Organization Science
Vol. 15, No. 4, July–August 2004, pp. 481–494
ISSN 1047-7039 | EISSN 1526-5455 | 04 | 1504 | 0481

DOI 10.1287/orsc.1040.0078

Exploration vs. Exploitation: An Empirical Test of the Ambidexterity Hypothesis

Zi-Lin He
Department of Management, University of Otago, P.O. Box 56, Dunedin, New Zealand, zilinhe@business.otago.ac.nz

Poh-Kam Wong
NUS Entrepreneurship Centre, National University of Singapore, 14 Prince George's Park, Singapore 118412, pohkam@nus.edu.sg

While exploration and exploitation represent two fundamentally different approaches to organizational learning, recent literature has increasingly indicated the need for firms to achieve a balance between the two. This balanced view is embedded in the concept of ambidextrous organizations. However, there is little direct evidence of the positive effect of ambidexterity on firm performance. This paper seeks to test the ambidexterity hypothesis by examining how exploration and exploitation can jointly influence firm performance in the context of firms' approach to technological innovation. Based on a sample of 206 manufacturing firms, we find evidence consistent with the ambidexterity hypothesis by showing that (1) the interaction between explorative and exploitative innovation strategies is positively related to sales growth rate, and (2) the relative imbalance between explorative and exploitative innovation strategies is negatively related to sales growth rate.

Key words: technological innovation; innovation strategy; ambidextrous organization

1. Introduction

A central concern of corporate strategy has to do with making choices about how much to invest in different types of activities. Two broad types of qualitatively different learning activities between which firms divide attention and resources—exploration and exploitation—have been proposed in the literature. Exploration implies firm behaviors characterized by search, discovery, experimentation, risk taking and innovation, while exploitation implies firm behaviors characterized by refinement, implementation, efficiency, production and selection (Cheng and Van de Ven 1996, March 1991).

The conceptual distinction between exploration and exploitation has been used as an analytical construct, explicitly or implicitly, in a wide range of management research areas, including strategic management (e.g., Winter and Szulanski 2001), organization theory (e.g., Holmqvist 2004, Van den Bosch et al. 1999), and managerial economics (e.g., Ghemawat and Ricart i Costa 1993). These studies have shown that exploration and exploitation require substantially different structures, processes, strategies, capabilities, and cultures to pursue and may have different impacts on firm adaptation and performance. In general, exploration is associated with organic structures, loosely coupled systems, path breaking, improvisation, autonomy and chaos, and emerging markets and technologies. Exploitation is associated with mechanistic structures, tightly coupled systems, path dependence, routinization, control and bureaucracy, and stable markets and technologies (Ancona et al. 2001, Brown and Eisenhardt 1998, Lewin et al. 1999). The returns associated with exploration are more variable and distant in time, while the returns associated with exploitation are more certain and closer in time. In other words, explorative firms generate larger performance variation by experiencing substantial success as well as failure, while exploitative firms are likely to generate more stable performance.

While the conceptual distinction between exploration and exploitation and their implications for strategy and structure have been intensively studied, there has been surprisingly little empirical investigation of the interaction effect between the two—Does the simultaneous pursuit of both activities add to or detract from each other's value? Notwithstanding the popular "ambidexterity" premise suggested by Tushman and O'Reilly (1996) (that firms need to achieve a "balance" between the two to achieve superior performance), there have been few empirical findings reported in the literature on how exploration and exploitation can jointly influence firm performance.

This paper seeks to test the ambidexterity hypothesis in the specific context of firms' approach to technological innovation. We apply the exploration versus exploitation construct to characterize how firms strategically prioritize their investment in technological innovation with explorative versus exploitative objectives, and examine their joint effects on the sales growth performance of these firms. Based on a sample of 206 manufacturing firms, we find that explorative and exploitative innovation strategies influence sales growth performance differently through two intermediary variables—product and process innovation intensities. More importantly, using two alternative measures of joint effects, "fit as moderating" and "fit as matching" (Venkatraman 1989), we find evidence consistent with the ambidexterity hypothesis by showing that (a) the interaction between explorative and exploitative innovation strategies is positively related to sales growth rate, and (b) the relative imbalance between explorative and exploitative innovation strategies is negatively related to sales growth rate.

2. Theory and Hypotheses

2.1. The Distinction and Tension Between Exploration and Exploitation

The distinction between exploration and exploitation has been highlighted in a wide range of management literature. In organization theory research, scholars have long distinguished between structures designed for efficiency and those designed for innovation, for example, mechanistic versus organic structures (Burns and Stalker 1961). Similarly, single-loop versus double-loop learning (Argyris and Schön 1978) and local search versus "long jump" (Levinthal 1997) are differentiated in organizational learning research. In strategy research, Burgelman's (1991, 2002) internal ecology model of strategy making distinguishes between two types of strategy processes, variation-reducing induced processes and variation-increasing autonomous processes. In managerial economics, static efficiency and dynamic efficiency are distinguished from each other, with the former involving continuous search for improvement along a fixed production function, while the latter requires discontinuous shift from one production function to another that is more profitable (see Ghemawat and Ricart i Costa 1993 for a review). As succinctly summarized by March (1991), the distinction between "exploration of new possibilities" and "exploitation of old certainties" captures a number of fundamental differences in firm behavior and strategy that have significant consequences on firm performance.

There is a tension between exploration and exploitation. On the one hand, adaptation to existing environmental demands may foster structural inertia and reduce firms' capacity to adapt to future environmental changes and new opportunities (Hannan and Freeman 1984). On the other hand, experimenting with new alternatives reduces the speed at which existing competencies are improved and refined (March 1991). A failed explorative effort may disrupt successful routines in a firm's existing domains, without any significant success in the new field to compensate for the loss in existing business (see, e.g., Mitchell and Singh 1993).

This tension may also cause firms to be trapped into dynamics of accelerating exploration or exploitation (March 1991, Levinthal and March 1993). On the one hand, the self-reinforcing nature of organizational learning makes it attractive for a firm to maintain its current focus and to augment its current capabilities even if the environment has changed, thus causing core capabilities to be turned into core rigidities (Leonard-Barton 1995). To counter such an excessive focus on exploitation that results in organizational myopia (Radner 1975) and competency traps (Levitt and March 1988), the need for "going beyond local search" (Rosenkopf and Nerkar 2001) has been very much emphasized in the literature. For example, Peter (1990) advocated a radical self-generating innovation strategy that obsoletes itself from the inside, including licensing the firm's most advanced technology and selling off old winners to force dependence on the new. Similarly, D'Aveni (1994) strongly argued that no firm can build a competitive advantage that is sustainable because today's strength becomes tomorrow's weakness so quickly. Instead of trying to create stability and equilibrium, firms must actively work to disrupt their own advantages and the advantages of competitors by creating a series of temporary advantages (D'Aveni 1994). The strategic logic here is to counterbalance exploitation with exploration.

On the other hand, Levinthal and March (1993) have argued that the balance can also be skewed towards excessive exploration that is equally destructive: "…failure leads to search and change which lead to failure which leads to even more search, and so on" (p. 105). The inability of many otherwise innovative firms to achieve success in the marketplace can be traced at least partly to their tendency to constantly explore new products and unfamiliar markets without allocating enough resources to exploit their competences in a more familiar or narrower niche.

In sum, exploration and exploitation are fundamentally different logics that create tensions. They compete for firms' scarce resources, resulting in the need for firms to manage the trade-offs between the two. However, there may be a synergistic effect between the two as well, and hence there is a need for firms to manage the balance between the two.

2.2. Balancing Exploration and Exploitation—The Ambidexterity Hypothesis

Although trade-offs between exploration and exploitation are certainly necessary because they compete for scarce resources, March (1991) also suggested that maintaining an appropriate balance between exploration and exploitation is critical for firm survival and prosperity. As argued by Levinthal and March (1993, p. 105), "The basic problem confronting an organization is to engage in sufficient exploitation to ensure its current viability and, at the same time, to devote enough energy to exploration to ensure its future viability." Similarly, Burgelman (1991, 2002) has proposed that a combination of variation-reducing induced strategic processes and variation-increasing autonomous strategic processes in strategy making would give firms a chance to outrun environmental selection pressures. His analysis suggests that firms may have to keep both processes in play at all times, even though this means that firms never completely maximize their benefits from the current domain.

The need for an appropriate balance between exploration and exploitation has been crystallized by Tushman and O'Reilly's (1996) conceptualization of the ambidextrous organization. They used a "juggler" metaphor to describe an ambidextrous firm that has the capabilities to both compete in mature markets (where cost, efficiency, and incremental innovation are critical) and develop new products and services for emerging markets (where experimentation, speed, and flexibility are critical). More specifically, they argued that an ambidextrous firm that is capable of operating *simultaneously* to explore and exploit is likely to achieve superior performance than firms emphasizing one at the expense of the other. The concept of ambidexterity is also implicit in the more recent conceptualization of dynamic capabilities by Eisenhardt and Martin (2000), who suggested that overall, dynamic capabilities require a blend of the two different strategic logics, namely, the logic of exploration and the logic of exploitation. Ancona et al. (2001, p. 658) likewise argued that dynamic capabilities "are rooted in streams of innovation—in simultaneously exploiting and exploring." According to Katila and Ahuja (2002), exploitation of existing capabilities is often needed to explore new capabilities, and exploration of new capabilities also enhances a firm's existing knowledge base—Exploration and exploitation form a dynamic path of absorptive capacity.

While theoretically predicting a positive interaction effect between exploration and exploitation provided that the firms adopt the ambidextrous organizational design they advocated, Tushman and O'Reilly (1996) did not provide further empirical support beyond citing several case studies. They suggested that, in practice, few firms may succeed at managing ambidexterity, because exploration and exploitation are fundamentally different logics that require very different strategies and structures, and the resulting tensions between the two are difficult to reconcile. Implicit in their argument is that, unless these tensions are well managed, firms that try to pursue both exploration and exploitation may actually end up worse off, i.e., the interaction effect between exploration and exploitation may turn out to be negative rather than positive. Thus, the empirical case for ambidexterity may be ambiguous.

Apart from Tushman and O'Reilly (1996), a few other studies also provided empirical support for the ambidexterity hypothesis, but only in a limited way. For example, Knott (2002) found that exploration and exploitation coexisted in Toyota's product development, and concluded that the two are likely to be complementary "since it is non-optimal to combine them if they are substitutes" (p. 340). Bierly and Daly (2001) did formally test the impact of ambidexterity on firm performance with a sample of 98 manufacturing firms and found no significance, but their results need to be interpreted with caution because they did not control for the influences of other factors. Katila and Ahuja (2002) used search scope (propensity to cite different patents) and search depth (propensity to cite certain patents repeatedly) to proximate exploration and exploitation learning. They found a positive interaction effect between search scope and search depth on new product development, but did not test their effects on firm performance.

In sum, despite the growing theoretical support for the need to balance exploration versus exploitation in the management literature, empirical evidence for the ambidexterity hypothesis has so far been largely anecdotal and inconclusive.

2.3. The Ambidexterity Hypothesis in the Context of Technological Innovation

We propose to test the ambidexterity hypothesis in the particular context of technological innovation. Following the established literature (e.g., Poole and Van de Ven 1989), we distinguish technological innovation from organizational innovation. While organizational innovation involves changes to organizational structures and administrative processes, this paper focuses on how firms commercialize new technological knowledge and ideas into new products or processes. Although technological innovation represents only a subset of organizational learning activities, such a focus makes this study more manageable.

While various typologies of technological innovation strategy have been used in the existing innovation management literature, none has been explicitly grounded in the exploration versus exploitation construct. For example, Zahra and Das (1993) summarized the four most commonly used typologies of innovation strategy as: (1) pioneer versus follower posture; (2) product versus process innovation (or both); (3) the intensity of investment in innovation (low versus middle versus high); and (4) the sources of innovation—internal versus external (or both). None of these draws directly on the exploration versus exploitation distinction. Henderson (1999) classified innovation strategies into proprietary versus standards-based strategies, and suggested that the former may be more related to technological exploration while the latter may be more related to technological exploitation, but did not pursue the relationship further.

In this paper, we extend the exploration versus exploitation construct to define a new typology of technological innovation strategy along two generic dimensions: (1) an explorative innovation dimension to denote technological innovation activities aimed at entering new product-market domains and (2) an exploitative innovation dimension to denote technological innovation activities aimed at improving existing product-market positions. We will refer to these two generic dimensions as explorative innovation strategy and exploitative innovation strategy in the rest of the paper.

While most firms are likely to pursue some combination of explorative and exploitative innovation, we can define a firm to be "ambidextrous" in terms of innovation strategy in two ways.[1] First, we can regard a firm as ambidextrous if it scores high on both explorative and exploitative innovation strategies, in which case the product of the two scores would be a good proxy measure of ambidexterity. Second, we can examine the absolute difference between the two scores: A firm is regarded as ambidextrous if it has relatively equal emphasis on both dimensions. In this case, even a firm that has a low emphasis on both innovation strategies may get classified as ambidextrous. These two different ways of defining ambidexterity correspond to the two types of strategic fit—"fit as moderating" and "fit as matching"—in the strategy literature (Venkatraman 1989). In our case, a positive "fit as moderating" test would mean that exploration and exploitation add value to each other to improve firm performance, i.e., there is a positive interaction effect between the two on firm performance. On the other hand, the "fit as matching" test is concerned with whether a match (a smaller absolute difference) between exploration and exploitation can enhance firm performance. Hence, we posit the following two versions of the ambidexterity hypothesis:

Hypothesis 1a. *There is a positive interaction effect between explorative and exploitative innovation strategies on firm performance.*

Hypothesis 1b. *The relative imbalance* (*absolute difference*) *between explorative and exploitative innovation strategies is negatively related to firm performance.*

The above formulations of the ambidexterity hypothesis make no assumption about which innovation strategy has more influence on firm performance, i.e., the main effect of each strategy. Prior literature has highlighted potential pitfalls in inferring which innovation strategy is more effective in terms of firm performance, as "the returns from the two options vary not only with respect to their expected values, but also with respect to their variability, their timing, and their distribution within and beyond the firm" (March 1991, p. 71).

While nothing specific can thus be said about the relative impact of explorative and exploitative innovation on firm performance levels, prior literature strongly suggests that an exploitative innovation strategy is more likely to result in less intertemporal performance variability than an explorative innovation strategy (Levinthal and March 1993, McGrath 2001). Similarly, if we examine a cross-section of firms, firms that emphasize explorative innovation should exhibit greater performance dispersion than those that emphasize exploitative innovation. While it would be interesting to test both intertemporal and cross-sectional performance variability of firms emphasizing either exploration or exploitation, limitations of data availability precluded us from examining the former. Hence, we only hypothesize the following:

Hypothesis 2. *Firms that specialize in explorative innovation strategy exhibit larger intragroup variation in performance, relative to their mean values of performance, than firms that specialize in exploitative innovation strategy.*

Following this logic, ambidextrous firms as defined according to the first criterion[2] (high scores on both explorative and exploitative innovation strategies) can be expected to reap synergies in terms of achieving a lower intragroup variance-to-mean performance ratio when compared with firms that emphasize only explorative innovation. Hence, we further hypothesize the following:

Hypothesis 3. *Ambidextrous firms* (*scoring high on both explorative and exploitative innovation strategies*) *exhibit smaller intragroup variation in performance, relative to their mean values of performance, than firms that specialize in explorative innovation strategy.*

3. Data and Methods

3.1. Survey Data

Data for this study were drawn from a survey of innovation behavior and performance of manufacturing firms in Singapore and the State of Penang in Malaysia during 1999–2000. The sampling frame was constructed from the databases provided by the Economic Development Board of Singapore and Penang Development Corporation, because these two government agencies maintained the most complete coverage of manufacturing firms in Singapore and Penang, respectively. The survey approach was used because of the lack of archival data providing the detailed information needed to measure firm innovation strategy and performance.

Questionnaires were sent to the CEOs of 1,872 manufacturing firms in Singapore and 950 manufacturing firms in Penang. Responses with missing data as well as doubtful or contradictory answers that could not be clarified by follow-up telephone calls were removed from the sample. A total of 371 valid responses from Singapore and 192 valid responses from Penang were achieved at the end of the surveys, yielding response rates of 19.8% and 20.2%, respectively. We found the firms in the two samples to be quite similar in terms of distribution by firm size and R&D intensity, percentage of innovating firms, and percentage of foreign firms. Response rates differed only slightly between industry sectors, ranging from 21.6% for chemicals to 19.0% for electronics, although foreign firms and larger firms tended to have a higher response rate.

To control for the fact that some of the respondent firms may be engaged in so little technological innovation activity that it may not be meaningful to speak of an innovation strategy for such firms, we defined a minimum threshold of innovation activities to filter out such low-innovation firms. Following the widely adopted definition of OECD (OECD-EUROSTAT 1997), we classified a firm as innovating if it introduced (1) a new or substantially improved product in the last three years (product innovation) or (2) a new or substantially improved production process through new equipment or re-engineering in the last three years (process innovation). Only 206 firms (137 from Singapore and 69 from Penang) were found to be innovating according to this definition. Therefore, the valid sample size for this study was 206.

3.2. Variables

(a) *Dependent Variable.* The dependent variable is sales growth rate, measured as self-reported compounded average sales growth rate in the last three years (from 1996 to 1999 with 1996 as the base year). While a 3-year period may not be suitable for studying large global high-tech firms in advanced economies that are willing to engage in long-term innovation projects spanning 5–10 years, it should be appropriate for this study because most firms in Singapore and Malaysia carry out technological innovations with shorter project durations and payback periods. Among 206 firms in our sample, only three firms (1.5%) reported an average project duration (from innovation idea to full implementation) of more than three years; while 142 firms (68.9%) reported an average project duration of less than one year. Similarly, 31 firms (15.0%) reported an average payback period of more than three years for innovation projects; while 136 (66.0%) firms reported an average payback period of less than two years.

While recognizing that firm performance is a multidimensional concept, we focused only on average sales growth rate in this study for several reasons. First, sales growth estimates are more easily available and reliable than profitability estimates from a survey. Unlike profitability measures like ROA, etc., sales growth does not suffer from accounting measurement problems. Second, sustained sales growth has been found to be a reliable proxy indicator of other dimensions of superior firm performance, including long-term profitability and survival (Timmons 1999, Henderson 1999). In this study, we were able to extract the reported sales and financial performance data of 90 firms from 1996 to 1999 from various archival sources (*Singapore 1000*, *Singapore SME 500*, *Financial Highlights of Companies on the SES*, *Malaysia Corporate Handbook*, and *ISI Emerging Markets*). We found the survey-based sales growth rate of this subsample to be significantly correlated with the archival-based sales growth rate ($r = 0.821$, $p = 0.000$), ROS ($r = 0.351$, $p = 0.001$), ROA ($r = 0.276$, $p = 0.018$), ROS growth ($r = 0.398$, $p = 0.000$), ROA growth ($r = 0.418$, $p = 0.000$).

(b) *Independent Variable.* Because exploration versus exploitation is a general and broad concept, previous studies have suggested a diverse range of operationalizations, e.g., the radicalness of innovation (Bierly and Chakrabarti 1996), patent search scope and depth (Katila and Ahuja 2002), the degree to which search behavior is both technological and organizational boundary spanning (Rosenkopf and Nerkar 2001), and a composite measurement of the newness of business development projects (McGrath 2001).

Following Bierly and Daly (2001) and Katila and Ahuja (2002), we regard exploration and exploitation as two distinct dimensions of learning behavior, rather than as two ends of a unidimensional scale. We developed eight Likert-scale items to measure how firms divide attention and resources between innovation activities with explorative versus exploitative objectives in the last three years. These items were designed to measure how important it is for a firm to carry out innovation projects to enter new product-market domains or to improve existing product-market efficiency (e.g., introduce new generation of products versus improve existing product quality; open up new markets versus reduce production cost). Collectively, we believe that these items capture some essence of "exploration of new possibilities" and "exploitation of old certainties." The three-year timeframe for the innovation strategy construct was chosen to be concurrent with that of sales growth rate discussed earlier. Prior research has indicated that innovation strategy tends to be quite stable across a number of years (Bierly and Chakrabarti 1996). While the firms in our sample had different age profiles, all of them were more than 3 years old, with a mean age of 15.68 and a median age of 11. It is thus reasonable to assume that most of the firms have been pursuing a stable innovation strategy for the three-year, or an even longer, period.

We did not use scales related to radical versus incremental innovation because exploration versus exploitation should be used with reference to a firm's *ex-ante* strategic objectives in pursuing innovation, whereas the radical versus incremental innovation is often used in an *ex-post* outcome sense. Moreover, exploration versus exploitation should be used with reference to a firm itself and its existing capabilities, resources, and processes, not to a competitor or at the industry level. An exploration activity to one firm might be an exploitation activity to another, or vice versa. Furthermore, relatively few

Table 1 Factor Analysis for Innovation Strategy

Objectives for undertaking innovation projects in the last 3 years (1 = not important to 5 = very important)	Exploitative innovation strategy	Explorative innovation strategy
Cronbach alpha	0.807	0.752
Introduce new generation of products	−0.042	**0.706**
Extend product range	0.067	**0.844**
Open up new markets	0.099	**0.786**
Enter new technology fields	0.085	**0.707**
Improve existing product quality	**0.554**	0.235
Improve production flexibility	**0.827**	−0.004
Reduce production cost	**0.868**	0.002
Improve yield or reduce material consumption	**0.892**	−0.010

Notes. Extraction method: Principal component analysis. Rotation method: Varimax with Kaiser normalization. Explained variance: 65%.

firms in our sample engaged in breakthrough innovation activities like firms in the United States, Japan, and Europe. Similarly, we did not use patent data to operationalize exploration versus exploitation (e.g., Katila and Ahuja 2002, Rosenkopf and Nerkar 2001) because relatively few firms in our sample reported significant patenting activities.

Factor analysis (Table 1) was used to reduce the eight items into two variables that can be interpreted as explorative innovation strategy and exploitative innovation strategy with acceptable Cronbach alphas (0.752 and 0.807, respectively). Confirmatory factor analysis (CFA) also showed good discriminant validity (a significant Chi-square difference between a one-factor model and two-factor model, $p = 0.000$). As suggested by several researchers, we centered the independent variables on their means before creating the interaction term (e.g., Venkatraman 1989). For testing Hypotheses 2 and 3 about performance variation associated with different innovation strategies, we used "median cut-off" criterion to define different groups of firms. All firms were first ranked in descending order of explorative or exploitative innovation strategy factor scores. Firms that fell in the upper half were classified as explorative or exploitative, respectively. A firm was then defined as ambidextrous if it belonged to both the explorative and exploitative group.

(c) *Intermediary Variables.* A key challenge in isolating the impact of strategy variables on firm performance is to identify appropriate intermediary organizational or operational performance variables through which the impact of strategy variables is transmitted. Prior research has shown that a path model that incorporates such intermediary variables is likely to perform better than the reduced model that correlates strategy variables with firm performance variables directly (see, e.g., Zahra and Das 1993).

We modeled the impact of innovation strategy on market performance as a two-stage process in which innovation strategy affects innovation performance that, in turn, affects sales growth rate. We included two intermediary variables to measure innovation performance: product innovation intensity and process innovation intensity. Product innovation intensity is measured as the percentage of total annual sales that consist of new/improved products introduced over the last three years. Process innovation intensity is measured as the percentage of annual production volume using new/improved processes introduced over the last three years. Natural log of product and process innovation intensities were used to compensate for skewness. Prior research has shown that product and process innovation intensities have positive impacts on firm performance in general and sales growth in particular (e.g., Skinner 1992, Zahra and Das 1993, Zairi 1992), justifying their choice as intermediaries variables. This path model approach is also consistent with Eisenhardt and Martin's (2000, p. 1,106) argument that "dynamic capabilities are necessary, but not sufficient, conditions for competitive advantage," and hence their impacts on firm performance must be measured through their effects on the firm's resource configuration (new products and processes in our case).

Conceptually, both explorative and exploitative innovation strategies can affect product and process innovation. Traditional technological life cycle (TLC) theory (e.g., Abernathy and Utterback 1978) suggests that exploration may have the highest payoff in the early stage of TLC (characterized by radical product innovation and competing product designs) and that exploitation may have greater payoff in the later post-dominant design stage, when incremental process innovation to reduce costs becomes more important. However, other paths of influence are also possible. In particular, an exploitative innovation strategy may influence product innovation performance through emphasizing incremental improvements of existing products; likewise, an explorative innovation strategy may affect process innovation performance through discovering entirely new process technologies (e.g., in semiconductor and chemical industries). Therefore, rather than preselecting certain paths, we empirically tested for the significance of all paths in the path model.

(d) *Control Variables.* The following variables—total fixed asset, firm age, nationality of foreign subsidiaries' majority shareholder, geographic location (Singapore = 1, Penang = 0), share of export in turnover, R&D spending as a percentage of total sales, and industry dummies—were used as control variables. We controlled for firm size and age as they have been found to influence firm growth (Carroll and Hannan 2000). Natural log of total fixed asset and firm age were used to compensate for skewness. The export intensity measure was used because a firm's growth could be affected by its linkage with global markets. Prior research has found the nationality of foreign subsidiaries to be a significant factor in the context of Singapore and Penang where the presence of multinational corporations (MNCs) is very significant, and Japanese-owned subsidiaries appear to have poorer performance than those of American and European origin (see, e.g., Wong 2002).

Five broad industry sectors were used as control variables, namely electronics, chemicals, machinery and equipment, metal and mineral products, and a combined sector for "others." However, because these industry controls may not capture the technological dynamism of different markets, OECD's (1996) definition of technology classes (high, medium-high, medium-low, and low) was also used as an alternative control measure. We collapsed medium-low and low-technology classes into a single low-technology class because of the small number of cases found in the low-technology category, and relabeled medium-high as medium instead. As the two different sets of controls yielded very similar results, we will only report the results with technology-class controls.

It would be desirable to control for prior-period sales growth because it may influence current-period sales growth as well as current-period innovation strategy through slack and changes in a firm's aspiration levels (Cyert and March 1963). While slack could encourage exploration, lack of slack may also have the same effect; as pointed out by Levinthal and March (1993), when a firm is operating below its aspiration level (e.g., negative sales growth rate), the firm may become more explorative as it falls further below the target until it approaches a survival point. Unfortunately, constraints of the survey methodology, including unreliable recall by respondents about their firms' performance in a much earlier period, did not allow us to capture a measure of prior-period sales growth (1993–1996) as a control. Nevertheless, we managed to collect sales data for 44 firms in our sample for the previous period (1993–1996) using various archival data sources as mentioned earlier. Based on data for these 44 firms, we found no significant correlation between current- and prior-period sales growth rates ($r = 0.156$, $p = 0.199$). We also found the year-to-year sales growth rates to have no significant correlation with each other. This fluctuation in sales growth is consistent with the previous "random growth" literature (see Sutton 1997 for a review). Moreover, the prior-period sales growth rate was not significantly correlated with either explorative ($r = 0.217$, $p = 0.126$) or exploitative ($r = 0.187$, $p = 0.188$) innovation strategy. Although we could not rule out the possibility of endogeneity between sales growth and innovation strategy, the above evidence suggests that this problem may not be serious in our study.

3.3. Analysis Methods

We chose both hierarchical regression and path analysis to test Hypothesis 1. Hierarchical regression adds controls, explanatory variables, and joint effect terms incrementally to gauge their relative contributions, while path analysis gives a comprehensive picture of the relative strengths of all hypothesized relationships. ANOVA analysis was used to test Hypotheses 2 and 3. Because Hypotheses 2 and 3 indicate the test for Hypothesis 1 was subject to the heteroskedasticity problem, we report White-heteroskedasticity-robust estimates. Although the regression results differed slightly from the path analysis results, the overall conclusions were not affected by the choice of the methods.

Because only innovating firms were included in analysis, Heckman's (1979) two-stage regression was used to detect possible sample selection bias. In Step 1, the inverse Mills ratio was obtained from probit regression (to predict whether a firm is innovating) using all 563 observations. In Step 2, the inverse Mills ratio was included as an additional variable to explain the variation in sales growth rate, using the 206 innovating firms. The inverse Mills ratio was not significant in any regression at the 0.10 level, and there were no material changes to the results for other variables. Because sample selection bias did not seem to be serious, we will not report the inverse Mills ratio adjusted results.

4. Results

4.1. Hierarchical Regression Results

Table 2 shows the regression results for innovation performance.[3] Explorative innovation strategy is found to significantly influence product innovation, but not process innovation. In contrast, exploitative innovation strategy is found to affect both product and process innovation. R&D spending intensity has a very strong impact on product innovation intensity, but not on process innovation intensity. Among the other control variables, high-technology firms tend to have higher product innovation intensities, but this effect becomes insignificant when R&D spending intensity is included. European firms appear to have better innovation performance. Bigger firms have higher process innovation intensities, while older firms have lower process innovation intensities.

Table 3 summarizes the regression results for Hypotheses 1a and 1b. Regressions 2–5 show that only

Table 2 Regression for Innovation Performance

	Product innovation intensity (log)				Process innovation intensity (log)			
	1	2	3	4	5	6	7	8
Location	−0.037 (0.742)	−0.009 (0.937)	−0.022 (0.846)	0.005 (0.967)	−0.144 (0.225)	−0.143 (0.239)	−0.154 (0.193)	−0.153 (0.208)
High technology	0.317** (0.039)	0.241 (0.109)	0.318** (0.037)	0.245 (0.102)	0.237 (0.159)	0.235 (0.164)	0.246 (0.143)	0.242 (0.150)
Medium technology	0.188 (0.122)	0.141 (0.247)	0.187 (0.125)	0.144 (0.243)	−0.079 (0.551)	−0.081 (0.546)	−0.068 (0.607)	−0.070 (0.598)
Japan	0.048 (0.763)	0.062 (0.686)	0.038 (0.809)	0.052 (0.734)	0.208 (0.216)	0.208 (0.216)	0.215 (0.193)	0.215 (0.193)
North America	0.031 (0.838)	0.056 (0.700)	0.033 (0.825)	0.059 (0.687)	0.108 (0.545)	0.109 (0.544)	0.119 (0.495)	0.120 (0.493)
Europe	0.392** (0.043)	0.405** (0.039)	0.397** (0.038)	0.409** (0.034)	0.439* (0.075)	0.439* (0.076)	0.429* (0.084)	0.429* (0.085)
Firm age (log)	−0.027 (0.709)	−0.014 (0.845)	−0.023 (0.756)	−0.010 (0.892)	−0.158* (0.065)	−0.158* (0.065)	−0.158* (0.065)	−0.158* (0.066)
Firm size (log of total fixed asset)	0.023 (0.493)	0.032 (0.330)	0.021 (0.525)	0.030 (0.367)	0.082** (0.020)	0.082** (0.022)	0.080** (0.025)	0.080** (0.027)
Share of export in turnover	0.002 (0.134)	0.002 (0.159)	0.002 (0.136)	0.002 (0.160)	−0.002 (0.387)	−0.002 (0.388)	−0.001 (0.395)	−0.001 (0.395)
Explorative innovation strategy	0.156*** (0.002)	0.140*** (0.005)	0.124** (0.030)	0.111** (0.047)	0.023 (0.790)	0.022 (0.798)	0.059 (0.458)	0.058 (0.471)
Exploitative innovation strategy	0.106* (0.055)	0.097* (0.071)	0.087 (0.146)	0.081 (0.168)	0.160** (0.016)	0.160** (0.016)	0.191*** (0.007)	0.190*** (0.007)
Explorative innovation strategy × Exploitative innovation strategy	−0.080 (0.238)	−0.090 (0.176)			−0.038 (0.691)	−0.038 (0.687)		
|Explorative innovation strategy − Exploitative innovation strategy|			−0.048 (0.443)	−0.040 (0.509)			0.099 (0.223)	0.099 (0.223)
R&D spending intensity		0.032** (0.029)		0.031** (0.038)		0.001 (0.939)		0.002 (0.919)
R^2	0.165	0.190	0.163	0.186	0.152	0.152	0.158	0.158
Adjusted R^2	0.113	0.135	0.111	0.131	0.099	0.095	0.106	0.101
Change in R^2		0.025**		0.023**		0.000		0.000

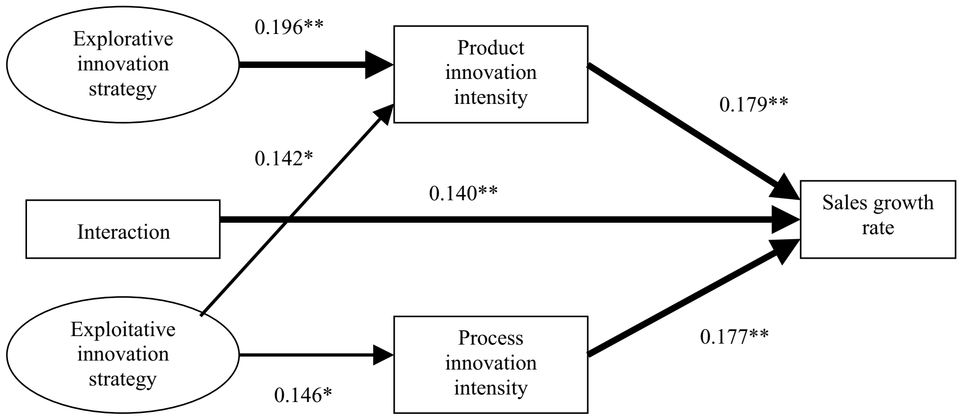
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$; two-tailed test; White-heteroskedasticity-robust estimate; p value in parenthesis; constant included.

Table 3 Regression for Sales Growth Rate

	Average sales growth rate							
	1	2	3	4	5	6	7	8
Location	−5.281 (0.159)	−4.272 (0.245)	−4.541 (0.230)	−4.309 (0.258)	−4.180 (0.273)	−5.053 (0.179)	−4.787 (0.206)	−4.806 (0.206)
High technology	8.581** (0.030)	6.080 (0.150)	6.033 (0.158)	5.719 (0.175)	5.934 (0.158)	8.327** (0.038)	8.114** (0.040)	8.269** (0.037)
Medium technology	−1.287 (0.717)	−1.238 (0.733)	−1.395 (0.706)	−1.189 (0.747)	−1.492 (0.683)	−1.354 (0.709)	−1.100 (0.762)	−1.453 (0.687)
Japan	−11.776*** (0.007)	−12.247*** (0.009)	−12.159*** (0.010)	−12.425*** (0.008)	−12.554*** (0.008)	−11.711*** (0.010)	−12.001*** (0.008)	−12.021*** (0.008)
North America	−0.855 (0.858)	−1.060 (0.825)	−0.885 (0.857)	−0.688 (0.886)	−1.245 (0.800)	−0.302 (0.951)	−0.161 (0.974)	−0.567 (0.908)
Europe	−2.561 (0.534)	−6.264 (0.166)	−6.384 (0.166)	−6.510 (0.163)	−6.212 (0.188)	−2.950 (0.483)	−3.035 (0.479)	−2.721 (0.525)
Firm age (log)	−2.054 (0.429)	−1.295 (0.618)	−1.309 (0.614)	−1.205 (0.635)	−1.239 (0.628)	−1.878 (0.465)	−1.752 (0.486)	−1.855 (0.465)
Firm size (log of total fixed asset)	0.416 (0.684)	−0.148 (0.884)	−0.141 (0.891)	−0.145 (0.885)	−0.124 (0.903)	0.358 (0.725)	0.340 (0.732)	0.392 (0.698)
Share of export in turnover	0.051 (0.251)	0.048 (0.281)	0.047 (0.308)	0.039 (0.405)	0.046 (0.320)	0.052 (0.255)	0.046 (0.313)	0.050 (0.275)
R&D spending intensity	−0.096 (0.770)	−0.317 (0.402)	−0.315 (0.413)	−0.362 (0.346)	−0.342 (0.376)	−0.130 (0.705)	−0.157 (0.648)	−0.158 (0.643)
Product innovation intensity (log)		4.244 (0.113)	4.280 (0.132)	4.727 (0.102)	4.163 (0.142)			
Process innovation intensity (log)		4.686** (0.025)	4.812** (0.021)	4.557** (0.030)	5.080** (0.015)			
Explorative innovation strategy			0.325 (0.823)	0.374 (0.806)	−0.943 (0.593)	1.091 (0.444)	1.188 (0.411)	−0.005 (0.997)
Exploitative innovation strategy			−0.824 (0.600)	−1.297 (0.417)	−1.870 (0.276)	0.367 (0.807)	−0.064 (0.966)	−0.516 (0.754)
Explorative innovation strategy × Exploitative innovation strategy				4.539** (0.035)			4.229** (0.030)	
|Explorative innovation strategy − Exploitative innovation strategy|					−3.026* (0.074)			−2.598 (0.123)
R^2	0.107	0.160	0.161	0.175	0.170	0.110	0.122	0.116
Adjusted R^2	0.061	0.108	0.099	0.110	0.104	0.055	0.063	0.057
Change in R^2		0.053***	0.001	0.014**	0.009*[a]		0.012**	0.006[b]

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$; two-tailed test; White-heteroskedasticity-robust estimate; p value in parenthesis; constant included.
[a] Compared to Model 3, [b] Compared to Model 6.

Figure 1 Standardized Parameter Estimates for Path Analysis—Fit as Moderating



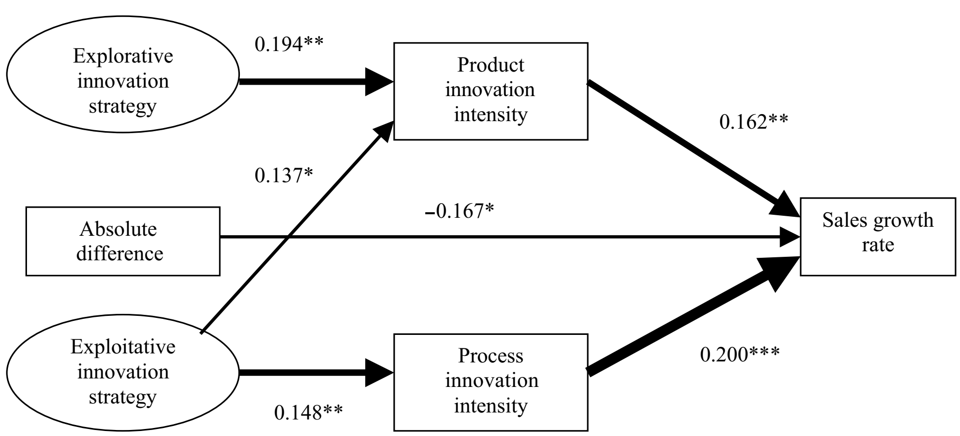
Notes. Chi-square = 146.887; d.f. = 107; $p = 0.006$; Normed chi-square = 1.373; GFI = 0.933; CFI = 0.952; NFI = 0.861; RMSEA = 0.046.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$; two-tailed test. This simplified model does not show control variables, error terms, or the indicator variables of the latent constructs. Two latent constructs, explorative innovation strategy and exploitative innovation strategy, are represented by ovals. Observed variables are represented by rectangles.

process innovation intensity appears to influence sales growth rate, not product innovation intensity. Japanese subsidiaries seem to under-perform when compared with firms of other nationalities. Firms in high-tech industries seem to achieve higher sales growth rates (Regression 1), but when firms' innovation intensities are accounted for, the impact of the high-tech dummy becomes insignificant (Regression 2). Regressions 4 and 5 test the ambidexterity Hypotheses 1a and 1b, respectively. Regression 4 shows that the interaction effect between the two innovation strategies on sales growth rate is positive and significant ($p = 0.035$), while Regression 5 shows that the absolute difference between the two strategies is negatively related to sales growth rate ($p = 0.074$). When the two intermediary variables of innovation performance are not included, significant results are still found for "fit as moderating" ($p = 0.030$, Regression 7) but not for "fit as matching" ($p = 0.123$, Regression 8). Overall, Hypotheses 1a and 1b are supported, although the support for Hypothesis 1b is weaker.

4.2. Path Analysis Results

Figures 1 and 2 provide the path analysis results of testing "fit as moderating" and "fit as matching," respectively. The path analysis results are similar to the earlier regression results, except that product innovation intensity shows a significant impact on sales growth rate in the path analysis. The goodness-of-fit statistics indicate acceptable model fit. Results for the control variables (not reported here) are similar to those of earlier regression analyses.

Figure 2 Standardized Parameter Estimates for Path Analysis—Fit as Matching



Notes. Chi-square = 141.599; d.f. = 107; $p = 0.014$; Normed chi-square = 1.323; GFI = 0.936; CFI = 0.961; NFI = 0.873; RMSEA = 0.043.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$; two-tailed test. This simplified model does not show control variables, error terms, or the indicator variables of the latent constructs. Two latent constructs, explorative innovation strategy and exploitative innovation strategy, are represented by ovals. Observed variables are represented by rectangles.

Table 4 ANOVA for Sales Growth Rate[a,b]

	N	Mean	S.D.	S.D./Mean
No-emphasis (1)	65	10.13	15.81	1.56
Exploitative (2)	35	9.96	14.75	1.48
Explorative (3)	47	8.59	21.15	2.46
Ambidextrous (4)	59	17.43	27.64	1.59

[a] (4) and (3) have higher scores on explorative strategy than (1) and (2) ($p = 0.000$). (4) and (2) have higher scores on exploitative strategy than (1) and (3) ($p = 0.000$). Same for Table 5.

[b] Test of Homogeneity of Variances: Levene statistic = 3.185 ($p = 0.025$); equal variances assumption is rejected.

4.3. ANOVA Analysis Results

To investigate the performance variation of different innovation strategies, we divided the sample into four groups based on the previously defined "median cut-off" criterion: the ambidextrous group, the explorative and exploitative groups (net of the ambidextrous firms), and a residual "no-emphasis" group consisting of the remaining firms that emphasize neither explorative nor exploitative innovation. The results in Table 4 show that the explorative group exhibits the highest standard deviation/mean sales growth rate ratio, followed by the ambidextrous group and no-emphasis group, with the exploitative group scoring the lowest ratio.

To obtain a formal test, we regressed the four standard deviation values against the four mean sales growth values weighted by group size ($R^2 = 0.67$) (Table 5). For the no-emphasis and exploitative groups, the actual standard deviation is below the lower bound of the 95% confidence interval, implying smaller variation relative to their mean values. For the explorative group, the actual standard deviation is above the upper bound of the 95% confidence interval, implying larger variation. The actual standard deviation of the ambidextrous group is within the 95% confidence interval, and very close to the predicted standard deviation, implying normal variation. Therefore, both Hypotheses 2 and 3 are supported, i.e., explorative firms exhibit higher intragroup performance variation than exploitative or ambidextrous firms. Among all control variables, we found that only the electronics sector dummy was significantly related to the innovation strategy groups at 0.05 significance level. After dropping the electronics firms in our sample and repeating the same procedure, we found the results were similar, i.e., without electronics firms, both Hypotheses 2 and 3 remain supported.

4.4. Sensitivity Analysis

We repeated the test of Hypothesis 1a using the median cut-off criterion for defining ambidexterity and found similar results. We performed further sensitivity analysis for the test of Hypothesis 1a using progressively more stringent cut-off criteria. Table 6 shows that when the criterion to be ambidextrous becomes more stringent, the relationship between ambidexterity and sales growth rate becomes less significant. When a firm is ambidextrous only if it scores in the upper quarter for both strategies (in this case, the firm would have to rate a majority of the eight objectives for undertaking innovation projects as "very important"), the relationship between ambidexterity and sales growth rate becomes insignificant ($p = 0.363$). Although this may be due to the small number of problems (only 26 firms meet this requirement), it seems to suggest that firms may run into organizational difficulties when pursuing both strategies equally aggressively, causing the positive interaction effect to disappear.

Regarding the weaker support for Hypothesis 1b, we suspect that very low levels of both strategies may not be ambidextrous (albeit balanced according to the second criterion of ambidexterity). For example, when we dropped cases scoring the lowest 15% of both strategies (excluding seven cases as a result), we found stronger results for Hypothesis 1b—$\beta = -3.841$ ($p = 0.064$) in Regression 5 and $\beta = -3.478$ ($p = 0.093$) in Regression 8, respectively, in Table 3. The path analysis results were also improved when we dropped these seven cases—$\beta = -0.214$ ($p = 0.044$) compared with $\beta = -0.167$ ($p = 0.073$) in Figure 2.

5. Discussion

This paper applies the exploration versus exploitation construct to develop a new typology of technological innovation strategies that captures the different logics of exploration and exploitation as applied to technological innovation activities. We formulate a path model with two intermediary variables to investigate the impacts of the two different innovation strategies and their joint effects on firm performance. We have tested and found

Table 5 Regression-Based S.D. Analysis

	Weight	Mean	S. D.	Predicted S.D.	Lower bound of 95% confidence interval	Upper bound of 95% confidence interval
No-emphasis	65	10.13	15.81	18.20	17.74	18.66
Exploitative	35	9.96	14.75	18.00	17.53	18.47
Explorative	47	8.59	21.15	16.37	15.81	16.93
Ambidextrous	59	17.43	27.64	26.88	26.12	27.65

Table 6 Comparison of Path Analysis Results for Different Grouping Methods

Path	Median cut-off grouping[a]	3/8 cut-off grouping[b]	1/4 cut-off grouping[c]
Explorative innovation strategy → product innovation intensity	0.193** (0.018)	0.180** (0.026)	0.180** (0.026)
Exploitative innovation strategy → process innovation intensity	0.150* (0.056)	0.146* (0.064)	0.149* (0.058)
Product innovation intensity → sales growth rate	0.170** (0.026)	0.185** (0.019)	0.175** (0.024)
Process innovation intensity → sales growth rate	0.177** (0.015)	0.179** (0.014)	0.182** (0.014)
Ambidextrous firms (dummy) → sales growth rate	0.269*** (0.008)	0.193** (0.049)	0.077 (0.363)
Exploitative innovation strategy → product innovation intensity	0.145* (0.056)	0.136* (0.074)	0.139* (0.070)
Explorative innovation strategy → sales growth rate	−0.126 (0.189)	−0.093 (0.308)	−0.053 (0.553)
Exploitative innovation strategy → sales growth rate	−0.184* (0.061)	−0.139 (0.139)	−0.078 (0.371)

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$; two-tailed test; p value in parenthesis. Results for control variables not shown.
[a] A firm was labeled as ambidextrous if it scored the upper half for both strategies (59 cases).
[b] A firm was labeled as ambidextrous if it scored the upper 3/8 for both strategies (42 cases).
[c] A firm was labeled as ambidextrous if it scored the upper quarter for both strategies (26 cases).

support for the two alternative interpretations of the ambidexterity hypothesis by showing that (1) the interaction between explorative and exploitative innovation strategies is positively related to sales growth rate—"fit as moderating;" and (2) the relative imbalance (absolute difference) between explorative and exploitative innovation strategies is negatively related to sales growth rate—"fit as matching."

This paper makes two contributions to the organization learning and innovation management literature. First, this paper provides new empirical evidence of the positive effect of ambidexterity in the context of technological innovation. While the beneficial effect of balancing exploration and exploitation has been hypothesized in the literature, there have been few studies providing direct empirical evidence. This paper takes into account two somewhat different conceptual interpretations of ambidexterity and has found empirical support for both interpretations. Thus, although our study did not explicitly address the issue of what organizational design principles are appropriate for ambidexterity, our findings lend support to the case for pursuing ambidextrous organization designs. While our findings are limited to the specific context of technological innovation, we suggest that the methodological approach of this paper may be adapted to test the ambidexterity hypothesis in other management research domains as well.

Second, this paper adds to our understanding of innovation management by extending the exploration versus exploitation construct to characterize how firms prioritize their resources for technological innovation. Just as the exploration versus exploitation construct has generated significant insights in other domains of management research, we believe that our operationalization of technological innovation strategies grounded on the exploration versus exploitation distinction may have a number of important implications for innovation management as well.

One obvious managerial implication is the need for senior managers to become more explicitly aware of the need to allocate resources between explorative versus exploitative innovation. While existing innovation management practices have been largely founded on established typologies with corresponding resource allocation and performance benchmark metrics (e.g., percentage allocation of R&D expenditure into basic versus applied research or product versus process innovation), senior managers may need to consider introducing new metrics to prioritize resource allocation and benchmark performance along the explorative versus exploitative innovation dimensions. The proposed eight-item measure in this paper could be a useful starting point towards the development of such new metrics.

Another implication from this paper is the need for senior managers to manage explorative and exploitative innovation simultaneously in "a steady-state perspective," beside "a life cycle perspective" (Winter and Szulanski 2001, p. 731). Burgelman (2002, p. 354) identified two organizational adaptation patterns: (1) a punctuated equilibrium pattern involving a series of discrete periods, each focused on exploration or exploitation, and (2) a more continuous evolutionary process of balancing exploration and exploitation. Our findings suggest the need for managers to manage the tension between exploration and exploitation on a *continuous* basis, e.g., through the development of "synthesizing capability" to create competitive advantage out of conflicting forces as advocated by Nonaka and Toyama (2002), the adoption of ambidextrous organizational design principles as advocated by Tushman and O'Reilly (1996), or the pursuit of a "semi-structures" design to compete "on the edge of chaos" as suggested by Brown and Eisenhardt (1998).

Besides providing empirical evidence on the potential benefits of ambidexterity, our findings also suggest that there may be limits to ambidexterity, possibly due to the fact that the organizational tension inherent between exploration and exploitation may become unmanageable when both are pushed to extreme limits. We also find that very low levels of both exploration and exploitation may not contribute to superior firm performance, and such firms therefore should not be regarded as ambidextrous. These findings indicate the complexity and delicacy of managing the balance between exploration and exploitation.

This study is subject to a number of limitations. First, the eight Likert-scale measures we used to construct innovation strategies may have captured only limited dimensions of the exploration versus exploitation distinction. Future research needs to examine the usefulness of additional measures.

Second, the effective balance between exploration and exploitation may vary significantly with market and technological dynamism. Due to sample size limitations, we were only able to use rather aggregated industry dummies and technology classes as control variables. Future research should assemble a larger sample to provide more fine-grained controls for market and technological environmental factors, and to examine how the optimal balance between exploration and exploitation may be contingent on such environmental factors.

Third, due to data limitations, we could not investigate the impact of explorative and exploitative innovation on long-term performance (10 years or more), which will be necessary if we want to examine highly technology-intensive firms in more advanced economies. To address this issue, future research needs to assemble longitudinal data over a sufficiently long period.

Acknowledgments

The authors would like to thank the two anonymous reviewers, Marshall Scott Poole, Kathleen Eisenhardt, Robert Hoskisson, Kwanghui Lim, and Sankaran Venkataraman for their helpful comments that improved this paper. This study was supported by the Entrepreneurship Centre of the National University of Singapore and the Economic Development Board (EDB) of Singapore. All errors and omissions are, of course, the authors'.

Endnotes

[1]The following simple mathematical representation may be useful to clarify how the ambidexterity hypothesis can be tested. Assume that a firm allocates α and $1-\alpha$ units of resources for exploitation (X) and exploration (Y), respectively, with X having a performance distribution of $N(\mu_1, \sigma_1^2)$, and Y a performance distribution of $N(\mu_2, \sigma_2^2)$, where $\mu_1 < \mu_2$ and $\sigma_1^2 < \sigma_2^2$ (if $\mu_1 > \mu_2$, firms are likely to specialize in exploitation. However, under severe selection conditions, a firm can only survive with a draw from the far right-hand tail of the performance distribution, i.e., the mean is not relevant anymore and only luck matters). If X and Y are independent, i.e., there are no synergistic effects between exploration and exploitation, the firm as a whole will have a performance distribution $N(\mu, \sigma^2)$, where $\mu = \alpha\mu_1 + (1-\alpha)\mu_2$, and $\sigma^2 = \alpha^2\sigma_1^2 + (1-\alpha)^2\sigma_2^2$. If synergistic benefits are larger than the organizational coordination and communication costs involved in balancing the conflicting goals of exploration and exploitation, $\mu > \alpha\mu_1 + (1-\alpha)\mu_2$ and/or $\sigma^2 < \alpha^2\sigma_1^2 + (1-\alpha)^2\sigma_2^2$, i.e., the firm may achieve either higher average return (at the same or lower variance) or lower variance (at the same or higher average return), by pursuing exploration and exploitation simultaneously. The extent of "imbalance" between exploration and exploitation can be measured by $|(1-\alpha)-\alpha|$, while the "interaction" between exploration and exploitation can be measured by $(1-\alpha)*\alpha$. The postulated synergistic effect between exploration and exploitation may be positively related to $(1-\alpha)*\alpha$ and/or negatively related to $|(1-\alpha)-\alpha|$.

[2]The second measure was not used to test Hypothesis 3 because very low levels of both strategies may not be ambidextrous, but it is very difficult to define how low is "very low." See §4.4 for a further discussion.

[3]Table of means, standard deviations, and correlations is not reported here due to page limitation but is available on request.

References

Abernathy, W. J., J. M. Utterback. 1978. Patterns of industrial innovation. *Tech. Rev.* **80** 40–47.

Ancona, D. G., P. S. Goodman, B. S. Lawrence, M. L. Tushman. 2001. Time: A new research lens. *Acad. Management Rev.* **26** 645–663.

Argyris, C., D. A. Schön. 1978. *Organizational Learning: A Theory of Action Perspective*. Addison-Wesley, Reading, MA.

Bierly, P., A. Chakrabarti. 1996. Generic knowledge strategies in the U.S. pharmaceutical industry. *Strategic Management J.* **17**(Winter) 123–137.

Bierly, P., P. S. Daly. 2001. Exploration and exploitation in small manufacturing firms. *61th Annual Meeting Acad. Management*, Washington, D.C. (August 3–8).

Brown, S. L., K. M. Eisenhardt. 1998. *Competing on the Edge: Strategy as Structured Chaos*. Harvard Business School Press, Boston, MA.

Burgelman, R. A. 1991. Intraorganizational ecology of strategy making and organizational adaptation: Theory and field research. *Organ. Sci.* **2** 239–262.

Burgelman, R. A. 2002. Strategy as vector and the inertia of coevolutionary lock-in. *Admin. Sci. Quart.* **47** 325–357.

Burns, T., G. M. Stalker. 1961. *The Management of Innovation*. Tavistock, London, U.K.

Carroll, G. R., M. T. Hannan. 2000. *The Demography of Corporations and Industries*. Princeton University Press, Princeton, NJ.

Cheng, Y. T., A. H. Van de Ven. 1996. Learning the innovation journey: Order out of chaos? *Organ. Sci.* **7** 593–614.

Corporate Handbook. 2000, 1999, 1998, 1997. A definitive guide to listed companies on KLSE main board. CEIC Holdings Ltd., Singapore.

Corporate Handbook. 2000, 1999, 1998, 1997. A definitive guide to listed companies on KLSE second board. CEIC Holdings Ltd., Singapore.

Cyert, R. M., J. G. March. 1963. *A Behavioral Theory of the Firm*. Prentice Hall, Englewood Cliffs, NJ.

D'Aveni, R. 1994. *Hypercompetition: Managing the Dynamics of Strategic Maneuvering*. Free Press, New York.

Eisenhardt, K. M., J. A. Martin. 2000. Dynamic capabilities: What are they? *Strategic Management J.* **21** 1105–1121.

Financial Highlights of Companies on the Stock Exchange of Singapore. 1995–1999. CBRD, National University of Singapore, Singapore.

Ghemawat, P., J. E. Ricart i Costa. 1993. The organizational tension between static and dynamic efficiency. *Strategic Management J.* **14**(Winter) 59–73.

Hannan, M. T., J. H. Freeman. 1984. Structural inertia and organizational change. *Amer. Sociological Rev.* **49** 149–164.

Heckman, J. J. 1979. Sample selection bias as a specification error. *Econometrica* **47** 153–162.

Henderson, A. D. 1999. Firm strategy and age dependence: A contingent view of the liabilities of newness, adolescence, and obsolescence. *Admin. Sci. Quart.* **44** 281–314.

Holmqvist, M. 2004. Experiential learning processes of exploration and exploitation within and between organizations: An empirical study of product development. *Organ. Sci.* **15** 70–81.

Katila, R., G. Ahuja. 2002. Something old, something new: A longitudinal study of search behavior and new product introduction. *Acad. Management J.* **45** 1183–1194.

Knott, A. M. 2002. Exploration and exploitation as complements. N. Bontis, C. W. Choo, eds. *The Strategic Management of Intellectual Capital and Organizational Knowledge: A Collection of Readings*. Oxford University Press, New York, 339–358.

Leonard-Barton, D. 1995. *Wellsprings of Knowledge*. Harvard Business School Press, Boston, MA.

Levinthal, D. A. 1997. Adaptation on rugged landscapes. *Management Sci.* **43** 934–950.

Levinthal, D. A., J. G. March. 1993. The myopia of learning. *Strategic Management J.* **14** 95–112.

Levitt, B., J. G. March. 1988. Organizational learning. *Annual Rev. Sociology* **14** 319–340.

Lewin, A. Y., C. P. Long, T. N. Carroll. 1999. The coevolution of new organizational forms. *Organ. Sci.* **10** 535–550.

March, J. G. 1991. Exploration and exploitation in organizational learning. *Organ. Sci.* **2** 71–87.

McGrath, R. G. 2001. Exploratory learning, innovative capacity, and managerial oversight. *Acad. Management J.* **44** 118–131.

Mitchell, W., K. Singh. 1993. Death of the lethargic: Effects of expansion into new technical subfields on performance in a firm's base business. *Organ. Sci.* **4** 152–180.

Nonaka, I., R. Toyama. 2002. A firm as a dialectical being: Towards a dynamic theory of a firm. *Indust. Corporate Change* **11** 995–1009.

OECD. 1996. *Science, Technology and Industry Outlook 1996*. OCED, Paris, France.

OECD-EUROSTAT. 1997. *Proposed Guidelines for Collecting and Interpreting Technological Innovation Data, Oslo Manual*, 2nd ed. OECD, Paris, France.

Peter, T. 1990. Get innovative or get dead. *California Management Rev.* **33** 9–26.

Poole, M. S., A. H. Van de Ven. 1989. Towards a metatheory of innovation process. *49th Annual Meeting Acad. Management*, Washington, D.C. (August 13–16).

Radner, R. 1975. A behavioral model of cost reduction. *Bell J. Econom.* **6** 196–215.

Rosenkopf, L., A. Nerkar. 2001. Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management J.* **22** 287–306.

Singapore 1000. 1997, 1998, 1999, 2000. Report: Previous year performance. DP Information Network Pte. Ltd., Singapore.

Singapore SME 500. 1997, 1998, 1999, 2000. Report: Previous year performance. DP Information Network Pte. Ltd., Singapore.

Skinner, W. 1992. The shareholder's delight: Companies that achieve competitive advantage from process innovation. *Internat. J. Tech. Management* **7** 41–48.

Sutton, J. 1997. Gibrat's legacy. *J. Econom. Literature* **35** 40–59.

Timmons, J. 1999. *New Venture Creation: Entrepreneurship for the 21st Century*, 5th ed. Irwin/McGraw-Hill, Boston, MA.

Tushman, M. L., C. O'Reilly. 1996. Ambidextrous organizations: Managing evolutionary and revolutionary change. *California Management Rev.* **38** 8–30.

Van den Bosch, F. A. J., H. W. Volberda, M. de Boer. 1999. Coevolution of firm absorptive capacity and knowledge environment: Organizational forms and combinative capabilities. *Organ. Sci.* **10** 551–568.

Venkatraman, N. 1989. The concept of fit in strategy research: Toward verbal and statistical correspondence. *Acad. Management Rev.* **14** 423–444.

Winter, S. G., G. Szulanski. 2001. Replication as strategy. *Organ. Sci.* **12** 730–743.

Wong, P. K. 2002. Globalization of American, European and Japanese production networks and the growth of Singapore's electronics industry. *Internat. J. Tech. Management* **24**(7/8) 843–869.

Zahra, S. A., S. R. Das. 1993. Innovation strategy and financial performance in manufacturing companies: An empirical analysis. *Production Oper. Management* **2** 15–37.

Zairi, M. 1992. *Competitive Benchmarking: An Executive Guide*. Technical Communications (Publishing) Ltd., Letchworth, U.K.