Strategic Management Journal
Strat. Mgmt. J., **34**: 1010–1018 (2013)
Published online EarlyView 12 February 2013 in Wiley Online Library (wileyonlinelibrary.com) DOI: 10.1002/smj.2042
*Received 3 November 2010; Final revision received 20 December 2012*

# RESEARCH NOTES AND COMMENTARIES

# EXTENDING THE FIRM VS. INDUSTRY DEBATE: DOES INDUSTRY LIFE CYCLE STAGE MATTER?

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*A series of* Strategic Management Journal *studies have debated the extent to which business-unit, corporate parent, and industry effects explain variance in firm performance. Despite evidence that the industry life cycle impacts competition and performance, the life cycle concept has yet to be incorporated into the firm vs. industry debate. Building on ideas from systems theory, we use longitudinal data from 1,957 firms in 49 industries to examine the relative importance of business-unit, corporate parent, and industry effects during the growth, maturity, and decline stages of the industry life cycle. We find that corporate parent and industry effects increase as industries move through the life cycle while business-unit effects decrease between maturity and decline. Thus, the life cycle concept should be incorporated within the firm vs. industry debate.*


## INTRODUCTION

Explaining the determinants of firm performance has long been a central goal of strategic management research (Nag, Hambrick, and Chen, 2007). In a seminal paper, Nelson (1991) argued in favor of recognizing differences among companies belonging to the same line of business and against following the common assumption that all firms would behave similarly given a set of environmental circumstances. A series of studies has tested this tenet by examining the extent to which firm and industry factors explain performance. This research stream is sometimes referred to as the variance decomposition literature because of its focus on determining how much performance variance is explained by different levels of analysis. The stream is prominent enough that Misangy and colleagues (2006: 571) characterized the examination of firm vs. industry effects as a 'fundamental debate' within strategic management.

Our paper is devoted to introducing the life cycle concept into theorizing about this fundamental debate. Systems theory provides our motivation for doing so (cf. Short *et al.*, 2007).

Keywords: industry life cycle; business-unit, corporate parent, and industry effects; variance decomposition; hierarchical linear modeling
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A systems theory approach to understanding organizational phenomena contends that organizations and their environments should be studied not as individual entities but rather as arrangements of interconnected elements (Scott and Davis, 2006). One implication of this emphasis on connectivity involves how change unfolds. When the nature of one element of a system experiences change, the nature of the other elements of the system are likely to also change, as are the relationships among various elements within the system (Ashmos and Huber, 1987). Thus, if an element of a system is prone to change but investigations of the system do not account for this change, such investigations are unlikely to accurately capture relationships within the system.

Past research makes it clear that the nature of industries evolves over time through a life cycle (e.g., Agarwal, Sarkar, and Echambadi, 2002; Argyres and Bigelow, 2007; Miles, Snow, and Sharfman, 1993). Given this context, systems theory suggests that the system of elements that determine firm performance will be reconfigured as the life cycle shifts from one stage to another. Although the literature contains a significant body of variance decomposition research, none of these studies have accounted for the potential effects of changes in life cycle stages.

Previous studies generally have found that the business unit explains roughly 32 to 44 percent of the variance in performance, the corporation explains two to 18 percent, and the industry explains four to 19 percent (e.g., McGahan and Porter, 1997; Misangyi *et al.,* 2006; Roquebert, Phillips, and Westfall, 1996; Rumelt, 1991). Such findings are based on databases such as COMPUSTAT that include thousands of publicly held firms spread across hundreds of industries. One potential limitation of findings based on very broad samples is that the findings inevitably are averages across the growth, maturity, and decline stages of the life cycle.[1] This is because various industries that are included in databases such as COMPUSTAT are in different life cycle stages when data are gathered.

Yet, because the nature of within-industry competition changes across the life cycle (Miles *et al.,* 1993), such averages may not accurately describe *any* of the stages. If a study finds, for example, that the industry explains 10 percent of the performance variance across all firms it examines, this could simply be a product of averaging effects of five percent, seven percent, and 18 percent across the growth, maturity, and decline stages of the life cycle. In such a scenario, the 10 percent finding does not adequately reflect any of the three sets of conditions.

In response, we (a) examine whether or not shifts in the life cycle do indeed reshape the antecedents to performance (as systems theory suggests should happen) and (b) examine the exact nature of these changes in order to build new knowledge about a central issue within the strategic management field—the determinants of firm performance (Nag *et al.,* 2007). In his classic exposition of what makes theory interesting, Davis (1971: 313) asserted that 'an interesting proposition [is] always the negation of an accepted one.' If the nature of firm and industry effects changes across life cycle stages, as systems theory suggests, this would be interesting in that past theorizing appears to have tacitly assumed that life cycle stage does not matter. Our paper also aims to contribute to research on the industry life cycle. Investigations of why some firms outperform others in different stages of the life cycle tend to center on decisions made at the business-unit level (e.g., Miles *et al.,* 1993). Using a computer simulation, however, Ganco and Agarwal (2009) recently found preliminary evidence that initiatives taken at the corporate parent level matter and that their influence varies across stages of the life cycle. Our paper takes a next logical step by uncovering the size of the corporate parent effect in different stages.

## THEORY AND HYPOTHESES

Investigations of the industry life cycle often examine three main stages: growth, maturity, and decline (Miles *et al.,* 1993).[2] Our expectation

[1] During the earliest stage of the life cycle (referred to by many authors as 'introduction' or 'ferment'), few firms are publicly traded. Because variance decomposition studies, including ours, rely on archival data from publicly held firms, such studies do not include the ferment stage. This may not be a limitation, however, because (as an anonymous reviewer pointed out) industries are typically not yet established during the ferment stage.

[2] Different authors postulate slightly different stages over the growth-maturity portion of the life cycle. Our approach follows that of Agarwal and colleagues (2002), who reviewed life cycle research and settled on growth and maturity to characterize this portion of the life cycle within their study.




DOI: 10.1002/smj

is that, within the system that drives firm performance, industry effects will be weakest in the growth stage. The growth stage usually is characterized by high levels of heterogeneity between firms, such as unstandardized products, high product variation, and market share instability (Mazzucato and Semmler, 1999). In addition, the high rate of new entry during the growth stage brings in firms that differ in their resources and capabilities, creating additional between-firm heterogeneity (Madsen and Walker, 2002). These differences across products, resources, and capabilities ultimately lead to substantial variance in market positions (Tushman and Anderson, 1986) and profitability (Knott, 2003) across competitors. Industry conditions are important drivers of these differences, but the strategic decisions made by business units and their corporate parents are likely to be stronger antecedents.

In the maturity stage, change becomes less radical and more incremental. Established industry norms and organizational routines become more rigid and standardized. A shakeout occurs during the transition from growth to maturity whereby weak competitors exit and concentration increases among the competitors that remain (Carroll, 1985). Stark price competition and scale economies start benefiting larger firms pursuing cost leadership strategies, jeopardizing the success of mid-to-small-sized firms and further reinforcing the dominant design (Jovanovic and MacDonald, 1994). Hence, with limited intra-industry heterogeneity at maturity, industry effects will tend to become more important than they are during growth.

These same forces continue and intensify into the decline stage, as more firms exit and the industry concentrates around the few remaining competitors. Growth vanishes, resulting in intensified rivalry and shakeout except for the strongest competitors (Porter, 1980). Efforts to meaningfully differentiate often fail and the surviving firms look to scale economies, international markets, and other efficiency or process-oriented advantages to compete. This concentration continues the trend toward lower intra-industry heterogeneity in the decline stage, implying a further increase in the importance of industry effects. In sum, we predict that:

*Hypothesis 1: Industry effects will be stronger in the decline stage than in the maturity stage and stronger in the maturity stage than in the growth stage.*

When considering how business-unit and corporate parent effects evolve over time within the system that drives performance, a central issue is the degree to which the performance of business units in a particular life cycle stage will be tightly or loosely coupled to decisions made at the business-unit level vs. decisions made at the corporate parent level. Building on past theory and research, we expect that both effects will be important in all three stages, but that their relative importance will change over time. Specifically, business-unit effects will be stronger early in the life cycle than they will be later in the life cycle while corporate parent effects will be weaker early in the life cycle than they will be later in the life cycle.

Relatively young industries tend to include a wide variety of competitive strategies as firms seek to differentiate their offerings from those of their rivals in a quest to gain higher margins (Miles *et al.,* 1993). Under these circumstances, firms can influence their likelihood of success primarily through business-level initiatives such as creating new products, building customer loyalty, and competitive positioning (Miles and Snow, 1978). The prominence of business-unit effects declines as the life cycle shifts into later stages, however, because the opportunity for business-unit initiatives to create differentiation is reduced. Indeed, Miles *et al.* (1993: 163) are explicit in noting in their examination of industry life cycle effects on variety that, 'as industries move through the life cycle, variety decreases....' As the variety of competitors' offerings narrows, firms experience shrinking margins and are forced to compete on price (Porter, 1980).

Under these circumstances, decisions made at the corporate parent level grow in importance. Relevant initiatives include, for example, devising processes for efficiently extracting profits from units within late stage industries (i.e., milking 'cash cows'), providing financial buffers while attempting to revitalize a business unit in the hope of averting or reversing decline, and identifying a good exit strategy if necessary. In sum, as the industry life cycle progresses from growth to maturity to decline, the basis of competition shifts away from initiatives that are taken at the business level (i.e., attempts at differentiation) and toward initiatives that are taken at the corporate level (i.e.,



DOI: 10.1002/smj

efforts to build efficiency, improved processes, and scale).[3] This leads us to predict that:

*Hypothesis 2: Corporate parent effects will be stronger in the decline stage than in the maturity stage and stronger in the maturity stage than in the growth stage.*

*Hypothesis 3: Business-unit effects will be higher in the growth stage than in the maturity stage and higher in the maturity stage than in the decline stage.*

## METHOD

### Sample

We use value of shipments time series data from the *Annual Survey of Manufacturers* (ASM) aggregated to the level of four-digit Standard Industrial Classification (SIC) codes in order to classify industries into different life cycle stages. We aggregate to the four-digit level to be consistent with the industry definitions used in previous variance decomposition studies. Additionally, this level of aggregation is advantageous as it maps directly to the business-unit data used in our analysis. Value of shipments data are attractive because they provide reliable and comprehensive estimates of year-to-year industry sales based on a census of private and public companies. The analysis is based on all industries covered by the ASM that did not have any adverse events and had at least 30 years of continuous coverage; 49 industries fit this description. The data are adjusted for inflation using the Consumer Price Index provided by the *Bureau of Labor Statistics.* The ASM in SIC code format is available for the 1949–1994 time frame, which allows us to use a relatively long time series to enhance reliability (the entire available history was used to estimate the regime switching models for each industry).

For the variance decomposition, we rely on the COMPUSTAT *Industry Segments* dataset for 1979 to 1994 to obtain return on assets (ROA) for firms in the 49 industries. We follow convention in decomposition studies and limit our inquiry to business units with at least $10 million in sales and assets (e.g., Misangyi *et al.,* 2006). Due to the restrictions imposed by the hierarchical linear modeling (HLM) procedure we use, we also limit our sample to continuous observations within each stage. The resulting ROA sample has 14,293 observations linked to 49 industries and 1,957 companies represented by 3,179 unique segments. The sample is divided (following our first-stage analysis) into growth (n = 3,757), maturity (n = 7,267), and decline (n = 3,269) subsets.

### Performance measure

We use ROA as a measure of firm performance. ROA is the most widely used metric of accounting profitability and the most common performance variable in variance decomposition studies (McGahan and Porter, 2002). ROA is obtained by dividing operating income by total assets. Both inputs are obtained from COMPUSTAT.

### Industry classification

One factor that limits the potential usefulness of the life cycle as a planning concept is that the idealized life cycle curve is not typically observed (Cox, 1967). In order to address the common criticism that most life cycle curves display multiple 'bumps' or 're-cycles,' our model needs to accommodate multiple shifts back and forth from one stage to another. Economists have scrutinized time series similar to the ones associated with industry sales that exhibit multiple breaks in their behavior. One of the most accepted approaches is Hamilton's latent-state regime switching method. It has been used to model business cycles and unemployment changes among other phenomena (Hamilton, 1989; Chauvet, Juhn, and Potter, 2001). We use this approach to classify industries into growth, maturity, and decline stages based on longitudinal changes in the aggregate value of shipments.[4]

### Random coefficients modeling

Once we obtain the life cycle stage for each industry at each time, we proceed to the variance

[3] Our models do not assume a zero sum game between firm and industry effects. Instead, corporate, business, and industry effects could all explain more variance over time by reducing the temporal variance/error term. Thus, an increase in the industry effect need not come at the expense of a firm effect.

[4] As an anonymous review pointed out, our implicit assumption that competition changes in step with the aggregate value of shipments may be questionable.



DOI: 10.1002/smj

decomposition by estimating random coefficient models for ROA (using three different subsamples corresponding to growth, maturity, and decline stages). We use the HLM 7 software, which allows us to capture both clustering and cross-classification in a single model. In particular, we use a four-way cross-classified and nested mixture model where repeated ROA observations are clustered by segment, which is simultaneously cross-classified by the respective industry and corporate parent.

Examining corporate effects via other variance decomposition techniques such as ANOVA would require that our sample be limited to multi-unit firms. One of the advantages of HLM is that it does not impose this requirement (Short *et al.,* 2009), which allows us to include single business-unit firms in our sample. For such firms, corporate and business unit effects are synonymous.

## RESULTS

### Changes in life cycle stages

Using Hamilton's (1989) model, we assume that an industry belongs to one of three latent regimes (growth, maturity, or decline) at any time *t*. We omit the initial stages of industry development as our focus is on established, publicly traded companies. The nonstationary time series that characterizes the industry, $\{y_t\}$, is the growth rate of the industry at time *t*. We calculate the growth rate by first differencing the logarithm of industry sales. Based on results generated from other datasets (Hamilton, 1989; Lahiri and Wang, 1994), a first order autoregressive process is specified for each regime $S(t) \in \{1,2,3\}$ as follows:
with $\varepsilon_t \sim N(0,\sigma^2)$. This process specifies industry growth rates $\mu_1$, $\mu_2$, and $\mu_3$, that differ depending on life cycle stage. The dynamics of $y_t$ can be obtained once we define the probabilities of shifts or changes between the regimes. The specification proposed by Hamilton (1989) is a Markovian process of the following form:

$$\begin{aligned}\Pr(S_t = j|S_{t-1} = i, S_{t-2} = k, \ldots, \psi_t)\\ = \Pr(S_t = j|S_{t-1} = i) = \rho_{ij}\end{aligned} \qquad (1)$$

where $\psi_t$ represents all the past values of $y_t$ prior to time *t* and $\rho_{11}, \rho_{12}, \rho_{21}, \rho_{22}, \rho_{31}, \rho_{32}$ are transitional probabilities associated with regime switches.[5] Based on the distributional assumptions, the conditional probability is:

$$f(y_t|S_t = i, \psi_t) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{(y_t - \mu_i - \phi y_{t-1})^2}{2\sigma^2}\right] \qquad (2)$$

The joint probability of $y_t$ and $S_t$ is then given by the product of the conditional and marginal probabilities, namely for the first regime:

$$f(y_t, S_t = 1|\psi_t) = f(y_t|S_t = 1, \psi_t)\Pr(S_t = 1|\psi_t). \qquad (3)$$

The conditional density for an observation at time *t* is the summation of these joint probability terms over all possible values of $S_t$:

$$f(y_t|\psi_t) = \sum_{j=1}^{3} f(y_t, S_t = j|\psi_t). \qquad (4)$$

Parameters are estimated with a maximum likelihood procedure.[6] Probabilities of the series being in a certain state given the data observed up to that point in time are obtained as a byproduct of an algorithm akin to the Kalman filtering procedure, thus they are commonly referred to as 'filtered' probabilities (Hamilton, 1989). We also utilize a 'full sample smoother' to calculate the probability of being in state *j* based on the entire observed information for each industry using an algorithm proposed by Kim (1994). Smoothed probabilities reduce the influence of outliers and prevent them from inducing unwarranted shifts in industry stages. The smoothed probabilities (Hamilton, 1989) are used to classify industries into one of the three distinct states. We calculated these smoothed probabilities for each state/year combination and assigned the industry in that particular year to the industry stage with the highest probability. Estimation was carried out

[5] The advantage of this specification is that regime switches are allowed between any two stages, not just from growth to maturity to decline, which allows us to accommodate multiple shifts back and forth from one stage to another allowing for a realistic depiction of the industry development.

[6] The probability law for the observed data denoted by $\theta$ can be formulated through 11 population parameters: $\theta = (\mu_1, \mu_2, \mu_3, \sigma^2, \phi, \rho_{11}, \rho_{12}, \rho_{21}, \rho_{22}, \rho_{31}, \rho_{32})'$.

using GAUSS software utilizing its OPTMUM add-on optimization package.

After completing the classification procedure, for each industry, we looked at the number of years for which the smoothed probabilities had been estimated vs. the number of switches that took place. Pooled estimates across all industries indicate that, on average, industries shift stages every four years, with the most frequent shift being from growth to maturity (27%), followed by the shift from maturity back to growth (23%), and from maturity to decline (19%). Less frequent shifts were registered from decline to maturity (16%), decline to growth (9%), and growth to decline (6%). As expected, the data are consistent with a highly recursive view of the industry life cycle. Interestingly, over half the transitions are back and forth between growth and maturity, suggesting that industries are generally successful at adding bumps to the life cycle prior to decline. In terms of average ROA across the different stages, our analysis revealed that profitability within growth industries (14.18%) was higher than within declining (10.26%) and mature (10.22%) industries.

### Importance of industry life cycle to explaining performance

As shown in Table 1, all three effects are significant within each life cycle stage except for the corporate parent effect in the growth stage. Table 1 also shows that the strength of all three effects changes during the industry life cycle. In support of Hypothesis 1, industry effects explain a greater percentage of performance variance in the decline stage than in the maturity stage (11.42% vs. 9.22%), in maturity vs. in growth (9.22% vs. 4.55%), and in decline vs. in growth (11.42% vs. 4.55%).[7] In support of Hypothesis 2, the corporate parent level explains a greater percentage of variance in the decline stage than in the maturity stage (25.35% vs. 13.32%), in maturity vs. growth (13.32% vs. 3.30%), and in decline vs. in growth (25.35% vs. 3.30%). Hypothesis 3 attracted partial support. Business-unit effects are stronger in the growth and maturity stages, where they account for 46.14 percent and 45.96 percent of variance in ROA, respectively, than in the decline stage (30.04%). The business-unit effect is nearly identical, however, in the growth and maturity stages. Lastly, the 'temporal variance' row of Table 1 refers to unsystematic year-to-year variance in performance, which some previous studies refer to as *error* variance.

## DISCUSSION

Building on ideas from systems theory, we examined the relative importance to performance of business-unit, corporate parent, and industry effects during the growth, maturity, and decline stages of the industry life cycle. Overall, our findings suggest that as firms go through growth, maturity, and decline, industry and corporate parent effects explain more variance in performance, while business-unit effects decrease. These results offer some important implications.

Beginning in the growth stage, we observed a generally high importance of business-unit effects. Growth is associated with high variety in strategic approaches, products, and positions due to exploration on the part of incumbents and the net entry of new firms with diverse value and cost drivers, all of which appear to increase intra-firm performance heterogeneity and the importance of business-unit effects, as expected (Miles *et al.,* 1993). Average profitability is highest, but variation at the business-unit level suggests that firms have very different experiences in the industry. This is consistent with the more indirect findings of previous studies that exit also peaks (in addition to entry) during the growth stage (Klepper, 1996). More generally, research aimed at uncovering the mechanisms by which the effects of the business level become dampened during decline simultaneously with the emergence of strong industry effects could make significant contributions to the literature.[8]

When examining our overall sample we found that 15.50 percent of the variance in performance is attributed to the corporate parent level—a

[7] We report the results of our hypotheses following the approach used in previous variance decomposition studies that used HLM (e.g., Short *et al*., 2007, 2009). As noted by Short and colleagues (2009: 57) in their study of firm and industry effects, 'HLM provides no statistical tests' to compare variance explained, so conclusions are based on 'comparing the amount of variance explained' to see if differences are substantial.

[8] We are grateful to an anonymous reviewer for offering this insight.




DOI: 10.1002/smj

Table 1. Variance decomposition results

| | GROWTH | | | MATURITY | | | DECLINE | | | SAMPLE (1978–1994) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | VC | Variance explained | p-value | VC | Variance explained | p-value | VC | Variance explained | p-value | VC | Variance explained | p-value |
| Industry | 0.001 | 4.55% | <0.001 | 0.002 | 9.22% | <0.001 | 0.003 | 11.42% | <0.001 | 0.001 | 4.20% | <0.001 |
| Corporate parent | 0.001 | 3.30% | ns | 0.003 | 13.32% | <0.001 | 0.006 | 25.35% | <0.001 | 0.004 | 15.50% | <0.001 |
| Business unit | 0.014 | 46.14% | <0.001 | 0.011 | 45.96% | <0.001 | 0.008 | 30.04% | <0.001 | 0.010 | 38.46% | <0.001 |
| Temporal variation | 0.014 | 46.01% | | 0.007 | 31.50% | | 0.008 | 33.19% | | 0.011 | 41.84% | |
| Total | 0.030 | 100.00% | | 0.023 | 100.00% | | 0.025 | 100.00% | | 0.025 | 100.00% | |
| N | 3,757 | | | 7,267 | | | 3,269 | | | 17,773* | | |

* The difference between stage-specific and overall sample sizes is caused by the fact that we limit our stage-specific samples to continuous observations within each stage.

result that is consistent with previous studies (e.g., McGahan and Porter, 1997; Misangyi *et al.,* 2006; Roquebert *et al.,* 1996; Rumelt, 1991). Yet, our examination of corporate-level variation when accounting for life cycle stage reveals how findings from previous studies may obscure important patterns. Corporate effects increased dramatically as the industry life cycle progressed—ranging from 3.3 percent in the growth stage to over 25 percent in the decline stage. This suggests that business units with relatively weak corporate parents (or single segment firms) stand almost as good a chance of superior performance in growth industries as units with stronger performing parents, whereas the latter enjoy more significant advantages in mature and declining industries. Such findings should encourage additional theorizing about why corporate parent effects increase over time. Scholars could further contribute by building theory to provide managers with guidance regarding the different types of strategies and resources that may be needed to maximize firm performance as the corporate level grows in importance.

Industry accounted for just 4.2 percent of variation in the full sample. This is consistent with other studies that looked at manufacturing industries rather than a broad cross-section of COMPUSTAT industries and used variance component-based methodology; for example, Rumelt (1991) attributes four percent of variation to nontransient industry effects while Mauri and Michaels (1998) find that industry accounts for 5.8 percent of ROA variation in their 15-year sample. Our study is also in line with McGahan and Porter (2002), who showed a drastic drop in industry importance in their manufacturing subsample.

The rising tide of industry growth might be expected to 'lift all boats' causing industry effects to play more of a role in the growth stage; however the results indicate that the importance of industry peaks in the decline stage. The common takeaway from structure-conduct-performance-based arguments is that firms looking to take advantage of the industry environment should seek growth opportunities as positive industry conditions lead to higher performance (e.g., Porter, 1980). We concur in that we see higher average profitability; but this is not automatically driven by industry growth conditions. In fact, our results suggest that industry conditions in later stages are more determinative of an individual firm's performance in the industry.

One avenue for future research would be examining whether devoting additional resources to industry analysis in later stages of the life cycle pays off with stronger firm performance. Juxtaposing the increasing importance of the industry late in the life cycle with the decreasing role of business-unit effects highlights the need for theorizing about the interplay between competitive imitation and the reduction of business-level opportunities for new value creation over time.

We relied on a conceptualization of the industry life cycle that includes growth, maturity, and decline (Miles *et al.,* 1993). This framework aligned well with our use of the generally large, publicly traded firms found in the COMPUSTAT database that we used to draw our sample. Other studies examining the life cycle have examined firms in the early ferment stage, but including this stage in an examination of how business-unit, corporate parent, and industry effects change over life cycle stages would be a formidable challenge because industries are often not established at the ferment stage. However, the benefits of collecting such data could yield a significant addition to knowledge about the determinants of firm performance. Consequently, we encourage future research to build on this limitation of our study.

## CONCLUSION

Over the last two decades, a series of studies has examined firm and industry effects. The 'fundamental debate' (Misangyi *et al.,* 2006: 571) about the extent to which the firm and the industry explain performance heterogeneity has addressed many important questions, but also has left others unanswered. One of these unanswered questions was whether or not the roles of the business unit, corporate parent, and the industry vary across the stages of the industry life cycle. We found that the importance of business unit, corporate parent, and the industry vary across different stages of the life cycle, suggesting that future inquiry needs to account for the life cycle when decomposing performance variance.

## ACKNOWLEDGEMENTS

The authors thank Bill Moore, Bill Hesterly, Anthony Di Benedetto, and Can Uslay for their helpful comments on previous drafts of this manuscript. They are also grateful to James Hamilton for his generous advice on regime switching methodology.

## REFERENCES

Agarwal R, Sarkar MB, Echambadi R. 2002. The conditioning effect of time on firm survival: an industry life cycle approach. *Academy of Management Journal* **45**: 971–994.

Argyres N, Bigelow L. 2007. Does transaction misalignment matter for firm survival at all stages of the industry life cycle? *Management Science* **53**(8): 1332–1344.

Ashmos DP, Huber GP. 1987. The systems paradigm in organizational theory: correcting the record and suggesting the future. *Academy of Management Review* **12**: 607–621.

Carroll GR. 1985. Concentration and specialization: dynamics of niche width in populations of organizations. *American Journal of Sociology* **90**(6): 1261–1283.

Chauvet M, Juhn C, Potter, S. 2001. Markov switching in disaggregate unemployment rates. In *Advances in Markov-Switching Models*, Hamilton JD, Raj B (eds). Physica-Verlag: Heidelberg, Germany; 61–88.

Cox W. 1967. Product life cycles as marketing models. *Journal of Business* **40**(4): 375–384.

Davis MS. 1971. That's interesting! Towards a phenomenology of sociology and a sociology of phenomenology. *Philosophy of the Social Sciences* **1**: 309–344.

Ganco M, Agrawal R. 2009. Performance differentials between diversifying entrants and entrepreneurial start-ups: a complexity approach. *Academy of Management Review* **34**: 228–252.

Hamilton J. 1989. A new approach to the analysis of time series and the business cycle. *Econometrica* **57**(2): 357–384.

Jovanovic B, MacDonald G. 1994. The life cycle of a competitive industry. *Journal of Political Economy* **102**(2): 322–347.

Kim C. 1994. Dynamic linear models with Markov-switching. *Journal of Econometrics* **60**: 1–22.

Klepper S. 1996. Entry, exit, growth, and innovation over the product life cycle. *American Economic Review* **86**(3): 562–583.

Knott AM. 2003. Persistent heterogeneity and sustainable innovation. *Strategic Management Journal* **24**(8): 687–705.

Lahiri K, Wang JG. 1994. Predicting cyclical turning points with a leading index in a Markov switching model. *Journal of Forecasting* **13**: 245–263.

Madsen TL, Walker G. 2002. The evolution of heterogeneity in performance. In *Academy of Management Best Papers Proceedings*. Denver: CO; V1–V6.

Mauri AJ, Michaels MP. 1998. Firm and industry effects within strategic management: an empirical




DOI: 10.1002/smj

examination. *Strategic Management Journal* **19**(3): 211–219.

Mazzucato M, Semmler W. 1999. Market share instability and stock price volatility during the industry life cycle: the U.S. automobile industry. *Journal of Evolutionary Economics* **9**(1): 67–96.

McGahan AM, Porter ME. 1997. How much does industry matter, really? *Strategic Management Journal, Summer Special Issue* **18**: 15–30.

McGahan AM, Porter ME. 2002. What do we know about variance in accounting profitability? *Management Science* **48**(7): 834–851.

Miles G, Snow CC, Sharfman MP. 1993. Industry variety and performance. *Strategic Management Journal* **14**(3): 163–177.

Miles RE, Snow CC. 1978. *Organizational Strategy, Structure, and Process.* McGraw-Hill: NewYork.

Misangyi VF, Elms H, Greckhamer T, Lepine JA. 2006. A new perspective on a fundamental debate: a multilevel approach to industry, corporate, and business unit effects. *Strategic Management Journal* **27**(6): 571–590.

Nag R, Hambrick DC, Chen M-J. 2007. What is strategic management, really? Inductive derivation of a consensus definition of the field. *Strategic Management Journal* **28**(9): 935–955.

Nelson RR. 1991. Why do firms differ and how does it matter? *Strategic Management Journal* **12**(Winter Special Issue): 61–74.

Porter M. 1980. *Competitive Strategy*. Free Press: New York.

Roquebert JA, Phillips RL, Westfall PA. 1996. Markets vs. management: what 'drives' profitability? *Strategic Management Journal* **17**(8): 653–664.

Rumelt RP. 1991. How much does industry matter? *Strategic Management Journal* **12**(3): 167–185.

Scott WR, Davis GF. 2006. *Organizations & Organizing: Rational, Natural and Open Systems*. Upper Saddle River, NJ: Pearson Prentice Hall.

Short JC, Ketchen DJ Jr, Palmer TB, Hult GTM. 2007. Firm, strategic group, and industry influences on performance. *Strategic Management Journal* **28**(2): 147–167.

Short JC, McKelvie A, Ketchen DJ Jr, Chandler G. 2009. Firm and industry effects on firm performance: a generalization and extension for new ventures. *Strategic Entrepreneurship Journal* **3**(1): 47–65.

Tushman ML, Anderson P. 1986. Technological discontinuities and organizational environments. *Administrative Science Quarterly* **31**: 439–465.