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# TITLE

# Open innovation where it really matters: The U-shaped relationship between relative open innovation and innovation performance in developing countries

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# Open innovation where it really matters:
# The U-shaped relationship between relative open innovation and innovation performance in developing countries

## Abstract

In the innovation literature, there are mixed findings as to the influence of open innovation on innovation performance, which may be due to the predominantly exclusive focus on the level of open innovation rather than on its comparison with closed innovation (i.e., relative open innovation) thereby considering the costs associated with opening up. To address this issue, we empirically examine how relative open innovation is related to innovation performance. Our fieldwork is based on 130 Serbian firms. This sample is relevant because embracing open innovation can bring several benefits to firms from developing countries but, at the same time, the contextual limitations that firms in such countries have, make the adoption of open innovation costly. Using ordinary-least-squares regression, we find a U-shaped relationship between relative open innovation and innovation performance. We contribute to the literature by showing that firms with either low or high relative open innovation achieve a greater innovation performance than those with medium-level relative open innovation. This is due to the fact that the costs associated with opening up (i.e., transitioning from closed to open innovation) are highest at the medium level of relative open innovation, and especially prominent in developing countries.

## Keywords

Closed innovation; open innovation; innovation performance; relative open innovation; U-shaped relationship

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## 1. Introduction

In recent decades, open innovation has emerged as an alternative approach to innovation management (e.g., Bagherzadeh, Markovic, and Bogers, 2021; Dabić et al., 2021; Obradović, Vlačić, and Dabić, 2021). Whilst, traditionally, firms relied on R&D activities to develop relevant innovations, open innovation adopts a broader perspective to such development by purposefully going beyond organizational boundaries, thereby enabling inflows and outflows of ideas, information, and knowledge (e.g., Bagherzadeh, Markovic, Cheng, and Vanhaverbeke, 2020; Chesbrough and Bogers, 2014). While some empirical studies have found that embracing open innovation positively impacts innovation performance (e.g., Du, Leten, and Vanhaverbeke, 2014), others have shown a lack of impact (e.g., Miotti and Sachwald, 2003) and, in some cases, even a negative impact (Un, Cuervo-Cazurra, and Asakawa, 2010). These varied findings (for a review, see Zhang, Ma, Liang, and Garrett, 2024) may be due to the fact that most previous studies have only focused on the level of open innovation but have not contrasted it with that of purely internal innovation processes (i.e., closed innovation). Therefore, previous studies have mainly dealt with the concepts of closed and open innovation in an 'orthogonal way,' namely, as completely independent approaches to innovation management. However, in reality, these two approaches are not mutually exclusive, as they often share resources – at least to a certain extent – which highlights the importance of studying open innovation at a relative level (see Dahlander, O'Mahony, and Gann, 2016).

Although the two approaches to innovation management —open innovation and closed innovation— may seem to be diametrically opposite, both are ways of organizing the innovation process with the aim of boosting innovation performance. In fact, manifold activities performed under either approach often share the same pool of resources, such as the R&D budget, R&D

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personnel's time or managerial attention (Hottenrott and Lopes-Bento, 2016). On the premise that firms have limited resources, it is logical to anticipate that involvement in open innovation comes at the cost of closed innovation, or vice versa. Therefore, without considering the intensity of one approach against the other (i.e., relative open [closed] innovation), we run the risk of being unable to properly estimate the impact of open innovation on innovation performance, and thereby confirm whether such impact is actually positive, negative, or inexistent. Thus, open innovation ought to be studied in relative terms as, in reality, most firms embrace open and closed innovation simultaneously, albeit at varying levels. Accordingly, this article considers open and closed innovation as two ends of a continuum, with the assumption that most firms are located somewhere in-between the two ends, and empirically investigates how relative open innovation affects innovation performance.

Although open innovation and closed innovation often share the same pool of resources, there are some critical differences between the two approaches which may generate some organizational challenges. This is the case in manifold organizations, such as IBM or Procter & Gamble, which face – or have faced – substantial changes related to organizational aspects (e.g., introducing new roles like technology scouting or restructuring the R&D department) as a consequence of embracing open innovation (e.g., Deck, 2008; Salter, Criscuolo, and Ter Wal, 2014). These organizational changes, in order to accommodate open innovation, often generate different costs (e.g., coordination costs), particularly if firms had previously only followed a closed innovation approach (see Kelly and Amburgey, 1991 and Haveman, 1992). However, embracing open innovation can also bring benefits, such as improved access to novel and complementary resources, better identification of customer needs and desires, time-to-market reduction, and risk sharing (e.g., Iglesias, Markovic, Bagherzadeh, and Singh, 2020; Zhang et al., 2024). Thus, considering both costs and benefits is essential to understand how relative open innovation influences innovation performance (e.g., Cassiman and Valentini, 2016).

Considering the costs and benefits of adopting open innovation is especially important for firms in developing countries. On one hand, firms in developing countries generally face a dearth of resources, institutional silos, recurrent political and economic downturns, and limited – or even inexistent – governmental support, making the adoption of open innovation costly (e.g., Markovic et al., 2021). On the other hand, open innovation can actually be beneficial for firms in these countries, as it can provide them with access to previously unavailable resources, such as specialized knowledge or technology. Given these costs and potential benefits, investigating the influence of relative open innovation on innovation performance becomes especially relevant in developing countries. Accordingly, we rely on a cross-industrial sample of 130 Serbian firms. We use Serbia as a prototype market of developing countries because, despite the country's willingness and efforts to make open innovation attractive (Development Agency of Serbia Report, Republic of Serbia, 2023), companies in Serbia not only face significant budgetary issues and lack of a systematic cross-institutional support, but also fail to have advanced open innovation skills and a culture of openness (Beraha and Đuričin, 2022).

The data were analyzed using the ordinary-least-squares (OLS) regression. Based on the three-step procedure recommended by Lind and Mehlum (2010), our results show a U-shaped relationship between relative open innovation and innovation performance, which remains robust across various model specifications. This U-shaped relationship implies that firms with either low or high relative open innovation achieve a greater innovation performance than those with medium-level relative open innovation. This may be due to the fact that the costs associated with opening up (i.e., transitioning from closed to open innovation) are highest at the medium level of relative open innovation. These initial costs associated with opening up could be one of the main reasons why firms from developing countries, like Serbia, can not afford to adopt – or rather slowly adopt – open innovation. Our findings contribute to the literature by emphasizing the importance of studying open innovation in relative terms, rather than absolute, when estimating its impact on innovation performance. Examining open innovation in relative terms allows to overcome the current misunderstanding on whether its influence on innovation performance is positive, negative, or inexistent. In addition, our findings contribute to the literature by considering the costs of opening up, which is largely called for by previous research (e.g., Audretsch and Belitski, 2023; Bogers et al., 2017; Cassiman and Valentini, 2016; Randhawa, Wilden, and Hohberger 2016), and specifically by doing so in the context of a developing country, like Serbia, where such costs are especially prominent (see Markovic et al., 2021).

Our findings are also relevant from the managerial point of view, as they imply that firms in developing countries can improve their performance by embracing open innovation, if they can manage to overcome the initial cost of opening up. However, closed firms that start to open up need to be aware that they are likely to suffer from a low innovation performance until they reach a certain threshold of openness – one that allows them to predominantly rely on open innovation, rather than on a similar level of closed and open innovation at the same time. Thus, firms wanting to open up should put in place practices to accelerate the openness process and be ready to assume some costs related to performance at the beginning of the openness process when they still depend on some closed innovation initiatives.

## 2. Theoretical background and hypothesis development

In this section, we present the theoretical underpinning and rationale leading to our hypothesized effect. First, we explain the concept of relative open innovation. Second, we discuss the costs

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associated with opening up the innovation process. Third, we present the benefits of opening up such process. Finally, we hypothesize a relationship between relative open innovation and innovation performance.

## 2.1 Conceptualization of relative open innovation

Open innovation calls for firms to make their organizational boundaries permeable during the innovation process (Bagherzadeh, Gurca, Brunswicker, 2022; Chesbrough and Bogers, 2014; Markovic, Bagherzadeh, Vanhaverbeke, and Bogers, 2021). In practice, however, firms are rather selective. Some may open up only one stage of the innovation process (e.g., ideation, development, launch), while others may provide access to a combination of stages, or even to the entire process (see Ind, Iglesias, and Markovic, 2017). There is also variation in the adoption of open innovation in terms of organizational structure. While some firms set up dedicated units and roles, others solely incorporate a 'new mission' to the tasks of existing personnel. When it comes to collaboration with external partners, the number and types of partners also vary across firms (e.g., Bagherzadeh et al., 2021; Majchrzak, Jarvenpaa, & Bagherzadeh, 2015). In addition to these most usual variation examples, the adoption of open innovation could differ in many other aspects[1]. The crux of the matter is to consider and acknowledge the existence of variation as to the adoption of open innovation when assessing its performance outcomes.

Considering this variation, the implementation of any aspect of open innovation requires resources. On the premise that firms have limited resources, resource allocation points toward the extent to which firms engage in closed versus open innovation. If we consider closed and open innovation to be two extremes of a continuum, where closed innovation is located at left end and

[1] Different mechanisms can be adopted for open innovation, such as crowdsourcing (see Bagherzadeh & Gurca, 2024; Bagherzadeh et al., 2023; and Moghaddam et al., 2022).

open innovation at the right polarity (see Dahlander et al., 2016; Ind et al., 2017), the more firms move toward the right extreme, the higher their level of relative open innovation will be. As long as firms invest resources in innovation-related activities, the measurement of relative open innovation would be able to project all firms along the continuum, making the extent of engaging in open innovation comparable between them.

## 2.2 Costs associated with relative open innovation

In discussing the challenges of opening up the innovation process, we consider two main costs from the innovation management literature: legitimacy and complexity (e.g., Chiaroni, Chiesa, and Frattini, 2010; Hottenrott and Lopes-Benot, 2016).

### *2.2.1 Legitimacy*

Adopting open innovation resembles undergoing an organizational change (Chiaroni, Chiesa, and Frattini, 2010; Deck, 2008). Huy et al. (2014) concluded that a successful organizational change depends largely on whether the change is seen as legitimate. In light of the literature on institutional theory (Meyer and Rowan, 1977; Meyer and Scott, 1983), legitimacy can be associated with 'taken-for-grantedness.' Thus, the perception of open innovation as a legitimized way of organizing the innovation process would imply that openness is taken for granted by organizational members.

Carroll and Hannan (1989, p. 525) linked legitimacy of a new organizational form to its prevalence: "[A]n organizational form is legitimated to the extent that relevant actors regard it as 'natural' way to organize for some purpose." They suggested that increasing the incidence of a new organizational form is likely to facilitate that such new form becomes considered as 'natural' and legitimate over time. Accordingly, it is plausible to expect that opening up organizational

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boundaries progressively is likely to result in organizational members perceiving open innovation as a 'natural' and legitimate way to innovate over time. Subsequently, as open innovation gains legitimacy over time, the potential resistance to it caused by the 'not-invented-here' syndrome is likely to decrease which, in turn, would make resource allocation more feasible (Kale, Dyer, and Singh, 2002). Therefore, gaining legitimacy over time is likely to reduce the costs associated with transitioning from closed to open innovation, and this cost reduction will occur more quickly as open innovation takes over.

Thus, it is important to recognize that the relationship between open innovation and legitimacy may not be linear, because once open innovation gains certain legitimacy, enhancing it further is likely to have a limited additional impact on its legitimacy; that is, the positive relationship between the two can be expected to increase at a decreasing rate. Subsequently, over time, legitimacy is likely to reach a 'plateau' as the degree of open innovation continues to increase. As noted by Carroll and Hannan (1989, p. 525), "once a form becomes prevalent, further proliferation is unlikely to have much effects on its taken-for-grantedness."

The literature has identified two main approaches to legitimizing open innovation: (1) creating dedicated units and specialized roles, and (2) ensuring senior managers' commitment. First, the creation of dedicated units and specialized roles can help firms attain a better information processing system, new incentive mechanisms, and HR training (Antons and Piller 2015; Calof, Meissner, and Razheva 2018). This can foster recognition which, in turn, is likely to boost the legitimacy of the open innovation process. Second, several studies have emphasized the importance of involving senior managers when adopting open innovation (Brunnswicker and Chesbrough, 2018). For instance, Peeters, Massini, and Lewin (2014) concluded that senior managers are more effective in fostering organizational change than middle-level managers,

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because their involvement often brings legitimacy to such change. Similarly, in a study with 200 open innovation managers, Wang, Cardon, Li, and Li (2023) confirmed that open innovation is more likely to gain legitimacy when senior managers engage in internal communication with their organizational members.

### *2.2.2. Complexity*

Unlike closed innovation, which is limited to organizational boundaries, open innovation requires firms to interact with different sets of external partners, which exponentially increases the complexity of managing the innovation process (Hottenrott and Lopes-Benot, 2016). However, embracing open innovation exponentially boosts complexity not only as a result of augmenting the number of parties involved, but also because of the interdependence of these parties. This is mainly because there are critical differences between working with members inside vs. outside the organization. Members belonging to the same organization tend to have similar work methods and routines. This commonality greatly facilitates the work process and makes it easier to complete the tasks. However, such a commonality is not so prominent – and may even be fully absent – when working with members outside the organization – for example, when developing innovations with diverse types of partners (e.g., suppliers, competitors, universities) who have different characteristics, processes, and knowledge sets (e.g., Bagherzadeh, Ghaderi, and Fernandez, 2022; Hottenrott and Lopes-Bento, 2016, Markovic et al., 2020). Accordingly, previous studies have found that a firm's collaboration with different types of partners requires different management approaches and skills (Barnes, Pashby, and Gibbons, 2002; Faems, De Visser, Andries, and Van Looy, 2010), which is likely to generate an exponential increase in the complexity of managing the innovation process.

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To manage and alleviate such complexity, firms often need to modify organizational structures and establish new management practices (Chiaroni, Chiesa, and Frattini, 2010). For example, Faems et al. (2010) suggested that, in order to deal with the complexity resulting from collaborating with diverse partners, firms ought to set up a dedicated alliance function at the corporate level. Similarly, Gemunden, Salomo, and Holzle (2007) emphasized the usefulness of establishing new roles, such as gatekeepers and innovation champions, when embracing open innovation. As illustrated by the case of P&G Connect & Develop (Dodgson, Gann, and Salter, 2006), the firm created two new practices (i.e., "The Sims" computer game, Eureka database) to facilitate collaboration with outsiders and to better leverage upon external knowledge (see also Huston and Sakkab, 2006; Prugl and Shreier, 2006). These organizational additions or changes usually take place in a gradual fashion, based on the level of openness. Managing the complexity that derives from openness is costly. For instance, Cassiman and Valentini (2016) argued that embracing closed and open innovation initiatives simultaneously generates some costs, due to the need to manage both types of approaches at the same time. Similarly, studying the relationship between firm performance and the technology alliance portfolio, Faems et al. (2010) revealed a significant cost-increasing effect associated with the diversity of partners, which generates complexity.

Based on the above rationale, it is plausible to expect that relative open innovation exponentially increases complexity which, in turn, leads to an exponential increase in the cost of handling both closed and open innovation at the same time.

*2.2.3 Linking relative open innovation and costs (legitimacy and complexity)*

To sum up the rationale above, our argument is twofold. First, we argue that as relative open innovation increases, its legitimacy follows, thereby decreasing the potential resistance to change

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and marginalizing the 'not-invented-here' syndrome. That is, legitimacy is a positive function of relative open innovation and can be expected to increase at a decreasing rate as the incidence of open innovation initiatives increases over time. Moreover, legitimacy decreases the costs associated with transitioning from closed to open innovation, and such costs reduction is likely to occur more quickly as relative open innovation augments. Second, we argue that relative open innovation exponentially increases complexity, due to the organizational additions or changes that opening up implies. That is, complexity is an exponential positive function of relative open innovation, and it exponentially increases costs. Combining the two sets of arguments, we expect that the costs of handling closed and open innovation simultaneously would be the highest when firms reach a moderate level of relative open innovation. Thus, we expect an inverted U-shape relationship between relative open innovation and costs.

Firms from developing countries (e.g., Serbia) face considerable challenges in transitioning from closed to open innovation due to a lack of resources, institutional voids, political and economic instability, and insufficient (or even inexistent) governmental support (see Markovic et al., 2021). These contextual challenges can impede the adoption of open innovation and make the process of opening up the innovation process even more costly. Thus, while the costs associated with relative open innovation, primarily stemming from legitimacy and complexity, are present in all cases of opening up the innovation process, they are even more pronounced in developing countries, and thus the expected inverted U-shaped relationship between relative open innovation and costs would have a higher tipping point in such countries.

### 2.3 Benefits associated with relative open innovation

In addition to costs, opening up the organization to the external world can also bring benefits, such as great access to complementary resources, accelerating the knowledge development process, sharing the risks of developing new products and technologies, and reducing the time to market (e.g., Bagherzadeh et al., 2020; Bogers et al., 2017; Hottenrott and Lopes-Bento, 2016; Laursen and Salter, 2006). These are only a few examples of benefits that a great body of the innovation literature has already examined, which are especially important for firms in developing countries due to their dearth of resources (see Markovic et al., 2021).

In essence, as they open up, firms from developing countries would have the opportunity to increase the breadth and depth of their information sources and partners, which is likely to lead to an increasing resource recombination that, in turn, can generate manifold benefits, such as those listed above. However, this positive relationship between relative open innovation and its benefits is likely to increase at a decreasing rate because the additional resources gathered over time tend to stagnate (Hottenrott and Lopes-Bento, 2016; Laursen and Salter, 2006).

### 2.4 Hypothesized relationship

Considering the above arguments concerning the relationship between relative open innovation and (1) costs (i.e., an inverted U shape) and (2) benefits (i.e., either positive linear or positive at a decreasing rate), it is plausible to expect a U-shaped relationship between relative open innovation and innovation performance (Figure 1). Thus, we hypothesize that:

*Hypothesis: There is a U-shaped relationship between relative open innovation and innovation performance.*

----- INSERT FIGURE 1 -----

## 3. Method

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To test our hypothesis, we designed a survey and collected data from Serbian firms. The survey was conducted from December 2019 to January 2020. The questionnaire was first translated from English to Serbian by professors from the fields of management and innovation. To make sure that the items remained true to their original scales, a back-translation process was applied to translate the items from Serbian into English. Then, the initial version of the survey was piloted to 6 managers. Based on their comments and feedback, some of the items were revised and slightly edited, without deviating – in terms of meaning and rigor – from their original scales. The survey was sent to 500 randomly selected firms from the General Authority for Statistics database. The invited participants were given 21 days to complete the questionnaire. After excluding the observations that did not pass the attention checks or had missing values, the final working dataset contained 130 observations, yielding a final response rate of 26%. Table A1 presents the distribution of sample firms by their basic characteristics.

Innovation performance was the dependent variable. We considered it a multi-faceted construct, including aspects related to product/service development process (Blindenbach-Driessen, Van Dalen, and Van Den Ende, 2010; Narasimhan and Das, 2001), customer achievement (Schleimer and Shulman, 2011), and market performance (Homburg and Pflesser, 2000). We used seven items to measure this construct. The questionnaire asked respondents to indicate the extent to which their initial expectations about innovation performance were met, including success in: product/service development costs, product/service quality, achieving customer satisfaction, providing value to existing customers, keeping current customers, sales, and profits. A five-point Likert scale was used, with 1 for not meeting the initial expectations and 5 for exceeding the initial expectations. This approach to measuring innovation performance, based on initial expectations, offers some advantages such as reflecting the differences in unobserved factors influencing the relationship between relative open innovation and innovation performance. It could be the case that firms in industries that greatly benefit from open innovation are expected to set higher initial expectations for their innovation performance than those in industries where open innovation provides limited advantages. Thus, the initial expectations regarding their innovation performance can reflect these differences in unobserved factors. To check for the validity of the innovation performance construct, we conducted confirmatory factor analysis. After removing the item of success in keeping current customers with the lowest loading (0.418), the validity of the construct was confirmed (CFI=0.984, SRMR=0.045, RMSEA=0.074). The average variance extracted (AVE) was 0.49 and the composite reliability (CR) 0.845. Since the value of AVE was close to the minimal accepted threshold, we used alternative measurement with a better AVE in the robustness check.

Our independent variable, relative open innovation, measured the extent to which firms devoted resources to open innovation relative to closed innovation. We considered innovation as entailing a three-stage process: ideation, development, and launch. We asked the respondents to distribute 100 points to indicate the relative amount of time in a typical week their employees interact with individuals within and outside the organization at each innovation stage[2]. We then took a simple average over the three stages and used it as the measure of relative open innovation. The variable took a value from 0 to 1, with zero indicating only interacting with individuals inside the firm and one for only interacting with individuals from outside the firm. To account for the potential curvilinearity between relative open innovation and innovation performance, we also included the square term of relative open innovation. The approach of asking respondents to

[2] Our measure for relative open innovation is relevant because it relies on a concrete notion of 'time spent' on open innovation activities.

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distribute 100 points between internal and external interaction allowed us to operationalize our conceptualization that closed and open innovation are two ends of a continuum, which enabled us to compare the extent of engaging in open innovation across firms. This also forced the respondents to recognize the costs of engaging in open innovation. Given the fixed amount of time, being open and interacting with individuals from outside the firm was logically at the expense of being closed and interacting with internal individuals only. Dahlander et al. (2016) used a similar approach to measure the extent to which IBM employees paid attention to external information and people.

The number of collaboration partners is likely to affect both the time allocated to interacting with them and innovation performance (e.g., Markovic and Bagherzadeh, 2018; Van Beers and Zand, 2014). Thus, we controlled for the diversity of collaboration partners. Our survey asked respondents to indicate the types of collaboration partners during the innovation process, including ideation, development, and launch stages. There were 11 types of partners: business partners, competitors, consultants, consumers and users, government relations, private research institutes, professional and trade institutions, standard setting organizations, suppliers, universities, and other partners. We then counted the number of different partners across the entire innovation process. Thus, the variable partner diversity ranged from 0 to 11.

The relationship between relative open innovation and innovation performance may depend upon the quality of collaboration partners. We have no data directly measuring this. However, we considered that firms with a better innovation performance compared to their competitors in the past are more likely to attract high-quality collaboration partners. Thus, in our survey, we asked respondents to indicate how well their firms performed over the past 12 months compared to their main competitors in three aspects with regard to new products and services: number, sales, and profitability. Respondents indicated it on a Likert scale from 1, significantly worse than competitors, to 7, significantly better than competitors. Since the three items were highly correlated with correlation coefficients from 0.62 to 0.85, we used principal component analysis to reduce the three dimensions into one component, which explained 83% of the variance. We then named the component 'past competitive position' and used it as a control variable. Furthermore, more innovative firms tend to have a better financial performance so that they are more likely to have slack resources, which is likely to increase their intention to engage in collaboration. Thus, controlling for the past competitive position in innovation also partially deals with the self-selection concern.

We also controlled for firms' basic characteristics, including sales, firm size (measured by number of employees), R&D expenses, marketing expenses, ownership structure, market condition (B-to-B or B-to-C), export share, and firm age. These eight variables were categorical and self-reported in the survey. We used them to capture the extent of firm heterogeneity[3]. Our regression model was the following:

Innovation performance = β0 + β1 relative open innovation + β2 relative open innovation^2 + control variables

## 4. Results

### 4.1 Main analyses

Table 1 presents the descriptive statistics of all variables in the main analysis. Innovation performance has a mean of zero because it is a factor variable generated from six items. The simple

[3] For the variables of sales, firm size, R&D expenses, and marketing expenses, we provided an 'I don't know/I am not sure' option in addition to the options with different ranges of values. This approach allowed us to minimize the number of missing values. In our regression analysis, we treated the options of ranges and 'I don't know/I am not sure' as categories of the corresponding variable.

average of innovation performance across the 130 observations from the raw data is approximately 3.5, which means that a typical firm met their initial expectations with regard to innovation performance to a large extent or fully. Our sample shows a range of relative open innovation from 0.033 to 0.973, which implies that all firms in our sample engaged in closed and open innovation simultaneously. The mean level of relative open innovation is moderate at 0.386. A typical firm spent about 39% of their time interacting with individuals from outside the organization during the innovation process. The diversity of collaboration partners ranges from no collaboration to 11 different partners, with a mean value of 4.1. Past competitive position is the component extracted from three highly correlated items, and ranges from -5.097 to 2.694. The simple average of the three items indicating firm past competitive position is 4.9, meaning that a typical firm performed slightly better than their competitors in the past 12 months. The rest of control variables are categorical. Among the 130 firms in our sample, approximately 45% have annual sales lower than 25 million euros. Approximately half of the sample are firms with less than 500 employees, with R&D expenses lower than 1 million euros, with marketing expenses lower than 500 thousand euros, and that operate in both B-to-B and B-to-C markets. There are 53 firms which are subsidiaries of foreign companies. About 16% of the firms in the sample have no export sales, but about 36% of them have export sales accounting for more than 75% of annual sales. For firm age, about 56% of firms were established 20 years ago and 13% within five years at the time of survey.

----- INSERT TABLE 1 -----

Table 2 shows the correlations matrix of variables in the main analysis. The correlation between innovation performance and relative open innovation is about 0.1. As expected, the correlations among the variables of sales, firm size, R&D expenses, marketing expenses, and firm age are moderate to high because all of these variables are categorical. A higher level indicates, also, an increasing value of the corresponding variable, except for the last level “I don’t know/ I am not sure”. All other correlations are moderate to low.

----- INSERT TABLE 2 -----

We used ordinary-least-squares (OLS) regression for further data analysis. While plotting the error terms against the predicted value of innovation performance, we observed heteroscedasticity. Thus, we estimated robust standard errors in all our regressions to make the inferences valid regardless of heteroscedasticity. We also checked the assumption of normal distribution of error terms. The plot of error terms shows a normal distribution with a Shapiro-Wilk W statistic of 0.99 (p-value=0.82).

Table 3 presents the regression results of the main analysis. To simplify the presentation, we do not show the estimations for the eight control variables of firm basic characteristics comprising sales, firm size, R&D expenses, marketing expenses, ownership structure, market condition, export share, and firm age. Model 1 includes only the 10 control variables (partner diversity, past competitive position, and the eight control variables of firm basic characteristics). As expected, past competitive position is positive and significant. However, the diversity of partners is positive but not significant. Model 2 is the linear model, including the variable of relative open innovation and all 10 control variables. The coefficient of relative open innovation is positive but not significant. Model 3 adds the squared term of relative open innovation. The coefficient of relative open innovation becomes negative and significant with a p-value of 0.018, and the coefficient of the squared term is positive and significant with a p-value of 0.012. The coefficients of relative open innovation and its squared term are also jointly significant with a F-statistics of 3.31 (p-value = 0.0419). This indicates that a U-shaped relationship is likely to exist between innovation performance and relative open innovation. To visualize the relationship, we

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plotted the predicted value of innovation performance at different levels of relative open innovation, using the coefficients estimated in Model 3. Figure 2 depicts a U shape with a turning point well located within the data range.

----- INSERT TABLE 3 -----

To confirm the existence of a U-shaped relationship, we performed several tests taking the advice of Haans, Pieters, and He (2016) to follow Lind and Mehlum's (2010) three-step procedure. First, the coefficient of the variable in concern and its squared term need to be significant and with expected signs. As shown in Model 3, the coefficient of relative open innovation is negative and significant (β=-2.212, p-value=0.018), while the coefficient of the squared term of relative open innovation is positive and significant (β=2.784, p-value=0.012). Next, the slopes at the lower and upper ends of the data range need to be sufficiently steep. The variable of relative open innovation ranges from 0.033 to 0.973. At the lower end of 0.033, the slope is -2.026 and significant (p-value=0.009) and at the upper end, the slope is 3.207 and significant (p=0.007). Then, the turning point needs to be within the data range. Figure 2 shows that the turning point of the predicted U shape is around 0.4. As suggested by Haans et al., (2016), we used the Fieller method (Fieller, 1954) to calculate the confidence interval for the turning point given our finite sample. The estimated turning point is at 0.397 with 95% Fieller interval between 0.226 and 0.541, which suggests that the turning point is well located within the data range. The results of the three-step procedure confirm the U-shaped relationship between innovation performance and relative open innovation.

----- INSERT FIGURE 2 -----

The estimations of the control variables are also consistent with our expectations. The coefficient of past competitive position is positive and significant as in Model 1 and Model 2. After including the variable of the squared term of relative open innovation, the coefficient of partner diversity became significant at the 10% level with a p-value of 0.082. This result is consistent with the literature that the diversity of collaboration partners facilitates innovation performance (e.g., Beck and Schenker-Wicki, 2014; Van Beers and Zand, 2014). In fact, some previous studies have used the number of collaboration partners to indicate the breadth of open innovation and have concluded a positive linear relationship between open innovation and innovation performance. In this sense, our Model 3 goes beyond the literature and shows that given the breadth of open innovation (measured by the diversity of collaboration partners), relative open innovation contributes to innovation performance.

### 4.2 Robustness check

One may challenge our results by raising the concern of common method bias, because a single respondent from each firm responded to the whole survey. However, since we modelled a quadratic relationship, common method bias cannot inflate the relationship between relative open innovation and innovation performance (Siemsen, Roth, and Oliveira, 2010). In addition, we designed the survey to reduce potential common method bias (Podsakoff, MacKenzie, Lee, and Podsakoff, 2003). We asked the question of relative open innovation at the beginning of the survey, and the question of innovation performance toward the end. The separation of the dependent and the independent variables in the survey reduces the probability that respondents connect the two and bias their answers. Thus, it was unlikely for our respondents to predict, ex-ante, a U-shaped relationship between two variables that are proximally separated in a survey. In addition, we used different types of response options for the dependent and the independent variables. We asked

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respondents to indicate their firm's innovation performance (dependent variable) using a five-point Likert scale. For relative open innovation (independent variable), we requested respondents to distribute 100 points between closeness and openness. Compared to directly asking the respondents to indicate their open innovation level, our approach reduced the chances that respondents overemphasize such level. Therefore, even if respondents inflated their innovation performance, the chance that the independent variable is also inflated is limited.

Furthermore, we performed several robustness checks. First, we checked whether the results hold with alternative dependent variables. In the main analysis, innovation performance is a construct with six items. Although the goodness of fit statistics is accepted, its AVE (0.49) is slightly lower than the conventional accepted level (0.5). Thus, we removed one item with the lowest loading (0.51) and formed a construct 'innovation performance 2' as an alternative measure of the dependent variable. The validity of the construct is confirmed through confirmatory factor analysis (CFI=0.976, SRMR=0.042, RMSEA=0.099); the AVE is 0.529 and the CR is 0.845. We then used 'innovation performance 2' as the dependent variable in our OLS regression with the independent variable and the 10 control variables. Model 4 in Table 4 shows the estimations. Similar to the main analysis, the coefficient of relative open innovation is negative and significant ($\beta$=-2.167, p-value=0.020), and the coefficient of the squared term of relative open innovation is positive and significant ($\beta$=2.726, p-value=0.014). The slope at the two ends of relative open innovation is with expected sign and significant. When relative open innovation is at the value of 0.333, the slope is negative (-1.986) and significant (p-value=0.010); it becomes positive (3.139) and significant (p-value=0.007) when relative open innovation has the value of 0.973. The estimated turning point is at 0.398 within the 95% Fieller interval between 0.230 and 0.547. Thus, the results are similar to the main analysis. Figure 3 plots the predicted value of innovation performance 2 at different levels of relative open innovation based on the estimations of model 4.

----- INSERT TABLE 4 -----

----- INSERT FIGURE 3 -----

Instead of using confirmatory factor analysis, we also used an alternative operationalization for our dependent variable by creating another dependent variable 'innovation performance 3', which is calculated as the simple average of the six items used in 'innovation performance'. The variable of 'innovation performance 3' ranges from 1.3 to 5 with a mean of 3.5. Model 5 shows the results. Except for replacing innovation performance with 'innovation performance 3', the rest of variables remain the same as in the main analysis. Again, our results hold under this model specification. The coefficient of relative open innovation is negative and significant (β=-3.386, p-value=0.010), while the coefficient of the squared term of relative open innovation is positive and significant (β=4.887, p-value=0.005). The slope at the lower end is negative (-3.510) and significant (p-value=0.005). It becomes positive (5.678) and significant (p-value=0.002) at the higher end. The estimated turning point is at 0.392 with 95% Fieller interval between 0.260 and 0.496. Figure 4 plots the predicted value of innovation performance 3 at different levels of relative open innovation based on the estimations of model 5 in Table 4.

----- INSERT FIGURE 4 -----

Thereafter, we considered the possibility that the observed relationship is S-shaped rather than U-shaped. Accordingly, we added a cubic term of the variable of relative open innovation in the regression equation. As shown in model 6, although the coefficient of the cubic term of relative open innovation is significant (β=7.743, p-value=0.017) and the coefficient of the squared term of

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relative open innovation is marginally significant (β=-8.070, p-value=0.078), the coefficient of relative open innovation is not significant (β =2.031, p-value=0.266). This shows that the relationship between innovation performance and relative open innovation is not S-shaped. We repeated the same exercise using the two alternative dependent variables ‘innovation performance 2’ and ‘innovation performance 3’. The results are similar and presented in Table A2 in the Appendix.

Our last robustness check aimed to tackle the concern that the U shape may be driven by a few extreme observations. As suggested by Haans et al., (2016), we censored our independent variable of relative open innovation by winsorizing at 99% and 1%. The variable of relative open innovation ranges from 0.033 to 0.973, and the 1% and 99% range of the variable is 0.033 to 0.8 (both included). Among the 130 observations, there is only one observation whose value of relative open innovation is out of the range of 0.033 and 0.8. Thus, we used 0.8 to replace its original value (0.973) and conducted the same OLS regression as in the main analysis. To distinguish the censored from the original variables, we named them ‘censored relative open innovation’ and ‘censored relative open innovation square.’ Model 7 shows the estimations. The coefficients of ‘censored relative open innovation’ and ‘censored relative open innovation square’ are with expected sign and significant at 10% (β=-1.839 p-value=0.069 for ‘censored relative open innovation’, and β=2.323 p-value=0.059 for ‘censored relative open innovation square’). The slope when ‘censored relative open innovation’ has the value of 0.033 is negative (-1.684011) and significant (p-value=0.036), and the slope at the higher end (censored relative open innovation=0.8) is positive (1.878) and significant (p-value=0.035). The estimated turning point occurs at 0.396. Although with reduced significance level, the results are similar to those from the main analysis.

## 5. Discussion and conclusion

### 5.1 Theoretical contribution

In the previous literature, there are mixed findings as to how open innovation influences innovation performance. A potential reason is that most previous studies have treated open and close innovation as completely independent approaches to innovation management. However, these two approaches often share the same resources and, thus, a firm's commitment to one takes place at the expense of the other. Therefore, it becomes important to study open innovation in relative terms, meaning to contrast it with closed innovation. Surprisingly, however, there remains a dearth of research on how relative open [closed] innovation influences innovation performance (see Dahlander et al., 2016).

Our study addresses this lack of research and contributes to the innovation literature by studying open innovation in relative rather than absolute terms, finding a U-shaped relationship between relative open innovation and innovation performance. Although this U-shaped relationship may seem contradictory compared to the findings of prior studies, which have generally shown an inverted U-shaped relationship between open innovation and innovation performance (e.g., Bianchi et al., 2016; Greco, Grimaldi, and Cricelli, 2016; Hottenrott and Lopes-Bento, 2016; Kobarg, Stumpf-Wollersheim, and Welpe, 2019; Laursen and Salter, 2006), it actually is not necessarily the case. This is because our study conceptualizes and measures open innovation differently, in relative terms, so by contrasting it against closed innovation, while prior research has dealt with it in absolute terms, so without comparing it with closed innovation. Studying open innovation in relative terms is important and represents a relevant contribution because it allows to consider the costs of managing both closed and open innovation simultaneously, which reflects the reality in the majority of companies nowadays. More specifically, studying open innovation at a relative level enables an assessment of the opportunity costs of opening up, which derive from legitimacy and complexity costs. This is because, based on the assumptions that firms have limited resources and embrace innovation, engaging in open innovation would require reallocating at least some of the resources originally attributed to closed innovation processes.

Considering this opportunity cost of opening up is crucial, particularly when examining the relationship between open innovation and innovation performance (see Audretsch and Belitski, 2023; Gambardella and Panico, 2014). Our U-shaped relationship which entails such opportunity cost, implies that there are two optimal levels of relative open innovation (i.e., low and high) as the legitimacy and complexity costs are minimal at such levels. These costs are probably the key limitation to the adoption of open innovation in developing countries, and explain why manifold firms in such countries can not adopt it or slowly do so. Thus, our research addresses the call to conduct more studies considering the costs of open innovation (e.g., Audretsch and Belitski, 2023; Cassiman and Valentini, 2016; Dabic, Daim, Bogers, and Mention, 2023), which is especially relevant in resource scarcity contexts, such as developing countries like Serbia (see Markovic et al., 2021). It specifically does so by considering the costs associated with opening up (i.e., legitimacy and complexity) and the subsequent opportunity cost related to resource reallocation from closed to open innovation.

### 5.2 Managerial implications

In addition to its theoretical contributions, our research has several key implications for managers. The currently dominant approach that managers follow when opening up their organizations is ambidexter; they tend to balance closed and open innovation initiatives (e.g., Laursen and Salter, 2006). However, based on the findings of our study, this is not optimal, as adopting a medium level of relative open innovation (balancing closed and open innovation) is likely to decrease innovation performance, because of the initial costs of opening up.

If firms want to open up and gather external resources for innovation purposes, which is especially important in developing countries due to limited resources (e.g., specialized knowledge or technology), they ought to be aware of the costs of transitioning from closed to open innovation. Two key potential costs comprise legitimacy and complexity, and managers ought to be ready to handle them internally. Legitimacy costs are likely to decrease once organizational members start accepting open innovation as a practice. In contrast, complexity costs are likely to increase exponentially as the organization opens up. In fact, we would expect that complexity costs increase even more rapidly if firms are unable to legitimize the opening-up process. Therefore, we recommend that firms beginning to adopt open innovation should first focus on legitimizing the practice within their organizations. In order to do so, firms should introduce dedicated units, specialized roles, training sessions, and ensure senior managers' commitment to handle the opening-up process and support the organizational change that such process will entail (e.g., Markovic et al., 2020; Salter et al., 2014). Continuous managerial support throughout the process is of utmost importance for making open innovation legitimate over time, especially in the context of developing countries, like Serbia, where the costs of opening up are particularly high. Once open innovation is legitimized, it becomes less costly for firms to mobilize their internal resources to address the complexities arising from increasing levels of relative open innovation.

### 5.3 Limitations and future research

Regardless of its theoretical contributions and managerial implications, our study also has certain limitations. First, despite their theoretical plausibility, our study does not measure the costs

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associated with opening up – namely, legitimacy and complexity. Thus, future research could gain empirical insights into these two costs and how they impact the process of opening up as well as whether and how they are potentially interrelated. Second, although we operationalize innovation performance in two different ways to enhance our measurement reliability, our measures remain self-reported. Therefore, future studies could use more objective measures of innovation performance, such as the number of products or services developed. Third, while our measurement of innovation performance captures some industry-specific characteristics in the relationship between open innovation and innovation performance, and a recent meta-analysis study (Zhang et al., 2024) suggests that industry characteristics do not moderate this relationship, we still acknowledge the need to control for industry characteristics in future studies.

Fourth, despite the fact that focusing on firms in a specific country has allowed us to control for country-level factors potentially impacting innovation performance (thereby enhancing internal validity), the external validity of our findings may remain limited. However, we believe that our findings are likely to be applicable to firms in other developing countries, particularly from Eastern Europe, at least to a certain extent, because such countries share some common characteristics, such as a lack of resources, institutional voids, recurring political and economic instability, and limited governmental support, resulting in a similar level of costs associated with the process of opening up. While all firms are expected to face legitimacy and complexity costs when opening up, firms from developing countries are likely to encounter higher costs due to their specific characteristics. Therefore, our findings from a developing country (i.e., critical case4) facing higher costs of adopting open innovation, can be logically generalized to other more

[4] Developing countries, like Serbia, are considered critical cases, as they present the least favorable conditions for managing the costs associated with opening up the innovation process.

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developed countries where the costs are lower (see Flyvbjerg, 2006). However, future research can replicate our study in other developing or more developed countries to confirm it empirically.

Fifth, and despite the fact that we only argue about the relationship between relative open innovation and innovation performance, our findings are based on cross-sectional data, and therefore establishing causality is a concern. To clearly establish such causality, future research could use longitudinal data. Finally, the fact that we have collected the data in 2019-2020 may limit the temporal validity of our findings. However, it is unlikely that the costs and benefits related to opening up an organization change radically in a short period of time, as this would imply structural organizational changes, and thus we consider that our data remains relevant nowadays. That said, in the near future, it would be interesting to conduct a follow-up study, not only related to developing countries but also to their more developed counterparts.

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## Figures and Tables

Figure 1. U-shaped relationship between relative open innovation and innovation performance

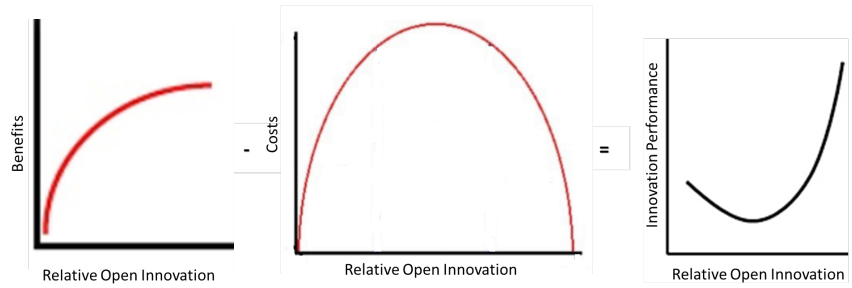


Figure 2. The predicted value of innovation performance at different levels of relative open innovation (main analysis)

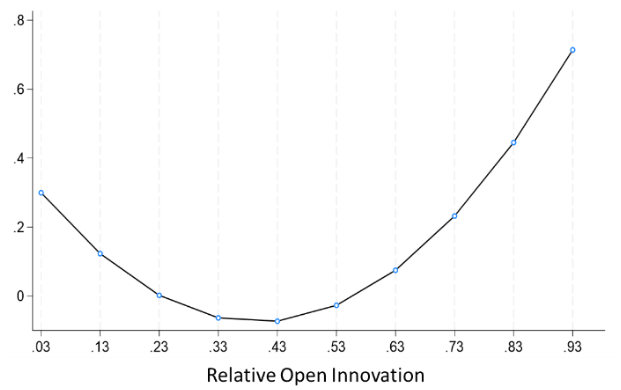


Figure 3. The predicted value of innovation performance 2 at different levels of relative open innovation (robustness check)

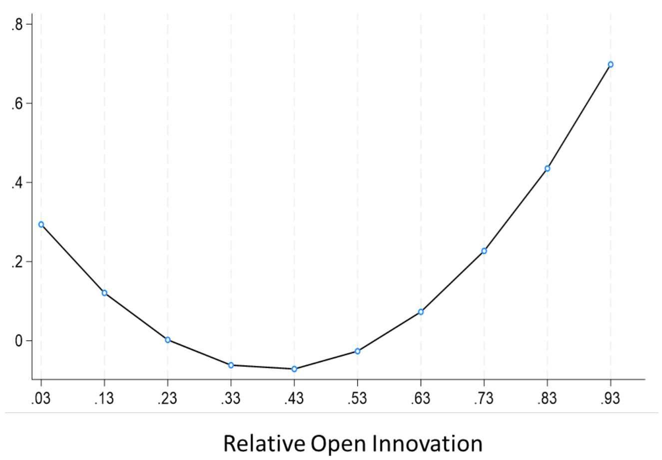

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Figure 4. The predicted value of innovation performance 3 at different levels of relative open innovation (robustness check)

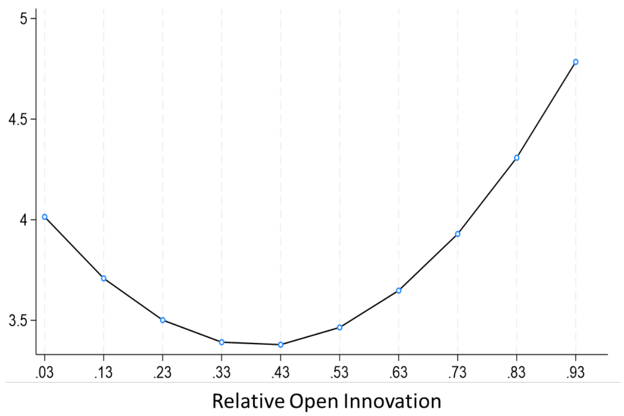


Table 1. Descriptive statistics

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Innovation performance | 130 | 0 | .415 | -1.139 | .862 |
| Relative open innovation | 130 | .386 | .165 | .033 | .973 |
| Partner diversity | 130 | 4.131 | 2.377 | 0 | 11 |
| Past competitive position | 130 | 0 | 1.574 | -5.097 | 2.694 |
| Sales | 130 | 7.285 | 3.748 | 1 | 13 |
| Firm size | 130 | 5.046 | 3.006 | 1 | 10 |
| R&D expenses | 130 | 5.708 | 5.407 | 1 | 13 |
| Marketing expense | 130 | 3.346 | 2.261 | 1 | 7 |
| Ownership | 130 | 2.192 | 1.114 | 1 | 4 |
| Market condition | 130 | 2.162 | .888 | 1 | 3 |
| Export share | 130 | 3.154 | 1.577 | 1 | 5 |
| Firm age | 130 | 3.146 | 1.1 | 1 | 4 |

Table 2. Correlations matrix of variables

| | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Innovation performance | | | | | | | | | | | |
| 2 | Relative open innovation | .113 | | | | | | | | | | |
| 3 | Partner diversity | .114 | .028 | | | | | | | | | |
| 4 | Past competitive position | .329 | .092 | -.035 | | | | | | | | |
| 5 | Sales | .042 | -.058 | .074 | .019 | | | | | | | |
| 6 | Firm size | -.007 | -.149 | .088 | .030 | .637 | | | | | | |
| 7 | R&D expenses | .036 | -.056 | .090 | -.038 | .591 | .585 | | | | | |
| 8 | Marketing expenses | .004 | -.157 | .118 | -.013 | .682 | .668 | .662 | | | | |
| 9 | Ownership structure | .072 | -.063 | .090 | .177 | .297 | .391 | .260 | .235 | | | |
| 10 | Market condition | .029 | .016 | .196 | .131 | .263 | .389 | .230 | .281 | .180 | | |
| 11 | Export share | .062 | -.093 | -.049 | -.175 | .040 | .097 | .130 | .183 | .107 | -.046 | |
| 12 | Firm age | -.039 | -.006 | .114 | .092 | .578 | .553 | .351 | .434 | .211 | .174 | -.089 |

N = 130

Table 3. Estimating the relationship between innovation performance and relative open innovation

| Model: | 1 | 2 | 3 |
|---|---|---|---|
| Dependent variable: Innovation performance | | | |
| Independent variable: | | | |
| Relative open innovation | | 0.055 | -2.212* |
| | | (0.288) | (0.914) |
| Relative open innovation square | | | 2.784* |
| | | | (1.084) |
| Partner diversity | 0.024 | 0.024 | 0.032+ |
| | (0.018) | (0.018) | (0.018) |
| Past competitive position | 0.081** | 0.081** | 0.075** |
| | (0.029) | (0.029) | (0.028) |
| Other control variables[1] | Yes | Yes | Yes |
| Constant | -0.122 | -0.150 | 0.183 |
| | (0.141) | (0.207) | (0.236) |
| Observations | 130 | 130 | 130 |
| $R^2$ | 0.427 | 0.428 | 0.469 |

Robust standard errors in parentheses
$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$

Notes:
1. All control variables are included. The row of "other control variables" include eight categorical variables indicating sales, firm size, R&D expenses, marketing expenses, ownership structure, market condition, export share and firm age.

Table 4. Robustness check

| Model: | 4 | 5 | 6 | 7 |
|---|---|---|---|---|
| Dependent variable: | Innovation performance 2 | Innovation performance 3 | Innovation performance | Innovation performance |
| Independent variable: | | | | |
| Relative open innovation | -2.167$^{*}$ | -3.836$^{**}$ | 2.031 | |
| | (0.910) | (1.442) | (1.811) | |
| Relative open innovation square | 2.726$^{*}$ | 4.887$^{**}$ | -8.070$^{+}$ | |
| | (1.079) | (1.689) | (4.515) | |
| Relative open innovation cubic | | | 7.743$^{*}$ | |
| | | | (3.162) | |
| Censored relative open innovation | | | | -1.839$^{+}$ |
| | | | | (0.997) |
| Censored relative open innovation square | | | | 2.323$^{+}$ |
| | | | | (1.212) |
| Partner diversity | 0.032$^{+}$ | 0.053$^{+}$ | 0.033$^{+}$ | 0.030 |
| | (0.018) | (0.030) | (0.018) | (0.018) |
| Past competitive position | 0.075$^{**}$ | 0.123$^{**}$ | 0.079$^{**}$ | 0.080$^{**}$ |
| | (0.028) | (0.044) | (0.028) | (0.029) |
| Other control variables[1] | Yes | Yes | Yes | Yes |
| Constant | 0.177 | 3.813$^{***}$ | -0.182 | 0.137 |
| | (0.234) | (0.374) | (0.238) | (0.240) |
| Observations | 130 | 130 | 130 | 130 |
| $R^2$ | 0.468 | 0.505 | 0.496 | 0.448 |

Robust standard errors in parentheses
$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$

Notes:
1. All control variables are included. The row of "other control variables" includes eight categorical variables indicating sales, firm size, R&D expenses, marketing expenses, ownership structure, market condition, export share and firm age.

## Appendix

Table A1. Distribution of sample firms by characteristics

| Sales | Frequency (N) | (%) |
|---|---|---|
| <250 thousand euros | 8 | 6.2 |
| 250 thousand - 500 thousand euros | 7 | 5.4 |
| 500 thousand - 1 million euros | 7 | 5.4 |
| 1 million - 5 million euros | 15 | 11.5 |
| 6 million - 10 million euros | 10 | 7.7 |
| 11 million - 25 million euros | 12 | 9.2 |
| 26 million - 50 million euros | 15 | 11.5 |
| 51 million - 100 million euros | 5 | 3.8 |
| 101 million - 250 million euros | 7 | 5.4 |
| 251 million - 500 million euros | 12 | 9.2 |
| 501 million - 1 billion euros | 5 | 3.8 |
| Over 1 billion euros | 12 | 9.2 |
| Don't know | 15 | 11.5 |
| Total | 130 | 100 |

| Firm size | Frequency (N) | (%) |
|---|---|---|
| 1-20 | 20 | 15.4 |
| 20 - 99 employees | 15 | 11.5 |
| 100 -249 employees | 13 | 10 |
| 250 - 499 employees | 16 | 12.3 |
| 500 - 999 employees | 9 | 6.9 |
| 1000 - 4999 employees | 18 | 13.8 |
| 5,000 –7,499 employees | 1 | 0.8 |
| 7,500 - 9,999 employees | 2 | 1.5 |
| 10,000 employees or more | 33 | 25.4 |
| Don't know / Not sure | 3 | 2.3 |
| Total | 130 | 100 |

| R&D expenses | Frequency (N) | (%) |
|---|---|---|
| Less than 500 thousand euros | 56 | 43.1 |
| 500 thousand - 1 million euros | 11 | 8.5 |
| 1 million - 5 million euros | 7 | 5.4 |
| 5 million - 10 million euros | 3 | 2.3 |
| 11 million - 25 million euros | 2 | 1.5 |
| 26 million - 50 million euros | 2 | 1.5 |
| 51 million - 100 million euros | 0 | 0 |
| 101 million - 250 million euros | 4 | 3.1 |
| 251 million - 500 million euros | 0 | 0 |

| | | |
|---|---|---|
| 501 million - 1 billion euros | 2 | 1.5 |
| 1 billion - 5 billion euros | 0 | 0 |
| More than 5 billion euros | 2 | 1.5 |
| Don't know / Not sure | 41 | 31.5 |
| Total | 130 | 100 |

| Marketing expenses | Frequency (N) | (%) |
|---|---|---|
| Less than 100 thousand euros | 43 | 33.1 |
| 101 thousand - 500 thousand euros | 19 | 14.6 |
| 501 thousand - 1 million euros | 11 | 8.5 |
| 1 million - 5 million euros | 17 | 13.1 |
| 6 million - 10 million euros | 8 | 6.2 |
| Over 10 million euros | 11 | 8.5 |
| Don't know | 21 | 16.2 |
| Total | 130 | 100 |

| Ownership structure | Frequency (N) | (%) |
|---|---|---|
| The firm is the main group | 56 | 43.1 |
| The firm is a branch of a Serbian company | 7 | 5.4 |
| The firm is a branch of a foreign company | 53 | 40.8 |
| Something else | 14 | 10.8 |
| Total | 130 | 100 |

| Market condition | Frequency (N) | (%) |
|---|---|---|
| Primarily in B to B market | 42 | 32.3 |
| Primarily in B to C market | 25 | 19.2 |
| Operating in both B to B and B to C markets | 63 | 48.5 |
| Total | 130 | 100 |

| Export share | Frequency (N) | (%) |
|---|---|---|
| 0% | 21 | 16.2 |
| < 25% | 41 | 31.5 |
| 26-50% | 13 | 10 |
| 51-75% | 7 | 5.4 |
| >75% | 48 | 36.9 |
| Total | 130 | 100 |

| Firm age | Frequency (N) | (%) |
|---|---|---|
| 0-5 years | 17 | 13.1 |
| 6-10 years | 19 | 14.6 |
| 11-20 years | 22 | 16.9 |
| More than 20 years | 72 | 55.4 |
| Total | 130 | 100 |

Table A2. Robustness check

| Model: | 8 | 9 |
|---|---|---|
| Dependent variable: | Innovation performance 2 | Innovation performance 3 |
| Independent variable: | | |
| Relative open innovation | 1.945 | 3.748 |
| | (1.813) | (2.707) |
| Relative open innovation square | -7.793$^{+}$ | -14.510$^{*}$ |
| | (4.511) | (6.585) |
| Relative open innovation cubic | 7.504$^{*}$ | 13.838$^{**}$ |
| | (3.156) | (4.594) |
| Partner diversity | 0.034$^{+}$ | 0.055$^{+}$ |
| | (0.018) | (0.029) |
| Past competitive position | 0.079$^{**}$ | 0.129$^{**}$ |
| | (0.028) | (0.044) |
| Other control variables[1] | Yes | Yes |
| Constant | -0.177 | 3.160$^{***}$ |
| | (0.238) | (0.380) |
| Observations | 130 | 130 |
| $R^2$ | 0.494 | 0.539 |

Robust standard errors in parentheses
$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Notes:
1. All control variables are included. The row of "other control variables" includes eight categorical variables indicating sales, firm size, R&D expenses, marketing expenses, ownership structure, market condition, export share and firm age.

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