



# The S-shaped relationship between open innovation and financial performance: A longitudinal perspective using a novel text-based measure

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## ABSTRACT

Research on the financial performance outcomes of open innovation has been equivocal and often relies on cross-sectional data and problematic assumptions about the role of the external context. A longitudinal perspective is crucial for gaining a better understanding of the potential of decreasing innovation utility as well as the conditions under which the costs of open innovation may counteract its benefits. Additionally, much of the research largely ignores the potential role and benefits of closed innovation. In this study, we address these issues by developing a theory related to how the benefits and costs of open innovation lead to an S-shaped relationship between the degree of openness – ranging from closed to low, medium, and high levels of open innovation – and a firm's financial performance. Furthermore, we investigate two possible contingencies in which this relationship is more pronounced: in industries with high appropriability, optimizing firms' ability to extract value from innovation and in dynamic industries, where coordinating high open innovation activities amid rapid changes is exceedingly costly. To test our hypotheses, we create a longitudinal measure for firms' degree of open innovation by using machine-learning content analyses to build an open innovation dictionary and then applying this dictionary to analyze the 10-K annual reports of >9000 publicly listed firms in the U.S. between 1994 and 2017. The results support our theorizing that the relationship between the degree of open innovation and firm financial performance is S-shaped and that industries' appropriability regimes and environmental dynamism are critical boundary conditions for this relationship.

## 1. Introduction

Firms have traditionally dedicated substantial resources to internal research and development (R&D) activities to produce innovations required for achieving a sustained competitive advantage (Dahlander et al., 2021; Freeman, 1982; Garud et al., 2013). In recent years, firms have increasingly drawn on collaborations with external partners to augment these innovation activities (Chesbrough and Bogers, 2014; Ogink et al., 2022; West et al., 2014), as can be seen in the emergence of crowdsourcing, innovation ecosystems, platform business models, and

open-source software (Bogers et al., 2017; Foege et al., 2019; Randhawa et al., 2016; Schäper et al., 2020). Accordingly, a body of empirical research has emerged to investigate the performance effect of this open innovation approach (e.g., Faems et al., 2010; Laursen and Salter, 2006; Ovuakporie et al., 2021). This research provides insights into how firms exchange ideas, knowledge, and technologies across their organizational boundaries to broaden their pool of available knowledge, enhance internal ideation processes accordingly, and reduce the risks and expenses associated with R&D activities (Bertello et al., 2022; Criscuolo et al., 2017; Stanko et al., 2017).

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However, this same research suffers from theoretical and empirical shortcomings that constrain scholarly understanding of the outcomes of open innovation. First, prior studies on the *financial* performance outcomes of open innovation are equivocal, which is especially problematic in light of related research showing an inverted U-shaped relationship between the degree of open innovation and *innovation* performance (Laursen and Salter, 2006). Decreasing innovation utility from open innovation and the fact that firms incur significant costs from open innovation (Faems et al., 2010) have led to calls to examine the financial drawbacks of open innovation (Bogers et al., 2017; Ebersberger et al., 2021; Goulart Heinzen and Lavarda, 2021) and reevaluate the role that *closed* innovation plays in an open innovation paradigm (Holgersson et al., 2022). Second, a more holistic view of open innovation means that understanding the boundary conditions shaping the cost-benefit balance is crucial to a more accurate theory of its firm-level performance outcomes. Unfortunately, existing literature has devoted little attention to the contexts in which the benefits of open innovation may outweigh its costs. Third, existing studies tend to rely on cross-sectional data as well as crude proxies for open innovation (e.g., Lu and Chesbrough, 2021), further limiting the literature's empirical basis for theoretical inferences regarding causal effects on performance (Du et al., 2014; Ebersberger et al., 2021; Piezunka and Dahlander, 2019).

We attempt to address these lacunae by explicating the relationship between open innovation and firm financial performance. We argue that firms' innovation output can benefit from opening their innovation activities, but the benefit will eventually reach a plateau, while the costs mount up quickly as open innovation intensity rises. Further, because even a little open innovation involves non-trivial costs, we posit that closed innovation outperforms low levels of open innovation. These arguments lead us to predict an S-shaped relationship between open innovation and financial performance, whereby financial performance is higher for closed innovation or moderately open innovation than for low or high levels of open innovation. Further, we contend that these patterns are more pronounced in high appropriability industries where firms can more easily extract the value from their innovations and in dynamic industries where coordinating open innovation activities amid rapid changes is exceedingly costly.

We test these assertions by operationalizing firms' degree of open innovation in a longitudinal, structured, and large-scale way. Drawing on a growing body of literature that analyzes texts to quantify organizational constructs (Bellstam et al., 2020; Hoberg and Lewis, 2017; Nadkarni and Chen, 2014), we leverage a machine-learning approach to create a dictionary on open innovation based on the 1000 most-cited articles of scholarly research in this domain. Subsequently, we use this dictionary to quantify the degree of firm-level open innovation by analyzing the 10-K annual reports of 9103 publicly listed firms in the U. S. between 1994 and 2017. Then, we combine these open innovation scores with archival datasets to test our hypotheses. The results support our arguments of an S-shaped relationship between open innovation and financial performance that depends on the industries' appropriability regime and dynamism as critical boundary conditions.

This study contributes to the literature in at least three important ways. First, by considering both the benefits and the costs of open innovation, we provide a better understanding of its performance implications. We theorize and find that the relationship between the degree of open innovation and financial performance is S-shaped. This finding highlights the value of closed innovation and advances a more holistic theory of the performance outcomes of open innovation to include those that are financial. Second, our theory and findings contextualize open innovation by showing how the industries' appropriability regime and environmental dynamism are critical contingencies to its performance effects. Finally, we derive a text-based measure that captures firms' degree of open innovation in longitudinal, large-scale data. Our measure enables researchers to go beyond cross-sectional survey data, which is frequently used in open innovation research, to assess the degree of open innovation over time for a broad range of firms across different

industries. The underlying methodology can serve as a blueprint for scholars seeking to derive other quantitative measures of innovation.

## 2. Theory and hypotheses

### 2.1. Open innovation and financial performance

Since Chesbrough (2003) first described it, the concept of open innovation has received considerable attention from both academics and managers and profoundly impacted research and practice around firm innovation (Ahuja et al., 2008; Alam et al., 2022; Randhawa et al., 2016). Open innovation occurs when firms collaborate with different partners throughout the innovation process (Almirall and Casadesu-Masanell, 2010; Wyrwich et al., 2022). It spans a broad variety of organizational forms such as technology licensing (Steensma and Corley, 2000), R&D alliances (Li et al., 2012), innovation ecosystems (Vasudeva et al., 2020), innovation platforms (Parker and van Alstyne, 2018), and innovation alliance networks (Vasudeva et al., 2013, 2020).

While there is extensive research on how open innovation can enhance innovation performance by improving knowledge recombination, new product development, and time-to-market (e.g., Grimpe and Kaiser, 2010; Laursen and Salter, 2006), the findings from research examining the relationship between open innovation and financial performance have been ambiguous (Ogink et al., 2022; West and Bogers, 2014). First, Faems et al. (2010) argue and find that diversity in technology alliance portfolios positively affects firms' financial performance. However, they also find that technology alliance portfolio diversity significantly increases the cost for personnel because more employees are required for managing the network. They conclude that open innovation ultimately decreases profitability, as its costs are greater than the value it adds. Second, Belderbos et al. (2010) postulate an inverted U-shaped relationship between open innovation and firm financial performance, finding that explorative technological activities increase firms' financial performance, while collaborative technological activities decrease firms' market value. Finally, Rothaermel and Alexandre (2009) find that the relationship between firms' technology sourcing mix and financial performance follows an inverted U-shape, with a maximum return at about 61 % external sourcing.

Two further studies relate forms of openness and financial performance. First, Du et al. (2014) examine the links between market-based and science-based openness in R&D projects, on the one hand, and project-level financial performance, on the other. They argue and find that the performance effect of openness in R&D projects depends on the correct management of the partnerships. Their results indicate that formally managed market-based partnerships increase the financial performance of R&D projects, whereas loosely managed market-based partnerships decrease it. As for openness in science-based partnerships, these scholars only find a positive relationship to the financial performance of R&D projects if the partnerships are loosely managed. In a further study, Andries and Faems (2013) examine patent licensing as a peculiar form of outbound openness and find no positive or negative effect of licensing patents on firms' financial performance. They conclude that this finding casts doubt on the argument that licensing is an open innovation practice that yields additional financial returns for firms.

Taken together, these studies show that research on the financial performance implications of open innovation yields inconsistent findings and suffers from theoretical and empirical shortcomings that constrain scholarly understanding of the outcomes of open innovation.

### 2.2. The benefits and costs of open innovation

#### 2.2.1. Benefits of open innovation

Several authors suggest that a way to advance open innovation theorizing would be to focus on the benefits and costs of open versus closed innovation (Cassiman and Valentini, 2016) and thereby

uncovering the so far implicit link between open innovation and financial performance (Ogink et al., 2022; West and Bogers, 2014). Scholars have found that open innovation can enhance innovation performance as it accelerates new product development and reduces time-to-market for new products and services through broadening access to information on new technologies and markets, leveraging complementarities across the value chain, and sharing the costs and risks involved in R&D processes (Dahlander et al., 2021; Grimpe and Kaiser, 2010; Ovuakporie et al., 2021). In that regard, open innovation enables firms to capture market share and reap the returns from their innovations (Chesbrough et al., 2018; Lauritzen and Karafyllia, 2019). However, it needs to be said that a large number of collaboration partners can increase the complexity of managing the innovation process and the danger of value appropriation challenges resulting from competitors' imitative efforts (Laursen and Salter, 2006; Li et al., 2012), because open innovation activities can risk leaking critical knowledge to competitors, who can use this information to develop and market competing technologies, products, and services (Veer et al., 2016) without remunerating the focal firm (Foegen et al., 2017). Such opportunistic behavior can lead to significant revenue losses and diminish firms' performance (Li et al., 2012) if open innovation is pursued excessively.

Open innovation can serve as a tool to access external knowledge (Dahlander and Gann, 2010; Mihm and Schlapp, 2019). Searching for information beyond organizational boundaries can help firms overcome the tendency to exploit existing knowledge while neglecting the exploration of new knowledge (Gambardella et al., 2017; Lopez-Vega et al., 2016) – a tendency known as the myopia of organizational learning (Levinthal and March, 1993). Strategically relying on distant search and external knowledge, thus, helps firms to continually augment their innovation activities (Afuah and Tucci, 2012; Bogers et al., 2019; Gupta et al., 2007), sparking innovation through combining internal and external knowledge (Goulart Heinzen and Lavarda, 2021; Ritala and Hurlmelinna-Laukkanen, 2013; Schilling, 2015) and jointly leveraging marketing activities and R&D (Adner and Kapoor, 2010; Jacobides et al., 2018).

Beyond that, open innovation can enable firms to commercialize otherwise unused internal ideas and knowledge outside their boundaries through selling or out-licensing them to their partners, who use the information to create new products and sell them to their customers (Dahlander et al., 2021). This commercialization can generate additional revenue streams from internal knowledge that would not have been used otherwise (Bogers et al., 2017; Foegen et al., 2019). Taking all factors into consideration, open innovation is associated with benefits that range from accessing valuable external knowledge (Dahlander and Gann, 2010) to realizing synergies in R&D activities (Chesbrough et al., 2014) to generating additional revenue streams from commercializing unused internal knowledge (Foegen et al., 2019). All of these benefits can improve a firm's financial performance.

### 2.2.2. Costs of open innovation

Despite its benefits, open innovation comes with two specific kinds of costs: adjustment costs and coordination costs. *Adjustment costs* include the costs of transferring existing resources to new areas of operation (Hashai, 2015); they result from the initiation of each new open innovation activity for which firms have to build new structures for collaboration (Kale and Singh, 2010), such as by recruiting new employees or shifting and training existing ones (Helfat and Eisenhardt, 2004), building internal management systems or dedicated business units (Tan and Mahoney, 2006), and purchasing or modifying equipment (Hashai, 2015). Other adjustment costs include the expenses associated with the maintenance and administration of open innovation structures that have been created. Examples of these expenses are those for the distribution of staff, for travel, for rent, and for digital infrastructure (Boudreau, 2010; Hennart, 1991; Li et al., 2019). Adjustment costs cause initial inefficiencies that can distort operations and lead to imperfect resource

allocations (Cohen and Levinthal, 1990; Fernhaber and Patel, 2012), as existing routines or knowledge are still missing. As the degree of open innovation activities rises, the growth of adjustment costs per unit declines as firms build up the required knowledge and routines in the new areas of operation to enhance efficiency, such as by improving the distribution of staff, which reduces wage costs, and maintaining and improving the digital infrastructure. Hence, the margin of adjustment costs of open innovation is also likely to decrease with the degree of openness.

*Coordination costs* mainly arise from the management of the partnership portfolio and include the costs associated with the continued identification, initiation, and management of partnerships, especially with regard to the seeking, processing, transferring, and protecting of knowledge (Foegen et al., 2019; Hennart, 1991). These costs increase as the number of open innovation partners and initiatives increases. It is expensive to identify, assimilate, and utilize a multitude of external knowledge inputs at the same time (Dahlander et al., 2021). Searching too broadly may lead to a set of ideas and opportunities that is too large to be effectively managed, comes at the wrong time and place, and/or cannot be sufficiently pursued (Ebersberger et al., 2021; Katila and Ahuja, 2002; Koput, 1997). Likewise, the management of partnerships can require the simultaneous use of non-scale free resources across several partnerships, which can create friction associated with coordination costs (Hashai, 2015). Coordination costs are lowest when there is a clear focus on a limited set of business activities (Uotila et al., 2009): in the present case, a small number of partnerships. Another essential type of coordination cost in collaborative research projects arises from firms' efforts to defend their intellectual property, such as through patents, copyrights, and trademarks, as well as to litigate the ownership of ambiguously-owned intellectual property (Wen et al., 2016). The costs of these legal activities can impact firms' performance (Li et al., 2012). Coordination costs are likely to increase with the degree of open innovation, especially as the intensity of engaging in open innovation activities increases (Parker and van Alstyne, 2018).

### 2.3. The relationship between open innovation and financial performance

Considering the benefits and costs of open innovation, these opposing effects require joint consideration to fully understand how the degree of open innovation affects firms' performance. While a few studies address the benefits and costs of openness in innovation (Faems et al., 2010; Felin and Zenger, 2020; Grimpe and Kaiser, 2010), there is less research on how these factors collectively influence financial performance (Bogers et al., 2017; Stanko et al., 2017). A holistic picture of the performance-enhancing effects of open innovation should also consider how such effects change with the degree of openness (Felin and Zenger, 2014, 2020; Leiponen and Helfat, 2010).

Based on the theoretical background that has emerged in this domain, we conceptually differentiate among four levels of open innovation activities as conducted by a focal firm: closed, low, medium, and high. As mentioned above and further explained below, we suggest that the relationship between open innovation and financial performance is nonlinear, taking the functional form of an S-shape. This relationship results from the benefits and costs that arise at different degrees of open innovation. Fig. 1 visualizes our theorizing, showing how different benefits and costs associated with open innovation relate to firm performance – all combined into a single hypothesis to capture the S-shaped relationship between open innovation and financial performance.

Before we consider different degrees of openness, we first address *closed* innovation as a situation in which a firm conducts all innovation activities in-house (Felin and Zenger, 2014, 2020) – what we would traditionally call a vertically integrated model (Chandler, 1962; Freeman, 1982). Even though open innovation has become more common, generally closed innovation leads to superior performance than low levels of open innovation. Indeed, Laursen and Salter (2006) have shown that, even though it is not optimal, there is a performance effect

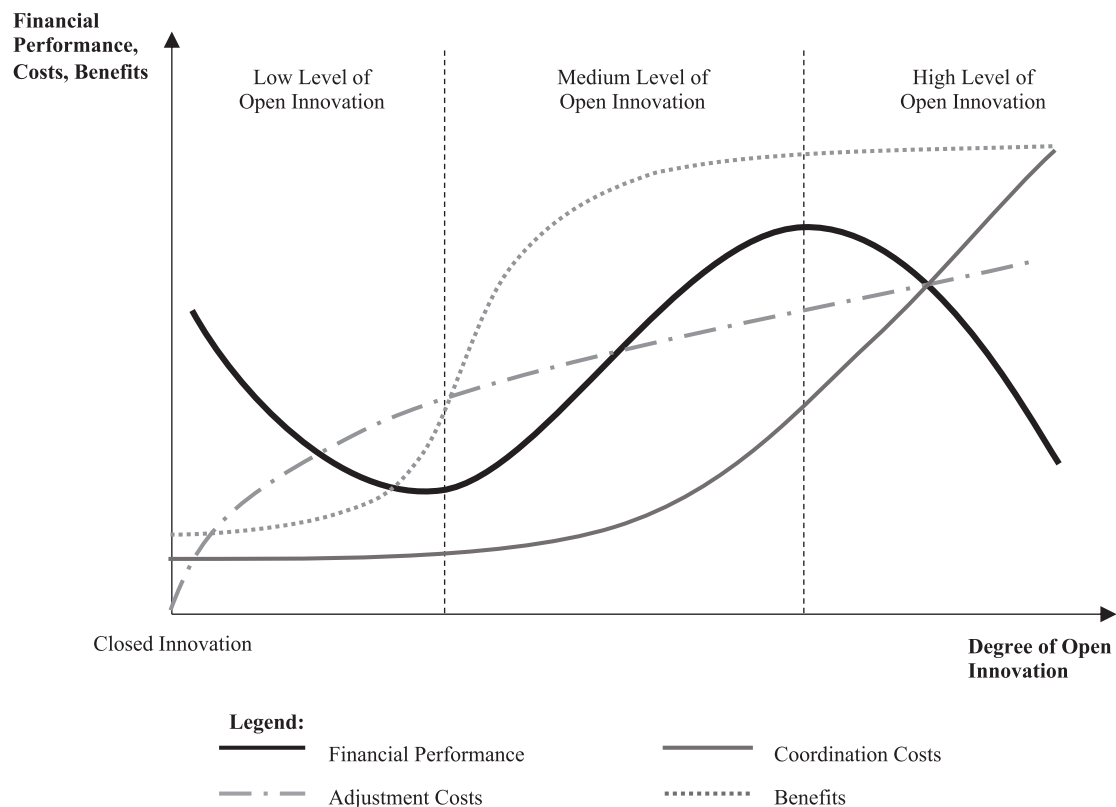


Fig. 1. The open innovation–financial performance relationship.

of using not a single external knowledge source for innovation.

A firm carrying out a *low* level of open innovation opens its closed organizational boundaries to only one or very few firms (Almirall and Casadesus-Masanell, 2010; Felin and Zenger, 2020). The benefits that the focal firm can expect from this level of open innovation are modest, as the possibilities for realizing synergies and exploiting knowledge are limited. The coordination costs are negligible at these low levels, due to the small number of partners, so the transaction costs are low as well (Hashai, 2015). However, there are adjustment costs that mount up quickly for establishing the structures for collaboration and joint activities. Moreover, at low levels of open innovation, firms lack supporting routines and knowledge (Fernhaber and Patel, 2012), which creates problems for business decisions and resource allocations. Taking these factors together, we expect that the adjustment costs undermine the small benefits of open innovation at low levels of openness.

Firms with *medium* levels of open innovation collaborate with multiple open innovation partners. The benefits of these interactions are higher, letting firms recover their adjustment costs. They can realize synergies in R&D, build up experience in combining and absorbing external knowledge, and commercialize unused knowledge (Dahlander and Gann, 2010; Lauritzen and Karafyllia, 2019; Ovuakporie et al., 2021). They incur slightly higher adjustment costs than firms with low levels of open innovation. Yet their managers can use the knowledge and experience they have developed to improve resource allocations, avoid mistakes in business decisions, and apply more nuance to the management of their operations (Hashai, 2015). At this point, routines are established, reducing inefficiencies. Though higher openness goes hand in hand with higher complexity in partnerships, the coordination costs will still only be moderately higher as the number of partners remains reasonably manageable (Brockhoff, 1992; Duysters and Lokshin, 2011; Ebersberger et al., 2021). Hence, we expect that the benefits of open innovation will outweigh the negative aspects of a medium level of open innovation.

Despite its benefits, open innovation is subject to diminishing returns

at *high* levels of open innovation. Part of the problem is the organizational difficulty of integrating external knowledge and aligning it with internal knowledge and external knowledge (Cohen and Levinthal, 1990; Laursen and Salter, 2014; West and Bogers, 2014). Simultaneously, the coordination costs skyrocket as the costs of searching for knowledge and partners increase exponentially with the extent to which firms pursue open innovation (Bogers et al., 2017; Huizingh, 2011; Salge et al., 2012; Stanko et al., 2017). For example, the transaction costs for transferring technologies among more than two firms become much higher than between only two firms as the contractual arrangements become more complex (Felin and Zenger, 2020; Kale et al., 2000). The larger the number of partners a firm collaborates with, the greater the complexity of managing this portfolio of partnerships (Brockhoff, 1992), while the returns diminish due to searching and coordination costs (Foegel et al., 2017). The complexity can seriously dampen the efficiency of R&D investments among a broader set of partners (Dahlander and Gann, 2010; Felin and Zenger, 2014), such that we expect an increasingly negative effect of coordination costs on financial performance that is exacerbated by the rising adjustment costs when open innovation efforts are extended beyond a certain point. In short, we expect that the coordination costs outweigh the benefits of open innovation at high levels of open innovation.

Fig. 1 integrates these forces to formulate the S-shaped relationship between open innovation and financial performance. By gradually establishing viable structures and related operations, firms can benefit from opening their innovation activities. However, the pay-off of open innovation activities reaches a turning point, after which adverse performance effects emerge. As open innovation activity begins and increases, the coordination costs take over, resulting in an S-shape link between open innovation and firm financial performance.

**Hypothesis 1.** The relationship between open innovation and financial performance is S-shaped, starting with a positive performance for closed innovation and then following a negative slope at low levels of



open innovation, a positive slope at medium levels of open innovation, and a negative slope at high levels of open innovation.

### 2.3.1. The role of contingencies for open innovation-financial performance link

While the S-shaped relationship explains how different degrees of open innovation can lead to different levels of performance, open innovation and its benefits and costs are also subject to certain boundary conditions (Salge et al., 2013; Stanko et al., 2017), such as firm-specific moderating effects (Ovuakporie et al., 2021) and higher-level moderating effects in the network or industry (Bogers et al., 2017). Felin and Zenger (2014) argue that closed innovation will lead to superior performance relative to open innovation under conditions of complex problems, low-powered incentives, and access to property rights. In line with the dependence of closed innovation on strong property rights, it can be expected that the appropriability regime plays a role in the effectiveness of closed and open initiatives (Holgersson et al., 2022). Similarly, Barbic et al. (2021) show that the legal regime and the disturbances in the environment influence the opening and closing of innovation. More generally, environment-level conditions will affect the ways that closed and open innovation, across different levels, which will lead to firm-level performance effects (Felin and Zenger, 2014; Jacobides et al., 2006).

### 2.3.2. The effect of industries' appropriability regimes

The concept of the appropriability regime goes back to the seminal work of Teece (1986) on profiting from innovation. Teece (1986, 287) defines the appropriability regime as "the environmental factors, excluding firm and market structure, that govern an innovator's ability to capture the profits generated by an innovation." He argues that this property rights environment comprises two dimensions, the nature of the technology and the efficacy of legal mechanisms of protection in an industry, and goes on to suggest that the appropriability regime of an industry within which a firm operates is tight if these factors enable easy protection of innovations and weak if they do not.

Efficient legal protection mechanisms enable firms to reap the benefits from open innovation even at higher degrees of open innovation (Stefan and Bengtsson, 2017). Firms in industries characterized by legal and regulatory regimes emphasizing property protection will find it easier to set up and enforce legal contracts if they can maintain an overview of their partnership network (Foegen et al., 2017). Being in such an industry will improve the focal firm's position if litigation becomes necessary (Foegen et al., 2019). Such environments will enable firms to maintain the benefits even at high degrees of open innovation (Felin and Zenger, 2020; Foegen et al., 2017).

Taking these factors into consideration, we expect that a tight appropriability regime rooted in the efficacy of the legal system will affect the firms' ability to extract value from innovation even at high degrees of open innovation.

**Hypothesis 2.** A tight appropriability regime will moderate the cubic relationship between open innovation and firm financial performance, such that the benefits, and thus the firm financial performance, will increase at high degrees of open innovation.

### 2.3.3. The effect of environmental dynamism

Environmental dynamism is characterized by instability, turbulence, and an absence of patterns in environments (Dess and Beard, 1984; Jurkovich, 1974; Miles et al., 1974; Miller and Friesen, 1983). Dynamic environments make it difficult to predict how fast and in which direction the market will develop (Jung et al., 2020); they require firms to constantly respond to shifts and changes. We expect that environmental dynamism is a critical boundary condition for the open innovation-financial performance link, as it will affect the coordination costs at the various degrees of open innovation.

As the degree of open innovation increases, the size and complexity

of the partner network typically increase as well (Cruz-González et al., 2015; Shaik and Levina, 2019). In partner networks, not only does the focal firm respond to changes in the environment, but each of the partner firms does the same (Ogink et al., 2022), which in turn leads to constant changes in each connection or relationship in that partner network (Gulati et al., 2000). Thus, we argue that the coordination costs for the focal firm do not increase linearly, with a focus on its own costs of change, but rather exponentially, with the inclusion of some of the total coordination costs of change of all partner firms in the network, which will diffuse through the network. In other words, if we understand a firm as being part of an open innovation network with strong ties, a shift at one end of the network is likely to affect most or all of the interactions within the network (Dittrich and Duysters, 2007; Rost, 2011), making it costly for each participant to adapt to them (Gulati et al., 2000).

Taking these arguments into account, we expect that especially for high degrees of open innovation, a dynamic environment will affect the coordination costs, amplifying their negative effect at high degrees of open innovation.

**Hypothesis 3.** Dynamic environments will moderate the cubic relationship between open innovation and firm financial performance, such that the coordination costs will be higher, decreasing firm financial performance at high degrees of open innovation.

## 3. A text-based measure of open innovation

### 3.1. Overview

Together with the growth of open innovation, a body of research has emerged to empirically study how organizations leverage external sources of knowledge in their innovation processes. Conducted by the Statistical Office of the European Community (Eurostat), the Community Innovation Survey (Mairesse and Mohnen, 2002, 2010) has given rise to many studies that assess the impact of openness for innovation using representative survey data. Laursen and Salter's (2006) seminal paper has become the standard reference for operationalizing open innovation as the breadth of external search – the number of external sources of knowledge or information for innovation that a firm relies on – and linking this measure to the firms' innovation performance. Based on that paper, it has become an established finding that there is an inverted U-shaped relationship between open innovation and innovation performance (e.g., Grimpe and Kaiser, 2010; Laursen and Salter, 2006; Leiponen and Helfat, 2010).

Despite their progress in assessing the performance implications of open innovation, the studies that have been conducted in this area have some notable limitations. First, they are mainly based on cross-sectional survey data and cannot account for the longitudinal effects of open innovation, particularly those that play out only after several years (e.g., Lu and Chesbrough, 2021). Second, due to the limitations on the availability of data, most studies are restricted to using innovation performance as an outcome variable, leaving the (arguably more critical) effect on financial performance mostly unexplored. Third, prior studies focused on firms' use of external sources of knowledge for innovation (so-called "inbound" open innovation) and often neglected other modes of openness in which knowledge may flow out of the firm or when more collaborative innovation efforts are employed ("outbound" and "coupled" open innovation) (Dahlander et al., 2021). Much of the open innovation literature remains detached from related literature streams such as those on strategic alliances, user innovation, innovation ecosystems, and firm networks (Cassiman and Valentini, 2016; Mihm and Schlapp, 2019). We argue that a more integrative approach to conceptualizing and operationalizing open innovation beyond search openness could be beneficial. Hence, we draw on a growing body of literature from various disciplines, such as finance, management, and accounting, to use textual analysis to quantify organizational behavior (e.g., Bellstam et al., 2020; Hoberg and Lewis, 2017).

We conducted a two-stage content analysis to derive a measure that uses textual data to capture open innovation as the firm's strategic choice of the degree of openness in innovation. This analysis objectively and systematically identifies specific characteristics of text data, searching the text for selected words, ideas, and meanings to identify interpretable topics (Hoberg and Lewis, 2017). The technique relies on two main components: a *dictionary* that contains the most frequent keywords of a theme, in our case of open innovation, and an *algorithm* that uses this dictionary to analyze textual information (e.g., Lowry et al., 2016). Fig. 2 depicts our approach.

### 3.2. Open innovation dictionary

To create our *open innovation dictionary*, we followed and combined open- and closed-language approaches (Harrison et al., 2019). First, we used Google Scholar to search for the one thousand most-cited open innovation studies to establish the input text data for creating the dictionary. We ran a search query for the term *open innovation* to capture all relevant studies that were published up to February 2020, the time of our data collection. We carefully cleaned the sample of texts for all text documents unrelated to open innovation per se and excluded studies that were not in English. Furthermore, we cleaned and unified the data by (1) converting all text to lowercase, (2) removing familiar English stop words, (3) stemming all words, and (4) using n-gram routines to include sequences of words (Antons et al., 2016). This last procedure is needed to ensure that the identification of sequences of words captures specific concepts that occur as textual compounds (e.g., open innovation, outbound innovation, and knowledge transfer). Our final dataset consists of 925 studies with about 6 million words in total.

Second, we applied an unsupervised machine learning algorithm to identify proper categories and keywords describing the content of the data (Behl et al., 2014; Tan et al., 2009). Moreover, it provides reliable concept extraction and thematic clustering without human biases (Randhawa et al., 2016). The algorithm identifies key concepts and themes within open innovation literature based on the frequency and co-occurrence of keywords. It also extracts the relationship between these concepts and proposes a name for each category (Randhawa et al., 2016).

To obtain a rigorous open innovation dictionary that describes the concept of open innovation, we applied a two-stage process and experimented with different numbers of topics (Antons et al., 2016; Bellstam et al., 2020). Identifying the optimal number of topics is essential as it has to capture the actual diversity of themes within the text corpus (Antons et al., 2016). Our approach to determining the final dictionary is a gradual reduction of topics and words. We first used topic modeling to create an initial dictionary, which we then gradually reduced in three steps from 23 topics and 353 words to 9 topics and 51 words. An expert evaluation was conducted at every stage. The initial dictionary with 23 topics and 353 words was edited by the author team as they went over each category and keyword, eliminating or renaming terms. To better understand the meaning of the words and overarching categories, we manually revisited each category to see how the keywords were used in the context of the text data. The output was a dictionary with 14 topics and 134 keywords. At this point, we brought in three academic researchers, experts in open innovation, to independently assess the proposed topics and keywords and to make suitable adjustments. These adjustments included (1) deleting inadequate keywords, (2) combining categories, and (3) labeling category names. This procedure resulted in a dictionary with 11 topics and 75 keywords. In a second round of revision, the experts reduced the dictionary to nine topics and 51 words. Table 1 provides an overview of our final topics and keywords in the open innovation dictionary.

### 3.3. Calculating the open innovation score

After creating the open innovation dictionary, we applied it to tex-

tual data. We downloaded all 10-K annual reports from 1994 to 2018 from the United States Securities and Exchange Commission (SEC) database. Our data thus consists of around 239,000 10-K annual reports of 34,258 publicly listed firms in the U.S. between 1994 and 2018. We used our open innovation dictionary to feed an algorithm that analyzed these 10-K annual reports. We ensured rigorous analysis of the textual data by removing common stopwords and blank spaces and stemming all words in the reports. In determining the final score, we built on prior representations of text-based measures (e.g., Hubbard et al., 2018; Moss et al., 2018; Uotila et al., 2009) and calculated the *open innovation score* ( $\theta_{f,t}$ ) as the number of words that are common to both the text and the open innovation dictionary ( $D_{f,t}$ ) in relation to the length (number of words) of each annual report ( $T_{f,t}$ ) for each firm  $f$  in year  $t$ :

$$\theta_{f,t} = \frac{D_{f,t}}{T_{f,t}} \quad (1)$$

Given that we analyzed large-scale text data, the algorithm required immense computing power. Hence, we used a high-performance computer cluster to calculate our final measure. While the score can lie between 0 and 100 %, the empirically observable maximum is 4.42 %. This score represents a firm's degree of open innovation activity relative to its overall business activity.

### 3.4. Examining the open innovation score

When examining the open innovation score for firms with high and low degrees of open innovation, we can observe that the highest degrees of open innovation are present in electronics, pharmaceutical, and computer firms – those commonly denoted as high-tech (e.g., Hecker, 1999). This finding aligns with Chesbrough and Crowther (2006), who underscore the importance of open innovation in high-tech and knowledge-intensive industries. By contrast, the energy supply, insurance, and coal industries possess the lowest degree of open innovation. This is not surprising for industries in which demand is relatively stable and prices are often regulated (Chaganti and Sambharya, 1987; Nason and Patel, 2016).

### 3.5. Comparison to other measures

Following the methodological approach of Demerjian et al. (2012) and Hoberg and Maksimovic (2015), we validated our open innovation score by comparing it to other, more indirect proxies of open innovation, as well as to general measures of firms' innovation activity that are commonly used in management studies. We used data on alliances from the SDC Platinum database to validate our open innovation score against data on firms' alliances. This approach builds on the premise that opens innovation activities, particularly those that are outbound (Mazzola et al., 2012), serve as proxies for firms' search for innovation outside their boundaries (Dahlander et al., 2021; Huizingh, 2011; West and Bogers, 2014). Hence, we extracted the number of (1) alliances, (2) alliance partners, (3) R&D alliances, and (4) technology transfer alliances as tentative indications of external searches for innovation (e.g., Huang and Rice, 2012; Laursen and Salter, 2006; Leiponen and Helfat, 2010). We further compared our measure against general measures of firm innovation, such as (1) R&D intensity, (2) the number of patent applications, and (3) citation-weighted value of patents (e.g., Kogan et al., 2017). Summary statistics and correlations are shown in Table 2.

Overall, the comparisons between our open innovation score and other indicators of open innovation and general firm innovation show consistently positive and significant correlations. While the correlations are low – a finding that corresponds to other studies that develop and compare text-based and accounting measures (Hoberg and Lewis, 2017; Bodnaruk et al., 2015) – they still provide indications that our text-based measure captures information on open innovation activity.

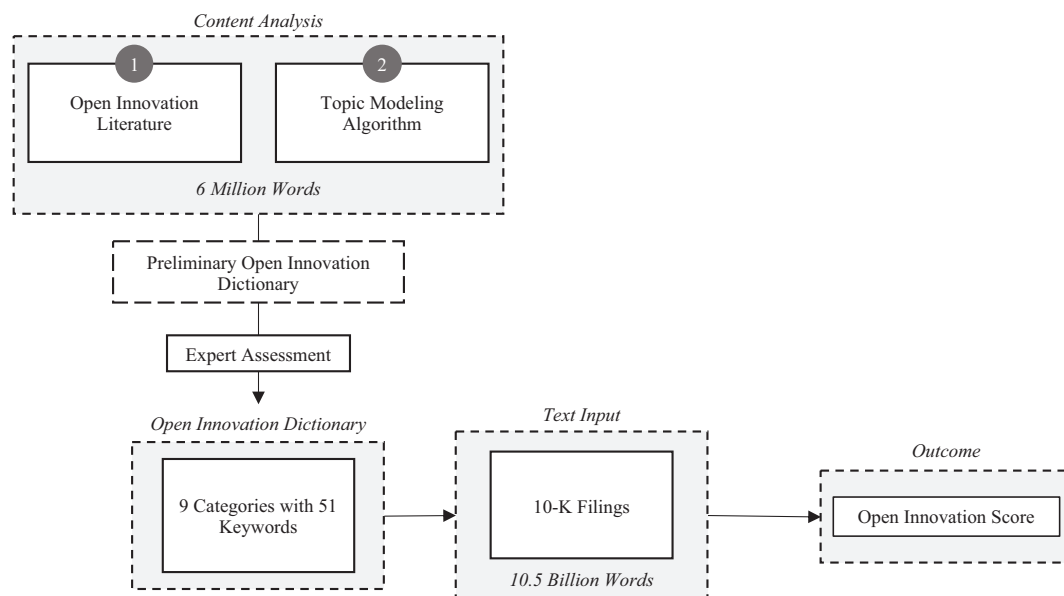


Fig. 2. Overview of our approach to create the open innovation score.

## 4. Empirical methodology

### 4.1. Sample construction

To probe the hypothesized S-shaped relationship between the degree of open innovation and financial performance, we merged our open innovation score with data on security prices and accounting data from the CRSP/Compustat merged database (CCM), including controls of standard drivers of financial performance (e.g., Deb et al., 2017). To achieve consistency with prior research using financial performance as a dependent variable (e.g., Deb et al., 2017; Kim and Bettis, 2014), we excluded utilities (SIC 4900–4999), financial institutions (SIC 6000–6999), governmental organizations (SIC 9100–9199), and non-classifiable establishments (SIC 9900–9999). Our final baseline sample comprised 65,087 firm-year observations of publicly listed firms in the U.S. between 1994 and 2017. To rule out the possibility of outliers distorting our inferences, we winsorized the data on the 1st and 99th percentile (e.g., Deb et al., 2017; Haans et al., 2016). Table 3 provides summary statistics for our sample.

### 4.2. Variable definitions

#### 4.2.1. Dependent variable

We used firms' Total Q, a substantially improved variant of Tobin's  $q$ , to capture firms' financial performance. Total Q is defined as the ratio of (1) the sum of the market value of outstanding equity and the book value of outstanding debt less the current assets of a firm in the numerator, and (2) the book value of physical capital and intangible capital in the denominator (Peters and Taylor, 2017). Incorporating intangible capital – which Tobin's  $q$  ignores – is indispensable, particularly for an adequate assessment of the effects of any form of innovation activities, as intangible assets can account for up to 34 % of a firm's total capital (Corrado and Hulten, 2010), and industries are becoming more service- and technology-based (Peters and Taylor, 2017). Intangible assets comprise the sum of a firm's knowledge capital and organizational capital using the perpetual inventory method.<sup>1</sup> Prior studies examining innovation-related performance effects recommend the use of a market-based

measure for financial performance (e.g., Bharadwaj et al., 1999; Bhaskarabhatla and Hegde, 2014; Fosfuri and Giarratana, 2009). In line with our theorizing, Total Q approximates a firm's long-term profitability and corporate growth prospects (Erickson and Whited, 2012). Extensive robustness checks confirm that Total Q outperforms Tobin's  $q$  and other measures of growth opportunities.

#### 4.2.2. Explanatory variables

We used the *open innovation score* as our main independent variable to capture firms' degrees of open innovation. To account for the proposed non-linearity, we followed the standard approach of probing S-shaped relationships (e.g., Berry and Kaul, 2016; Chen et al., 2012; Hashai, 2015) and included the second (*open innovation score squared*) and third (*open innovation score cubic*) polynomial terms of the independent variable in our model.

#### 4.2.3. Moderators

To capture the strength of the industry's *appropriability regime*, we leveraged prior works that identified industries as high-litigation and low-litigation based on the prevalence of litigation within these industries (Koh et al., 2014; Zolotoy et al., 2020). Following these works, we captured high litigation industries as those with the four-digit SIC codes of biotechnology (2833–2836), computers (3570–3577; 7370–7374), electronics (3600–3674), and retailing (5200–5961), and all others as low-litigation industries. We created a dummy variable that takes the value of one for high litigation, representing industries with tight appropriability regimes, and zero for low litigation, representing industries with loose appropriability regimes.

We measure *environmental dynamism* through systematic risk (Miller and Friesen, 1983) defined by the Fama-French Market Model (Fama and French, 1993). This model captures the level of co-movement of a firm's stock price with a portfolio of all stocks in the market. We create a dummy that takes the value of one for high dynamism, i.e., higher systematic risk than the industry mean, and zero for low dynamism.

#### 4.2.4. Control variables

To control for other potential explanations of financial performance, we included several control variables in our model. First, we included *industry Total Q* as the mean value of the dependent variable on a four-digit SIC level. Further, we accounted for *firm size*, defined as the natural logarithm of net income (Crocchi and Petmezas, 2015), as larger firms are

<sup>1</sup> Total Q is available via the Peters and Taylor data library (on WRDS). For further details on the calculation of these additional components, please see Peters and Taylor (2017).

**Table 1**  
Topics and keywords of the open innovation dictionary.

Topic number	Topic label	Keywords
1	External & internal knowledge flows	External sources Internal and external knowledge
2	Strategic alliances & external partners	Alliances Partners Joint Collaboration Relationships Cooperation Strategic alliances External partners Joint ventures
3	Open innovation	Innovation Open Openness Open innovation Degree of openness
4	User innovation	User innovation Lead user
5	Knowledge sharing	Exchange Share Collaborative Knowledge sharing Knowledge transfer Knowledge creation External knowledge
6	Open source software	Open source Open source software
7	Inbound & outbound open innovation	Outbound Inbound Inbound open innovation Inbound and outbound Outbound open innovation Outbound activities Open innovation activities Inbound activities Inbound open innovation activities Inbound innovation Outbound innovation
8	Adoption & diffusion	Diffusion Adoption Adoption and diffusion Diffusion and adoption Open innovation adoption
9	Exploration & exploitation	Exploitation Exploration Exploration and exploitation Technology exploitation Knowledge exploration Knowledge exploitation External technology exploitation Technology exploration

associated with lower growth prospects (Josefy et al., 2015). Similarly, we included *firm growth* as the annual sales growth rate calculated as the natural logarithm of sales growth (Deb et al., 2017; Kim and Bettis, 2014). Beyond that, we controlled for the *undistributed cash flow*, a firm’s potential to generate cash that can trigger firm growth, calculated as the operating income before depreciation, minus the total income taxes, minus the year-to-year changes in deferred taxes, minus the gross interest expenses on total debt, minus the sum of preferred dividend payable on cumulative preferred stock and dividend paid on noncumulative preferred stock, minus the total amount of dividend declared on common stock, and scaled by total assets (Kim and Bettis, 2014).

Research suggests that market measures of firm value are strongly correlated with R&D expenditures (e.g., Hall, 1992). Therefore, we included *R&D intensity*, measured as R&D expenditures divided by net sales, and *advertising intensity*, measured as advertising expenditures

divided by net sales (Deb et al., 2017; Lee and Lieberman, 2009). We replaced missing values of R&D and advertising expenditures with zero and included one dummy each for missing data on R&D and advertising spending (e.g., Blagoeva et al., 2020; Koh and Reeb, 2015), which helps to circumvent potential bias towards R&D-intensive firms (Himmelberg et al., 1999). We capped the limits of both intensities at one (Deb et al., 2017; Kim and Bettis, 2014).

Beyond that, we controlled for *potential slack*, defined as the ratio of total debts to total assets, and reflecting the financial resources that can be accessed from the outside of the firm to finance investments and thus promote firm growth. The ratio was subtracted from one so that higher values denote higher potential slack (Deb et al., 2017). We dropped negative values to rule out bias from highly indebted firms (Alti, 2006). Following Deb et al. (2017) and Kim and Bettis (2014), we included *capital intensity*, calculated as capital expenditures divided by total assets, as higher expenditures are a natural trigger of financial performance. To account for unobserved heterogeneity across periods, we included *year dummies* (Deb et al., 2017; Kim and Bettis, 2014).

### 4.3. Statistical model

We took several steps to ensure the adequacy of our model specification. First, a Hausman test confirmed the predominance of a fixed-effects model over random-effects. We, therefore, estimated a firm fixed-effects model to prevent unobserved heterogeneity from multiple observations per firm. Second, we detected the first-order autocorrelation using a Wooldridge test (Wooldridge, 2013) and introduced an industry-adjusted measure of the dependent variable as a control variable (Gentry and Shen, 2013). Third, we found heteroscedasticity using a Breusch-Pagan test. Thus, we included robust standard errors clustered at the firm level. Fourth, variance inflation factors showed that multicollinearity was of minor concern, as all values were well below critical thresholds. Finally, we included year dummies to control for year effects.

## 5. Results

### 5.1. Regression results of the open innovation-financial performance relationship

To test the S-shaped relationship between open innovation and financial performance, we estimated the following model:

$$TQ_{f,t} = \beta_0 + \beta_1\theta_{f,t} + \beta_2\theta_{f,t}^2 + \beta_3\theta_{f,t}^3 + \varepsilon_t + \gamma_f + \omega_{f,t} \quad (2)$$

where the dependent variable  $TQ_{f,t}$  is Total Q for firm  $f$  in year  $t$ . The independent variable  $\theta_{f,t}$  (and its second polynomial  $\theta_{f,t}^2$  and the third polynomial  $\theta_{f,t}^3$ ) denotes the open innovation score for firm  $f$  in year  $t$ . The model also includes the intercept ( $\beta_0$ ), year fixed effects ( $\varepsilon_t$ ), firm fixed effects ( $\gamma_f$ ), and control variables ( $\omega_{f,t}$ ). To probe an S-shaped functional form, the  $\beta_3$  coefficient is of key concern. A significant and positive  $\beta_3$  is associated with a strictly monotonically increasing curve, whereas a significant and negative  $\beta_3$  is associated with a strictly monotonically decreasing curve.

There are three conditions for identifying an S-shaped functional form (Haans et al., 2016; Lind and Mehlum, 2010). First, the coefficient  $\beta_3$  needs to be negative and statistically significant. Second, the curve’s slopes before, between, and after the two extrema points, i.e., the local maximum and local minimum, need to be sufficiently steep and statistically significant, and negative for the left part, positive for the middle part, and negative again for the right part. Third, the inflection point needs to be located within the data range, as otherwise, the S-shape may be incomplete.

Table 4 shows the results. As expected, we observed positive effects of several growth-oriented control variables, including industry Total Q,



**Table 2**  
Comparison of the open innovation score to other measures for collaboration and innovation.

	Mean	Standard deviation	Open innovation score	Number of alliances	Number of alliance partners	Number of R&D alliances	Number of technology transfer alliances	R&D intensity	Number of patent applications	Citation-weighted value of patents
Open innovation score	1.77	0.76	–	0.08*	0.05*	0.06*	0.03	0.06*	0.05*	0.07*
Number of alliances	1.97	3.28	0.05*	–	0.39*	0.36*	0.33*	0.02*	0.33*	–0.06*
Number of alliance partners	1.48	28.97	0.03*	0.16*	–	0.23*	0.13*	–0.11*	0.22*	–0.11*
Number of R&D alliances	0.26	1.05	0.04*	0.62*	0.10*	–	0.21*	0.18*	0.25*	0.10*
Number of technology transfer alliances	1.41	1.75	0.04*	0.46*	0.06*	0.37*	–	0.18*	0.14*	0.13*
R&D intensity	0.04	0.10	0.07*	0.04*	–0.08*	0.11*	0.12*	–	0.02	0.55*
Number of patent applications	33.60	165.19	0.01*	0.48*	0.07*	0.26*	0.23*	0.04*	–	0.20*
Citation-weighted value of patents	0.09	0.31	0.03*	–0.04*	–0.06*	–0.02	–0.01	0.26*	9e <sup>–4</sup>	–

Notes: R&D intensity is calculated as the R&D expenditures scaled by sales. Spearman correlations are presented in the upper right, while Pearson correlations are presented in the lower left. Values with a star indicate statistical significance at the 5 % level.

**Table 3**  
Descriptive statistics and correlations.

Variable	Mean	STD	1.	2.	3.	4.	5.	6.	7.	8.	9.
1. Total Q	1.15	1.44									
2. Open innovation score	1.77	0.76	0.06***				*				
3. Firm size	5.79	2.12	–0.04***	–0.25***							
4. Firm growth	0.05	1.23	–0.03***	–0.12***	0.26***						
5. Undistributed cash flow	0.06	0.22	0.06***	–0.05***	0.20***	–0.20***					
6. R&D intensity	0.04	0.11	0.08***	0.07***	–0.26***	–0.03***	–0.27***				
7. Advertising intensity	0.01	0.03	0.03***	0.02***	0.01***	–0.01*	–0.05***	0.03***			
8. Potential slack	0.76	0.22	0.10***	0.07***	–0.18***	–0.05***	0.03***	0.21***	0.02***		
9. Capital intensity	0.05	0.06	–0.01*	0.04***	–0.01**	–0.03***	0.10***	–0.10***	–0.02***	–0.09***	

Notes: Significance levels: \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1.

**Table 4**  
Fixed-effects regression analyses explaining the effects of open innovation on firm financial performance.

Dependent variable	Model (1)		Model (2)	
	Total Q		Total Q	
	$\beta$	SE	$\beta$	SE
<b>Controls</b>				
Industry total Q	0.29***	0.014	0.30***	0.013
Firm size	–0.05***	0.018	–0.05***	0.019
Firm growth	0.02***	0.005	0.02***	0.005
Undistributed cashflow	0.52***	0.036	0.51***	0.036
R&D intensity	–0.83***	0.190	–0.84***	0.192
Missing R&D expenditures	0.02	0.042	0.01	0.042
Advertising intensity	–0.49	0.682	–0.50	0.677
Missing advertising expenditures	0.02	0.032	0.02	0.033
Potential slack	0.53***	0.060	0.54***	0.061
Capital intensity	1.51***	0.145	1.48***	0.147
<b>Explanatory</b>				
Open innovation score			–0.31***	0.079
Open innovation score squared			0.16***	0.038
Open innovation score cubic			–0.02***	0.005
Intercept	0.53***	0.123	0.63***	0.135
R <sup>2</sup>	0.142		0.144	
Firm-fixed effects	Yes		Yes	
Year-fixed effects	Yes		Yes	
N	65.087		65.087	

Notes: Robust standard errors clustered at the firm level are reported in parentheses. Significance levels: \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1.

potential slack, and capital intensity in Model 1. Model 2 indicates the results of estimating Eq. 2. We found a negative and statistically significant effect of the *open innovation score*  $\theta_{f,t}$  ( $\beta = -0.31$ ; SE = 0.079; p = 0.000), a positive and statistically significant effect of *open innovation score squared*  $\theta_{f,t}^2$  ( $\beta = 0.16$ ; SE = 0.038; p = 0.000), and a negative and statistically significant effect of *open innovation score cubic*  $\theta_{f,t}^3$  ( $\beta = -0.02$ ; SE = 0.005; p = 0.000) on financial performance. The three 95 % confidence intervals [ $\theta_{f,t} = -0.466|-0.156$ ;  $\theta_{f,t}^2 = 0.088|0.236$ ;  $\theta_{f,t}^3 = -0.032|-0.011$ ] did not include zero, so there is a very low probability that the observed cubic effect is due to chance. The cubic effect satisfies the first condition of an S-shaped curve. To examine the two remaining conditions for an S-shape, it was necessary to analyze the first, second, and third derivatives of the functional form.<sup>2</sup>

We determined the minimum and maximum to probe the remaining conditions. We selected three specific values for these points and inserted them in the first derivation to examine the slopes and conduct slope tests. We chose (1) the median value between the intercept and the minimum point, (2) the median value between the minimum and maximum point, and (3) the median value between the maximum point and the root of the function. In line with our theorizing, we found a positive intercept for closed innovation, a negative and significant slope

<sup>2</sup> First derivative:  $\frac{d\theta_{f,t}}{d\theta_{f,t}} = -0.06\theta_{f,t}^2 + 0.32\theta_{f,t} - 0.31$ ; second derivative:  $\frac{d^2\theta_{f,t}}{d\theta_{f,t}^2} = -0.12\theta_{f,t} + 0.32$ ; third derivative:  $\frac{d^3\theta_{f,t}}{d\theta_{f,t}^3} = -0.12$ .

for the left part, a positive and significant slope for the middle part, and a negative and significant slope for the right part of the function. These findings indicated the existence of an S-shaped relationship between open innovation and financial performance. Further, we split the data based on the two critical points of our cubic explanatory variable and ran three linear regressions to check if the slopes were consistent with the predicted shape of the curve (Haans et al., 2016). The regression below the first critical point showed a negative relationship between open innovation and performance. The regression below the second critical point showed a positive relationship. The regression above the second critical point again showed a negative relationship. Together, these findings supported the existence of an S-shaped relationship. Finally, we needed to find the roots of the second derivative to determine the inflection point. Following Haans et al. (2016) and Hirschberg and Lye (2005), we applied the Fieller method and found that the 95 percent confidence interval of the left to right inflection point was located within our data range.<sup>3</sup> In sum, all conditions for an S-shaped relationship were met. The visualization in Fig. 3 confirms the S-shaped relationship. These findings support Hypothesis 1 suggesting an S-shaped functional form for the open innovation-performance relationship.

### 5.2. Results of the contingencies for the open innovation-financial performance link

In Hypothesis 2, we examined the influence of the strength of the industry's appropriability regime on the cubic relationship between open innovation and financial performance. We tested this relationship by distinguishing between tight appropriability regimes in high-litigation industries and loose appropriability regimes in low-litigation industries. While we expect that the general cubic functional form persists in both environments, we expected in Hypothesis 2 that it would be more pronounced in tight appropriability regimes than in loose appropriability regimes. In particular, we expect that a tight appropriability regime rooted in the efficacy of the legal system will enhance the firms' ability to extract value from innovation even at high degrees of open innovation. A comparison of the coefficients in Table 5 for tight appropriability regime (Model 1) and loose appropriability regime (Model 2) indicates that in tight appropriability regimes, the effects sizes of open innovation are larger, such that the position of the cubic shape is located further to the right on the horizontal axis and its curvature is more pronounced (see Fig. 4a). In Fig. 4a, we see that the cubic relationship has higher financial performance implications in tight appropriability regimes than in loose appropriability regimes. Moreover, in situations with high degrees of open innovation, the performance implications decrease more sharply in loose appropriability than in tight appropriability regimes. An analysis of the marginal effects confirms that these two regressions are statistically different. This pattern supports Hypothesis 2 and suggests that the relationship between open innovation and financial performance is stronger in industries with tight appropriability regimes than in industries with loose appropriability regimes, especially at high degrees of open innovation.

In Hypothesis 3, we investigated the effect of dynamic environments on the cubic relationship between open innovation and financial performance. We suggested that the cubic relationship would be more pronounced in stable environments than in dynamic environments. Comparing the coefficients in Table 5 (Model 3, Model 4), we find that in highly dynamic environments, the position of the S-shape is located further left on the horizontal axis and its curvature is more pronounced (see Fig. 4b). In Fig. 4b, we can see that the cubic relationship exhibits higher financial performance effects in dynamic environments than in stable environments. However, at high levels of open innovation, the

cubic relationship has stronger negative performance effects in dynamic environments than in stable environments. It creates an intersection, after which stable environments have higher financial performance effects than dynamic environments. An examination of the marginal effects indicates that these two regressions are statistically distinct. This evidence supports our finding that high environmental dynamism decreases the performance implications of open innovation.

### 5.3. Robustness checks

We conducted several checks to test the robustness of our results. First, we excluded the 10-K405 and 10-KSB forms from our sample and reran our analyses. The SEC eliminated the 10-K405 form in 2002 and the 10-KSB in 2009. Our results remain fully robust.

Second, we used alternative measures to quantify financial performance. Following Kim and Bettis (2014), we ran our analysis with Tobin's  $q$  as our dependent variable, defined as the firm's market value divided by its total assets (Kim and Bettis, 2014; O'Brien and Folta, 2009). Following standard procedures, we dropped all observations of Tobin's  $q$  that exceeded a threshold of 10 (Kim and Bettis, 2014). Our results were fully robust when using Tobin's  $q$ , despite the critical shortcomings of this measure as compared to Total Q.

Third, we included several other control variables that are alternative explanations of financial performance. We introduced a lagged measure of our Total Q (Deb et al., 2017), firm age (Demerjian et al., 2012), and amount spent on acquisitions (Fresard, 2010) as control variables, and found fully robust results. We also used a random-effects model to calculate our cubic relationship and found fully robust results.

Fourth, to rule out the influence of sector-level heterogeneity on investment, we confined our sample to the manufacturing industries (NAICS 310000-339999) (Chen, 2008; Kim and Kung, 2017; Tong et al., 2008) and found, again, that our results were fully robust.

Finally, to address endogeneity, we tested the sensitivity of our results to potential omitted variable bias. Despite our extensive set of control variables and the use of fixed effects, we performed tests to examine potential bias related to omitted variables that might challenge our findings. Based on approaches in recent studies (e.g., Hubbard et al., 2017; Quigley et al., 2020; Xia et al., 2022), we determined the impact threshold of confounding variable (ITCV) for the main relationship between OI and financial performance. This technique helps to assess the degree to which potential confounding variables could alter an inference regarding a regression coefficient. Our analyses using two-tailed tests found that 50.31 % is the invalidation threshold. This result means that to invalidate our findings, 32738 firm-year observations would need to be replaced with observations for which the effect of the open innovation score cubic was zero. As contexts of analysis vary such that there is no absolute standard for such impact thresholds (Larcker and Rusticus, 2010; Xia et al., 2022), we conjecture, in line with the studies above, that it is very unlikely for more than half of our estimates to stem from bias, which makes us believe that our results are unlikely to be driven by confounding variables. Moreover, although less relevant for our model specification, the result shows an ITCV of 0.0072, meaning that partial correlations between the cubic term of the OI score and financial performance with a confounding omitted variable would have to be about 0.085 (the square root of 0.0072) to overturn our results. This result suggests that to overturn our results, a correlated omitted variable would need to be 3.54 times stronger than the current strongest predictor in the model. In sum, these additional analyses suggest that our findings for an S-shaped functional form of the open innovation-performance relationship are unlikely to be driven by an omitted variable.

In continuation, we also performed an instrumental variable (IV) approach to reduce further endogeneity concerns relating to potential omitted variables. We combined a latent IV estimation (e.g., Lewbel, 2012; Piao and Zajac, 2016) with the inclusion of an external IV. An adequate IV should meet the relevance condition, i.e., be correlated with

<sup>3</sup> We calculated two Fieller intervals for the left and right part of the function. The range of the 95 % confidence interval is [0.82|1.37] for the left part and [3.40|4.22] for the right part of the function.

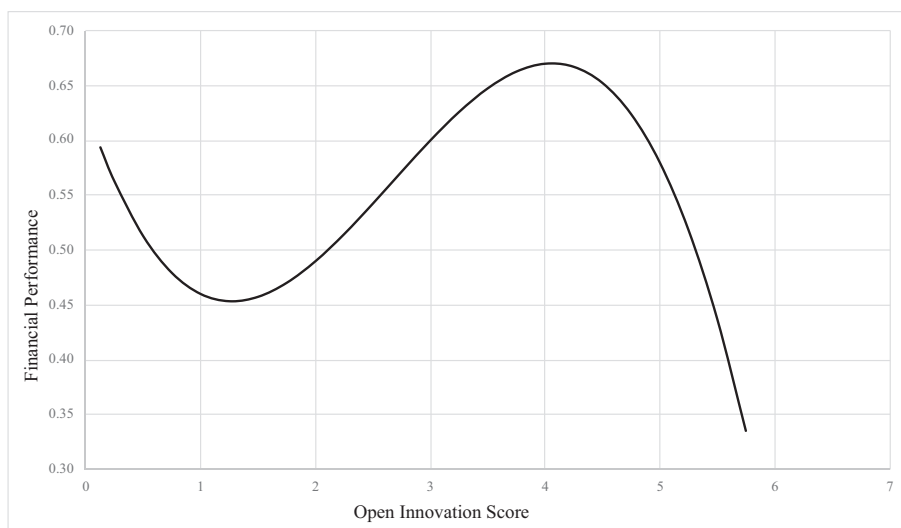


Fig. 3.

$$Y = f(X) = 0.63 - 0.31X + 0.16X^2 - 0.02X^3$$

where: Y = Financial Performance; X = Open Innovation Score.

Notes: This graph was plotted using the parameters of the main model in Table 4.

Plot of the S-shaped relationship between open innovation and firm financial performance.

Table 5

Fixed-effects regression analyses explaining the effects of open innovation on firm financial performance for firms in environments of high dynamism and low dynamism, and in high and low litigation industries.

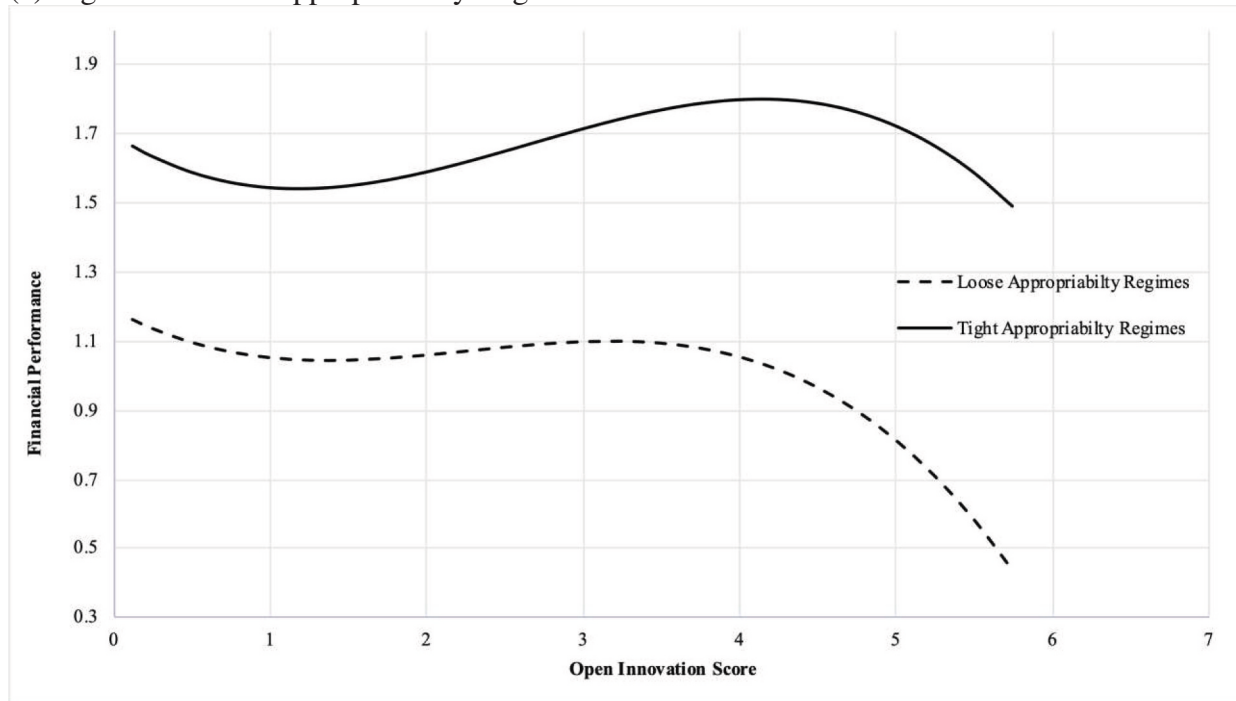
Dependent variable	Model (1) Tight appropriability regimes		Model (2) Loose appropriability regimes		Model (1) Low dynamism		Model (2) High dynamism	
	Total Q		Total Q		Total Q		Total Q	
	$\beta$	SE	$\beta$	SE	$\beta$	SE	$\beta$	SE
Controls								
Industry total Q	1.50***	0.080	0.72***	0.038	0.66***	0.044	0.83***	0.053
Firm size	-0.24***	0.079	-0.11***	0.045	-0.15***	0.048	-0.18***	0.053
Firm growth	0.05***	0.011	0.03***	0.006	0.03***	0.007	0.03***	0.008
Undistributed cashflow	0.12***	0.017	0.08***	0.009	0.06***	0.009	0.16***	0.014
R&D intensity	-0.14***	0.024	-0.02	0.033	-0.03	0.030	-0.12***	0.026
Missing R&D expenditures	-0.11	0.088	0.08*	0.047	-3e <sup>-3</sup>	0.007	0.04	0.066
Advertising intensity	0.04	0.026	-0.06**	0.024	-0.03	0.019	-0.03	0.029
Missing advertising expenditures	0.02	0.062	0.01	0.038	-0.07*	0.038	0.11**	0.050
Potential slack	0.14***	0.025	0.10***	0.015	0.07***	0.016	0.12***	0.019
Capital intensity	0.09***	0.019	0.09***	0.010	0.07***	0.011	0.09***	0.013
Explanatory								
Open innovation score	-0.30***	0.172	-0.25***	0.087	-0.21**	0.098	-0.35***	0.112
Open innovation score squared	0.16**	0.081	0.13***	0.041	0.10**	0.046	0.20***	0.056
Open innovation score cubic	-0.02*	0.012	-0.02***	0.006	-0.01*	0.007	-0.03***	0.008
Intercept	1.71***	0.145	1.18***	0.077	1.07***	0.085	1.53***	0.106
R <sup>2</sup>	0.094		0.170		0.109		0.180	
Firm-fixed effects	Yes		Yes		Yes		Yes	
Year-fixed effects	Yes		Yes		Yes		Yes	
N	18.057		47.016		31.656		33.422	

Notes: Robust standard errors clustered at the firm level are reported in parentheses. Significance levels: \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1.

financial performance, and meet the exogeneity condition, i.e., not be correlated with the residuals of our main model (e.g., Bascle, 2008; Semadeni et al., 2014). As open innovation activities are a very specific type that might be endogenously chosen from among a focal firm’s overall innovation activities, identifying a set of viable instruments is problematic. The use of an augmented latent IV estimation (via the “ivreg2h” command in Stata with the fixed effects option) helps to circumvent the issue of finding a set of IVs by statistically constructing additional instruments and thereby also helps “to improve the efficiency of the IV estimator” (see documentation of ivreg2h package). We follow prior work (e.g., Greene, 2000; Kennedy, 2003) in including open

innovation score<sub>t-1</sub> as an instrumental variable, given that “lagged endogenous variables tend to directly affect the focal endogenous variables without imposing direct impact on the outcome variables” (Piao and Zajac, 2016: p. 1438) which are commonly used in panel data. Estimating a linear model specification, our results indicate that the coefficient of the open innovation score is positive and statistically significant ( $\beta = 0.12$ ; SE = 0.031; p = 0.000), which aligns with the positive linear effect of our main model when not using an instrumental variable approach. Again, the confidence interval (0.058|0.180) did not include zero, substantiating that the observed effect is due to chance and supporting a causal interpretation of the effect of open innovation on

(a) Tight and Loose Appropriability Regimes



(b) High and Low Dynamism

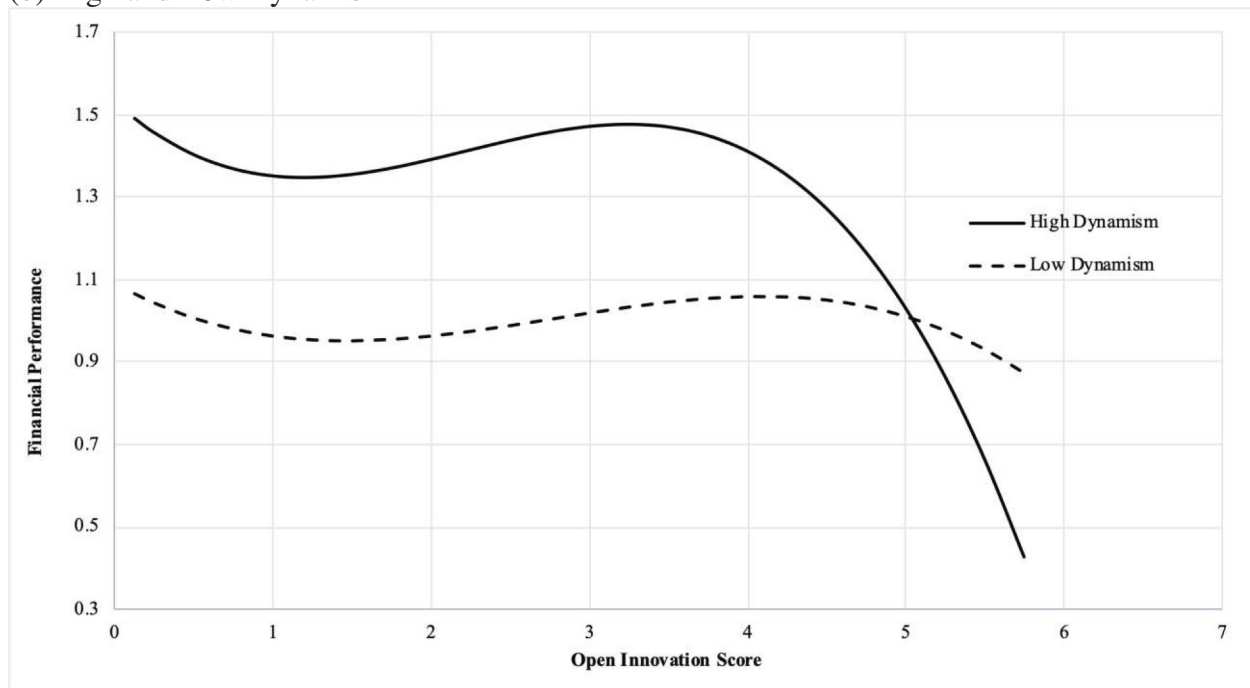


Fig. 4. The effect of the contingencies on the open innovation-financial performance relationship.

financial performance.

5.4. Post-hoc analysis

Our theorizing emphasizes the potential effects of open innovation on firms' benefits and costs. In this post-hoc analysis, we go beyond prior works that theorize similarly about non-linear relationships but do not measure them directly (e.g., Hashai, 2015; Lu and Beamish, 2004). As for the benefits, we leverage a measure of the value of innovation output

by Kogan et al. (2017). As for the cost side, we found a measure for coordination costs by Im et al. (2013) as the difference between selling, general, and administrative expenses, on the one hand, and research and development expenses, on the other. Our regression results in Table A1 of Appendix A show that our open innovation measure affects the benefits and costs in a non-linear way, which tentatively supports our reasoning regarding the latent constructs of benefits and costs that drive the S-shaped relationship. We are aware that such direct assessments of benefits and costs are still new territory for both management and



innovation literature, and should be followed by studies interested only in explaining benefits and/or costs.

## 6. Discussion

### 6.1. Findings

In this study, we empirically examined the open innovation-firm financial performance link. For this purpose, we operationalized firms' degree of open innovation in a longitudinal, structured, and large-scale way and combined the resulting score with archival datasets to test our hypotheses. The results of our fixed-effects regression analyses indicate that the link between open innovation and firm financial performance is S-shaped, with closed innovation and medium levels of open innovation yielding high financial returns while low levels and high levels of open innovation lead to low financial returns. This functional form indicates that even when open innovation is the norm, closed innovation can still be a financially viable option and that firms are not well-advised to open up their innovation processes as far as possible.

Beyond that, we find that industries' appropriability regimes and environmental dynamics are critical boundary conditions for our main relationship, particularly at high levels of open innovation. On the one hand, firms that operate in an industry with a tight appropriability regime can extract more value at higher levels of open innovation than firms in industries with loose appropriability regimes. We argue that this phenomenon results from firms' ability to harvest the benefits of their innovation effort within a tight appropriability regime. On the other hand, we find that firms that are exposed to high environmental dynamism find themselves in a position in which high levels of open innovation yield poorer financial returns than they do for firms operating in stable environments. We attribute this finding to the exponentially growing coordination costs that accompany the growing need for constant change among innovation partners.

Finally, our post-hoc analyses further substantiate the underlying benefits and costs of open innovation that drive the empirical patterns of our main relationship, as we find that our open innovation score is non-linearly related to firms' value of innovation output and coordination costs.

### 6.2. Contribution to open innovation research

This study contributes to the literature about open innovation in several important ways. First, it contributes to a better understanding of the financial performance implications of open innovation. Assuming that different degrees of openness in the innovation process result in different benefits and costs, our post-hoc analysis shows tentative evidence that open innovation is non-linearly related to coordination costs and benefits in terms of the value of innovation output. From this analysis and our theoretical considerations, we derive an S-shaped relationship between the degree of open innovation and firm financial performance. Whereas previous studies examining this relationship found an inverted U-shape (e.g., Belderbos et al., 2010; Grimpe and Kaiser, 2010; Laursen and Salter, 2006; Rothaermel and Alexandre, 2009), we find an S-shape. This finding shows that closed innovation is a good alternative for innovation processes from a financial perspective, even in times of an open innovation paradigm. Indeed, we find that a substantial degree of open innovation is necessary until the performance implications of openness are greater than those of closed innovation. However, the financial performance implications are highest for medium levels of open innovation. Firms that truly want to benefit from open innovation must therefore skillfully navigate the level of openness in their innovation processes. All things considered, our study confirms that the link between open innovation and financial performance is more complex than previously assumed.

Second, our theory and findings advance a more contextualized view of open innovation by explicating an industry's appropriability regime

and environmental dynamism as critical boundary conditions for its performance effects (e.g., Felin and Zenger, 2020; Foeger et al., 2019; Ogink et al., 2022). The two contingencies each relate to one of the two aspects of benefits and costs of open innovation. Whereas an industry's appropriability regime corresponds to the benefits of open innovation, as it is an external factor that determines firms' ability to appropriate the returns from their open innovation activities, environmental dynamism corresponds to the costs of open innovation, as it is an external factor that is particularly critical for the coordination costs of open innovation activities. We argue and show that tight appropriability regimes matter especially for high levels of open innovation, as they prolong the positive effect of high levels of open innovation on firm financial performance. By contrast, our findings indicate that high levels of open innovation can have devastating consequences to financial outcomes if firms operate in dynamic environments.

Third, we contribute to the literature by deriving a text-based measure that captures firms' degree of open innovation in a longitudinal, large-scale setting. Building on our open innovation dictionary, our machine-learning algorithm is versatile, able to assess firms' degree of open innovation activities using any form of text input, including analysts' reports, product announcements, and even newspaper articles. Our open innovation measure is based on publicly available annual reports in a cross-industry, longitudinal setting. This approach circumvents the shortcomings of using corporate surveys, which are often limited to a cross-sectional setting. Likewise, even short time horizons of longitudinal studies may hamper the detection of more nuanced relationships (e.g., Ebersberger et al., 2021; Piezunka and Dahlander, 2019). Our study is among very few open innovation studies that have a longitudinal instead of a cross-sectional design. Our measure enables open innovation scholars to leverage the concept of open innovation in new ways, particularly by combining it with archival datasets that include information about firms' attributes and various performance measures (e.g., Bogers et al., 2017; Chesbrough et al., 2018; Huizinga, 2011).

As our measure can be easily merged with other archival datasets, we enable future researchers to empirically examine the effect of open innovation on different sets of resources (e.g., Barney, 1991), managerial capabilities (Sirmon et al., 2011), top management teams (Hambrick and Mason, 1984), organizational structure (DeCanio et al., 2000), the organizational task environment (Dess and Beard, 1984), institutional arrangements (Nelson and Nelson, 2002), and social capital (Tsai and Ghoshal, 1998). Drawing these connections would make it possible to empirically test theory that connects open innovation with major management theories such as the resource-based view (Barney, 1991), the behavioral theory of the firm (Cyert and March, 1963), and the dynamic capabilities view (Teece et al., 1997).

Finally, our study not only theorizes and empirically tests the relationship between open innovation, on the one hand, and benefits and costs, on the other, but also shows a negative effect of R&D intensity on firm financial performance, which should be accounted for when making the decision to follow either a closed or an open approach to innovation.

### 6.3. Practical implications

Our study yields important implications for practitioners, especially those interested in assessing the financial performance implications of their open innovation activities. Our results indicate that the open innovation-firm financial performance link follows a complex pattern, making the decision of whether to engage in open innovation much more complicated than a simple yes or no. Indeed, closed innovation can have considerable positive implications for firms' finances even under a paradigm of open innovation. At the same time, a strategy of medium openness in the innovation process is the one that results in the best financial performance. Practitioners should be aware, however, that closed innovation without the need to create and maintain a partner

network is naturally easier to manage than medium open innovation, where one must always find the right degree of openness – that is, the right activities to the right extent, as well as the right number of partnerships at the right intensity. For this reason, a recommendation for practitioners can by no means be to always invest as much as possible in open innovation. Rather, it may be that even a reduction of activities to those that are particularly promising tends to lead to medium open innovation and thus ideal financial performance. It is therefore important for managers to regularly assess the benefits and costs of open innovation.

Moreover, our analyses of the contingencies of our main relationship make the picture even more complex. While it may make sense in dynamic environments to deliberately limit open innovation activities in order not to fall victim to immense coordination costs, a firm in an industry with a tight appropriability regime may benefit from daring to be more open. The reason for this is that in dynamic environments, the financial performance for high open innovation values drops rapidly, as coordination costs increase very quickly. In contrast, an environment with a tight appropriability regime creates the opportunity to stretch the positive effect of open innovation on financial performance longer. We attribute this to the ability of firms to better capture the value of their own innovations under such a regime. Against this backdrop, we advise managers of firms engaging in open innovation to carefully and constantly assess the dynamics in the environment and their ability to appropriate returns from their innovations.

#### 6.4. Policy implications

Beyond its implications for practitioners, this study yields important implications for policymakers, especially with regard to the boundary conditions of our main effect. Many of the global issues and challenges that societies face today, including the climate crisis, poverty and hunger, pandemics, health care, and digitization, can only be solved collaboratively through cooperative innovation processes, that is, open innovation (Bertello et al., 2022; Chesbrough, 2020; McGahan et al., 2021). For this reason, policymakers must create a political and market environment that enables effective open innovation ecosystems among citizens, politics, firms, non-profit organizations, and other stakeholders (Ahn et al., 2019; Chesbrough and Di Minin, 2014). Our findings suggest that such an environment should provide stability for firms and the opportunity to appropriate the rents created by innovations. Clear legislation and well-structured markets can help cushion environmental dynamics even in times of crisis. Furthermore, the creation of a good legal system and the reduction of corruption can help firms to pursue collaborative activities related to innovation without having to worry about value expropriation (Foege et al., 2017; Veer et al., 2016), which is essential for creating an effective innovation ecosystem within a country.

#### 6.5. Limitations and future research

Our study has some limitations that provide fertile ground for future research. First, the data used in this study is related to publicly listed firms from the U.S. Thus, this study focuses on larger companies based in only one country. It would be interesting to analyze small and medium-sized companies as well as companies from other geographical areas to check if our findings hold for these cases as well (Van de Vrande et al., 2009; Vanhaverbeke, 2017; Vanhaverbeke et al., 2018). Moreover, future research could include different environmental contingencies and assess the effectiveness of open innovation activities under heterogeneous conditions (Randhawa et al., 2016), thus broadening the scholarly understanding of open innovation (Huizingh, 2011).

Second, regarding our content analysis, it is important to determine an appropriate list of words and a dictionary that describes the open innovation landscape. Our algorithm processed and categorized frequent words; however, we manually revised the list and excluded

inappropriate words. Our cautious, conservative approach ensured only modest levels of subjectivity. Future research could revisit our open innovation measure to create an alternative word list and dictionary or create sub-scores based on our measure to analyze the different concepts of open innovation further and give further nuance to how open innovation shapes financial performance.

Third, our open innovation score may be biased due to the hype about open innovation. Companies may overemphasize the value of open innovation and use related terms to promote their company and its openness to the outside world, which might strengthen their relationships with customers, partners, or investors.

Fourth, we acknowledge that despite our evidence that supports the genuine open innovation effects on firm financial performance, omitted variables might be an issue – as open innovation may likely be applied in some of a firm's set of various innovation activities (e.g., Du et al., 2014). While we addressed these endogeneity concerns with our ITCV analyses, we cannot fully rule out that endogeneity might explain some of our findings, as, given the absence of a natural experiment, we leverage a large archival data set.<sup>4</sup> Hence, we encourage future experimental studies to revisit the relationship.

Fifth, a noteworthy shortcoming of our study is the difficulty in capturing the effects of open innovation on the underlying benefits and costs. While there is limited guidance in the management and innovation literature on conducting such analyses, we were able to provide some substantiation for benefits (innovation output) and costs (coordination costs), albeit in an imperfect manner. Despite these efforts, we acknowledge that the use of benefits and costs in this study is largely as an abstraction. As such, our arguments and analyses, despite being limited in this sense, can serve as important starting points for future studies to further develop more accurate and direct measures of the various benefits and costs of open innovation. Our study provides a framework around which such measures could be organized and developed towards a more concrete understanding of how open innovation shapes organizational outcomes.

Lastly, we validate our findings for a battery of dependent variables capturing firm financial performance. However, activities of open innovation can have further consequential features, including effects on the real economy, such as disrupting a nascent industry, altering the distribution of market shares, and triggering technological dynamism. Examining such effects in future research can be of importance not only to scholars but also to practitioners and policymakers.

## 7. Conclusion

In this study, we discussed the benefits and costs of closed innovation and open innovation, arguing that the relationship between the degree of open innovation and firm financial performance is S-shaped. We further proposed that this pattern depends on the appropriability regimes and environmental dynamism of the focal industries, which affect firms' ability to extract value from their innovations and the coordination costs arising from open innovation activities, respectively. The results of our fixed-effects regression analyses support our theorizing. Overall, this study contributes to the literature on open innovation by facilitating a more nuanced scholarly discourse; elaborating on and showing the financial performance implications of open innovation for firms; discussing the merits of closed innovation in an open innovation paradigm; advancing a more contextualized view of open innovation by explicating the industries' appropriability regime and environmental dynamism as critical contingencies to its performance effects; and creating a longitudinal measure for open innovation.

<sup>4</sup> We thank an anonymous reviewer for bringing this point to our attention.

**CRedit authorship contribution statement**

- *Thomas Schäper*: Conceptualization, Theory, Methodology, Writing, Reviewing and editing
- *Christopher Jung*: Conceptualization, Methodology, Writing, Reviewing and editing
- *Johann Nils Foege*: Conceptualization, Theory, Writing, Reviewing and editing
- *Marcel Bogers*: Conceptualization, Theory, Writing, Reviewing and editing
- *Stav Fainshmidt*: Conceptualization, Theory, Writing, Reviewing and editing

- *Stephan Nüesch*: Conceptualization, Theory, Writing, Reviewing and editing.

**Declaration of competing interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Data availability**

Data will be made available on request.

**Appendix A. The effects of open innovation on benefits and costs**

When explicating how open innovation affects firm performance, we distinguish between the underlying benefits and costs. Although disentangling these underlying effects is a challenging task, here we attempt to do so as best as possible with available data. While prior work on nonlinear relationships offered theoretical explanations that the phenomenon in question can shape underlying costs and benefits (e.g., [Berry and Kaul, 2016](#); [Hashai, 2015](#); [Lu and Beamish, 2004](#)), our efforts are a step forward in substantiating the underlying mechanisms empirically. We draw from prior literature that suggests ways to capture relevant costs and benefits of open innovation: (1) coordination costs and (2) innovation output value. Although our theorization is not limited to these specific benefits and costs, they allow us to substantiate our arguments in a more granular, illustrative manner.

First, following [Im et al. \(2013\)](#), we measure coordination costs as the difference between selling, general, and administrative expenses and research and development expenses. [Im et al. \(2013\)](#) indicate that this measure reflects the expenses that arise from coordinating organizational activities and, hence, is “an appropriate surrogate for coordination costs” (p. 477). Although this measure captures coordination costs for the organization as a whole rather than for open innovation activity, in particular, our arguments would suggest that, on average, increasing open innovation activities should correlate with overall coordination costs by increasing innovation coordination costs. Second, to capture the benefits of open innovation, we use the estimated value of innovation output produced by a firm in a given year. Specifically, we follow [Kogan et al. \(2017\)](#) and sum up all citation-weighted values of patents granted to the focal firm in a given year and then use the logarithm to account for skewness. This measure allows us to assess the relationship between open innovation and the value of innovation produced by the firm, regardless of the costs required to achieve said value. Our set of two dependent variables comprises measures of costs and benefits that are at least partly backward-looking, thus, we use a lagged model structure with a one-year lag of all explanatory variables (e.g., [Sanders & Hambrick, 2007](#)). We maintain the same control variables to ensure coherence with our main analyses.

[Table A1](#) depicts the results of our regression analyses. Regarding costs, Model 1 shows that coordination costs grow exponentially with an increasing degree of open innovation activity, as indicated by a positive and statistically significant cubic term of the effect of open innovation on coordination costs ( $\beta = 24.34$ ;  $SE = 10.976$ ;  $p = 0.027$ ). Regarding benefits, via the estimated market value of patents as a function of open innovation, Model 2 shows a positive and statistically significant direct effect of open innovation on benefits ( $\beta = 0.11$ ;  $SE = 0.005$ ;  $p = 0.031$ ), and a quadratic relationship as indicated by a negative squared term ( $\beta = -0.02$ ;  $SE = 0.011$ ;  $p = 0.124$ ). This result suggests that benefits grow with a decreasing degree of open innovation activity at the margin, although there is a non-trivial possibility of 13 % that the quadratic relationship is driven by chance. In sum, this evidence supports our arguments regarding the benefits and costs of open innovation.

**Table A1**

Regression analyses explaining the effect of open innovation on costs (coordination costs) and innovation benefits (market value of innovation).

Dependent variable	Model (1) Costs of open innovation		Model (2) Benefits of open innovation	
	Coordination costs		Market value of patents	
	$\beta$	SE	$\beta$	SE
Controls				
Firm size	147.14	38.316***	0.91	0.039***
Firm growth	14.61	7.380**	0.01	0.008
Undistributed cashflow	-149.99	73.392**	-0.04	0.074
R&D intensity	315.172	119.37***	2.03	0.230***
Missing R&D expenditures	-113.61	99.805	4e <sup>-3</sup>	0.094
Advertising intensity	1258.41	1246.755	0.16	1.171
Missing advertising expenditures	5.86	44.326	-0.11	0.057*
Potential slack	-132.61	60.512**	0.59	0.106***
Capital intensity	-384.24	235.157	0.42	0.321
Explanatory				
Open innovation score	322.94	184.142*	0.11	0.050**
Open innovation score squared	-176.68	83.23**	-0.02	0.011
Open innovation score cubic	24.34	10.976**		
Intercept	-761.54	305.942**	-2.50	0.266***
R <sup>2</sup>		0.130		0.707
Firm-fixed effects		Yes		Yes
Year-fixed effects		Yes		Yes
N		29.362		15.594

Notes: Variables are not standardized. Robust standard errors are reported in parentheses. Significance levels: \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1.

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