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Effective Strategy Making and Risk-Return Relationships

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Abstract

It has been shown that a model of strategic responsiveness based on the concept of strategic fit and heterogeneity in response capabilities across firms yield the observed negative association between economic returns and variation in returns. While these model relationships apply to cross-sectional relationships, the longitudinal risk-return associations that empirically display lower negative correlations were not considered. Hence, we use the intuition of adaptive fit in a dynamic model of strategic responsiveness and use simulations to show that this model also can explain the observed differences between longitudinal risk-return associations. We compare simulated model outcomes to the reported results of firms in representative industries and find that the simulated results are consistent with empirical data.

Key Words: Risk-return relationships, Strategic response capabilities

Introduction

The ability to create sustainable excess returns with favorable risk-return characteristics is the essence of strategic management. Analyses of empirical data consistently show a negative association between cross-sectional economic returns and the variance in returns (Baird and Thomas, 1985; Bettis, 1982; Bowman, 1980, 1982, 1984; Bromiley, 1991; Fiegenbaum and Thomas, 1986, 1988, 2004; Miller and Bromiley, 1990; Miller and Chen, 2003, 2004). Yet, the explanations for the observed inverse risk-return relationship vary considerably claiming support from prospect theory (Kahneman and Tversky, 1979, 1984; Tversky and Kahneman, 1986), the behavioral theory of the firm (Cyert and March, 1963; March and Shapira, 1987, 1992), strategy conduct (Bowman, 1980, 1982), left-skewed return data (Henkel, 2003), and other statistical artifacts (Ruefli et al., 1999).

A recent model of strategic responsiveness pursue Bowman's (1980) original inclination that effective management has a positive influence on both the mean and the variance of performance (Andersen, Denrell and Bettis, 2007). They introduce a relatively simple model of effective strategy adaptation and show how the ability to create a better environmental fit under dynamic conditions can lead to inverse cross-sectional risk-return relationships within industries. These results indicate that strategic responsiveness is an important element of effective management. The model shows how the inverse cross-sectional association between risk and return can derive from heterogeneous response capabilities across firms. However, the modeling approach does not explain the longitudinal association between risk and return found in some studies suggesting that performance may influence risk attitudes over time (Bromiley, 1991; Miller and Chen, 2004). This is an important difference, because a longitudinal relationship means that firms are capable in varying degrees of adapting performance and risk simultaneously. Such a phenomenon would suggest that at least some firms are able to adapt their core activities in a significant way counter to the conclusions of inertia theory (Hannan and Freeman, 1984). While the literature typically has tried to explain both cross-sectional and longitudinal risk-return associations using the same theory or model, the explanation for the cross-sectional association may differ from the explanation of the longitudinal association. Accordingly, Andersen, Denrell and Bettis (2007) suggest that different rationales may explain the discrepancy in magnitude between cross-sectional and longitudinal risk-return relationships. As shown by Miller and Chen (2004), the correlation between ROA and the standard deviation of ROA in the next period is typically less negative than the average cross-sectional correlations. It is not obvious what causes this difference but it is possible that heterogeneity in responsiveness may generate a negative cross-sectional association whereas the influence of performance outcomes on risk attitudes may explain the longitudinal association. Hence, there may be a need for more comprehensive models and detailed empirical analyses to investigate these different perspectives further.

In this note, we use simulation analyses on a dynamic model of strategic fit with heterogeneous response capabilities to show how the introduction of dynamic relationships, path dependencies, and organizational learning scenarios can lead to the observed discrepancies between cross-sectional and longitudinal risk-returns. An empirical examination of comprehensive datasets from representative industries during the period 1991-2000 is used to validate the simulated model outcomes. Based on these analytical efforts, the study concludes that a dynamic strategic responsiveness model conforms to observed cross-sectional and longitudinal risk-return relationships. Finally, we discuss the implications of these results and suggest possible extensions of the modeling framework.

From a normative perspective there are numerous situations where businesses must learn about the changes that are always occurring in environmental variables, and then adapt to what they have learned. Quantitative demand, consumer tastes, technology, government policies, and other environmental variables are always changing and firms must respond to these changes or find themselves at a competitive disadvantage. Such changes run the gamut from incremental and evolutionary (modest changes in demand) to revolutionary (new technological paradigms). Even incremental changes can cumulate over time to require a substantial adaptation on the part of successful firms. An adaptive perspective is that firms can change but differ in their ability to engage in these kinds of changes. That is, firms must change to be successful. The differences in adaptive ability have profit and risk implications that can have serious consequences for firms. In contrast, inertia theory (e.g. Hannan and Freeman, 1984) suggests that large firms cannot change core activities without risking survival. Inertia theory suggests that adaptation is risky and likely to result in failure.

In this context, we introduce and examine a simulation model that allows us to analyze the impact on profit of simple learning processes and adaptation. Some of our results are trivial. For example, as would be expected, with the introduction of the standard economic apparatus of profit and loss calculation, we find that optimal learning occurs before perfect learning. (What is surprising is how far below perfect leaning it occurs.) Some results are not trivial. For example, we find that learning provides a possible explanation for the Bowman paradox (Bowman, 1980), where risk and return are negatively correlated (higher returns are associated with lower risk, and vise versa) over time longitudinally.

A Strategic Responsiveness Model

Strategic change, adaptability, and responsiveness have been a central concern in strategic management for a long time. In fact, strategic management as taught and studied around the world has at its center the concept of adaptation. Firms are able to sense change in the world and reconfigure resources to adapt to the changes. This paradigm is easily discernable in any MBA classroom. Furthermore, its presence is seen in a huge body of research aimed at identifying proper strategies given environmental conditions and firm resources and competencies. This adaptive strategy is commonly referred to as achieving strategic fit.

The established concept of strategic fit (Andrews, 1971; Hofer and Schendel, 1978; Fiegenbaum, Hart and Schendel, 1996; Siggelkow, 2001) constitutes the basic underpinning of the strategic responsiveness model. High performance is achieved when the firm is able to align its strategy so it corresponds to the requirements imposed by the environmental conditions that exist at any given point in time. As environmental conditions change, achieving strategic fit will require that the key elements of the strategy are changed appropriately. This could include choices about product and service features, production and administrative processes, logistics and inventory management practices, etc., that should be matched to current customer needs, technological capabilities, and management techniques. The more a firm is unable to achieve an optimal fit on these parameters, the more firm performance will suffer as revenues are sub optimized, economic inefficiencies increase, inventories become excessive, etc. Hence, strategic fit is conceived broadly to consider external environmental conditions, such as, including changes in demand patterns, competitive structure, technological development, etc., as well as internal environmental conditions comprising elements of organizational structure, resource configuration, etc. (Andrews, 1971; Schendel and Hofer, 1979; Barney, 1991; Porter, 1996).

The idea of strategic fit is consistent with analytical approaches to gain third order organizational alignment (e.g., Porter, 1996) as well as the resource based view where performance derives from best use of unique firm resources (Barney, 1986, 1991). Hence, when environmental conditions change over time, there is a need for strategic responsiveness that allows the firms to adapt and retain strategic fit at different points in time. This entails resources and capabilities that enable environmental assessments, development of responsive alternatives, and reconfiguration of firm resources to enact appropriate adaptations to the strategy. This is quite comparable to the conceptualization of dynamic capabilities as the firm's ability to apply recognized resources in effective responses to dynamic environmental conditions (e.g., Teece, Pisano, and Shuen, 1997; Adner and Helfat, 2003; Teece, 2007).

An underlying tenet of strategic responsiveness is that the resources and capabilities required to achieve optimal strategic fit on an ongoing basis is distributed heterogeneously across firms. That is, some firms display a relatively high ability to adapt key elements of their strategy in response to ongoing environmental change whereas others clearly are unable to accomplish this possibly as organizational inertia variously sets in (e.g., Hannan and Freeman, 1984). Nonetheless, if firms display heterogeneous response capabilities, it can have a significant influence on the cross-sectional risk-return outcomes of ex post performance measures analyzed across portfolios of firms operating within comparable environmental conditions (Andersen, Denrell and Bettis, 2007).

Building on the Andersen, Denrell and Bettis (2007) model, we depict strategic responsiveness as a simple period-to-period adaptation process. The strategic fit perspective suggests that a given resource endowment in the firm can achieve an optimal performance outcome at a given point in time under existing technological limitations of the economy at large. This is expressed as production frontiers in classical economics and investment opportunity sets in financial economics depicting the upper bounds of prevailing technological capacity. This upper level for optimal firm performance is expressed by a value K. A firm can consistently achieve the optimal performance, K, in the rather unlikely scenarios that the firm is able to assess the environment accurately and respond in a manner that creates perfect strategic fit at any moment. However, a firm that is better at achieving near strategic fit is obviously better off than a firm that is unable to do so. In principle, the value of K can differ between firms depending as a function of individual resource endowments, it could be influenced by macro-economic developments, and might also change over time as technological capabilities in society improve. While a constant K constitutes an analytical restriction, we maintain that assumption here for the sake of simplicity also considering that a relaxation will be of little consequence to the analytical outcomes. To simplify things further in the ensuing analysis, we only consider one strategic parameter even though we could include a string of strategic parameters to reach comparable analytical outcomes. The profitability of firm i during period t can then be expressed in the base model as follows.

$$P_{t,i} = K - r \,|\, c_{t,i} - d_{t,i} \,|^{a}$$

In this model, $c_{t,i}$ represents a single key environmental parameter at time t that, for example, could reflect current demand, process capabilities, technological know how, or the like. $d_{t,i}$ is a strategic parameter, or a discretionary decision variable, indicating the firm's current strategic position against environmental parameter c. When the firm position deviates from the current environmental condition ($d_{t,i} \neq c_{t,i}$), performance will be less than optimal as a certain 'penalty' imposed I the profit function. Hence, a high performing firm would, for example, be able to adjust its production levels in period t to the change in demand and thereby optimize revenue flows without incurring excessive adaptation costs. If a firm is unable to create a perfect strategic fit, performance will be below K in some proportion to the mismatch against the current environmental condition. The coefficients r and l determine how large the imposed penalty will be. In general, the coefficients are assumed to be positive with a exceeding 1. That is, performance suffers progressively when the firm's strategy deviates substantially from the requirements imposed by current environmental conditions. The coefficients describe the relative size and character of the mismatch disadvantage that may differ across different industry contexts. Hence, the coefficients would be relatively low in munificent industries whereas they are considerably higher in hostile and competitive environments.

Andersen, Denrell and Bettis (2007) used a similar model to show that heterogeneous abilities among firms to adapt to key strategic parameters over time is associated with observed inverse cross-sectional risk-return relationships. However, they did not extend the analysis to consider longitudinal risk-return relationships that also have been observed to reflect negative correlations but at somewhat lower levels. In their discussion of the phenomenon, they asserted that while the strategic responsiveness model could explain the negative cross-sectional correlation between average returns and the standard deviation in returns, the longitudinal risk-return correlations might arise from other dynamic relationships including environmental framing. For example, the risk propensity of strategic decisions makers might be affected by preceding performance levels, as suggested by proponents of prospect theory and the behavioral theory of the firm (Kahneman and Tversky, 1979, 1984; Tversky and Kahneman, 1986; Cyert and March, 1963; March and Shapira, 1987, 1992). In this case, poor or below expected performance outcomes in one period might induce decision makers to increase risk taking in subsequent periods thereby invoking a particular longitudinal risk-return dynamic. To enlighten the implied cross-sectional/longitudinal risk-return conundrum, we conducted extended simulations based on the strategic responsiveness base model, which allows us to assess the relationships between the two performance constructs.

The Model Simulations

For simplicity, we assume that coefficient *r* that reflects the linear performance effect of a mismatch will be constant at level 1 in the following analyses. In contrast, we allow the more influential coefficient *a* that indicates exponential performance effects of mismatch to vary between values 1, 2, and 3. The models were programmed in Excel with simulations performed on the basis of the Excel random number generator. The simulations were based on 500 firm observations over 25 time-periods. The simulations calculated average performance and the standard deviation in performance over the 25 periods. Then the cross-sectional correlation between average performance and the standard deviation of performance was determined for the 25 periods as was the average longitudinal correlation. The average longitudinal correlation was determined as the average value of the entire period of the risk-return correlations between five-period average performance and the subsequent five-period standard deviation in performance. That is, the longitudinal risk-return measure indicates the relationship between performance risk and the performance level during the preceding period.

The simulations considered three versions of the base model: (1) both the environmental and the strategy variables (*c* and *d*) develop stochastically following a normal distribution with a given mean, (2) both the environmental and the strategy variables (*c* and *d*) develop stochastically but are path-dependent, and (3) the environmental variable (*c*) develops stochastically and is path-dependent whereas the strategy variable (*d*) follows a learning trajectory where by the firm can adjust its position according to environmental information from the previous period.

Model 1

This depiction of the strategic responsiveness construct is closest to the original model in Andersen, Denrell and Bettis (2007) in the sense that both the environmental context and the firm position follow a stochastic process described by a normal distribution as defined by a given mean and standard deviation. Hence, there is no direct link between the environmental variable from one period to the next nor between the firm position over time. Instead, the random nature of the two variables is characterized by their outcomes over time complying with the contours of a normal distribution.

The model is specified as follows:

$$P_{t,i} = K - r \mid c_{t,i} - d_{t,i} \mid^{a}$$

$$K = 100$$

$$r = 1$$

$$c_{t,i} = \mathrm{N}(100, s.d.)$$

$$d_{t,i} = \mathrm{N}(100, s.d.)$$

For all three models, the simulations were performed for different values of the exponential coefficient of the profit function (a = 1, 2 and 3) and different values for the standard deviation (*s.d.* = 1, 2 and 3) in the environmental and strategy variables (c and d). They constitute important characteristics of the competitive environment in which the firm operates and provided an opportunity to assess potential effects of the competitive dynamic.

The simulations reveal a significant cross-sectional risk-return relationship but did not discern any material longitudinal risk-return relationship (Figure 3). The simulated cross-sectional risk-return relationships correspond to the levels observed in empirical data. These results are consistent with the empirical assessment and discussion conducted in Andersen, Denrell and Andersen (2007) and should not surprise because the model provides no linkage between model parameters over time.

Model 2

This corresponds to the previous model 1 with one minor exception, namely that the values of both the environmental context and the firm position are linked to the values of the variables in the previous period including a stochastic deviation.

The model is specified as follows:

$$P_{t,i} = K - r \mid c_{t,i} - d_{t,i} \mid^{a}$$

$$K = 100$$

$$r = 1$$

$$c_t = \mathrm{N}(c_{t-1}\ ,\ s.d.)$$

$$d_t = \mathrm{N}(d_{t-1}\ ,\ s.d.)$$

The simulations show a significant cross-sectional risk-return relationship of comparable size to the previous model 1 (Figure 4) and also significant longitudinal risk-return relationships ranging between -0.179 and -0.639 within line with observed coefficients. The longitudinal risk-return relationship reported by Bromiley (1991) measured between five-year intervals in manufacturing firms (SIC 3000-3999) during the period 1976-87 amounted to -0.47. The longitudinal risk-return relationships reported by Miller and Chen (2004) measured between eight-quarter intervals in manufacturing firms (SIC 2000-3999) during the period 1991-2000 amounted to -0.37 and -0,42 across two different sub-periods. The size of the longitudinal risk-return relationships observed in the simulation results depend on the model parameters but correspond to the observed correlations within reasonable parameter values.

Model 3

This corresponds to the previous model 2 with the exception that the firm can learn about the environmental context in the previous period and adapt its strategy position accordingly. The firm can engage in different degrees of learning reflected in a learning rate (l) that can vary between 0 and 1 in intervals of 0.1. In the simulations we only perform calculations for the interval between 0.0 and 0.7 because the outcomes for higher learning rates become trivial. The learning rate indicates the ratio by which the firm can adapt its current position in relation to the previous periods observed environmental context. A learning rate of 0.0 means that no learning and hence no adaptation takes place at all, whereas a learning rate of 0.1 indicates a marginal adjustment according to the actual environment in the previous period. The model does impose any learning costs to the implied adaptive capability.

The model is specified as follows:

$$P_{t,i} = K - r \mid c_{t,i} - d_{t,i} \mid^{a}$$

$$K = 100$$

$$r = 1$$

$$c_t = \mathrm{N}(c_{t-1}\ , s.d.)$$

$$d_t = l\, c_{t-1} + (1 - l)d_{t-1}$$

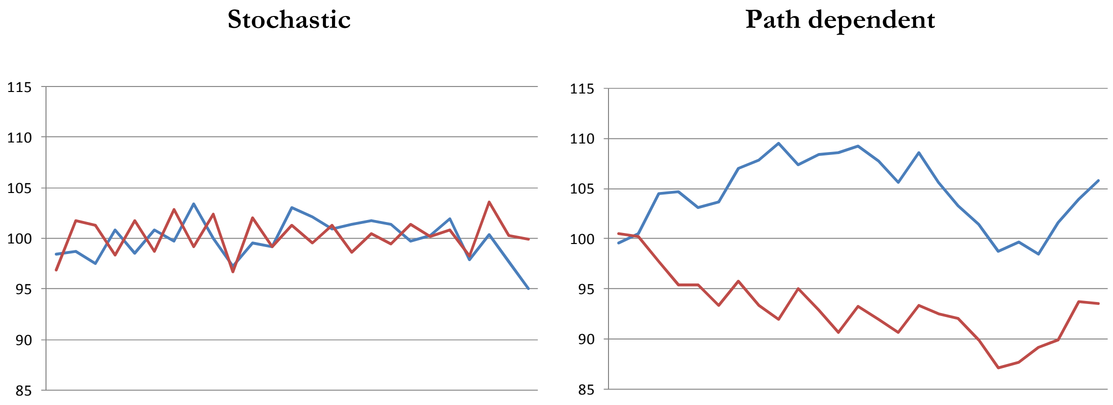
$$l = 0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6 \text{ and } 0.7$$

The simulations show significant cross-sectional longitudinal risk-return relationships for lower learning rates. The risk-return relationships depend on model parameters and the longitudinal risk-return relationship is only discernable at low learning rates ($l \leq 0.2$). When no learning takes place, the longitudinal risk-return relationships are somewhat above the values observed in previous studies. The commonly observed longitudinal risk-return relationships correspond to a low learning rate ($l \approx 0.1$).

Empirical Validation

Implications for Strategic Management

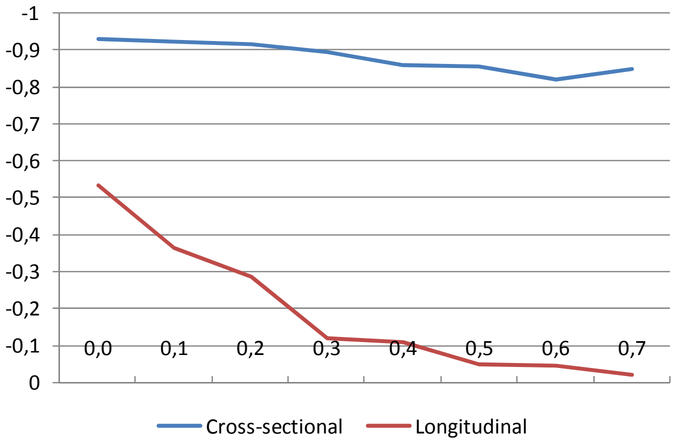
Figure 1. Stochastic and Path Dependent Parameter Developments



Stochastic

Path dependent

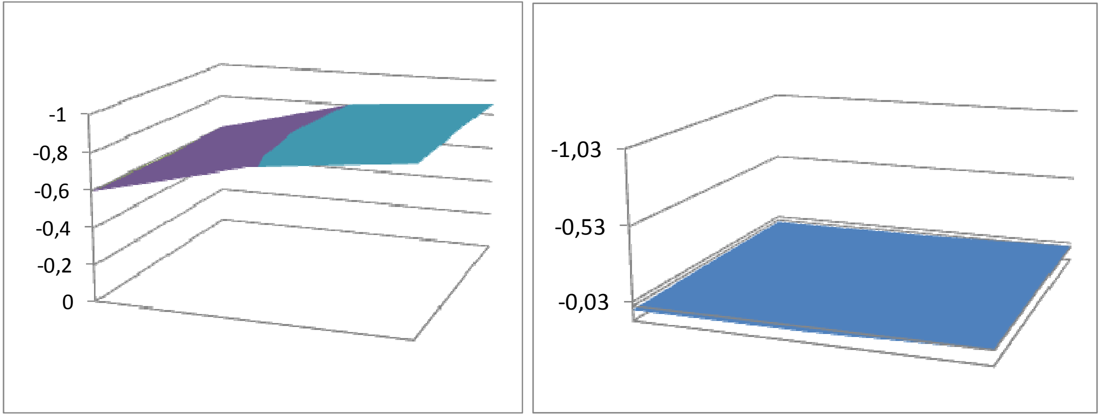
Figure 2. **Risk-Return Relationships and Learning**



learning rate (*l*) ranging from 0.0 to 0.7

Note: Simulation results with fixed model parameters (*a* = 2; *s.d.* = 2)

Figure 3. Overview of Experimental Simulation Results – Model 1



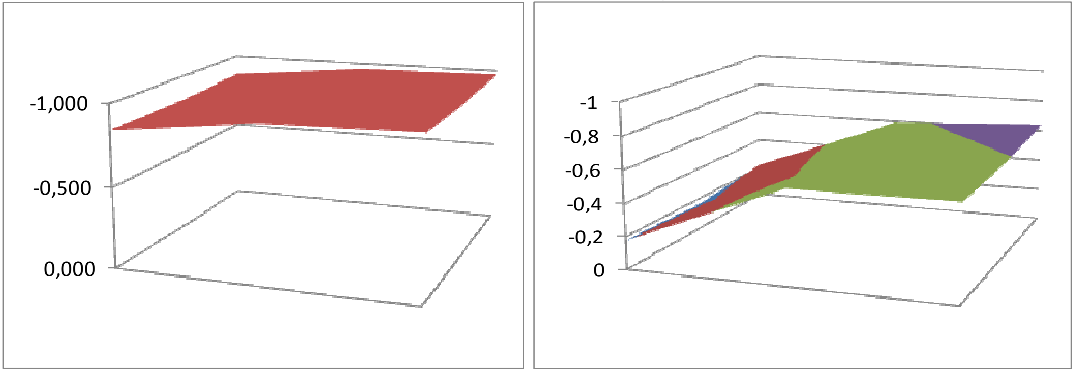
The cross-sectional risk-return relationship

The longitudinal risk-return relationship

s.d. \ ***a***	1	2	3
1	0,026	0,03	0,001
2	0,015	-0,021	0,003
3	0,014	0,014	-0,004

s.d. \ ***a***	1	2	3
1	-0,003	0,033	0,008
2	-0,008	-0,026	0,018
3	-0,011	0,027	0,001

Figure 4. Overview of Experimental Simulation Results – Model 2



The cross-sectional risk-return relationship **The longitudinal risk-return relationship**

s.d. \ ***a***	1	2	3
1	-0,843	-0,950	-0,969
2	-0,844	-0,946	-0,965
3	-0,870	-0,959	-0,975

s.d. \ ***a***	1	2	3
1	-0,179	-0,575	-0,584
2	-0,161	-0,525	-0,594
3	-0,216	-0,587	-0,639

Figure 5. **Overview of Experimental Simulation Results – Model 3**
(Increasing learning rates: 0.1, 0.2, and 0.3)

The cross-sectional risk-return relationship **The longitudinal risk-return relationship**