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Dynamic Openness for Network-enabled Product and Process Innovation:

A Panel-data Analysis

Effie Kesidou*
Professor of Economics of Innovation and Sustainability
Head of Graduate School (Business Faculty)
Department of Economics
Leeds University Business School
University of Leeds
E.Kesidou@leeds.ac.uk
+44(0)113 3434514

Ram Narasimhan
University Distinguished Professor Emeritus,
John H. McConnell Endowed Professor Emeritus
Department of Supply Chain Management
The Eli Broad Graduate School of Management
Michigan State University
632 Bogue Street, Room 344
East Lansing, Michigan 48824
narasimh@ msu.edu
+1 (517) 353-6381

Serdal Ozusaglam
Postdoctoral Research Fellow & Research Associate
NICRE - National Innovation Centre Rural Enterprise
ERC - Enterprise Research Centre
Warwick Business School
University of Warwick
serdal.ozusaglam@wbs.ac.uk
+44(0) 2476523939

Chee Yew Wong
Professor of Supply Chain Management
Department of Management
Leeds University Business School
University of Leeds
C.Y.Wong@leeds.ac.uk
+44(0)113 3437945

* Corresponding Author

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Abstract

Purpose – Prior research on open innovation has not investigated *changes* in knowledge acquisition strategies of firms over time overlooking how *learning* from past knowledge acquisition can change subsequent search strategies. Also, prior research has focused principally on product innovation overlooking process innovation. The objectives of this paper are to introduce the concept of *dynamic openness,* which is defined as temporal changes in external knowledge search strategy, and explore four dynamic openness strategies- *Closing Down, Opening Up, Persistent Open* and *Persistent Closed-* to examine the impact of these strategies on both product and process innovation.

Design/methodology/approach – The authors used a panel dataset of 16,021 firms based on five waves (2009-2017) of the UK Community Innovation Survey (UKIS). All models are estimated using firm and year Fixed Effects method to control for endogeneity that arises from unobserved heterogeneity. Endogeneity and robustness tests were carried out to ensure the validity of results.

Findings – The results show that firms do use *dynamic openness* strategies over time leveraging learning from past searches. Specifically, the study indicates that *Closing Down* is not an effective strategy for either type of innovation. For process innovation firms should pursue *Opening Up* strategy rather than *Persistent Open* strategy, whereas for product innovation firms could pursue either strategy, highlighting important contextual differences.

Originality– This paper contributes to the literature on knowledge acquisition in open innovation: (a) by theorizing the underlying reasons — learning from past collaborations, absorptive capacity, and external knowledge heterogeneity — why firms pursue one dynamic openness strategy over another; and (b) by extending literature by delineating the dynamic openness strategies that firms should pursue in *process innovation* versus *product innovation.*

Keywords Dynamic Openness, Product/Process innovation, Panel data, Open Innovation

Paper type Research paper

1. Introduction

Open innovation requires continual search for new knowledge, technologies, processes, and services from external knowledge sources (Laursen and Salter, 2006, 2014; Tsinopoulos *et al.*, 2018). Suppliers, customers and competitors are the conventional sources of external knowledge for innovation (Billington and Davidson, 2013; Bahemia *et al.*, 2017; Prajogo, 2021). Emerging technologies (e.g., IOTs, Blockchain, AI) afford opportunities for both types of innovation, prompting firms to increasingly search for external knowledge from a *broader* "knowledge network" to innovate (Lorenz *et al.*, 2020). This broader network encompasses universities, research laboratories (Amara and Landry, 2005), conferences, trade fairs, scientific journals, trade/technical publications, and professional and industrial associations, besides suppliers (Bogers *et al.*, 2018).

Innovation performance depends on knowledge sharing among network partners (Katila and Ahuja, 2002; Chesbrough, 2003) and a firm's ability to combine knowledge from heterogeneous knowledge domains and sources, especially for product innovation (Love *et al.*, 2014). These studies have utilized cross-sectional data to investigate openness and its impact on innovation, not longitudinal data to investigate whether firms change their knowledge acquisition strategies over time. This omission ignores changes in openness of firms over time due to *learning*. A recent study by Hewitt-Dundas *et al.* (2019) affirms the effect of learning by showing that past collaborators often form new, successful collaborations that promote innovation in subsequent time periods. Learning from knowledge acquired in the past can enhance a firm's absorptive capacity, allowing it to increase, decrease or maintain the *number* (i.e., *breadth*) and *variety* (i.e., composition) of knowledge sources in the future (Leiponen and Helfat, 2010; Seepana et al., 2021). We refer to these temporal adjustments in external knowledge search strategy as *dynamic openness*.

We posit firms change external knowledge search breadth by adopting one of four dynamic openness strategies – (a) increase or (b) decrease search breadth, and (c) remaining open or (d) closed without a change in search breadth. These four, mutually exclusive strategies are adequate to investigate changes in search breadth across two time periods in our panel data. A more comprehensive analysis of dynamic

openness and its effect on innovation would require a much larger dataset or analytical methods utilizing a continuous time, dynamic model. We refer to these strategies as: *Opening Up*, *Closing Down*, *Persistent Open* and *Persistent Closed*, respectively. We note that we do not capture in our analysis "variety" or composition of knowledge acquired from external sources. The secondary dataset we have utilized does not allow examination of the dimension of variety due to inadequate sample size. Consequently, we focus only on search breadth in our analysis of dynamic openness. We elaborate on this issue later in the conclusion section.

Persistent Open strategy refers to Open firms (Breadth$_{t-1}$ > 0) that continue using the same number of sources over time without change in external search breadth (ΔBreadth=0 or Breadth$_t$ - Breadth$_{t-1}$ = 0). *Persistent Closed* strategy refers to Closed firms (Breadth$_{t-1}$ = 0) that remain closed over time (ΔBreadth=0). Although these strategies may seem static, they are dynamic openness strategies in that they require an evaluation of the benefits of a change in search breadth in each time period and a purposeful decision to maintain status quo. *Opening Up* (ΔBreadth>0) and *Closing Down* (ΔBreadth<0) correspond to an increase and a decrease of external knowledge sources. These strategies are frequently used by firms in diverse industries. For example, Cisco used *Opening Up* strategy in its Open Daylight initiative (Appleyard and Chesbrough, 2017). In late 1990s, Nissan adopted *Closing Down* strategy when it `de-embedded` its *keiretsu* suppliers as part of the "Nissan Revival Plan" to focus on intrafirm goals (Sting *et al.* 2019). BMW utilized *Opening Up* strategy in acquiring knowledge from external sources such as Microsoft (Majchrzak et al., 2019), when innovating their Internet-of-Things (IOT) platform to enable process innovation. BMW also collaborated with Nvidia, to innovate automated guided vehicles in their plants to increase the speed and flexibility of material handling (Lorenz et al., 2020: 1133).

Openness literature suggests diminishing returns from external knowledge search in product innovation (Laursen and Salter, 2006); however, emerging evidence for this in process innovation is inconclusive. The relationship between search breadth and innovation is shown to be positive by Tsinopoulos *et al.* (2018), while Terjesen and Patel (2017) show a negative relationship. The potential absence of diminishing returns from openness in process innovation is not surprising as product and

process innovation have dissimilar goals and use different internal capabilities and external sources of knowledge (Cabagnols and Le Bas, 2002). We address the lack of agreement about the effects of search breadth on process innovation and also account for the effects of learning over time in testing the effects of dynamic openness strategies with a panel dataset.

Studies examining knowledge search for process innovation are limited. Process innovation, which pertains to how a product or service is delivered, has often been considered a second-order innovative activity (Reichstein and Salter, 2006). It may entail *organizational process innovation* including changes in purchasing practices, personnel and management practices and *technological process innovation* encompassing "new elements introduced into an organization's production system or service operation" (Walker, 2014). Relatively few articles focus on the strategic management of process innovations. Keupp et al (2012) observe that: "the neglect of process innovations seems problematic… since antecedents that may promote product innovation do not necessarily also spur process innovations". This paper theorizes how contextual differences interact with dynamic openness strategies to affect product and process innovation.

A strategic question for open firms is to choose between *Opening Up and Persistent Open* strategies. The benefits of increasing search breadth in product innovation might be mitigated by knowledge leakage risk (e.g., Google's abandonment of *Opening Up* in the development of Android OS). Consequently, product innovators may prefer *Persistent Open* strategy, with selected, strategic technological partners contributing to innovation. Process innovation has broader scope involving operations, logistics, information systems and other knowledge domains to improve cost, productivity, flexibility, responsiveness, service, and other process outcomes. Therefore, process innovation requires accessing more diverse, heterogeneous knowledge from a larger number of external knowledge sources. Process knowledge is readily available to all firms, making knowledge leakage less of a concern. Consequently, process innovators might pursue an *Opening Up* strategy. These differences might explain why open firms could benefit from increasing search breadth for process innovation whereas the "optimal search breadth" for product innovation might be smaller. We test these conjectures relating

to product and process innovation, by comparing the probabilities of successful innovation across firms that have implemented *Persistent Open*, *Opening Up* and *Closing Down* strategies.

This paper contributes to current literature on open innovation in multiple ways: (a) it enables theory development by introducing the concept of dynamic openness and explicating a typology of dynamic openness strategies; (b) by theorizing the underlying reasons —learning from past and external knowledge heterogeneity— it explains why a firm pursues a specific dynamic openness strategy; (c) it prescribes dynamic openness strategies that firms should pursue in process innovation versus product innovation; and (d) it overcomes endogeneity related drawbacks of cross-sectional data analysis. Next, we discuss theoretical underpinnings and hypothesis development.

2. Theoretical Development and Hypotheses

The benefit of open innovation is rooted in the value of knowledge heterogeneity. Laursen and Salter (2006, 2014) coined the term "external search breadth" to represent knowledge heterogeneity, which studies have shown is associated with innovation in general (Amara and Landry, 2005), and specifically, product innovation and technological innovation (Leiponen and Helfat, 2010). The search for heterogeneous external knowledge, however, might be constrained by organizational limitations.

There is a limit to how many ideas and sources of information a firm can effectively manage and use (Ocasio, 1997). It is difficult to exploit all ideas when there are too many of them due to the so-called "attention allocation problem" (Koput, 1997). Learning from external sources is also fraught with limitations imposed by absorptive capacity and bounded rationality (Simon, 1991). It is argued in these studies that diminishing returns arise from the rising costs of maintaining and integrating knowledge from wide network ties (Leiponen and Helfat, 2010; Piening and Salge, 2015). Consequently, prior literature suggests that beyond a threshold, increases in external search breadth reduce the probability of product innovation implying an "optimal" search breadth and that "over-search" leads to diminishing returns (Laursen and Salter, 2006). These arguments suggest that while heterogeneity of external information is essential for innovation in openness, its beneficial effects are constrained by absorptive capacity, bounded rationality, integration costs and attention allocation problem. We refer to these constraints collectively as organizational limitations.

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It is unclear whether and how these organizational limitations affect the open innovation strategy of process innovators. With few exceptions (e.g., Tsinopoulos *et al.,* 2018), prior literature has largely overlooked process innovators, presuming that their open innovation strategy is similar to that of product innovators. Yet, product innovation differs from process innovation as they "…have different aims and require different resources and capabilities, in terms of technology trajectories, relationships among the supply chain members and absorptive capacity" (Hullova *et al.,* 2016, p. 930). It is still inconclusive if external search breadth exerts a positive (Tsinopoulos *et al.,* 2018) or a negative effect (Terjesen and Patel, 2017) on process innovation. Terjesen and Patel (2017) argue that diminishing returns of search breadth apply only to product innovation, especially when a firm selectively uses deep knowledge sources. However, the literature offers limited theoretical reasons for the different effects of openness on product and process innovation. We conjecture that learning over time plays an important role in explaining the different effects of openness on product and process innovation. We develop this idea further in the next section.

2.1 A dynamic view of openness

Dynamic openness suggests limitations posed by bounded rationality, absorptive capacity and attention problems can change over time due to learning from past acquisition of external knowledge. The notion of learning from openness was introduced by Love *et al.* (2014) based on the conjecture that learning can inform necessary changes in the knowledge sources used by a firm over time. Using the Irish Innovation Panel dataset for the period 1991-2008, they concluded that having external linkages in previous time periods has a positive effect on the relationship between current search breadth and innovation due to learning effects. They conclude "…future research on open innovation should pay more attention to the time/learning dimension in examining how openness affects innovation" (Love *et al.,* 2014, p.1714), which motivates our study.

The concept of dynamic openness incorporates the time dimension with explicit consideration given to changes in search breadth over time. Appleyard and Chesbrough (2017) and Zaggl *et al.* (2020) show that firms do switch from closed to open and vice versa to enable specific innovations. However, such

simplistic "open to closed" and "closed to open" strategic changes of search breadth do not consider that open firms can reduce, maintain, or increase search breadth.

We measure search breadth by the number of external sources that a firm uses. We propose a typology comprised of four dynamic openness strategies. The first two strategies - *Persistent Open and Persistent Closed -* refer to no change in the number of external knowledge sources used. Besides few case studies (Zaggl *et al.,* 2020), these dynamic openness strategies have not been examined in current literature. Learning from past experience, open firms may decrease openness (ΔBreadth<0) by eliminating some existing knowledge sources. We call this strategy *Closing Down.* This strategy might be appropriate when firms decide they have learned enough from external sources and eliminate some sources that have become less useful, preferring to exploit knowledge from current source(s) (Appleyard and Chesbrough, 2017). To avoid knowledge leakage, firms often pursue *Closing Down* when commercializing innovations. *Closing Down* strategy can change open firms to closed (Breadth$_t$ = 0) or reduce their search breadth in the next period (ΔBreadth<0).

Learning effects from openness could also lead to an increase in absorptive capacity, causing firms to increase search breadth (ΔBreadth>0) to explore new knowledge (Katila and Ahuja, 2002); we refer to this dynamic strategy as O*pening Up. Opening Up* strategy can be used by originally closed firms (Breadth$_{t-1}$ = 0) as well as by open firms (Breadth $_{t-1}$ > 0). Learning from external knowledge sources will improve a firm's absorptive capacity so that it can continue to benefit from *Opening Up* (Leiponen and Helfat, 2010), unmitigated by this organizational limitation. Using this foundational discussion of learning vis-a-vis absorptive capacity, dynamic openness and associated strategies, we develop the hypotheses to be tested in the next section.

2.1.1 Closing Down versus Persistent Open and innovation performance

We focus on questions previously not addressed for open firms that use several external knowledge sources for innovation. Should they sustain the same external search breadth by being persistently open? Should they pursue a *Closing Down* strategy by decreasing search breadth or pursue *Opening Up* by increasing their breadth? What are the effects of these search strategies on product and process innovation? We first undertake a comparison of *Persistent Open* and *Closing Down* strategies.

Persistent Open is a valid dynamic openness strategy because the costs associated with building diverse channels of external communication and integration of knowledge from diverse sources might preclude opening up further. Persistency in openness would reduce costs of managing these relationships due to accumulated experience from the past and learning effects. This strategy can be pursued to achieve stability and to gain time to absorb diverse knowledge from established knowledge sources as time is required to explore and exploit knowledge from external sources (Katila and Ahuja, 2002). Firms may use this strategy to gradually switch from an "exploration" to an "exploitation" mode, accelerating innovation. *Persistent Open* strategy could indicate that the innovation process has matured to the stage where innovation problems are solved using existing knowledge sources. From the perspective of absorptive capacity, bounded rationality, and knowledge integration cost, both product and process innovators can benefit from such a persistent open strategy. Openness literature also suggests that being persistently open can be disadvantageous to a firm's efforts in both product and process innovations. Persistently open firms use the same knowledge sources and elements repeatedly because they might be addressing familiar, solvable problems. Even though maintaining the same knowledge sources allows firms to focus on mastering a set of technologies, it could impose limitations of path dependency associated with technological trajectories (Katila and Ahuja, 2002). Moreover, when a firm maintains the same number of knowledge sources, it misses the opportunity to access new innovations or ideas from other knowledge sources (O'Connor and Rice, 2001).

Alternatively, *Closing Down* strategy might be pursued by firms that have acquired enough knowledge and ideas from external sources to commercialize innovations by exploiting current knowledge. There might be no immediate need for more external knowledge and the cost of continued search may not be justified (Laursen and Salter, 2006). *Closing Down* can also occur due to limited absorptive capacity or a focus on other innovation tasks instead of searching for more external knowledge. For product innovation, *Closing Down* might be used to prevent knowledge leaks when commercializing new products.

We posit that firms that access a variety of knowledge sources through *Persistent Open* strategy, rather than pursuing a *Closing Down* strategy are likely to realize beneficial effects on absorptive

capacity and combinative capabilities that offset other organizational limitations. The heterogeneity of sources and knowledge can be expected to promote creativity in innovation and problem solving. Firms that pursue a *Persistent Open* strategy increase absorptive capacity by continuously learning from a stable set of knowledge sources over time using cycles of exploration and exploitation (Katila and Ahuja, 2002). Such learning effects would not manifest when firms reduce external search breadth, potentially arguing against *Closing Down* strategy.

Thus, we conjecture being persistently open is generally more beneficial than closing down for both innovation types. Based on this discussion, we formally state the following hypotheses.

H1a. Firms that adopt a C*losing Down* strategy are less likely to generate *product innovations* compared to firms that pursue a P*ersistent Open* strategy.

H1b. Firms that adopt a C*losing Down* strategy are less likely to generate *process innovations* compared to firms that pursue a P*ersistent Open* strategy.

It should be noted that *Persistent Open* strategy corresponds to the idea of openness in open innovation literature, where it is asserted to have beneficial effects on (product) innovation. These hypotheses, however, test persistent openness against the dynamic openness strategy-Closing Down, which the open innovation literature does not address.

2.1.2 Opening Up versus Persistent Open and innovation performance

Laursen and Salter (2006) argue *Opening Up* might not have a significant effect on product innovation, especially for firms that already have many external knowledge sources. However, current trends in technological innovations afford firms the opportunity to access more ideas and heterogeneous knowledge for innovation by increasing search breadth. Consequently, *Opening Up* might be better than pursuing *Persistent Open* strategy, a view that conflicts with current literature. This possibility is suggested by actions of firms in the pharmaceutical industry. Large pharmaceutical firms pursue *Opening Up* strategy to generate new drugs by partnering with highly innovative small biotechnology firms or through community sourcing (Linder *et al.,* 2003).

Openness to achieve product innovation, however, might be constrained by the need to prevent knowledge leaks. In product innovation, typically firms strategically rely on a few promising new technologies, and fewer partners as knowledge sources than for process innovation wherein knowledge leak is of lesser concern. Although open firms generally benefit from increasing search breadth in product innovation, literature suggests that once an "optimal search breadth" is reached there is no incentive to further increase search breadth, since the benefits of opening up are thought to be outweighed by search and knowledge acquisition costs, knowledge integration and exploitation costs, and indirect costs imposed by organizational constraints. Moreover, openness may only be required early in an innovation project and firms typically reduce knowledge sources when they begin to commercialize the innovation (Appleyard and Chesbrough, 2017). These arguments for and against opening-up in pursuit of product innovation suggest the hypothesis (stated in probabilistic terms) that *Opening Up,* while generally beneficial, might not dominate *Persistent Open* strategy in product innovation.

> *H2a.* O*pening Up* and *Persistent Open* strategies are equally likely to generate *product innovations.*

Process innovation involves introducing "new elements…into operations" through changes in materials, specifications, work and information flow, and equipment to produce a product or render a service (Reichstein and Salter, 2006, p1). Organizational limitations and their effects on process innovation when openness strategy is pursued are less researched and understood (Peining and Salge, 2014). Despite this, process innovation involving "new or significantly improved production, supply chain, and administrative process" is increasingly "seen as an important source of competitiveness and organizational power" (Piening and Salge, 2015, p80). Although the benefits of openness for process innovation are limited by organizational constraints due to attention problem and absorptive capacity, there are subtle differences between product and process innovations vis-a-vis these limitations.

Process innovation requires knowledge about new production technologies, materials, operating and information systems, customers' purchasing and consumption processes, and other factors. Consequently, expertise from logistics, production, purchasing and information systems is needed to

absorb external knowledge from these domains and increase absorptive capacity for innovation (Terjesen and Patel, 2017). Information might be acquired about best practices from a variety of sources in and outside the industry, from consultants, universities and even competitors (Markham, 2000; Reichstein and Salter, 2006; Potter and Paulraj, 2020). Firms seek external sources of process technology knowledge with less concern for knowledge leakage because these sources are often familiar with product technology *and* process technology (Robertson *et al.,* 2012) and protection from intellectual property rights (IP). A few years ago, Merck decided to pursue *Opening Up* and outsourced drug manufacturing and testing to suppliers with superior process capabilities. Merck's patents and intellectual property rights (IP) precluded knowledge leaks. Johnson and Johnson has pursued *Opening Up* via early supplier involvement in drug discovery and manufacturing, significantly reducing costs through process innovation. The contractual arrangements with these strategic suppliers guarantee protection of IP. For process innovation, knowledge from different sources can be treated as a complementary asset (Tsinopoulos *et al.,* 2018) without concern for knowledge leaks. Therefore, sourcing process knowledge is less restrictive than sourcing product knowledge. These arguments imply that search breadth is likely to be higher for process innovation compared to product innovation suggesting *Opening Up* might be superior to *Persistent Open* strategy.

From a product/technology life cycle (PLC/TLC) perspective, in the latter phases need for new knowledge sources for process innovation is high as the rate of technological change in process design is higher (Klepper, 1996), while product innovation requires fewer new knowledge sources (Katila and Ahuja, 2002). Process innovation is required to support product innovation in the latter stages of PLC (Robertson *et al.,* 2012) to improve manufacturing priorities such as cost, quality, and agility (Hamermesh and Silk, 1979). Since firms spend more time in growth and mature phases than in product introduction, the need for external knowledge sources for process innovation will be more common. These PLC/TLC based arguments also suggest that process innovation is more likely with *Opening Up* than *Persistent Open* strategy. Based on this discussion, we state the following hypothesis.

H2b. Opening Up strategy is more likely to generate *process innovations* compared to *Persistent Open* strategy.

H2a and H2b differ in their comparisons of *Opening Up* and *Persistent Open* strategies regarding the likelihood of success in two different innovation contexts. This set of hypotheses stemming from our arguments are intended to test and underscore contextual differences between product and process innovations. While *H2a* does not assert the superiority of *Opening Up* over *Persistent Open* strategy, *H2b,* in contrast, does assert such superiority.

3. Data and Methodology

3.1 Sample

The data for this paper were drawn from the U.K. Community Innovation Survey (UKIS), which collects information on innovation initiatives[1] of U.K. firms. UKIS is an official survey administered by the Office of National Statistics (ONS) on behalf of the Department for Business, Energy and Industrial Strategy in the UK. The data are collected biennially using a stratified random sample[2] drawn from the ONS's Inter-Departmental Business Register (IDBR), which ensures that the data are representative of the UK population of firms across all regions, sectors, and firm size. The survey has been validated and been checked for non-response bias [3](DBEIS, 2019). The interpretability, reliability, and validity of the survey were assessed by extensive pilot testing.

The analysis is based on five waves of the biennial UKIS data collected during 2009-2017. The survey sampled approximately 30,000 UK firms per wave with approximately 50% average response rate. We considered only innovative firms in *at least* two waves of the survey. The dataset comprises 16,021 firms for a sample size of 42,229 observations[4] of external breadth. Since not all firms in our

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[1] The survey offers a variety of measures related to innovation, e.g., research and development (R&D), innovation performance (product and process innovation), scientific and supply chain collaboration for innovation, and knowledge sources for innovation in addition to demographic data.

[2] The stratification uses three variables: (1) Region: all nine regions in the UK, (2) Sectors: all sectors including manufacturing and services. (3) Firm size: small, medium and large firms. Accordingly, the stratified random sample is representative of the total population of UK firms with ten or more employees.

[3] The statisticians at the Office of National Statistics used 'weighting' in order to compensate for the businesses that did not respond to the survey and those not selected for the sample. The responses were weighted back to the total business population of those in the IDBR. On average each respondent represents 13 enterprises in the population ensuring that the sample is representative of the population and does not suffer from non-response bias. See: https://www.gov.uk/government/collections/community-innovation-survey

[4] The key explanatory variables - External Search Strategies- are calculated by assessing the changes in the number of external sources of knowledge a firm uses over time, thus, minimum of a two-year period is necessary. Thus, the observations for the External Search Strategy variables are 26,208.

dataset responded to the survey in all waves, we obtained an unbalanced panel of 26,208 changes in external search breadth over the five waves (c.f. Love *et al.,* 2014).

Common method bias (CMB): CMB is one of the important issues inherent in survey data. The UKIS addresses: a) common rater effect, (b) item characteristics effect, (c) item context effect, and (d) measurement context effect (Podsakoff *et al.,* 2003; Malhotra *et al.,* 2006) by anonymizing the responses to minimize social desirability, by using simple and concise definitions based on the Oslo Manual (OECD), and by placing the dependent and explanatory variables in different sections of UKIS survey. To obviate measurement context effect stemming from a single respondent, the questionnaire is administered at the *firm* level and completed by the Director, Chief Executive Officer or the R&D manager in the same way as the Yale survey (Cohen and Levinthal, 1990). To check for CMB, we conducted the marker variable test. We use "*lnSize*" as the marker variable since it is the least correlated (see Table I) with the other variables. The objective variable *lnSize* indicates the total number of employees and is unlikely to suffer from respondent bias. Both the signs and coefficients obtained from the CMB model and our main models are almost identical indicating that CMB is not a concern.

Table I here

3.2 Dependent variables: Product innovation and process innovation

Table I presents the definition and measurement of all the variables. Both new product and process introductions are commonly used as broad measures of innovation (Zhang *et al.,* 2014) because they are essential and mutually complementary parts of an operations strategy that relies on external knowledge from the supply network (Narasimhan and Narayanan, 2013).

Product Innovation refers to the introduction of new or significantly improved goods or services to the *market*. This definition of product innovation addresses two aspects of innovation: introduction of new or significant improvements in quality or the development of distinct benefits for the user; and, whether product innovations are new to the market (DBEIS, 2019). The questionnaire asks firms to report only significant innovations introduced to the market before their competitors. Prior studies

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associate this variable with radical technological change that typically requires more research-based information and knowledge (Amara and Landry, 2005; Rodriguez *et al.,* 2017).

Process Innovation is defined as the introduction of new or significantly improved processes that are new to the *industry* (DBEIS, 2019). Both measures for product and process innovation have been used extensively in the innovation literature (Nieto and Santamaría, 2007); in particular, research based on Community Innovation Survey (CIS) dataset (Amara and Landry, 2005). The use of the words *new to the market* and *industry* in the questionnaire helps respondents to consider only radical innovation.

3.3 Independent variables: Breadth and External Search strategies

In line with open innovation literature, we introduce a continuous variable, *Breadth,* which measures the *number* of external knowledge sources used by firms in their innovation activities. Survey respondents indicated *both* the use and importance of knowledge for innovation from the 11 sources[5], using the four-point Likert-scale: '*not used'*, '*low importance'*, '*medium importance'*, '*high importance'*. Following Terjesen and Patel (2017) and Laursen and Salter (2006), we considered only '*high importance'* knowledge sources used for innovation[6]. Accordingly, we created *Breadth* as follows: first, a dummy variable is created for each source and coded as "1" if a source of knowledge was of '*high importance*' for innovation and coded as "0" otherwise. Second, we computed the composite score across all 11 knowledge sources. If none of the 11 knowledge sources was of '*high importance*' for innovation for a business, then its *Breadth* score was "0". Hence, the composite score for *Breadth* had a range from 0 to 11, and it reflects the heterogeneity of knowledge sources and the importance of these knowledge sources for innovation. These 11 items have high internal consistency and scale reliability (Cronbach's alpha of 0.73).

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[5] The 11 external sources are: (1) Within your business or enterprise group; (2) Suppliers of equipment, materials, services or software; (3) Clients or customers from the public and/or private sector; (4) Competitors or other business in your industry; (5) Consultants, commercial labs or private R&D institutes; (6) University or other higher education institutes; (7) Government or public research institutes; (8) Conferences, trade fairs or exhibition; (9) Professional and industry association; (10) Technical, industry or service standards; (11) Scientific journals and trade / technical publications.

[6] We have also conducted robustness analysis testing the sensitivity of our construct to different levels of importance such as 'medium-importance' and 'high-importance' knowledge sources as well as to the 'use' of knowledge irrespective of its importance. The results remain robust with the initial analysis and are discussed in section 4.3.

This paper captures changes in *External Search Strategies* (i.e., *Breadth*) across time. The panel dataset allows us to capture dynamic openness based on current and previous breadth of firms (Breadth$_t$ – Breadth$_{t-1}$). We operationalize the four *External Search Strategies* as follows: *Persistent Open* is a dummy variable that takes the value of 1 if "Breadth$_{t-1}$ > 0" and "Breadth$_t$ – Breadth$_{t-1}$ = 0", and 0 otherwise. *Persistent Closed* is a dummy variable that takes the value of 1 if "Breadth$_{t-1}$ = 0" and "Breadth$_t$ – Breadth$_{t-1}$ = 0", and 0 otherwise. *Closing Down* is a dummy variable that takes the value of 1 if "Breadth$_{t-1}$ > 0" and "Breadth$_t$ – Breadth$_{t-1}$ < 0", and 0 otherwise. *Opening up* is a dummy variable that takes the value of 1 if "Breadth$_t$ – Breadth$_{t-1}$ > 0", and 0 otherwise.

3.4 Control variables

We include additional variables in the analysis to control for other determinants of innovation. *R&D* increases absorptive capacity and generates knowledge useful for innovation (Cassiman and Veugelers, 2002). Firm size (*lnSize*) is a proxy for resource endowment and a determinant of innovation (Mairesse and Mohnen, 2002). We control for a firm's type of formal collaboration (*Scientific Collaboration*[7] and *Supply Chain Collaboration*[8]) as collaboration is a key determinant of innovation (Vilena *et al.,* 2011; Prajogo et al., 2021). We consider differences in market structure (*Market),* as variations in technological opportunities, consumer preferences and competitiveness can encourage (discourage) firm's engagement in innovation. Industry variance is controlled for with five industry dummy variables based on the two-digit SIC code (*Industry*). Finally, we included time dummies to control for economy wide effects across time (*Year*).

3.5 Econometric specification and identification strategy

We examine the effects of *Breadth* and *External Search Strategies* on the probability of *Product Innovation* and *Process Innovation*. Since both dependent variables are binary, we fit a logistic (or logit) regression model. The model in equation (1) includes control variables, year, and industry fixed effects.

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[7] Collaboration with: (i) higher education institutions, (ii) government/public research institutes.

[8] Collaboration with: (i) other enterprises within the group, (ii) suppliers of equipment, materials, components, or software, (iii) clients or customers, (iv) competitors or enterprises in the firm's industry and (v) consultants, commercial labs, or private R&D institutes.

$$\text{logit } (y_{it}^*) = \alpha + \beta_{1-7}^* controls_{it} + \delta_2 Time_i + \delta_3 Industry_i + \varepsilon_{it} \tag{1}$$

In equation (1), y_{it}^* represents one of two innovation output variables (product or process innovation in Table I), α represents the constant, β_{1-7}^* captures the individual effects of a vector of control variables[9], δ_2 and δ_3 represent the time and industry fixed effects. ε_{it} represents the idiosyncratic random error term.

The second model in equation (2) includes Breadth$_t$ and its square (Breadth$_{sq}$) to assess the potential diminishing effects of search breadth asserted by cross sectional studies (Laursen and Salter, 2006). Although this is not a primary objective of this study, we felt that examining this issue with our panel data might affirm (or disaffirm) claims in the literature based on cross-sectional data analysis.

$$\text{logit } (y_{it}^*) = \alpha + \beta_{1-7}^* controls_{it} + \gamma_2 Breadth_{it} + \gamma_3 Breadth\_sq_{it} + \delta_4 Time_i + \delta_5 Industry_i + \varepsilon_{it} \tag{2}$$

We test H1a-b and H2a-b using equation (3), which includes three distinct dummy variables corresponding to the strategies: *Closing Down, Opening Up*, and *Persistent Closed*. The *Persistent Open* dummy is used as the base category for comparing the effects of the other three external search strategies. In equation (3), γ_2 represents the coefficient for *Closing Down* (H1a-b) and γ_3 represents the coefficient for *Opening Up* (H2a-b).

$$\text{logit } (y_{it}^*) = \alpha + \beta_{1-7}^* Controls_{it} + \gamma_2 Closing\ Down_{it} + \gamma_3 Opening\ Up_{it} +$$
$$\gamma_4 Persistent\ Closed_{it} + \delta_3 Time_i + \delta_4 Industry_i + \varepsilon_{it} \tag{3}$$

Accordingly, the model in equation (3) including our key independent variables could be extended to FE estimation method as follows:

$$\text{logit } (y_{it}^*) = (a_i + u_i) + \beta_{1-7}^* Controls_{it} + \gamma_2 Closing\ Down_{it} + \gamma_3 Opening\ Up_{it} +$$
$$\gamma_4 Persistent\ Closed_{it} + \delta_3 Time_i + \delta_4 Industry_i + \varepsilon_{it} \tag{4}$$

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[9] The model 1,2,3 and 4 estimate a coefficient for each control variable, however to save space we added only one coefficient (1-7*) in the functional form of the model.

Endogeneity from unobserved heterogeneity: Unlike prior research, we did not employee a cross-sectional or a Pooled OLS estimation as it could generate biased and inconsistent estimates due to endogeneity arising from differences in the characteristics of firms that explain variations in the probability to innovate (Laursen and Salter, 2006). Specifically, a Pooled OLS estimation could attach predictive power to explanatory variables, which occur due to firm's heterogenous time-invariant characteristics. Thus, we overcome endogeneity arising from time-invariant heterogeneity by employing a Fixed Effects (FE) estimation in all models in equations (1-4), whereby the firm specific differences (a_i) are captured by the intercepts (Greene, 2002; Wooldridge, 2002). Specifically, in FE the parameter estimates of time-invariant variables are absorbed by the intercept (a_i+u_i) because the time-invariant variables are specific to an entity and should not be correlated with other entity specific characteristics. The FE estimation assesses the net effect of time-variant variables on the outcome variable, which controls for endogeneity that arises from unobserved heterogeneity.

Endogeneity from contemporaneous simultaneity: We overcome endogeneity arising in cases whereby the probability of *Product* or *Process Innovation* and *External Search Strategies* could be simultaneously determined, by embedding in the construction of the *External Search Strategies* one-year lags as explained in section 3.3 (i.e., *Breadth_t – Breadth_{t-1}*). Using one-year lags in the construction of the key explanatory variables obviates contemporaneous reverse causality (Clemens et al, 2012). This identification strategy utilizes the lagged value of the explanatory variable to "exogenize" it when estimating the effect of *External Search Strategies* on either *Product* or *Process Innovation*. The assumption made is that since y_{it}^* (*Product* or *Process Innovation*) cannot possibly cause *Breadth_{t-1}*, this rules out concerns that *External Search Strategies* is endogenous to *Product* or *Process Innovation*.

4. Analysis and Results

4.1 Preliminary analysis

We conducted the analysis in STATA Version 16. Table II depicts the correlation coefficients, descriptive statistics of the dependent and independent variables, and the Variance Inflation Factors (VIFs) of the independent variables. Table II shows 10% of the observations in the sample introduced a *Product innovation* and 16% a *Process innovation*. In line with previous studies, the mean value of

Breadth of the sampled firms is 0.88 with standard deviation of 1.51. Both the pairwise correlation coefficients of the variables (P< 0.001) and the VIFs of the independent variables were used to check for multicollinearity among the independent variables. The VIFs of our independent variables vary from 1.03 to 4.26 (<10) suggesting that multicollinearity is not a concern (Neter *et al.,* 2004). Also, 24% of the sample firms engage in *R&D* activities, on average, the sampled firms have 362 employees, 10% of firms engaged in *Scientific Collaboration.* and 25% of firms engaged in *Supply Chain Collaboration.*

Table II here

Next, the transition probability matrix (TPM) in Table III shows the probability of changing from being *Closed* to *Open* and *vice versa* across 2009-2017. The diagonal values in the TPM denote the fraction of firms that persist in the same state. Clausen *et al.* (2012) and Tavassoli and Karlsson (2015) differentiate between strong and weak persistence. If the sum of the diagonal values is equal to or greater than 100% and the single diagonal values of the TPM matrix are greater than 50%, then this indicates strong persistence. The TPM shows that 70% of closed firms remained closed between two observation periods (*Persistent Closed*) and 30% of closed firms adopted the *Opening Up* strategy. Table III shows that 43% of open firms adopted a *Closing Down* strategy and 57% of open firms remained open between two observation periods [by adopting either a *Persistent Open* or an *Opening Up* strategy]. Overall, this analysis indicates that although there is strong persistence in the external search strategy, some firms do alter their external search strategy over time supporting our idea of dynamic openness.

Table III here

Table IV shows the summary statistics for each of the four dynamic openness strategies and for the two innovation types. Our data show that the external search strategies differ between product and process innovators. While close to one third of the observations for *Persistent Open* observations involved either product or process innovation, the Opening Up strategy seems to differ in the number of observations for product (17%) and process innovators (32%). There are approximately twice as many process innovators who chose *Opening Up* strategy compared to product innovators in our sample. Similarly, 3% of the *Persistent Closed* observations are process innovators while only 1.5% are

for product innovators, and 16% of the *Closing Down* observations correspond to process innovators and only 10% correspond to product innovators. These preliminary analyses support the concept of dynamic openness strategies.

Table IV here

4.2 Panel-data analysis

Table V presents the results of the logit estimations. The results for the control variables are in line with prior studies. Models 1 and 2 show the effects of search breadth on innovation for comparison with cross-sectional studies. Model 1 includes only the control variables, year, and industry fixed effect dummies, for the two dependent variables **-** *Product Innovation* (in column 1) and *Process Innovation* (in column 2). Model 2 includes the linear term *Breadth* and the quadratic term (*Breadth_sq)* to test for possible non-linearity suggested by Laursen and Salter (2006). Model 3 tests H1a-b and H2a-b by comparing the dummy variables for *External Search Strategy - Closing Down, Opening Up,* and *Persistent Closed*, with *Persistent Open* strategy as the base category. All three models are estimated using Fixed Effects to account for unobserved heterogeneity.

Model 2 presents the results pertaining to *Breadth*. The coefficient of $Breadth_t$ is positive and statistically significant indicating a positive relationship between external search breadth and both product and process innovations. The estimated coefficients are 0.54 (p<0.001) and 0.75 (p<0.001) for product and process innovation, respectively. Our results show that $Breadth_t\_sq$ has a negative and statistically significant (p<0.001) coefficient for both product innovation (-0.05) and process innovation (-0.07). Combined, these results assert that the relationship between *Breadth* and product/process innovation is curvilinear (inverted U-shaped), affirming assertions of over-search in current literature. Specifically, these findings highlight the significance of firms` external knowledge search for product and process innovation and point out that when firms over-search (i.e., use too many knowledge sources), they experience decreasing returns to innovation performance.

Table V here

Model 3 in Table V presents the results of the panel-data analysis, which tests H1a-b and H2a-

b. Model 3 examines whether the changes in external search strategies (*Closing Down*, *Opening Up, Persistent Closed*) are significantly more or less likely to achieve product and process innovation, compared to the *Persistent Open* strategy as the base category. H1a-b state that the probability of product and process innovation is lower for firms that choose *Closing Down* (from being open) compared to firms that remain persistently open. The estimated coefficients for *Closing Down* are negative -0.42 (p<0.001) and -0.4 (p<0.001) and statistically significant for product and process innovation, respectively. These results provide strong evidence supporting H1a and H1b. As expected, similar findings apply to *Persistent Closed* in comparison with *Persistent Open*.

H2a and H2b posit that the probability of product innovation is not different for firms that choose *Opening Up* compared to remaining *Persistently Open,* but a higher probability is expected for process innovation. The estimated coefficient for *Opening Up* is positive and insignificant for product innovation, and positive (0.31) and statistically significant at p<0.001 level for process innovation. The results show that there is no statistical difference between *Persistent Open* and *Opening Up* with respect to product innovation, supporting H2a. In contrast, our results show that *Opening Up* increased the probability of process innovation compared to *Persistent Open* strategy, supporting H2b.

4.3 Robustness and sensitivity analysis

We carried out several robustness tests to verify the consistency of our analyses. First, we used an alternative measure for the dependent variable that captures a firm's intensity of product innovation, i.e., *Innovation Intensity*. UKIS asks firms to report the proportion of their sales attributable to product innovations new to the market. *Innovation Intensity* is measured in percentages and ranges between 0-100. Thus, we estimated a Tobit model to account for both right and left censored dependent variable. The results were consistent with those in Table V for *Product Innovation* in Model 3; all relevant coefficients are statistically significant, and the direction of the relationships was the same[10]. Specifically, firms with a *Closing Down* strategy compared to firms that remain *Persistent Open* (base category) experienced a decrease in their *Innovation Intensity*. The estimated coefficient for *Closing*

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[10] For brevity we did not include the Tables of the robustness analysis. We can provide them upon request.

Down was negative (-3.067) and statistically significant at p<0.01 level. Consistent results were also obtained for the estimated coefficient of the *Opening Up* strategy, which is positive and insignificant, suggesting that there was no statistical difference between *Persistent Open* and *Opening Up* strategies with respect to *Innovation Intensity* (product).

Second, we tested the sensitivity of our results by replacing the key independent variables -*External Search strategies*- with alternative measures that account for: (a) different levels of the *importance* of knowledge sources for innovation and (b) the *use* of knowledge irrespective of its importance. As explained in section 3.3 we operationalize the four *External Search Strategies* based on the current and previous *Breadth* of external knowledge search of firms ($Breadth_t - Breadth_{t-1}$). Here, we re-estimated our models by constructing *Breadth* (and subsequently the four *External Search Strategies*) in two different ways: (a) If a source of knowledge was of '*medium importance*' or '*high importance*' for innovation then this source was coded as 1 and coded 0 if it was of '*low importance*' or '*not used';* (b) If a source of knowledge was of '*low importance*' or '*medium importance*' or '*high importance*' for innovation then this source was coded as 1 and coded 0 if it was '*not used*'. The results were consistent with those in Table V for *Product Innovation* and *Process Innovation* in Model 3.

Third, although we controlled for unobserved time-invariant heterogeneity and simultaneity from contemporaneous reverse causality, the explanatory variables may not be strictly exogenous (Reed, 2015). To investigate whether endogeneity affects our results, we employed an Instrumental Variable (IV) Fixed Effects estimation. By adapting a Canonical Data Model (CDM) developed by Crépon, Duguet and Mairesse (1998), we examined a firm's innovation patterns in two steps: The first step examined the driver of innovation inputs (R&D). We used one-year lag of a variable that measures '*Investments on Training Activities*' to identify R&D. The second step examined the impact of innovation inputs and external knowledge sources upon innovation outputs (the so-called *knowledge production function* depicted in equations 3 and 4). The results of the Instrumental Variable estimation indicated that the coefficients of *External Search Strategies* remain consistent with those in Table V.

5. Discussion and implications

5.1 Discussion of the results

Our study introduced the idea of *dynamic openness* and explicated four search strategies - *Persistent Open, Persistent Closed, Closing Down*, and *Opening Up* and examined their impact on innovation performance. Unlike previous studies, we used a unique panel dataset to show that *Opening Up* increases the probability of process innovation compared to *Persistent Open* strategy but *Opening Up* is not superior to *Persistent Open s*trategy in product innovation. This affirms product innovators might not gain from exploring new knowledge sources beyond a threshold search breadth as suggested in literature. *Persistent Open* strategy increases the probability of both product and process innovation compared to *Closing Down* strategy. These results suggest that process innovators might benefit more from openness than product innovators.

Our study contributes to open innovation literature in four ways. First, we inform openness literature that has not considered changes in search breadth over time and has considered external search strategy narrowly as being either open or closed. In this "static view" of openness, no distinction is made between a firm that is opening up and one that is persistently open. It does not distinguish between a firm that is closing down and a closed firm. We proposed the concept of dynamic openness to show that firms do actively change their external search strategies over time beyond being just open or closed. We presented empirical evidence in Table IV that supports our typology of dynamic openness strategies. This paper creates a new foundation for openness literature to understand why firms choose to stay open with the same knowledge sources over time instead of opening up or closing down. Staying open without changing the number of external sources might imply that firms continue to learn by adopting this strategy. In contrast, learning from past searches might cause firms to close down if they felt external knowledge sources are no longer useful. Our empirical analysis shows "stability" (*Persistent Open*) as opposed to closing down knowledge sources, is an important dynamic openness strategy, which gives firms time to explore and exploit new knowledge from a stable number of knowledge sources.

Second, our results demonstrate that *Persistent Open* strategy can support both product and process innovations. *Persistent Open* firms are more likely to be both product and process innovators compared to *Persistent Closed* and *Closing Down* firms. This result affirms prevailing views in the literature that

firms must continue to engage with external knowledge "ecosystem." We offer a new theoretical perspective, that being persistently open might give time for firms to overcome organizational limitations.

Third, we identify constraints specific to product innovators and show a differential impact on product innovation and process innovation stemming from *Opening Up* and *Persistent Open* strategies. While past literature assumes organizational limitations lead to diminishing effects of breadth on both product and process innovations, we theorized three additional and unique consideration facing product innovators – knowledge leakage, selective knowledge sources, and technology life cycle. Our hypotheses were formulated in recognition of these factors in product innovation. Avoidance of knowledge leakage is unique to product innovators. Our analysis shows process innovators benefit more from *Opening Up* than from pursuing *Persistent Open* strategy, whereas we found no benefits for product innovators to choose *Opening Up* over *Persistent Open*. Although *Opening Up* might trigger diminishing returns due to over search and risk of knowledge leak in product innovation, our results (the estimated coefficients) show that process innovators might have a larger "band width" to innovate from a larger pool of knowledge sources because they might not suffer from organizational limitations to the same degree as product innovators.

Fourth, our results convey a more nuanced understanding of openness strategy for product innovators vis-à-vis organizational constraints. Our results suggest that *Persistent Open* strategy might give firms time to overcome the organizational constraints and pursue further opening up. Our results suggest that product innovators might need to balance "over-search" effects using a stability strategy. Moreover, our results confirm that both product and process innovations cannot be realized with just increasing search breadth. Both innovation types are associated with scientific and supply chain collaboration that capture a different aspect of external search for knowledge. The results from our panel data suggest the importance of a new perspective of innovation network that emphasizes dynamic management of knowledge flows from a diverse knowledge network.

5.2 Theoretical implications

The proposed typology can facilitate new research that may lead to a better understanding of dynamic openness strategies. While our database permits comparing changes in openness over two periods only, the typology proposed in this paper can be a springboard for more extensive investigation of these strategies over several periods to capture changes in dynamic openness over three or more periods, including a mix of *Persistent*, *Opening Up*, and *Closing Down* strategies over time. Ideally, this investigation should be done via dynamic modeling techniques enabling researchers to construct a more complete theory of openness strategies and innovation outcomes. For example, investigation over several time periods will enable us to better understand the effect of "clock speed" on external search strategies. It can be conjectured that the "churn" of knowledge sources would be higher in high clock speed compared to a low clock speed environment. Although our results suggest that opening up is not better than being persistently open for product innovators, clock speed might influence this result. *Opening Up* might be more efficacious in high clock speed environments. An investigation into this conjecture might further refine our theoretical understanding of dynamic openness. Our results show that *Persistent Open*, a stable strategy, is useful in product innovation. We have theorized the role of learning and organizational limitations that support this strategy. It is plausible that the result could also be explained by asset specific investments on the part of the firm and its network partners. It might be more difficult for capital intensive firms (e.g., automotive firms) to pursue *Opening Up* strategy compared to firms that are system integrators (e.g., Cisco Systems, Apple). The theory of dynamic openness can be extended further if it is studied in conjunction with different governance types – arms-length or contractual versus relational governance. Our theorizing would imply that persistence or closing down will be compatible with contractual governance. *Opening Up* might prove to be compatible with relational governance. Our theorizing in the paper suggests that the concept of dynamic openness encompasses product and process issues, absorptive capacity (learning), governance (contractual/relational), Market considerations (Clock speed) and structural issues (asset specificity). Our paper exposes these theoretical connections, paving the way for fuller understanding of openness strategies and theory building. The theoretical contribution that we have made in this paper by proposing and validating the concept of dynamic openness and associated strategies can be a springboard for investigating clock speed, asset specificity and others to better understand dynamic openness strategies.

The theorizing and the results also suggest that product and process innovations might have different optimal search breadths due to unique considerations. We have theorized the reasons why and how this difference between product and process innovation arises due to organizational limitations. These constraints might be mitigated by information and communication technologies (ICT). ICT reduces cost of direct ties, and integration through knowledge management systems (KMS) can reduce the others. This insight can extend *Opening Up* as a strategy and avoid the diminishing returns of over-search mentioned in the literature. Investigating this further would help develop a contingent theory of dynamic openness strategies.

While the focus was on search based on the *number* of knowledge sources, i.e., heterogeneity of knowledge sources, this perspective can be complemented by studying the types of knowledge sources used. Our results show open firms that added knowledge sources are more likely to achieve process but not product innovation. There might be particular knowledge sources that matter more for process or product innovation. Future research could identify important knowledge sources and explain innovation performance based on the *types* of knowledge (knowledge for value appropriation, problem solving, disruptive technologies etc.) provided by each. The right combination, *knowledge portfolio*, of internal and external knowledge may also matter.

6. Conclusion, limitations, and future research

Although the ideas of external knowledge search and openness have been studied in the organizational learning (Katila and Ahuja, 2002) and innovation literatures (Laursen and Salter, 2006), dynamic openness is a concept new to the open innovation literature. Past studies on innovation have focused on network structures, (Ahuja, 1998), but seldom consider the idea of search breadth and dynamic openness. These studies do not specifically address heterogeneous knowledge flows and their relationship to learning, absorptive capacity and organizational constraints that might limit the exploitation of such knowledge flows. In contrast, we focus on the acquisition of heterogeneous knowledge through external search. We introduced the concept of dynamic openness based on temporal adjustment of search breadth. Both product and process innovation literatures assert conflicting conclusions. For example, diminishing returns of external search breadth are asserted for product

innovation (Terjesen and Patel, 2017). These studies however utilized cross-sectional data and a "static" conception of openness to reach this conclusion without offering detailed explanation for such diminishing effects. We have added some clarity to this debate by carrying out a longitudinal study and examining the impact of dynamic openness strategies. We have offered a theoretical perspective that invokes learning from past searches and potential role of organizational constraints in our theorizing. This line of inquiry can be extended in future studies. Although our ideas and analysis in this paper focused only on *breadth*, a more complete examination of dynamic openness would require examination of "variety" aspects of external knowledge search also. In this we were handicapped by data (sample size) limitations. We acknowledge this limitation of our study and call for a future study to focus on "variety" as well as "breadth".

We recognize the following limitations of our study. We conceptualize dynamic openness as the *number* of external knowledge sources as other researchers have done. Our analysis does not account for the types of knowledge, the types of knowledge sources, nor the depth of relationships with the knowledge sources, which limits fuller understanding of dynamic openness. Exploiting knowledge of low complexity differs from exploiting complex knowledge. The issue of complexity of knowledge could not be accommodated within the current study since we lacked data. We acknowledge this limitation of our study. Future research and new data are required to address these limitations.

While our econometric analysis focuses on the propensity to innovate as the dependent variable, other measures of innovation performance e.g., sales from innovation products, can be used to carry out a similar analysis. This would help to understand how and why dynamic openness strategies impact various innovation performance measures. Additionally, in-depth case studies would complement this paper by shedding light on the context and process of dynamics openness. Future research could examine *how* firms learn *when* the right time is to change their openness strategy and *how* firms identify and exploit their knowledge portfolio that arises from different knowledge sources.

Table I. Definition of the variables

Variables	Definition
Product Innovation	Binary variable that takes the value of 1 if a business introduced new or significantly improved goods and/or services that are new to its market, and 0 otherwise.
Process Innovation	Binary variable that takes the value of 1 if a business introduced new or significantly improved processes for producing or supplying goods and/or services that are new to its industry, and 0 otherwise.
Breadth	Continuous variable that measures the number of different types of external sources of knowledge used by a business in its innovation activities. This variable has a range of 0-11.
Open	Binary variable that takes the value of 1 if a business used at least one external sources of knowledge in its innovation activities, and 0 otherwise.
External Search Strategies:	
Persistent Open	Binary variable that takes the value of 1 if a business has been open and has sustained the same number of external sources of knowledge compared to previous year ($Breadth_{t-1} > 0$ and $Breadth_t - Breadth_{t-1} = 0$), and 0 otherwise.
Persistent Closed	Binary variable that takes the value of 1 if a business has been closed over the years ($Breadth_{t-1} = 0$ and $Breadth_t - Breadth_{t-1} = 0$), and 0 otherwise.
Closing Down	Binary variable that takes the value of 1 if a business has reduced the number of external sources of knowledge compared to previous year ($Breadth_t - Breadth_{t-1} < 0$), and 0 otherwise.
Opening Up	Binary variable that takes the value of 1 if a business has increased the number of external sources of knowledge compared to previous year ($Breadth_t - Breadth_{t-1} > 0$), and 0 otherwise.
R&D	Binary variable that takes the value of 1 if a business undertakes internal and/or external research and development, and 0 otherwise.
lnSize	Natural logarithm of number of employees.
Scientific Collaboration	Binary variable that takes the value of 1 if a business cooperates with universities and/or government research institutes, and 0 otherwise.
Supply Chain Collaboration	Binary variable that takes the value of 1 if a business cooperates with their enterprise group, and/or with suppliers, and/or clients, and/or competitors, and/or consultants, and 0 otherwise.
Market	Categorical variable indicating the main business market. This variable takes the value of: 1, if a business conducts business regionally. 2, if a business conducts business in the UK. 3, if a business conducts business in Europe. 4, if a business conducts business Internationally.

Table II. Correlation matrix and descriptive statistics of the variables

		1	2	3	4	5	6	7	8	9	10	11	Obs.	Mean	Std. Dev.	VIF
1	Product Innovation	1											42,229	0.1	0.3	a
2	Process Innovation	0.3045	1										42,229	0.16	0.37	a
3	Breadth	0.3436	0.3966	1									42,229	0.88	1.51	2.32
4	Persistent Open	0.1636	0.1644	0.1873	1								26,208	0.07	0.26	b
5	Persistent Closed	-0.2405	-0.3102	-0.5304	-0.2490	1							26,208	0.44	0.49	4.26
6	Closing Down	0.0071	-0.0017	-0.1411	-0.1524	-0.4793	1						26,208	0.23	0.42	3.14
7	Opening Up	0.1680	0.2547	0.6230	-0.1670	-0.5255	-0.3216	1					26,208	0.26	0.43	3.32
8	R&D	0.4279	0.378	0.4586	0.2225	-0.369	0.0254	0.2609	1				42,229	0.24	0.43	1.55
9	Size	0.0339	0.0708	0.0655	0.0323	-0.0577	0.0262	0.0211	0.0952	1			42,229	362.5	2006.5	1.03
10	Scientific Collab.	0.2896	0.2479	0.3743	0.1082	-0.2155	0.0077	0.172	0.3501	0.0137	1		42,229	0.1	0.28	1.34
11	Supply Chain Collab.	0.3638	0.425	0.5256	0.2015	-0.3766	-0.0043	0.3102	0.5011	0.0166	0.4837	1	42,229	0.25	0.43	1.69
12	Market	0.2408	0.1671	0.2141	0.1286	-0.2127	0.0654	0.0963	0.3339	0.0183	0.1687	0.2189	37,489	2.33	1.13	1.17

- [a]: Variance Inflation Factor is calculated only for independent variables.
- [b]: Variance Inflation Factor is not calculated for the base category `persistent open`.
Note: All reported correlation coefficients are statistically significant at 1% level.

Table III. Transition probability matrix

	Closed	Open	Total
Closed	11,511 (70%)	4,984 (30%)	16,495 (100%)
Open	4,141 (43%)	5,572 (57%)	9,713 (100%)
Total	15,652 (60%)	10,556 (40%)	26,208 (100%)

Note: *Closed*: Business does not use any external sources of knowledge (i.e. Open=0).
      Open: Business uses at least one external sources of knowledge (i.e. Open=1).

Table IV. Summary statistics of External Search Strategies by Product and Process innovators

	N	Product Innovator		Process Innovator	
		Mean	Std. Dev.	Mean	Std. Dev.
Persistent Open (0/1)	1,922	0.27	0.44	0.38	0.48
Persistent Closed (0/1)	11,511	0.015	0.12	0.03	0.18
Closing Down (0/1)	5,944	0.1	0.29	0.16	0.36
Opening Up (0/1)	6,831	0.17	0.38	0.32	0.46
Total	26,208				

Table V. Logit Estimations External Search Strategies for Product and Process innovation

VARIABLES	Model 1		Model 2		Model 3	
	(1) Product Innovation	(2) Process Innovation	(3) Product Innovation	(4) Process Innovation	(5) Product Innovation	(6) Process Innovation
Breadth	-	-	0.54***	0.75***	-	-
			(0.045)	(0.06)		
Breadth_sq	-	-	-0.05***	-0.07***	-	-
			(0.006)	(0.005)		
External Search Strategies:						
Closing Down vs Persistent Open	-	-	-	-	-0.42***	-0.4***
					(0.16)	(0.12)
Opening Up vs Persistent Open	-	-	-	-	0.07	0.31***
					(0.15)	(0.12)
Persistent Closed vs Persistent Open	-	-	-	-	-0.71***	-1.2***
					(0.25)	(0.18)
Controls:						
R&D	1.25***	0.84***	1.04***	0.6***	1.24***	0.6***
	(0.08)	(0.06)	(0.08)	(0.07)	(0.15)	(0.1)
lnSize	-0.18*	0.03	-0.2**	-0.003	-0.16	0.34
	(0.01)	(0.074)	(0.1)	(0.28)	(0.23)	(0.17)
Supply chain Collaboration	1.14***	1.43***	0.9***	1.1***	1.02***	1.2***
	(0.77)	(0.06)	(0.08)	(0.06)	(0.14)	(0.1)
Scientific Collaboration	0.43***	0.21***	0.4***	0.22***	0.55***	0.26***
	(0.09)	(0.08)	(0.09)	(0.08)	(0.16)	(0.12)
Markets:						
UK vs Regional	-0.03	0.1	-0.1	0.11	-0.13	0.02
	(0.16)	(0.1)	(0.16)	(0.11)	(0.28)	(0.16)
Europe vs Regional	-0.06	0.23**	-0.17	0.2	-0.025	0.26
	(0.18)	(0.12)	(0.19)	(0.13)	(0.33)	(0.21)
International vs Regional	0.21	0.37***	0.007	0.31**	0.1	0.5*
	(0.18)	(0.13)	(0.19)	(0.14)	(0.33)	(0.22)
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
N	6,719	11,036	6,719	11,036	2,459	4,487
LR Chi^2	1174.7***	1626.8***	1347.9***	2204.7***	459***	797.4***

Note: Standard error in parenthesis. *p<0.05, **p<0.01, ***p<0.001.

References

Amara, N. and Landry, R. (2005), "Sources of information as determinants of novelty of innovation in manufacturing firms: Evidence from the 1999 statistics Canada innovation survey", *Technovation*, Vol. 25 No. 3, pp. 245-259.

Appleyard, M.M. and Chesbrough, H.W. (2017), "The dynamics of open strategy: from adoption to reversion", *Long Range Planning*, Vol. 50 No. 3, pp. 310-321.

Bahemia, H., Squire, B. and Cousins, P. (2017), "A multi-dimensional approach for managing open innovation in NPD", *International Journal of Operations & Production Management*, Vol. 37 No. 10, pp. 1366-1385.

Billington, C. and Davidson, R. (2013), "Leveraging open innovation using intermediary networks", *Production and Operations Management*, Vol. 22 No. 6, pp. 1464-1477.

Bogers, M., Foss, N. J. and Lyngsie, J. (2018), "The "human side" of open innovation: The role of employee diversity in firm-level openness", *Research Policy*, Vol. 47 No. 1, pp. 218-231.

Cabagnols, A. and Le Bas, C. (2002), "Differences in the determinants of product and process innovations: The French case", Kleinknecht, A. and Mohnen, P. (Ed.), *Innovation and Firm Performance*, Palgrave Macmillan, pp. 112-149.

Cassiman, B. and Veugelers, R. (2002), "R&D cooperation and spillovers: some empirical evidence from Belgium", *American Economic Review*, Vol 92 No 4, pp. 1169-1184.

Chesbrough, H. (2003), "The logic of open innovation: managing intellectual property", *California Management Review*, pp. 33-58.

Clausen, T., Pohjola, M., Sapprasert, K. and Verspagen, B. (2012), "Innovation strategies as a source of persistent innovation", *Industrial and Corporate Change*, Vol 21 No 3, pp. 553-585.

Clemens, M.A., Radelet, S., Bhavnani, R.R., and Bazzi, S. (2012), "Counting chickens when they hatch: Timing and the effects of aid on growth", The Economic Journal, Vol. 122, pp. 590–617.

Cohen, W.M. and Levinthal, D.A. (1990), "Absorptive capacity: a new perspective of learning and innovation", *Administrative Science Quarterly*, Vol 35, pp. 128-152.

Crépon, B., Duget, E. and Mairesse, J. (1998), "Research, innovation and productivity- an econometric analysis at the firm level". *National Bureau of Economic Research*, Vol. 6696.

DBEIS. (2019), "U.K. Innovation Survey", *Department of Business, Energy & Industrial Strategy, London*, available at: https://www.gov.uk/government/collections/community-innovation-survey (accessed 20th March 2021).

Greene, W.H. (2003), *Econometric Analysis*, Pearson Education India.

Hamermesh, R.G. and Silk, S.B. (1979), "How to compete in stagnant industries", *Harvard Business Review*, Vol 57 No 5, pp. 161-168.

Hewitt-Dundas, N., Gkypali, A. and Roper, S. (2019), "Does learning from prior collaboration help firms to overcome the 'two-worlds' paradox in university-business collaboration?", *Research Policy,* Vol 48 No 5, pp. 1310-1322.

Hullova, D., Trott, P. and Simms, C.D. (2016), "Uncovering the reciprocal complementarity between product and process innovation", *Research Policy*, Vol 45 No 5, pp. 929-940.

Katila, R. and Ahuja, G. (2002), "Something old, something new: a longitudinal study of search behavior and new product introduction", *Academy of Management Journal*, Vol 45 No 8, pp. 1183-1194.

Klepper, S. (1996), "Entry, exist, growth, and innovation over product life cycle", *The American Economic Review*, Vol 86 No 3, pp. 562-583.

Koput, K.W. (1997), "A chaotic model of innovation search: some answers, many questions", *Organization Science*, Vol 8 No 5, pp. 528-542.

Laursen, K. and Salter, A.J. (2006), "Open for innovation: the role of openness in explaining innovation performance among U.K. manufacturing firms", *Strategic Management Journal*, Vol 27 No 2, pp. 131-150.

Laursen, K. and Salter, A.J. (2014), "The paradox of openness: Appropriability, external search and collaboration", *Research Policy*, Vol 43 No 5, pp. 867-878.

Leiponen, A. and Helfat, C.E. (2010), "Innovation objectives, knowledge sources, and the benefits of breadth", *Strategic Management Journal*, Vol 31 No 2, pp. 224-236.

Linder, J.C., Jarvenpaa, S. and Davenport, T.H. (2003), "Toward an innovation sourcing strategy", *MIT Sloan Management Review*, pp. 43-39.

Lorenz, R., Benninghaus, C., Friedli, T. and Netland, T.H. (2020), "Digitization of manufacturing: the role of external search", *International Journal of Operations & Production Management*, Vol. 40 No. 7/8, pp. 1129-1152.

Love, J.H., Roper, S. and Vahter, P. (2014), "Learning from openness: the dynamics of breadth in external innovation linkages", *Strategic Management Journal*, Vol 35, pp. 1703-1716.

Mairesse, J. and Mohnen, P. (2002), "Accounting for innovation and measuring innovativeness: an illustrative framework and an application", *American Economic Review*, Vol 92 No 2, pp. 226-230.

Malhotra, N.K., Kim, S.S. and Patil, A. (2006), "Common method variance in IS research: A comparison of alternative approaches and a reanalysis of past research" *Management Science*, Vol 52 No 12, pp. 1865–1883.

Markham, S. (2000), "Corporate championing and antagonism as forms of political behaviour: an R&D perspective", *Organization Science*, Vol. 11 No. 4, pp. 429-447.

Narasimhan, R. and Narayanan, S. (2013), "Perspectives on supply network-enabled innovation", *Journal of Supply Chain Management*, Vol 49 No 4, pp. 27-42.

Neter, J., Kutner, M.H., Nachtsheim, C.J. and Wasserman, W. (1996), *Applied linear statistical models*, Chicago: Irwin, Vol. 4, p. 318.

Nieto, M.J. and Santamaría, L. (2007), "The importance of diverse collaborative networks for the novelty of product innovation", *Technovation*, Vol 27 No 6-7, pp. 367-377.

O'Connor, G.C. and Rice, M.P. (2001), "Opportunity recognition and breakthrough innovation in large established firms", *California Management Review*, Vol 32 No 2, pp. 95-116.

Ocasio, W. (1997), "Towards an attention-based view of the firm", *Strategic management journal*, Vol 18 No S1, pp. 187-206.

OECD. (1997), "Oslo Manual - The Measurement of Scientific and Technological Activities, Proposed Guidelines for Collecting and Interpreting Technological Innovation Data". *Organization for Economic Co-operation and Development*, available at: http://www.oecd.org/dataoecd/35/61/2367580.pdf

Piening, E.P. and Salge, T.O. (2015), "Understanding the antecedents, contingencies, and performance implications of process innovation: A dynamic capabilities perspective", *Journal of Product Innovation Management*, Vol 32 No 1, pp. 80-97.

Podsakoff, P.M., MacKenzie, S.B., Lee, J-Y. and Podsakoff, N.P. (2003), "Common Method biases in behavioural research: A critical review of the literature and recommended remedies", *Journal of Applied Psychology*, Vol 88 No 5, pp. 879–903.

Potter, A., & Paulraj, A. (2020). Building supplier innovation triads: the effects of leadership relationships and alliance partner diversity. *International Journal of Operations & Production Management*, Vol 40 No 2, pp. 144-172.

Prajogo, D., Mena, C., & Chowdhury, M. (2021). The role of strategic collaborations and relational capital in enhancing product performance–a moderated-mediated model. *International Journal of Operations & Production Management*, Vol 41 No 3, pp. 206-226.

Reichstein, T. and Salter, A. (2006), "Investigating the sources of process innovation among UK manufacturing firms", *Industry and Corporate Change*, Vol 15 No 4, pp. 653-682.

Robertson, P.L., Casali, G.L. and Jacobson, D. (2012), "Managing open incremental process innovation: absorptive capacity and distributed learning", *Research Policy*, Vol 41, pp. 822-832.

Rodriguez, M., Doloreux, D. and Shearmur, R. (2017), "Variety in external knowledge sourcing and innovation novelty: Evidence from the KIBS sector in Spain", *Technovation*, Vol 68, pp. 35-43.

Seepana, C., Huq, F. A., & Paulraj, A. (2021). Performance effects of entrepreneurial orientation, strategic intent and absorptive capacity within coopetitive relationships. *International Journal of Operations & Production Management*, Vol 41 No 3, pp. 227-250.

Sting, F.J., Stevens, M. and Tarakci, M. (2019), "Temporary de-embedding buyer–supplier relationships: A complexity perspective", *Journal of Operations Management*, Vol 65 No 2, pp. 114-135.

Tavassoli, S. and Karlsson, C. (2015), "Persistence of various types of innovation analyzed and explained", *Research Policy*, Vol 44 No 10, pp. 1887-1901.

Terjesen, S. and Patel, P.C. (2017), "In search of process innovations: The role of search depth, search breadth, and the industry environment", *Journal of Management*, Vol *43* No 5, pp. 1421-1446.

Tsinopoulos, C., Sousa, C.M. and Yan, J. (2018), "Process innovation: open innovation and the moderating role of the motivation to achieve legitimacy", *Journal of product innovation management*, Vol 35 No 1, pp. 27-48.

Villena, V.H., Revilla, E. and Choi, T.Y. (2011), "The dark side of buyer-supplier relationships: A social capital perspective", *Journal of Operations Management*, Vol 29 No 6, pp. 561-576.

Wilhelm, M. and Dolfsma, W. (2018), "Managing knowledge boundaries for open innovation – lessons from the automotive industry", *International Journal of Operations & Production Management*, Vol 38 No 1, pp. 230-248.

Wooldridge, J.M. (2002), *Econometric analysis of cross section and panel data*, MIT press.

Zaggl, M. A., Schweisfurth, T.G. and Herstatt, C. (2020), "The dynamics of openness and the role of user communities: A case study in the ecosystem of open source gaming handhelds", *IEEE Transactions on Engineering Management*, Vol 67 No 3, pp. 712-724.

Zhang, G.P., Yu, J. and Xia, Y. (2014), "The payback of effective innovation programs: Empirical evidence from firms that have won innovation awards", *Production and Operations Management*, Vol 23 No 8, pp. 1401-1420.