Process Innovation and Performance: The Role of Divergence

Abstract

Process innovation is a key determinant of performance. While extant literature paints a clear picture of the drivers of process innovation, the effect of process innovation on performance has received little attention. This paper contributes to theory building in this important area and examines how divergence of process innovation impacts performance. Divergence concerns the extent to which the *observed* level of process innovation diverges from the *expected* level of process innovation. Positive (negative) divergence occurs when the observed level of process innovation is higher (lower) than expected. In turn, we consider how divergence acts as a driver of performance. This approach is useful and important for managers and theory development as it provides insight into situations where a firm may have “too little” or “too much” process innovation. We use survey and archival data from 5,594 firms across 15 countries and find negative divergence to reduce performance under high competitive intensity, whereas positive divergence is detrimental under high environmental uncertainty. Thus, divergence advances understanding as, in contrast with previous work, we do not suggest that more innovation is always better. These findings contribute to understanding the process innovation-performance relationship and has important implications for strategic management research and practice alike.

Introduction

Process innovation is the extent to which a firm introduces ideas or improvements in processes or organizational procedures (cf. Anderson and West, 1996). It is specific to each organization and considered a key determinant of performance (Damanpour 2010; Piening and Salge (2015). Despite this however, two clear limitations apply to the process innovation literature. The first is the relatively small amount of empirical evidence available regarding the relationship between process innovation on performance. The second are the inconclusive results (Cf. Piening and Salge, 2015; Chiva et al. 2014). Indeed, positive effects (e.g. Ar and Baki, 2011; He and Wong, 2004), a negative effect (e.g. Mavondo, Chimhanzi, and Stewart 2005), and both positive and negative effects are reported (e.g. Baer and Frese 2003).

The research objective is to address the lack of conclusive findings on the process innovation-performance relationship. We argue inconclusive findings may have arisen because prior research has not sufficiently addressed the heterogeneity in this relationship and that for every firm a different "level" of process innovation may be appropriate to optimal performance. As process innovation is specific to each firm, with each firm operating in a different environment and facing different drivers that may foster process innovation (Venkatraman 1989, Anderson, 1988), we argue that examining the heterogeneity in the process innovation-performance linkage is critical to acquire a good understanding the impact of process innovation. In response, we take a novel approach and focus on divergence as one essential aspect of heterogeneity by examining how *divergence* of process innovation impacts performance. Divergence concerns the extent to which the *observed* level of a firm's process innovation deviates from the *expected* level, based on the presence, or absence, of relevant drivers of process innovation. Studying divergence is valuable to understand why firms with a certain *expected* level of process innovation, yield different levels of observed process innovation and what this implies for their performance. Such divergence has different valence. First, positive divergence occurs when the observed level of process innovation is higher than expected.

Second, negative divergence occurs when the company's observed level of innovation is lower than expected i.e. when a firm produces less process innovations than one might expect, based on available drivers.

Studying divergence is relevant because it impacts performance. The premise of this paper is that divergence is a useful means of understanding the process innovation-performance link, which helps address the inconclusive results found thus far. Two views arise, i) positive divergence can be beneficial to performance, and ii) negative divergence can be beneficial to performance.

This study identifies which of these explanations gets support under different contextual settings. In addition, it tells a fine-grained story on how process innovation impacts performance at the most detailed (i.e. individual) level of contingency theory (Venkatraman, 1989). This firm-specific approach suggests each firm is heterogeneous in its drivers that foster process innovation, such as organizational learning, and that the availability of these drivers, relative to the level of process innovation, explains performance. This approach clearly contributes because it introduces and identifies a new aspect of heterogeneity in the process innovation-performance link and uncovers a positive divergence (or "too much") as well as a negative divergence (or "too little"). This approach is also useful as it suggests that one should not only focus on the expected level of process innovation, but also consider its divergence to achieve a comprehensive understanding of the process innovation – performance relationship. Our key argument is that the focus should not be on more vs. less innovation *per se* but on whether such level of innovation is expected based on the drivers within context (or not). Thereby, we challenge the view often held in the innovation literature that more innovation is better.

In addition, we expand the literature that has demonstrated the important impact of environmental factors on organizational change and innovation practice (cf. Wischnevsky et al. 2014) by studying how the business environment affects the impact of divergence in the process innovation – performance relation. In doing so, we take a contingency approach. Contingency theory elevates two key aspects of the business environment; environmental uncertainty and competitive intensity and our aim is to investigate how these environmental factors *impact* the relationship between the divergence (from process innovation) and performance (cf. Drazin and Van de Ven, 1995),

Our findings reveal unique insights into the contingent nature of the process innovation-performance relationship and suggest that negative divergence (i.e., less innovation than expected) is harmful to performance under conditions of high competitive intensity, whereas positive divergences (i.e., more innovation than expected) is detrimental under high environmental uncertainty. The analyses rely on a large sample (N=5,594 firms) of both survey and archival data, collected from a wide sample of industries and countries. We analyze this data using a two-step random-effects estimator.

Brief Literature review

Process innovation has an internal focus and typically concerns techniques of producing and marketing goods or services and may be reflected through, for example, lean product development processes or total quality management practices, and focuses on improvements in effectiveness and efficiency (Piening and Salge, 2015). In contrast to product innovation, process innovation has not been frequently studied. Yet, in almost all industries process innovations are possible, in contrast to product innovation, and process innovations have the potential to influence performance (Jiménez-Jiménez and Sanz-Valle 2011). For example, process innovation may create advantages that are difficult for competitors to observe and imitate (Damanpour, 2010). Piening and Salge (2015) even go as far as to suggest that process innovation, due to its continuous contribution to improving the technological and administrative processes, is one of the most important sources of competitiveness for firms in dynamic or fast-moving industries. However, because of the difficulties in properly implementing process innovations, advantage may disappear and the literature on process innovations (see Table 1) suggests a chequered pattern of positive associations between process innovation, negative associations, and nil associations. The task of this paper is to contribute to this literature by presenting a novel lens through which to consider process innovations; *divergence*. Our theory and analysis is at the firm level and we aim to explain both the drivers and outcomes of process innovation using this lens.

Table 1. Literature on the process innovation-performance link

Title, authors, and year	Independent variable(s)	Dependent variable	Effect found	Method	Setting
Understanding the Antecedents, Contingencies, and Performance Implications of Process Innovation: A Dynamic Capabilities Perspective. Piening and Salge (2015).	Process innovation propensity and effectiveness.	Performance	+ for propensity, 0 for effectiveness	Survey	2038 manufacturing and service firms from 22 industries in Germany.
Organizational learning, innovation and internationalization: A complex system model. Chiva, Ghauri, and Alegre (2014).	Breadth of a firm's innovation-related activities	Financial performance	inconclusive	Qualitative	18 interviews in two firms in the Spanish clothing industry.
Antecedents and performance impacts of product versus process innovation: Empirical evidence from SMEs located in Turkish science and technology parks. Ar and Baki (2011).	Process innovation	Sales, profitability, and market share	+	Survey	270 managers in small and medium-sized enterprises, science and technology parks in Turkey.
Innovation, organizational learning, and performance. Jiménez-Jiménez and Sanz-Valle (2011).	Process innovation	Employee turnover and absenteeism, product quality, internal process coordination, company and product image, market share, profitability, and productivity	+	Survey (using a personal interview, using a structured questionnaire, to collect data)	451 firms in the service and manufacturing industries in Spain.

Learning orientation and market orientation: Relationship with innovation, human resource practices and performance. Mavondo, Chimhanzi, and Stewart (2005).	Process innovation	Marketing effectiveness and financial performance	-	Survey	227 firms in the high-tech, professional services and hospitality industries in Australia.
Exploration vs. exploitation: An empirical test of the ambidexterity hypothesis. He and Wong (2004).	Process innovation intensity	Sales growth	+	Survey	206 manufacturing firms in Singapore and Malaysia.
Innovation is not enough: Climates for initiative and psychological safety, process innovations, and firm performance. Baer and Frese (2003).	Twelve types of process innovations	Return on assets (ROA) and firm goal achievement	+ and -	Survey	47 mid-sized companies across a range of industries in Germany.

The concept of Fit

Studying divergence is useful as it concerns a contingency at the individual (firm) level. Accordingly, we take a contingency approach that is based on the *fit as matching* and *fit as moderation* notions. (Venkatraman, 1989). First, we discuss the fit as matching perspective, then, the drivers needed to achieve fit, and, finally, the fit as moderation perspective.

Fit as matching

The fit as matching perspective introduced by Venkatraman (1989) conceptualizes fit by matching (in our case) process innovation to its drivers. By employing the fit as matching approach, we account for the drivers of process innovation which is useful since firms operate in contexts of multiple and often conflicting contingencies where each driver adds to the expected level of process innovation. Moreover, accounting for an extensive set of drivers is arguably a more comprehensive approach to the issue of process innovation (Drazin and Van de Ven, 1985).

Key drivers of process innovation

A relatively well-developed picture of the drivers of process innovation exists in the literature which highlights both internal and external drivers. We discuss each in turn. Internal drivers include market orientation (e.g. Theoharakis and Hooley, 2008) and organizational learning (e.g. Chiva et al., 2014; Ar and Baki, 2011). The rationale is that process innovation is frequently due to expressed needs of customers (Baker and Sinkula, 1999). Moreover, open-mindedness and shared values are key characteristics of organizational learning, which may significantly help firms' process innovation (Sinkula, Baker, and Noordewier, 1997). Firm size also impacts process innovation; some argue larger firms have greater means for helping innovation, while others argue larger firms display greater inertia that could delimit innovation. In addition, whether a firm is a market challenger or follower likely correlates with process innovation. Firms possessing greater market power have a stronger incentive to adopt process innovations, because they can expect to appropriate the performance benefits derived from such changes (Wischnevsky, Damanpour and Mendez, 2011).

In addition, external, market-based drivers of process innovation include environmental uncertainty and competitive intensity (e.g. Amit and Schoemaker, 1993). Evidence suggests that the more dynamic, hostile or heterogeneous the competitive environment, the more firms rely upon process innovation to launch new products and services at a faster rate than competitors (Calantone, Schmidt, and Di Benedetto, 1997). Moreover, process innovation may vary across industries or countries. National culture, which reflects patterns of thinking, feeling, and acting rooted in common values and conventions of a society (Hofstede, 2001), is also likely to affect process innovation. Ambos and Schlegelmilch (2008) for instance, suggests that high uncertainty avoidance likely hinders a firm's capability to innovate while Nakata and Sivakumar (1996) provide evidence masculinity positively relates with process innovation. As no set of drivers is complete, we discuss sensitivity to omitted variables in the "Additional tests" section.

Fit as moderation

The fit as moderation perspective provides the means to assess the influence of divergence on performance in different contexts. This perspective is an important complement to *fit as matching* as several studies have emphasized that the effect of divergence of innovation is strongly contingent on the organizational environment (Wischnevsky et al. 2012 Cepeda-Carrion et al. 2011) and that a comprehensive understanding of this fit requires studying the moderating role of environmental factors. Specifically, we examine whether divergence of process innovation's relationship with performance varies systematically with environmental uncertainty and competitive intensity as argued previously (e.g. Amit and Schoemaker, 1993). These two aspects of the business environment have been proposed in contingency theory as they relate to unstable, off-equilibrium, situations. We do not hypothesize a main effect of divergence as our assumption is that, at least in the short-term, one of an equilibrium. That is, if firms could gain performance by increasing process innovation, a re-estimation of our model would again result in a prediction where, on average, divergence is zero. Thus, testing for a main effect *on average*–as a regression model implies–is not useful. Moreover, context strongly determines whether divergence of innovation increases or decreases performance (Anderson, 1988). Accordingly, we focus on examining the moderating effects of the business context on this relation.

Hypotheses

For each hypothesis, we argue separately why positive and negative divergence may relate to lower performance. We do this first for environmental uncertainty, then turning to competitive intensity.

Environmental uncertainty. Changes in industry structure, (in)stability of market demand, and probability of environmental shocks are important elements in producing environmental uncertainty. At the same time, several studies stress the need of organizational support for process innovation (Baer and Frese, 2003). This essentially relates to the notion that innovation is driven by firms' potential to absorb, assimilate and exploit market knowledge (Cohen and Levinthal, 1990).

Firms with a positive divergence may find themselves short of the means needed to effectively develop and support process innovation under environmental uncertainty as in high uncertainty and ambiguity contexts, the presence of knowledge is essential to successfully implementing process innovations (Chiva et al., 2014). Firms that generate process innovations in combination with little support are likely to perform less well. The exploration-exploitation paradox that is central to adapting to the environment (Gupta, Smith, and Shelley, 2006) also suggests that under circumstances that require adaptation, such as high environmental uncertainty, firms need to strike a balance between exploration activities, such as learning or being market oriented, and exploitation activities, such as process innovation. Building on the arguments of Gupta, Smith, and Shelley (2006), who expect that performance is highest when exploration and exploitation are well balanced, we add to this that the point for which performance improves (and declines) is firm-specific.

The preceding arguments focus on the negative performance emanating from positive diverge. We now turn to discuss the expected effect of negative divergence. Under greater uncertainty, firms with negative divergence are likely to perform less well because of not fully exploiting their market sensing and learning (Piening and Salge, 2015; Cepeda-Carrion et al., 2012). This implies organizational inefficiencies that are particularly detrimental in uncertain markets when proactiveness and rapid responsiveness are needed. Moreover, investing in supporting aspects, such as market orientation and learning, is of limited use if the valuable and timely knowledge they provide are under-used in design of process innovations, as reflected by negative divergence. Note that the preceding suggests that for both positive and negative divergence performance declines relative to no divergence. This is captured by the following hypotheses:

H1a/b: Under higher environmental uncertainty, (H1a) positive divergence and (H2b) negative divergence is associated with lower performance.

Competitive intensity. Competitive intensity refers to the level of inter-firm rivalry in a given market (Jaworski and Kohli, 1993), which is typically associated with increased pressure on organizations to realize efficiency gains (Slater and Narver, 1994). Positive divergence may be harmful under greater competitive intensity when firms attempt to produce more process innovations than properly supported. When competitive intensity is high, it is important for firms to produce effective innovations that can meet or outcompete competition. Under positive divergence firms have been able to produce innovations more than the drivers that are in place would suggest. While this may be positive in terms of having achieved greater process innovation than the drivers suggest, it is likely that such innovations lack the required support to make them successful. For example, successful innovations require cross-functional collaboration (De Luca and Atuahene-Gima, 2007). When positive divergence occurs, organizational learning, market orientation, and other elements required for cross-functional collaboration are not present to a commensurate degree. Particularly when competitive intensity is high, this likely means that the produced innovations are less likely to compare favorably to competition (which, on average has no divergence). Moreover, just like environmental uncertainty, high competitive intensity is also a risky situation that requires adaptation and good balance between exploration and exploitation (Gupta, Smith, and Shelley, 2006). Thus, positive divergence is likely associated with lower performance. Turning to negative divergence, also organizations that are lower than expected on process innovation are at a competitive disadvantage, as the scope for efficiency gains is limited and they are less likely to respond effectively to market opportunities and threats. More specifically, product-related innovations that are key to dealing effectively with competitors, are often facilitated by process innovations (Piening and Salge, 2015). Having the required drivers, such as developed understanding of customer and supplier needs, without using them in designing and refining organizational processes, again points to inefficient use of resources. Moreover, especially under intense competition when price competition is typically intense and need for organizational efficiencies is particularly great, failure to build sustainability of success via sufficient levels of process innovation is likely to be damaging. Therefore, our second hypothesis is:

H2a/b: Under higher competitive intensity, (H2a) positive divergence and (H2b) negative divergence is associated with lower performance.

Method

Data

We use a combination of survey and archival data to test our hypotheses. Survey data was collected in Australia, Austria, Brazil, Finland, Germany, Greece, Hong Kong (SAR), Hungary, Ireland, Mainland China, the Netherlands, New Zealand, Slovenia, the United Kingdom, and the United States.

These countries were selected as they present a high degree of variance in terms of economic development. The survey data is bolstered by secondary data drawn from the Economist Intelligence Unit and Hofstede (2001).

Survey procedure. From each country, a random sample was drawn from national sampling frames including Dun and Bradstreet, ProBusiness, REACH, and Kompass databases. From these national sampling frames, firms with less than 20 employees and non-commercial firms were eliminated. The remaining firms were stratified into small (20-99 employees), medium (100-499 employees), and large (500 or more employees). From the remaining firms, a random sample was drawn and approached using pen-and-pencil surveys. Part of the study design was to draw on a heterogeneous range of firms spanning consumer products and services and business products and services. These industries were chosen as they could be retrieved from the aforementioned national sampling frames.

In each country, an academic expert managed and coordinated data collection activities. The research design was set up to explore the relationship between marketing practices and performance, and therefore targeted the chief marketing officer (in some firms termed marketing or sales director). Chief marketing officers generally have a good overview of the company but because they are rarely in charge of process innovation, there is a much smaller chance of “talking up” the key variables if this study. In cases where a firm did not have a chief marketing officer, the general manager or chief executive officer was invited to participate.

The target sample size for each country was at least 150 observations, which is exceeded for every country. Confidentiality was assured to each informant, and a follow up survey was sent after two weeks if no response had been obtained after the first wave. The net response of the total data collection effort is 5,594 firms. This unique data set combines many common perceptual measures used in previous work with secondary information and enables us to reliably establish an expectation of process innovation for each firm, against which an observed level is compared. Based on the work of Armstrong and Overton (1977), we tested for non-response bias through comparing firms that responded in the first and second wave on the means of the variables included in our models. No systematic differences were found, suggesting no non-response bias. Table 2 shows the net response, language of survey administration, and the response rate per country.

Table 2. Response characteristics

Country	N	Survey language	Response rate
Australia	247	English	24%
Austria	223	German	22%
Brazil	293	Portuguese	11%
Finland	317	English	25%
Germany	362	German	28%
Greece	305	Greek	45%
Hong Kong (SAR)	462	Chinese	23%
Hungary	510	Hungarian	29%
Ireland	628	English	62%
Mainland China	361	Chinese	23%
the Netherlands	167	Dutch	12%
New Zealand	433	English	53%
Slovenia	681	Slovene	87%
the United Kingdom	445	English	13%

The United States	160	English	12%
Total	5.594		

An etic approach was adopted, comparing constructs across multiple countries, and testing construct equivalence through a series of interviews designed to compare the meaning of these constructs. Subsequently, constructs were translated into the native language/spelling and subsequently translated back into English to test for equivalence following the recommendations of Harkness, van de Vijver, Mohler and fur Umfragen (2003). The main questionnaire was extensively pilot tested to refine measurement, check understanding and confirm the applicability of measurement scales and items. We also tested for the cross-cultural equivalence of our measures. Configural and metric invariance of the measures used were supported (Steenkamp and Baumgartner, 1998). Also, for each scale separately, configural invariance of the one-factor model was supported. The Incremental Fit Index, the Comparative Fit Index, and the Root Mean Square Error of Approximation (RMSEA) indicated acceptable model fit. The χ^2 of the model is significant, which is expected given the large sample size (Steenkamp and van Trijp, 1991). In addition, we tested for equality of factor loadings, which was also supported by the data.

This study relies on subjective firm performance measures. In support of this choice, Hult et al., (2008) show that in international contexts perceptual performance can be more reliable than secondary data as certain contexts, such as China, objective measures are often biased for political purposes.

Measures

We use a battery of perceptual and archival measures. The perceptual measures allow for rich measurement and good construct validity and are based on well-developed, valid, and reliable multi-item scales. The country-level measures used in this study, GDP per capita and national culture, are drawn from secondary sources.

Dependent variables

Process innovation is defined as concrete change in processes that has both novelty and value, relative to current practice (West and Farr 1990). Four items adapted from West and Farr (1990) and that have been extensively used (e.g. Shipton et al. 2013) were adopted to formatively measure a firm's process innovation. The four items are measured on a five-point Likert-type scale from 1 (strongly disagree) to 5 (strongly agree). These items solicited responses on companies' relative degree of innovation in (1) deciding what methods to pursue in achieving their targets and objectives, (2) initiating new procedures or systems, (3) developing new ways of achieving targets and objectives of the company, and (4) initiating changes in the job contents and work methods of the staff. Note that our definition does not require absolute novelty of the innovation (at the industry-level), only newness for the organization and also includes an emphasis on changes in how targets are set and the job contents and work methods to achieve those. As our data spans many countries and industries, the focus on process innovation serves the objectives of the study well as other metrics of innovation (e.g. patents) are uncommon in certain industries or countries.

Performance. This construct is at the firm level and is formatively based on two items. Respondents were asked to indicate the performance of their firm in the last financial year on the following two dimensions: (1) sales volume achieved relative to main competitors, and (2) market share achieved relative to main competitors. Response options ranged from 1 (strongly disagree) to 5 (strongly agree).

Independent variables

Environmental uncertainty. This formative construct measures the degree of change in the focal company's industry. The construct comprises two items; the respondents were asked whether the pace of change is rapid from the perspectives of (1) customer wants, needs and expectations, and (2) technological developments. Response options for the items ranged from 1 (strongly disagree) to 5 (strongly agree). Together, the formative items encompass two dimensions of environmental uncertainty: market uncertainty and technological uncertainty.

Competitive intensity. This formative construct was measured by five items that capture the intensity of price competition and aggressiveness of the competitors' behavior, and risk of new competitors entering the market. Sample items are 'In our markets, competition for sales is intense,' and 'In our markets, there is a significant threat that new firms will enter the market'. The items are adapted from the scales of Jaworski and Kohli (1993) and O'Cass and Weerawardena (2010), response options ranging from 1 (strongly disagree) to 5 (strongly agree). This is a formative scale.

Market orientation. This construct reflects market orientation as an organizational culture. We adopted the scale of Narver and Slater (1990), which encompasses three dimensions of market orientation: customer orientation, competitor orientation, and inter-functional coordination. Sample items are 'our objectives and strategies are driven by the creation of customer satisfaction,' 'Top management regularly discuss competitors' strengths and weaknesses,' and 'Business functions are integrated to serve market needs.' Response options ranged from 1 (not at all) to 7 (to an extreme extent). The scale's Cronbach-alpha in the pooled sample is 0.84, ranging from .77 (China) to .83 (The United States) for the individual countries.

Organizational learning. This construct mirrors organizational attitude towards learning. Similar to Baker and Sinkula (1999), learning refers to an organization cultural characteristic that reflects the value a firm places on responding to changes in the business environment and constantly challenging the assumptions that frame the organization's relationship with the environment. The construct was operationalized by bringing together four central attributes of organizational learning; commitment to learning, being open-minded, shared vision (Sinkula, Baker, and Noordewier, 1997), and intra-organizational knowledge sharing (Moorman and Miner, 1998). Sample items are 'Managers agree that our company's ability to learn is the key to competitive advantage' and 'Employee training and learning is seen as an investment rather than an expense.' Response options for the items ranged from 1 (strongly disagree) to 5 (strongly agree). The scale's Cronbach-alpha in the pooled sample is 0.79 while the minimum alpha is .67 (China) and the maximum is .82 (United Kingdom).

Firm size. Meta-analytical findings suggest that firm size relates to process innovation (Vincent, Bharadwaj, and Challagalla, 2004). Firm size is measured using 7 categories; 0-19 employees, 20-99, 100-299, 300-499, 500-999, 1000-1499, and 1500 or over.

Market position. This variable captures the firm's position in its key market. The managers were asked on a scale to identify whether their firm is the overall market leader or follower.

Industry. We asked firms to report if the firm's main offering is mostly a product or a service, and whether it is targeted to business or consumer markets. We constructed four dummies with balanced offerings as the baseline category.

National culture. Scores of four dimensions of national culture; uncertainty avoidance, individualism, power distance, and masculinity are used following Hofstede (2001). The scores between the sample countries regarding all the cultural dimensions vary substantially; for instance, uncertainty avoidance ranges from 29 to 112.

GDP per capita. This country-level variable was drawn from the secondary data of the Economist and is measured in terms of purchasing power.

Table 3 displays descriptive statistics and correlation coefficients for each of the variables. To assess the measurement properties of our formative constructs, we calculated the variance inflation factor scores (VIF) per construct. We observe, noting that all items load significantly, that the highest VIF is 2.63 at the item level. This is well below the common VIF standard of <10 and the more stringent <5 (Mooi, Sarstedt, and Mooi-Reçi, 2018) and also below the strictest reported standard of <3 (Petter, Straub, and Rai, 2007). This suggest that there is limited collinearity among indicators, which implies that it is easy to determine the distinct influence of each individual indicator on the formative variable (see Diamantopoulos and Winklhofer 2001), illustrates that the indicators adequately capture the multidimensional nature of the construct (MacKenzie, Podsakoff, and Podsakoff, 2011). We also considered nomological validity, heeding the suggestions by MacKenzie, Podsakoff, and Podsakoff (2011) by specifying a model where performance is a function of innovation and where innovation is, in turn, dependent on competition and uncertainty. This is the closest possible specification to our theoretical model. The relationships are all significant and the signs consistent with those reported in Table 4 and 5. This suggests that the focal construct relate to other constructs, as specified in the nomological network, thus increasing confidence in the validity of the indicators (MacKenzie, Podsakoff, and Podsakoff, 2011).

Table 3. Bivariate Correlations (*n = 4,616)* and Descriptive Statistics

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Performance	-												
2. Process innovation	0.192	-											
3. Environmental uncertainty	0.038	0.187	-										
4. Competitive intensity	0.013	0.060	0.364	-									
5. Market orientation	0.124	0.343	0.133	0.122	-								
6. Organizational learning	0.128	0.458	0.195	0.130	0.423								
7. Firm size	0.063	-0.019	-0.023	0.014	-0.024	-0.019	-						
8. Market position	-0.191	-0.126	0.008	-0.041	-0.028	-0.050	-0.208	-					
9. GDP per capita	0.070	-0.016	0.018	0.074	-0.130	-0.054	0.065	-0.082	-				
10. Power distance	-0.108	0.058	0.109	0.010	0.073	0.138	-0.092	0.095	-0.642	-			
11. Uncertainty avoidance	-0.061	-0.057	-0.138	0.023	0.211	0.056	-0.072	0.061	-0.357	0.217	-		
12. Individualism	0.052	-0.101	-0.110	-0.072	-0.106	-0.212	0.109	-0.022	0.485	-0.816	-0.203	-	
13. Masculinity/femininity	0.069	-0.032	-0.041	-0.211	-0.150	-0.155	0.088	0.049	-0.017	-0.329	-0.239	0.389	-
Mean	3.520	3.528	3.568	3.600	4.935	3.948	3.074	3.790	25,347.880	47.174	59.107	57.329	55.892
Standard Deviation	1.203	0.811	0.814	0.559	0.952	0.694	1.360	1.577	9,290.992	19.822	24.260	24.894	20.887
Minimum	0	1	1	1	1	1	1	1	6,270	11	29	20	14
Maximum	10	6	5	5	7	5.5	7	7	41,529	80	112	91	88

Note: Items 9-13 are country-level correlations weighted for country size. Correlations |0.03| or over are significant at $p<0.05$ (2-sided)

Analytical approach

Our analysis requires us to consider (1) endogeneity of process innovation, (2) account for process innovation being below *or* above the predicted (i.e., expected) level, and (3) account for the clustered nature of our data. To deal with these challenges we adopt a two-step procedure suggested as suggested by Garen in *Econometrica* (1984). This approach allows estimating the effect of endogeneity of a continuous variable (i.e., process innovation) on a continuous outcome variable (i.e., performance). This approach has been used for substantive reasons as well as for the benefit of avoiding endogeneity issues. Substantively, this approach allows us to estimate the expected level of process innovation based on a theory-ascribed set of drivers of process innovation (discussed extensively in the "Key drivers of process innovation" section). This expected level is unique to each firm and calculated (i.e. predicted) by regression analysis in the first step. From this, we calculate the divergence, which is the extent to which the observed level of process innovation diverges from the theory-based level of process innovation in step 2. Such divergence may result from a variety of reasons, including idiosyncratic management (styles), culture, or unobserved capabilities. Such divergence may be either positive or negative divergence (i.e., either more or less process innovation than the expected level suggests).

In the first step, we estimate the expected level of process innovation for each firm by simultaneously including an extensive set of firm- and market-specific drivers of process innovation taken from prior theory. The drivers include environmental uncertainty, competitive intensity, market orientation, organizational learning, firm size, market position, main industry, GDP per capita, and the four cultural dimensions of Hofstede. We use a random-effects approach to explain process innovation. Notationally, our model is therefore as follows with $_j$ referring to countries, $_i$ referring to individual firms, u_j referring to between-country differences[1], and e_{ij} referring to individual, firm-level divergences:

$$Process\ innovation = \alpha_1+\beta_1 Uncertainty_{ij}+\beta_2 Competition_{ij}+\beta_3 Market\ orientation_{ij} +\beta_4 Organizational\ learning_{ij}+\beta_5 Firm\ size_{ij}+\beta_6 Market\ position_{ij}+\beta_7 Consumer\ products_{ij} +\beta_8 Consumer\ services_{ij}+\beta_9 Business\ products_{ij}+ \beta_{10} Business\ services_{ij} +\beta_{11} GDP\ per\ capita_j+\beta_{12} Power\ distance_j+\beta_{13} Uncertainty\ avoidance_j +\beta_{14} Individualism_j+\beta_{15} Masculinity/femininity_j+Country\ dummies_j+u_j+e_{ij}$$

To capture the performance effect of process innovation based on theory, we use the vector of observed variables $x\beta$ to estimate an expected level of process innovation, noted as $\hat{y}$.

Next, we retain the predictions $\hat{y}$ (i.e., expected level of process innovation) from the first step to explain performance. We calculate the divergence as $y-\hat{y}$ for each firm and relabel this from e_{ij} to η for ease of notation. We do not assume that the performance effects of η are linear. In this we follow Mooi and Ghosh (2010) and Bercovitz, Jap, and Nickerson (2006). Empirically we construct two separate variables: η_{neg} which takes on the absolute value of the negative residual when present and zero else, and η_{pos} which takes the value of the positive residual and zero else.

In the second analytical step, we analyze the performance outcomes. We omit a set of identifying variables (cf. Mooi and Ghosh, 2010) that are not expected to influence performance *a priori*. This results in the following second-stage model:

$$Performance=\alpha_2+\beta_1\hat{y}+\beta_2\,\eta_{posij} +\beta_3\,\eta_{negij} +\beta_4\,\eta_{posij}*Uncertainty_{ij}+\beta_5\,\eta_{negij}*Uncertainty_{ij} +\beta_6\,\eta_{posij}*Competition_{ij}+\beta_7\,\eta_{negij}*Competition_{ij}+\beta_8 Uncertainty_{ij} +\beta_9 Competition_{ij}+\beta_{12} Market\ orientation_{ij} +\beta_{13} Organizational\ learning_{ij} +\beta_{14} Firm\ size_{ij} +\beta_{15} Market\ position_{ij}+\beta_{16} Consumer\ products_{ij}+ \beta_{17} Consumer\ services_{ij} +\beta_{18} Business\ products_{ij}+ \beta_{19} Business\ services_{ij}+\beta_{20} GDP\ per\ capita_j +\beta_{21} Power\ distance_j+\beta_{22} Uncertainty\ avoidance_j+\beta_{23} Individualism_j +\beta_{24} Masculinity/femininity_j+Country\ dummies_j+u_{j2}+e_{ij2}$$

We estimated the above two models using random effects models, since some of our variables (i.e., GDP, country culture, and country dummies) are constant within panels, rendering fixed effects

[1] Note that we exclude the country-level differences u_p. The u_p controls for unobserved country differences in process innovation beyond our observed country characteristics GDP and culture.

estimation impossible. To identify the second stage equation, we omit a set of identifying variables that are not expected to influence performance *a priori* (cf. Mooi and Ghosh, 2010).

Results

Key findings and tests of hypotheses

The results of our hypothesis tests are reported in Table 4. Firstly, we find support for H1a that under higher environmental uncertainty, positive divergence is associated with lower performance (p <.05). We do not find support for H1b, which states that under higher environmental uncertainty negative divergence is associated with lower performance (p>.05). Turning to H2, we do not find that under higher competitive intensity positive divergence is associated with lower performance (p>.05). We do, however, find support for H2b which states that under higher competitive intensity, negative divergence is associated with lower performance (p<.05). Turning to the remaining estimated effects we find that the predicted level of process innovation relates to higher performance (p<.01). We do not find any effect of the deviations themselves, whether low (p>.05) or high (p>.05). This is in line with our argument that there is no gain from diverging in itself. For our control variables, we find negative performance covariates for environmental uncertainty (p<.01), for business products (p<.01) and for high power distant cultures (p<.01). For uncertainty avoidant cultures, in turn, the covariate is positive (p<.01).

As these testing of our hypothesis depends on a first-stage regression, we also have a set of additional results shown in Table 5. We find that environmental uncertainty positively (p<0.01) relates to process innovation while competitive intensity correlates negatively with process innovation (p<0.01). The results also suggest that both market orientation (p<0.01) and organizational learning (p<0.01) positively relate to firms' process innovation. Firm size (p<0.10) and market position (p<0.01) both relate negatively to process innovation. We also find GDP per capita and the dimensions of national culture all correlate significantly with process innovation (p<0.01). Before we discuss the implications of these findings, we first discuss several *post hoc* tests and alternative explanations.

Table 4. Process Innovation and Performance (*n = 4,616)*

Variable	Performance
$\widehat{Innovation}$	2.284***
η_{pos}	0.141
η_{neg}	0.123
η_{pos} * Environmental uncertainty (H1a)	-0.108**
η_{neg} * Environmental uncertainty (H1b)	0.018
η_{pos} * Competitive intensity (H2a)	0.010
η_{neg} * Competitive intensity (H2b)	-0.113**
Environmental uncertainty	-0.123***
Competitive intensity	0.060
Market orientation	-0.308
Organizational learning	-0.769
Industry: Consumer products	-0.032
Industry: Consumer services	0.017
Industry: Business products	-0.121***
Industry: Business services	-0.010
GDP per capita	-0.000
Power distance	-0.018***
Uncertainty avoidance	0.015***
Individualism	0.009
Masculinity/femininity	0.009
Country dummies	included
Constant	-0.055

Legend: * p<0.1; ** p<0.05; *** p<0.01, two-sided

$\widehat{Innovation}$ refers to expected level of innovation, η_{pos} refers to positive divergence and η_{neg} refers to negative divergence.

Table 5. Predicting Process Innovation (*n = 5,523)*

Variable	Process Innovation
Environmental uncertainty	0.077***
Competitive intensity	-0.068***
Market orientation	0.202***

Organizational learning	0.396***
Firm size	-0.016*
Market position	-0.046***
Industry: Consumer products	0.014
Industry: Consumer services	0.018
Industry: Business products	0.045
Industry: Business services	0.043
GDP per capita	-0.000***
Power distance	0.023***
Uncertainty avoidance	0.011***
Individualism	0.029***
Masculinity/femininity	-0.001***
Country dummies	included
Constant	-2.070***

Legend: * $p<0.1$; ** $p<0.05$; *** $p<0.01$, two-sided

Additional tests

We performed a series of tests to assess model robustness. These include the Hausman specification tests, tests for misspecification of the first-stage model, the Breusch and the Pagan Lagrangian multiplier test for random effects. We also discuss the potential implications of common method bias. Finally we consider the relationship between innovation and performance through a set of t-tests.

Hausman specification test considers potential differences in parameter estimates between the consistently estimated fixed effects estimator and the more efficient (but potentially inconsistent) random effects estimator. We therefore conducted the Hausman test for the process and performance equations separately whereby in each case equivalence of random effects coefficients was tested against a fixed effects model. Per convention, non-panel varying covariates were dropped. The results of both Hausman tests ($p>0.05$) indicate that the random effects coefficients were not significantly different from the fixed effects coefficients. Consistent with common practice, we therefore prefer the efficiency and consistency of the random effects model (Greene, 2003).

Misspecification of the first-stage model could affect our results in the second stage. While we cannot claim our first stage model is complete, the question is if it is reasonably completely specified. We firstly rely on theory, as discussed in the section on *Key drivers of process innovation*. Secondly, we conducted Ramsey's RESET test to test for possible misspecification. The results (p>0.10) suggest the model is not misspecified.

The Breusch and Pagan Lagrangian multiplier test for random effects considers whether the variances of our countries are jointly equal to zero. If this test is not rejected, pooled regression is possible. The results, however, show that the variances are unequal, suggesting models that account for group differences (such as random effects models) need to be considered. The Breusch and Pagan Lagrangian multiplier test for the outcome equation (χ^2 (1) = 7183.40, p<0.05) clearly indicates this to be the case.

Common method variance could potentially inflate relationships between the independent and dependent measures of our study. Two arguments make it unlikely that common method bias inflates relationships in this study. Firstly, we tested for potential common method bias using Harman's one factor test (Podsakoff, MacKenzie, Lee, and Podsakoff, 2003). If a single factor emerges from the factor analysis, or if one factor accounts for the majority of the variance, common method bias is a concern. Our results clearly indicate multiple factors with the first factor accounting for only 21.59% of the variance, suggesting common method bias is not a concern. Secondly, following the logic of Siemsen, Roth, and Oliveira (2010), if common method bias is present, it seriously deflates nonlinear effects, including interactions. As our key hypotheses are based on nonlinear effects, any presence of common method bias would stack the odds against finding significant effects.

Relationship between innovation and performance: we also tested the relationship between innovation and performance at different levels of innovation. To this end we constructed 3 indicators; the first indicating if innovation was equal to or above 3 (zero else), the second indicating this for equal to or above 4 (zero else), and the third when innovation was equal to or above 5 (zero else). Specifically for the first indicator p<.01 (t=9.04; m1=3.59, sd=1.20; m0=3.16, sd=1.15), for the second *p*<.01 (t=11.09; m1=3.77, sd=1.16; m0=3.37, sd=1.20), and for the third p<.01 (t=6.61; m1=3.97, sd=1.35; m0=3.49, sd=1.18). Evidently, the results indicate that for each step, performance increases. We also calculated the correlation between innovation and performance trimming the 5% most innovative firms. The change in correlation (from r=.238 to r=.223) is insignificant.

Discussion and Conclusions

In this paper, we explore the performance effects of process innovation. Rather than suggesting a general process innovation-performance relationship (as previous studies have done) we argue that the level of process innovation that best fosters performance depends on individual firm attributes. Thereby our study offers three new novel insights to the understanding of process innovation.

Theoretical contributions

This study expands the literature on process innovation by introducing the role of divergence in the process innovation – performance relationship. As our first contribution, we present new and unique insights into the relationship between *divergence* and performance. We argue that each firm has an "ideal" level of process innovation, based on drivers, relative to which performance diminishes. Specifically, we argue that *divergence from the firm's expected level of process innovation* is associated with reduced performance during high environmental uncertainty or high competitive intensity. Furthermore, we argue that there can be "too much" process innovation. Previously the majority of empirical work in this area, with rare exceptions including Rosenbusch et al. (2011), suggests that more innovation is better for firms. Our novel approach reveals that the process innovation-performance link is best explained by driver-based expectations rather than by the extent of innovation (e.g. Chiva et al., 2014). In particular, we find that the degree of fit with respect to firm and business environmental characteristics is an important determinant of performance. This presents potentially useful insights into the mixed evidence in the extant studies on the process innovation-performance relationship (e.g., Ar and Baki, 2011; Mavondo, Chimhanzi, and Stewart 2005).

Second, our findings highlight that when a positive divergence is observed, performance is lower under higher environmental uncertainty. This suggests that during environmental uncertainty, process innovation beyond what is expected per theory is detrimental for performance, potentially because of lack of absorptive capacity and knowledge-creating resources needed to develop and support process innovation (Cepeda-Carrion et al., 2012). We also find that negative divergence is associated with lower performance under higher competitive intensity. This suggests that "too little" process innovation can be particularly risky to firms' performance in competitive marketplace, when price competition calls for efficiency gains via process improvements. Having strong knowledge-creating resources without using them in designing and refining organizational processes - which negative divergence suggests - further points to inefficient use of resources. In sum, our findings strongly suggest that the relationship between process innovation and performance is more nuanced and context-dependent than scholars have previously argued.

Third, our methodological approach is new to the innovation literature. One of its strengths lies in our conceptualization of the expected level of process innovation being based on regression predictions. Therefore, it is free from endogeneity concerns. It is well known that endogeneity can yield bias whose magnitude and direction is difficult to predict. Through our two-stage approach of predictions and divergences, we can better understand the effects of process innovation as well as provide evidence on the normative implications of following the advice of theory. In doing this, we suggest a methodology that allows for a very fine-grained approach to contingency theory which is firm-specific.

Managerial implications

Some argue the existence of an academia-practitioner gap, with both living in different worlds (e.g. Reibstein et al., 2009). Our findings suggest that theory is not only useful to practitioners but has a crucial and central role regarding decisions relating to efficiency and effectiveness of scarce resources, in the field of process innovation. More specifically, we demonstrate that the prior work on process innovation seems to be useful in that, relative to a theory-predicted level, divergence diminishes performance in our global sample of companies across a wide range of industries. While we do not claim that all managers seek guidance from theory to guide their decision-making, we do claim that the ability to theorize and model innovation is sufficiently well developed to have a positive effect on "real" management decisions. Based on our findings, we conclude that theory provides valid cues for firms on how much to innovate.

In addition, we suggest that firms should not strive for more innovation per se. Our findings suggest that positive divergence or too much innovation is detrimental for performance under environmental uncertainty, while negative divergence, or too little innovation is harmful to performance under competitive uncertainty. Thereby our findings resemble the classical Goldilocks dilemma where one of the three bears finds it "too hot" (i.e., positive divergence), one "too cold" (i.e., negative divergence) and where one is "just right" (i.e., predicted). Our findings do however suggest that what is "just right" can be predicted by our model of process innovation. Managers also often compare the innovation of their firm relative to others. We suggest that there is a level of "just right" which is different from trying to achieve the highest possible level of process innovation.

Moreover, our divergence approach is also useful to comparing performance to that of other firms, typically referred to as benchmarking. What we suggest is that firms should use a method, like the one proposed in this paper, to understand how performance was achieved. Our approach allows managers to benchmark how well other firms turn drivers into process innovation and compare their own levels to this. While the effects we cite for innovation drivers (e.g. an estimated standardized effect of 0.202 for market orientation) are specific, they present opportunities for managers to create useful benchmark indices. Subsequently, firms could use this information to understand if their available means to innovate help them produce lower or higher innovation than expected based on the benchmark. This would help firms understand the ideal level of process innovation, and their efficiency in driving process innovation.

Future research and limitations

Our theory and findings suggest that divergence can reduce performance. Much like, for example, transaction cost theory where divergence has been argued to reduce performance (e.g. Mooi and Ghosh, 2010), we call for further theory development that explicitly accounts for how drivers account for innovation, relative to which performance is explained. Such further development is important as it moves the discussion on innovation away from its focus on developing greater innovation to one where match between the organization and its environment to innovation is central.

An assumption of our model is that the drivers of process innovation are linearly additive. That is, each driver contributes to process innovation as indicated by the weighting of the regression coefficient, but no complementarities are assumed. Specifying such complementarities, and the many different forms in which these may occur (interactions, three-way interactions, quadratic effects, and other), is difficult ex-ante but a key question for further research.

Finally, this paper introduces an approach to understanding process innovation that could equally be used for, for example, product innovation or exploratory and exploitative innovation.

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