ENTREPRENEURIAL ORIENTATION-AS-EXPERIMENTATION AND FIRM PERFORMANCE: THE ENABLING ROLE OF ABSORPTIVE CAPACITY

PANKAJ C. PATEL,1 MARKO KOHTAMÄKI,2,3* VINIT PARIDA,3 and JOAKIM WINCENT3,4
1 Department of Management, Ball State University, Muncie, Indiana, U.S.A.
2 Department of Management, University of Vaasa, Vaasa, Finland
3 Entrepreneurship and Innovation, Luleå University of Technology, Luleå, Sweden
4 Hanken School of Economics, Helsinki, Finland

According to the perspective of entrepreneurial orientation-as-experimentation, entrepreneurial orientation (EO) increases variability in innovation outcomes. Although increased variability in the innovation portfolio could increase performance, it could also lead to a decline in performance. We propose that absorptive capacity plays a role in both increasing and managing variations in innovation outcomes. Potential absorptive capacity enhances the effects of EO on variability in innovation outcomes, whereas realized absorptive capacity helps transform and exploit variability in innovation outcomes to enhance firm performance. Copyright © 2014 John Wiley & Sons, Ltd.

INTRODUCTION

Countering “the notion that it pays to pursue an EO,” Wiklund and Shepherd (2011: 295) questioned whether entrepreneurial orientation (EO) is a normative strategic posture that increases competitiveness. They also proposed that EO-as-experimentation explained both the bright and dark sides of EO. Entrepreneurial efforts such as taking risks, proactively developing radically innovative products, or pioneering nascent markets are bound to have a higher probability of both successes and failures, thereby leading to variable outcomes from innovation efforts.1 Because

“innovations are characterized by prior uncertainty and posterior variance in performance,” firms can expect failures if they want to innovate successfully (Taylor and Greve, 2006: 726). EO entails exploratory learning; therefore, firms must both

1 An invention refers to a knowledge combination that could be commercialized (e.g., a patent), whereas innovative outcome

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create and manage variability to improve performance. Yet, few studies have empirically examined the EO-as-experimentation view to provide critical insights regarding underlying conditions that may explain why certain EO firms benefit more from EO-as-experimentation compared to others.

We propose that absorptive capacity (ACAP) can help manage the double-edged nature of variability in innovation outcomes that result when EO enables the firm to create the requisite variety and manage this variety to increase performance (Teece, 2007). Specifically, potential absorptive capacity (PACAP), which entails acquiring and assimilating knowledge, enables firms to experiment by increasing variability in innovation outcomes. Realized absorptive capacity (RACAP), which entails transforming and exploiting knowledge, helps firms effectively exploit opportunities resulting from increased variability. In the present study, we extend prior research by explaining the role of ACAP in managing the double-edged nature of EO-as-experimentation.

THEORETICAL DEVELOPMENT AND HYPOTHESES

To corroborate the EO-as-advantage view, Rauch and colleagues (2009) conducted a meta-analysis of 53 samples representing 14,259 firms. They found that, across different industries, firms, and cultural contexts, the correlation between EO and performance was significant ($r = 0.24$). However, from the EO-as-experimentation view, pursuing three dimensions of EO—proactiveness, risk taking, and innovativeness—could also increase variations in performance and possibly lead to failure. Proactiveness requires firms to take long-term gambles on expressed and latent market needs that may lead to highly successful or unsuccessful outcomes (Slater and Narver, 1998). Innovativeness requires broader searches to develop products and processes that differ dramatically from past products that in turn offer the “potential for extreme profits or extreme losses” (Singh and Fleming, 2010; Taylor and Greve, 2006: 723). The third dimension of entrepreneurial orientation, risk taking, requires firms to undertake uncertain and ambiguous knowledge recombinations, which in turn increases the variance of the firm’s return on investment (Hill and Snell, 1989). This, too, leads to increased variety in innovation outcomes (Lassen, Gertsen, and Riis, 2006).

Based on evolutionary economics, the routines of variation, selection, and retention are necessary to derive value from inventions (Nelson and Winter, 1982). To innovate successfully, firms must accept both the potential downside and upside of innovations. Explaining a firm’s inability to continuously find value-creating innovations, Coad and Rao (2008: 646) stated that innovation is “more uncertain than playing a lottery, because it is a ‘game of chance’ in which neither the probability of winning nor the prize can be known for sure in advance.” The fact that the potential gains of innovation are contingent on variance in innovation outcomes is also evident in the context of venture capital (VC) investments, in which successes are rare and failures are common (e.g., Tian and Wang, 2014). The inability to consistently find winners and super-winners is also evident in the high failure rates of innovation within corporations (Van der Panne, Van Beers, and Kleinnecht, 2003). This indicates that learning curve advantages are less likely to be realized in exploratory, trial-and-error innovation efforts (Cheng and Van de Ven, 1996). Thus, continuing from evolutionary economics, capabilities that help increase and manage variability in the outcomes of the innovation process could be central to increasing mean returns from extreme innovation outcomes.

Drawing on the need to manage variation—selection—retention in developing innovation competencies (Nelson and Winter, 1982), the concept of absorptive capacity was originally presented by Cohen and Levinthal (1990) and was later conceptualized by Zahra and George (2002). Absorptive capacity is a cumulative construct, wherein PACAP provides the requisite knowledge variety to increase knowledge recombinations. Transformation and exploitation related to RACAP help firms

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2 Our testing approach uses variability in the forward citations of patents in a firm’s patent portfolio as a proxy for variability in innovation outcomes (cf. footnote 1). Patents are defined as a form of invention and non-self forward citations proxy for innovation outcomes (Hagedoorn and Cloodt, 2003; Hall, Jaffe, and Trajtenberg, 2005). Patents receiving zero-to-low forward citations are perceived as having a lower innovation value (but are not considered failures), and patents receiving higher forward citations have a higher mean innovation value. A patent portfolio with higher variability in forward citations reflects variance in innovation outcomes. Because EO is a firm-level strategic orientation, variability in innovation outcomes, or variance of forward citations in a firm’s patent portfolio, represents the successes and failures of firm innovation activities. A detailed description of the measure is included in the Methodology and Data section.
manage variation more effectively by selectively combining divergent knowledge combinations with their existing resource base. Taken together, PACAP drives experimentation and RACAP provides the structure to manage that experimentation, which leads toward higher firm performance.

Potential absorptive capacity

PACAP acts as a kaleidoscope to provide managers with new patterns for resource and capability combinations by connecting and integrating external knowledge with internal knowledge to create unexpected and unforeseen knowledge combinations (Kanter, 1988). PACAP promotes variation in innovation outcomes (Tsai, 2001) by helping firms acquire external knowledge from customers, competitors, and suppliers (Ahuja and Katila, 2001) and assimilate acquired knowledge to facilitate innovations (Laursen and Salter, 2006). EO, as an organization-wide capability, increases the firm’s willingness to engage in search behavior, and PACAP, as a boundary-spanning knowledge absorption capability, helps improve search outcomes.

Higher levels of EO combined with PACAP facilitate efforts toward combining diverse knowledge components. In exploring the value of innovation derived from teams, researchers have found that greater cognitive diversity within a team (compared to lower cognitive diversity among lone inventors) increases variance in innovation outcomes (cf. Girotra, Terwiesch, and Ulrich, 2007; Taylor and Greve, 2006). Similarly, PACAP increases diversity in knowledge components to increase recombinant uncertainty or uncertainty in ex ante identification of value-creating combinations of knowledge components (Fleming, 2001; Sorenson and Fleming, 2004). Firms cannot consistently leverage EO and PACAP to identify only value-creating innovations. Instead, they must accept the inevitable outcome of recombinant uncertainty; that is, they must accept greater variation in innovation outcomes (Fleming, 2001). Knowledge recombination efforts under higher EO and PACAP are less likely to be based on routinized learning curves and more likely to be based on nonroutinized trial-and-error learning in volatile and ambiguous knowledge bases (Cheng and Van de Ven, 1996; Thomke, Von Hippel, and Franke, 1998). Such learning, however, may not help firms avoid future mistakes (Huber, 1991; cf. Covin, Green, and Slevin, 2006).

Singh and Fleming (2010: 41) posited “that a greater probability of breakthroughs comes at the cost of a greater probability of failures.” The ability to acquire and synthesize external knowledge and assimilate it within the organization is critical for proactive organizations seeking extraordinary and new solutions to address customers’ latent needs (Hurley and Hult, 1998; Titus, Covin, and Slevin, 2011). PACAP feeds proactive knowledge-creation processes to increase the variety of innovation possibilities (Liao, Welsch, and Stoica, 2003; Zahra and George, 2002). For the innovativeness dimension of EO, PACAP increases variability in innovation outcomes (Fosfuri and Tribó, 2008) by facilitating knowledge exploration (Smith, Collins, and Clark, 2005), expanding knowledge bases (Minbaeva et al., 2003), and increasing inventive capacity (Argote, McEvily, and Reagans, 2003). To enhance the risk-taking dimension of EO, high PACAP provides access to distant technological domains. Specifically, in pursuing divergent knowledge combinations, the availability of diverse information lowers the perception (Vlek and Stallen, 1980) and the probability of losses (Sokolowska and Pohorille, 2000) and increases the perception of controllability (Vlek and Stallen, 1980). Such perceptions could lead to either breakthrough innovations or detrimental failures. This suggests that PACAP reinforces EO efforts to strive for a broad range of innovative outcome possibilities, with the likelihood of realizing both breakthroughs and failures.

Overall, increasing EO and higher PACAP provides an infrastructure for acquiring and assimilating external knowledge to increase recombinant opportunities in the technological search. Knowledge recombination efforts at higher levels of PACAP and EO allow firms to more fully explore the peripheries of innovation possibilities (Simonton, 1999). To this background, we make the following prediction:

**Hypothesis 1:** With an increasing EO, at higher levels of potential absorptive capacity (PACAP), the variability in innovation outcomes is greater.

Realized absorptive capacity

Whereas PACAP increases variability in innovation outcomes under increasing EO, RACAP provides the selection and retention routines (Nelson and Winter, 1982) needed to manage
variability. To increase firm performance under greater recombinant uncertainty (Fleming, 2001), firms must have the capabilities to transform new knowledge and combine it with existing resources and competencies. The transformation component of RACAP allows firms to renew their interpretation and comprehension of commercialization possibilities and allows for synergy, recodification, and bisociation of knowledge recombinations with existing core competencies (Zahra and George, 2002). The exploitation component of RACAP allows firms to apply novel resource configurations to new products and services. Benefits from increasing variation in innovation outcomes could be realized under higher RACAP, because it could limit familiarity traps by introducing knowledge recombinations from distant technical domains, avoid maturity traps by challenging reliable and predictable knowledge-conversion processes, and minimize propinquity traps by limiting the disposition to exploit known knowledge domains (Ahuja and Lampert, 2001).

Exploitative learning related to RACAP enables firms to manage and exploit increasing knowledge diversity (Camisón and Forés, 2010). Through the transformation and exploitation components of RACAP, firms develop selection routines to identify and commercialize viable innovations from a broad range of potential innovation alternatives (Mueller et al., 2012). Because transformation requires firms to select knowledge recombinations that readily transfer to existing resources and capabilities, RACAP improves a firm’s ability to abandon less valuable initiatives and capitalize on innovation opportunities that are potentially more successful (cf. Foss, Lyngsie, and Zahra, 2013).

As high EO firms proactively introduce innovations into markets, realized absorptive capacity enables trials, internal learning, and rapid adjustments (Sapienza et al., 2006). Zahra and George (2002: 778) noted that the transformation component of RACAP enables firms to develop new perceptual schema and change existing innovation routines. This view highlights the importance of effective knowledge transfer (Zhao and Anand, 2009) and resource flexibility to meet market needs through rapid adjustments (Meyers, Sivakumar, and Nakata, 1999). Thus, RACAP helps firms manage variation in innovation outcomes by increasing the likelihood of exploiting potentially valuable innovations and leading to improved firm performance.

This discussion leads us to posit our second hypothesis:

Hypothesis 2: With increasing variability in innovation outcomes, higher levels of realized absorptive capacity lead to higher mean firm performance.

METHODOLOGY AND DATA

Our analysis is based on combining three data sources from firms in the high-technology industry: (1) a two-wave survey (EO and PACAP from a 2007 survey and RACAP from a 2009 survey), (2) patent data (variability in forward citations of patents approved and/or filed between 2007 and 2009), and (3) sales growth from 2010 to 2012 based on archival data. We focused on the high-technology industry, because it tends to be growth oriented, active in reporting patents, and possesses high levels of EO and ACAP.

Survey Wave 1

For the first wave of the survey, we identified 3,737 firms, listed in the 2007 AffärsData directory, that were 10 years or younger, had between 10 and 50 employees, and operated in computer products (SNI 62010) or computer systems (SNI 62020). To balance the survey cost and sample size required for a statistical power of 0.80, a cover letter and the survey were mailed in mid-2007 to a random sample of 1,471 firms. Seventy-four surveys were returned due to a wrong address, and 47 firms indicated that they had a policy of not responding to surveys. We ultimately received 372 responses, of which 51 responses were incomplete, and 7 were from respondents within the same company. The final sample consisted of 314 responses. We compared respondents to nonrespondents on the dimensions of firm age, number of employees, log of sales, and natural log of net profit and found no significant differences.

Survey Wave 2

In March 2009, the 314 firms from survey Wave 1 were contacted again for a follow-up survey. We received responses from 201 firms for a retention rate of 64.04 percent (overall response rate of 13.66% [201/1,471]). There were no significant
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differences in firm age, number of employees, log of sales, and natural log of net profit among the retained and the non-retained firms. Using Google Patents, we identified patents approved for or filed by the 201 firms between 2007 and 2009. We identified patents for 171 firms and dropped the remaining 30 firms. Sweden is one of the few countries in which private firms are required to report financial performance data certified by a chartered accountant and is available to the public. We dropped 24 firms that did not have complete financial performance information in AffärsData. Because information on the acquisition of small firms is difficult to triangulate from news releases, we could not differentiate between survival and acquisitions for these 24 firms. Our final sample, therefore, consisted of 147 small firms representing 663 firm year observations.

**Dependent variable: sales growth**

Drawing on organizational theory, if firms effectively manage variation through EO-as-experimentation, then such firms would realize increased growth over time (Burgelman, 1991). Indeed, EO is a growth orientation (Lumpkin and Dess, 1996), and the effectiveness of EO is “appropriately measured using criteria that reflect a firm’s success at translating entrepreneurial opportunities into growth trajectories” (Covin et al., 2006: 58). We therefore used sales growth as the outcome variable—the compounded sales growth rate from 2010 to 2012 as \( \left( \frac{\text{venture sales in 2012}}{\text{venture sales in 2010}} \right)^{\frac{1}{3}} \). The median industry (at the six-digit SNI code level) compounded sales growth rate from 2010 to 2012 was subtracted from the firm’s compounded sales growth rate.

**Independent and moderator variables: EO, PACAP, and RACAP**

EO was measured in the 2007 survey Wave 1 using modified scales from Covin and Slevin’s (1989) and Lumpkin and Dess’s (2001) scale. We used a modified version of the ACAP scale by Jansen, Van den Bosch, and Volberda (2005). PACAP was measured in the 2007 survey Wave 1, and RACAP was measured in the 2009 survey Wave 2. The individual scale items, item loadings, and Cronbach’s alpha for the independent and moderating variables are listed in the online supporting information Table S1.

**Mediator variable: variation in innovation outcomes**

We used variability in the forward citations of the patents in a firm’s patent portfolio as a proxy for variation in innovation outcomes. The number of forward citations a patent receives represents its inventive importance (Hagedoorn and Cloodt, 2003; Jaffe, Trajtenberg, and Henderson, 1993) and is strongly related to product launches and innovation performance (Hagedoorn and Cloodt, 2003; Harhoff, Scherer, and Vopel, 2003; Trajtenberg, 1990). We operationalized this in two steps. First, we identified all patents that were approved for or filed by the venture during the 2007 and 2009 period. Next, we identified forward citations of all approved or filed patents (that were eventually granted) until 2013. Because patent approval and visibility are affected by lead times at the patent office, the forward citations from 2007 to 2013 of approved or filed patents during 2007 and 2009 is representative of variability of commercialization value of the generated knowledge during the period 2007–2009.

Second, because patent citation propensity varies across industry classes, we adjusted for differences in forward patent citation propensity across technology classes. We drew on a fixed effects approach based on the interaction between the primary technology class of the patent and the year of patent approval (Hall et al., 2005). We identified all patents available in Google Patents for each technology class in each year from 2007 to 2009. Next, we averaged the forward citations for the patents approved or filed during this period in each technology class in each year. We subtracted the average forward citations of all patents in a given technology class year from the total forward citations for a patent approved or filed in the same technology class year for the venture. For example, if a patent was approved or filed for a venture in 2008 in technology class 381 (electrical audio signal processing systems and devices) and received six forward citations until 2013, we subtracted, say, the four average forward citations until 2013 for all patents approved or filed in class 381 in year 2008. This step was repeated for each approved or filed patent in a firm’s patent portfolio from 2007 to 2009. The technology class year adjusted forward citation values for each patent were used to calculate the standard deviation of the forward citations for all firm patents.
Control variables

The first five control variables are based on mean values of measurements between 2007 and 2012. To control for the liabilities of newness and smallness, we included firm age, or years since founding, and firm size, or natural log of assets. Because debt curbs innovation and risk taking, we included debt ratio. Because more-efficient firms are less likely to engage in innovation, we included labor productivity (log sales divided by log of number of employees). Higher R&D intensity (ratio of log of R&D expenditures to log of sales) leads to increased experimentation and thus proxies for the firm’s innovation capabilities. To control for past performance, we used compounded sales growth between 2006 and 2009. Finally, to control for industry conditions, we included an industry dummy (reference category SNI 62020). To control for self-selection bias because we dropped 30 firms without patents and 24 firms that may have failed or been acquired, we controlled for two inverse Mill’s ratios based on Heckman’s self-selection approach. In first-stage probits for estimating the two inverse Mill’s ratios, we used year of founding, the three-year (2005–2007) mean of sales and operating profit, the average number of employees, and an industry dummy (reference category SNI 62020).

Although the mediator and outcome measures were drawn from archival sources, and EO, PACAP, and RACAP were measured at different points in time, the likelihood of common method bias is low but cannot be ruled out. Harman’s one-factor analysis (eight factors explained 88.72% of variance, and the first factor explained 22.09% of variance) and including the method factor did not improve model fit (Podsakoff et al., 2003). Next, to ensure consistency in measurement, all measures were included in both waves of the survey. In 63 firms, different respondents completed the survey in each wave. Based on differences in paired t-tests between Wave 1 and Wave 2, the ratings of scale items were not statistically different between the 2007 and 2009 waves in these 63 firms (see online supporting information Table S2). Furthermore, measures of interrater agreement ICC(1) was within acceptable range.

Analytical approach

We used structural equation modeling to test a system of simultaneous equations of constructs. If measurement errors in constructs were likely to be higher, then the scale items are loaded on the constructs, and the structural model and measurement model are estimated simultaneously. In the current framework, the scales were well established; therefore, we used the path analysis model to test the structural model and the mean values of scale items for each construct. Because using residual covariance matrix as an input into the main analysis leads to more conservative estimates (cf. Bollen et al., 2010; Haagen and Vittadini, 1991), we derived a residual covariance matrix by using the control variables to predict covariances among all remaining variables in the model. The path analysis model was tested using latent moderated structural equation modeling (LMS) in MPlus 6 (Klein and Moosbrugger, 2000), as LMS estimates are less biased and efficient for modeling interactions in small samples (Klein and Muthén, 2007; Schermelleh-Engel, Klein, and Moosbrugger, 1998).

Before drawing inferences from the path model, the fit of the proposed model against alternate models was established. The proposed model was significantly different from a saturated model ($p = 0.000$). The model fit for the proposed model ($\chi^2/df = 2.87; \text{CFI} = 0.953; \text{Tucker Lewis Index} [\text{TLI}] = 0.947; \text{RMSEA} = 0.057 \text{[90\% C.I.} = 0.043, 0.071])$ provided a better fit than the full mediation model ($\chi^2/df = 3.66; \text{CFI} = 0.883; \text{TLI} = 0.872; \text{RMSEA} = 0.122 \text{[90\% C.I.} = 0.104, 0.140])$. Next, neither adding a path between PACAP and sales growth in the current model ($\Delta \chi^2(\Delta df) = 0.96, p > 0.10$) nor adding a path between EO and RACAP in the current model ($\Delta \chi^2(\Delta df) = 1.11, p > 0.10$) improved the model fit. Therefore, we continued with the proposed model, which was more parsimonious. The variance inflation factors were below the recommended cutoff of 10 (Tabachnick and Fidell, 2007).

RESULTS

Table 1 presents the mean, standard deviation, and correlations among the variables. As preliminary support for Wiklund and Shepherd (2011), we found EO increases variance in innovation outcomes proxied as variability in forward citations (Figure 1: $\beta = 0.032, p < 0.05$). PACAP strengthens the effects of EO on variability in forward patent citations (Hypothesis 1: $\beta = 0.023, p < 0.05$).
With an increasing EO, higher levels of PACAP lead to higher variability in the forward patent citations (see supporting information Figure S1a). Next, Hypothesis 2 proposed that RACAP reinforces the effects of variability in forward patent citations on sales growth ($\beta = 0.042$, $p < 0.05$). With increasing variability in forward patent citations, we found higher levels of RACAP lead to increased sales growth more so than do low levels of RACAP (Figure S1b). EO did not have an inverted-U relationship with variability in forward patent citations ($\beta = -0.007$, $p > 0.10$), and variability in forward patent citations did not have an inverted-U relationship with sales growth ($\beta = -0.010$, $p > 0.10$).

Post hoc analyses

To confirm whether experimentation driven by high EO and high PACAP should lead to innovation failures and successes, we conducted three tests. First, if experimentation based on variation, selection, and retention leads to adaptation in the technological landscape, then firms with higher variability would also have higher mean innovation outcomes ($\text{EO} \times \text{PACAP} \rightarrow \text{mean forward citations}$ [$\beta = 0.179$, $p < 0.10$]).

Second, based on Reuer and Leiblein (2000), we split a firm’s patent portfolio into two groups: patents with forward citations above the mean forward citations in a firm’s patent portfolio (Group 1) and patents with forward citations at or below the mean forward citations in a firm’s patent portfolio (Group 2). The second-order root upper partial moment or upside variability in forward citations in Group 1 is represented by

$$\sqrt{\sum_{i, \text{forward citation}>\text{mean}} \frac{(\text{Forward citation}_i - \text{mean forward citations})^2}{N}}$$

where patent $i$ in a portfolio of $N$ patents in Group 1 has forward citations above the mean. A similar procedure was followed to calculate downside variability for patents with forward citations at or below the mean (Group 2). Confirming earlier arguments, interaction between the EO and PACAP increased downside ($\beta = 0.157$, $p < 0.05$) and upside variability ($\beta = 0.085$, $p < 0.10$) in forward citations. Thus, firms with higher EO and PACAP were unable to consistently pick out winners and super-winners. Finally, the inferences remained the same for the three-year mean operating profit (Hypothesis 1: $\beta = 0.027$, $p < 0.05$; Hypothesis 2: $\beta = 0.264$, $p < 0.05$) and were marginally supported

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We thank an anonymous reviewer for suggesting this additional test.
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A total of 147 firms followed from 2007 to 2012.

Unstandardized estimates reported:

* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$

for Hypothesis 1 but not supported for Hypothesis 2 for three-year mean return on sales (Hypothesis 1: $\beta = 0.019$, $p < 0.10$; Hypothesis 2: $\beta = 0.014$, $p = 0.17$).

CONCLUSION

A recent meta-analysis found small-to-medium positive effects of EO on performance (Rauch et al., 2009: 778), but also indicated that past studies did not consider the effects of EO on failure. Wiklund and Shepherd (2011) posited that, while EO could lead to firm failure, firms that manage experimentation realize higher performance than firms not engaging in experimentation. Our results synthesize these findings by focusing on how EO translates into higher performance under increasing variability. A study by Covin et al. (2006) found that higher proficiency in learning from strategic failures under increasing EO lowered sales growth. If a greater focus on learning from failures is not sufficient to increase performance, entrepreneurial firms could learn to manage the variability in innovation outcomes. Moreover, variability in forward citations represents a proximal outcome of experimentation efforts and helps illuminate the relationship between EO-as-experimentation on survival and EO-as-advantage on performance. We do not posit EO-as-experimentation as a liability but rather as a necessity to create the requisite variability in innovation outcomes. While PACAP increases variance in the innovative output by adding novel skills and knowledge to innovative, risky, and proactive pursuits under EO, RACAP is necessary to ultimately ensure financial returns by selecting from diverse knowledge recombinations and exploiting viable combinations through existing capabilities. Thus, we contribute to the strategic management and entrepreneurship literature by explaining the role of ACAP in effectively managing the double-edged nature of EO and innovation outcome variance. A recent study by Wiklund and Shepherd (2011) called for greater emphasis on identifying and employing such new dependent variables, because they facilitate a better understanding of the underlying mechanisms related to the underexplored EO-as-experimentation perspective. We hope the measure of variability in forward patent citations we use in the present study allows future researchers to complement the distal measures of outcome variance with more proximal outcomes of EO.

The present study has several limitations. First, we acknowledge the potentially lower validity of patent-related innovation measures. Second, although we control the covariance between PACAP and RACAP, process data could explain how interconnections between them could help
manage variability in innovation outcomes further. Third, compared to the high-technology industry where patent filings are common, in low- and medium-technology industries, we expect that the pace and degree of experimentation would differ. In conclusion, moving from the traditional perspective of EO-as-advantage and drawing on the EO-as-experimentation approach, we found that EO increases variability in innovation outcomes, which then increases sales growth. Absorptive capacity is central to managing the dual-edged nature of EO as a variance-increasing capability.

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REFERENCES


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**SUPPORTING INFORMATION**

Additional supporting information may be found in the online version of this article:

- Figure S1. Moderation effects. (a) The moderation effects of PACAP on variability in forward citations.
- Table S1. Measurement model.
- Table S2. Inter-rater agreement between the two waves of survey responses.