Demystifying Variance in Performance: Toward a Multilevel Longitudinal Perspective of Strategic Management

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DEMYSTIFYING VARIANCE IN PERFORMANCE: TOWARD A MULTILEVEL LONGITUDINAL PERSPECTIVE OF STRATEGIC MANAGEMENT

By

Guangrui Guo

A DISSERTATION

Submitted to the Faculty of the University of Miami in partial fulfillment of the requirements for the degree of Doctor of Philosophy

Coral Gables, Florida

December 2015
UNIVERSITY OF MIAMI

A dissertation submitted in partial fulfillment of
the requirements for the degree of
Doctor of Philosophy

DEMYSTIFYING VARIANCE IN PERFORMANCE: TOWARD A MULTILEVEL
LONGITUDINAL PERSPECTIVE OF STRATEGIC MANAGEMENT

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Drawing upon complexity theory, this dissertation contributes both to inquiry on relative importance of business–unit, corporation, industry, and year effects on firm performance and to development of a multilevel longitudinal perspective of strategy. Empirically, this dissertation generates important new insights about variation in performance. This dissertation is the first to (1) capture substantial stable corporation–industry interaction effects that were confounded with stable effects of business unit, corporation, and industry in results of previous studies, (2) demonstrate that stable effects of corporation, industry, corporation–industry interaction, taken together, are of similar relative magnitude to that of stable BU effects, (3) reveal that random and nonlinear year effects are important and significant, and (4) locate all categorical sources of performance variability. Additionally, utilizing Markov Chain Monte Carlo methods in Bayesian framework, this dissertation provides inference statistics for the estimated relative effects of these components. Theoretically, this research provides a broad framework to accommodate existing theories of strategy, leading to a multilevel longitudinal perspective of strategic management. Additionally, findings of this research add support for complexity theory.
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Chapter 1
Introduction

A defining aim of strategic management research is to pinpoint drivers of organizational performance, to understand variation in organizational performance, and ultimately, to offer a substantial guide to executives of how to achieve high organizational performance. Long-term efforts have been made to approach this issue in the field of strategic management. Theoretically, a variety of theoretical frameworks on performance have been introduced or advanced to explore drivers of and, in doing so, to explain variation in firm performance, such as resource–based view (RBV) (Dierickx and Cool, 1989, Barney, 1991, Wernerfelt, 1984), dynamic capabilities perspective (Teece, 2007; Teece, Pisano, and Shuen, 1997), theories of corporate strategy (Chandler, 1962; Eisenhardt and Piezunka, 2011; Galbraith, 1974; Hansen, 1999, 2002; Porter, 1987; Rumelt, 1974; Williamson, 1975, 1985), industrial organization (IO) (Porter, 1979, 1980, 1981), evolutionary theory (Nelson and Winter, 1982), social network theory (Burt, 1982; Granovetter, 1985; Lin, 1999; Gulati, Nohria, and Zaheer, 2000), and institutional theory (DiMaggio and Powell, 1983; Meyer and Rowan, 1977; Scott, 1995). Nonetheless, each of these theoretical frameworks has its own level of and unit of analysis, its own view of the firm as well as the firm’s environment, and its own set of assumptions, underlying mechanisms, and thus, explanations for firm performance (Mathieu and Chen, 2011). In addition, these have been fragmented rather than integrated, and competing rather than complementary (Porter, 1991; Teece, 2011). On the other hand, the dominant theoretical frameworks of strategic management are static or cross-sectional, explaining performance diversity at a given point in time, rather than dynamic, explaining firm
performance variability through the processes by which firm performance is created (Porter, 1991; Teece, 2011).

Empirically, a prominent stream of literature has examined relative importance of effects on performance of corporation, industry, business unit, and year by decomposing variance in firm performance (e.g., Hough, 2006; Karniouchina et al., 2013; McGahan and Porter, 1997, 2002; Misangyi et al., 2006; Roquebert, Phillips, and Westfall, 1996; Rumelt, 1991; Schmalensee, 1985; Wernerfelt and Montgomery, 1988). Historically, results of studies in this stream of research were conflicting (Bowman and Helfat, 2001; Hough, 2006; Misangyi et al., 2006). However, most recent studies found that overall, business unit’s stable effects were the most important, while corporation, industry, and year effects were usually significant but much smaller (McGahan et al., 2002; Hough, 2006; Karniouchina et al., 2013; Misangyi et al., 2006). Although both observations from business reality and the conceptual consensus among scholars are that business unit, corporate, and industry effects are interdependent (Bowman et al., 2001; Greckhamer et al., 2008; McGahan et al., 2002; Rumelt, 1991), so far no direct empirical evidence has been captured to support this plausible argument (Greckhamer et al., 2008). Findings from this stream of research have sometimes been used to argue for the explanatory power of above–mentioned theoretical frameworks on firm performance. Arguably, these recent empirical findings indicate that business unit–specific resources are most important for performance, but corporate strategy, industry structure, and time are much less important though very significant. The results also imply that these effects are both independent (lack of interaction effects) and stable (marginal year effects) (Thomas and D’Aveni, 2009), and thus an integrated (Dess et al., 1995; Jauch and Osborn, 1981;
Mahtieu et al., 2011; Stimpert and Duhaime, 1997) and dynamic theory of strategic management (Monge, 1990; Porter, 1991; Rumelt, 2007; Teece, 2007; Teece et al., 1997) do not seem to be warranted. Moreover, these results seem to show that some of aforementioned theories of strategic management such as institutional theory (DiMaggio and Powell, 1983; Meyer and Rowan, 1977; Scott, 1995; Zucker, 1987) and evolutionary theory (Nelson and Winter, 1982) do not play a role in explaining variation in performance, although empirical evidence from other streams of literature indicated the contrary (Barnett and Hansen, 1996; Chang, 1996; Walker, Madsen, and Carini, 2002; Fortune and Mitchell, 2012; Khanna and Rivkin, 2006; Kogut and Zander, 2003).

With the benefit of hindsight, this research identifies a weakness in foregoing antecedent empirical studies: although most of these studies relied on longitudinal multilevel datasets, largely due to the inadequacy of employed statistical approaches, such as components–of–variance (COV) (McGahan et al., 1997; Rumelt, 1991) and analysis of variance (ANOVA) (McGahan et al., 2002), these studies have not adequately captured some complex underlying structures or longitudinal properties that are inherent in multilevel longitudinal data. This inadequacy results in several limitations. One is that interaction effects among different factors, especially the effects of interaction between corporation and industry, were not captured (Bowman et al., 2001; McGahan et al., 2002; Rumelt, 1991). As a result, the description and partition of stable variance in performance were likely biased (Bowman et al., 2001). Another limitation is that estimated year effects might be incomplete. Consequently, previous studies had 30 percent to 80 percent of the total variance in performance left with no specific sources, which was referred to as error term (McGahan et al., 1997, 2002), transient effects (Rumelt, 1991), across–time
variance (Misangyi et al., 2006), year-to-year variance (Short et al., 2006), or volatility (Thomas et al., 2009).

From the lens of complexity theory and utilizing multilevel longitudinal models, this research endeavors to address above empirical limitations and, drawing upon the empirical results of this study, to explore a multilevel longitudinal perspective of strategic management. Theoretically, conceptualizing business reality as a complex adaptive system within which firms are subsystems, this study attempts to provide a broad framework for thinking about multilevel longitudinal properties of firm performance, and, in doing so, to integrate currently salient theoretical frameworks of strategic management into a longitudinal multilevel framework. Indeed, from a longitudinal multilevel perspective, each of the different theories discussed earlier likely explains a particular part of the same total variance in firm performance from a particular perspective, and the inherent mechanisms that explain such variance within each of these level-specific perspectives are likely related to each other across both levels and perspectives (Mathieu et al., 2011). In addition, when over-time changes both within and without firms are introduced as sources of dynamic variance into the theoretical framework of strategic management, it is possible to establish a theoretical framework integrating both systematic and dynamic features of business reality into one framework.

Empirically, drawing on cross-classified longitudinal multilevel models with interactions, this research attempts to provide a broad framework for conducting quantitative, empirical studies of multilevel longitudinal drivers of firm performance. This study partitions total variance in firm performance into stable variance and dynamic variance, and sources of these two parts of variance are explored respectively. In addition
to traditional sources of stable variance, this dissertation endeavors to also identify and capture stable industry–corporation interaction effects to demonstrate interdependency among these components. This study also attempts to capture random as well as nonlinear year effects to obtain more complete year effects in order to locate sources of dynamic variance in firm performance.

The present research generates important empirical, methodological, theoretical, and practical new insights about sources of variation in firm performance. Empirically, to the best of my knowledge, this study is the first to (1) partition total variance in performance into stable and dynamic variance, (2) capture substantial stable corporation–industry interaction effects that were confounded with stable effects of business unit, corporation, and industry in results of previous studies, (3) demonstrate that stable effects of corporation, industry, corporation–industry interaction, taken together, are of similar relative magnitude to that of stable business unit effects, (4) reveal that random and nonlinear year effects are important and significant, (5) locate all categorical sources of total variance in performance, (6) reveal that dynamic variance has become increasingly important over time.

Methodologically, this study advances multilevel modeling in the field of strategic management by both adding a level of corporation–industry interaction in traditional cross–classified models to capture interaction effects and adding random as well as nonlinear time effects to capture complete time effects. Additionally, utilizing Markov Chain Monte Carlo (MCMC) methods of estimation in Bayesian framework (Browne, 2012; Goldstein, 2011; Rasbash et al., 2012; Spiegelhalter, Carlin, and van der Linde, 2002), this research is the first in strategic management literature to provide inference
statistics for the estimated relative effects of these components. This is important since comparisons between estimated effects with inference statistics are more valid than otherwise. This new method provides us with more confidence in the results that we obtained. Theoretically, this research applies complexity theory to examine a defining issue in the field of strategic management. The empirical results add support for complexity theory by demonstrating that the interactions between components at higher levels have substantial effects on components at a lower level, and by indicating that business units including their outcome (performance) change nonlinearly over time. Additionally, from the perspective of complexity theory, this research explores the outlines of a broad theoretical framework of strategy which attempts to integrate current salient theories. Practically and managerially, first, this research indicates that it is substantially important for executives to evaluate the extent of fit between the corporate and new industry, before entering a new industry or deciding to merge or acquire a business unit. Second, this research reminds executives that they have to shift their attention from static firm resources and industry structure to over–time changes both within and without firms. Now and in the future, the majority of above–normal performance is likely to be from appropriate adaptations of firms to the changes in business environment.

The structure of the rest of this dissertation is organized as follows. Chapter 2 describes and discusses complexity theory as justification for the empirical investigations. Chapter 3 provides a comprehensive inventory of empirical studies in the research line of, and alternative approaches to performance variance decomposition. Chapter 4 introduces the dataset used in this research, and explores the inherent structure of the data.
Especially, I analyze the sources of variance in longitudinal multilevel data and define stable variance as well as dynamic variance. Chapter 5 empirically decomposes variance in performance. Chapter 6 discusses theoretical implications of this study for strategic management. Chapter 7 discusses contributions, managerial implications, and limitations of this research and offers avenues of future research.
Chapter 2
Complexity Theory and Performance Variance Decomposition

This chapter describes and discusses complexity theory and its application in management to provide an overarching theoretical framework for this dissertation.

2.1 Essentials of Complexity Theory

Complexity theory grew out of systems theory and theories of nonlinear dynamical system. Complexity theory is a holistic perspective that conceptualizes reality as a complex adaptive system. This holistic paradigm is a shift from the conventional reductionism which has been the dominant scientific approach in Western theories and believes that the behaviors of systems can be fully understood by analyzing their component parts (Eisenhardt et al. 2011; Hanneman, 1988; Merali and Allen, 2011). Complexity theory analyzes systems based upon the links and interactions between the components or subsystems and the environment within which these exist.

Complexity theory has been used across various scientific fields including biology (Kauffman, 1993, 1995, 2004), computer science (Holland, 1975, 1996, 1998, Simon, 1996), and physics (Gell–Mann, 1994; Bar–Yam, 1997; Ellis, 2005). Complexity theory has also been applied to many fields of social disciplines (Byrne and Callaghan, 2014) including economics (Arthur, 1989; Anderson et al. 1998, Hodgson, 2006; Room, 2011), education (Haggis, 2008; Phelps and Graham, 2010), and public policy (Haynes, 2012; Gerrits, 2012).

With respect to management, complexity theory has been utilized in a variety of research fields such as organization theory (Anderson, 1999; Burnes, 2005; Chiles at al., 2004), and technology and innovation (Frenken, 2006). Two important collections on the topic of complexity theory and management, which have an overlapping set of

While complexity theory has been widely applied in both natural and social science, there is no single unified Theory of Complexity (Mitleton–Kelly, 2003). Rather, complexity theory incorporates several different theories that have arisen from studies in different disciplines. Mitleton–Kelly (2003) summarized these studies as five main areas of research. These are (1) complex adaptive systems, (2) dissipative structures, (3) autopoiesis (non-equilibrium), (4) chaos theory, and (5) increasing return as well as path dependence. As such, complexity theory is not a methodology but rather a conceptual framework, a way of thinking, and a way of seeing the reality.

### 2.2 Key Concepts and Features of Complexity Theory and Strategic Management

The following concepts and features of complexity theory are important for understanding and application of complexity theory in management.

**System and subsystem**

The concept of system is central to recent developments in complexity theory. A system is a set of dynamically interacting or interdependent components or subsystems which form an integrated whole (Maguire, 2011). It is composed of both the subsystems and the relations among them (Hanneman, 1988). A subsystem is a partition of the whole
system, which fulfils the conditions of a system itself, but also plays a role in the operation of the whole system. All systems are subsystems of higher systems and are composed of lower sub–subsystems and therefore, have a natural hierarchy. Each and every part influences and affects every other part of the system.

**Closed system and open system**

A system can be considered closed or open. An open system exchanges information, energy, and material with its environment (Kast and Rosenzweig, 1972). The behavior of open systems can only be understood holistically in the context of their environment in terms of interaction with and adaption to the changing system.

**Emergence and complexity**

In complexity theory, complex adaptive systems tend to exhibit emergent properties. Emergence is generally regarded as the process through which a complex combination of subsystems generates higher level phenomena that cannot be explained by understanding lower level subsystems (Kauffman, 1995). New system level patterns may emerge in a system when interactions between the subsystems occur (Mitleton–Kelly, 2003), and these new patterns are qualitatively different from lower level patterns (Eoyang, 2011). Thus, a system can have emergent qualities that are not analytically tractable from the attributes of internal subsystems in isolation (Baas and Emmeche, 1997). Emergence is the core feature of complexity. Emergence is a function of holism, whereby system level characteristics do not result from additive effects of subsystems but instead from interactions between subsystems (Lansing and Kremer, 1993). Accordingly, complex systems are nonlinear. The emergent properties are independently observable and empirically verifiable patterns (Amagoh, 2008).
Complexity of structure

Structure involves conceptual portioning and modeling how subsystems interact (Prietula, 2011). A basic concept in complexity theory is that of hierarchical relationships between subsystems of a system (Kast and Rosenzweig, 1972), and thus a system is basically multilevel (Dominici and Levanti, 2011). The central theme of hierarchical or multilevel thinking is that organizations are nested in a business system. In effect, management scholars have long acknowledged the hierarchical or multilevel structure of business reality. Hitt, Beamish, Jackson, and Mathieu (2007: 1387) presented Figure 1 as a conceptual hierarchical structure of business reality.

Figure 1

A conceptual of hierarchical structure of business reality

![Diagram of hierarchical structure](source: Hitt, Beamish, Jackson, and Mathieu (2007: 1387))

The overall logic is that individuals are nested in work groups, which in turn are nested in larger organizational units, such as departments or strategic business units, which are nested in national or multinational organizations, such as corporations. Furthermore,
organizations are nested in networks of inter–organizational relationships, such as industries and strategic alliances, which in turn are nested in overall performance environments, such as nations or institutions. Especially, interactions between subsystems make the structure even more complex. In chapter 3, I present an operationalized hierarchical structure of business system with interactions.

Adaption and co–evolution

Adaption refers to the change process in complex systems. When systems make the change in order to achieve a certain aim, or in response to a change in the environment (higher level), these systems are known as complex adaptive systems. Complex adaptive systems are dynamic and able to adapt in and with a changing environment. It is important to note that there is no isolation between a system and its environment when we say that a system always adapts to a changing environment. Instead, this concept is about a subsystem that is closely related with all other subsystems, and taken together, these make up a whole system. Thus, adaption needs to be viewed as co–evolution with all other related subsystems. With co–evolution, subsystems can change over time according to their interactions with one another and with the environment (higher levels in the system).

Nonlinear systems and nonlinear change in complex adaptive systems

Complex adaptive systems are nonlinear and may generate nonlinear changes (Styhre, 2002). Since complex adaptive systems are full of interactions, system level characteristics do not result from additive effects of subsystems but rather result from interactions between subsystems (Lansing and Kremer, 1993), and thus, these are nonlinear. Thus subsystems change because changes within and without these subsystems.
When changes result from interactions, these changes cannot be straight line but rather are nonlinear.

2.3 Implications of Complexity Theory for Performance Variance Decomposition

In strategic management, complexity theory conceptualizes firms as complex adaptive subsystems embedded in a whole complex adaptive system: business system. This has some implications for organizational theory and research (Hitt et al., 2007).

First, in general, a business system is composed of such complex subsystems or sub–subsystems as business units, corporations, and industries. The performance of business units is a property (outcome) of sub–subsystems: business units, which are nested within both corporations and industries. Thus, when examining the relative effects of business unit, corporation, and industry on performance of business unit, we have to take into consideration complexity of the structure of the business system. Accordingly, multilevel modeling, which decomposes performance variance into hierarchical levels of system, is a more realistic approach to decomposition of firm performance than single level modeling, such as ANOVA or COV. Additionally, interactions between subsystems, such as corporation and industry, may have substantial effects on performance of business units, and these interactions may lead to emergence of new patterns of variance partition. By modeling this way, I attempt to reveal some complex properties of the business system.

Second, business units as subsystems of the business system are dynamic and change over time. Variability of business unit performance (the outcome of subsystems) is not only driven by difference across business units but also driven by evolutions of
these business units. The evolution of these business units are subject to over–time changes occurring within business units and without business units.

Third, business units including the outcome of business units (performance) may change nonlinearly over time. Thus, time effects, which represent effects of over–time changes in the system, on business unit performance may be nonlinear. Since a given business unit, as a complex adaptive subsystem, takes different co–evolution path to match the other changing subsystems and environment, the results of the evolutions of different business units may be distinct (Lissack, 2002). Accordingly, time effects may be not identical across business units, corporations, or industries.

Next chapter review reviews both empirical studies and alternative approaches to performance variation decomposition from the lens of complexity theory.
Chapter 3
Review of Empirical Studies of and Alternative Approaches to Firm Performance Variance Decomposition

This chapter reviews both empirical studies of and alternative approaches to performance variance decomposition. Main stream studies in this line of research usually model relative stable effects on firm performance of business unit, corporation, industry, and year. Appendix A summarizes the research setting, approach, and main results of the most influential papers in this line of research and Appendix B summarizes alternative approaches to performance variance decomposition.

3.1. Review of Empirical Studies of Performance Variance Decomposition

Since Schmalensee’s (1985) research on relative importance on performance of industry and corporation, a great deal of strategic management studies have been devoted to examining to what extent firm performance – typically represented as return on asset (ROA) – is determined by membership of industries, membership of parent corporations, or idiosyncrasy of the firm itself distinct from other firms (McGahan, 2009). This chapter reviews the most influential papers in this stream of literature.

Schmalensee (1985) utilized components of variance (COV) approach to decomposing variance in ROA of US manufacturing firms in a single year (1975) dataset from the Federal Trade Commission (FTC)’s Line of Business Program. He found that corporation (termed “firm”) effects did not exist, that industry effects were significant and substantial explaining 19.59 percent of variance in business unit performance, and that business unit

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1 Some studies extended this stream of research by adding business group effects or country as well as institution effects (Bhattacharjee and Majumdar, 2011; Chang and Hong, 2002; Diaz Hermelo and Vassolo, 2012; Khanna and Rivkin, 2010, 2006; Majumdar and Bhattacharjee, 2014; Makino, Isobe, and Chan, 2004; McGahan and Victer, 2010; Short, Ketchen, Palmer, and Hult, 2007; Tong et al., 2008) and these all found significant group, or country, or institution effects. For comparison with the results of mainstream studies in this research line, this dissertation decomposes performance into traditional components: business unit, corporation, industry, and year.
(measured by market share) effects were significant but explained a negligible portion (0.62%) of total variance. 80.41 percent of the total variance were termed “error”. Schmalensee (1985: 349) argued that the absence of corporate effects indicated “that knowing a firm’s profitability in market A tells nothing about its likely profitability in a randomly selected market B.” These findings and interpretations argued for the importance of industry structure.

Wernerfelt and Montgomery (1988), following Schmalensee, used Tobin’s $q$ as represent of performance and data from both 10 K reports in Trinet Large Firm database as well as FTC data (1976). They also found strong industry (2-digit SIC) effects (19.48%) as well as a trivial market share effects (0.94%). However, they found significant business unit (measured by “corporate focus”) effects (2.61%), which is not consistent with the results of Schmalensee’s (1985) study. 76.97 percent of total variance was not accounted for.

Rumelt (1991) improved Schmalensee’s (1985) method both by using a 4-year (1974–77) dataset from FTC Reports on manufacturing firms and by modeling business unit as a unique source of variance rather than using market share as a proxy for business unit effects. He used both COV and nested ANOVA to estimate his model, but he offered COV as his primary method. His results\(^2\) from COV estimation were similar to Schmalensee’s (1985), which revealed negligible corporate effects (0.80%) and small stable industry effect (8.28%). Nonetheless, Rumelt found very large stable business unit effects (46.38%). Thus, Rumelt (1991) concluded that stable business unit effects were much more important than industry effects and corporation effects. Other scholars have interpreted the small relative stable effects of corporation as demonstrating that corporate

\(^2\) The results were from Rumelt (1991, Sample A as reported in table 3, p. 178)
strategy was not important for performance of business unit (Brush, Bromiley, and Hendricks, 1999). 36.87 percent of total variance were not accounted for and termed “error”. However, his results from ANOVA indicated that effects of business unit, corporation, industry, and year accounted for 41.3 percent, 10.9 percent, 10.3 percent, and 0.1 percent, respectively, of the total variance in performance of business unit.³

Roquebert et al. (1996) were one of the first to use Compustat Business Information industry Segment Data. Using a 7–year (1985–91) dataset⁴ of manufacturing industries and variance components analysis (VCA) model estimated with maximum likelihood method (ML), they confirmed that stable industry effects were significant (10.2%) and stable business unit effects were the most important (37.1%). Nevertheless, their results revealed evidence of important corporation effects (17.9%), which is inconsistent with those in Rumelt’s (1991) results. In addition, their results indicated that the magnitude of the stable corporate effects declined with the corporate diversification. 32.0 percent of total variance were not accounted for and termed “error”.

McGahan et al. (1997) used a 14–year (1981–94) dataset from Compustat Business Segment data including all sectors in the economy except finance and government. They employed both COA and nested ANOVA methods both of which incorporated first order autocorrelation to accommodate persistence in shocks to different components, but with a focus on COV. The main results from their COV method indicated that effects of business unit, corporation, industry, and year accounted for 31.71 percent, 4.33 percent, 18.68 percent, and 2.39 percent, respectively, of the total variance in business unit performance. The main results from their nested ANOVA method indicated that effects

³ The industry–year effects were 7.1% and are incorporated here as part of dynamic variance (Misangyi et al. (2006)
⁴ The Roquebert et al. (1996) dataset only included corporations that had at least 2 business units.
of business unit, corporation, industry, and year accounted for 35.1 percent, 9.1 percent, 9.4 percent, and 0.3 percent, respectively, of the total variance in business unit performance. Their results also indicated that relative stable effects of these components are strongly different across sectors of the economy. For example, in manufacturing, stable effects of business unit were more important than in any other sectors, and, of corporation and industry, were less. 48.04 percent of total variance were not accounted for and termed “error” for COV results and 33.2 percent for ANOVA results.

Brush et al. (1999) used a two–stage least–squares (2LS) continuous variable model and a 10–year (1986–1995) dataset from Compustat Business Segment data including all sectors except finance. They restricted observation to corporations with 3 and 4 segments. Their core findings were that both corporation and industry had important effects on business unit performance and that ratio of corporation effects and industry effects was 1.7 for standardized coefficients and greater than 1 for $R$ and $R^2$.

In a seminal paper, McGahan et al.’s (2002) utilized an improved ANOVA method, a simultaneous ANOVA in regression analysis paradigm, to re–analyze the same dataset used in their 1997 paper. Again, they integrated first order autocorrelation in the simultaneous ANOVA model to accommodate persistence in shocks to different components. They attempted to reconcile results from various prior studies and to obtain new results and thus insights. The empirical results indicated that business unit, corporation, industry, and year accounted for 32.5 percent, 8.8 percent, 8.9 percent, and 0.8 percent, respectively, of the total variance in business unit performance. Finally, they came to a currently commonly accepted conclusion that overall, stable business unit effects were the most important, while stable corporation, industry, and year effects were
usually significant but much smaller. 49.0 percent of total variance were not accounted for and termed “error”.

Hough (2006) and Misangyi et al. (2006) were the first to use longitudinal multilevel models (LMLM) to decompose variance in business unit performance. Hough used a 5–year (1995–99) dataset from Compustat’s Research Insight, excluding observations with only 1 or 2 year of data. She discussed advantages and disadvantages of, and compared results of alternative approaches. Especially, she called for extensive utilization of LMLM strategy research. Appropriately modeling the cross–classified structure between corporation and industry in a three level model, she obtained empirical results which indicated that business unit explained 40.1 percent, corporation explained 20.2 percent, industry explained 5.3 percent, and fixed linear year explained less than 1 percent of the total variance in business unit performance, leaving 34.5 percent of total variance were not accounted for and termed “error”. Misangyi et al. (2006) also appropriately modeled the cross–classified structure between corporation and industry. Nonetheless, they used a 16–year (1985–99) dataset which was a stratified random sample from Compustat Business Segment data. Their main findings suggested that effects of business unit, corporation, industry, and fixed linear year accounted for 36.6 percent, 7.2 percent, 7.6 percent, and 0.8 percent, respectively, of the total variance in business unit performance, leaving 47.8 percent of total variance were not accounted for and termed “time”. Additionally, they provided a good example of how to calculate year effects in LMLM paradigm. Most recently, Karniouchina et al. (2013) extended this steam of literature by introducing the effects of industry life cycle. They used a 16–year (1979–94) dataset from Compustat Business Segment database. However, they limited their samples to
continuous observations within each stage of industry life cycle. Also taking into consideration of the cross–classified structure between corporation and industry, they captured similar results as Hough (2006), McGahan et al. (2002), and Misangyi et al. (2006). Their results indicated that business unit, corporation, and industry accounted for 38.46 percent, 15.20 percent, and 4.20 percent of the total variance in business unit performance respectively, leaving 41.84 percent of the total variance uncounted for and termed “temporal variation.”

Overall, although historically empirical results from studies in this stream of literature were controversial, most recent studies came to a common conclusion that business unit effects were the most important, while corporation, industry, and year effects were usually significant but much smaller. Especially, year effects are trivial although significant.

However, several concerns have been raised and not addressed yet. As discussed in chapter 2, complexity theory conceptualizes business units as complex adaptive subsystems in a whole complex adaptive system: business system. In a complex adaptive system, the outcome of a subsystem is subject to interactions between subsystems and with higher level systems. Brush et al. (1999), McGahan et al. (2002) and Rumelt (1991) also noted that interactions amongst these components might have substantial influence on business unit performance. Nevertheless, due to the assumptions of models used before, interaction effects have not been captured yet. Second, as discussed in chapter 2, complexity theory also suggests that business units as complex adaptive subsystems change nonlinearly over time, and thus time effects as representatives over–time changes in the system is nonlinear and not identical. However, due to the inadequacy of
previously used approaches, prior studies could only captured fixed linear year effects, leaving potential fixed nonlinear year effects, random linear effects, and random nonlinear effects in the so called error term. Third, dynamic properties of the data have not been explored (Adner and Helfat, 2003). Taken together these concerns suggest that previous analyses of the relative importance of these components may bias.

The next section reviews alternative approaches to performance variance decomposition in order to discuss how to remediate these possible biases in the results of previous studies.

3.2 Review of Alternative Approaches to Performance Variance Decomposition

Generally, three parametric approaches have been utilized in this research stream: (1) components of variance (COV) (aka variance component analysis), (2) nested or simultaneous analysis of variance (ANOVA), and (3) multilevel modeling (LMLM) (aka hierarchical linear model or mixed effects model). Each approach is reviewed in terms of its strengths, limitations, and potential to produce biased results in the context of performance variance decomposition.

3.2.1 Components of Variance (COV)

Some early studies in this stream of literature used COV (Chang et al., 2000; McGahan et al., 1997; Roquebert et al., 1996; Rumelt, 1991; Schmalensee, 1985). The strength of COV is that it provides explicit variance decomposition for calculating relative importance of different components. However, this approach requires the assumptions (1)

5 Ruefli and Wiggins (2003) employed a non-parametric approach to stratifying performance into categories from inferior performance to modal performance to superior performance and then estimated an ordinal regression model. Thus, it is not comparable.

6 Brush et al. (1999) used two-stage least squares (2SLS) as an alternative method to estimate relative importance of different components. However, 2SLS can only model subsamples in which all corporations must have the same number of business segments. See Hough (2006) for a detailed discussion about 2SLS.
that effects of different components are independent (Garson, 2012; McGahan et al., 1997, 2002; Rumelt, 1991) and identically distributed (Garson, 2012), (2) that residuals from observations are uncorrelated and normally distributed (Garson, 2012), and (3) that residuals have a constant variance (Garson, 2002). Thus, when these assumptions are violated, estimates may be potentially biased (Brush et al., 1997). Additionally, Brush et al. (1997) discovered through simulation that COV may produce unreliable results. Moreover, COV can only model fixed year effects but not random year effects and thus, estimated year effects may be incomplete. Furthermore, COV cannot capture significant but small effects (Brush et al., 1997). Finally, COV does not model interaction structures in data. Thus, when there are interactions, estimates may be inaccurate. As a result, COV has been largely superseded by linear mixed models (Garson, 2012). Mainly due to the inadequacy of the approach, COV results of performance variance decomposition have been controversial (Brush et al., 1997).

3.2.2 Nested and Simultaneous ANOVA

Other early studies employed nested analysis of variance (ANOVA) (McGahan et al., 1997, 2002; Rumelt, 1991; Wernerfelt et al., 1988). Nested ANOVA calculates incremental $R^2$ or adjusted $R^2$ by progressively adding components into the model. Respective increments to $R^2$ or adjusted $R^2$ represent the relative importance of different components. However, this method requires the assumptions of (1) sphericity of variance–covariance, and (2) normality as well as independence of the residuals (Hedeker and Gibbons, 2006). ANOVA is generally robust to these assumptions (Garson, 2012:32), although estimates may possibly be biased when these assumptions do not hold. Thus, ANOVA paradigm has produced much more consistent and insightful empirical findings
than COV has. Particularly, ANOVA results of Rumelt (1991) were more reliable and consistent than those of COV, though he offered COV as the flagship method. It is noteworthy that McGahan et al. (2002) creatively incorporated first-order autoregressive model into simultaneous ANOVA. This creation might not only accommodate persistence in shocks to different effects but also partially overcome the issue of sphericity of the variance–covariance. Consequently, the results of McGahan et al. (2002), which indicated that year effects, stable industry effects, stable corporation effects, and stable business segment effects were all important, are more consistent and insightful. However, the main limitations of ANOVA are its inabilitys to model random year effects (Hoffman, 2015) and interaction effects (McGahan et al., 2002). Thus, year effects estimated by ANOVA may be incomplete, and when there are interactions, the unmodeled interaction effects are unevenly confounded with other effects, potentially producing biased results.

3.2.3 Longitudinal Multilevel Modeling (LMLM)

From the lens of complexity theory, single level modeling such ANOVA and COV cannot capture complex properties of business unit performance. LMLM promises to address above-mentioned issues inherent in both COV and ANOVA (Hoffman, 2015; Wu, 2010). First, LMLM directly partitions variance in outcome into each level (Hoffman, 2015). Through the partition, LMLM relaxes the assumption of independence among lower level units nested in the same higher level units. Second, LMLM can estimate unbalanced data efficiently (Enders, 2010; Raudenbush and Bryk, 2002). Third, LMLM can model complex structures in data, such as multiple-classification, interaction, and multiple-membership (Browne, Goldstein, and Rasbash, 2001; Leckie, 2013b;
Patterson, 2013) and thus, address the issue of collinearity among business segment, corporation, and industry (McGahan et al., 2002; Rumelt, 1991). Fourth, while COV and ANOVA can only employ categorical exploratory variables (Brush et al., 1997; McGahan et al., 1997, 2002), LMLM allows both categorical and continuous exploratory variables, whether time–invariant or time–varying, to substantially explain detected variance. Thus, although decomposition of variance is the final output of COV and ANOVA, it is only the starting point of further analyses of LMLM and the variance decomposition provides insight in the directions where further explanation may fruitfully be sought. As a consequence, LMLM offers a promising way to move beyond descriptive models of variance decomposition toward inferential models which can examine relationships and thus test multilevel theories (Hough, 2006). Finally, using random intercept, random effects of explanatory variables, and a large variety of alternative variance–covariance structures, LMLM can address autocorrelation issues (Hoffman, 2015; Short et al., 2006).

Employing LMLM, some recent studies (e.g., Hough, 2006; Karniouchina et al., 2013; Majumdar and Bhattacharjee, 2014; Misangyi et al., 2006; Short et al., 2006; Short et al., 2009) endeavored to overcome assumption limitations of COV and ANOVA. Additionally, Hough (2006), Karniouchina et al. (2013), and Misangyi et al. (2006) modeled cross–classified structures. These previous LMLM studies all obtained similar results to those of McGahan et al. (2002). This research extends above LMLM studies by adding an interaction classification or component (corporation–industry combination) to capture industry–corporation interaction effects and by adding random as well as nonlinear year to capture more complete year effects. Moreover, all prior estimation
methods used in this research stream are in frequentist or traditional statistical framework and could not provide inference statistics for the estimated relative effects of different components. Utilizing MCMC methods in Bayesian framework, this dissertation provides inference statistics for the estimated relative effects of these components, which offers both scholars and practitioners more confidence in the estimated results and corresponding conclusion.

3.3 A Related Research Line and Dynamic Model for Panel Data

In a parallel research stream (McGahan, 2009), studies examined over–time persistence of different effects on performance (e.g., Bou and Satorra, 2007, 2010; Diaz Hermelo and Vassolo, 2012; Diaz Hermelo, Hetiennot, and Vassolo, 2014; Gschwandtner, 2012; Furman and McGahan, 2002; McGahan and Porter, 1999, 2003). These studies used a variety of autoregressive models, which are usually referred to as transitional models or dynamic model for panel data (DMPD). There are three modern approaches to the analysis of longitudinal data. These are marginal model, LMLM, and DMPD (Rabe–Hesketh and Skrondal, 2012; Wu, 2010). Both LMLM and DMPD are sophisticated approaches to analyzing longitudinal data. However, these two have different viewpoints on correlation among observations. For LMLM, observations are correlated because they are from the same subject and share the same underlying processes. Thus, LMLM captures the correlation by introducing random intercepts, random slopes, and appropriate variance–covariance structures (Hoffman, 2015). For DMPD, on the other hand, observations are correlated because the past influences the present. Accordingly, DMPD directly models relationship between current outcome and previous outcomes by using the latter as predictors. Choice between these two largely depends on research questions
and academic disciplines. Using DMPD, Bou et al. (2007, 2010) and Diaz Hermelo et al. (2014) examined persistence of performance as well as decomposing variance in performance or abnormal performance into firm level, sector (industry) level, and country level. These two studies also captured country–industry (sector) interaction effects. The present dissertation, however, decomposes performance variance into traditional components: business unit, corporation, industry, and year effects. In particular, this study captures stable effects of corporation–industry interaction as well as random and nonlinear year effects on performance. LMLM and DMPD are complementary approaches to analyzing longitudinal or panel data. These capture the dynamic nature in longitudinal data from different perspectives.
Chapter 4
Longitudinal Multilevel Data and Sources of Variance

This chapter introduces the data used in this research and explores the inherent structure of the data. Especially, I analyze the sources of variance in longitudinal multilevel data and define stable variance as well as dynamic variance.

4.1 Compustat Business Segment Data

This research relies on Compustat Business Segment data, the primary data source used in most recent studies in this stream of literature. The Compustat Segment data provide information on companies that is publicly traded in the United States of America. The Compustat Segment data include yearly information on both corporations and their business units – represented by business segments. A business segment is an industry segment or product line reported by a company. For each business segment, the database includes annual information on Data Item Availability Code, Business Segment Name, Business Segment, Capital Expenditures, Customer Name, Depreciation, Depletion and Amortization, Number of Employees, Equity in Earnings – Unconsolidated Subsidiary, Foreign Governments, Identifiable Assets, Identification Code, Investments at Equity, Operating Profit, Order Backlog, Principal Product Name, Principal Product SIC, Research and Development–Company Sponsored, Research and Development–Customer Sponsored, Sales (Net) SALES, Sales of the Principal Product, Sales to Domestic Government, Sales to Foreign Government, Sales to Principal Customer, SIC Codes (Primary and Secondary), Source Code, and Update Code.
4.2 Dataset used in this Dissertation

To ensure that results of this research are comparable to those of previous studies, this study uses Compustat Business Segment data (1979–1996) which include all available data before Financial Accounting Standards for business segment reporting changed on June 30, 1997. Performance is represented by return on assets (ROA), which is calculated as the ratio of operating profit to identifiable assets in percent. Business segment is used to represent Business unit (McGahan et al., 1997, 2002). This dataset contains 207,348 observations, which record over–time repeated observations of business segments from 1979 to 1996. After dropping 446 duplicate observations, the dataset has 206,902 observations. This dataset is screened following steps used by McGahan et al. (1997, 2002). Step 1: 2604 observations without a primary standard industrial classification (SIC) designation are dropped. Step 2: 27,656 observations of business segments operating in SICs listed as “not elsewhere classified,” “non–classifiable establishments,” or “government, excluding finance.” are dropped. Step 3: 22,488 observations of business segments operating in industries designated as “depository institutions.” are excluded because returns are not with those in other industries. Step 4: 2,343 observations of business segments that are the only ones in an industry in a given year (monopolies) are excluded. Step 5: 4,235 observations of business segments that are in this dataset for only one year are also excluded. Step 6: 46,171 observations of small business segments with sales or assets less than $10 million are excluded. In addition, 2,244 observations are dropped due to missing data for operating profit or identifiable assets. Finally, because the last three steps produce new monopolies and only–one–year

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observations, step 4 and step 5 are repeated, resulting in the exclusion of 2,150 more observations.

Ultimately these screening steps yield 97,011 observations for an average of 5390 per year. This screened 18–year dataset represents the activities of 15,451 distinct business segments, belonging to 8,588 corporations and operating in 778 industries. Industries are represented by four–digital SIC codes. The average business segment posts 6.28 year of data. The mean ROA of this sample is 10.60 percent with a variance of 253.53 percent. Table 1 reports the annual number of observations, average assets, average profit, and median profit of this dataset. This dataset is comparable to those used in previous studies (e.g., McGahan et al., 1997, 2002; Misangyi et al., 2006).

This 18–year dataset provides several advantages for examining the relative effects of business unit, corporation, industry, and year. First, the typical 6.26–year time series on each business segment enables this research to capture true stable effects over this long period of time and true time (represented by year) effects. As I will discuss in detail later disentangling stable effects from dynamic effects is the critical step to correctly decompose variance in firm performance. Second, this dataset includes all sectors of economy but financial and government sectors. This dataset covers 778 industries, which allows this research to give analyses of the effects of these components in the economy as a whole.

This dataset also has several disadvantages. First, the average assets of a business segment in Compustat Business Segment data are $844.02 million, which is bigger than those of an actual business unit (McGahan et al., 1997; 2002). This may lead to bias in the results of the analyses. Second, industries defined by 4–digital SIC codes may not
map correctly to the actual distinctions between industries in some cases, which actually influence performance of business units. Thus, we need to be cautious when interpreting empirical results.

4.3 Underlying Structure in the Data

Strategic management scholars have long conceptualized business reality as a complex adaptive system of highly interdependent elements. Conceptually, over–time repeated observations are nested within business segment, and business segments are separately nested within both corporations, and industries (Hough, 2006; Karniouchina et al., 2013; Misangyi et al., 2006). To appropriately analyze longitudinal multilevel data, each unit at every level in the structure must have a unique identifier (Browne, Goldstein, and Rasbash, 2001). This dataset contains three original identifiers: gvkey for corporation, sics1 for industry, and sid: an intra–corporation business segment identifier. We create one additional identifier: bsid. Bsid is created by combining gvkey and sid, and it represents business segment by giving each business segment a unique ID.

At level 1 are over–time repeated observations, which are nested in business segments, level 2. At level 3, we have both corporation and industry because business segments are cross–classified with respect to both (Hough, 2006; Misangyi et al., 2006). Business segments belonging to a given corporation may operate in different industries and a particular industry may have business segments from many different corporations, so business segments are cross-classified with respect to both their parent corporation and the industry in which they operate. Following Browne et al. (2001) and Leckie (2013a), Figure 2 presents a standard cross-classified classification diagram which assumes that higher level units, corporation and industry, have additive effects on business segments.
Table 1. Screened Compustat Business Segment Data (1979–96)

<table>
<thead>
<tr>
<th>Year</th>
<th>Number of Observations</th>
<th>Average Assets ($mil)</th>
<th>Average Profit</th>
<th>Median Profit</th>
<th>Year</th>
<th>Number of Observations</th>
<th>Average Assets ($mil)</th>
<th>Average Profit</th>
<th>Median Profit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All years</td>
<td>97011</td>
<td>844.02</td>
<td>10.60</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1979</td>
<td>4722</td>
<td>417.51</td>
<td>15.77</td>
<td>14.02</td>
<td>1988</td>
<td>5129</td>
<td>878.55</td>
<td>10.34</td>
<td>9.87</td>
</tr>
<tr>
<td>1981</td>
<td>5227</td>
<td>491.22</td>
<td>14.02</td>
<td>12.50</td>
<td>1990</td>
<td>5103</td>
<td>1057.12</td>
<td>9.50</td>
<td>9.06</td>
</tr>
<tr>
<td>1982</td>
<td>5195</td>
<td>541.36</td>
<td>11.30</td>
<td>10.88</td>
<td>1991</td>
<td>5219</td>
<td>1047.34</td>
<td>8.41</td>
<td>8.36</td>
</tr>
<tr>
<td>1983</td>
<td>5283</td>
<td>571.37</td>
<td>11.32</td>
<td>10.80</td>
<td>1992</td>
<td>5491</td>
<td>1042.53</td>
<td>9.07</td>
<td>8.69</td>
</tr>
<tr>
<td>1984</td>
<td>5199</td>
<td>610.17</td>
<td>11.93</td>
<td>11.62</td>
<td>1993</td>
<td>5767</td>
<td>1046.06</td>
<td>9.01</td>
<td>8.77</td>
</tr>
<tr>
<td>1985</td>
<td>5194</td>
<td>672.03</td>
<td>10.35</td>
<td>10.29</td>
<td>1994</td>
<td>6066</td>
<td>1135.56</td>
<td>9.34</td>
<td>9.03</td>
</tr>
<tr>
<td>1987</td>
<td>5256</td>
<td>791.31</td>
<td>10.07</td>
<td>9.86</td>
<td>1996</td>
<td>5992</td>
<td>1337.12</td>
<td>8.76</td>
<td>9.00</td>
</tr>
</tbody>
</table>

*Mean ratio of operating income to identifiable assets in percent.
This, however, implies that the effects that a particular industry has on business segments are identical for all business segments operating in that industry, irrespective of which corporation these belong to. Likewise, this also implies that effects that a given corporation has on its business segments are identical, irrespective of which industry these operate in.

However, from both theoretical and managerial perspectives, I believe that effects that an industry has on business segments actually vary according to which corporation the business segments belong to and that effects a corporation has on its business segments actually vary according to which industry these operate in. Theoretically, complexity theory suggests that interactions between higher level subsystems (here corporation and industry) have influence on business units. In corporate strategy literature, effects of corporation on performance of a business segment results from factors related to its
membership of a multi–business unit corporation. Some corporate–level factors influencing performance are scope of the firm, core competencies, organizational structure, organizational climate, planning and control, and corporate management (Bowman et al., 2001). I argue that these factors may enable a corporation to provide advantage for some of its business segments operating in some industries, but disadvantage in some other industries. Put differently, some industries are more attractive to some corporations but less attractive to others, or an industry may have profound influence on business segments from some corporations but less on business segments from some other corporations. For example, firm scope subsumes selection of industries for business segments to operate in. Entering into industries by related diversification (Rumelt, 1974) or vertical integration (Williamson, 1975, 1985) may increase chances of business segments of some corporations to gain abnormal performance. Hitt and Ireland (1985) indicated that industry type moderates the relationship between corporate competencies and firm performance. Thus, the effects of corporation–industry interaction on performance are important. Methodologically, a necessary step for cross–classification models is to check whether a random effects of interaction between the cross–classified levels (here industry and corporation) should be specified in the models (Patterson, 2013; Shi, Leite, and Algina, 2010). Stated statistically, corporate and industry interact with one another and no longer have additive effects on business segments (Bowman et al., 2001; Leckie, 2013b) due to the interaction between these. We introduce corporation-industry interaction effects as a new classification in the model and create a new identifier (gxs) for this classification by combining corporate and industry to give a unique ID to each corporation-industry combination. There are 15,073 corporation–industry combinations
in the dataset. The combinations are by definition cross-classified with respect to corporation and industry (Leckie, 2013a).

Figure 3 presents a classification diagram with corporation-industry combination included and all our models are based on this diagram. Over-time repeated observations (level 1) are nested within business segments (level 2), business segments are nested within corporation–industry combinations (level 3), and the combinations are in turn cross-classified with respect to corporation and industry (both conceptually at level 4). Of course, business segments are also cross-classified with respect to corporation and industry. Since previous studies did not separately model corporation–industry interaction effects, we argue that these effects were confounded with industry, corporate, and business segment effects in previous studies. Simulation studies in statistics also indicated that when interaction effects were omitted in cross-classified models, variance at interaction level would unevenly confounded with those in other levels. Thus, when corporation–industry combination (level 3) is introduced into the model, we can separate corporation–industry interaction effects from corporate, industry and business segment effects. Accordingly, isolated effects of corporate, industry, and business segment will reduce.
Based on the discussion about the structure in the data, next section explores the underlying feature of the data.

4.4 Underlying Features of the Data

As showed in last section, the screened dataset is an unbalanced longitudinal or panel dataset with complex underlying structures and temporal properties.

The defining feature of longitudinal data is that these consist of observations obtained repeatedly from the same individuals or subjects at multiple points in time (Fitzmaurice et al., 2012; Zimmerman and Nunez–Anton, 2010). Longitudinal data are referred to as being balanced when all individuals observed have the same number of repeated observations obtained at a common set of occasions (points in time) with no observations
missing, and considered unbalanced otherwise. In Compustat Business segment data, business segments enter and exit the data at different points in time, so datasets from Compustat Business segment data are unbalanced (McGahan et al., 2002).

The first distinctive feature of longitudinal data is that these are nested or clustered. Take Compustat Business segment data for example, multiple over–time repeated measurements from the same business segment are clustered within that business segment, business segments belonging to a given corporation are clustered in that corporation, and business segments operating in a particular industry are also clustered in that industry. Generally, measurements of the outcome on units within a cluster tend to be considerably more alike than measurements on units in different clusters. This similarity or correlation resulting from clustering invalidates the critical assumption of independence, which is the cornerstone of classical statistical methods, such as linear regression and analysis of variance (ANOVA). Hierarchical nature of the clustering creates the multilevel structure in the data. Thus, methods for analyzing longitudinal multilevel data must account for correlation within clusters (Fitzmaurice et al., 2012; Free, 2004; Zimmerman et al., 2010) and relax the assumption of independence.

The second distinctive feature of longitudinal data is that the overt–time observations are ordered in time and not necessarily exchangeable and that observations that are closer in time may simply be more related than those from further apart in time. This feature is usually defined as serial correlation.

The third feature of longitudinal data is that variance in the outcome comes from both within–individual variance and between–individual variance (Curran, and Bauer, 2011; Fitzmaurice et al., 2012; Hoffman and Stawski, 2009). Here within–individual variance
refers to dispersion of performance from one occasion (point in time) to another over a period of time. Between–individual variance refers to dispersion of performance across business segments. Since within–individual variance results from the dynamic processes of over–time performance change, it is defined as dynamic variance. Of note, in previous studies, this dynamic variance was named “error term”. Rumelt (1991) insightfully noted that the error term may be year–to–year variation that is specific to each business unit. I accordingly call effects that result in dynamic variance dynamic effects. Since between–business segment variance captures the static difference of average performance across business segments, corporations, and industries over a period of time, it is defined as stable variance. Accordingly, I call effects that result in stable variance stable effects. Thus, distinguishing dynamic effects from stable effects is critical for understanding sources of variance in performance. Previous studies in this stream of literature focused on examining sources of stable variance but left dynamic variance as error term with no specific resources. More sophisticated methods are needed to simultaneously capture serial correlation and stable as well as dynamic variance.

In the next chapter, utilizing longitudinal multilevel models, I empirically examine stable effects of business segment, corporation, industry, and potential effects of interaction between corporation and industry.
Chapter 5  
Decomposing Variance in Business Unit Performance

Aforementioned discussion shows that longitudinal multilevel data depart from all most every assumption inherent in COV or ANOVA. As introduced in Chapter 2, LMLM promises to address all limitations with COV or ANOVA in terms of handling longitudinal multilevel. In effect, multilevel longitudinal modeling is an appropriate approach to modeling complex adaptive systems. Drawing on LMLM this chapter examines relative influence of business segment, corporation, industry, and the potential effects of interaction between corporation and industry that we discussed in Chapter 3.

5.1 Longitudinal Multilevel Models (LMLM)

As introduced in Chapter 3, the Compustat Business Segment data have three distinctive features. The first is that these data are nested or clustered: over–time observations of business segments are nested or clustered in business segment. The second is that total variance in business unit performance are comprised of stable variance and dynamic variance. The third is that there is serial correlation inherent in these data. Here I explain in detail how LMLM is capable of capturing above–mentioned inherent features in the data.

First, LMLM addresses the clustering issue and relaxes the assumption of independence of observations among lower level units (e.g., business segments) in the same higher level units (e.g., corporations or industries) by explicitly partitioning total variance in performance into each levels (Hoffman, 2015; Hesketh and Skrondal, 2012). When total stable variance in business segment performance is decomposed into levels of business segment, corporation, and industry, at each level, observations are independent, though in the whole sample observations are clustered. Second, LMLM directly
decomposes total variance in business unit performance into stable variance and dynamic variance. Third, LMLM takes advantage of a large variety of alternative variance–covariance structures to model these patterns of serial correlation in the longitudinal data even when the. Some of the alternative variance–covariance structures are Unstructured, Compound Symmetry Heterogeneous, and First–Order Auto–Regressive (AR1) (Hoffman, 2015; Hesketh and Skrondal, 2012). For example, Short, Ketchen, Bennet, and du Toit (2006) compared longitudinal models with different variance–covariance structures.

5.2 Decomposing Stable Variance

To appropriately decompose variance in business segment performance and capture stable effects of corporation–industry interaction, a series of unconditional means multilevel models are fitted to the dataset. An unconditional means multilevel model is a model with no predictors at any level; it simply describes and partitions variance in outcome into different levels (Fitzmaurice et al., 2012; Hoffman, 2015; Singer and Willett, 2003).

5.2.1 Construction of Unconditional Means Multilevel Models

To explore stable variance, this research first fits a two level unconditional means model to partition the variance into dynamic variance and stable variance (Hoffman, 2012; Singer et al., 2003).

Model 1: Level 1: \( \text{ROA}_i = \alpha_{0i} + e_{i} \)

\[ \text{Level 2: } \alpha_{0i} = \beta_{00} + b_{0i}, \]

where, as with all unconditional means models (Fitzmaurice et al., 2012; Hoffman, 2015; Raudenbush et al., 2002; Singer et al., 2003), this model assumes that:
\[ \varepsilon_t \sim N(0, \sigma_e^2), \ b_{0i} \sim N(0, \sigma_{b_0}^2). \]

Model 1 is used to partition the total variance in ROA into dynamic variance and stable variance when only level 1 (over–time observations) and level 2 (business segment) are specified in the model. ROA \(_t\) is the performance of business segment \(i\) in year \(t\). \(\alpha_{0i}\) is over–time mean ROA of business segment \(i\). \(\beta_{00}\) here is grand–mean ROA of all business segments in the dataset. \(\varepsilon_t\) is within–business segment residual and \(b_{0i}\) is between–business segment residual. Accordingly, \(\sigma_e^2\) is dynamic variance, and \(\sigma_{b_0}^2\) is stable variance. Of note, in Model 1, business segment picks up all stable variance (\(\sigma_{b_0}^2\)) when neither corporation nor industry is included in this model (McGahan et al., 2002).

Model 2 is used to decompose variance in ROA when over–time observations (level 1), business segment (level 2), corporate (level 4), and industry (level 4), but not corporation–industry combination (level 3), are specified in the model. These levels are depicted in Figure 3.

Model 2:  
Level 1: \(\text{ROA}_{tijk} = \alpha_{0ijk} + \varepsilon_{tijk}\)

Level 2: \(\alpha_{0ijk} = \beta_{00jk} + b_{0ijk}\)

Level 4: \(\beta_{00jk} = \gamma_{000} + c_{00j} + d_{00k}\),

where we assume that:

\[ \varepsilon_{tijk} \sim N(0, \sigma_e^2), \ b_{0ijk} \sim N(0, \sigma_{b_0}^2), \ c_{00j} \sim N(0, \sigma_{c_0}^2), \ \text{and} \ d_{00k} \sim N(0, \sigma_{d_0}^2). \]

\(\text{ROA}_{tijk}\) is the performance of business segment \(i\) in year \(t\), which belongs to corporation \(j\) and operates in industry \(k\). \(\alpha_{0ijk}\) is over–time mean ROA of business segment \(i\). \(\beta_{00jk}\) is mean ROA of all business segments which belong to corporation \(j\) and operate in industry \(k\). \(\gamma_{000}\) is grand–mean ROA of all business segments in the dataset. \(\varepsilon_{tijk}\) is within–business segment residual, \(b_{0ijk}\) is between–business segment residual, \(c_{00j}\)
is between–corporation residual, and $d_{000k}$ is between–industry residual. Accordingly, $\sigma_e^2$ is dynamic variance, $\sigma_{b_0}^2$ is between–business segment variance, $\sigma_{c_0}^2$ is between–corporation variance, and $\sigma_{d_0}^2$ is between–industry variance. Note that as discussed earlier, Hough (2006), Karniouchina et al. (2013), and Misangyi et al. (2006) all recognized this cross–classified structure in their datasets and fitted models exactly the same as Model 2 in this study.

Model 3 extends aforementioned previous LMLM by adding the corporation–industry combination (level 3). Note that all levels in Figure 3 are modeled in Model 3.

Model 3: Level 1: $\text{ROA}_{tijnk} = \alpha_{0ijnk} + e_{tijnk}$

Level 2: $\alpha_{0ijnk} = \beta_{00mjk} + b_{0ijnk}$

Level 3: $\beta_{00mjk} = \gamma_{000jk} + i_{00mjk}$

Level 4: $\gamma_{000jk} = \lambda_{0000} + c_{000j} + d_{000k}$,

where this model assumes that:

$e_{tijnk} \sim N(0, \sigma_e^2)$, $b_{0ijnk} \sim N(0, \sigma_{b_0}^2)$, $i_{00mjk} \sim N(0, \sigma_{i_0}^2)$,

$c_{000j} \sim N(0, \sigma_{c_0}^2)$, and $d_{000k} \sim N(0, \sigma_{d_0}^2)$.

Model 3 is used to capture corporation–industry interaction effects. $\text{ROA}_{tijnk}$ is the performance of business segment $i$ in year $t$, which belongs to combination $m$ of corporation $j$ and industry $k$. $\alpha_{0ijnk}$ is the over–time mean ROA of business segment $i$. $\beta_{00mjk}$ is mean ROA of all business segments in the combination $m$ of corporation $j$ and industry $k$. $\gamma_{000jk}$ is mean ROA of all business segments which belong to corporation $j$ and operate in industry $k$. $\lambda_{0000}$ is the grand–mean ROA of all business segments in the dataset. $e_{tijnk}$ is within–business segment residual, $b_{0ijnk}$ is between–business segment residual, $i_{00mjk}$ is between–combination residual, $c_{000j}$ is between–corporation residual, and $d_{000k}$ is
between–industry residual. Accordingly, $\sigma^2_e$ is dynamic variance, $\sigma^2_{b_0}$ is between–business segment variance, $\sigma^2_{i_0}$ is between–combination variance, $\sigma^2_{c_0}$ is between–corporation variance, and $\sigma^2_{d_0}$ is between–industry variance.

5.2.2 Bayesian estimation using Markov Chain Monte Carlo (MCMC) Methods

All models in this dissertation are fitted with MCMC methods in Bayesian framework (Browne, 2012; Goldstein, 2011; Rasbash et al., 2012; Spiegelhalter, Carlin, and van der Linde, 2002). Hence, I briefly introduce MCMC methods used in this research, highlighting their merits in decomposing variance in business unit performance.

One of the barriers to high quality empirical research in strategic management is the common confusion between models and methods. When models and methods are confused, there is a proclivity to view a combination of a method and a model (e.g., OLS regression) as a ubiquitous instrument for data analysis rather than to view a model as an image of business reality which can be estimated by a variety of methods. A model is an abstract picture of the business reality, the construction of which relies on theories, empirical generalizations of previous studies, and even intuitions (Tuma and Hannan, 1984). For example, the longitudinal models constructed above are statistical abstract of what I think the business reality should be: a dynamic multilevel system replete with interactions. On the contrary, a method is a set of procedures employed to fit a model to data and to evaluate the results of the estimation (Tuma and Hannan, 1984). For example, theoretically the models constructed above can be fitted or estimated and evaluated with ML or IGLS and RML or RIGLS in frequentist framework. These can also be estimated with MCMC methods in Bayesian framework. However, to the best of my knowledge, in
practice for complex longitudinal multilevel models, MCMC is the only currently available method.

Although MCMC methods can be used in both a frequentist framework and a Bayesian framework, these are usually used for Bayesian modeling (Goldstein, 2011). MCMC methods incorporate prior distribution assumption and, using “Gibbs sampling”, or “Metropolis–Hastings sampling” or combination of these to sample form posterior distributions of the model parameters, yield parameter chains from which point and interval estimates of all unknown parameters in the model are constructed (Browne, 2014). MCMC methods are more general in that these can fit more complex statistical models since MCMC algorithms are iterative and it easy to extend the algorithms to more complex structures. MCMC methods are simulation-based procedures so that rather than simply producing point estimates, the methods are run for many iterations and at each iteration these are designed to produce a sample of the unknown parameters from the joint posterior distribution. After an appropriate number of iterations, a sample of values from the posterior distribution of the unknown parameters is generated. Thus, this method can derive accurate interval estimates. Especially, MCMC methods can give the point estimate, standard error, and central interval of any function of parameters, such as percentages of variances (Browne, 2012; Goldstein, 2011). Thus, when decomposing variance in business unit performance, MCMC methods can provide reference statistics, such as standard error, for both the absolute effects (variances) and relative effects (percentages) of different components. This is a milestone for the development of this stream of research, since inference statistics for relative effects of different components can advance this line of research from being descriptive to being inferential.
5.2.3 Results of Stable Variance Decompositions from MCMC Estimation

In this dissertation, all models are fitted with a burn–in of 100,000 iterations followed by 1,000,000 monitoring iterations. As discussed above all percentages are obtained as functions of variances and thus, have inference statistics. Appendix C presents the outputs of Model 1, Model 2, and Model 3. Appendix D and Appendix E present parameter’s chain of each variance and each percentage respectively.

5.2.3.1 Results of Stable Variance Decomposition

Table 2 presents results of fitting Model 1, Model 2, and Model 3 to the screened Compustat business Segment dataset (1979–1996).

Table 2. Results from MCMC estimation of Model 1, Model 2, and Model 3a

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fixed effects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>$\beta_0 = 10.13$ (0.11)</td>
<td>$\gamma_{000} = 10.81$ (0.22)</td>
<td>$\lambda_{0000} = 10.71$ (0.21)</td>
</tr>
<tr>
<td><strong>Random Effects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level 4 Corporation $\sigma_{c_0}^2$</td>
<td>16.01 (1.42)</td>
<td>5.60 (0.49)</td>
<td>10.91 (1.41)</td>
</tr>
<tr>
<td>Level 4 Industry $\sigma_{d_0}^2$</td>
<td>18.16 (1.72)</td>
<td>6.35 (0.57)</td>
<td>15.22 (1.58)</td>
</tr>
<tr>
<td>Level 3 Combination $\sigma_{m_0}^2$</td>
<td></td>
<td></td>
<td>46.18 (2.39)</td>
</tr>
<tr>
<td>Level 2 Business segment $\sigma_{b_0}^2$</td>
<td>152.26 (2.14)</td>
<td>53.72 (0.38)</td>
<td>84.09 (2.50)</td>
</tr>
<tr>
<td>Level 1 Over–time repeated observations $\sigma_e^2$</td>
<td>131.15 (0.66)</td>
<td>46.28 (0.38)</td>
<td>128.30 (0.65)</td>
</tr>
<tr>
<td><strong>Total Variance</strong></td>
<td>283.41 (2.17)</td>
<td>285.78 (2.60)</td>
<td>284.70 (2.48)</td>
</tr>
<tr>
<td><strong>DIC</strong></td>
<td>761606</td>
<td>761224</td>
<td>759873</td>
</tr>
</tbody>
</table>

a All percentages are estimated as functions of variances.

We see that all coefficients and variances in the three models are significant, that estimated total variances are statistically identical and that the inference statistics for the percentages provide more confidence in the obtained results. Results of Model 1 show...
that for this dataset, stable variance ($\sigma^2_{b_0}$) accounts for 53.72 (0.38) percent of the total variance in performance, and dynamic variance ($\sigma^2_e$) accounts for 46.28 (0.38) percent. From results of Model 2, we see that when only business segment, industry, and corporation are specified in the cross-classified model, their effects account for 42.12 (0.63) percent ($\sigma^2_{b_0}$), 6.35 (0.57) percent ($\sigma^2_{d_0}$), and 5.60 (0.49) percent ($\sigma^2_{c_0}$) of total variance respectively. These results are consistent with results in many recent studies (McGahan et al., 2002; Hough, 2006; Karniouchina et al., 2013; Misangyi et al., 2006). However, when corporate–industry combination is added in Model 3, the corporation–industry interaction effects are extracted from previously confounded effects. Results of Model 3 show that effects of corporation–industry interaction account for 16.22 (0.82) percent of total variance, and the business segment effects decrease by 30.12 (2.42) percent. In addition, variances that are separately accounted for by corporation and industry also decrease from 5.60 (0.49) percent to 3.83 (0.49) percent and from 6.35 (0.57) percent to 5.34 (0.53) percent respectively, since the interaction effects also absorb variances from these two. Moreover, in Model 3, corporation, industry, and their interaction together account for 25.39 (0.90) percent of the total variance, while business segment accounts for 29.54 (0.83) percent ($\sigma^2_{b_0}$). Furthermore, according to the Deviance Information Criterion (DIC), Model 3 fits the data far better than the other two models since Model 3 has a much lower DIC (DIC = 759873) than Model 1 (DIC = 761606) and Model 2 (DIC = 761224). This indicates that Model 3 captures the

---

8 In parentheses following estimates are standard errors.

9 \(\left(\sigma^2_{b_0}(\text{model 2}) - \sigma^2_{b_0}(\text{model 1})\right)/\sigma^2_{b_0}(\text{model 2}) = 30.12\% (2.42\%)\)

10 \(\left(\sigma^2_{c_0}(\text{model 3}) + \sigma^2_{d_0}(\text{model 3}) + \sigma^2_m(\text{model 3})\right)/\text{total variance (model 3)} = 25.39\% (0.90\%).\)

11 DIC is a MCMC version of Akaike’s Information Criterion (AIC), and the fit of models is compared via DIC (Spiegelhalter et al., 2002): models with smaller DIC-values are preferred to those with larger ones. A difference of 5 or more is considered substantial (Leckie and Goldstein, 2015; Lunn et al., 2012).
underlying structure in the data much better than the other two models do. It is important to note that it is only possible to capture the corporate–industry interaction effects in this cross–classification model when there is more than one observation for at least some corporation–industry combinations (Goldstein, 2011; Leckie, 2013a, 2013b; Patterson, 2013), as is the case in this dataset. Finally, we see that percentages of stable variance and dynamic variance are quite consistent across Model 1, Model 2, and Model 3, indicating that ratio of stable variance to dynamic variance is constant in a given dataset regardless of how the structure of higher levels is specified. This suggests that stable variance and dynamic variance are caused by separate drivers.

5.2.3.2 A Brief Introduction of MCMC Parameters’ Chain

Here I briefly introduce how to interpret a parameter’s chain produced by MCMC. Figure 4 is for the percentage of level 3 (corporation–industry combination) variance in Model 3.

Figure 4
Percent of Level 3 Variance (combination)
The upper left–hand cell simply reproduces the entire trace for percentage of level 3 variance. The upper right–hand cell presents a kernel density (a smoothed histogram) estimate of the posterior distribution. The second row of boxes plots the autocorrelation (ACF) and partial autocorrelation (PACF) functions. The third row consists of some accuracy diagnostics. The left-hand box plots the estimated Monte Carlo standard error (MCSE) of the posterior estimate of the mean against the number of iterations. The MCSE is an indication of the accuracy of the mean estimate. The right–hand box contains two contrasting accuracy diagnostics. It suggests that for the parameter of percentage of level 3 (corporation–industry combination) variance, the estimated chain lengths are 23,695 and 20,378 for 2.5% and 97.5% quantiles respectively. Thus, 1000,000 iterations satisfy these requirements. It also suggests that to quote the estimated percentage of level 3 (corporation–industry combination) variance as 16.22% (2–digit significant) with the desired accuracy requires the chain to run only 441 iterations. Thus, 1000,000 iterations also satisfy this requirement.

The bottom box contains some numerical summaries of the data as well as the mean (with its MCSE in parenthesis). This box also contains the mode and median estimates. To estimate both 90% and 95% intervals, this box also contains the appropriate quantiles of the distribution. For example a 95% central interval (Bayesian credible interval) runs from 14.63 to 17.83. Also in the bottom row of the box details of the run length of the Markov chain are given.

From figures in Appendix D and Appendix E, we see that 1000,000 iterations satisfy requirements for all estimated parameters.
5.3 Year Effects and Dynamic Variance

While the sources of stable variance in performance are examined in Model 3, the sources of dynamic variance ($\sigma^2_e$) have not been specified yet. Given that 45.07 (0.42) percent of total variance is dynamic variance, it merits further investigation. In previous studies, this part of variance was often referred to as error term (Hough, 2006; McGahan et al., 1997, 2002), across–time variance (Misangyi et al., 2006), year–to–year variance (Rumelt, 1991; Short et al., 2006), or volatility (Thomas et al., 2009). Misangyi et al. (2006) realized that the “error” reported by previous COV and ANOVA studies was actually the across–time variance. Rumelt (1991) insightfully recognized that the “error” might be year–to–year variations that were specific to each BU. As discussed earlier, from longitudinal multilevel perspective, this part of variance is attributable to over–time changes and interactions among these changes at each level. All these changes can be classified into (1) continuous changes or (2) discontinuous changes. Dynamic variance results from both continuous changes and discontinuous changes. These over–time changes are termed time–varying variables in longitudinal multilevel framework. Continuous time–varying variables can be represented by polynomial of time, but discontinuous changes cannot.

On the other hand, almost all previous studies modeled year effects and concluded that year effects accounted for a significant but minimal portion of total variance in performance (e.g., McGahan et al., 1997, 2002; Misangyi et al, 2006; Rumelt, 1991). In these studies, year effects were assumed to capture year–to–year macroeconomic fluctuations which equally influenced performance of all business segments (Khanna and Rivkin, 2001; McGahan et al., 1997, 2002; Rumelt, 1991). Thus, although not explicitly stated, the year effects in these previous studies were not related to stable effects. These
year effects were introduced to represent the macroeconomic changes that had identical effects on all business segments, corporations, and industries. In other words, previous studies utilized fixed linear year to represent year-to-year macroeconomic changes which were partial sources of dynamic variance in performance. Thus, in previous studies fixed linear year was already used to explain dynamic variance. In addition to fixed linear year effects, this dissertation models random linear year as well as fixed and random nonlinear year to represent more complete continuous changes and explain more dynamic variance.

I argue that in addition to aforementioned identical year effects, year may also have different effects on different business segments because changes both within and without business segments may have unique effects on each business segment, and that year effects may be nonlinear because changes both within and without business segments may have different influences on performance in different years. Put differently, performance of each business segment changes uniquely and unevenly over time. In the same vein, year effects may also differ across both corporations and industries. To capture random as well as nonlinear year effects and demonstrate that more dynamic variance may be accounted for by year effects, this dissertation fits a series of nested unconditional longitudinal models.

5.3.1 Constructing Unconditional Longitudinal Models

An unconditional longitudinal model is a model with time (here $YEAR$) as the only time-varying (level 1) predictor and no substantive predictors at any other level, which helps evaluate the baseline amount of dynamic variance (Raudenbush et al., 2002; Singer et al., 2003).
In Model 4, fixed linear year is added at level 1 of Model 3 to capture fixed linear year effects.

\[
\begin{align*}
\text{Model 4: ROA}_{tmijk} &= \alpha_{0imjk} + \alpha_{1imjk} \text{YEAR}_{tmijk} + e_{tmijk} \\
\alpha_{0imjk} &= \beta_{00mjk} + b_{0imjk} \\
\alpha_{1imjk} &= \beta_{10} \\
\beta_{00mjk} &= \gamma_{000jk} + i_{00mjk} \\
\beta_{10} &= \gamma_{100} \\
\gamma_{000jk} &= \lambda_{0000} + c_{000j} + d_{000k} \\
\gamma_{100} &= \lambda_{1000},
\end{align*}
\]

where we assume that

\[
\begin{align*}
e_{tmijk} &\sim N(0, \sigma^2_e), \\b_{0imjk} &\sim N(0, \sigma^2_b_{00}), \\
i_{00mjk} &\sim N(0, \sigma^2_i_{00}), \\
c_{000j} &\sim N(0, \sigma^2_c_{00}), \text{ and } \\
d_{000k} &\sim N(0, \sigma^2_d_{00}).
\end{align*}
\]

Model 4, as with previous studies, captures the linear year effects that are identical for all business segments regardless of their attributes. Of note, definitions of \(\alpha_{0imjk}\) and \(\beta_{00mjk}\) are different from those in previous models because year is specified in the model. \(\alpha_{0imjk}\) is the estimated initial ROA of business segment \(i\) which belongs to combination \(m\) of corporation \(i\) and industry \(k\), when \(Year = 0\). \(\beta_{00mjk}\) is the estimated mean initial ROA of combination \(m\) when \(Year = 0\). \(\alpha_{1imjk}\) is the linear year effects on ROA of business segment \(i\), which is in combination \(m\). \(\beta_{10}\), \(\gamma_{100}\), and \(\lambda_{1000}\) are mean linear year effects at business segment level, corporation–industry combination level, and corporation–industry cross–classification level respectively. Linear year effects are set fixed at each level (\(\alpha_{1imjk} = \beta_{10} = \gamma_{100} = \lambda_{1000}\)). \(\text{YEAR}_{tmijk}\) is defined as the number of years since the first year of the analysis (Hough, 2006; McGahan et al. 1997, 2002; Rumelt, 1991). For
example, \( \text{YEAR} \text{t}_m\text{i}_{mjk} = 0 \) for data in year 1979. All other parameters are as described in previous models.

As shown in Model 4, longitudinal multilevel models estimate year effects by specifying year as a time–varying explanatory variable at level 1 to explain the dynamic variance \( (\sigma_e^2) \). Year effects equal the amount of dynamic variance \( (\sigma_e^2) \) explained or reduced by year.

In Model 5, Model 4 is altered by setting linear year effects random at business segment level, corporation level, and industry level.\(^{12}\)

\[
\text{Model 5: } \text{ROA}_{t_{mjk}} = \alpha_{0_{mjk}} + \alpha_{1_{mjk}} \text{YEAR}_{t_{mjk}} + e_{t_{mjk}}
\]

\[
\alpha_{0_{mjk}} = \beta_{00_{mjk}} + b_{0_{mjk}}
\]

\[
\alpha_{1_{mjk}} = \beta_{10_{mjk}} + b_{1_{mjk}}
\]

\[
\beta_{00_{mjk}} = \gamma_{000_{jk}} + i_{00_{mjk}}
\]

\[
\beta_{10_{mjk}} = \gamma_{100}
\]

\[
\gamma_{000_{jk}} = \lambda_{0000} + c_{000_{j}} + d_{000_{k}}
\]

\[
\gamma_{100} = \lambda_{1000} + c_{100_{j}} + d_{100_{k}},
\]

where we assume that

\[
e_{t_{mjk}} \sim N(0, \sigma_e^2), i_{00_{mjk}} \sim N(0, \sigma_i^2),
\]

\[
\begin{bmatrix}
    b_{0_{t_{mjk}}} \\
    b_{1_{t_{mjk}}}
\end{bmatrix}
\sim \mathcal{N}
\begin{bmatrix}
    0 \\
    0
\end{bmatrix}
\begin{bmatrix}
    \sigma_{b_0}^2 & \sigma_{b_0 b_1} \\
    \sigma_{b_1 b_0} & \sigma_{b_1}^2
\end{bmatrix},
\]

\[
\begin{bmatrix}
    c_{000_{j}} \\
    c_{100_{j}}
\end{bmatrix}
\sim \mathcal{N}
\begin{bmatrix}
    0 \\
    0
\end{bmatrix}
\begin{bmatrix}
    \sigma_{c_0}^2 & \sigma_{c_0 c_1} \\
    \sigma_{c_1 c_0} & \sigma_{c_1}^2
\end{bmatrix},
\]

\[
\begin{bmatrix}
    d_{000_{k}} \\
    d_{100_{k}}
\end{bmatrix}
\sim \mathcal{N}
\begin{bmatrix}
    0 \\
    0
\end{bmatrix}
\begin{bmatrix}
    \sigma_{d_0}^2 & \sigma_{d_0 d_1} \\
    \sigma_{d_1 d_0} & \sigma_{d_1}^2
\end{bmatrix}.
\]

Model 5 tests the argument that random linear year effects are significant and important. \( \beta_{10_{mjk}} \) is the mean linear year effects on combination \( m \) and \( b_{1_{mjk}} \) is between–

\(^{12}\) Since random year effects cannot be captured at corporation–industry combination level, this study does not set year effects random at this level. Same is the case with Model 6.
business segment residual of linear year effects within combination \( m \). \( \lambda_{1000} \) is grand–mean year effects, \( c_{100j} \) is between corporation residual of linear year effects, and \( d_{100k} \) is between industry residual of linear year effects. \( \sigma_{b1}^2 \) is between–business segment variance in linear year effects within combination \( m \). \( \sigma_{b1b0} \) and \( \sigma_{b0b1} \) are covariance between \( b_{00imjk} \) and \( b_{10imjk} \). \( \sigma_{c1}^2 \) is between–corporation variance in linear year effects within combination \( m \). \( \sigma_{c1c0} \) and \( \sigma_{c0c1} \) are covariance between \( c_{000j} \) and \( c_{100j} \). \( \sigma_{d1}^2 \) is between–industry variance in linear year effects within combination \( m \). \( \sigma_{d1d0} \) and \( \sigma_{d0d1} \) are covariance between \( d_{000k} \) and \( d_{100k} \). All other parameters are as described in previous models.

In Model 6, Model 4 is altered by setting both linear year and quadratic year random at business segment level, corporate level, and industry level.

Model 6: \( \text{ROA}_{tmijk} = \alpha_{0imjk} + \alpha_{1imjk} \text{YEAR}_{tmijk} + \alpha_{2imjk} \text{YEAR}_{tmijk}^2 + e_{tmijk} \)

\[
\begin{align*}
\alpha_{0imjk} &= \beta_{00mjk} + b_{0imjk} \\
\alpha_{1imjk} &= \beta_{10mjk} + b_{1imjk} \\
\alpha_{2imjk} &= \beta_{20mjk} + b_{2imjk} \\
\beta_{00mjk} &= \gamma_{000jk} + i_{00mjk} \\
\beta_{10mjk} &= \gamma_{100} \\
\beta_{20mjk} &= \gamma_{200} \\
\gamma_{000jk} &= \lambda_{0000} + c_{000j} + d_{000k} \\
\gamma_{100} &= \lambda_{1000} + c_{100j} + d_{100k} \\
\gamma_{200} &= \lambda_{2000} + c_{200j} + d_{200k},
\end{align*}
\]

where we assume that

\( e_{tmijk} \sim N(0, \sigma_e^2), i_{00imjk} \sim N(0, \sigma_i^2), \)
Model 6 includes linear year and quadratic year and sets both random at business segment level, corporation level, and industry level to capture both random and nonlinear year effects (including random linear, fixed nonlinear, and random nonlinear year effects) in addition to fixed year effects. I add the nonlinear year in the model to reflect my observation that business unit performance does not change at a constant rate over these years. $\alpha_{2imjk}$ is the quadratic year effects in year $t$ on ROA of business segment $i$, which is in the combination $m$ of corporation $i$ and industry $k$. $\beta_{2mjk}$ is the average quadratic year effects across business segments within combination $m$ and $b_{2imjk}$ is between–business segment residual of quadratic year effects within combination $m$. $\sigma_{b2}^2$ is between–business segment variance in quadratic year effects within combination $m$. $\sigma_{b0b2}$ and $\sigma_{b2b0}$ are covariance between $b_{0imjk}$ and $b_{2imjk}$; $\sigma_{b1b2}$ and $\sigma_{b2b1}$ are covariance between $b_{1imjk}$ and $b_{2imjk}$. $\sigma_{c2}^2$ is between–corporation variance in quadratic year effects within combination $m$. $\sigma_{c0c2}$ and $\sigma_{c2c0}$ are covariance between $c_{000j}$ and $c_{200j}$; $\sigma_{c2c1}$ and $\sigma_{c1c2}$ are covariance between $c_{100j}$ and $c_{200k}$. $\sigma_{d2}^2$ is between–industry variance. $\sigma_{d2d0}$ and $\sigma_{d0d2}$ are covariance between $d_{000k}$ and $d_{000k}$; $\sigma_{d2d1}$ and $\sigma_{d1d2}$ are covariance between $d_{100j}$ and $d_{200k}$. All other parameters are as described in previous models.
5.3.2 Results of Year Effect Estimations

Table 3 presents results from MCMC estimation of Model 4, Model 5, and Model 6. As discussed above all percentages are obtained as functions of variances. Appendix B presents the parameter’s chain of each variance and each percentage.

5.3.2.1 Fixed Year Effects

As discussed above, longitudinal multilevel models estimate year effects by calculating the amount of dynamic variance ($\sigma_e^2$) explained by year. Comparing results of Model 4 and Model 3 shows that 2.14 (0.71) percent\textsuperscript{13} of the dynamic variance in ROA is accounted for by fixed linear year effects. Thus, fixed linear year effects only account for 0.97(0.32) percent\textsuperscript{14} of the total variance in ROA. This result is consistent with recent studies (McGahan et al., 2002; Misangyi et al., 2006). Of note, Misangyi et al. (2006) also appropriately used this method to estimate fixed linear year effects.

5.3.2.2 Random and Nonlinear Year Effects

Comparing Model 5 with Model 3 shows that fixed and random linear year effects together account for much more variance: 16.70 (0.63) percent\textsuperscript{15} of dynamic variance which equals 7.52 (0.31) percent\textsuperscript{16} of total variance. Comparing Model 6 with Model 3 shows that total year effects account for 24.76 (0.57) percent\textsuperscript{17} of dynamic variance which equals 11.16 (0.30) percent\textsuperscript{18} of total variance. Thus, in addition to fixed linear effect (0.97%), random and quadratic year effects account for 10.19 (0.31) percent\textsuperscript{19} of total variance. Additionally, Model 6 has a far lower DIC (739853), indicating that this

\textsuperscript{13} (\sigma_e^2 (model 3) - \sigma_e^2 (model 4))/\sigma_e^2 (model 3) = 2.14% (0.71%).
\textsuperscript{14} (\sigma_e^2 (model 3) - \sigma_e^2 (model 4))/\text{total variance (model 3)} = 0.97% (0.32%).
\textsuperscript{15} (\sigma_e^2 (model 3) - \sigma_e^2 (model 5))/\sigma_e^2 (model 3) = 16.70% (0.63%).
\textsuperscript{16} (\sigma_e^2 (model 3) - \sigma_e^2 (model 5))/\text{total variance (model 3)} = 7.52% (0.31%).
\textsuperscript{17} (\sigma_e^2 (model 3) - \sigma_e^2 (model 6))/\sigma_e^2 (model 3) = 24.76% (0.57%).
\textsuperscript{18} (\sigma_e^2 (model 3) - \sigma_e^2 (model 6))/\text{total variance (model 3)} = 11.16% (0.30%).
\textsuperscript{19} (\sigma_e^2 (model 3) - \sigma_e^2 (model 6))/\text{total variance (model 3)} - (\sigma_e^2 (model 3) - \sigma_e^2 (model 4))/\text{total variance (model 3)} = 10.19% (0.31%).
model fits the data much better than all previous models. This analysis demonstrates that some year effects are nonlinear and that some year effects differ across business segments, corporations, and industries.

5.4 Other Relevant Results from the MCMC Estimation of Model 6

In this section, I discuss and interpret results other than of decomposition of variance in business unit performance.

Model 6 reports a negative fixed linear year effect [-1.11(0.09)], indicating that overall business segments’ performance decreased during the period of our dataset. This is consistent with McGahan’s (1999) observation. However, the positive fixed quadratic year effect [0.04 (0.01)] shows that the decreasing was neither steady nor gradual.

At corporation level, variances of both linear [0.72(0.19)] and quadratic year [0.003(0.001)] are significant, indicating that year effects are different over corporations. Neither the covariance between linear year and initial corporation ROA [-0.59(0.53)] nor the variance between quadratic year and initial corporation ROA [0.01(0.03)] is significant. These indicate that initial performances of diversified corporations do not predict their future performance trends, which may imply that the adapting capabilities of diversified corporations are higher than those of single business firms.

At industry level, variances of both linear year [1.95(0.23)] and quadratic year [0.005(0.001)] are significant, indicating that year effects are nonlinear and different over industries. Negative variance between linear year and initial industry ROA [-5.84(0.83)] indicates that the higher the initial industry ROA the flatter the slope of ROA change. Since the fixed effects are negative, a flat slope means slow decreasing over time. This
Table 3. Results from MCMC estimation of Model 4, Model 5, and Model 6

<table>
<thead>
<tr>
<th></th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>S.E.</td>
<td>Coefficient</td>
</tr>
<tr>
<td>Intercept: $\lambda_{0000}$</td>
<td>14.34</td>
<td>0.22</td>
<td>14.84</td>
</tr>
<tr>
<td>Year: $\lambda_{1000}$</td>
<td>-0.44</td>
<td>0.01</td>
<td>-0.53</td>
</tr>
<tr>
<td>Year square: $\lambda_{2000}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Fixed effects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Random Effects</strong></td>
<td>Variance/</td>
<td>Variance/</td>
<td>Variance/</td>
</tr>
<tr>
<td></td>
<td>Covariance</td>
<td>Covariance</td>
<td>Covariance</td>
</tr>
<tr>
<td>Level 4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Corporation: $\sigma_{c_1c_0}$</td>
<td>10.14</td>
<td>1.45</td>
<td>11.44</td>
</tr>
<tr>
<td>Year/intercept:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_{c_1c_0}$</td>
<td>-0.42</td>
<td>0.23</td>
<td>-0.53</td>
</tr>
<tr>
<td>Year: $\sigma_{c_1}^2$</td>
<td>0.11</td>
<td>0.03</td>
<td>0.70</td>
</tr>
<tr>
<td>Year square/Year:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_{c_1c_1}$</td>
<td>0.01</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year square/Year:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_{c_1c_1}$</td>
<td>-0.04</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>Year square: $\sigma_{c_1}^2$</td>
<td>0.003</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>Level 4</td>
<td>Industry: $\sigma_{d_2}^2$</td>
<td>13.20</td>
<td>1.44</td>
</tr>
<tr>
<td>Year/intercept:</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_{d_2d_0}$</td>
<td>-1.31</td>
<td>0.20</td>
<td>-5.86</td>
</tr>
<tr>
<td>Year: $\sigma_{d_2}^2$</td>
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<td>0.02</td>
<td>1.96</td>
</tr>
<tr>
<td>Year square/intercept:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_{d_2d_0}$</td>
<td>0.23</td>
<td>0.04</td>
<td></td>
</tr>
<tr>
<td>Year square/Year:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_{d_2d_0}$</td>
<td>-0.10</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>Year square: $\sigma_{d_2}^2$</td>
<td>0.005</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>Level 3</td>
<td>Combination: $\sigma_{i2}$</td>
<td>47.58</td>
<td>3.45</td>
</tr>
<tr>
<td>Level 2</td>
<td>Business segment: $\sigma_{b0}$</td>
<td>84.58</td>
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</tr>
<tr>
<td>Year/intercept:</td>
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<td></td>
</tr>
<tr>
<td>$\sigma_{b0b_0}$</td>
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<td>0.45</td>
<td>-23.71</td>
</tr>
<tr>
<td>Year: $\sigma_{b0}^2$</td>
<td>1.53</td>
<td>0.05</td>
<td>10.56</td>
</tr>
<tr>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_{b0b_0}$</td>
<td>0.65</td>
<td>0.08</td>
<td></td>
</tr>
<tr>
<td>Year square/Year:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_{b0b_0}$</td>
<td>-0.51</td>
<td>0.02</td>
<td></td>
</tr>
<tr>
<td>Year square: $\sigma_{b0}^2$</td>
<td>0.029</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>Level 1</td>
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<td>0.65</td>
</tr>
<tr>
<td>DIC</td>
<td>757851</td>
<td>746401</td>
<td>739853</td>
</tr>
</tbody>
</table>

\(a\) Difference between this and $\sigma_{e2}^2$ (model 3) is accounted for by fixed linear year effects.

\(b\) Difference between this and $\sigma_{e2}^2$ (model 3) is accounted for by linear year effects random at business segment level, corporation level, and industry level.

\(c\) Difference between this and $\sigma_{e2}^2$ (model 3) is accounted for by linear year effects and nonlinear year effects both random at business segment level, corporation level, and industry level.
indicates that industries with high performance at the beginning tend to keep their position over time.

At business segment level, variances of both linear \([10.54(0.44)]\) and quadratic year \([0.029(0.001)]\) are significant, indicating that year effects are nonlinear and different over business segments. Negative variance between linear year and initial business segment ROA \([-23.60(1.44)]\) indicates that the higher the initial business segment ROA the flatter the slope of ROA change. Since the fixed effects are negative, a flat slope means slow decreasing over time. This indicates that overall business segments with high performance at beginning tend to keep their position over time.

5.5 Comparison of This Research with Previous Studies

Column 1 of Table 4 summarizes the final results of this research. In Table 3, I compare the results with those of selected previous studies. First, this dissertation successfully extracts corporation–industry interaction effects (16.22%) out of previously confounded effects. Second, we see that in addition to small fixed linear year effects (0.97%), this study also captures random and nonlinear year effects (10.19%). After adding random and nonlinear year, 24.76 percent of dynamic variance, which equals 11.16 percent of total variance, is accounted for by year effects.

5.6 The Role of Time and Sources of Dynamic Variance

As the empirical results indicated, year effects accounts 24.76 percent of dynamic variance in business unit performance. I now discuss the role of time and further explore sources of dynamic variance. In longitudinal multilevel models, the outcome variable can be explained or predicted by two kinds of independent variables: time–varying (at level 1), and time–invariant independent variables (at levels higher than level 1) (Frees, 2004;
Raudenbush et al., 2002; Singer et al., 2003). Time-varying variables refer to variables that change over time at all levels. Time-varying variables can both be internal (within business segment) or external (without business segment) (Singer et al., 2003). The outcome variable in longitudinal data is always time-varying. Other examples of time-varying variables are year, capital expenditure, and sales. Time-varying variables specified at level 1 can also be industry level or corporation level variables that change over time, such as industry concentration and corporate R&D. Time-invariant variables are variables that do not change or cannot be changed during the period of interest. For example, entry mode is a time-invariant variable because entry mode is fixed and cannot be changed over time once an entry is completed.

As discussed above, fixed and random linear and quadratic year account for about 24.76 percent of dynamic variance. However, there is still approximately 75.24 percent of the dynamic variance unaccounted for. In an attempt to understand more of the unaccounted for variance, I further explore the role of time. Conceptually, performance changes over time but not because of time. Rather, performance changes because of over-time changes both within and without business segments. Thus, I argue that dynamic variance is attributable to over-time changes from all levels. All over-time changes can be classified into (1) continuous changes and (2) discontinuous changes. Mathematically, all over-time changes can be expressed as functions of time. Whatever their function forms are, these functions can be approximated by a polynomial of time via Taylor’s series expansion as long as the functions are differentiable. Stated differently, if we could observe every differentiable change and specify each in the model, there would be no room for TIME at level 1.
Table 4. Comparison of this study with selected previous studies

<table>
<thead>
<tr>
<th>Source of data</th>
<th>Years covered</th>
<th>No. of observations</th>
<th>Sectors covered</th>
<th>Approach</th>
<th>Effects (S.E.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Source of data</td>
<td>Years covered</td>
<td>No. of observations</td>
<td>Sectors covered</td>
<td>Approach</td>
</tr>
<tr>
<td>Compustat</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Fixed linear year</td>
</tr>
<tr>
<td>Compustat</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Random and nonlinear year</td>
</tr>
<tr>
<td>Compustat</td>
<td>1995–99</td>
<td>19,405</td>
<td>All</td>
<td>Multilevel model</td>
<td>Business segment</td>
</tr>
<tr>
<td>Compustat</td>
<td>1995–99</td>
<td>19,405</td>
<td>All</td>
<td>Multilevel model</td>
<td>Corporation–industry interaction</td>
</tr>
<tr>
<td>Compustat</td>
<td>1995–99</td>
<td>19,405</td>
<td>All</td>
<td>Multilevel model</td>
<td>Corporation</td>
</tr>
<tr>
<td>Compustat</td>
<td>1995–99</td>
<td>19,405</td>
<td>All</td>
<td>Multilevel model</td>
<td>Industry</td>
</tr>
<tr>
<td>Compustat</td>
<td>1995–99</td>
<td>19,405</td>
<td>All</td>
<td>Multilevel model</td>
<td>Dynamic Variance</td>
</tr>
<tr>
<td>Misangyi et al. (2006)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Fixed linear year</td>
</tr>
<tr>
<td>Karniouchina et al. (2013)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Random and nonlinear year</td>
</tr>
<tr>
<td>McGahan et al. (2002)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Business segment</td>
</tr>
<tr>
<td>Rumelt (1991) Sample B</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Corporation–industry interaction</td>
</tr>
<tr>
<td>Hough (2006)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Corporation</td>
</tr>
<tr>
<td>Hough (2006)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Industry</td>
</tr>
<tr>
<td>Hough (2006)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Dynamic Variance</td>
</tr>
<tr>
<td>Misangyi et al. (2006)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Fixed linear year</td>
</tr>
<tr>
<td>Karniouchina et al. (2013)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Random and nonlinear year</td>
</tr>
<tr>
<td>McGahan et al. (2002)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Business segment</td>
</tr>
<tr>
<td>Rumelt (1991) Sample B</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Corporation–industry interaction</td>
</tr>
<tr>
<td>Hough (2006)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Corporation</td>
</tr>
<tr>
<td>Hough (2006)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Industry</td>
</tr>
<tr>
<td>Hough (2006)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Dynamic Variance</td>
</tr>
<tr>
<td>Misangyi et al. (2006)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Fixed linear year</td>
</tr>
<tr>
<td>Karniouchina et al. (2013)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Random and nonlinear year</td>
</tr>
<tr>
<td>McGahan et al. (2002)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Business segment</td>
</tr>
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<td>Rumelt (1991) Sample B</td>
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<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Corporation–industry interaction</td>
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<tr>
<td>Hough (2006)</td>
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<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Corporation</td>
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<tr>
<td>Hough (2006)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Industry</td>
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<tr>
<td>Hough (2006)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Dynamic Variance</td>
</tr>
<tr>
<td>Misangyi et al. (2006)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Fixed linear year</td>
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<td>Karniouchina et al. (2013)</td>
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<td>All</td>
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<td>Random and nonlinear year</td>
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<td>McGahan et al. (2002)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Business segment</td>
</tr>
<tr>
<td>Rumelt (1991) Sample B</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Corporation–industry interaction</td>
</tr>
<tr>
<td>Hough (2006)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Corporation</td>
</tr>
<tr>
<td>Hough (2006)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Industry</td>
</tr>
<tr>
<td>Hough (2006)</td>
<td>1979–96</td>
<td>97,011</td>
<td>All</td>
<td>Multilevel model</td>
<td>Dynamic Variance</td>
</tr>
</tbody>
</table>

---

*a* Given the unreliable issues of COV results (Brush et al., 1997), the results are only compared with multilevel model results and ANOVA results.

*b* Observations with only 1 or 2 years of data were excluded.

*c* Stratified random sample.

*d* Sample limited to continuous observations within each stage.

*e* Estimated by adding fixed linear year at level 1 in model 2 and calculating the amount of dynamic variance accounted for by fixed linear year effects.

*f* $\frac{(\sigma^2_e (model 3) - \sigma^2_e (model 0))}{\text{total variance}_{(model 3)}} \times \frac{\text{total variance}_{(model 3)} - (\sigma^2_e (model 3) - \sigma^2_e (model 4))}{\text{total variance}_{(model 3)}} = 10.19\% (0.31\%)$.

*g* $\frac{\sigma^2_e (model 0)}{\text{total variance}_{(model 3)}} = 33.91\% (0.35\%)$.

*h* $\frac{\sigma^2_e (model 4)}{\text{total variance}_{(model 3)}} = 44.10\% (0.45\%)$.

*i* The industry–year effects were 7.1% and are incorporated here as part of dynamic variance (Misangyi et al., 2006).
Statistically, polynomial of time is used to represent missing variables in panel data to reduce degree of endogeneity, implying that unobserved over–time changes can be partially represented by time. Thus, in longitudinal multilevel models, polynomial of time is used at level 1 to represent the summation of all differentiable functions of over–time changes from all levels and their interactions. However, the other kind of over–time changes, discontinuous or abrupt changes, cannot be approximated by a polynomial of time, because although over–time discontinuous changes can also be expressed as functions of time, these functions are not differentiable. Thus, dynamic variance in Model 6 is partially accounted for (about 25%) by summation of over–time continuous changes both within and without business segments and their interactions. The remaining 75 percent is attributable to summation of abrupt over–time changes and their interactions, and the interactions between continuous and discontinuous changes. Some examples of over–time discontinuous changes are CEO turnover, disruptive innovation, and industrial deregulation. To summarize these arguments, Table 5 presents sources of variance partitioned into stable and dynamic effects. It is very important to notice that as some previous studies demonstrated, the proportions are not stable over time or across locations. Karniouchina et al. (2013) found that relative effects of these factors on performance and partition of stable effects change with the evolution of industry life cycle. Khanna and Rivkin, (2001) found that relative importance of sources of stable variance in performance varies across institutional (country) contexts.
Table 5. All sources of variance in ROA: Compustat Segment data (1979–1996)

<table>
<thead>
<tr>
<th>Sources of variance</th>
<th>Percentage</th>
<th>Subtotal</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Stable effects</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Corporation</td>
<td>3.83%</td>
<td></td>
</tr>
<tr>
<td>Industry</td>
<td>5.34%</td>
<td></td>
</tr>
<tr>
<td>Corporation–industry Interaction</td>
<td>16.22%</td>
<td></td>
</tr>
<tr>
<td>Business segment</td>
<td>29.54%</td>
<td>54.93%</td>
</tr>
<tr>
<td><strong>Dynamic effects</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Over–time continuous changes at each level and their interactions</td>
<td>11.16%</td>
<td></td>
</tr>
<tr>
<td>Over–time discontinuous changes at each level, their interactions, and interactions among continuous changes and discontinuous changes</td>
<td>33.91%</td>
<td>45.07%</td>
</tr>
</tbody>
</table>

5.7 Nature of Stable Effects and Dynamic Effects

All previous studies attempted to capture stable effects rather than dynamic effects. As illustrated in Table 5, total stable effects amount to 53.89 percent of the total variance in performance in the data from 1979 to 1996. From a longitudinal multilevel model perspective, this proportion is referred to as intra–class correlation (ICC) which indicates that 54.93 percent of total variance in performance is attributable to unobserved or unspecified time–invariant variables at business segment, corporation, and industry level. ICC also represents the average correlation between over–time repeated observations (Hedeker and Gibbons, 2006). Thus, the higher the average correlation between pairs of over–time repeated observations, the higher the stable effects and the lower the dynamic effects. The average correlation between pairs of over–time repeated observations changes across time, industry, and corporation. Thus, the ratio of stable effects to dynamic effects is not constant but varies across business segment, corporation, industry, and time. To illustrate the dynamic nature of ICC, I fit Model 1 to additional 16 rolling over 18–year–window datasets from Compustat Business segment data, beginning in 1980–1997 and ending in 1995–2012. I use the same screening steps as described earlier to create these 16 18–year datasets. Table 5 presents the results, which indicate that variance in performance increases dramatically in recent years as
showed in Figure 5, that stable effects account for less and less percentage of the variance in performance, and that more and more variance in performance is attributable to dynamic effects. These indicate that ICC, the average correlation between pairs of over–time repeated ROAs, has been decreasing, which suggests that importance of time–invariant attributes of each level has been decreasing and the importance of time–varying attributes of each level has been increasing. Indeed, in the first 18–year–window dataset (1980–1997), about 54 percent of total variance in performance is attributable to stable effects. However, in the last 18–year–window dataset (1995–2012) only about 17 percent of total variance in performance is attributable to stable effects. Conversely, more and more portion of variation in performance is from over–time changes: in the first 18–year–window dataset (1980–1997), about 46 percent of total variance in performance is attributable to dynamic effects, but this grows to more than 83 percent in the final 18–year windows dataset (1995–2012). These dramatic and previously unexplored dynamics in the relative importance of dynamic sources of variance have strong implications (to be discussed later) for academia and practitioners.
Table 6. Results from fitting Model 1 to 16 rolling over 18–year–window datasets from Compustat Business segment data (1980–2012)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of observations</td>
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<td>99009</td>
<td>100426</td>
<td>101541</td>
<td>102573</td>
<td>103504</td>
<td>104186</td>
<td>104633</td>
</tr>
<tr>
<td>Number of business segments</td>
<td>15710</td>
<td>15774</td>
<td>16816</td>
<td>17395</td>
<td>17661</td>
<td>17677</td>
<td>17624</td>
<td>17518</td>
</tr>
<tr>
<td>Number of Corporations</td>
<td>8992</td>
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<td>9626</td>
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</table>
Figure 5
Total variance in performance of 17 18–year windows (1979–2012)
Chapter 6
Theoretical Implications for Strategic Management

The empirical results and analyses of this research indicate that total variance in firm performance result from both stable variance and dynamic variance, that all levels and interactions across these levels in the system of business reality are important sources of stable variance in firm performance, and that over–time changes within and without firms are substantial sources of dynamic variation in firm performance. Thus, to comprehensively understand firm performance, we need a theoretical framework of strategic management that links stable attributes of each level to firm performance, that links the interactions within and across levels to firm performance, and that links over–time changes within and without firms to firm performance. Put differently, we need a theoretical framework that explains both stable variance and dynamic variance in firm performance. These suggest that an integrated or systematic dynamic theory of strategic management is warranted.

6.1 A Multilevel Longitudinal Perspective of Strategic Management

Drawing on the lens of complexity theory, a multilevel longitudinal perspective of strategic management conceptualizes the business reality as a complex adaptive system in which a firm is a subsystem, theorizes the business reality from both systematic and dynamic viewpoints, and models the business reality with longitudinal multilevel models. Informed by the empirical results of this study, I argue that a systematic dynamic theory has to be both multilevel and longitudinal.
6.1.1 Multilevel Aspects of a Multilevel Longitudinal theoretical Framework of Strategic Management

Structurally, four elements of a multilevel longitudinal theoretical framework of strategic management are identified. They are *structure of the business system, focal level of analysis, focal unit of analysis*, and *multilevel relationship* (Mathieu et al., 2010).

*Structure of the business system* refers to how a theory specifies the hierarchical arrangement of the phenomena of interest. For example, Figure 3 of this study is the structure of the business system that I believe mirrors the business reality. *Focal level of analysis* refers to the level of the business system of which a theory is intended to explain the variance in performance, and to which generalizations are intended to apply. The empirical results of this study indicate that stable variance at each level is important, and thus we need level–specific theories to explain variance at each level. Thus, each of these level–specific theories has to articulate which level of the business system it intends to anchor in. For example, the focal level of RBV is firm level while it is industry level for IO. *Focal unit of analysis* refers to the entity of which total variance in the outcome is to be explained, and which theoretical generalizations are about. For example, in this study business unit is the focal unit of analysis. Other possible focal units of analysis are corporation and industry. Once the focal level of analysis and the focal unit of analysis are identified, multilevel relations, which are about how predictors below, within, or above the focal level of analysis influence the outcome variable of the focal unit of analysis, can be explored.
6.1.2 Dynamic Aspects of a Multilevel Longitudinal Theoretical Framework of Strategic Management

As the empirical results indicate that the portion of dynamic variance in total performance variance is getting higher and higher. Accordingly, a theoretical framework intended to explain dynamic variance is more than warranted. I identify four elements for a dynamic theoretical framework of strategic management. They are direct drivers of the over–time changes of performance, effects of stable attributes of higher levels, and mechanisms of the changes of higher level attributes.

Direct drivers of the over–time changes of performance refer to those time–varying independent variables that trigger the changes of performance. For example, what, how, and when changes occurring at business level, corporate level, or industry level determine the changes of performance are critical to explain dynamic variance. Effects of stable attributes of higher levels refer the mechanism through which effects of those direct drivers are moderated by business–specific attributes, and effects of those business–specific attributes are moderated by both corporation–specific attributes and industry–specific attributes. In the same vein, both corporation–specific attributes and industry–specific attributes are moderated by institution–specific attributes. Mechanisms of the over–time changes of higher level attributes refers to why some attributes of business unit, corporation, and industry change over time but some others do not.

6.1.3 A Multilevel Longitudinal Perspective of Strategic Management: Integrating Both Multilevel Aspects and Longitudinal Aspects

A multilevel longitudinal perspective of strategic management is supposed to simultaneously explain stable variance and dynamic variance. Accordingly, theories at
the lowest level must be about the dynamic processes through which firm performance changes over time. Theories at higher levels have to link the stable attributes of a particular level to firm performance changes. Thus, a multilevel longitudinal perspective of strategic management can accommodate both equilibrium and process in one theoretical framework.

The next section examines two current dominant theoretical frameworks of strategic management through the lens of a multilevel longitudinal perspective.

6.2 Salient Theoretical Frameworks of Strategic Management

As highlighted in Chapter 1, the field of strategy has had as a defining mission the understanding of variation in performance among firms. While most theoretical frameworks of strategic management have been developed to likely explain the same variance in firm performance, these have tended to be divided by the level of and unit of analysis, with which these approach this issue, and these have also been distinguished by being static or dynamic (processual). This section first examines two dominant theories of strategic management in terms of their level of analysis and potential to explain dynamic business processes.

6.2.1 Resource-based-view (RBV)

Resource–based view has been one of the most prominent theoretical frameworks which focuses on the inside of a firm and endeavors to understand, describe, and explain the origin and persistence of competitive advantage through the heterogeneous internal attributes of a firm. This framework views a firm as a bundle of resources (Barney, 1991; Dierickx & Cool, 1989; Penrose, 1959; Penrose, 2009; Wernerfelt, 1984), and when the bundle of resources is simultaneously of value, rarity, inimitability, and non–
substitutability, it leads to sustained competitive advantage, and subsequent long-lasting superior performance. Resources are everything in and of a firm including: physical capital resources, human capital resources, and organizational capital resources among others.

Recent important development of this approach focuses on the capabilities that a firm can use to exploit and combine resources (Amit and Schoemaker, 1993), processes of resource acquisition and deployment (Hansen, Perry, and Reese, 2004; Helfat et al., 2009; Maritan and Peteraf, 2011; Sirmon, Hitt, Ireland, and Gilbert, 2011), and the micro-foundations of resource-based view (Teece, 2007).

Through the lens of systematic dynamic perspective, I identify several limitations of RBV. First, this approach has remained a single firm–level rather than a multilevel approach. The interactions between resources and environment have been oversimplified and thus, its explanations of firm performance have likely been biased. The first type of interactions is those among resources themselves. The value of an individual resource is contingent upon other resources. It is the bundle of resources that matters, not the individual resources taken separately. The second type of interactions is those between a business unit that owns a bundle of resources and its corporate–parent. That is, the effects of bundle of resources are moderated by the attributes of the corporate–parent. A corollary is that a bundle of resources that a business unit own has no inherent value. The amount of value always depends on who owns the business unit. For example, Koller, Goedhart, and WesselsGeneral (2010: 413) offered an example to illustrate this argument. General Mills acquired Pillsbury for $10.4 billion from Diageo in 2001. Not long after the purchase, Pillsbury’s pretax cash flows increased by more than $400 million per year,
and its operating profits increased by roughly 70 percent. Diageo’s core business is in alcoholic beverages, while both General Mills and Pillsbury sell packaged foods. Under Diageo, Pillsbury was run entirely separately from Diageo’s core business, because the two companies’ manufacturing, distribution, and marketing operations rarely overlapped. In contrast, General Mills substantially reduced costs in Pillsbury’s purchasing, manufacturing, and distribution, because significant costs were duplicated in their operations. On the revenue side, General Mills boosted Pillsbury’s revenues by introducing Pillsbury products to schools in the United States where General Mills already had a strong presence. And the positive interaction effects worked both ways: for instance, Pillsbury’s refrigerated trucks were used to distribute General Mills’ newly branded refrigerated meals. Clearly, interaction effects between Pillsbury and General Mills was much better than those between Pillsbury and Diageo. Better interaction effects help the economy by redirecting resources to their highest-value use. The third kind of interactions is those between resources and industries. As Porter argued, resources are valuable only if these “allow firms to perform activities that create advantages in particular markets” (1991:108). Thus, the effects of a bundle of resources are moderated by attributes of industries in which this is used. The effects of a particular bundle of resources may be negative, zero, or positive, when it is used in different industries.

Second, RBV is intrinsically a static or cross-sectional framework, and thus it can only explain firm level stable variance. RBV has been unable to trace the temporal change of an individual firm’s performance, nor to identify the effect of temporal resource change of a particular firm, let alone the interactions between internal changes and external changes. In other words, RBV endeavors to explain the competitive discrepancy among
firms at a given point in time with a given bundle of resources, rather than across the life span of firms with temporally changing resources. For example, the value of a bundle of resources may change over time if corporations, industries, or institutions change. Thus, what was once valuable may become deleterious over time.

In summary, RBV only intends to explain isolated firm level stable variance but not variance from interaction and dynamic processes, which may lead biased explanations of firm performance.

6.2.2 Industrial Organization (IO)

Before the emergency of RBV, the competitive force framework was the dominant paradigm in this field. According to this paradigm, a firm’s performance in the marketplace depends critically on the characteristics of the industry environment in which it competes. Industry structure determines the behavior or conduct of firms, whose joint conduct then determines the collective performance of the firms in the marketplace (Porter, 1980; Porter, 1981). Through the lens of longitudinal multilevel perspective, I also identify several limitations of this approach. First, IO is a single industry level framework which does not pay enough attention to the idiosyncrasy of each firm in the same industry or interactions between firm and industry. Second, it has a static perspective and views the firm as a free-standing and passive entity. As a result, IO only explains industry level stable variance. From the lens of systematic dynamic perspective, we need to develop theories on why industries change over time, the effects of industry changes on firm performance, and how firms can adapt to take advantage of industry changes.
6.3 Toward a Multilevel Longitudinal Perspective of Strategic Management

This section first identifies the attributes of fragmented static theories and then identifies several existing theories that have potential to contribute to develop a multilevel longitudinal perspective of strategic management.

Conceptualizing the business reality as a complex adaptive system in which a firm is a subsystem, the multilevel longitudinal perspective has the potential to offer a broad framework to incorporate existing theories and discover relations among them. I use an extended classification diagram (Figure 6) to illustrate how a multilevel longitudinal perspective may incorporate some dominant theories of strategy.

Level 1 addresses dynamic processes of business unit, and we are interested in such questions as why performances of some business units are stable but others are not, and why performances of some business units increase over time but others decrease. Put statistically, we are interested in explanations of dynamic variance. Evolutionary theory (Nelson and winter, 1982), dynamic capabilities perspective (Teece et al., 1997; Teece, 2007, Helfat and Peteraf, 2003; Helfat et al., 2009), and dynamic systems (Forrester, 1961; Morecroft, 2007; Sterman, 2000; Warren, 2008) may contribute to answering these questions. Level 2 addresses stable business units’ attributes and their relation to over–time average stable performance. RBV and first order routines or zero–level routines (Winter, 2003) may contribute to explore these relations. Level 3 and level 4 address effects of interactions between different factors. Strategic fit theory (Venkatraman and Camillus, 1984; Venkatraman, 1989; Zajac, Kraatz, and Bresser, 2000) and contingency theory may contribute to this level. Level 5 addresses effects of attributes of corporation, industry, and location. Theories of corporate strategy, IO, and agglomeration theory all
relate to this level. Level 6 addresses country, and thus institution theory and international business theories are related to this level. It is also important to investigate drivers of changes at each level. For example, we need to know why and how industries evolve over time and why and how firms change. McGahan (2004) and Teece (2007) shed light on these issues. Importantly, these theories can function simultaneously in the models and thus interactions of these theories can be explored and complexity theory (Allen, Maguire, and Mckelvey; 2011) may contribute to the overall interactions of the business system. In sum, each relevant theory can find a position in the system and exploring the dynamic processes of interactions among these may create new theoretical and practical insights for strategic management.
Figure 6

An extended classification diagram
Chapter 7
Conclusions, Contributions, Discussion, Limitations, and Future Research

The field of strategic management has had as a central issue the sources of performance variability among firms. While all theoretical frameworks attempt to explain the total variance in the same outcome: performance, these have tended to be divided by the level of analysis, the unit of analysis, and the assumptions about the firms and their environment. Moreover, these existing theories are often competing rather than complementary. This research applies a multilevel longitudinal perspective to approach the issue of performance diversity. It suggests that such a perspective not only is a powerful empirical approach to capture corporation–industry interaction effects and random as well as nonlinear time effects on firm performance, but that it has the potential to unify currently dominant theories in the strategy literature.

7.1 Empirical Findings

Empirically, this study employs cross–classified longitudinal multilevel models to re–examine the relative importance of business unit, corporation, industry, and year effects on business unit performance. By adding an interaction classification to capture corporation–industry interaction effects and by adding random as well as nonlinear year to capture more complete year effects, this research extends previous studies in this stream of literature. These methodological refinements generate several important new insights. First, this study finds that corporation–industry interaction effects are substantially important. This empirically confirms an important argument in the literature that effects of these components are inter–correlated rather than independent (Bowman et al., 2001; Brush et al., 1997; McGahan et al., 2002; Misangyi et al., 2006; Rumelt, 1991). Second, while previous studies concluded that stable business segment effects far
Outweighed those of corporation and industry, the findings indicate that stable effects of corporation, industry, and corporation–industry interaction, taken together, are of similar relative magnitude to stable business segment effects. Third, in addition to fixed linear year effects, random and nonlinear year effects can explain a considerable part of dynamic variance. This sheds light on the mysterious dynamic variance: it results from over–time changes at each level. Finally, by introducing MCMC methods, this research provides inference statistics for the estimates of relative effects of these components.

These results also suggest that effects of business segment–corporation and business segment–industry interaction may also be important. These indicate that business segment, corporation, and industry influence performance in an interactive way rather than in an independent way, which suggests that an integrated or systematic theory on how interactions of these factors influence performance is warranted.

I also establish links between dynamic effects and both over–time continuous and discontinuous changes and ultimately locate all sources of variance in performance. This is an important step in the journey to further understand determinants of performance. Moreover, the analyses of rolling over 18–year–window datasets indicate that variance in performance is getting larger and larger in recent years and that compared to stable effects, dynamic effects account for more and more variance in performance over time. These suggest that dynamic processes that generating variation in performance are getting more and more important in this era of hypercompetition (D’Aveni, 1994), temporary advantage (D’Aveni, Dagnino, and Smith, 2010), and high velocity environment (Eisenhardt, 1989). Thus, more academic and practical attention should be shifted to the dynamic processes of performance change (Porter, 1991; Teece et al., 1997).
As these findings advance our understanding of components of variability in performance, we need to be cautious when interpreting the empirical results. First, these results just show the respective relevance of stable effects but not the respective relevance of complete effects, because each component or level contributes to both stable effects and dynamic effects. To understand complete relevance of each component, the respective relevance of dynamic effects has to be explored, too. As Adner et al. (2003:1012) noted, “[T]he omission of the time–varying dimension of the corporate effect hampers our ability to fully understand the effect of corporate strategy.” As showed earlier, this study uses linear and nonlinear year as proxies for continuous changes to explain a substantial amount of dynamic variance. The remaining dynamic variance results from discontinuous changes or abrupt changes at each level such as CEO turnover, disruptive innovations, and industrial deregulations. Dynamic theories (Porter, 1991), such as dynamic capability perspective (Teece, 2007; Teece, Pisano, and Shuen, 1997), evolutionary theory (Nelson and Winter, 1982), industry evolution (McGahan, 2004), and dynamic systems (Forrester, 1961; Morecroft, 2007; Sterman, 2000; Warren, 2008) will likely guide future efforts to better understand dynamic variance. Second, the importance of corporation–industry interaction effects suggests that other interactions may also be important. This implies that the components of performances variability are interdependent and that current theories on performance should be considered complementary rather than competing.

In sum, these findings shed new light on the sources of variation in performance and suggest that interactions among these factors and over–time changes from each level are dominant sources of variation in performance, and therefore, a systematic dynamic theory
of strategy is warranted. From a practical standpoint, these findings suggest that managers should focus their attention on interactions of these factors and the over–time changes within and without a company.

7.2 **Further Empirical Research**

More studies are needed to investigate the nature of stable and dynamic effects and their relationship. Another promising direction is to explain variance at each level by adding explanatory variables. As this dissertation improves understanding of sources of variance in performance, it is important to note that variance has just been located but not explained yet. A technological next step is to explain or reduce variance at each level.

McGahan and Porter (2002:850) contended that in this stream of studies, “[n]ew hypotheses about connections between effects promise to open up a whole new level of statistical inquiry. Consider Model 6: at level 1, future studies may specify time–varying variables from each level, such as capital expenditure, new product introduction, R&D investment, CEO turnover, industrial deregulation, and institutional changes to examine drivers of ROA over–time changes. Time–invariant variables may also be included at every other level to explain (1) why over–time average performance are different across business segments, corporations, industries, and countries, (2) why effects on performance of time–varying variables are different across business segments, corporations, industries, and countries. Still another promising direction is to add location and country in the model to test effects of business segment, industry, corporation, location country, and interactions among these on performance. Other measurements of the outcome such as productivity and sales can also be modeled with this method.
Furthermore, an important application of this method is to test persistency of abnormal performance (McGahan and Porter, 1999, 2003; Thomas and D’Aveni, 2009).

7.3 Theoretical Implications of This Research

Conceptualizing the business reality as a complex adaptive system in which a firm is a subsystem, the multilevel longitudinal perspective used this dissertation offers a broad framework which may accommodate existing theories of strategic management and discover relations among them. This is a promising direction for future theoretical research. In addition, this research adds support to complexity theory by demonstrating that interaction effects between subsystems (corporation and industry) are substantially important and significant. Compared with previous studies, the results of this research indicate that the interaction effects lead to an emergent pattern of the system that cannot be observed by just modeling the system in isolation. Furthermore, by demonstrating that business unit performance changes nonlinearly over time and each business unit, corporation and industry changes uniquely over time, this research adds further support to complexity theory. These findings reveal properties of both adaption and emergence in the business system as a whole and in subsystems, all of which are complex adaptive systems.

7.4 Limitations of This Study

One of the limitations of this dissertation is that I do not model the multiple–industry–membership effects: since most business segments in this dataset have a secondary SIC code and thus operate in multiple industries. However, since the Compustat Business Segment database does not provide information about asset and profit split between
industries, multiple–membership effects (Browne, 2001, 2012; Goldstein, 2011) cannot be specified.

Evidence from agglomeration research indicated that location and location–industry interaction have important effects on performance (McCann and Folta, 2008; Shaver and Flyer, 2000). Evidence from international business (Makino, Isobe, and Chan 2004; McGahan and Victer 2010; Khanna and Rivkin, 2006, and Tong, Alessandri, Reuer, Chintakananda, 2008) found strong effects on performance of country and industry–country interaction. Conceptually, a corporation may operate in several countries and an industry may appear in several countries. Thus, corporations and industries may be members of more than one country. This requires modeling the multiple–country–membership structure. Taking into consideration of these omitted effects, I can reasonably expect more interaction effects that will absorb more variance from individual effects of business segment, corporation, industry, location, and country. Another limitation of this research is that I only examine accounting performance (ROA). Other measurements of performance such as firm growth are not analyzed.

7.5 Empirical Implications

First, these findings suggest that managers should focus their attention on interactions of these factors and the over–time changes within and without a company. Second, because this method allows each business segment to have its own model to predict its performance trajectory more precisely by borrowing information from all business segments, this method may help each firm evaluate influence on its performance of various changes and formulate its strategy and path for future development.
## Appendices

### Appendix A. Studies examining relative importance of business unit, corporation, and business unit on performance

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<tr>
<th>Paper</th>
<th>Sample (data, year, restrictions)</th>
<th>Unit of analysis and dependent variables</th>
<th>Models and Methods</th>
<th>Findings</th>
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<td>Trinet Large Firm Data 10K reports FTC data (1976)</td>
<td>Business Unit Tobin’s q</td>
<td>COV OLS F–tests</td>
<td>Industry (2–digit SIC) effects (19.48%) Market share effects (0.94%). Burniness unit effects (2.61%), “Error” term was 76.97% of total variance.</td>
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<td>Rumelt (1991)</td>
<td>FTC data (1974–1977) Manufacturing firms</td>
<td>Business Unit ROA</td>
<td>COV and analysis of variance (ANOVA) OLS F–tests</td>
<td>Industry effects: 7.84% (COV) or 10.3% (ANOVA) Corporation effects: 7.84% (COV) or 10.3% (ANOVA). Business unit effects: 46.38% (COV) or 41.3% (ANOVA) Year effects: 0.2% (COV) or 0.1% (ANOVA) “Error” term was 36.87% (COV) or 37.4% (ANOVA) of total variance.</td>
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<td>Roquebert et al. (1996)</td>
<td>Compustat Business Segment (1985–1991) Manufacturing corporations with at least 2 business segments</td>
<td>Business segment ROA</td>
<td>COV Maximum likelihood (ML)</td>
<td>Industry effects: 10.2% Market share effects (17.9%). Business unit effects (37.1%), “Error” term was 32.0% of total variance.</td>
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### Appendix A. Studies examining relative importance of business unit, corporation, and business unit on performance (Cont’d.)

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<th>Unit of analysis and dependent variables</th>
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<th>Findings</th>
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<td>McGahan and Porter</td>
<td>Compustat Business Segment (1981–1994) All sectors except finance</td>
<td>Business segment ROA</td>
<td>COV and ANOVA with first order autocorrelation OLS F–tests</td>
<td>Industry effects: 18.68% (COV) or 9.4% (ANOVA) Corporation effects: 4.33% (COV) or 9.1% (ANOVA). Business unit effects: 31.71% (COV) or 35.1% (ANOVA) Year effects: 2.39% (COV) or 0.3% (ANOVA) “Error” term was 36.87% (COV) or 37.4% (ANOVA) of total variance</td>
</tr>
<tr>
<td>Brush and Bromiley</td>
<td>Compustat Business Segment (1986–1995) All sectors except finance Sample restricted to corporations with 3 and 4 business segments</td>
<td>Business segment ROA</td>
<td>Two–stage linear regression OLS F–tests</td>
<td>Ratio of corporate effects to industry effects was 1.7 Ratio of corporate effects to industry effects in terms of $R^2$ and $R$ was greater than 1</td>
</tr>
<tr>
<td>McGahan and Porter</td>
<td>Compustat Business Segment (1981–1994) All sectors except finance</td>
<td>Business segment ROA</td>
<td>ANOVA with first order autocorrelation OLS F–tests</td>
<td>Industry effects: 8.9% Corporation effects: 8.8% Business unit effects: 32.5% Year effects: 0.8% “Error” term was 49.0%</td>
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<td>Hough</td>
<td>Compustat Business Segment (1995–1999) All sectors except finance Excludes observations with only 1 or 2 years</td>
<td>Business segment ROA</td>
<td>Multilevel models</td>
<td>Industry effects: 5.3% Corporation effects: 20.2% Business unit effects: 40.1% Year effects: &lt;0.1% “Error” term was 34.5%</td>
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Appendix A. Studies examining relative importance of business unit, corporation, and business unit on performance (Cont’d.)

<table>
<thead>
<tr>
<th>Paper</th>
<th>Sample (data, year, restrictions)</th>
<th>Unit of analysis and dependent variables</th>
<th>Models and Methods</th>
<th>Findings</th>
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<td>Misangyi et al. (2006)</td>
<td>Compustat Business Segment (1985–1999) All sectors except finance Stratified random sample</td>
<td>Business segment ROA</td>
<td>Multilevel models</td>
<td>Industry effects: 7.6%  &lt;br&gt;Corporation effects: 7.2%  &lt;br&gt;Business unit effects: 36.6%  &lt;br&gt;Year effects: 0.8%  &lt;br&gt;“Error” term was 47.8</td>
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<tr>
<td>Karniouchina et al. (2013)</td>
<td>Compustat Business Segment (1979–1994) Manufacturing corporations with continuous observations with each industry cycle</td>
<td>Business segment ROA</td>
<td>Multilevel models</td>
<td>Industry effects: 4.20% &lt;br&gt;Corporation effects: 15.20% &lt;br&gt;Business unit effects: 38.46% &lt;br&gt;Year effects: n/a &lt;br&gt;“Error” term was 47.8</td>
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### Appendix B. Alternative Approaches to Performance Variance Decomposition

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<th>Strengths</th>
<th>Weaknesses</th>
<th>Examples</th>
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<td>Explicit variance decomposition</td>
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<td>McGahan et al. (1997)</td>
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<td>Robust to departure from assumptions</td>
<td>Inability to model random or nonlinear year effects</td>
<td>Roquebert et al. (1996)</td>
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<td>Rumelt (1991)</td>
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<td>McGahan et al. (1997, 2002)</td>
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<td>Inability to model random or nonlinear year effects</td>
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<td>Joint normal distribution of residuals</td>
<td>Explicit variance decomposition</td>
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<td>Hough (2006)</td>
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<td>Misangyi et al. (2006)</td>
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<td>Readily to handle missing data</td>
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### Appendix C. Outputs of MCMC Estimation

#### Model 1

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-2*loglikelihood: 761224.34

DIC: 12794.48

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| Units: ind     | 778  |
| Units: corp_ind| 15073|
| Units: bu      | 15451|
| Units: over_time| 97011|
Model 3

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**Fixed Part**

| cons    | 10.71 | 0.21   | 10.71    | 10.3      | 11.13 | 19998 |

**Random Part**

**Level: corp**

| cons/cons | 10.91 | 1.41   | 10.89    | 8.18      | 13.71  | 5682  |

**Level: ind**

| cons/cons | 15.22 | 1.58   | 15.14    | 12.32     | 18.52  | 67518 |

**Level: corp_ind**

| cons/cons | 46.18 | 2.39   | 46.16    | 41.56     | 50.89  | 13843 |

**Level: bu**

| cons/cons | 84.09 | 2.5    | 84.07    | 79.25     | 89.03  | 21865 |

**Level: over-time**

| cons/cons | 128.30 | 0.65   | 128.29   | 127.03    | 129.57 | 641866 |

-2*loglikelihood:

| DIC:   | 759873.29 |
| pD:    | 13641.17  |

Units:

| Units: corp | 8588 |
| Units: ind | 778  |
| Units: corp_ind | 15073 |
| Units: bu | 15451 |
| Units: over-time | 97011 |
## Model 4

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-2*loglikelihood:
DIC: 757851.19
pD: 13722.64

Units:
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- Units: corp_ind: 15073
- Units: bu: 15451
- Units: over_time: 97011
### Model 5

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Random Part

Level: corp

| cons/cons | 11.44 | 2.56   | 11.33    | 6.78      | 16.76 | 1856   |
| time/cons | -0.42  | 0.23   | -0.41    | -0.90     | -0.02 | 1527   |
| time/time  | 0.11   | 0.03   | 0.11     | 0.06      | 0.17  | 1629   |

Level: ind

| cons/cons | 23.27 | 2.51   | 23.16    | 18.68     | 28.51 | 73430  |
| time/cons | -1.31  | 0.20   | -1.30    | -1.73     | -0.93 | 69341  |
| time/time  | 0.19   | 0.02   | 0.19     | 0.15      | 0.24  | 59235  |

Level: corp_ind

| cons/cons | 48.05 | 4.30   | 48.26    | 42.91     | 53.52 | 843    |

Level: bu

| cons/cons | 144.03 | 6.01   | 143.81   | 133.95    | 154.38 | 1658  |
| time/cons | -11.13 | 0.45   | -11.13   | -12.02    | -10.25 | 13460 |
| time/time  | 1.53   | 0.05   | 1.52     | 1.42      | 1.63  | 12435 |

Level: over_time

| cons/cons | 106.87 | 0.60   | 106.87   | 105.73    | 108.06 | 332745 |

-2*loglikelihood:

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- ind  | 778
- corp_ind | 15073
- bu    | 15451
- over_time | 97011
Model 6

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<tr>
<td>cons/cons</td>
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-2*loglikelihood:

DIC: 739853.37
pD: 21225.75
Units: corp 8588
Units: ind 778
Units: corp_ind 15073
Units: bu 15451
Units: over_time 97011
Appendix D. MCMC estimation of parameters

Model 1

Estimation of $\beta_0$

Variance Level 1–overtime (dynamic)
Variance level 2–business unit (stable)

Model 2

Estimation of $\beta_0$
Level 1 variance: dynamic

Level 2 variance: business unit
Level 4 variance: industry

Level 4 variance: corporation
Model 3

Estimation of $\beta_0$

Level 1 variance: dynamic
Level 2 variance

Level 3 variance
Leve 4 industry variance

![Graph showing MOMC diagnostics for leve 4 industry variance with summary statistics.](image)

Leve 4 corporate variance

![Graph showing MOMC diagnostics for leve 4 corporate variance with summary statistics.](image)
Appendix E. MCMC estimation of percentages

Model 1

Percentage of dynamic variance: overtime

![Graph showing dynamic variance](image1)

Summary Statistics:
- Parameter mean: 0.25 (0.00 - 0.50)
- 95% credible interval: 0.15 - 0.35
- 99% credible interval: 0.10 - 0.40

100000 actual iterations during every iteration. Effective sample size (ESS) = 66236.

Percentage of stable variance: business unit

![Graph showing stable variance](image2)

Summary Statistics:
- Parameter mean: 0.45 (0.25 - 0.65)
- 95% credible interval: 0.35 - 0.55
- 99% credible interval: 0.30 - 0.60

100000 actual iterations during every iteration. Effective sample size (ESS) = 64388.
Model 2

Percent of level 1 variance (overtime)

Percent of level 2 variance (business unit)
Level 4 percentage: industry

Level 4 percentage: corporation
Model 3

Percent of level 1 variance (overtime)

![Graph showing percent of level 1 variance for Model 3.](image1)

Percent of level 2 variance (business unit)

![Graph showing percent of level 2 variance for Model 3.](image2)
Percent of level 3 variance (combination)

<table>
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Percent of level 4 variance (industry)

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Percent of level 4 variance (corporation)

Footnote 9_Percent
Footnote 10_percent

Footnote 13_percent
References


