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AN EMPIRICAL EXAMINATION OF VACILLATION THEORY

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Research summary: *Since Nickerson and Zenger (2002) proposed how vacillation may lead to organizational ambidexterity, large-sample empirical tests of their theory have been missing. In this paper, we empirically examine the performance implications of vacillation. Building upon vacillation theory, we predict that the frequency and scale of vacillation will have inverted U-shaped relationships with firm performance. We test our hypotheses using patent-based measures of exploration and exploitation in the context of technological innovation and knowledge search.*

Managerial summary: *Firms often shift their focus on technological innovation and knowledge search from seeking new and novel knowledge (i.e., exploration) to extending and refining existing knowledge (i.e., exploitation) or* vice versa*. We examine how the frequency and scale of firms vacillating between exploration and exploitation may affect their performance. We find that both too infrequent or too frequent changes and a too small or too large scale of changes are not desirable.*

INTRODUCTION

Building upon the seminal work of March (1991) and Tushman and O'Reilly (1996), strategy and management scholars have paid considerable attention to the subject of organizational ambidexterity. Recently, an explanation of how organizational ambidexterity may manifest–known as vacillation between exploration and exploitation–has been discussed in a few theoretical studies (Boumgarden, Nickerson, and Zenger, 2012; Gulati and Puranam, 2009; Nickerson and Zenger, 2002). Vacillation theory suggests that vacillation between discrete formal organizational structures will temporarily create an ambidextrous informal organization with both characteristics of exploration and exploitation.

Despite substantial progress in our understanding of organizational ambidexterity, only a few qualitative studies but no large-sample statistical studies on the vacillation hypothesis have been conducted (Adler, Goldoftas, and Levine, 1999; Boumgarden *et al.*, 2012; Brown and Eisenhardt, 1997). Although case-based qualitative studies offer valuable contributions of their own, their contributions are more about theory building and hypothesis generation rather than hypothesis testing (Eisenhardt, 1989). The absence of large-sample statistical tests on the performance implications of vacillation has not only stymied the evaluation of theoretical predictions on vacillation, but

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more critically, this absence has hampered further theoretical sophistication of the subject.

In this study, drawing upon vacillation theory, we predict that the frequency and scale of vacillation between exploration and exploitation and firm performance will have inverted U-shaped relationships. We test our hypotheses using a sample of 4,195 U.S. companies in 229 industries from 1983 to 2007. Following existing studies (Katila and Ahuja, 2002; Rosenkopf and Nerkar, 2001; Stuart and Podolny, 1996; Wadhwa and Kotha, 2006; Wadhwa, Phelps, and Kotha, 2009), we measure exploration and exploitation using patents. Hence, in this study, exploration and exploitation are limited to the context of technological innovation and knowledge search.

THEORY AND HYPOTHESES

Vacillation frequency and firm performance

Nickerson and Zenger (2002) explain that firms vacillating between discrete formal organizational structures or goals benefit from an ambidextrous organization that temporarily emerges from vacillation. An ambidextrous organization emerges and then disappears during vacillation because changes in the formal organization structure are followed by lagged changes in the informal organization. An informal organization, defined as organizational routines supporting a formal organizational structure, cannot be modified as quickly as a formal organization structure (Cyert and March, 1963; March and Simon, 1958; Nelson and Winter, 1982; Nickerson and Zenger, 2002). As an informal organization for exploration gradually changes into an informal organization for exploitation and *vice versa*, the informal organization that is in transition temporally achieves the characteristics of both exploration and exploitation.

Nickerson and Zenger (2002) maintain that optimal vacillation frequencies vary across organizations and are determined by their inertia levels. Their key argument is that inertia determines the change speed of the informal organization following the formal organization change: the stronger the inertia, the slower the informal organization change. Hence, when the organization has strong inertia, (although it will take longer for the ambidextrous informal organization to emerge, once it does) it will retain the desirable ambidextrous characteristics longer. This idea indicates that one benefit of inertia is that the temporarily emerging ambidextrous informal organization will retain the desirable ambidextrous characteristics longer for the organization with strong inertia. In comparison, firms with weak inertia have to vacillate more frequently because their temporary ambidextrous informal organization will vanish more quickly.

The idea that each organization has an optimal vacillation frequency suggests that if an organization deviates from the optimal vacillation frequency, its performance will decline. Nickerson and Zenger's (2002) numerical analysis based on their theoretical model also supports the inverted U-shaped relationship. Following Nickerson and Zenger (2002), we predict that the frequency of vacillation between exploration and exploitation and firm performance will have an inverted U-shaped relationship.

> *Hypothesis 1: The frequency of vacillation between exploration and exploitation and firm performance have a within-firm inverted U-shaped relationship.*

The inverted U-shaped relationship suggests that firms may not always vacillate at optimal frequency. Nickerson and Zenger (2002) explain that managers decide when to vacillate based on their observation of performance gap between the actual performance level and the desired performance level. That is, as the performance declines and falls short of the desired level, managers may initiate vacillation in an attempt to improve firm performance. If managers were fully rational, they would always know the optimal timing to initiate vacillation and we would also always observe the optimal vacillation frequency.

In line with Boumgarden *et al.* (2012) and Nickerson and Zenger (2002), we assume that managers are boundedly rational. That is, managers often miss the optimal timing to initiate vacillation, because they cannot fully predict the consequences of initiating vacillation at a certain time, *ex ante*. Certain choices of vacillation timing may later turn out to be suboptimal because managers cannot fully and accurately identify and incorporate many internal and external factors when they decide vacillation timing (Simon, 1955). For example, former HP CEO John Young (1978–1992) comment on his decision to vacillate from a centralized structure to a decentralized one, "If I had my life to live over again, I would have [decentralized] earlier, maybe as much as two years" (Nickerson and Zenger, 2002: 549).

Vacillation scale and firm performance

Vacillation between exploration and exploitation may vary in scale as well as in frequency. When firms vacillate between more intensive levels of exploration and exploitation, they are conducting large-scale vacillation.[1] More intensive levels of exploration and exploitation indicate that firms have devoted more resources and time to exploration and exploitation. For example, they may have allocated greater financial, organizational, and human resources and pursued exploration (or exploitation) over a substantial period of time.

When firms vacillate between more intensive levels of exploration and exploitation, the ambidextrous informal organization emerging from vacillation lasts longer because intensive levels of exploration (exploitation) create strong inertia toward exploration (exploitation) and thus make it more difficult and slower for the firm to vacillate back to exploitation (exploration) (Lavie and Rosenkopf, 2006). In other words, intensive pursuit of exploration (exploitation) increases the firm's inertia and slows down the vacillation speed. As a result, when firms have pursued more intensive levels of exploration (exploitation) before they initiate vacillation, the ambidextrous informal organization emerging during vacillation will last longer. Hence, a greater vacillation scale can generate an advantage of a longer-lasting ambidextrous organization and contribute to firm performance. However, an excessive increase in the vacillation scale may not be desirable because excessively intensive exploration (exploitation) can create overly strong inertia and make initiation of vacillation back to exploitation (exploration) very costly, reducing the performance advantage of a longer-lasting ambidextrous organization (Lavie and Rosenkopf, 2006; Levinthal and March, 1993; Nickerson and Zenger, 2002). Therefore, firms will benefit from increasing the vacillation scale only up to a certain point, leading to an inverted U-shaped relationship between the vacillation scale and firm performance.

There may be yet another explanation for the inverted U-shaped relationship between the vacillation scale and firm performance. When firms vacillate on a small scale or between low levels of exploration and exploitation, the benefit from vacillation should also be small because the exploration would not generate sufficiently new knowledge, and the exploitation would not fully realize the commercial potential of the exploration.[2] As firms vacillate between more intensive levels of exploration and exploitation (i.e., increasing vacillation scale), such a problem will decrease. Increasing exploration will generate more sufficient new knowledge both in quality and quantity. Increasing exploitation will realize fuller commercial potential of the new knowledge created from exploration. However, beyond a certain level (i.e., optimal scale), further increase in vacillation scale may be detrimental for several reasons. First, overly intensive exploration will end up creating excessively novel knowledge, which may be too disconnected and dissimilar from the firm's existing knowledge base. If so, it will be very difficult to utilize or exploit this new knowledge generated from exploration. Second, overly intensive exploitation will restrict the firm's ability to vacillate back to exploration because overly intensive exploitation will narrow the firm's technological path and absorptive capacity (Cohen and Levinthal, 1990). Third, pursuing overly intensive levels of exploration (exploitation) will increase the likelihood of permanent loss of routines for exploitation (exploration). When firms focus on one type of routines at the expense of another, they "forget" these neglected routines (Nelson and Winter, 1982). Loss of routines in large-scale vacillation can substantially increase the cost of vacillation. Based on these arguments, we predict

[1] We acknowledge that not all large-scale vacillation consists of reversing from intensive or prolonged exploration (exploitation) before initiating vacillation. Instead, large-scale vacillation may be a result of reversing from a low-level exploration (exploitation) to intensive or prolonged exploitation (exploration). In the latter case large-scale vacillation, the vacillation may not be subject to greater inertia. However, in the vacillation scale axis, the largest vacillation scale would consist of the highest symmetric levels of exploration and exploitation before and after vacillation. To explain the inverted U-shaped relationship, we focus on the largest scale vacillation, which would consist of vacillating between the most intensive exploration (exploitation) to the most intensive exploitation (exploration).

[2] Again, we acknowledge that small-scale vacillation is not equivalent to vacillation between symmetrically low levels of exploration and exploitation. However, in the vacillation scale axis, the smallest vacillation scale is made up of the lowest symmetric levels of exploration and exploitation.

that there will be an inverted U-shaped relationship between the vacillation scale and firm performance.

Hypothesis 2: The scale of vacillation between exploration and exploitation and firm performance have a within-firm inverted U-shaped relationship.

METHODS

Sample and data

Our sample includes U.S. public firms across 229 industries. Among the sample firms, SIC code 737 (computer programming, data processing, and other computer related services) makes up the largest portion of the sample with 13.2 percent, followed by SIC code 283 (drugs) with 4.8 percent. We use multiple data sources to construct our sample: COMPUSTAT, CRSP, and the United States Patent and Trademark Office's (USPTO) patent database. After matching the firms withdrawn from these databases and excluding firms from the finance industry (*SIC* codes 600 through 699) where firms have different accounting schemes and patent activity is not a major output of knowledge creation, we are left with 36,033 firm-years and 4,195 firms from 1983 to 2007.

Our measure of exploration and exploitation is based on technological innovation, which is a widely used firm activity to operationalize exploration and exploitation in empirical research (He and Wong, 2004; Jansen, Van Den Bosch, and Volberda, 2006; Katila and Ahuja, 2002; Rosenkopf and Nerkar, 2001). Patents have several important advantages as a measure of exploration and exploitation. First, exploration and exploitation have been conceptually most closely related to and defined in terms of technological innovation and knowledge search in the literature (Andriopoulos and Lewis, 2009; He and Wong, 2004; Jansen, Van Den Bosch, and Volberda, 2005; March, 1991; Rosenkopf and Nerkar, 2001; Tushman and O'Reilly, 1996). Second, patents are objective and replicable measures of technological innovation and knowledge search (Griliches, 1990; Sampson, 2007). Third, patents are measures of technological innovation and knowledge search with strong and clear performance implications (Bloom and Van Reenen, 2002; DeCarolis and Deeds, 1999; Griliches, 1990; Hall, Jaffe, and Trajtenberg, 2005).

Measures

Dependent variable (Tobin's Q)

The dependent variable in this study is *Tobin's Q*. A market-based value such as *Tobin's Q* is considered particularly useful in ambidexterity research since a market-based value reflects both short-term performance and long-term performance prospects (Lavie, Kang, and Rosenkopf, 2011; Lubatkin and Shrieves, 1986; Uotila *et al.,* 2009).[3] Exploration and exploitation activities influence company performance in different ways over different time periods; for example, the ultimate effects of exploration on firms are more distant whereas exploitation has a more immediate effect. In addition, compared to accounting measures of profitability, *Tobin's Q* has the advantage of reflecting market expectations of competitiveness in terms of knowledge creation as measured by patents, which we use to operationalize exploration and exploitation (Levitas and McFadyen, 2009; Megna and Klock, 1993).[4]

Explanatory variables (vacillation frequency/scale)

Our explanatory variables, *vacillation frequency* and *vacillation scale*, are created through the following steps. First, we operationalize *exploration* with the patents filed during a given year and in

[3] For example, Uotila *et al.* (2009: 223) explain that "Exploration and exploitation activities have been argued to influence company performance in different ways and over different time periods. This makes studying the effect of the balance between the two on company performance using accounting-based performance measures problematic, as the ultimate effects of exploration on company financials are more often distant, while exploitation has a more immediate effect. Consequently, instead of using accounting-based measures of performance, we used the market-based measure of Tobin's Q as our dependent performance variable. Market value based measures such as Tobin's Q have the advantage of capturing short-term performance and long-term prospects (Allen, 1993; Lubatkin and Shrieves, 1986), allowing us to operationalize both short- and long-term performance effects using a single performance variable."

[4] Empirical economics research on patents and their performance implications has strongly preferred market-based measures such as Tobin's Q over accounting-based measures (Austin, 1993; Griliches, 1990; Griliches, Hall, and Pakes, 1991; Pakes, 1985). For example, Griliches (1990: 1682) explains that "The use of stock market values as an output indicator of the research process has one major advantage. All other indicators of success, such as profits or productivity, are likely to reflect it only slowly and erratically. On the other hand, when an event occurs that causes the market to reevaluate the accumulated output of a firm's research endeavors, its full effect on the expected present value of a firm's future net cash flows should be recorded immediately."

technical classifications for which the focal firm has not historically filed, and *exploitation* with the patents filed during a given year and in technical classifications for which the focal firm has historically filed (Ahuja and Lampert, 2001; Rosenkopf and Nerkar, 2001). Since firms often file both types of patents in a given year, we measure a firm's focus on exploration and exploitation as a ratio variable. When a firm filed more patents in new patent classes (i.e., not filed previously) than previously filed classes at time *t,* we indicate that the firm has a focus on exploration over exploitation at time *t*. A firm's *focus* is computed as follows:

$$f_{it} = \frac{R_{it}}{TP_{it}} - \frac{T_{it}}{TP_{it}},$$

where f_{it} denotes firm *i*'s focus ratio at time *t*; R_{it} and T_{it} are the number of firm *i*'s patents identified as *exploration* and *exploitation* at time *t,* respectively. TP_{it} indicates the total number of patents filed at time *t*. Therefore, if R_{it} is larger than T_{it}, f_{it} has a positive value, meaning that the innovation focus of firm *i* is more toward exploration than exploitation at time *t*. If R_{it} is smaller than T_{it}, f_{it} has a negative value, meaning that the innovation focus of firm *i* is more toward exploitation than exploration. Hence, *focus* is a ratio indicating how much more exploratory or exploitative the portfolio of patents are compared to being "balanced" (i.e., when *focus* is 0).

Using this *focus* measure, we identify a *vacillation* event at the time period of *t* when a firm's focus has shifted from one activity to another between time $t-1$ and time *t*. When there is a vacillation event between time $t-1$ and *t,* f_{it-1} and f_{it} has an opposite sign (i.e., $f_{it-1} * f_{it} < 0$). *Vacillation scale* is defined as the extent to which a firm changes its focus from exploitation to exploration *or vice versa* at time *t* of a vacillation event. The *vacillation scale*, denoted as s_{it}, is computed as follows:

$$s_{it} = g\left(f_{it}, f_{it-1}\right) \cdot \left|f_{it} - f_{it-1}, \right|,$$

where $g(f_{it}, f_{it-1})$ is an indicator function of a vacillation event between time *t* and time $t-1$. The value of $g(f_{it}, f_{it-1})$ is 1 if there is vacillation and 0 otherwise. We measure *vacillation scale*, s_{it}, by multiplying the difference between two consecutive time periods (i.e., $|f_{it} - f_{it-1}|$) by the vacillation-event identifier indicating whether there is a sign change between f_{it-1} and f_{it}. *Vacillation frequency* is defined as how many vacillation events occur within a time period. The more vacillation events that occur within a time period, the more frequent the vacillation between exploration and exploitation. In measuring *vacillation frequency,* we need to beware of determining a time frame during which the number of vacillation events will be counted, because the time frame for frequency cannot be matched to that of vacillation. Since each vacillation event is identified yearly in this study, the time frame used to measure frequency should be at least more than two years. At the same time, since other variables for testing the hypotheses are updated yearly within a firm, *vacillation frequency* should be a yearly-updated variable. To reconcile this granular issue, we count the number of vacillations performed by the firm over the last five years (from year $t-4$ to year *t*) and divide it by five to calculate the vacillation frequency.[5]

Control variables

We control for a number of industry- and firm-level characteristics.

- *Industry asset size.* Industry asset size is controlled for by aggregating the total assets for firms with a given three-digit SIC code.
- *Industry average T*obin's *Q*.The industry-level performance, operationalized as Tobin's Q in our study, is used by firms as a reference point for future strategies by comparing their aspiration levels and performance (Bromiley, 1991; Cyert and March, 1963). *Industry average Tobin's Q* is the aggregation of Tobin's Q for firms with a given three-digit SIC code.
- *Market share.* Market share of a focal firm is controlled for by dividing the annual revenue of a firm by the aggregated total revenue within each three-digit SIC industry.
- *Firm age.* Younger firms are more likely to be more flexible than older firms in vacillation between exploration and exploitation; hence, we control for *firm age* using the natural logarithm of the number of years since incorporation. *Firm age* is also a measure of inertia.

[5] We use alternative moving windows (*i.e.*, three, four, six, seven, and eight years) as well and find that the result remain consistent using a five-year moving window.

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- *Current ratios and administrative expenditures.* We also control for slack resources, which are measured as the current ratios and the administrative expenditures (Bromiley, 1991).
- *Firm size* is measured as the number of employees.
- *Knowledge pool growth* is the total number of patents applied for by a given firm at a given year.
- *Return-on-asset* and *R&D intensity* are controlled for.
- *Change without vacillation* is controlled for to deal with the following issue. Firms may change the level of exploration (or exploitation) without vacillation (i.e., a change in the firm's focus between exploration and exploitation). When a firm makes a change within either exploration or exploitation (i.e., when there is no sign change between f_{it-1} and f_{it}), the change may influence firm performance even though the change does not constitute a vacillation. We assign 1 to changes (i.e., $|f_{it}\text{-}f_{it-1}|$ (without sign change between f_{it-1} and f_{it})) that fall between 0.25 and 0.5, and 0 otherwise. Hence, this is a dummy variable. By controlling for this variable, we can explain the effect of vacillation on firm performance more precisely.
- *Prior year's Tobin's Q* is controlled for.
- *Diversification,* measured with the entropy measure of diversification based on each firm's patent portfolio, is controlled for.
- *Industry-level Herfindahl-Hirshman Index (HHI)* calculated using firm sales information controls for the level of competition at the industry level.
- *Firm growth* is measured as the change in the number of employees.
- *Industry average return-on-equity*, *change in the number of industry employees*, and *industry-level advertising expenditure* are controlled for to capture the level of environmental munificence (Raisch and Hotz, 2010; Yasai-Ardekani, 1989). Table 1 provides descriptive statistics for all variables used in the models.

Methodology

We account for endogeneity related to self-selection. A firm's choice to vacillate between exploration and exploitation is endogenous. That is, firms (more specifically, their managers) make decisions on vacillation based on their understanding of how such decisions will affect firm performance. We predict that firms that expect a positive effect of vacillation on firm performance will vacillate, while other firms that do not expect a positive effect will not vacillate. Therefore, this is a typical example of the endogeneity problem caused by self-selection (Hamilton and Nickerson, 2003; Shaver, 1998).

To mitigate this problem, we employ the self-selection correction proposed by Shaver (1998). Nickerson and Zenger (2002: 548) explain that "fickle behavior need not be functional; structural choices may reflect processes of imitation in which the latest fads or fashions are adopted with only limited examination." This observation suggests that vacillation between exploration and exploitation can be a result of imitating others. It also suggests that other firms' vacillation behavior may not affect the focal firm's performance, given that even the focal firm's vacillation as a result of imitation of others may not affect its performance. If so, variables that can capture the mimetic behavior can be ideal instrument variables. We use the number of vacillations by other firms in the same industry and region as our instrument variable because these firms are the most likely targets of imitation by focal firms (Cheng, Ioannou, and Serafeim, 2014; Henisz and Delios, 2001). In the first-stage probit regression, we regress vacillation by the focal firms on the number of vacillations made by other firms in the same industry and region and other control variables. Then, we calculate inverse Mills ratios based on the first-stage probit regression and include them in the second-stage regressions. Our models are estimated using firm- and year-fixed effect (i.e., firm and year dummies) models and account for heteroskedasticity in the error term.

RESULTS AND DISCUSSION

Descriptive statistics detailing the mean values, standard deviations, and bivariate correlations of the variables are reported in Table 1. We find several cases of high correlation among our variables. We check the variance inflation factor (VIF) values of our variables and find that the largest VIF value is 4.5 for *industry-level advertising expenditure*. Hence, we conclude that despite high correlations among several variables, there does not seem to be a threat of biased estimates due to multicollinearity of our variables. For further assurance, we run

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Table 1. Descriptive statistics (N = 36,033)

	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10
1. Tobin's Q	0.69	0.49	−1.00	2.50										
2. Prior year's Tobin's Q	0.78	0.96	−1.00	52.67	0.37***									
3. Industry average Tobin's Q	0.00	0.03	0.00	2.51	−0.01*	−0.01†								
4. Industry asset intensity	0.85	1.94	0.00	29.18	−0.04***	−0.04***	0.01*							
5. Market share	0.03	0.10	0	1	0.03***	0.00	0.00	0.09***						
6. Firm size	6.89	27.22	0.001	484	0.01	−0.02**	0.01†	0.43***	0.28***					
7. Current ratio	0.02	0.51	0	27.04	−0.04***	−0.02***	0.01	0.03***	0.05***	0.23***				
8. Administrative expenditures	0.00	0.02	0	2.43	0.00	0.02***	0.01†	0.00	−0.01*	−0.01	0.00			
9. Knowledge pool growth	5.02	66.16	0	2495.00	−0.02***	−0.02***	0.00	0.21***	0.14***	0.34***	0.00	0.00		
10. R&D intensity	0.05	0.09	0	2.10	0.02***	0.05***	0.03***	−0.07**	−0.13***	−0.07***	0.00	0.02***	0.01	
11. Change without vacillation	0.01	0.04	0	0.44	0.02**	0.01**	−0.01†	0.01†	0.04***	0.03***	0.01	0.01	0.03***	0.03***
12. Firm age	2.29	0.64	0.69	4.06	−0.13***	−0.17***	0.01*	0.08***	0.12***	0.08***	−0.02**	−0.03***	0.07***	−0.14***
13. ROA	1.26	0.93	0	18.47	0.03***	−0.02***	−0.04***	−0.05***	0.05***	−0.03***	−0.02***	−0.04***	−0.03***	−0.16***
14. Diversification (patent-based entropy)	0.88	0.29	0	1	−0.03***	−0.04***	0.01*	−0.03***	−0.06***	−0.07***	0.01	0.00	−0.16***	−0.13***
15. Firm size growth	0.14	1.09	−0.99	89.76	0.09***	0.23***	0.00	−0.01	−0.02***	−0.01	0.00	0.02***	−0.01	0.02***
16. Industry-average ROE	29791.3	47588.0	0	245374.9	−0.04***	0.03***	0.06***	0.25***	−0.16***	0.07***	0.02**	0.01*	0.02***	0.39***
17. Change in the number of industry employees	28.51	74.91	−381.65	559.10	0.04***	0.07***	0.01	0.00	−0.10***	0.02***	−0.01	0.01*	−0.01*	0.11***
18. Industry-level advertising expenditures	1570.40	2921.91	0	24708.82	−0.02***	0.02**	0.03***	0.39***	−0.13***	0.13***	0.01**	0.01	0.02***	0.23***
19. Industry-level HHI	0.18	0.14	0.01	1	−0.01	−0.03***	−0.01*	0.02***	0.38***	0.00	0.00	−0.01	0.02**	−0.19***
20. Vacillation frequency	0.37	0.13	0	1	0.03***	0.03***	−0.02***	−0.03***	−0.01*	−0.01**	0.00	−0.00	−0.01**	0.01**
21. Vacillation scale	0.05	0.20	0	1	0.01*	0.04***	−0.01*	−0.03***	−0.02***	−0.02***	0.00	0.00	−0.01***	0.04***
22. Inverse mills ratio	4.05	2.00	0.00	24.11	−0.02***	−0.05***	0.05***	0.14***	0.05***	0.08***	0.04***	0.02***	0.22***	−0.06***
23. Vacillation of other firms in the same industry and region	0.06	0.23	0	1	0.01†	0.04***	−0.01**	−0.03***	−0.02***	−0.02***	0.00	0.00	−0.01*	0.04***

	11	12	13	14	15	16	17	18	19	20	21	22
12. Firm age	0.03***											
13. ROA	−0.03***	0.10***										
14. Diversification (patent-based entropy)	−0.20***	0.00	0.09***									
15. Firm size growth	0.00	−0.09***	−0.01	0.00								
16. Industry-average ROE	−0.01**	−0.10***	−0.21***	−0.02**	0.01*							
17. Change in the number of industry employees	−0.02***	−0.06***	−0.04***	0.04***	0.04***	0.33***						
18. Industry-level advertising expenditures	0.00	−0.05***	−0.16***	−0.01**	0.00	0.84***	0.24***					
19. Industry-level HHI	0.00	0.08***	0.11***	0.04***	−0.01*	−0.35***	−0.20***	−0.28***				
20. Vacillation frequency	0.10***	−0.02**	−0.01*	−0.24***	0.01	−0.05***	−0.03***	−0.04***	−0.00			
21. Vacillation scale	−0.04***	−0.01**	−0.03***	−0.29***	0.01	−0.01*	−0.02***	−0.02***	−0.01*	0.50***		
22. Inverse mills ratio	−0.03***	0117***	0.23***	0.38***	−0.00	0.00	−0.01	0.03***	0.17***	−0.45***	−0.74***	
23. Vacillation of other firms in the same industry and region	−0.03***	−0.01	−0.03***	−0.30***	0.01	−0.02**	−0.03***	−0.02**	−0.01*	0.53***	0.93***	−0.79***

$^{\dagger}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

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Table 2. Distribution of vacillation in sample

# Vacillation events	# Firms vacillating	% Firms vacillating
0	3,494	83.29
1	136	3.24
2	271	6.46
3	68	1.62
4	100	2.38
5	26	0.62
6	40	0.95
7	20	0.48
8	14	0.33
9	9	0.21
10	9	0.21
11	3	0.07
12	2	0.05
13	1	0.02
14	2	0.05
Total	4,195	100

regressions without some of these controls and find that the result remains consistent. Table 2 shows the distribution of vacillation among our sample firms.

Table 3 shows the first-stage probit regression, where we regress vacillation by the focal firms on the number of vacillations made by other firms in the same industry and region and other control variables. Then, we calculate inverse Mills ratios based on the first-stage probit regression and include them in the second-stage regressions (Table 4). We find that the inverse Mills ratios are statistically significant in both Model 2 (vacillation frequency) and Model 3 (vacillation scale) as shown in Table 4. The result suggests that self-selection may be an issue for both vacillation frequency and scale.

We move on to test our main hypotheses on the effect of vacillation frequency and scale on firm performance. Table 4 shows that both *vacillation frequency* and *vacillation scale* have statistically significant inverted U-shaped relationships with *Tobin's Q*. This finding suggests that firms have optimal vacillation frequency and scale values and that deviating from these optimal values will result in a decline in performance. Hence, Hypotheses 1 and 2 cannot be rejected based on our analysis. Our regression results indicate that firm performance is maximized, on average, when *vacillation frequency* is at 0.46789 and *vacillation scale* at 0.63567.[6]

Table 3. First-stage probit regression

Dependent variable	Vacillation_{t+1}
Intercept	−4.877 (0.000) [−5.646−4.107]
Prior year's Tobin's Q	−0.014 (0.508) [−0.057 0.028]
Industry average Tobin's Q	−1.498 (0.835) [−15.566 12.570]
Industry asset size	−0.030 (0.597) [−0.142 0.082]
Market share	1.105 (0.007) [0.307 1.903]
Firm size	0.002 (0.099) [−0.000 0.004]
Current ratio	−0.140 (0.002) [−0.230−0.050]
Administrative expenditures	−2.208 (0.156) [−5.261 0.845]
Knowledge pool growth	−0.005 (0.000) [−0.008−0.003]
R&D intensity	−0.613 (0.362) [−1.930 0.704]
Firm age	0.018 (0.885) [−0.229 0.265]
ROA	−0.313 (0.003) [−0.517−0.110]
Diversification (patent-based entropy measure)	−0.639 (0.000) [−0.885−0.393]
Firm growth	−0.008 (0.450) [−0.030 0.013]
Industry-average ROE	0.000 (0.538) [−0.000 0.000]
Change in the number of industry employees	0.001 (0.157) [−0.000 0.002]
Industry-level advertising expenditures	−0.000 (0.726) [−0.000 0.000]
Industry-level HHI	−1.468 (0.010) [−2.582−0.355]
Vacillation of other firms in the same industry and region	7.059 (0.000) [−5.646−4.107]
Firm fixed effects	Yes
Year fixed effects	Yes
Kleibergen-Paap rk LM test	521.11 (0.000)
Sanderson-Windmeijer F test	150,000 (0.000)

The number of firm-year: 36,033, The number of firms: 4,195. P-values in parentheses; 95 percent confidence intervals in brackets.

Vacillation scale captures the scale of change in relative focus on exploration and exploitation.

[6] From Table 5, we obtain regression coefficients for vacillation frequency and scale.

$\text{Tobin's } Q_{t+1} = -0.109 * \text{vacillation frequency}_t^2 + 0.102 * \text{vacillation frequency}_t + \ldots$

$\text{Tobin's } Q_{t+1} = -0.398 * \text{vacillation scale}_t^2 + 0.506 * \text{vacillation scale}_t + \ldots$

We obtain the values that maximize Tobin's Q (0.46789 for vacillation frequency and 0.63567 for vacillation scale) by differentiating these equations.

Table 4. Firm- and year-fixed effects regressions (vacillation frequency and scale)

	Tobin's Q_{t+1}		
Dependent variable	Model 1	Model 2	Model 3
Intercept	0.947 (0.000) [0.834 1.060]	0.937 (0.000) [0.843 1.032]	0.782 (0.000) [0.641924]
Prior year's Tobin's Q	0.083 (0.000) [0.049 0.116]	0.082 (0.000) [0.051 0.114]	0.082 (0.000) [0.055 0.110]
Industry average Tobin's Q	0.162 (0.029) [0.016 0.307]	0.159 (0.039) [0.008 0.310]	0.117 (0.082) [−0.015 0.248]
Industry asset size	0.002 (0.545) [−0.004 0.008]	0.002 (0.671) [−0.006 0.009]	0.001 (0.710) [−0.004 0.006]
Market share	−0.181 (0.000) [−0.280−0.083]	−0.181 (0.002) [−0.293−0.069]	−0.150 (0.003) [−0.251−0.050]
Firm size	0.000 (0.014) [0.000 0.001]	0.000 (0.029) [0.000 0.001]	0.001 (0.004) [0.000 0.001]
Current ratio	−0.019 (0.000) [−0.024−0.014]	−0.019 (0.000) [−0.027−0.012]	−0.023 (0.000) [−0.031−0.015]
Administrative expenditures	−0.275 (0.431) [−0.960 0.409]	−0.280 (0.348) [−0.865 0.305]	−0.342 (0.299) [−0.988 0.304]
Knowledge pool growth	0.000 (0.029) [0.000 0.000]	0.000 (0.060) [−0.000 0.000]	0.000 (0.135) [−0.000 0.000]
R&D intensity	0.333 (0.000) [0.197 0.470]	0.333 (0.000) [0.189 0.477]	0.315 (0.000) [0.157 0.474]
Change without vacillation	0.102 (0.194) [−0.52 0.257]	0.095 (0.149) [−0.034 0.224]	0.129 (0.039) [0.007 0.251]
Firm age	−0.157 (0.000) [−0.186−0.129]	−0.157 (0.000) [−0.183−0.131]	−0.157 (0.000) [−0.185−0.128]
ROA	0.057 (0.000) [0.043 0.071]	0.057 (0.000) [0.044 0.070]	−0.048 (0.000) [0.035 0.062]
Diversification (patent-based entropy measure)	−0.021 (0.028) [−0.040−0.002]	−0.022 (0.035) [−0.042−0.002]	−0.034 (0.007) [−0.059−0.009]
Firm growth	0.009 (0.084) [−0.001 0.020]	0.010 (0.118) [−0.002 0.021]	0.009 (0.054) [−0.000 0.019]
Industry-average ROE	−0.000 (0.000) [−0.000−0.000]	−0.000 (0.000) [−0.000−0.000]	−0.000 (0.000) [−0.000−0.000]
Change in the number of industry employees	0.000 (0.037) [0.000 0.000]	0.000 (0.035) [0.000 0.000]	0.000 (0.016) [0.000 0.000]
Industry-level advertising expenditures	−0.000 (0.936) [−0.000 0.000]	−0.000 (0.931) [−0.000 0.000]	−0.000 (0.846) [−0.000 0.000]
Industry-level HHI	0.148 (0.001) [0.064 0.231]	0.147 (0.000) [0.075 0.219]	0.107 (0.011) [0.025 0.189]
Vacillation frequency		0.102 (0.039) [0.005 0.199]	
Vacillation frequency^2		−0.109 (0.084) [−0.234 0.015]	
Vacillation scale			0.506 (0.000) [0.244 0.768]
Vacillation scale^2			−0.398 (0.000) [−0.593−0.203]
Inverse mills ratio	0.004 (0.254) [−0.003 0.011]	0.006 (0.096) [−0.001 0.012]	0.035 (0.001) [0.014 0.056]
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Log likelihood	−12261.44	−12259.51	−12249.66
LR test (χ^2)	-	3.86 (0.145)	23.56 (0.000)

The number of firm-year: 36,033, The number of firms: 4,195. P-values in parentheses; 95 percent confidence intervals in brackets.

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Hence, the optimal value of 0.63567 in vacillation scale refers to a firm reaching its highest performance when the firm vacillates by this amount. The optimal vacillation frequency value of 0.46789 suggests that, on average, one vacillation between exploration and exploitation in 25.64 months (i.e., 2.14 years) is optimal for our sample firms.

An average firm in our sample seems to vacillate at the lower frequency and scale values than at the optimal values. Table 1 indicates that an average firm in our sample has vacillation frequency and scale values of 0.37 and 0.05. Therefore, for an average firm in our sample, an increase in vacillation frequency and scale by one standard deviation leads to an increase of 0.000932 and 0.07732 in Tobin's Q, respectively. This means that an average firm in our sample may improve its performance by vacillating more frequently and at a greater scale.

The greater absolute coefficient value of the square term of vacillation scale (−0.398) compared to that of vacillation frequency (−0.109) in our regressions indicates that changes in vacillation scale tend to have a greater impact on firm performance than changes in vacillation frequency. For example, an increase/decrease in vacillation frequency and scale by one standard deviation (0.13 for vacillation frequency and 0.20 for vacillation scale) from the optimal frequency and scale values leads to a decrease of 0.02202 and 0.14490 in Tobin's Q, respectively. Furthermore, the strictly positive confidence interval (95% CI = [0.244 0.768]) of vacillation scale and the strictly negative confidence interval (95% CI = [−0.593 −0.203]) of its square term corroborate a clearer inverted U-shaped relationship between vacillation scale and Tobin's Q than between vacillation frequency and Tobin's Q. Taken together, this suggest that while firms may benefit more by adjusting their vacillation scale than by adjusting their frequency, if their vacillation scale/frequency falls short of or exceeds the optimal values, at the same time, firms should be also more careful in adjusting their vacillation scale rather than adjusting their frequency, if their vacillation scale/frequency values are close to the optimal values.

The inverted U-shaped relationships between vacillation frequency/scale and Tobin's Q suggest that suboptimal values of vacillation frequency and scale can hamper firm performance. Given that firms may not always vacillate at optimal scales, managers may consider how to minimize the negative effect of vacillation. While vacillating between exploration and exploitation, employees go through changes in responsibilities, communication patterns, and informal and political coalitions (Nickerson and Zenger, 2002), which may diminish employee productivity, input and effort, as well as increase turnover, interpersonal conflict, and role uncertainties (Miller and Friesen, 1980). In addition, repeated vacillation may result in managers losing credibility with workers (Nickerson and Zenger, 2002). To alleviate these problems, managers may build trust with their employees by (1) clearly communicating the rationale for vacillation and accompanying changes (Jarvenpaa, Knoll, and Leidner, 1998; Ridings, Gefen, and Arinze, 2002), (2) interacting more personally and frequently (Adler, 2001; Brown and Eisenhardt, 1997), and (3) removing unnecessary hierarchical structures (Zaheer and Venkatraman, 1995). When employees have strong trust in their managers' judgment and vision, they are more convinced of and more readily accept and support the proposed changes and accompanying difficulties.

Managers may also consider building high-order capabilities and routines for change, termed dynamic capabilities (Teece, Pisano, and Shuen, 1997) or modification routines (Nelson and Winter, 1982). These high-order capabilities may take a form of formal functions or personnel in charge of planning and managing the changes (Kale, Dyer, and Singh, 2002; Schreiner, Kale, and Corsten, 2009). These formal functions and titles help firms change by promoting and justifying sufficient resource allocation for the intended goals and by signaling to employees the managers' strong commitment to the changes. These high-order capabilities can be improved by repeated experience and learning (Haleblian and Finkelstein, 1999; Kale and Singh, 2007; McDonald, Westphal, and Graebner, 2008).

Additional analysis and robustness check

Our explanatory variables (*vacillation frequency, vacillation scale*) measure the frequency and scale of change from exploration to exploitation and *vice versa.* However, firms may change their focus on exploration while not vacillating to exploitation and *vice versa*. To consider this issue, we construct a new variable that captures both (1) the scale of change in the presence of vacillation and (2) the scale of change in the absence of vacillation (i.e., change within exploration or exploitation). We

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name this new variable *change scale*. We similarly construct *change frequency*, which is the frequency of change with or without vacillation. We examine the performance implications of these new variables by including their linear and quadratic terms in our regressions (Table 5). The regression result shows that only the *change scale* and its quadratic term are statistically significant. In an unreported analysis, we use thresholds (i.e., 0.1, 0.2, 0.3, and 0.4) to identify a change. When thresholds are used, the *change frequency* and its quadratic terms are statistically significant for the threshold values of 0.3 and 0.4.

We also examine how the predicted relationships may be affected by firm size. We split our sample using the median value of firm size (Table 6).[7] In the split sample analysis, we find that *change without vacillation* is positive and significant for large firms only. While we have no conclusive explanation, one possibility is that large firms may be more sensitive to changes in firm focus on exploration and exploitation (even without vacillation). Regression coefficients also suggest that the optimal *vacillation scale* value is greater for small firms. While we cannot conclusively explain why, a possible speculation is that small firms with weaker inertia may benefit from larger-scale vacillation. If larger-scale vacillation takes more time to accomplish, the informal organization in transition may retain the ambidextrous nature longer. In other words, small organizations with weaker inertia may attempt to lengthen the duration of ambidextrous organization by seeking large-scale vacillation.[8]

CONCLUSION

Despite continued theoretical discussion on the value of vacillation between exploration and exploitation as an alternative solution for organizational ambidexterity, empirical evidence on the performance implications of vacillation has been

Table 5. Firm- and year-fixed effects regressions (change frequency and scale)

	Tobin's Q_{t+1}	
Dependent variable	Model 1	Model 2
Intercept	0.966 (0.000)	0.967 (0.000)
	[0.873 1.058]	[0.868 1.065]
Prior year's Tobin's Q	0.082 (0.000)	0.083 (0.000)
	[0.051 0.114]	[0.055 0.110]
Industry average Tobin's Q	0.167 (0.025)	0.167 (0.004)
	[0.021 0.313]	[0.052 0.282]
Industry asset size	0.002 (0.600)	0.002 (0.524)
	[−0.006 0.010]	[−0.004 0.008]
Market share	−0.193 (0.001)	−0.188 (0.001)
	[−0.302−0.083]	[−0.299−0.077]
Firm size	0.000 (0.031)	0.000 (0.014)
	[0.000 0.001]	[0.000 0.001]
Current ratio	−0.018 (0.000)	−0.019 (0.000)
	[−0.026−0.011]	[−0.025−0.013]
Administrative expenditures	−0.267 (0.368)	−0.267 (0.115)
	[−0.850 0.315]	[−0.599 0.065]
Knowledge pool growth	0.000 (0.034)	0.000 (0.002)
	[0.000 0.000]	[0.000 0.000]
R&D intensity	0.337 (0.000)	0.335 (0.000)
	[0.193 0.481]	[0.209 0.460]
Firm age	−0.158 (0.000)	−0.158 (0.000)
	[−0.184−0.132]	[−0.185−0.131]
ROA	0.058 (0.000)	0.058 (0.000)
	[0.046 0.071]	[0.045 0.072]
Diversification (patent-based entropy measure)	−0.014 (0.131) [−0.032 0.004]	−0.018 (0.068) [−0.037 0.001]
Firm growth	0.009 (0.118)	0.009 (0.043)
	[−0.002 0.021]	[0.000 0.019]
Industry-average ROE	−0.009 (0.000)	−0.000 (0.000)
	[−0.000−0.000]	[−0.000−0.000]
Change in the number of industry employees	0.000 (0.045) [0.000 0.000]	0.000 (0.031) [0.000 0.000]
Industry-level advertising expenditures	−0.000 (0.994) [−0.000 0.000]	−0.000 (0.958) [−0.000 0.000]
Industry-level HHI	0.154 (0.000)	0.154 (0.000)
	[0.082 0.227]	[0.079 0.229]
Change frequency	0.073 (0.129)	
	[−0.021 0.167]	
Change frequency^2	−0.031 (0.583)	
	[−0.140 0.078]	
Change scale		0.157 (0.013)
		[0.033 0.282]
Change scale^2		−0.172 (0.008)
		[−0.300−0.044]
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Log likelihood	−12259.45	−12260.4
LR test (χ^2)	11.92 (0.003)	10.02 (0.007)

The number of firm-year: 36,033, The number of firms: 4,195. P-values in parentheses; 95 percent confidence intervals in brackets.

[7] We also divide the sample by firm size quartiles. When we run our second-stage regressions in these four subsamples by firm size, we find that the relationships between vacillation frequency/scale and firm performance become mostly insignificant.

[8] We also examine the possibility that the firms that do not vacillate may have been mistakenly identified as performing small-scale vacillation. To address this issue, we remove the observation with the *vacillation scale* below the bottom two, three, five, seven, and ten percent, respectively, from our sample and rerun our regression models and find that the results remain consistent.

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Table 6. Firm size moderation effect (split-sample) tests

	Large firm			Small firm		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	1.003 (0.000)	1.002 (0.000)	0.903 (0.000)	0.867 (0.000)	0.856 (0.000)	0.622 (0.000)
	[0.864 1.143]	[0.862 1.141]	[0.724 1.082]	[0.725 1.008]	[0.713 1.000]	[0.398 0.846]
Prior year's Tobin's Q	0.078 (0.032)	0.078 (0.032)	0.078 (0.000)	0.109 (0.000)	0.109 (0.000)	0.109 (0.000)
	[0.007 0.149]	[0.007 0.149]	[0.042 0.115]	[0.081 0.138]	[0.081 0.138]	[0.086 0.131]
Industry average Tobin's Q	0.105 (0.287)	0.104 (0.289)	0.077 (0.247)	0.249 (0.184)	0.244 (0.191)	0.183 (0.060)
	[−0.088 0.297]	[−0.088 0.296]	[−0.053 0.206]	[−0.118 0.616]	[−0.122 0.610]	[−0.008 0.373]
Industry asset size	0.009 (0.000)	0.009 (0.000)	0.009 (0.002)	−0.032 (0.041)	−0.033 (0.037)	−0.034 (0.029)
	[0.004 0.014]	[0.004 0.014]	[0.003 0.014]	[−0.063−0.001]	[−0.064−0.002]	[−0.064−0.003]
Market share	−0.229 (0.000)	−0.229 (0.000)	−0.212 (0.000)	−0.022 (0.914)	−0.023 (0.913)	0.025 (0.894)
	[−0.335−0.123]	[−0.335−0.124]	[−0.323−0.101]	[−0.429 0.384]	[−0.427 0.382]	[−0.347 0.397]
Firm size	0.000 (0.060)	0.000 (0.061)	0.000 (0.039)	0.108 (0.018)	0.108 (0.018)	0.109 (0.014)
	[−0.000 0.001]	[−0.000 0.001]	[0.000 0.001]	[0.019 0.197]	[0.019 0.197]	[0.022 0.195]
Current ratio	−0.019 (0.000)	−0.019 (0.000)	−0.021 (0.000)	−0.489 (0.029)	−0.490 (0.028)	−0.494 (0.018)
	[−0.026−0.012]	[−0.026−0.012]	[−0.028−0.015]	[−0.928−0.050]	[−0.929−0.052]	[−0.903−0.084]
Administrative expenditures	0.086 (0.807)	0.085 (0.810)	0.047 (0.808)	−0.443 (0.657)	−0.449 (0.655)	−0.541 (0.037)
	[−0.607 0.779]	[−0.609 0.780]	[−0.329 0.422]	[−2.400 1.514]	[−2.418 1.521]	[−1.049−0.033]
Knowledge pool growth	0.000 (0.153)	0.000 (0.165)	−0.000 (0.498)	−0.001 (0.831)	−0.001 (0.808)	−0.001 (0.768)
	[−0.000 0.000]	[−0.000 0.000]	[−0.000 0.000]	[−0.006 0.005]	[−0.006 0.005]	[−0.007 0.005]
R&D intensity	0.593 (0.004)	0.593 (0.004)	0.586 (0.001)	0.298 (0.000)	0.297 (0.000)	0.272 (0.000)
	[0.195 0.991]	[0.194 0.991]	[0.225 0.947]	[0.150 0.447]	[0.149 0.446]	[0.136 0.409]
Change without vacillation	0.156 (0.025)	0.154 (0.025)	0.179 (0.015)	0.030 (0.853)	0.017 (0.916)	0.053 (0.720)
	[0.020 0.292]	[0.019 0.289]	[0.035 0.322]	[−0.288 0.348]	[−0.301 0.335]	[−0.235 0.340]
Firm age	−0.169 (0.000)	−0.169 (0.000)	−0.169 (0.000)	−0.150 (0.000)	−0.149 (0.000)	−0.149 (0.000)
	[−0.201−0.137]	[−0.201−0.138]	[−0.200−0.139]	[−0.191−0.108]	[−0.190−0.107]	[−0.193−0.105]
ROA	0.081 (0.000)	0.081 (0.000)	0.075 (0.000)	0.037 (0.000)	0.036 (0.000)	0.023 (0.020)
	[0.064 0.098]	[0.063 0.098]	[0.058 0.092]	[0.019 0.054]	[0.019 0.054]	[0.004 0.042]
Diversification (patent-based entropy)	−0.012 (0.388)	−0.012 (0.387)	−0.021 (0.113)	−0.028 (0.047)	−0.029 (0.043)	−0.048 (0.007)
	[−0.040 0.016]	[−0.040 0.016]	[−0.046 0.005]	[−0.056−0.000]	[−0.056−0.001]	[−0.082−0.013]
Firm growth	−0.000 (0.987)	−0.000 (0.987)	−0.001 (0.972)	0.018 (0.003)	0.018 (0.003)	0.017 (0.001)
	[−0.044 0.043]	[−0.044 0.043]	[−0.030 0.029]	[0.006 0.029]	[0.006 0.029]	[0.007 0.027]
Industry-average ROE	−0.000 (0.140)	−0.000 (0.148)	−0.000 (0.159)	−0.000 (0.027)	−0.000 (0.026)	−0.000 (0.027)
	[−0.000 0.000]	[−0.000 0.000]	[−0.000 0.000]	[−0.000−0.000]	[−0.000−0.000]	[−0.000−0.000]
Change in the number of industry employees	0.000 (0.015)	0.000 (0.015)	0.000 (0.008)	0.000 (0.418)	0.000 (0.399)	0.000 (0.143)
	[0.000 0.000]	[0.000 0.000]	[0.000 0.000]	[−0.000 0.000]	[−0.000 0.000]	[−0.000 0.000]
Industry-level advertising expenditures	−0.000 (0.214)	−0.000 (0.215)	−0.000 (0.157)	0.000 (0.317)	0.000 (0.331)	0.000 (0.320)
	[−0.000 0.000]	[−0.000 0.000]	[−0.000 0.000]	[−0.000 0.000]	[−0.000 0.000]	[−0.000 0.000]
Industry-level HHI	0.119 (0.005)	0.119 (0.005)	0.095 (0.059)	0.207 (0.001)	0.204 (0.001)	0.144 (0.034)
	[0.036 0.202]	[0.036 0.203]	[−0.004 0.194]	[0.086 0.329]	[0.081 0.326]	[0.011 0.276]
Vacillation frequency		0.027 (0.713)			0.173 (0.112)	
		[−0.117 0.170]			[−0.041 0.388]	
Vacillation frequency^2		−0.034 (0.755)			−0.255 (0.160)	
		[−0.245 0.178]			[−0.539 0.089]	
Vacillation scale			0.384 (0.028)			0.617 (0.006)
			[0.041 0.727]			[0.178 1.056]
Vacillation scale^2			−0.329 (0.016)			−0.441 (0.015)
			[−0.598−0.060]			[−0.794−0.085]
Inverse mills ratio	−0.001 (0.747)	−0.001 (0.816)	0.018 (0.176)	0.008 (0.109)	0.009 (0.075)	0.054 (0.001)
	[−0.008 0.006]	[−0.008 0.006]	[−0.008 0.044]	[−0.002 0.017]	[−0.001 0.020]	[0.022 0.086]
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	−1621.38	−1621.25	−1615.16	−8125.55	−8123.32	−8117.93
LR test (χ^2)	–	0.26 (0.878)	14.08 (0.001)	–	4.46 (0.108)	15.44 (0.000)
# Firms	2,303	2,303	2,303	2,821	2,821	2,821
# Obs (firm-year)	18,009	18,009	18,009	18,024	18,024	18,024

P-values in parentheses; 95 percent confidence intervals in brackets.

largely missing. In this study, building upon Nickerson and Zenger's (2002) vacillation theory, we test and find inverted U-shaped relationships between vacillation frequency/scale and firm performance using patent-based measures of exploration and exploitation.

Our study has limitations, which suggest avenues for future research. First, our patent-based measures of exploration and exploitation have some limitations and thus our findings and implications should be interpreted with caution. Most importantly, our empirical focus is limited to exploration and exploitation in technological innovation and knowledge search. Hence, our findings on the vacillation frequency and scale may also be limited to the context of innovation. We urge future researchers to examine the performance implications of vacillation in empirical contexts other than innovation. In addition, our measures may have some measurement error issues. For example, some firms' patent-related firm capabilities may be more or less effective than others in dealing with patent application and evaluation processes (Somaya, Williamson, and Zhang, 2007). Some firms may also be more or less willing to patent their inventions for strategic reasons (Kim and Marschke, 2005; Lerner, 1995), or obtaining patents may be more or less difficult during certain years or periods (Shane, 2004). While we control for firm differences in the tendency of patenting and firm and year fixed-effects to address those issues, future researchers may look for improved and more comprehensive measures of exploration and exploitation.

Second, our study does not provide an answer to the question of whether and when simultaneous balancing and vacillation can be substitutes (Gupta, Smith, and Shalley, 2006). For some firms, simultaneous balancing may be a more appropriate means to achieve ambidexterity, while for other firms, vacillation may be more effective. It would be interesting and meaningful to examine what factors explain the relative appropriateness of the two solutions for ambidexterity. Including ours, existing empirical studies have only separately examined the performance effect of either simultaneous balancing (He and Wong, 2004; Jansen *et al.*, 2005; Lavie, Haunschild, and Khanna, 2012; Uotila *et al.*, 2009) or vacillation (Boumgarden *et al.*, 2012; Brown and Eisenhardt, 1997) and have not compared performance effects of simultaneous balancing and vacillation. While our data limit our ability to investigate this research question in this study, we believe that this is a great research opportunity for scholars interested in the topic.

Third, we do not take into account of more detailed aspects of vacillation in our research, which future research may explore. Specifically, we do not consider how possible asymmetry in exploration and exploitation that constitute vacillation may affect the relationship between vacillation frequency/scale and firm performance. For example, vacillations of the same frequency and scale may vary in the exact levels of exploration and exploitation that constitute them (e.g., medium exploration to high exploitation versus high exploration to medium exploitation). Also, we do not make a distinction between vacillation from exploration to exploitation versus vacillation from exploitation to exploration. Our data show that the amount of time required for vacillation from exploration to exploitation (1.23 years) and from exploitation to exploration (3.51 years) differs ($t = 18.99$, $p = 0.000$). It is possible that such asymmetry may affect the theoretical predictions of Nickerson and Zenger (2002). Future research may incorporate these more fine-grained features of vacillation and develop a theory related to them. Furthermore, future research may attempt to extend vacillation theory by theorizing the factors that may substantially affect vacillation, other than inertia as discussed in Nickerson and Zenger (2002).

Our study intends to contribute to the discussion on ambidexterity and vacillation theory by providing large-sample statistical evidence for the predictions of vacillation theory. Nickerson and Zenger (2002) proposed how vacillation may lead to organizational ambidexterity, but large-sample empirical tests of their theory have been missing. This lack of large-sample empirical evidence has slowed the progress and further development of vacillation theory. We hope that our study serves as the groundwork for further theoretical development and empirical tests of vacillation theory and, more broadly, ambidexterity literature.

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