the important constructs, though not directly examined, but implicitly assumed, are duration, scheduling, endurance, and persistence. Similarly, the learning perspective in alliance research also stresses the alliance as a single entity.

Second, those scholars that have recognized the interdependent nature of multiple M&A and alliances (Haleblian & Finkelstein, 1999) have not addressed their periodicity and the fact that multiple initiatives can occur synchronously at the same level of analysis (e.g., firm) or across levels of analysis (e.g., firms and their competitive environment). In other words, M&A and alliance initiatives can demonstrate a discernable pattern in the timing of their occurrences conditioned by internal or external pacers. Thus, a temporal lens of M&As and alliances calls for theoretical development and empirical examination of temporal constructs.

APPENDIX C

[INDUSTRY CONTEXT]

Pharmaceutical industry in general

We define the pharmaceutical industry as well as its incumbents as those public and private organizations involved in the discovery, development, and manufacture of drugs and medications. Globally, the three largest drug markets are the United States, Europe and Japan.

Typically, the largest and best-known pharmaceutical firms have integrated value chains that consist of all those aforementioned functions. There are also some smaller and usually younger firms that are attempting to develop a narrower range of products. These firms are less likely to be fully integrated. Among the manufacturers are firms producing generic drugs—products that are in many ways equivalent to existing drugs whose patents have expired. Our study mainly deals with those smaller and younger firms that occupy a specific market niche as well as generic drug companies.

The modern era of drug discovery and development originated in the 19th century when researchers and scientists began to isolate and purify medicinal compounds and developed manufacturing techniques in a mass-production manner. While many drugs, such

as quinine and morphine, were extracted from plant substances, others were discovered and synthesized by techniques including combinatorial chemistry and recombinant DNA technology. Since its formation, the pharmaceutical industry has greatly aided medical progress, and many new drugs have been discovered, greatly improving the quality of life of modern human beings. During the past several decades, there have been some distinctive features that have characterized the global pharmaceutical industry.

First, the industry maintains rapid growth continuously. Its scale has started to maintain fast growth since the middle and late 20th century. The total amount of output (in terms of value) increased from US \$21.8 billion in 1970 to US \$602 billion in 2005 with an annual growth rate of 8.3%, more than double the growth rate of global GDP in the same period. The rapid growth rate was largely due to the fact that the industry was highly profitable (well above the average for all manufacturing industries as well as for Fortune 500 companies), thus attracting more and more entries over the years, and enhancing demand for prevention and treatment of many diseases over time. As a result, the industry has become increasingly concentrated over the past decade; the 10 firm concentration ratio increased from 12 percent in 1987, to around 20 percent in the middle of 1990s, and reached to almost 50 percent at the beginning of the twenty first century.

Second, the pharmaceutical industry has a very high rate of investment in R&D, with a correspondingly rapid pace of product innovation. U.S. firms, for example, spent over \$21 billion and \$24 billion in R&D in the United States and abroad in 1998 and 1999, respectively. These investments represent around 12 percent share of total revenue, a share that is nearly double that of most other industries, including office equipment, electronics, and telecommunications. In 2000, for the U.S research-based pharmaceutical industry, the

R&D/sales ratio was 15.6 percent compared to 10.5 percent for computer software, the next highest industry (Pharmaceutical Research Manufacturers Association, 2001). In a similar vein, the average R&D cost per new chemical entity (NCE) brought to the market was estimated at around \$802 million (DiMasi, Hansen, & Grabowski, 2002). The high cost and significant investment in R&D are largely due to three factors: 1) high return on investment in R&D generates strong incentives necessary to conduct R&D. R&D investment typically flows to clinical areas where relatively large markets exist—either large numbers of patients, or purchasers willing to pay prices that, in the long run, cover the costs and risks of these investments; 2) the process of drug discovery and development is extremely costly. Human clinical trials are required by law in many countries (such as by the FDA in the U.S) to establish proof of safety and efficacy. Typically, it takes around 10 to 15 years for a drug to pass through discovery stage (pre-clinical), human clinical stage, regulatory approval stage and eventually product launch stage; 3) Failure rates in each stage are extremely high. It is estimated that for “each new compound that is approved, roughly five enter human clinical trials and 250 enter preclinical testing” (Danzon, Nicholson, & Pereira, 2005:2). The cost of “dry hole”—those that fail, will be included in the total cost of R&D investment, therefore driving the total R&D cost significantly higher.

Third, high rates of innovation also help the pharmaceutical industry establish the patent system that aims to protect the large pharmaceutical companies and their drugs’ inventors. However, the patent system also generates controversy among the public. On the one hand, concern over the cost of health care and growing interest in health care reform has increased markedly throughout the 1980s. Consumer advocates pointed out the monopoly benefits of patent protection, evidence of oligopolistic behavior, and suggested extensive

government intervention to control the profits of pharmaceutical firms. On the other hand, industry spokespeople argued against government interference, suggesting that lower profits would decrease innovation. This is particularly the case in U.S where the patent system is well developed and maintained. It is estimated that patent protection allows the U.S pharmaceutical industry to produce nearly half of all patented drugs that were introduced globally between 1975 and 1994.

Patent protection, in addition to its effects on pricing and associated government intervention, also has a profound impact on industry evolution. Drug patents usually give twenty years of protection. However, they are applied before clinical trials begin, so the effective life of patent protection typically lasts twelve to sixteen years on average. During this period, the company who invented the patented drug has exclusive marketing rights. Once the patent expires, a drug is much less profitable. This creates severe problems for companies whose revenues are established on a few blockbuster drugs. Once these patents expire, the company's revenues can diminish within a few months, unless new compounds can be fueled through pipeline. This results largely from the entry of generic drug makers, which is a focus of our study. Generic drugs are those drugs that contain the same active ingredients that their brand name counterparts do and are tested to assure that they are therapeutically equivalent, but they may contain different inactive ingredients from those found in the brand name medications. Generic drugs are much cheaper because their manufacturers do not incur the cost of drug discovery or of proving the safety and efficacy of the drugs through clinical trials, and instead are able to reverse-engineer known drug compounds to allow them to manufacture bioequivalent versions. It is estimated that the generics basically come into the market with prices 15 to 20, maybe 25% less than that of the

brand name, which makes them a lot more profitable to market than they used to be (Rylander, 2007).

Fourth, the emergence and development of biotechnology have already blurred the industry boundary between pharmaceuticals and others. In particular, there is more and more convergence between the pharmaceutical and biotechnology industries, resulting in the biopharmaceutical industry. The technology that our sample firms focused on is mainly biotechnology-related. There are several distinctions between biotechnology and traditional pharmaceutical drugs. First, they differ by the way that they are produced. Traditional pharmaceutical drugs are relatively simple molecules that have been found primarily through trial and error to treat the symptoms of a disease or illness. To some extent, the process of trial and error is also called random screening that involves lots of serendipity and co-specialized technologies. Biotechnology-based drugs use large biological molecules known as proteins. The search process is usually more guided and path dependent (Ohba & Figueredo, 2007). Second, the biotechnology-based drugs are typically dosed through a large molecule that is injected while traditional pharmaceutical drugs can be administered through a small molecule via a tablet. Injected bio-based drugs usually have more side effects compared with traditional pharmaceutical drugs. However, biotechnology holds the promise of making landmark breakthroughs in new medical therapies to treat cancers, arthritis, bone fractures, and cardiovascular disease. Third, biotechnology-based drugs are usually easier and cheaper to manufacture. For instance, Genentech used a genetically engineered bacterium to enable the production of vast quantities of human insulin (widely used for the treatment of diabetes) at low cost. Previously, insulin was extracted from animals such as pigs and sheep, a process which was often expensive and caused unwanted side effects (e.g.,

allergic reactions). Lastly, regarding the process of pre-clinical and human clinical trials, biotechnology products have a higher chance of making it all the way through to approval. This is because protein peptide drugs (biotechnology) are essentially biologically-derived from replacements of missing “pieces” in people with given diseases. They are injected into people and are not seen as being broken down and gotten rid of by the body (Green, 2007).

Fifth, during the past decade, the demand of the market has also changed significantly largely due to the changing attitude of managed care organizations (such as health care insurance providers) and the government. A variety of reimbursement policies has been established regarding the price of existing branded drugs and generics which may adversely affect the development and launch of new branded drugs. Take the U.S., for example: historically, it has less government restriction on the pricing regime. However, the pharmaceutical companies face increasing pressure from the federal, state and local governments to propose the re-importation of cheaper drugs from adjacent countries such as Canada and Mexico. Meanwhile, powerful managed care organizations design certain financial incentives to encourage patients (doctors as well) to use generic or existing branded drugs rather than new branded drugs unless these new ones are measurably better than the alternatives (Kohl, Partner, Hogan & Hartson, 2006).

Specialty Pharmaceutical Industry

We define specialty pharmaceuticals as those firms that mainly deal with expensive medications that treat rare, chronic diseases inflicting a small proportion of the population (Mass, 2005). Those special diseases include but are not limited to Heophilia, Hepatitis C, Oology, HIV/AIDs and transplants, just to mention a few. A good example is Allergan. To

quote Allergan's top executive: "We are a specialty company. That's what we been. That's how we have been able to compete really effectively. We are an ophthalmology company for example when we compete in ophthalmology very effectively. We are the largest company in the world in ophthalmology. We are a neurology company with botox in a very specific area and we are a dermatology company and now plastic surgery company in the aesthetics business. So we have a good core capability to function very well in what we call a specialized marketplace" (Pal, 2007).

The specialty pharmaceutical market is a rapidly growing market. In 2003, the total market size was around U.S \$ 32.3, about 15% of total pharmaceutical industry (a further breakdown of specialty market can be found in Figure 6). Meanwhile, Medco's 2004 drug trend report also indicated that specialty drug spending grew 26.6% in 2003, a much faster pace than the 10.2% average increase in drug spending in general. In 2005, the global market size for specialty pharmaceutical products grew to US \$ 75 billion (Mergers & Acquisitions Report, 2006) with an annual increase of around 50% in just two years. The growth of specialty drug is particularly strong in the U.S. It is estimated, by 2010, that specialty-drug spending in the U.S. could reach \$99 billion by 2010, nearly double the \$54 billion spent in 2006 (Wall Street Journal, 2008).

Insert Figure 6 about here

The emergence of the specialty pharmaceutical industry is largely due to four possible reasons. First, there exists a niche market where big pharmaceutical firms do not demonstrate much interest due to its small market size. Small markets indicate that big pharmaceutical firms cannot effectively leverage their economies of scale, particularly in manufacturing, marketing, and distribution of these special drugs. For instance, in the United

State or even globally, most of the large pharmaceutical companies really do not want to develop a product that does not have sales potential of at least 500 million dollars a year. There's a whole economic threshold there at which only small players would have any interest in participating because large players don't want to deal with it. Big companies may also simply neglect these markets for special drugs because of the tendency of "blind spots", i.e. they focus too much on their core business and fail to see the opportunities that are emerging outside of these cores. For instance, as one of the pharmaceutical top executives mentioned, "I think the movement to niche markets, where the large companies just flatly ignored, blow some structure we're not gonna deal with that, so the small companies got all sorts of help for the small medium sized entrepreneurship. I think there is also, due to the consolidation and the mergers or maybe even a bit of boredom into sort of stagnant pharmaceutical world for so many years, people have decided to branch out and try something new to take care of knowledge and expertise to try to create something different, in a different model because they didn't like the way the business was being done, or they had a different vision" (Rylander, 2007).

Second, the change of patient trend also contributes to the burgeoning market of specialty pharmaceuticals. In particular, patients prefer chronic therapy over acute therapy over time. Chronic therapy typically takes more time to cure and costs more; however, it can have fewer side effects than acute therapy.

Third, as the competition among pharmaceutical firms (using an ecological term, these are generalists) become more and more intense, the set of generalist firms will be somewhat differentiated into different therapeutic areas. When the smaller generalist pharmaceuticals fail, their markets become free resources. As a result, adjacent generalist

pharmaceutical firms may secure these free resources. However, as some strategy researchers have argued, generalists may not secure the whole areas of free resources largely because “doing so might prove more costly than it is worth or entail loss of some of the firms’ existing target areas” (Carrol & Swaminathan, 2000: 719). As a result, it is in these released and less congested market areas that specialty pharmaceutical firms can find their viable space.

Fourth, the emergence of specialty pharmaceutical industry is also highly related to some external influences such as the emerging venture capital industry and more particularly the regulatory regime. For instance, in the United States, if less than 200,000 people have a particular condition it is classified by the federal government as an orphan disease.²² In 1984, Congress enacted the Orphan Drug Act to create incentives to encourage manufacturers to develop products for diseases affecting relatively small numbers of patients. Following the Act’s passage, many drugs were developed and introduced addressing these relatively rare diseases.

There are also several unique aspects regarding specialty pharmaceutical firms. First, the specialty drugs usually can charge quite a high price, resulting in higher profit markups (usually as much as 250% of its cost). Second, drugs companies that are specialized in certain therapeutic areas are eligible for certain privileges. For instance, in the United State, when firms file certain drugs to the FDA, there are normally US \$300,000 filing fees. However, for a specialty firm (whose products are used to cure orphan disease—whose target population is less than 200,000 people) the government will waive certain fees. Since most

²² We thank Dick Rylander, former president and founder of biopharmaceutical Strategies, LLC for bringing this issue up.

specialty pharmaceutical firms are small, young and therefore financially constrained, US \$ 200, 000 will be a huge amount of money to them. In addition to that, drugs that are developed for orphan diseases can also get special attention for review and approval. Usually, this means that drug firms can do either fewer studies or smaller samples, which mean that completion of these studies is quite quick. Third, the competitive arena in the specialty areas is quite different from that in traditional pharmaceutical field. The industry is rather young and firms within this particular industry compete in several ways. For private companies, they are competing for funding from venture capitalists and some kind of private equity funding. For public firms, they are competing for public investors, so their stock prices will go up. They also compete for strategic partners--the big pharmaceutical firms, which is also a form of financing. Fourth, since many specialty firms are small and young, they typically have not commercialized their product when they went into IPO. In fact, whether or not these firms can generate profit or certain revenue is not a necessary requirement for them to IPO. They do not even need to go through phase three clinical stage to go for IPO. The important issue here is to generate a good story that can attract public investors' interest. However, many firms do have phase two clinical stage data before they go to IPO. This issue is particularly related to the performance implication of small specialty pharmaceutical firms, which we will discuss in a later chapter.

M&As and Strategic Alliances in Pharmaceutical Industry

Mergers & Acquisitions Activities

As noted before, the concentration ratio in the pharmaceutical industry has steadily increased over time. Such an industry consolidation is largely the consequence of M&A

activities. The pace of M&As in this industry starts to pick up around the end of the 1980s. The average annual deal was worth around 4.3 billion U.S \$ at the beginning of the 1990s. The pace of consolidation rose to 25 billion in 1993 and 36.7 billion U.S \$ in 1995. Since then, the level of activity remained at a high level (except for 1997 when the Asian financial crisis hit the industry significantly) and reached a record high at 133 billion in 1999 and stabilized at around 60 to 70 billion thereafter (See Figure 7 for details). Behind the phenomenal M&A mania was the emergence of a pattern of activities during the past two decades.

Insert Figure 7 about here

The first is the mega mergers where both acquirer and target are large and well-known pharmaceutical firms. Examples include Roche's acquisition of Boehringer Mannheim in 1998, Pfizer's takeover of Pharmacia in 2003 and Sanofi-Synthelabo's acquisition of Aventis. The value of these mega-mergers typically exceeded US \$ 1 billion and created a huge impact on the industry and on society (such as employment, etc). The second pattern is the M&As between generics pharmaceutical firms. This type of acquisition is one of our major focuses in the current study. There have been some notable examples in this pattern. For instance, in 2006, Teva of Israel regained the no.1 position after it bought US rival Ivax for \$7.4 billion. Meanwhile, smaller generics producers have conducted M&As as well, with some strategic purpose (such as geographical expansion). An example would be Indian manufacturers buying in Europe and the US. The third pattern involves M&As between specialty pharmaceutical firms, which is another major type of acquisition within our sample firms. As competition among giant drug companies intensify, more market niche was either neglected or released, creating opportunity for the rapid growth of specialty firms.

Well-known examples include Protein Design Labs's acquisition of ESP Pharma and MGI pharma's acquisition of Guilford. The fourth trend is for large biotech companies to acquire other biotechs. Examples are the acquisition of Axxima by GPC Biotech and Immunex by Amgen. The last common type of deal has involved larger pharmaceutical firms fueling their drug pipelines with the acquisition of a smaller biotech firms. This trend is more recent. Examples are the Roche acquisition of Antisoma, the acquisition of Corixa and ID Biomedical by GlaxoSmithKline.

The determinants of M&A activity in the pharmaceutical (biotechnology) industry vary by different patterns of M&As. For mega mergers, they largely result from the excess capacity due to patent expirations and insufficient compounds in the pipeline, which can generate excessive production and marketing capacity (Danzon, et al., 2006). Generic mergers, on the other hand, can create value for generic drug companies through the instant economies of scale (i.e., manufacturing and administrative capacity). Generic drug firms need to achieve critical mass to lower their prices and compete aggressively for market share. For specialty firms' M&As, the issue of excessive capacity due to patent expiration, and motives of economics of scale are less relevant since specialty firms are usually smaller, and not fully integrated. These firms usually specialize in R&D devoted to either drug discovery or discovery-related technologies. They might use an M&A strategy (purchasing marketed drugs, etc.) to generate sufficient revenue in the hope that it can be used to fund their innovative projects. The motives behind the M&As between large pharmaceutical firms and small biotechnology firms lie in pharmaceutical firms' interest in adding and upgrading its pipeline in a way that is more cost effective than developing internally from scratch. From a biotechnology firm's perspective, acquisitions might be an exit strategy to realize venture

capitalists' and founders' investments. Finally, biotech-biotech M&As are driven by larger biotechnology acquirers' desire to achieve critical mass and economies of scale.

Strategic Alliance Activities

We adopt a broad view of alliances, which capture all types of cooperative activity including joint ventures, equity stakes, marketing agreement, licensing agreement, joint development of R&D, and other licensing agreements (such as distribution, co-promotion, etc). Over the past few decades, the role of alliances has become more and more critical for pharmaceutical companies to sustain their competitive advantage and meet their shareholders' expectations. In 2007, approximately 40 percent of revenues of the top 20 pharmaceutical firms' are expected to come from licensed products (Laroia & Krishnan, 2005).

Although there are some common theoretical rationales of why firms ally (such as organizational learning, transaction cost theory, resources-based view), our review tends to briefly point out the different motives for giant pharmaceutical/biotechnology firms, and small-medium size specialty / biotechnology firms, and then stress the key motivation for our sample firms, i.e. small and young specialty drug companies. Our review integrates theoretical views of alliances with interviews of key pharmaceutical executives. For big-pharmaceuticals, strategic alliances are a way to acquire new technological capabilities (Hoang & Rothaermel, 2005), innovative compounds (usually from small biotechnology or specialty firms), or complementary skill sets in downstream activities (such as marketing or distribution—usually from other big pharmaceuticals, e.g. Novartis drawing on GSK's sales forces to sell). Alliances, to big pharmaceuticals, are a strategic response to the changing

environment as mentioned above, such as the upcoming patent expiration, gap in existing pipeline, lower productivity of internal R&D, and reduction of profit from new product launch. Similarly, large bio-pharmaceutical firms' engagement in strategic alliances is more driven by the need to complement their technological capabilities in the aim to improve their financial structure and to obtain innovative drugs (Ohba & Figueiredo, 2007).

For small and medium size firms (either specialty or biotechnology), their motivation to enter strategic alliances is to achieve commercial application of their in-house innovative technological capabilities and to engage in new activities (e.g. drug commercialization in the global pharmaceutical market). Since small specialty firms do not have a downstream function, they have to draw on big-pharmaceuticals or big biopharmaceuticals to manufacture or market their products. Typically, these small firms will out-license their technologies to big-pharmaceutical firms and receive royalty revenues in return. In particular, specialty firms' overall market in a specific (U.S) context is rather small because of the nature of diseases they treat. So these firms will have to go international to access a unique market of patients globally. It is not economically feasible for them to set up a subsidiary or acquire existing pharmaceutical firms in those countries. Meanwhile, different countries have very different requirements for pricing, reimbursement and promotional efforts. It is a huge nightmare for large pharmaceutical firms to explore these markets alone. For instance, France has less pricing freedom regarding drug sales than that of U.S. It is financially rational to ally with a regional partner (e.g., a French company or other big company whose headquarter is in Europe such as Bayer) when small specialty firms try to enter into the French market. Small biotechnology firms face similar constraints when they plan to internationalize their product markets. For instance, Amgen was a small

company when they launched their Epogen, when they had actually a partner in the U.S (Johnson & Johnson). J&J maintained the right to sell Amgen's Epogen to the rest of the world (Pal, 2007).

Furthermore, small specialty and biotechnology firms also cooperate with large pharmaceutical firms on the development of drug. Typically, there are four stages in the development of a drug: one pre-clinical stage and three phases of clinical trials. Phase 1 is all about safety with a small number of people. Phase 2 is about beginning to show efficacy. In Phase 3, firms should achieve statistical validity based on large population. The total cost of running phases 1,2 and3 typically is in excess of a hundred million dollars. In particular, phases 1 and 2 may not be a major hurdle for most small specialty firms. It is phase 3 that is most costly and risky. If failed, the company's prospect will be quickly in jeopardy. Small specialty firms usually partner with large pharmaceutical firms to access latter' financial and human capitals to conduct phase 3 clinical trials. To quote a senior pharmaceutical executive: "So you need data that shows that you have a lead chemical compound. And then you need to partner with somebody who's got the resources to actually conduct that Phase 3 clinical trial. And that's really been the model that all these companies now use. Get good data and then form a strategic alliance with somebody big, somebody who has deep enough pockets to bring the thing to market" (Vanderlaan, 2007). Recent research also shows that products developed in an alliance between small and large pharmaceutical firms tend to have a higher probability of success (i.e. getting approval eventually), particularly in more complex phase 3 trials (Danzon, Nicholson, & Pereira, 2005, DiMasi, 2001; Arora,

Gambardella, Pommolli, & Riccaboni, 2000).²³ In addition, large pharmaceutical firms also prefer to cooperate with small specialty firms on developing phase 3 drugs, because the probability of success in phase 3 is usually 73% compare with 7% at pre-clinical stage, 23% at phase 1 and 33% at phase 2 (Fischette, 2004).

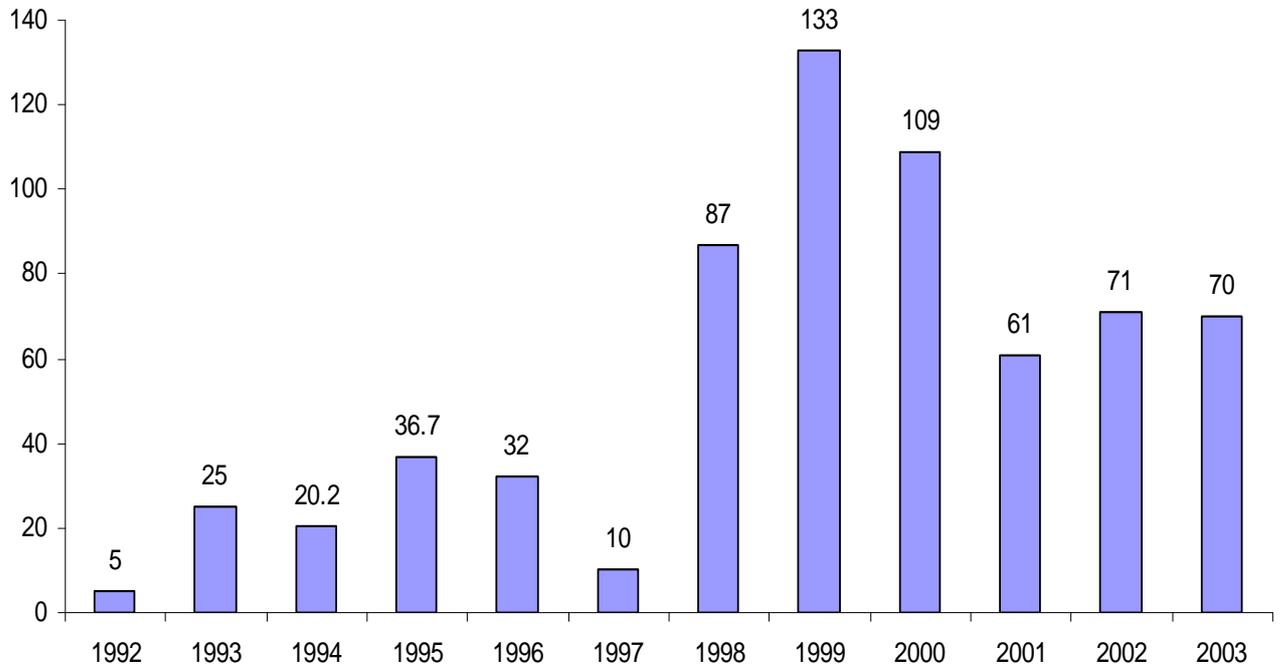
Last, small specialty firms' motivation to ally with large pharmaceutical firms is also related with transfer of status and the signaling effect. Small specialty firms or young biotechnology firms suffer from liability of smallness and/or newness. The strategy literature suggests that they can increase their chances of survival and access to external resources by gaining legitimacy via ties with prestigious businesses (Stuart, Hoang, & Hybels, 1999; Gulati & Higgins, 2003). In the competitive arena, small specialty firms compete for finance and investors' attention. For listed companies, their audience is public investor and institutional investors. For firms that struggle for IPO, their audience is venture capitalist and other individual investors. Allying with a large pharmaceutical firm allows a small specialty firm to send a signal of its quality to the financial markets under the assumption that there is an information asymmetry between specialty firms and investors, and pharmaceutical firms can better evaluate the quality of small specialty firms' technological know-how and managerial capability. This assumption is quite true particularly when small firms operate in specialty domains where knowledge is quite specialized and therefore less likely to be evaluated accurately by general public investor and venture capitalists. In other words,

²³ On the contrary, Pisano (1997) argued the opposite, i.e. products co-developed in an alliance are less likely to succeed in clinical trials than drugs that are developed by a single small firm. He proposed a "lemons" hypothesis that stressed the information advantages small firms have regarding their drug candidates. Danzon et al. (2005: 7) argued that "the positive benefit from collaboration with a more experienced partner appears to dominate any moral hazard effect that might result from the sharing of gains in alliance, and any lemons or adverse selection effects".

pharmaceutical firms, in this case, perform a validating function which is usually assumed by financial intermediaries (Nicholson, Danzon, McCullough, 2005).

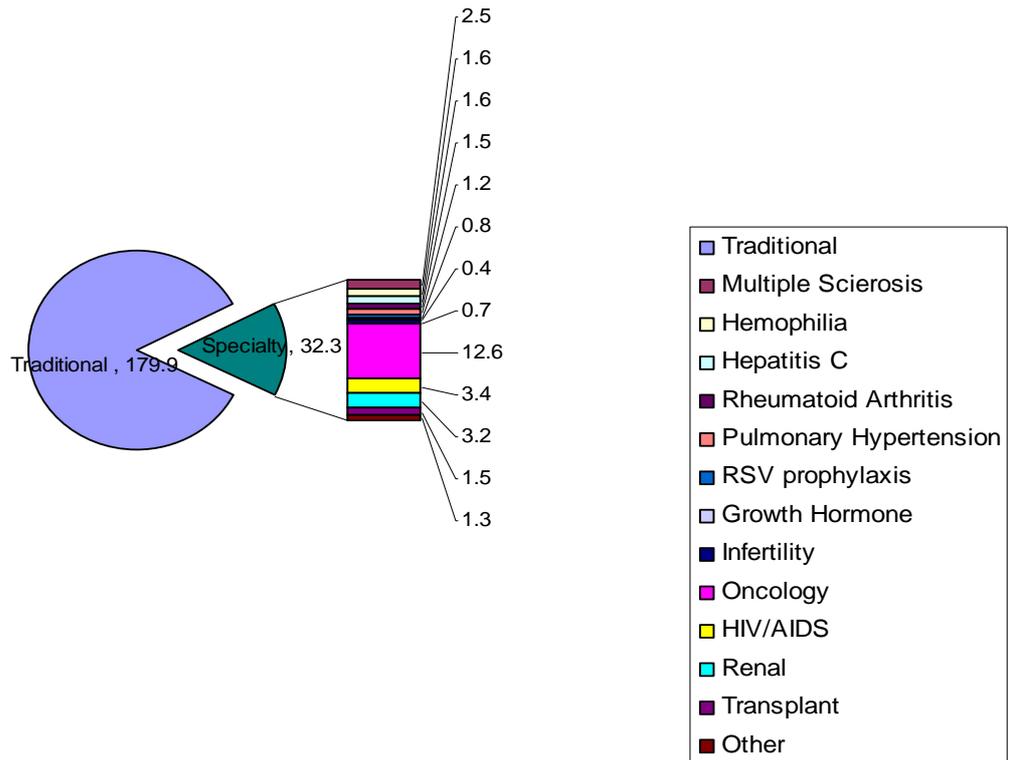
Figure 6. Global Pharmaceutical Industry Merger & Acquisition

(In terms of value: US \$ in billions)—A Historical View²⁴



²⁴ Source: Chemical Market Reporter, “Global Pharmaceutical M&As are already at a Record Pace,” Oct 4, 1999, Chemical Market Reporter, “The search for APIs Drives Pharmaceutical Mergers and Acquisitions,” Mar 17, 2003, Business Insights, “Pharmaceutical M&A: the third wave”, 1999, Pharmaceutical Business Strategies, “Pharma M&A report: First half of 2004”, Oct 2004, Mar 2008, Weilei Shi Estimates.

Figure 7. U.S Specialty Pharmaceutical Industry Breakdown by Therapeutic Areas in 2003 (US \$ in billions)²⁵



²⁵ Source: IMS Health, JP Morgan Industry Update, "Specialty Pharmacy: Conduit of Growth for Biotechnology," March 14, 2003, Bear Stearns Health Care Distribution, "Specialty Pharmacy Services: Among the Fastest-Growing Areas of Health Care," November 2003, Caremark Estimates.

APPENDIX D

[ORIGINAL RESULTLS BY USING STRANDAR DEVIATION AND SKEWNESS]

```
. xtgls      t_qlogf1  an_ac_a an_al_a assetlog roa indum stage  assetper  lev
> erage  branded  stock_a  rd_i_mf3 y1986-y2003, corr(ar1) force panel(hetero)
note: y2000 dropped due to collinearity
```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.5901)

```
Estimated covariances      =      37      Number of obs      =      372
Estimated autocorrelations =      1      Number of groups   =      37
Estimated coefficients     =      29      Obs per group: min =      2
                                           avg = 10.05405
                                           max =      17
                                           Wald chi2(27)     =      225.07
Log likelihood              = -197.0288   Prob > chi2         =      0.0000
```

```
-----+-----
t_qlogf1 |      Coef.   Std. Err.    z    P>|z|    [95% Conf. Interval]
-----+-----
an_ac_a  |      .00055   .0105441    0.05  0.958    -.020116   .0212161
an_al_a  |      .0351135  .0229229    1.53  0.126    -.0098146  .0800415
```

assetlog		-.2337202	.0421666	-5.54	0.000	-.3163652	-.1510752
roa		-.1512208	.1018236	-1.49	0.138	-.3507915	.0483499
indum		.0328416	.1874106	0.18	0.861	-.3344765	.4001597
stage		.0981044	.1017294	0.96	0.335	-.1012816	.2974903
assetper		.0257947	.0102508	2.52	0.012	.0057034	.0458859
leverage		.0011499	.003236	0.36	0.722	-.0051926	.0074925
branded		.117907	.1177893	1.00	0.317	-.1129557	.3487697
stock_a		.0001099	.0000302	3.65	0.000	.0000508	.000169
rd_i_mf3		-.0525234	.0283425	-1.85	0.064	-.1080737	.003027
y1986		-.1273341	.272965	-0.47	0.641	-.6623357	.4076674
y1987		-.1533508	.2471871	-0.62	0.535	-.6378285	.331127
y1988		-.0312864	.225205	-0.14	0.890	-.47268	.4101072
y1989		.1870456	.2259015	0.83	0.408	-.2557132	.6298044
y1990		.5192199	.2110845	2.46	0.014	.1055019	.932938
y1991		.3021853	.2184652	1.38	0.167	-.1259987	.7303692
y1992		.2839029	.2169942	1.31	0.191	-.141398	.7092037
y1993		.0442692	.2146253	0.21	0.837	-.3763887	.4649271
y1994		.4027005	.2109452	1.91	0.056	-.0107444	.8161455
y1995		.2898852	.1942536	1.49	0.136	-.0908449	.6706154
y1996		.1923953	.1654291	1.16	0.245	-.1318398	.5166304
y1997		-.0026853	.130814	-0.02	0.984	-.2590761	.2537054
y1998		.1915451	.1077766	1.78	0.076	-.0196932	.4027833
y1999		.0339534	.0761447	0.45	0.656	-.1152875	.1831943
y2001		-.4750673	.0687544	-6.91	0.000	-.6098234	-.3403112
y2002		-.0782955	.0943584	-0.83	0.407	-.2632346	.1066436
y2003		(dropped)					
_cons		1.209007	.3790103	3.19	0.001	.4661606	1.951854

```
-----
. xtgls      t_qlogf1  an_ac_a an_al_a sd_ac_al_a assetlog roa indum stage as
> setper leverage branded stock_a rd_i_mf3 y1986-y2003, corr(ar1) force pan
> el(hetero)
```

note: y2000 dropped due to collinearity

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.5893)

Estimated covariances	=	37	Number of obs	=	371
Estimated autocorrelations	=	1	Number of groups	=	37
Estimated coefficients	=	30	Obs per group: min	=	2
			avg	=	10.02703
			max	=	17
			Wald chi2(28)	=	247.40
Log likelihood	=	-193.4688	Prob > chi2	=	0.0000

t_qlogf1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
an_ac_a	-.037199	.0324257	-1.15	0.251	-.1007522	.0263542
an_al_a	-.0100595	.0382037	-0.26	0.792	-.0849373	.0648183
sd_ac_al_a	.1195873	.0907603	1.32	0.188	-.0582997	.2974743
assetlog	-.2337752	.0411761	-5.68	0.000	-.314479	-.1530715
roa	-.1312929	.1014749	-1.29	0.196	-.33018	.0675942
indum	.042134	.1869219	0.23	0.822	-.3242262	.4084942
stage	.0620177	.101514	0.61	0.541	-.136946	.2609815
assetper	.0227106	.0096034	2.36	0.018	.0038882	.0415329
leverage	.0016279	.0032696	0.50	0.619	-.0047805	.0080362
branded	.1102534	.1164456	0.95	0.344	-.1179758	.3384826
stock_a	.000107	.0000301	3.55	0.000	.0000479	.000166
rd_i_mf3	-.0534316	.0283283	-1.89	0.059	-.108954	.0020908
y1986	-.1206875	.2738924	-0.44	0.659	-.6575068	.4161319
y1987	-.14452	.2481311	-0.58	0.560	-.630848	.3418081
y1988	-.0372904	.2262817	-0.16	0.869	-.4807943	.4062135
y1989	.184033	.2268058	0.81	0.417	-.2604981	.6285641
y1990	.5211563	.2120409	2.46	0.014	.1055639	.9367488
y1991	.2931156	.2193282	1.34	0.181	-.1367598	.7229909
y1992	.2654784	.2181712	1.22	0.224	-.1621293	.6930862

```

y1993 | .0235998 .2160899 0.11 0.913 -.3999286 .4471282
y1994 | .3806566 .2119059 1.80 0.072 -.0346714 .7959846
y1995 | .2676275 .1951941 1.37 0.170 -.114946 .650201
y1996 | .1671863 .1661823 1.01 0.314 -.1585251 .4928976
y1997 | -.0333371 .1314649 -0.25 0.800 -.2910035 .2243294
y1998 | .1552661 .108282 1.43 0.152 -.0569628 .3674949
y1999 | .0363536 .0745322 0.49 0.626 -.1097269 .1824341
y2001 | -.4725593 .0646273 -7.31 0.000 -.5992265 -.3458921
y2002 | -.0758241 .0902657 -0.84 0.401 -.2527415 .1010934
y2003 | (dropped)
_cons | 1.276139 .3780912 3.38 0.001 .5350938 2.017184

```

```

-----
. xtgls      t_qlogf1  an_ac_a an_al_a sd_ac_al_a  sd_ac_al_a_sq assetlog roa
> indum stage assetper leverage branded stock_a rd_i_mf3 y1986-y2003, corr
> (ar1) force panel(hetero)
note: y2000 dropped due to collinearity

```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (-0.6453)

```

Estimated covariances      =      37      Number of obs      =      371
Estimated autocorrelations =      1      Number of groups   =      37
Estimated coefficients     =      31      Obs per group: min =      2
                                           avg = 10.02703
                                           max =      17
                                           Wald chi2(29)     =      475.10
Log likelihood              = -391.6767   Prob > chi2        =      0.0000

```

```

-----+-----
t_qlogf1 |      Coef.  Std. Err.      z    P>|z|      [95% Conf. Interval]

```

an_ac_a		.0424634	.0234222	1.81	0.070	-.0034433	.0883701
an_al_a		.0386134	.023724	1.63	0.104	-.0078848	.0851115
sd_ac_al_a		.224415	.0579727	3.87	0.000	.1107905	.3380395
sd_ac_al_a~q		-.0295568	.0030591	-9.66	0.000	-.0355526	-.023561
assetlog		-.2776147	.0260336	-10.66	0.000	-.3286397	-.2265897
roa		-.5225848	.1147618	-4.55	0.000	-.7475138	-.2976558
indum		-.1515877	.0898124	-1.69	0.091	-.3276167	.0244413
stage		.1207903	.0545888	2.21	0.027	.0137982	.2277825
assetper		.057169	.0179758	3.18	0.001	.0219371	.092401
leverage		.0104541	.0051404	2.03	0.042	.000379	.0205291
branded		.200365	.06026	3.33	0.001	.0822575	.3184724
stock_a		.0000158	.0000452	0.35	0.726	-.0000728	.0001045
rd_i_mf3		-.0693057	.0160154	-4.33	0.000	-.1006953	-.0379161
y1986		-.6280824	.4901867	-1.28	0.200	-1.588831	.3326659
y1987		-.5555775	.3839812	-1.45	0.148	-1.308167	.1970119
y1988		-.609248	.5055979	-1.21	0.228	-1.600202	.3817057
y1989		-.3245625	.3516591	-0.92	0.356	-1.013802	.3646767
y1990		.0938593	.4613549	0.20	0.839	-.8103797	.9980983
y1991		-.2004766	.3408572	-0.59	0.556	-.8685444	.4675912
y1992		-.3139529	.3796816	-0.83	0.408	-1.058115	.4302093
y1993		-.7344373	.3390946	-2.17	0.030	-1.39905	-.0698241
y1994		-.176859	.3486643	-0.51	0.612	-.8602284	.5065105
y1995		-.1991157	.3087169	-0.64	0.519	-.8041896	.4059583
y1996		-.3364063	.2673717	-1.26	0.208	-.8604452	.1876326
y1997		-.3605684	.2131319	-1.69	0.091	-.7782992	.0571624
y1998		.0013389	.1695245	0.01	0.994	-.3309231	.3336009
y1999		-.0183804	.187297	-0.10	0.922	-.3854757	.348715
y2001		-.4927651	.1831445	-2.69	0.007	-.8517217	-.1338086
y2002		-.1287235	.1414226	-0.91	0.363	-.4059067	.1484597
y2003		(dropped)					
_cons		2.110388	.4653319	4.54	0.000	1.198355	3.022422

```
-----
. xtglm t_qlogfl an_ac_a an_al_a sd_an_ac_a sd_an_al_a assetlog roa i
> ndum stage assetper leverage branded stock_a rd_i_mf3 y1986-y2003, corr(
```

> ar1) force panel(hetero)

note: y2000 dropped due to collinearity

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.5873)

Estimated covariances	=	37	Number of obs	=	371
Estimated autocorrelations	=	1	Number of groups	=	37
Estimated coefficients	=	31	Obs per group: min	=	2
			avg	=	10.02703
			max	=	17
			Wald chi2(29)	=	237.15
Log likelihood	=	-194.1621	Prob > chi2	=	0.0000

t_qlogf1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
an_ac_a	-.0343447	.0366602	-0.94	0.349	-.1061975	.0375081
an_al_a	.0355825	.0900724	0.40	0.693	-.1409561	.2121212
sd_an_ac_a	.1067719	.1004684	1.06	0.288	-.0901426	.3036863
sd_an_al_a	.0020537	.2180937	0.01	0.992	-.425402	.4295094
assetlog	-.2370858	.0419202	-5.66	0.000	-.3192479	-.1549238
roa	-.1334762	.1018686	-1.31	0.190	-.333135	.0661826
indum	.0382872	.1861804	0.21	0.837	-.3266196	.4031941
stage	.0689677	.103311	0.67	0.504	-.1335182	.2714535
assetper	.0233968	.0099674	2.35	0.019	.0038612	.0429325
leverage	.0015203	.0032778	0.46	0.643	-.0049041	.0079446
branded	.1143361	.1171161	0.98	0.329	-.1152072	.3438795
stock_a	.0001082	.0000302	3.58	0.000	.0000491	.0001674
rd_i_mf3	-.0534956	.0282262	-1.90	0.058	-.1088179	.0018267
y1986	-.1272893	.2726983	-0.47	0.641	-.6617681	.4071895
y1987	-.1486445	.2469416	-0.60	0.547	-.6326411	.3353522

y1988		-.0349651	.2249755	-0.16	0.876	-.4759089	.4059788
y1989		.1840771	.2256731	0.82	0.415	-.2582341	.6263882
y1990		.5182004	.2108484	2.46	0.014	.1049452	.9314556
y1991		.2922163	.2182873	1.34	0.181	-.1356189	.7200515
y1992		.2702516	.2171958	1.24	0.213	-.1554444	.6959476
y1993		.029376	.2151301	0.14	0.891	-.3922712	.4510233
y1994		.3841046	.2110101	1.82	0.069	-.0294676	.7976767
y1995		.2716468	.194578	1.40	0.163	-.1097191	.6530127
y1996		.1733819	.1657383	1.05	0.296	-.1514592	.4982231
y1997		-.0301726	.1312276	-0.23	0.818	-.2873739	.2270288
y1998		.1556947	.1087286	1.43	0.152	-.0574095	.3687988
y1999		.0363355	.0753522	0.48	0.630	-.1113521	.1840231
y2001		-.4682253	.0666418	-7.03	0.000	-.5988409	-.3376097
y2002		-.0707664	.0926303	-0.76	0.445	-.2523185	.1107857
y2003		(dropped)					
_cons		1.274681	.3783495	3.37	0.001	.5331301	2.016233

```
-----
. xtgls      t_qlogf1  an_ac_a an_al_a sd_an_ac_a  sd_an_al_a  sd_an_ac_a_sq
> sd_an_al_a_sq assetlog roa indum stage assetper leverage branded stock_
> a rd_i_mf3 y1986-y2003, corr(ar1) force panel(hetero)
note: y2000 dropped due to collinearity
```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.7481)

Estimated covariances	=	37	Number of obs	=	371
Estimated autocorrelations	=	1	Number of groups	=	37
Estimated coefficients	=	33	Obs per group: min	=	2
			avg	=	10.02703
			max	=	17
			Wald chi2(31)	=	270.84

Log likelihood = -174.1527 Prob > chi2 = 0.0000

t_qlogf1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
an_ac_a	-.0327714	.0386926	-0.85	0.397	-.1086076	.0430647
an_al_a	.0915564	.09168	1.00	0.318	-.088133	.2712459
sd_an_ac_a	.252696	.1178465	2.14	0.032	.0217211	.4836709
sd_an_al_a	-.0049894	.2418074	-0.02	0.984	-.4789232	.4689444
sd_an_ac_a~q	-.0189935	.0087749	-2.16	0.030	-.036192	-.0017951
sd_an_al_a~q	-.0523093	.0492249	-1.06	0.288	-.1487884	.0441697
assetlog	-.2967821	.0516952	-5.74	0.000	-.3981028	-.1954614
roa	-.1126182	.0965986	-1.17	0.244	-.3019479	.0767116
indum	.0428334	.2638343	0.16	0.871	-.4742722	.5599391
stage	.1873947	.1328877	1.41	0.158	-.0730604	.4478498
assetper	.0255002	.0090981	2.80	0.005	.0076683	.0433322
leverage	.002154	.0031174	0.69	0.490	-.003956	.0082639
branded	.1602839	.15864	1.01	0.312	-.1506449	.4712127
stock_a	.0001111	.0000312	3.55	0.000	.0000498	.0001723
rd_i_mf3	-.0402168	.0343356	-1.17	0.241	-.1075134	.0270797
y1986	-.1214238	.2616578	-0.46	0.643	-.6342637	.391416
y1987	-.1290246	.2315006	-0.56	0.577	-.5827574	.3247081
y1988	-.0127537	.2086179	-0.06	0.951	-.4216373	.3961298
y1989	.212814	.2067059	1.03	0.303	-.1923222	.6179502
y1990	.5074127	.1959793	2.59	0.010	.1233003	.8915251
y1991	.2995716	.2057978	1.46	0.145	-.1037846	.7029279
y1992	.2614818	.2103027	1.24	0.214	-.150704	.6736676
y1993	.0474141	.2113533	0.22	0.822	-.3668307	.4616589
y1994	.3602443	.2102117	1.71	0.087	-.0517632	.7722517
y1995	.2475651	.1956724	1.27	0.206	-.1359457	.6310759
y1996	.1672806	.1673833	1.00	0.318	-.1607847	.4953459
y1997	-.0415363	.1321446	-0.31	0.753	-.300535	.2174624
y1998	.1262143	.1063174	1.19	0.235	-.0821639	.3345926
y1999	.0230847	.0693182	0.33	0.739	-.1127765	.1589458
y2001	-.4315149	.0604057	-7.14	0.000	-.5499078	-.313122

```

y2002 | -.0212225 .0905729 -0.23 0.815 -.1987421 .1562971
y2003 | (dropped)
_cons | 1.196729 .4420794 2.71 0.007 .3302697 2.063189

```

```

. xtgls      roafl      an_ac_a an_al_a assetlog roa indum stage assetper leve
> rage branded rd_i_mf3 y1986-y2003, corr(ar1) force panel(hetero)

```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.0858)

```

Estimated covariances      =      37      Number of obs      =      373
Estimated autocorrelations =      1      Number of groups   =      37
Estimated coefficients     =      29      Obs per group: min =      2
                                           avg = 10.08108
                                           max =      17
                                           Wald chi2(27)     =      434.41
Log likelihood              = 222.6255      Prob > chi2        =      0.0000

```

```

-----
      roafl |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      an_ac_a | -.0011856   .0019809    -0.60  0.549   - .0050682   .0026969
      an_al_a | -.0060843   .0046749   -1.30  0.193   - .0152469   .0030783
      assetlog | .0080867   .0083868     0.96  0.335   - .0083511   .0245246
           roa | .4904614   .0476735   10.29  0.000     .397023   .5838998
           indum | .0182912   .0300403     0.61  0.543   - .0405867   .0771692
           stage | .0155706   .0126349     1.23  0.218   - .0091933   .0403346
      assetper | .0025429   .0038916     0.65  0.513   - .0050845   .0101704
      leverage | -.0018247   .0011135   -1.64  0.101   - .0040072   .0003578
      branded | -.0194784   .0152293   -1.28  0.201   - .0493272   .0103705

```

rd_i_mf3		-.0471055	.009602	-4.91	0.000	-.0659251	-.028286
y1986		.0587781	.1324152	0.44	0.657	-.200751	.3183072
y1987		.0437426	.1317823	0.33	0.740	-.214546	.3020313
y1988		.0511683	.1303376	0.39	0.695	-.2042887	.3066254
y1989		.0472088	.1311124	0.36	0.719	-.2097668	.3041844
y1990		.0296891	.1299686	0.23	0.819	-.2250447	.284423
y1991		.0663275	.130485	0.51	0.611	-.1894185	.3220734
y1992		.0300602	.1301873	0.23	0.817	-.2251022	.2852226
y1993		.0553994	.1300047	0.43	0.670	-.1994052	.3102039
y1994		.0597703	.1298111	0.46	0.645	-.1946547	.3141954
y1995		.0321904	.1301198	0.25	0.805	-.2228397	.2872204
y1996		.0694291	.1301982	0.53	0.594	-.1857547	.3246129
y1997		.014662	.1301288	0.11	0.910	-.2403857	.2697097
y1998		.0878949	.130251	0.67	0.500	-.1673924	.3431822
y1999		.0639286	.1298494	0.49	0.622	-.1905714	.3184287
y2000		.0550585	.1299362	0.42	0.672	-.1996117	.3097287
y2001		.0507731	.1300934	0.39	0.696	-.2042054	.3057515
y2002		.0484339	.1304401	0.37	0.710	-.207224	.3040918
y2003		(dropped)					
_cons		-.0977528	.1324755	-0.74	0.461	-.3574001	.1618944

```
-----
. xtgls      roaf1  an_ac_a an_al_a sd_ac_al_a assetlog roa indum stage asset
> per leverage branded rd_i_mf3 y1986-y2003, corr(ar1) force panel(hetero)
```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.0849)

Estimated covariances	=	37	Number of obs	=	372
Estimated autocorrelations	=	1	Number of groups	=	37
Estimated coefficients	=	30	Obs per group: min	=	2
			avg	=	10.05405

```

max = 17
Wald chi2(28) = 434.65
Prob > chi2 = 0.0000
Log likelihood = 221.3206

```

roaf1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
an_ac_a	-.0030595	.0051707	-0.59	0.554	-.0131938	.0070748
an_al_a	-.0084687	.0076203	-1.11	0.266	-.0234041	.0064668
sd_ac_al_a	.0054322	.0140897	0.39	0.700	-.0221832	.0330476
assetlog	.008508	.008445	1.01	0.314	-.0080439	.0250599
roa	.4913854	.0476876	10.30	0.000	.3979194	.5848513
indum	.020095	.0303118	0.66	0.507	-.0393149	.079505
stage	.0147437	.0129018	1.14	0.253	-.0105435	.0400308
assetper	.0021073	.0039092	0.54	0.590	-.0055547	.0097692
leverage	-.0017901	.0011239	-1.59	0.111	-.003993	.0004127
branded	-.0195154	.0152556	-1.28	0.201	-.0494158	.0103849
rd_i_mf3	-.0472237	.0096067	-4.92	0.000	-.0660526	-.0283948
y1986	.0597875	.1311572	0.46	0.649	-.1972758	.3168509
y1987	.0443413	.1305093	0.34	0.734	-.2114521	.3001348
y1988	.0512749	.1290557	0.40	0.691	-.2016696	.3042193
y1989	.0469998	.1298395	0.36	0.717	-.207481	.3014805
y1990	.0289546	.1286719	0.23	0.822	-.2232377	.2811147
y1991	.066855	.1291848	0.52	0.605	-.1863425	.3200526
y1992	.0294707	.1289025	0.23	0.819	-.2231735	.2821148
y1993	.0542836	.1287436	0.42	0.673	-.1980492	.3066164
y1994	.0591803	.1285337	0.46	0.645	-.1927412	.3111018
y1995	.0319733	.1288453	0.25	0.804	-.2205588	.2845054
y1996	.0693795	.1289317	0.54	0.591	-.1833219	.322081
y1997	.0135077	.1288723	0.10	0.917	-.2390774	.2660928
y1998	.0893445	.1291033	0.69	0.489	-.1636932	.3423823
y1999	.0646186	.1285978	0.50	0.615	-.1874285	.3166658
y2000	.0539101	.1286528	0.42	0.675	-.1982449	.306065
y2001	.0518903	.1288159	0.40	0.687	-.2005843	.3043649
y2002	.0488911	.1291535	0.38	0.705	-.2042451	.3020273

```

y2003 | (dropped)
_cons | -.0994903 .1312223 -0.76 0.448 -.3566812 .1577007

```

```

-----
. xtgls      roaf1  an_ac_a an_al_a sd_ac_al_a  sd_ac_al_a_sq assetlog roa in
> dum stage assetper leverage branded rd_i_mf3 y1986-y2003, corr(ar1) forc
> e panel(hetero)

```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.0665)

```

Estimated covariances      =      37      Number of obs      =      372
Estimated autocorrelations =      1      Number of groups   =      37
Estimated coefficients     =      31      Obs per group: min =      2
                                           avg = 10.05405
                                           max =      17
                                           Wald chi2(29)     = 459.93
Log likelihood              = 222.4331    Prob > chi2        = 0.0000

```

```

-----
      roaf1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      an_ac_a | -.0007885   .0056314    -0.14  0.889    - .0118259   .0102488
      an_al_a | -.0076409   .007657    -1.00  0.318    - .0226484   .0073666
      sd_ac_al_a | .0193102   .0161059     1.20  0.231    - .0122568   .0508773
sd_ac_al_a~q | -.002042   .0011019    -1.85  0.064    - .0042017   .0001178
      assetlog | .0009432   .0091623     0.10  0.918    - .0170145   .0189009
           roa | .493595    .0475253    10.39  0.000    .4004472   .5867428
           indum | .0076613   .0316569     0.24  0.809    - .054385    .0697077
           stage | .0249314   .0140105     1.78  0.075    - .0025286   .0523915
      assetper | .0028186   .0041363     0.68  0.496    - .0052884   .0109256
      leverage | -.0016653   .0011225    -1.48  0.138    - .0038654   .0005348

```

branded		-.012677	.0153755	-0.82	0.410	-.0428124	.0174583	
rd_i_mf3		-.0473557	.0095051	-4.98	0.000	-.0659853	-.028726	
y1986		.0625699	.1274931	0.49	0.624	-.187312	.3124518	
y1987		.0480705	.1267394	0.38	0.704	-.2003341	.2964752	
y1988		.0498911	.1254095	0.40	0.691	-.195907	.2956892	
y1989		.0459848	.1261102	0.36	0.715	-.2011867	.2931563	
y1990		.0258257	.1249893	0.21	0.836	-.2191489	.2708002	
y1991		.064249	.1254392	0.51	0.609	-.1816073	.3101053	
y1992		.019865	.1252175	0.16	0.874	-.2255569	.2652868	
y1993		.0467078	.1250085	0.37	0.709	-.1983043	.2917199	
y1994		.0503948	.1248445	0.40	0.686	-.1942958	.2950854	
y1995		.0225792	.1251403	0.18	0.857	-.2226912	.2678497	
y1996		.0616924	.1252334	0.49	0.622	-.1837605	.3071454	
y1997		-.0006682	.1251737	-0.01	0.996	-.2460041	.2446677	
y1998		.0812094	.1254327	0.65	0.517	-.1646341	.327053	
y1999		.0566042	.1249548	0.45	0.651	-.1883027	.301511	
y2000		.0486727	.1249508	0.39	0.697	-.1962264	.2935718	
y2001		.0464578	.1250897	0.37	0.710	-.1987135	.2916291	
y2002		.0444864	.1254515	0.35	0.723	-.201394	.2903669	
y2003		(dropped)						
_cons		-.0815041	.1277024	-0.64	0.523	-.3317962	.1687881	

```

-----
. xtgls      roafl  an_ac_a an_al_a sd_an_ac_a  sd_an_al_a  assetlog roa indum
> stage assetper leverage branded rd_i_mf3 y1986-y2003, corr(ar1) force p
> anel(hetero)

```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.0846)

Estimated covariances = 37 Number of obs = 372

Estimated autocorrelations = 1 Number of groups = 37


```

y2000 | .0551193 .1252718 0.44 0.660 -.190409 .3006476
y2001 | .0504286 .1254506 0.40 0.688 -.1954502 .2963073
y2002 | .0478558 .1258222 0.38 0.704 -.1987513 .2944629
y2003 | (dropped)
_cons | -.0985008 .128019 -0.77 0.442 -.3494134 .1524119

```

```

-----
. xtgls      roaf1  an_ac_a an_al_a sd_an_ac_a  sd_an_al_a  sd_an_ac_a_sq sd
> _an_al_a_sq assetlog roa indum stage  assetper  leverage  branded  rd_i_mf3
> y1986-y2003, corr(ar1) force panel(hetero)

```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.0710)

```

Estimated covariances      =      37      Number of obs      =      372
Estimated autocorrelations =      1      Number of groups   =      37
Estimated coefficients     =      33      Obs per group: min =      2
                                           avg = 10.05405
                                           max =      17
                                           Wald chi2(31)     = 458.91
Log likelihood              = 221.6477      Prob > chi2        = 0.0000

```

```

-----
      roaf1 |      Coef.  Std. Err.      z    P>|z|      [95% Conf. Interval]
-----+-----
      an_ac_a | -.0004547   .0058888   -0.08  0.938   -.0119966   .0110872
      an_al_a | -.0004627   .0189365   -0.02  0.981   -.0375776   .0366522
      sd_an_ac_a | .0152566   .0187452    0.81  0.416   -.0214833   .0519965
      sd_an_al_a | .0048873   .0495043    0.10  0.921   -.0921393   .1019139
sd_an_ac_a~q | -.0021702   .0015807   -1.37  0.170   -.0052683   .000928
sd_an_al_a~q | -.0079468   .0101076   -0.79  0.432   -.0277573   .0118638
      assetlog | .0000788   .0102904    0.01  0.994   -.0200899   .0202476

```

roa		.4966573	.0483574	10.27	0.000	.4018785	.5914362
indum		.0106899	.0317563	0.34	0.736	-.0515512	.0729311
stage		.0238541	.0148316	1.61	0.108	-.0052153	.0529235
assetper		.0031948	.0042997	0.74	0.457	-.0052324	.0116221
leverage		-.0016839	.0011423	-1.47	0.140	-.0039228	.0005549
branded		-.0132696	.0171576	-0.77	0.439	-.0468978	.0203586
rd_i_mf3		-.0473236	.0095388	-4.96	0.000	-.0660193	-.0286279
y1986		.0605337	.130616	0.46	0.643	-.1954691	.3165364
y1987		.046903	.1298061	0.36	0.718	-.2075121	.3013182
y1988		.0513405	.1284191	0.40	0.689	-.2003563	.3030373
y1989		.0469954	.1291181	0.36	0.716	-.2060714	.3000621
y1990		.0266008	.1280232	0.21	0.835	-.2243201	.2775217
y1991		.0646477	.1284677	0.50	0.615	-.1871443	.3164397
y1992		.0237988	.1282255	0.19	0.853	-.2275187	.2751162
y1993		.0495162	.1280287	0.39	0.699	-.2014154	.3004478
y1994		.0521869	.1279295	0.41	0.683	-.1985504	.3029242
y1995		.024306	.1282613	0.19	0.850	-.2270815	.2756935
y1996		.0652631	.1283432	0.51	0.611	-.186285	.3168111
y1997		.0048572	.1282513	0.04	0.970	-.2465107	.256225
y1998		.0852205	.1284739	0.66	0.507	-.1665837	.3370247
y1999		.0611133	.1280048	0.48	0.633	-.1897715	.3119981
y2000		.0553485	.1280705	0.43	0.666	-.1956652	.3063621
y2001		.0501865	.1282639	0.39	0.696	-.201206	.3015791
y2002		.0495707	.128624	0.39	0.700	-.2025278	.3016692
y2003		(dropped)					
_cons		-.0787131	.1311557	-0.60	0.548	-.3357735	.1783473

Original Results by Using Skewness

```
. xtgls      t_qlogf1  an_ac_a an_al_a assetlog roa indum stage  assetper lev
> erage branded stock_a rd_i_mf3 y1986-y2003, corr(ar1) force panel(hetero)
note: y2000 dropped due to collinearity
```

Cross-sectional time-series FGLS regression


```

y1994 | .4027005 .2109452 1.91 0.056 -.0107444 .8161455
y1995 | .2898852 .1942536 1.49 0.136 -.0908449 .6706154
y1996 | .1923953 .1654291 1.16 0.245 -.1318398 .5166304
y1997 | -.0026853 .130814 -0.02 0.984 -.2590761 .2537054
y1998 | .1915451 .1077766 1.78 0.076 -.0196932 .4027833
y1999 | .0339534 .0761447 0.45 0.656 -.1152875 .1831943
y2001 | -.4750673 .0687544 -6.91 0.000 -.6098234 -.3403112
y2002 | -.0782955 .0943584 -0.83 0.407 -.2632346 .1066436
y2003 | (dropped)
_cons | 1.209007 .3790103 3.19 0.001 .4661606 1.951854

```

```

-----
. xtgls      t_qlogf1  an_ac_a an_al_a skew_ac_al_a_stata_abs assetlog roa ind
> um stage  assetper  leverage  branded  stock_a  rd_i_mf3 y1986-y2003, corr(ar
> 1) force panel(hetero)
note: y2000 dropped due to collinearity

```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.5809)

```

Estimated covariances      =      37      Number of obs      =      370
Estimated autocorrelations =      1      Number of groups   =      37
Estimated coefficients     =      30      Obs per group: min =      2
                                           avg =      10
                                           max =      17
                                           Wald chi2(28)     =      205.27
Log likelihood              = -197.3368   Prob > chi2        =      0.0000

```

```

-----
t_qlogf1 |      Coef.  Std. Err.      z    P>|z|      [95% Conf. Interval]
-----+-----
an_ac_a | -.0002634  .0104808    -0.03  0.980    -.0208054    .0202787

```

an_al_a		.0348077	.0229218	1.52	0.129	-.0101183	.0797336
skew_ac_al~s		.0292413	.0425542	0.69	0.492	-.0541634	.112646
assetlog		-.2237539	.0423289	-5.29	0.000	-.3067169	-.1407909
roa		-.1595662	.1020811	-1.56	0.118	-.3596414	.0405089
indum		.0345407	.1844734	0.19	0.851	-.3270206	.396102
stage		.0782264	.1011918	0.77	0.439	-.1201058	.2765587
assetper		.0249778	.0113013	2.21	0.027	.0028276	.0471279
leverage		.001054	.0031844	0.33	0.741	-.0051874	.0072953
branded		.0907568	.1174344	0.77	0.440	-.1394104	.3209241
stock_a		.0001057	.0000299	3.53	0.000	.000047	.0001644
rd_i_mf3		-.0493073	.0282579	-1.74	0.081	-.1046918	.0060771
y1986		-.0302728	.2805015	-0.11	0.914	-.5800456	.5195
y1987		-.0426177	.2517474	-0.17	0.866	-.5360335	.4507982
y1988		-.0341281	.222866	-0.15	0.878	-.4709375	.4026812
y1989		.1950786	.2240187	0.87	0.384	-.24399	.6341471
y1990		.5209563	.2088446	2.49	0.013	.1116285	.9302841
y1991		.2950116	.2162751	1.36	0.173	-.1288798	.7189031
y1992		.2685828	.2152994	1.25	0.212	-.1533962	.6905619
y1993		.0282705	.2127287	0.13	0.894	-.3886701	.445211
y1994		.3945704	.2088497	1.89	0.059	-.0147675	.8039083
y1995		.2906435	.1922367	1.51	0.131	-.0861336	.6674205
y1996		.2010053	.1639911	1.23	0.220	-.1204114	.522422
y1997		.0037081	.1302221	0.03	0.977	-.2515226	.2589388
y1998		.2049297	.1082444	1.89	0.058	-.0072254	.4170847
y1999		.0491128	.0774704	0.63	0.526	-.1027265	.200952
y2001		-.4735404	.0721179	-6.57	0.000	-.6148889	-.3321919
y2002		-.0792051	.0977158	-0.81	0.418	-.2707246	.1123143
y2003		(dropped)					
_cons		1.221655	.3767387	3.24	0.001	.4832606	1.960049

```

-----
. xtgls      t_qlogfl  an_ac_a an_al_a skew_ac_al_a_stata_abs  skew_ac_al_a_st
> ata_sq assetlog roa indum stage  assetper  leverage  branded  stock_a  rd_i_m
> f3 y1986-y2003, corr(ar1) force panel(hetero)
note: y2000 dropped due to collinearity

```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.5679)

Estimated covariances	=	37	Number of obs	=	370
Estimated autocorrelations	=	1	Number of groups	=	37
Estimated coefficients	=	31	Obs per group: min	=	2
			avg	=	10
			max	=	17
			Wald chi2(29)	=	206.24
Log likelihood	=	-198.9085	Prob > chi2	=	0.0000

t_qlogf1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
an_ac_a	.0000118	.010313	0.00	0.999	-.0202014	.0202249
an_al_a	.0346402	.022607	1.53	0.125	-.0096688	.0789492
skew_ac_al~s	.0285119	.1010078	0.28	0.778	-.1694598	.2264836
skew_ac_al..	.001044	.041007	0.03	0.980	-.0793281	.0814162
assetlog	-.2220104	.0419049	-5.30	0.000	-.3041425	-.1398783
roa	-.1623645	.1025892	-1.58	0.113	-.3634357	.0387067
indum	.0310586	.1801909	0.17	0.863	-.3221091	.3842262
stage	.0740678	.0995782	0.74	0.457	-.1211019	.2692376
assetper	.0250668	.0115521	2.17	0.030	.0024252	.0477085
leverage	.0010355	.0032111	0.32	0.747	-.0052581	.0073292
branded	.0901389	.1153606	0.78	0.435	-.1359637	.3162414
stock_a	.0001049	.0000299	3.51	0.000	.0000463	.0001634
rd_i_mf3	-.0496324	.0279195	-1.78	0.075	-.1043536	.0050889
y1986	-.0290602	.2806169	-0.10	0.918	-.5790593	.5209389
y1987	-.0427832	.2523045	-0.17	0.865	-.5372908	.4517245
y1988	-.0365154	.2234861	-0.16	0.870	-.47454	.4015092
y1989	.1939604	.2248966	0.86	0.388	-.2468287	.6347496

y1990		.5207604	.2093554	2.49	0.013	.1104314	.9310894
y1991		.2904161	.2167114	1.34	0.180	-.1343304	.7151626
y1992		.2632144	.2154101	1.22	0.222	-.1589817	.6854105
y1993		.0214132	.2128457	0.10	0.920	-.3957567	.4385831
y1994		.3899641	.2089073	1.87	0.062	-.0194867	.7994148
y1995		.2870238	.1921448	1.49	0.135	-.0895732	.6636207
y1996		.1971162	.163795	1.20	0.229	-.1239162	.5181485
y1997		-.0001005	.1300999	-0.00	0.999	-.2550917	.2548907
y1998		.2040741	.1084344	1.88	0.060	-.0084534	.4166015
y1999		.0490798	.0780539	0.63	0.529	-.103903	.2020626
y2001		-.476942	.0730644	-6.53	0.000	-.6201457	-.3337384
y2002		-.0824199	.0982243	-0.84	0.401	-.2749361	.1100963
y2003		(dropped)					
_cons		1.231483	.3730066	3.30	0.001	.5004038	1.962563

```
-----
. xtgls      t_qlogf1  an_ac_a an_al_a skew_an_ac_a_stata_abs  skew_an_al_a_s
> tata_abs  assetlog roa indum stage  assetper leverage branded stock_a rd_
> i_mf3 y1986-y2003, corr(ar1) force panel(hetero)
note: y2000 dropped due to collinearity
```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.5886)

Estimated covariances	=	37	Number of obs	=	368
Estimated autocorrelations	=	1	Number of groups	=	37
Estimated coefficients	=	31	Obs per group: min	=	2
			avg	=	9.945946
			max	=	17
			Wald chi2(29)	=	208.87
Log likelihood	=	-194.4505	Prob > chi2	=	0.0000

t_qlogf1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
an_ac_a	-.0009681	.0103113	-0.09	0.925	-.0211778	.0192417
an_al_a	.0423462	.0243277	1.74	0.082	-.0053351	.0900275
skew_an_ac~s	.0812853	.0460426	1.77	0.077	-.0089566	.1715271
skew_an_al~s	-.0263488	.0477244	-0.55	0.581	-.119887	.0671893
assetlog	-.2418167	.0422875	-5.72	0.000	-.3246987	-.1589347
roa	-.1557806	.1018727	-1.53	0.126	-.3554474	.0438862
indum	-.0049126	.1872176	-0.03	0.979	-.3718523	.3620271
stage	.1022537	.100768	1.01	0.310	-.0952479	.2997552
assetper	.0272035	.0119458	2.28	0.023	.0037902	.0506168
leverage	.00117	.0032636	0.36	0.720	-.0052266	.0075666
branded	.0720392	.1192547	0.60	0.546	-.1616957	.3057741
stock_a	.0001082	.0000304	3.56	0.000	.0000486	.0001678
rd_i_mf3	-.046278	.0285943	-1.62	0.106	-.1023219	.0097659
y1986	-.1278931	.2737273	-0.47	0.640	-.6643887	.4086025
y1987	-.1690959	.2502836	-0.68	0.499	-.6596427	.321451
y1988	-.069145	.2254459	-0.31	0.759	-.5110107	.3727208
y1989	.14866	.2270935	0.65	0.513	-.2964351	.5937551
y1990	.5510517	.2114825	2.61	0.009	.1365535	.9655498
y1991	.333906	.2184821	1.53	0.126	-.0943109	.762123
y1992	.3256568	.2178764	1.49	0.135	-.1013731	.7526867
y1993	.0841397	.2149529	0.39	0.695	-.3371602	.5054395
y1994	.4337248	.2108063	2.06	0.040	.0205522	.8468975
y1995	.3129872	.1940171	1.61	0.107	-.0672795	.6932538
y1996	.2200532	.1654658	1.33	0.184	-.1042539	.5443603
y1997	.0171457	.1309216	0.13	0.896	-.2394558	.2737473
y1998	.2140268	.1082028	1.98	0.048	.0019532	.4261003
y1999	.066543	.0780131	0.85	0.394	-.0863598	.2194457
y2001	-.4584156	.0732253	-6.26	0.000	-.6019346	-.3148966
y2002	-.0515398	.0994544	-0.52	0.604	-.2464668	.1433873
y2003	(dropped)					
_cons	1.25831	.3822741	3.29	0.001	.509067	2.007554

```

. xtgls      t_qlogf1  an_ac_a an_al_a skew_an_ac_a_stata_abs  skew_an_al_a_st
> ata_abs  skew_an_ac_a_stata_sq  skew_an_al_a_stata_sq  assetlog roa indum st
> age  assetper  leverage  branded  stock_a  rd_i_mf3  y1986-y2003, corr(ar1) fo
> rce panel(hetero)
note: y2000 dropped due to collinearity

```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.5827)

```

Estimated covariances      =      37      Number of obs      =      368
Estimated autocorrelations =      1      Number of groups   =      37
Estimated coefficients     =      33      Obs per group: min =      2
                                           avg =  9.945946
                                           max =      17
                                           Wald chi2(31)     =      213.09
Log likelihood              = -193.5763   Prob > chi2         =      0.0000

```

t_qlogf1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
an_ac_a	-.0018951	.0100475	-0.19	0.850	-.0215878	.0177975
an_al_a	.0435398	.0245057	1.78	0.076	-.0044904	.09157
skew_an_ac~s	.2755406	.1096704	2.51	0.012	.0605905	.4904907
skew_an_al~s	-.0689373	.1194209	-0.58	0.564	-.302998	.1651235
skew_an_ac..	-.0717858	.0385269	-1.86	0.062	-.1472973	.0037256
skew_an_al..	.0205468	.0512184	0.40	0.688	-.0798393	.120933
assetlog	-.2591698	.042957	-6.03	0.000	-.343364	-.1749756
roa	-.1679056	.1015614	-1.65	0.098	-.3669623	.0311512
indum	-.0181977	.1826034	-0.10	0.921	-.3760938	.3396983
stage	.11717	.0997445	1.17	0.240	-.0783256	.3126657
assetper	.0332333	.0124953	2.66	0.008	.0087431	.0577236

leverage		.0011595	.0033053	0.35	0.726	-.0053187	.0076377
branded		.0518716	.1179948	0.44	0.660	-.179394	.2831373
stock_a		.0001114	.0000301	3.70	0.000	.0000523	.0001705
rd_i_mf3		-.0468271	.0288207	-1.62	0.104	-.1033145	.0096604
y1986		-.1082753	.2704375	-0.40	0.689	-.6383231	.4217725
y1987		-.1434625	.2475938	-0.58	0.562	-.6287373	.3418124
y1988		-.079964	.2223559	-0.36	0.719	-.5157736	.3558456
y1989		.1596037	.2243117	0.71	0.477	-.2800392	.5992467
y1990		.5585826	.2086585	2.68	0.007	.1496194	.9675458
y1991		.3401951	.2156722	1.58	0.115	-.0825147	.7629048
y1992		.331668	.2151699	1.54	0.123	-.0900572	.7533933
y1993		.0967467	.2126495	0.45	0.649	-.3200387	.5135321
y1994		.4383131	.208494	2.10	0.036	.0296725	.8469538
y1995		.3098377	.1919571	1.61	0.107	-.0663912	.6860667
y1996		.2199485	.1638875	1.34	0.180	-.101265	.5411621
y1997		.0168322	.1300367	0.13	0.897	-.238035	.2716994
y1998		.2170145	.1079359	2.01	0.044	.005464	.428565
y1999		.0581564	.0790705	0.74	0.462	-.0968189	.2131317
y2001		-.472014	.0741871	-6.36	0.000	-.617418	-.3266099
y2002		-.0555347	.0997013	-0.56	0.578	-.2509456	.1398763
y2003		(dropped)					
_cons		1.294201	.3759555	3.44	0.001	.5573423	2.031061

```

. xtgls      roaf1      an_ac_a an_al_a assetlog roa indum stage  assetper  lever
> age  branded      rd_i_mf3 y1986-y2003, corr(ar1) force panel(hetero)

```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.0858)

Estimated covariances	=	37	Number of obs	=	373
Estimated autocorrelations	=	1	Number of groups	=	37
Estimated coefficients	=	29	Obs per group: min	=	2

avg = 10.08108
max = 17

Wald chi2(27) = 434.41
Prob > chi2 = 0.0000

Log likelihood = 222.6255

roaf1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
an_ac_a	-.0011856	.0019809	-0.60	0.549	-.0050682	.0026969
an_al_a	-.0060843	.0046749	-1.30	0.193	-.0152469	.0030783
assetlog	.0080867	.0083868	0.96	0.335	-.0083511	.0245246
roa	.4904614	.0476735	10.29	0.000	.397023	.5838998
indum	.0182912	.0300403	0.61	0.543	-.0405867	.0771692
stage	.0155706	.0126349	1.23	0.218	-.0091933	.0403346
assetper	.0025429	.0038916	0.65	0.513	-.0050845	.0101704
leverage	-.0018247	.0011135	-1.64	0.101	-.0040072	.0003578
branded	-.0194784	.0152293	-1.28	0.201	-.0493272	.0103705
rd_i_mf3	-.0471055	.009602	-4.91	0.000	-.0659251	-.028286
y1986	.0587781	.1324152	0.44	0.657	-.200751	.3183072
y1987	.0437426	.1317823	0.33	0.740	-.214546	.3020313
y1988	.0511683	.1303376	0.39	0.695	-.2042887	.3066254
y1989	.0472088	.1311124	0.36	0.719	-.2097668	.3041844
y1990	.0296891	.1299686	0.23	0.819	-.2250447	.284423
y1991	.0663275	.130485	0.51	0.611	-.1894185	.3220734
y1992	.0300602	.1301873	0.23	0.817	-.2251022	.2852226
y1993	.0553994	.1300047	0.43	0.670	-.1994052	.3102039
y1994	.0597703	.1298111	0.46	0.645	-.1946547	.3141954
y1995	.0321904	.1301198	0.25	0.805	-.2228397	.2872204
y1996	.0694291	.1301982	0.53	0.594	-.1857547	.3246129
y1997	.014662	.1301288	0.11	0.910	-.2403857	.2697097
y1998	.0878949	.130251	0.67	0.500	-.1673924	.3431822
y1999	.0639286	.1298494	0.49	0.622	-.1905714	.3184287
y2000	.0550585	.1299362	0.42	0.672	-.1996117	.3097287
y2001	.0507731	.1300934	0.39	0.696	-.2042054	.3057515
y2002	.0484339	.1304401	0.37	0.710	-.207224	.3040918

```

y2003 | (dropped)
_cons | -.0977528 .1324755 -0.74 0.461 -.3574001 .1618944

```

```

-----
. xtgls      roaf1      an_ac_a an_al_a skew_ac_al_a stata_abs assetlog roa indum
> stage assetper leverage branded rd_i_mf3 y1986-y2003, corr(ar1) force pa
> nel(hetero)

```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.0826)

```

Estimated covariances      =      37      Number of obs      =      371
Estimated autocorrelations =      1      Number of groups   =      37
Estimated coefficients     =      30      Obs per group: min =      2
                                           avg = 10.02703
                                           max =      17
                                           Wald chi2(28)     = 437.64
Log likelihood              = 219.0916    Prob > chi2        = 0.0000

```

```

-----
      roaf1 |      Coef.   Std. Err.    z   P>|z|   [95% Conf. Interval]
-----+-----
      an_ac_a |  -.0013196   .002016   -0.65  0.513   -.0052708   .0026317
      an_al_a |  -.0059201   .0046967  -1.26  0.207   -.0151254   .0032851
skew_ac_al~s |   .001386    .0115662   0.12  0.905   -.0212832   .0240553
      assetlog |   .008822    .0084737   1.04  0.298   -.0077862   .0254301
           roa |   .4908905   .047714   10.29  0.000   .3973728   .5844082
           indum |   .0189414   .0299692   0.63  0.527   -.0397971   .0776799
           stage |   .0140295   .0127378   1.10  0.271   -.0109361   .0389952
      assetper |   .0024649   .0039341   0.63  0.531   -.0052458   .0101756
      leverage |  -.0018267   .0011153  -1.64  0.101   -.0040126   .0003592
      branded |  -.0207278   .0153563  -1.35  0.177   -.0508255   .0093699

```

rd_i_mf3		-.0472217	.0095848	-4.93	0.000	-.0660076	-.0284359
y1986		.0793037	.1357884	0.58	0.559	-.1868366	.3454439
y1987		.0512342	.1339997	0.38	0.702	-.2114005	.3138688
y1988		.0504686	.1300361	0.39	0.698	-.2043976	.3053347
y1989		.0469707	.1306477	0.36	0.719	-.2090942	.3030355
y1990		.029264	.1295444	0.23	0.821	-.2246385	.2831664
y1991		.0655919	.130058	0.50	0.614	-.1893171	.3205009
y1992		.0295624	.1297808	0.23	0.820	-.2248032	.2839281
y1993		.0548816	.129566	0.42	0.672	-.199063	.3088263
y1994		.0591017	.1293759	0.46	0.648	-.1944705	.3126738
y1995		.0316158	.1296577	0.24	0.807	-.2225086	.2857403
y1996		.0686498	.1297474	0.53	0.597	-.1856504	.3229501
y1997		.0135756	.1296936	0.10	0.917	-.2406192	.2677704
y1998		.0869753	.1298018	0.67	0.503	-.1674315	.341382
y1999		.0630366	.1294552	0.49	0.626	-.1906909	.3167641
y2000		.0540727	.1295578	0.42	0.676	-.1998559	.3080013
y2001		.0495724	.1296896	0.38	0.702	-.2046146	.3037594
y2002		.0469778	.1301203	0.36	0.718	-.2080532	.3020088
y2003		(dropped)					
_cons		-.0982898	.1319898	-0.74	0.456	-.3569851	.1604055

```

-----
. xtglsl      roafl      an_ac_a an_al_a skew_ac_al_a_stata_abs  skew_ac_al_a_stat
> a_sq assetlog roa indum stage assetper leverage branded rd_i_mf3 y1986-y
> 2003, corr(ar1) force panel(hetero)

```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.0674)

Estimated covariances	=	37	Number of obs	=	371
Estimated autocorrelations	=	1	Number of groups	=	37
Estimated coefficients	=	31	Obs per group: min	=	2

```

                                avg = 10.02703
                                max =      17
                                Wald chi2(29) = 463.60
                                Prob > chi2 = 0.0000
Log likelihood = 221.8388

```

roaf1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
an_ac_a	-.0014608	.0019738	-0.74	0.459	-.0053294	.0024078
an_al_a	-.0065638	.0046385	-1.42	0.157	-.0156551	.0025276
skew_ac_al~s	.0458833	.0254182	1.81	0.071	-.0039354	.0957021
skew_ac_al..	-.0215234	.0113982	-1.89	0.059	-.0438634	.0008166
assetlog	.0064757	.0083592	0.77	0.439	-.0099081	.0228595
roa	.497205	.0471912	10.54	0.000	.4047119	.5896981
indum	.0210041	.0297206	0.71	0.480	-.0372471	.0792554
stage	.0165666	.0126671	1.31	0.191	-.0082604	.0413936
assetper	.002912	.0037489	0.78	0.437	-.0044358	.0102597
leverage	-.0018554	.0011123	-1.67	0.095	-.0040354	.0003246
branded	-.0213725	.0151598	-1.41	0.159	-.0510852	.0083403
rd_i_mf3	-.0468564	.0094106	-4.98	0.000	-.0653008	-.0284119
y1986	.0797802	.134255	0.59	0.552	-.1833547	.3429151
y1987	.0504781	.1325194	0.38	0.703	-.2092552	.3102113
y1988	.0399096	.1288493	0.31	0.757	-.2126303	.2924496
y1989	.0407868	.1293156	0.32	0.752	-.2126671	.2942407
y1990	.0247555	.1282918	0.19	0.847	-.2266918	.2762027
y1991	.0585885	.1287504	0.46	0.649	-.1937577	.3109347
y1992	.0271023	.128439	0.21	0.833	-.2246335	.278838
y1993	.0516352	.1282672	0.40	0.687	-.1997638	.3030343
y1994	.0553994	.1280659	0.43	0.665	-.1956052	.3064039
y1995	.028875	.1283458	0.22	0.822	-.2226781	.2804281
y1996	.0659313	.1284366	0.51	0.608	-.1857998	.3176623
y1997	.0184477	.1283938	0.14	0.886	-.2331996	.270095
y1998	.0877915	.1284859	0.68	0.494	-.1640363	.3396192
y1999	.0687076	.1282304	0.54	0.592	-.1826194	.3200345
y2000	.0539517	.1282321	0.42	0.674	-.1973785	.305282

```

y2001 | .053365 .128374 0.42 0.678 -.1982433 .3049733
y2002 | .0447142 .1287986 0.35 0.728 -.2077264 .2971549
y2003 | (dropped)
_cons | -.0988954 .1305791 -0.76 0.449 -.3548257 .1570349

```

```

-----
. xtgls      roaf1  an_ac_a an_al_a skew_an_ac_a stata_abs  skew_an_al_a sta
> ta_abs  assetlog roa indum stage  assetper leverage branded rd_i_mf3 y1986
> -y2003, corr(ar1) force panel(hetero)

```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.0787)

```

Estimated covariances      =      37      Number of obs      =      369
Estimated autocorrelations =      1      Number of groups   =      37
Estimated coefficients     =      31      Obs per group: min =      2
                                           avg = 9.972973
                                           max =      17
                                           Wald chi2(29)     =      447.34
Log likelihood             = 217.8508      Prob > chi2        =      0.0000

```

```

-----
      roaf1 |      Coef.   Std. Err.    z    P>|z|    [95% Conf. Interval]
-----+-----
      an_ac_a |  -.0013501   .0020079   -0.67  0.501   -.0052856   .0025854
      an_al_a |  -.0050283   .0048858   -1.03  0.303   -.0146044   .0045478
skew_an_ac~s |   .0179385   .0119205    1.50  0.132   -.0054253   .0413024
skew_an_al~s |  -.0084184   .0120049   -0.70  0.483   -.0319477   .0151108
      assetlog |   .006741    .0084308    0.80  0.424   -.009783    .023265
           roa |   .4857402   .0479364   10.13  0.000   .3917865   .5796939
           indum |   .014734    .0311986    0.47  0.637   -.0464141   .0758822
           stage |   .0185762   .0124047    1.50  0.134   -.0057366   .042889

```

assetper		.0026837	.0042909	0.63	0.532	-.0057263	.0110937
leverage		-.0017364	.0011001	-1.58	0.114	-.0038925	.0004197
branded		-.0229857	.0156979	-1.46	0.143	-.053753	.0077816
rd_i_mf3		-.0464919	.0094882	-4.90	0.000	-.0650884	-.0278954
y1986		.0620892	.1310751	0.47	0.636	-.1948132	.3189916
y1987		.0386531	.1311136	0.29	0.768	-.2183248	.295631
y1988		.0336482	.1293947	0.26	0.795	-.2199608	.2872572
y1989		.0424705	.1301024	0.33	0.744	-.2125254	.2974665
y1990		.0308182	.128918	0.24	0.811	-.2218564	.2834927
y1991		.0691109	.129	0.54	0.592	-.1837244	.3219462
y1992		.033444	.1286789	0.26	0.795	-.218762	.28565
y1993		.0587445	.1283419	0.46	0.647	-.192801	.31029
y1994		.0625041	.128075	0.49	0.626	-.1885183	.3135265
y1995		.0359701	.1283811	0.28	0.779	-.2156522	.2875925
y1996		.0703236	.1284515	0.55	0.584	-.1814367	.3220839
y1997		.0124507	.128435	0.10	0.923	-.2392772	.2641786
y1998		.0881054	.1285483	0.69	0.493	-.1638446	.3400555
y1999		.0704842	.1284841	0.55	0.583	-.18134	.3223084
y2000		.0594936	.1284899	0.46	0.643	-.1923419	.3113292
y2001		.0500399	.128592	0.39	0.697	-.2019958	.3020755
y2002		.0483189	.1289698	0.37	0.708	-.2044572	.301095
y2003		(dropped)					
_cons		-.0975964	.1311156	-0.74	0.457	-.3545782	.1593854

```

-----
. xtgls      roafl  an_ac_a an_al_a skew_an_ac_a_stata_abs  skew_an_al_a_stat
> a_abs    skew_an_ac_a_stata_sq skew_an_al_a_stata_sq assetlog roa indum stag
> e assetper leverage branded rd_i_mf3 y1986-y2003, corr(ar1) force panel(he
> tero)

```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.0524)

```

Estimated covariances      =          37          Number of obs      =          369
Estimated autocorrelations =           1          Number of groups   =           37
Estimated coefficients     =          33          Obs per group: min =           2
                                                avg =  9.972973
                                                max =           17
                                                Wald chi2(31)     =          506.85
Log likelihood             =  220.2658          Prob > chi2       =          0.0000

```

```

-----+-----
      roaf1 |          Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      an_ac_a |   -.0021434   .0019642    -1.09   0.275    -.0059931   .0017063
      an_al_a |   -.0070332   .004875   -1.44   0.149    -.016588   .0025215
skew_an_ac~s |   .0564825   .0268133     2.11   0.035     .0039294   .1090357
skew_an_al~s |   .0298814   .0270117     1.11   0.269    -.0230607   .0828234
skew_an_ac.. |   -.016625   .0104796    -1.59   0.113    -.0371647   .0039147
skew_an_al.. |   -.0168754   .0123799    -1.36   0.173    -.0411395   .0073888
      assetlog |   .0030122   .0083829     0.36   0.719    -.013418   .0194423
           roa |   .491605   .0470891    10.44   0.000     .3993121   .583898
           indum |   .016616   .0309906     0.54   0.592    -.0441244   .0773565
           stage |   .0252245   .0128707     1.96   0.050    -1.52e-06   .0504506
      assetper |   .0032773   .0043402     0.76   0.450    -.0052293   .0117838
      leverage |  -.0015934   .0010825    -1.47   0.141    -.003715   .0005283
      branded |  -.0205433   .0153578    -1.34   0.181    -.0506441   .0095574
      rd_i_mf3 |  -.0465658   .0091738    -5.08   0.000    -.064546   -.0285855
           y1986 |   .0654247   .1283099     0.51   0.610    -.1860581   .3169076
           y1987 |   .0442324   .1283908     0.34   0.730    -.207409   .2958739
           y1988 |   .0257415   .1271041     0.20   0.840    -.223378   .274861
           y1989 |   .0394076   .1274835     0.31   0.757    -.2104555   .2892706
           y1990 |   .0243953   .1265288     0.19   0.847    -.2235966   .2723872
           y1991 |   .0609534   .1264462     0.48   0.630    -.1868767   .3087834
           y1992 |   .0259802   .1261001     0.21   0.837    -.2211714   .2731318
           y1993 |   .0506483   .1258616     0.40   0.687    -.1960359   .2973324
           y1994 |   .0594774   .1255039     0.47   0.636    -.1865057   .3054604

```

y1995		.0311527	.1258328	0.25	0.804	-.2154752	.2777805
y1996		.0681255	.1259035	0.54	0.588	-.1786409	.3148919
y1997		.0215887	.1259055	0.17	0.864	-.2251815	.2683589
y1998		.088704	.1259952	0.70	0.481	-.1582421	.3356501
y1999		.0759054	.1260318	0.60	0.547	-.1711124	.3229233
y2000		.0611441	.1260242	0.49	0.628	-.1858587	.3081469
y2001		.0539183	.1261547	0.43	0.669	-.1933403	.3011769
y2002		.0493916	.1264699	0.39	0.696	-.198485	.2972681
y2003		(dropped)					
_cons		-.1010998	.1285689	-0.79	0.432	-.3530903	.1508907

BIBLIOGRAPHY

- Albert, S. 1995. Towards a theory of timing: An archival study of timing decisions in the Persian Gulf War. *Research in Organizational Behavior*, 17: 1-70.
- Ancona, D.G., & Chong, C. 1996. Entrainment: pace, cycle, and rhythm in organization behavior. *Research in Organizational Behavior*, 18: 251-284.
- Ancona, D.G., Goodman, P.S., Lawrence, B.S., & Tushman, M.L. 2001 a. Time: A new research lens. *Academy of Management Review*, 26: 645-663.
- Ancona, D.G., Okhuysen, G.A., & Perlow, L.A. 2001b. Taking time to integrate temporal research. *Academy of Management Review*, 26: 512-529.
- Arora, A., Gambardella, A., Pammolli, F., & Riccaboni, M., 2000. The nature and the extent of the market for technology in biopharmaceuticals, *mimeo*.
- Audretsch, D.B. 1995. Innovation, growth and survival. *International Journal of Industrial Organization*, 13: 441-457.

- Barkema, H.G, Baum, J. A.C., & Mannix, E. A. 2002. Management Challenges in a New Time. *Academy of Management Journal*, 45: 5, 916-930.
- Barney, J. B. 1991. Firm resources and sustained competitive advantage. *Journal of Management*, 17: 99-120.
- Brown, F.A., Jr., Hastings, J.W., & Palmer, J.D. 1970. *The biological clock. Two views*. New York: Academic Press.
- Brown, S.L., & Eisenhardt, K.M. 1997. The Art of Continuous Change: Linking Complexity Theory and Time-paced Evolution in Relentlessly Shifting Organizations. *Administrative Science Quarterly*, 42:1-34.
- Bruton, G.D., Oviatt, B.M., & White, M.A. 1994. Performance of acquisitions of distressed firms. *Academy of Management Journal*, 37: 972-989.
- Butler, R. 1995. Time in Organizations: Its Experience, Explanations and Effects. *Organization Studies*, 16: 925-950.
- Carow, K., Heron, R., & Saxton, T. 2004. Do early birds get the returns? An empirical investigation of early-mover advantages in acquisitions. *Strategic Management Journal*, 25: 563-585.

- Carroll, G.R., & Hannan, M.T. 1990. Density delay in the evolution of organizational populations: A model and five empirical tests. Pp. 103-128 in Jitendra V. Singh (ed.), *Organizational Evolution*. Beverly Hills, CA: Sage.
- Chakravarthy, B.S. 1986. Measuring strategic performance. *Strategic Management Journal*, 7(5): 437-458.
- Chatterjee, S., Hadi, A.S., & Price, B. 2000. *Regression Analysis by Example, 3rd edition*. New York: John Wiley & Sons.
- Chung, K.H., & Pruitt, S.W. 1994. A simple approximation of Tobin's Q. *Financial Management* (Autumn), 70-74.
- Collier, Gene. 2007. NFL coaching landscape inviting for Tomlin. *Pittsburgh Post-Gazette*, July 29.
- Danzon, P.M., Nicholson, S., & Pereira, N.S. 2005. Productivity in pharmaceutical—biotechnology R&D: the role of experience and alliances. *Journal of Health Economics*, 24: 317-339.
- Dess, G. G. & Beard, D. W. 1984. Dimensions of organizational task environments. *Administrative Science Quarterly*, 29(1): 52-73.
- Dierickx, I., & Cool, K. 1989. Asset stock accumulation and sustainability of competitive advantage. *Management Science*, 35: 1504-1513.

DiMaggio, P.J., & Powell, W.W. 1983. The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 48: 147-160.

DiMasi, J.A. 2000. New drug innovation and pharmaceutical industry structure: Trends in the output of pharmaceutical firms. *Drug Information Journal*, 34: 1169-1194.

Dubin, R. 1978. *Theory Building*. Revised Edition. New York, NY: Free Press.

Edwards, J.R. 2002. Alternatives difference scores: Polynomial regression analysis and response surface methodology. In F.D. Rasgow & N.W. Schmitt (Eds.), *Advances in measurement and data analysis*: 350-400. San Francisco: Jossey-Bass.

Edwards, J.R., & Parry, M.E. 1993. On the use of polynomial regression equations as an alternative to difference scores in organizational research. *Academy of Management Journal*, 36: 1577-1613.

Eisenhardt, K.M. 1989. Making fast strategic decisions in high-velocity environments. *Academy of Management Journal*, 32: 543-576.

Employee Benefit News. 2005. Specialty pharmacy carve-out can yield savings.

- Fischette, C.T. 2004. What does big pharma want from biotech. *Asia Pacific Biotech news*, 8: 552-567.
- Frick, K.A., & Torres, A. 2002. Learning from high-tech deals. *McKinsey Quarterly*, 1:112-123.
- GeiBler, K.A. 2002. A culture of temporal diversity. *Time & Society*, 11: 131-140.
- Ginsberg, A., & Baum J.A.C. 1994. Evolutionary processes and patterns of core business change, In J.A.C. Baum., and J.V.Singh (Eds.), *Evolutionary Dynamics of Organizations*, 127-151. New York: Oxford University Press.
- Goodwin, B. 1970. Biological stability. In C.H. Waddington (Ed.), *Toward a theoretical biology*, Vol 3: 1-17. Chicago: Aldine.
- Greene, W.H. 2000. *Econometric analysis*. (4th Ed) Upper Saddle River, N.J.: Prentice Hall
- Grimm, C., & Smith, K. 1997. *Strategy as action: Industry rivalry and coordination*. Cincinnati, OH: South-Western College Publishing.
- Gulati, R. 1995. Does familiarity breed trust? The implications of repeated ties for contractual choice in alliances. *Academy of Management Journal*, 38: 85-112.

- Gulati, R., & Higgins, M.C. 2003. Which ties matter when? The contingent effects of interorganizational partnerships on IPO success. *Strategic Management Journal*, 24: 127-144.
- Haleblian, J., & Finkelstein, S. 1999. The Influence of Organizational Acquisition Experience on Acquisition Performance: A Behavioral Learning Perspective. *Administrative Science Quarterly*, 44: 29-56.
- Hamel, G. 1991. Competition for competence and inter-partner learning within international strategic alliances. *Strategic Management Journal*, 12: 83-103.
- Haspeslagh, P.C., & Jemison, D.B. 1987. Acquisitions—Myths and Reality. *Sloan Management Review*, 28: 53-58.
- Hayward, M.A. 2002. When do firms learn from their acquisition experience? Evidence from 1990-1995. *Strategic Management Journal*, 23: 21-39.
- Hennart, J.F., & Reddy, S. 1997. The choice between mergers/acquisitions and joint ventures: The case of Japanese investors in the United States. *Strategic Management Journal*, 18: 1-12.

- Hoffmann, W.H. 2007. Strategies for managing a portfolio of alliances. *Strategic Management Journal*, 28: 827-856.
- Homburg, C., & Bucerius, M. 2006. Is speed of integration really a success factor of mergers and acquisitions? An analysis of the role of internal and external relatedness. *Strategic Management Journal*, 27: 347-367.
- Huy, Q.N. 2001. Time, temporal capability, and planned change. *Academy of Management Review*, 26: 601-623.
- Inkpen, A.C., & Currall, S.C. 2004. The Coevolution of Trust, Control, and Learning in Joint Ventures. *Organization Science*, 15: 586-599.
- Jansen, K.J., & Kristof-Brown, A.L. 2005. Marching to the beat of a different drummer: examining the impact of pacing congruence. *Organizational Behavior and Human Decision Processes*, 97: 93-105.
- Johnson, P., & Duberley, J. 2000. *Understanding management research*. Thousand Oaks, CA: Sage Publications.
- Khuri, A.I., & Cornell, J.A. 1996. *Response surfaces: Designs and analyses*. New York: Marcel Dekker, Inc.

- Kogut, B. 1991. Joint ventures and the option to expand and acquire. *Management Science*, 37: 19-33.
- Kale, P., Dyer, J.H., & Singh, H. 2002. Alliance capability, stock market response, and long-term alliance success: The role of the alliance function. *Strategic Management Journal*, 23: 747-767.
- Laamanen, T., & Keil, T. 2008 Performance of serial acquirers: An acquisition program perspective. *Strategic Management Journal*, Forthcoming
- Lavie, D. 2007. Alliance portfolios and firm performance: A study of value creation and appropriation in the U.S. software industry. *Strategic Management Journal*, 28:1187-1212.
- Lee, C., Lee, K., & Pennings, J.M. 2001. Internal capabilities, external networks, and performance: A study on technology-based ventures. *Strategic Management Journal*, 22: 615-640.
- Lieberman, M.B., & Montgomery, D.B. 1988. First-mover advantages. *Strategic Management Journal*, 9(Summer Special Issue): 41-58.
- Lilly, B., & Walters, R. 1997. Toward a Model of New Product Preannouncement Timing. *Journal of Product Innovation Management*, 14:14-20.

McGrath, J.E., & Kelly, J.R. 1986. *Time and human interaction: Toward a social psychology of time*. New York: Guilford.

McNamara, G.M., Halebian, J.J., & Dykes, B.J. 2008. The performance implications of participating in an acquisition wave: Early mover advantages, bandwagon effects, and the moderating influence of industry characteristics and acquirer tactics. *Academy of Management Journal*, 51: 113-130.

Mergers & Acquisitions Report. 2006. Specialty pharma takeout valuations rise.

Mintzberg, H. 1990. The design school: Reconsidering the basic premises of strategic management. *Strategic Management Journal*, 11: 171-195.

Mosakowski, E., & Earley, P.C. 2000. A selective review of time assumptions in strategy research. *Academy of Management Review*, 25: 796-812.

Nerkar, A., & Roberts, P.W. 2004. Technological and product-market experience and the success of new product introductions in the pharmaceutical industry. *Strategic Management Journal*, 25(8/9): 779-799.

- Oatley, K., & Goodwin, B.C. 1971. The explanation and investigation of biological rhythms. In W.P.Colquhoun (Ed.), *Biological rhythms and human performance*, 1-38. New York: Academic Press.
- Oxley, J.E., & Sampson, R.C. 2004. The scope and governance of international R&D alliances. *Strategic Management Journal*, 25: 723-750.
- Parise,S., & Casher, A. 2003. Alliance portfolios: Designing and managing your network of business-partner relationships. *Academy of Management Executive*, 17: 25-39.
- Pettigrew, A.M. 1992. The character and significance of strategy process research. *Strategic Management Journal*, 13: 5-16.
- Pfeffer, J., & Salancik, G. 1978. *The external control of organizations*. New York: Harper & Row.
- Pisano, G. 1997. R&D performance, collaborative arrangements, and the market-for-know-how: A test of the 'lemons' hypothesis in biotechnology, *mimeo*.
- Popper, K.R. 1968. *The logic of scientific discovery*. Harper & Row: New York.
- Powell, T.C. 1992. Organizational alignment as competitive advantage. *Strategic Management Journal*, 13:119-134.
- Rothaermel, F.T. 2001. Incumbent's advantage through exploiting complementary assets via interfirm cooperation. *Strategic Management Journal*, 22:687-699.

- Rovit, S., & Lemire, C. 2003. Your bet M&A strategy. *Harvard Business Review*, 81: 16-17.
- Rumelt, R.P., Schendel, D.E., & Teece, D.J. 1994. *Fundamental issues in strategy*. Boston, MA: Harvard Business School Press.
- Skiggs, B.C., & Youndt, M. 2004. Strategic positioning, human capital and performance in service organizations: A customer interaction approach. *Strategic Management Journal*, 25(1): 85-98.
- Song, M.H., & Walkling, R.A. 2000. Abnormal returns to rivals of acquisition targets: A test of the 'acquisition probability hypothesis'. *Journal of Financial Economics*, 55: 143-171.
- Souza, G.G., Bayus, B.L., & Wagner, H.M. 2004. New-Product Strategy and Industry Clockspeed. *Management Science*, 50 : 537-549.
- Stata manual, 2005. *Stata longitudinal/Panel data reference manual (release 9)*.College Station, TX: Stata Press.
- Stuart, T.E., Hoang, H., & Hybels, R.C. 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. *Administrative Science Quarterly*, 44: 315-349.

Teece, D.J., Pisano, G., & Shuen, A. 1997. Dynamic capabilities and strategic management. *Strategic Management Journal*, 18: 509-533.

Thompson, J.D. 1967. *Organizations in action*. New York: McGraw-Hill.

Venkatraman, N. 1989. The concept of fit in strategy research: Toward verbal and statistical correspondence. *Academy of Management Review*, 14: 423-444.

Venkatraman, N., & Prescott, J.E. 1990. Environment-Strategy coalignment: An empirical test of its performance implications. *Strategic Management Journal*, 11: 1-23.

Vermeulen, F., & Barkema, H. 2002. Pace, rhythm, and scope: Process dependence in building a profitable multinational corporation. *Strategic Management Journal*, 23: 637-653.

Volberda, H.W., & Lewin, A.Y. 2003. Guest Editors' Introduction Co-evolutionary Dynamics Within and Between Firms: From Evolution to Co-evolution. *Journal of Management Studies*, 40: 2111-2136.

Wall Street Journal. Mar 20, 2008. Payers Aim to Rein in Specialty-Drug Spending. **BI**.

Williamson, I.O., & Cable, D.M. 2003. Organizational hiring patterns, interfirm network ties, and interorganizational imitation. *Academy of Management Journal*, 46: 349-358.

Zajac, E.J., & Bazerman, M. 1991. Blind spots in industry and competitor analysis: Implications of interfirm (mis)perceptions for strategic decisions, *Academy of Management Review*, 16: 37-56.

Zajac, E.J., Kraatz, M.S., & Bresser, R.K.F. 2000. Modeling the dynamics of strategic fit: A normative approach to strategic change. *Strategic Management Journal*, 21: 429-453.

Zollo, M., & Reuer, J.J. 2001. *Experience spillovers across corporate development activities*. Working paper no. 01-35, University of Pennsylvania, Philadelphia, PA.