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Firm Heterogeneity and Innovation Strategy Decisions

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Abstract

Research on innovation strategy has focused on dichotomic (yes or no) options and the determinants of technological (product and process) innovations. This paper includes a variety of innovation strategies to extend the Crepon–Duguet–Mairesse model suggested by Crépon et al. (1998). We extend the study of innovation strategy to nontechnological innovations (organizational and marketing), encompassing all possible combinations of innovative alternatives for the firm (16 strategies). Furthermore, we use a panel of four waves (2009–2010, 2011–2012, 2013–2014, and 2015–2016) of the Chilean innovation survey, which allows us to consider endogeneity using a fixed-effect multinomial logit model. Our results show the relevance of R&D spending per employee in all innovation strategies. Skilled employees positively affect organizational innovation strategies, and medium and large firms are more likely to choose strategies involving process and organizational innovation. The choice of innovation strategy is relevant to a firm's productivity. The coefficient increases monotonically from simple to semi-complex to complex strategies, all of which are positive and statistically significant. This study's results seem more plausible than those found in previous literature.

Keywords: innovation strategies, heterogeneous firms, multinomial logit estimation.
JEL codes: C35, M21, O30, O31.

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1. Introduction

Scholars have long demonstrated the role of innovation in competitive advantages for firms (Abdu and Jibir, 2018; Carboni and Russu, 2018; Godin, 2008; Tavassoli and Karlsson, 2016). Firms must develop an innovation strategy to engage in innovative activities, which can be understood as how organizations create and capture value and, most importantly, which innovations the firm decides to implement (Pisano, 2015). Most research in this area has focused on dichotomic decisions in which an organization decides whether to innovate on each available alternative (Barbosa et al., 2014; Divisekera and Nguyen, 2018; Teixeira and Santos, 2016); however, little is known about the determinants that make firms engage in multiple types of innovation simultaneously, which is known as a complex innovation strategy (Tavassoli and Karlsson, 2016).

Research shows innovation antecedents at the organization, industry, and country levels (Damanpour, 2014). Additionally, the literature on this subject has prioritized the study of antecedents and consequences of technological innovations (products and processes) (Birkinshaw et al., 2008; Volberda et al., 2013), with a focus on the manufacturing industry (Khosravi et al., 2019; Pippel, 2014). Early research in this area has also noted the potential contributions of nontechnological innovations, both organizational and marketing (Arrow, 1962b; Chandler, 1962; Evan, 1966; Kahn and Candi, 2021; Szczygielski et al., 2017; Walker et al., 2015), showing that technological and nontechnological innovations positively impact firm performance.

The extant literature has not extensively examined the coexistence of technological and nontechnological innovations, limiting our understanding of the determinants of innovation in situations where organizations must select among a diverse pool of innovative combinations. This study aims to understand how firms innovate and choose any combination of these four innovations: 1) processes, 2) products, 3) organization, and 4) marketing. The innovation decisions of firms are highly heterogeneous (Cecere, 2013; Fazlıoğlu et al., 2019; Tavassoli and Karlsson, 2016), even among firms of the same size or industrial sector; therefore, to comprehend innovation decisions, it is relevant to understand the determinants of how firms choose a combination of available innovation alternatives (Anzola-Román et al., 2018; Černe et al., 2016; Khosravi et al., 2019; Mothe and Nguyen-Thi, 2012). Examining decisions between different types of innovation or strategies allows us to identify behavioral differences that a simple focus on innovative and noninnovative firms cannot highlight (Barbosa et al., 2014; Divisekera and Nguyen, 2018; Teixeira and Santos, 2016; Zemplinerová et al., 2012a).

This paper extends the Crepon–Duguet–Mairesse (CDM) model (Crépon et al., 1998; Crespi and Zuniga, 2012), suggested by Crépon et al. (1998), which focuses on the determinant of innovation and the impacts on labor productivity. The CDM model analyzes i) whether to invest in research and development (R&D) (dichotomic decision), ii) the amount of R&D investment (continuous decision), iii) how knowledge production as a result of expenditure in R&D affects technological innovations (dichotomic decision), and iv) the impact on the output produced by using the new knowledge or innovation (continuous impact on productivity). Our main contribution affects the modeling of decisions iii) and iv).

First, regarding decision iii), our model recognizes that firms have many options regarding innovations, not just technological ones; thus, we include technological and nontechnological innovations into several portfolios or combinations of strategies ranging from simple (one type of innovation) to semi-complex and complex strategies. Previous studies have examined how firms benefit from implementing innovations as independent events (Adeyeye et al., 2015). In contrast, this study contributes to the innovation literature by going beyond the dichotomic "yes/no" decision to innovate, which is pervasive in the literature (Bhattacharya and Bloch, 2004). We consider that innovation decisions are characterized by a process involving a portfolio of different innovation strategies. We follow Karlsson and Tavassoli (2016) proposal to analyze the firm's decision within a series of innovation strategies instead of considering the four types of innovation as independent decisions. This paper examines innovation decisions as a selection among 16 possible innovation strategies that arise from combining the four types of innovation plus the alternative of not innovating. We use a panel of four waves of the Chilena innovation survey, using the waves 2009–2010, 2011–2012, 2013–2014, and 2015–2016.

Second, regarding decision iv), we hypothesize that different innovation strategies create value for stakeholders, increasingly ranging from simple to more complex strategies. We test this idea by extending the CDM model in Crespi and Zuniga (2012), including the effect of different innovation strategies (simple, semi-complex, and complex) on the equation of sales per employee (a measure of performance).

Third, unlike similar previous studies that consider several innovative strategies, we address the endogeneity problem, which Du et al. (2007), Karlsson and Tavassoli (2016), Carboni and Russu (2018), and Anzola-Román et al. (2018) do not control for. Unfortunately, endogeneity might be problematic when the model uses R&D expenditure as an explanatory variable (Cassiman and Veugelers, 2002). We estimate a fixed-effect multinomial logit model to correct endogeneity, in which a firm chooses one of several innovation strategies. Innovation strategies correspond to mutually exclusive options combining product, process, organizational, and marketing innovations (Damanpour and Aravind, 2011; Du et al., 2007). The fixed-effect multinomial logit model does not require an assumption for the heterogeneity distribution and is robust to endogeneity, that is, the correlation between the error terms and the explanatory variables (Börsch-Supan, 1990; Chamberlain, 1980). We also estimated the multinomial logit model using the instrumental variables approach and the multinomial logit using the control function approach for the robustness check. Patents protection, information sources, and cooperation sources were tested as instruments (Aboal and Garda, 2016; Álvarez et al., 2011, 2015; Crespi and Zuniga, 2012) and used to predict the value of R&D expenditure per capita. We tested whether the instruments passed 1) an underidentification test (Anderson canonical test) (F-test), 2) a weak identification test (Cragg–Donald Wald test), and 3) an exogeneity test (overidentification Sargan test).

Section 2 defines the different types of innovations in this study, differentiates between simple and complex strategies, and provides theoretical justifications for the relationship between a firm's characteristics and innovative activities. These definitions are followed by a description of the theoretical model (CDM model) and its relationship with innovation strategies. In section 3 we present the data, sample and analytical method.

Section 4 presents the results. They reveal heterogeneous effects of innovation strategy on the decision to innovate. The most relevant finding is that firms' R&D spending per employee is significant for all strategies; in some, when a firm opts for a strategy that includes organizational innovation, human capital is statistically significant and positive. Additionally, medium and large firms tend to choose strategies that combine two or more alternatives compared to small firms. After correcting for endogeneity, the variables measuring small firm size and group membership are no longer significant in determining different innovation strategies. In section 5 and 6 we discuss the implications of our study for research on the relationship between innovation strategies and types of innovation and conclude by listing the study's limitations and closing remarks.

2. Literature Review

2.1. Innovation Typology

Innovation can be classified under different dimensions, such as technological versus nontechnological, architecture versus modular, incremental versus radical, and enhancing versus destructive capabilities (Schilling, 2012). Likewise, different innovation processes exist, such as the generation, diffusion, and adoption of innovation. Distinguishing between technological and nontechnological innovations provides a better understanding of the different antecedents and consequences of innovation at the organizational level. Product and process innovations are categorized as technological innovations, while organizational and marketing innovations are nontechnological innovations (OECD, 2005). Product innovation means introducing a new product or service to meet a user's needs, whereas process innovation is the introduction of new elements to the production process or service operation (Damanpour, 2010; Utterback, 1994). We define organizational innovation as introducing new programs and practices for new approaches to strategy, structure, administrative systems, managerial processes, and organizing relationships with other enterprises (Birkinshaw et al., 2008; Damanpour, 2017; OECD, 2005). Marketing innovation is defined as improvements in product design, placement, promotion, or pricing (Deshpandé et al., 1993; OECD, 2005).

2.2. Simple versus Complex Innovation Strategies

The extant literature has extensively analyzed the differences between innovative and noninnovative firms in different contexts (e.g., countries and industries) and defined a set of variables that affect the propensity to innovate (Abdu and Jibir, 2018; Ayalew et al., 2019; Bhattacharya and Bloch, 2004; Du et al., 2007); however, more recent studies have recognized that firms can choose among four types of innovation: product, process, organizational, and marketing. Firms can also choose a combination of these innovation strategies (Agwu et al., 2019; Carboni and Russu, 2018; Karlsson and Tavassoli, 2016; Tavassoli and Karlsson, 2016).

Innovation decisions can be characterized as a tree decision in which firms decide whether to innovate; conditional on the decision, firms face several innovation strategies and choose the one that best fits their internal capacities and environment (Agwu et al., 2019). The literature shows a broad, more extended discussion on firms' decisions to innovate, emphasizing technological innovations (product, process, or both) and a recent, growing debate on the relevance of the complementarity of innovation decisions. The most relevant aspect is that all types of innovations are considered possible decisions for a firm (Agwu et al., 2019; Bartoloni and Baussola, 2018; García-Piqueres et al., 2020; Lee et al., 2019).

The literature has extensively discussed firms' binary innovation decisions and their implications for performance and technological innovations. For instance, out of 70 papers reviewed, 40% evaluate the effect of innovation on performance (Álvarez et al., 2015; Dachs et al., 2017; Evangelista and Vezzani, 2010, 2012; Falk, 2015; Geldes et al., 2017; Hashi and Stojčić, 2013; Hervas-Oliver et al., 2017; Mothe and Nguyen-Thi, 2012; Mothe and Thi, 2010; Pino et al., 2016; Szczygielski et al., 2017; Tavassoli and Karlsson, 2016). Only 14% of papers analyzed nontechnological innovation decisions (Egbetokun et al., 2015; Mothe and Nguyen-Thi, 2013; Robin and Schubert, 2013; Silva et al., 2013). Furthermore, only 5% analyzed the four types of innovation; however, they did so as separate decisions (Agwu et al., 2019; Carvalho et al., 2013; García-Piqueres et al., 2020). Only one paper considered a more comprehensive approach to asset innovation strategies (Karlsson and Tavassoli, 2016).

Karlsson and Tavassoli (2016) defined 16 innovation strategies derived from the possible combinations of the four types plus the option of no innovation. Depending on the combination, they defined *simple strategies* as those that include only one kind of innovation, low- and medium-complexity strategies; *complex strategies* simultaneously involve all four. They used a multinomial logit model to determine how firms' characteristics and environments affect innovation decisions.

According to the literature, firms' innovation effort is a pervasive theoretical variable to explain innovation, measured as spending on R&D activities. Scholars have shown that R&D activities affect firms' innovation decisions and performance (Abdu and Jibir, 2018; Adeyeye et al., 2015; Álvarez et al., 2015; Anzola-Román et al., 2018; Baum et al., 2019; Camisón and Villar-López, 2014). The literature on innovation has analyzed these relationships using the structural CDM model, which allows us to link the relationship between innovation activities, innovation outcomes, and their effects on firms' productivity by employing several equations. For instance, Crespi and Zuniga (2012) tested the relationship between technological innovations and Latin American firms' productivity, showing a positive relationship between R&D investment, innovation decisions, and productivity. Aboal and Garda (2016) found that firm size is a determinant in the Uruguayan manufacturing sector but not the services sector; in particular, firm size, cooperation activities, and public financing affect technological and nontechnological innovation decisions. In a modified version of the CDM model, Muinelo-Gallo (2017) used three categories of R&D intensity, finding a positive effect of R&D activities on product and process innovations.

The decision to innovate has been linked to other relevant variables, including firm size and competition level (Acs and Audretsch, 1988). Schumpeter (1934) argued that small firms have a greater propensity to innovate since they are more flexible to change than large firms and can obtain more benefits in small markets. Furthermore, innovation is necessary because firms must differentiate themselves in competitive markets to achieve better performance (Arrow, 1962b); however, since innovation development implies financing, firms with market power tend to be more innovative because they can access funding (Schumpeter, 2016). Therefore, the discussion of innovation starts with considering the effect of firm size on innovation. Acs and Audretsch (1988) indicated that industries with larger firms tend to be more innovative and that lower industrial concentration levels are associated with greater innovative activity. Schubert (2010) showed that a larger market share has a negative impact when firms decide only on technological innovation; however, it has a positive effect when firms combine technological and nontechnological innovation. Furthermore, Shukla (2019) showed that high industrial concentration negatively and significantly affects R&D intensity at the firm level.

Moreover, the innovation processes that firms develop involve generating knowledge, which occurs during their R&D activities or through the firm's ability to acquire knowledge from their environment (Milan et al., 2020); thus, human capital is relevant to learning from others and allowing ideas to flow within the firm. The literature suggests that human capital in the firm (defined as the level of employee training) positively affects the decision to innovate (Capozza and Divella, 2018; Protogerou et al., 2017; Ramírez et al., 2019) on R&D activities (Adeyeye et al., 2015).

2.3. A Brief Description of the CDM Model

The CDM model suggested by Crépon et al. (1998) focuses on i) whether to invest in innovations (dichotomic decision), ii) the amount of expenditure in R&D (continuous decision), iii) knowledge production as a result of investment in R&D generating innovation in processes or products (technological innovations), and iv) output produced using the new knowledge. These decisions are associated with specific econometric models. The model assumes there exists an unobserved (latent) firms' efforts in innovation (IE_i^*) given by

$$IE_i^* = z_i^{'}\beta + e_i$$

Z is a set of explanatory variables, β is a vector of coefficients to be estimated, and e_i is an error term. Since this variable is latent, the CDM model uses the log of the expenditure in R&D per employee as a proxy for effort in innovation, denoted by IE_i. Since many firms do not allocate resources for innovation (many times $IE_i = 0$), the IE_i is observable only when $IE_i > 0$. Since the expenditure is part of a firm's decision, we observed a dichotomic dependent variable, such as

$$ID_i = \begin{cases} 1 & \text{if } RD_i > 0 \\ 0 & \text{Otherwise.} \end{cases}$$

This dichotomic dependent variable corresponds to the discrete spending decision on innovation. Conditional on $ID_i = 1$, some firms spend a positive amount ($RD > 0$), corresponding to a continuous decision of how much to spend on R&D. Using a generalized Tobit model, Crespi and Zuniga (2012) estimated this two-part decision:

$$IE_i = z_i^{'}\beta + e_i \tag{1}$$

The probability of engaging in innovation is:

$$Pr(ID_i = 1) = Pr(IE_i > 0) = \Phi(w_i^{\prime}\alpha) \tag{2}$$

where w_i are explanatory variables, and α is a vector for parameters to be estimated. The model uses a bivariate normal distribution for the error terms in equations (1) and (2). That is, the discrete choice follows a normal distribution known as the conditional Probit model in which the variance is fixed to 1 ($\sigma_\varepsilon = 1$). Crespi and Zuniga (2012) call these equations a generalized Tobit model.

The CDM model has two more equations. The first is for the probability of adopting technological innovations:

$$TI_i = IE_i^{*}\gamma + x_i^{'}\delta + \mu_i \tag{3}$$

where TI includes any product or process innovation. Crespi and Zuniga (2012) also model this equation as a binary (probit) model. The variable TI_i takes the value of 1 if the firm introduces a new product or process at the firm level and 0 otherwise. The CDM model replaces the explanatory variable IE_i^{*} by the predicted $\widehat{IE_i^{*}}$ from equation (3), similar to a two-stage least squares (2SLS) model. In our specification we use IS_{ij} where j includes all the possible technological and nontechnological innovations that a firm i can develop as well as the possible combinations. The sub-index j is defined the value from 1 to 15 for each of the innovation strategies (IS) that the firm can carry out. We have left as a base scenario the decision not to innovate. We have defined that a simple innovation strategy is one that involves making a single innovation, a semi-complex strategy involves making two innovations and a complex strategy involves making 3 or 4 innovations.

Finally, the last equation is the equation that measures the impact of innovation on firms' performance. Crespi and Zuniga (2012) used labor productivity (Y_i) as a function of capital (k_i) and the dummy decision of technological innovations, and π_1 and π_2 are parameters to be estimated

$$Y_i = \pi_1 k_i + \pi_2 IS_{ij} + v_i \tag{4}$$

Our approach contributes to modeling equations (3) and (4) by including a more sophisticated set of innovative decisions IS_{ij}. Our model recognizes that firms i have significantly more options regarding innovations; they are not limited to just technological decisions; thus, we include technological (process and products) and nontechnological innovations (marketing and organizational). Additionally, our model recognizes that firms can choose a portfolio of these four alternatives ($j = 1, 2, \cdots, 15$ possible combinations, plus the option of not innovating). We model these 16 alternatives using a multinomial approach instead of the binary equation (3), and the 16 options are grouped into simple, semi-complex, and complex decisions; therefore, in equation (4), instead of using only the prediction of technological innovation probabilities, we used the likelihood of engaging in one of these three categories.

3. Data and Methodology

3.1. Data and Sample[1]

We empirically examined our hypotheses using data from the Chilean Innovation Survey administered by the Ministry of Economy. Chile is the only South American country to be a member of the Organization

[1]It is possible to access the research data by contacting the corresponding author.

for Economic Cooperation and Development (OECD). The design and methodology of the Chilean Innovation Survey followed the guidelines suggested by the OECD's OECD (2005), and the survey is similar to the Eurostat Community Innovation Survey (CIS). The Chilean Innovation Survey has been implemented every two years since 1995. The results from 9 panels have been published based on samples covering 95% of statistical representativeness regarding the distribution of companies by region (national representativeness), economic sector (economic activity representativeness), and the size of companies according to annual sales defined by the Ministry of Economy. This paper used information from a panel of four waves (2009–2010, 2011–2012, 2013–2014, and 2015–2016) of the Chilean Innovation Survey with similar variable definitions because for these 4 versions of the survey it is possible to construct a panel data according to the methodological indications of the Ministry of Economy. In this panel we have a total of 19,763 observations, but we have 8,736 firms that have observations in several versions of the survey. The distribution of these is 4,170 firms are duplicated once, 2,562 are duplicated twice and 2,004 are duplicated 3 times.

This survey allows us to study the four types of innovations upon which firms can decide, and the survey data also provides information on firm characteristics and various innovation-related activities. The survey included 19.763 firms, of which 5.685 (28%) developed at least one type of innovation; 38% of firms implement a simple strategy, 26% of firms implement a semi-complex strategy, and 35% implement a complex strategy. Notably, many firms chose a strategy involving multiple innovation alternatives. Table 1 shows the distribution of firms according to the type of innovation. Only 38% of the innovating firms decided on a single innovation, typically technological. In comparison, 62% of the firms opted for innovation strategies involving two or more innovations. Only 6% of firms had technological innovation strategies that combined products and processes, while 4.8% took a nontechnological approach that combined organizational and marketing.

3.2. Measures

3.2.1 Dependent variable

The dependent variable is the firm's innovation strategy within the 15 options presented in Table 1 plus the no innovation options; therefore, there are, $j = 1, \cdots, 16$ alternatives. The dependent variable, y_i, takes the value $y_i = 1$ if the firm chose the i^{th} alternative and $y_i = 0$ otherwise. We aim to analyze firms' choice of innovation strategy or not innovating among the 25 possible combinations of product, process, organizational, and marketing innovation.

Table 1: *Innovation Strategies*

Strategy	**Frequency**	**%**	**Strategy**	**Frequency**	**%**
Only technological			**Both technological and nontechnological**		
Product	434	7,6%	Product + ortanizational	133	2,3%
Process	742	13%	Product + Marketing	94	1,6%
Product + Process	354	6,2%	Process + organizational	492	8,6%
Only nontechnological			Process + marketing		
			Product + organizational + marketing	139	2,4%
Organizational	614	10,8%	Process + organizarional + marketing	453	7,9%
Marketing	397	6,9%	Product + process + organizational	395	6,9%
Organizational + marketing	278	4,8%	Product + process+ marketing	146	2,5%
			Product + process + organizational + marketing	865	15,2%
Innovator	5,685		No innovators	14,078	

3.2.2 Explanatory variables

We followed previous literature on the determinants of the propensity to innovate to determine the relevant explanatory variables. Table 2 presents the descriptive statistics of these explanatory variables.

The first group of variables is firm characteristics and includes the following. ***Age*** represents the *firm's age* and describes the learning characteristics or accumulation of knowledge over time; it is a proxy of the learning process and an indication of the life cycle (Agwu et al., 2019; Coad et al., 2016; Cucculelli and Peruzzi, 2020; Du et al., 2007). Age is the difference between the survey's year of application and the firm's creation date. ***Qualified employees*** measures the firm's absorptive capacity, representing the possibility of acquiring knowledge to develop innovations (Capozza and Divella, 2018; Carboni and Russu, 2018; Du et al., 2007; Ramírez et al., 2019; Tavassoli and Karlsson, 2015). It is quantified as the percentage of employees with tertiary or higher education from the firm's total number of employees. ***Size of the firm*** (number of employees) measures access to resources and possibilities for developing economies of scale or scope (Agwu et al., 2019; Álvarez et al., 2011; Anzola-Román et al., 2018; Cassiman and Veugelers, 2002; Evangelista and Vezzani, 2010; Mardones and Zapata, 2019; Martínez-Ros and Labeaga, 2002). We split this variable into four categories to differentiate firms. Micro firms have fewer than 10 employees, small firms have between 10 and 26 employees, medium-sized firms have 25 to 200 employees, and large firms have more than 200 employees. We differentiated by firm size to analyze differences between firms when choosing an innovation strategy; we include this variable because the literature traditionally uses only one size measure. Finally, we used ***R&D expenditure*** per employee of firms on these activities. Firms' knowledge development for innovation is a product of the effort invested into their internal and external ***R&D*** activities (Aboal and Garda, 2016; Álvarez et al., 2011; Benavente, 2005; Crespi and Zuniga, 2012; Du et al., 2007). We measured this effort by using the total amount firms spend on R&D activities.

The second group of variables represents the ***firm's environment***. Firms can access information and make innovation decisions based on their environment. ***Export*** is a dichotomic variable indicating whether the firm exported in the survey period; participation in foreign markets implies stronger competition and the need to adapt to international consumers (Aboal and Garda, 2016; Agwu et al., 2019; Carboni and Russu, 2018; Crespi and Zuniga, 2012; Egbetokun et al., 2015; García-Piqueres et al., 2020; Karlsson and Tavassoli, 2016; Mardones and Zapata, 2019). ***Group*** is a dummy variable that indicates whether the firm belongs to a group of companies. If so, then the firm has access to information from different markets; therefore, it may adopt innovations in a transversal way as a group strategy and not necessarily of the firm in particular (Agwu et al., 2019; Egbetokun et al., 2015; García-Piqueres et al., 2020; Geldes et al., 2017).

The third group of variables is **economic activity**; we included three dummies, ***agricultural, manufacturing***, and ***services***, to indicate and differentiate the activities in which firms participate (Álvarez et al., 2015; Gallego et al., 2012; Geldes et al., 2017; Karlsson and Tavassoli, 2016).

Table 2: *Descriptive Statistic of Variables*

Variable	Description	Mean	Std. dev	min	max
Innovated	Dummy = 1 if firms develop some innovation	0.28	0.45	0	1
	Firm's characteristic				
Age	Years of the firm since its creation	18.7	14.76	0	100
Qualified employment	Percentage of employees with tertiary education, master, and doctorate	0.43	0.36	0	1
Micro	Dummy = 1 when the firm has less than 11 employees	0.26	0.44	0	1
Small	Dummy = 1 when the firm has between 11 and 26 employees	0.20	0.40	0	1
Medium	Dummy = 1 when the firm has between 26 and 201 employees	0.34	0.47	0	1
Large	Dummy = 1 when the firm has more than 201 employees	0.17	0.38	0	1
Spending in R&D per employee	Per capita spending on R&D	14401.01	1646556	0	230 million
Export	Dummy = 1 if the firm exports	0.13	0.34	0	1
Group	Dummy = 1 if the firm belongs to a group	0.29	0.45	0	1
Agricultural	Dummy = 1 if the firm belongs to the agricultural sector	0.10	0.30	0	1
Manufacturing	Dummy = 1 if the firm belongs to the manufacturing sector	0.34	0.47	0	1
Service	Dummy = 1 if the firm belongs to the service sector	0.55	0.49	0	1

3.3. Model Specification and Estimation Strategy

We used the approach of Karlsson and Tavassoli (2016) to analyze how the explanatory variables affect the decision on innovation strategy. Using a multinomial logit estimation, we estimated the parameters associated with the probability of choosing each possible strategy. The theoretical model (Train, 2009) is as follows. Consider choosing from among $j = 1, \cdots, J$ innovation strategies. The "utility" achieved by choosing alternative j, by the firm "i" in period "t" is given by:

$$U_{ijt} = X_{ijt}\beta_j + \mu_{ij} + \epsilon_{ijt}$$

X is a set of explanatory variables that might change among firms, alternatives, and time. μ_{ij} captures the heterogeneity among firms, which could be treated randomly or as a fixed effect, and ϵ_{ijt} represents an error term capturing the ignorance of the researcher regarding the decision process. Using a Type I Extreme value distribution for this latter error term, we obtain the multinomial logit model, where the conditional probabilities that firm i $(i = 1, \cdots, N)$ chooses alternative j $(j = 1, \cdots, 16)$ conditional on the distribution of μ_{ij} is as follows:

$$Pr_{ijt} = Prob(IS_{ijt} = 1) = \frac{e^{X_{ijt}\beta_j + \mu_{ij}}}{\sum_1^l e^{X_{ilt}\beta_j + \mu_{ij}}} \tag{5}$$

Notice that the parameters must be normalized regarding one of the alternatives in the multinomial logit case. In our case, the normalizing alternative is the non-innovation option. All parameters of this option are set to zero, and the estimated parameters are interpreted compared to the baseline alternative (Wooldridge, 2002).

The model could use a random effect approach to eliminate the heterogeneity component, assuming a distribution for μ_{ij} or a fixed parameter approach. Extending the fixed-effect approach to nonlinear models is not straightforward for the curse of dimensionality. Unlike linear models, it is impossible to eliminate the constants (fixed effect per firm) by taking the differences concerning the mean of the variables. Furthermore, estimating one constant for each firm is not feasible since there are too many individuals (a large number of parameters cannot be identified consistently when the sample size increases). Fortunately, estimating a panel of multinomial logit models with fixed effects is possible; the estimation uses sufficient statistics suggested by Chamberlain (1980), details of which can be checked in Lancaster (2000) and the Stata manual. The FE multinomial logit model produces valid estimates under unobserved heterogeneity, which is associated with the firms' unobserved attributes (Börsch-Supan, 1990; Chamberlain, 1980).

The fixed-effect approach does not require an assumption for the distribution of the heterogeneity and is robust to endogeneity (i.e., the correlation between the μ_{ij} and the X_{ijt}). Endogeneity occurs with a structural association between innovation and innovation indicators (Cozzarin, 2016; Evangelista and Vezzani, 2010) or when unobserved factors lead firms to invest more in innovation activities (Cassiman and Veugelers, 2002; Crespi and Zuniga, 2012). We only observe firms conducting R&D activities; hence, a reverse causality could exist between innovation and R&D expenditures. Endogeneity results in biased and inconsistent parameters.

The extant literature typically used dichotomic probit or logit models to analyze the determinants of firms' propensity to innovate. When examining the four types of innovation as separate decisions, researchers have used multivariate probit models to test for correlations between innovation types (Agwu et al., 2019; Carboni and Russu, 2018; García-Piqueres et al., 2020). Researchers have also used a two-step approach to approximate firm decisions. The first stage explains the decision on whether to innovate, and the second stage explains the type of innovations developed, which can be done from an econometric perspective using a combination of probit and multinomial logit models Du et al. (2007). Other authors have also used count data and Poisson models to consider the integer nature of innovations (Martínez-Ros and Labeaga, 2010). Our models follow Karlsson and Tavassoli (2016) regarding econometric modeling of multivariate decisions.

We also use two other approaches to correct for endogeneity, estimating the multinomial logit model using instrumental variables and the multinomial logit using the control function approach. Instrumental variables are a classical solution for the endogeneity problem; an instrument must be correlated with the endogenous variable ($Cov(x_{ij}, Z_{ij}) \neq 0$) and uncorrelated with the regression errors ($Cov(u_{ij}, Z_{ij}) = 0$). Studies on longitudinal data use lags of the explanatory variables since they are suitable instruments with predictive power (Anzola-Román et al., 2018; Evangelista and Vezzani, 2012). When used as an explanatory variable, firms' R&D expenditure is estimated by an auxiliary equation using a set of instruments unrelated to R&D expenditure with the propensity to innovate. Firms' predicted spending is then used as an explanatory variable in innovation decisions (Álvarez et al., 2011; Miguel Benavente, 2006; Crespi and Zuniga, 2012; Dachs et al., 2017; Hashi and Stojčić, 2013; Robin and Schubert, 2013; Stanovcic et al., 2015). Furthermore, some researchers used instrumental variables to control for the endogeneity of organizational innovation as an explanatory variable of technological innovation (Cozzarin, 2016; Hervas-Oliver et al., 2017).

Regarding R&D expenditure, Crespi and Zuniga (2012) and Álvarez et al. (2015) suggested several instrumental variables, such as patent protection, cooperation in R&D, public financing, and information sources. Cooperation innovation activities relate to collaboration with other entities, such as companies within the group, suppliers, customers, consultants, universities, and public research institutes. Information sources capture different sources of information regarding innovations used by firms. Chile's innovation surveys contain a ***Sources of Information and Cooperation*** module in innovative activities, in which companies report the sources of information on innovations they used in the period on a scale of importance. The module considers A) internal sources of information; B) market sources, such as i) suppliers, clients, competitors, or companies of the same sector and consulting firms, laboratories, or private R&D institutes; C) the institutional sources consulted, which include i) universities or other higher education institutions, ii) public or government research institutes; and D) other sources of information, including i) conferences, fairs, and exhibitions, ii) scientific journals, technical, and commercial publications and patent databases, iii) professional and industrial associations, and iv) the internet. Aboal and Garda (2016) only used public financing as an instrumental variable, while Zemplinerová et al. (2012b) used the obstacles to innovation as explanatory variables of the decision to invest in R&D, the intensity of expenditure, and the firm's sources of information.

For the multinomial logit model and the multinomial logit with the control function approach, we tested whether the instruments passed i) an underidentification test (Anderson canonical test) (F-test), 2) a weak identification test (Cragg–Donald Wald test), and 3) an exogeneity test (overidentification Sargan test). This type of test is not available for nonlinear models; therefore, we follow a linear regression approach and run a regression using panel data with a dummy variable for innovation using three instruments: cooperation in R&D with other firms, patent protection, and their product of them. All tests are passed when innovation expenditure per employee is considered endogenous. We used these instruments to estimate a multinomial logit model using the prediction of the endogenous variables, similar to a 2SLS approach, and the multinomial logit using the control function approach. We ran an auxiliary regression for R&D expenditure using the instruments. We used the predicted R&D expenditure to estimate equation (5). The first step equation is of the following form:

$$RD_{ij} = X'_{ij}\beta + Z'_{ij}\delta + e_{ij} \tag{6}$$

where RD_{ij} is the log of the expenditure in R&D per employee, X_{ij} is the same set of explanatory variables used in equation (5), and Z_{ij} is a vector of instrumental variables that affect the firm´s RD_{ijt} (Aboal and Garda, 2016; Álvarez et al., 2011, 2015; Crespi and Zuniga, 2012). In the elaboration of the control function, we obtain the predicted $\widehat{RD}$ and the residual, $\hat{e}$ that is used in equation (5) as an independent variable. The results for equation (6) are shown in the Appendix.

4. Results

Our primary interest is in discussing equations (3) and (4) of the CDM model; therefore, we present the estimates of equations (1) and (2) in Appendix C. The results of these equations align with Crespi and Zuniga (2012), where medium and large firms and those using patent protection are more likely to spend on R&D activities. Firms that export, develop cooperative R&D activities, and seek information from external sources are also more likely to spend on R&D activities.

The results of equation (3) are shown in Table 3, presenting the innovation strategies as simple strategies, semi-complex (combining two innovations), and complex strategies (combining three or four innovations). The first relevant result is that R&D spending is positively and statistically significant in all 15 strategies. Knowledge generation through the firm's R&D activities is relevant for increasing the probability of all innovation strategies, These firms are up to twice as likely to choose an innovation strategy as those firms that do not innovate. The firm's age shows a positive and significant effect on the decision to undertake complex strategies, Older firms are 0.36 times less likely to choose a process, organizational and marketing strategy and 0.57 times less likely to choose the complex strategy[2] with respect to firms that do not innovate. Skilled employees have a positive and significant effect on the development of organizational innovations, nontechnological innovation, and complex organizational innovation strategies, these firms are up to 2 times more likely to choose an organizational innovation.

Concerning the simple strategy, the results show that medium and large firms are more likely to develop product and organizational innovations than other firms. While manufacturing firms would not innovate in processes. Regarding the development of semi-complex innovations, the results show that large firms are more likely to develop strategies involving technological innovations (product or process) and, like medium-sized firms and those that belong to a group of people, develop process and organizational innovations together. An interesting result is that medium-sized firms are up to 13 times more likely to choose the semi-complex product, process, and organizational strategy, while large firms are 28 times more likely to choose this strategy. Finally, service firms are more likely to develop a semi-complex strategy of nontechnological innovation.

In the decision of complex strategies, medium and large firms have a higher probability of developing a technological innovation strategy with organizational innovation, while large firms also develop all four strategies together. Furthermore, firms belonging to a group are more likely to develop all four innovations simultaneously. Large firms are 8 times more likely to choose the complex strategy, while firms that belong to a group are 4 times more likely to choose the strategy than firms that do not innovate.

By regressing equation (3) using the aggregate categories of strategies, i.e., for the choice of simple, semi-complex or complex strategies ($j = 1, 2$ or 3), we can observe the negative and significant effect of age on all strategies, the positive and significant effect of skilled employees on the choice of a complex strategy, as well as the negative and significant effect of manufacturing and service firms on the choice of a simple innovation strategy. For more details, please refer to Appendix F for the results.

Table 4 shows the estimates of equation (4)[3]. The choice of an innovation strategy is relevant to a firm's performance. This regression uses sales per employee to measure performance following the proposal of the CDM model. The most conspicuous result is that innovating firms have higher sales per employee than those that do not. One of this paper's main contributions is showing that the higher the complexity of the strategy, the higher the sales per employee. The coefficient increases monotonically from simple (0.16) to semi-complex (0.23) to complex strategies (0.28); they are all positive and statistically significant. This effect is obtained when we have included controls by year and sector (column 4); but when estimating with firm-level fixed effects (column 5) the positive and significant effect occurs for the semi-complex strategy. Then, when we look at the effect of productivity by type of strategy, the results show that those firms that include nontechnological innovations in their strategy have higher productivity (these results are presented in Appendix D). This result seems more plausible than the findings by Crespi and Zuniga (2012)—who show that nontechnological innovations harm productivity—and Aboal and Garda (2016)—who find a negative and significant impact in the manufacturing sector for

[2]We use relative-risk ratios, which is obtained as $\exp(\beta_j)$, because in a multinomial logit panel with fixed effects it is not possible to obtain the marginal effects of the variables. We have added in Appendix G all of the relative-risk ratios

[3]The capital variable is not included in our estimates because the innovation surveys used in Chile do not include it. However, according to the studies carried out for Chile and Latin America, this should have a positive effect on the productivity of the firms along with the innovation decision.

nontechnological innovations and the combination of technological and nontechnological innovations. For more detail in section 5 we discuss why our results differ from the work of Crespi and Zuniga (2012), where we also refer to what our results would look like if we replicate your estimate with our database. This estimate is available in Appendix H.

Table 3: *Multinomial Logit with fixed effects*[4]

	Single strategies				semi-complex strategies						complex strategies				
Strategy	**P**	**Pr**	**O**	**M**	**P+O**	**P+Pr**	**P+M**	**Pr+O**	**Pr+M**	**O+M**	**P+Pr +O**	**P+Pr +M**	**P+O +M**	**Pr+O +M**	**P+Pr +O+M**
N	434	742	614	397	133	354	94	492	149	278	395	146	139	453	865
Firm's characteristic															
Ln Age	-0.40	-0.23	-0.32	-0.09	-0.52	-0.34	-0.20	-0.11	-0.69	-0.30	0.02	-0.46	-0.45	-0.91***	-0.52***
	(0.31)	(0.23)	(0.21)	(0.28)	(0.42)	(0.38)	(0.58)	(0.24)	(0.55)	(0.34)	(0.32)	(0.40)	(0.51)	(0.29)	(0.23)
Qual. Employ.	-0.60	0.01	0.73**	0.01	0.30	-0.81	0.61	-0.15	0.25	1.11**	0.16	0.17	1.07	0.85***	0.75**
	(0.38)	(0.03)	(0.31)	(0.38)	(0.63)	(0.50)	(0.78)	(0.35)	(0.66)	(0.52)	(0.43)	(0.69)	(0.70)	(0.41)	(0.33)
Small	0.86	0.02	1.93***	0.38	1.27	2.05**	-9.04	0.96	15.88	-0.74	1.29	15.67	-11.94	0.07	0.83
	(0.76)	(0.59)	(0.71)	(0.75)	(1.09)	(1.00)	(1.47)	(0.95)	(0.83)	(1.25)	(0.96)	(24.66)	(1.88)	(0.81)	(0.77)
Medium	1.55**	0.23	1.93***	0.91	1.63	4.04***	17.91	1.95***	14.92	-0.82	2.56**	15.97	-12.12	1.05	1.20
	(0.76)	(0.53)	(0.65)	(0.74)	(1.27)	(1.26)	(1.57)	(0.90)	(0.83)	(1.30)	(0.98)	(24.66)	(1.75)	(0.97)	(0.82)
Large	1.99***	0.61	1.72**	1.28	2.74***	4.50***	18.97	2.06***	14.94	0.15	3.34***	16.03	-9.86	1.40	2.09**
	(0.87)	(0.60)	(0.72)	(0.88)	(1.36)	(1.30)	(1.57)	(0.93)	(0.83)	(1.41)	(1.07)	(24.66)	(1.75)	(1.05)	(0.87)
Ln(R&D)	0.65***	0.66***	0.50***	0.52***	0.55***	0.67***	0.56***	0.66***	0.75***	0.62***	0.72***	0.82***	0.80***	0.71***	0.74***
	(0.05)	(0.04)	(0.04)	(0.05)	(0.08)	(0.05)	(0.09)	(0.04)	(0.08)	(0.06)	(0.05)	(0.10)	(0.08)	(0.05)	(0.04)
Firm's environment															
Export	1.26***	0.55	-0.23	0.33	1.70	0.36	-0.09	0.19	0.82	1.44***	0.39	-0.42	-0.26	0.41	0.34
	(0.64)	(0.49)	(0.44)	(0.54)	(0.94)	(0.75)	(1.07)	(0.55)	(0.96)	(0.69)	(0.58)	(1.02)	(0.87)	(0.67)	(0.42)
Group	0.34	0.46	0.27	0.32	0.15	1.28***	-0.41	0.56***	0.43	0.27	0.43	-0.24	-0.14	0.56	1.44**
	(0.39)	(0.29)	(0.25)	(0.34)	(0.60)	(0.45)	(0.89)	(0.33)	(0.51)	(0.48)	(0.35)	(0.67)	(0.69)	(0.44)	(0.32)
Economic activity															
Manuf.	-1.07	-1.54***	-0.96	0.78	-1.10	-0.64	15.76	-0.68	-0.23	-3.01**	0.44	-15.41	15.07	-0.31	-1.68
	(1.16)	(0.74)	(0.83)	(1.61)	(1.50)	(1.14)	(3.71)	(0.91)	(1.68)	(1.47)	(1.44)	(3.14)	(2.30)	(1.20)	(2.06)
Service	-1.55	-1.04	-0.96	-0.78	-1.82	-1.62	15.84	-0.55	-3.03	-4.44**	-0.41	-13.82	17.87	0.96	-2.64
	(1.15)	(0.74)	(0.83)	(2.61)	(1.56)	(1.58)	(3.71)	(1.33)	(1.80)	(1.63)	(1.20)	(3.14)	(2.30)	(1.40)	(2.17)

Notes: P = Product, Pr = Process, M = Marketing, and O = Organizational. Standard errors are in parenthesis. *** = sig. at 1%, ** = sig. at 5%, and * = sig. at 10%.

[4]Our total sample is 19,763 observations, of which 8,736 are unique companies with repeated observations in the various versions of the surveys

Table 4: *Impact on Labor Productivity—Log Sales per Employee*

	(1)	(2)	(3)	(4)	(5)
Innovation	0,34***				
	(0,031)				
Expenditure (R&D) per employee		0,05***			
		(0,006)			
Simple strategy			0,16***	0,13 ***	-0,049
			(0,03)	(0,00)	(0,21)
Semi-complex strategy			0,23***	0,23 ***	0,007 *
			(0,04)	(0,00)	(0,07)
Complex strategy			0,28***	0,26 ***	-0,03
			(0,03)	(0,00)	(0,38)
Small	-0,45***	-0,44***	-0,45***	-0,42***	-0,46***
	(0,031)	(0,03)	(0,03)	(0,00)	(0,00)
Medium	-0,46***	-0,45***	0,46***	-0,43***	-1,14***
	(0,0)	(0,02)	(0,02)	(0,00)	(0,00)
Large	-0,51***	-0,48***	-0,53***	-0,47***	-2,34***
	(0,0)	(0,03)	(0,03)	(0,00)	(0,00)
Manufacturing				0,12***	
				(0,00)	
Service				0,24***	
				(0,00)	
2011				0,22***	
				(0,00)	
2013				0,23***	
				(0,00)	
2015				0,23***	
				(0,00)	
Obs	16.375	19.375	19.095	19.095	19.095
R2	0,021	0,023	0,021	0,027	

To compare whether productivity increases occur because of changes in sales or changes in employment, we present in Table 5 the results of equation (4). In this table, columns 1, 2, and 3 have as dependent variable the firm's sales (sales), and columns 4, 5, and 6 have as dependent variable the firm's employment level. For both estimates, the results show that innovation has a positive and significant effect on sales and employment compared to firms that do not innovate. In relation to the parameters obtained, the innovation decision has a greater effect on sales.

We analyze the robustness of the results presented in Table 3 assuming the existence of endogeneity. For this we perform 2 additional estimations of equation (5) using in one of them the predicted R&D expenditure and in another one we work the control function. The results presented in Table 3 show fewer statistically significant variables when compared to these 2 additional estimations, affecting the significance of the variables firm size, belonging to a group of companies and economic activity. The results of the 2 additional estimations are reported in Appendix B.

Table 5: *Impact on Labor Productivity—Log Sales per Employee*

	Log sales			*Log employment*		
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation	0,36***			0,13***		
	(0,00)			(0,00)		
Expenditure (R&D) per employee		0,27***			0,12***	
		(0,00)			(0,00)	
Simple strategy			0,26***			0,10***
			(0,00)			(0,00)
Semi-complex strategy			0,37***			0,12***
			(0,00)			(0,00)
Complex strategy			0,74***			0,16***
			(0,00)			(0,00)
Small	0,85***	0,86***	0,86***	1,46***	1,46***	1,45***
	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)
Medium	2,23***	0,24***	2,23***	2,84***	2,84***	2,85***
	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)
Large	4,44***	4,46***	4,43***	5,14***	5,14***	5,11***
	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)
Obs	19,622	19,622	19,622	19,139	19,139	19,139
R2	0,5	0,5	0,5	0,87	0,87	0,87

5. Discussion

Firms that decide to innovate seek to change or improve their competitive position. Measures of successful innovation include increased sales, entrance into a new market, strengthening of position in the industry, and adapting to changes in the environment (González-Blanco et al., 2019; Karlsson and Tavassoli, 2016). Empirical evidence shows that innovative firms perform better in some indicators than those that do not innovate (Abdu and Jibir, 2018; Tavassoli and Karlsson, 2016) as can be seen in columns 1, 2, and 3 of Table 4.

This paper discusses how firms choose an innovation strategy (simple, semi-complex, or complex) among 4 innovation options and 16 possible combinations. The four innovations include both technological and nontechnological innovations: product, process, organizational, and marketing innovations. Our analysis complements the discussion regarding the multiple innovation decisions (not binary) among heterogeneous firms. This heterogeneity reflects varying resources and capabilities among firms which leads them to choose different innovation strategies for profit maximization (Agwu et al., 2019; Anzola-Román et al., 2018; Carboni and Russu, 2018; Fazlıoğlu et al., 2019).

5.1. Firm Antecedents on Innovation Strategy

Firm characteristics have diverse effects on innovation decisions. Our results in Table 3 show that firms' effort to engage in R&D activities increases the probability of choosing any of the 15 possible strategies. Karlsson and Tavassoli (2016) used dichotomous variables to measure the development of internal and external R&D activities, showing that spending on R&D activities is only relevant in 12 strategies. Our results align with the findings of Carboni and Russu (2018) and García-Piqueres et al. (2020), who showed a positive and statistically significant effect of R&D spending on all types of innovation. Aboal and Garda (2016) found similar results, where the intensity of R&D expenditure positively affects the probability of including technological and nontechnological innovations.

Firm size is another way to approximate firm capabilities. Following Schumpeter (1942), we differentiated firms into four strata according to the number of employees. Our results in Table 3 for firm´s characteristics indicated that larger firms are more likely to innovate, especially using complex strategies, particularly in innovations that involve organizational innovation. This result is similar to Carboni and Russu (2018), Karlsson and Tavassoli (2016), Du et al. (2007), and Evangelista and Vezzani (2010); however, these papers do not differentiate by firm size.

In contrast to García-Piqueres et al. (2020), firm size has a positive and statistically significant effect on the probability of choosing organizational innovation in simple and complex strategies. Indeed, Anzola-Román et al. (2018) and Agwu et al. (2019) showed that medium-sized firms are likelier to choose organizational innovation. These strategies focused on knowledge management and searching for internal efficiency (Bartoloni and Baussola, 2018; Fazlıoğlu et al., 2019; Lee et al., 2019), as proposed by Černe et al. (2016), Cucculelli and Peruzzi (2020), Schubert (2010) and Plehn-Dujowich (2009). Furthermore, this finding is relevant for medium-sized firms in the growth process and must adapt their internal processes. We did not find significant evidence to support Álvarez et al. (2015), Arrow (1962a), and Plehn-Dujowich (2009), who hypothesized that small firms tend to focus on product innovation (Mardones and Zapata, 2019) as they face more competition and must seek a market niche through differentiation; however, our result is relevant for medium and large firms.

Skilled employees are a relevant resource for developing innovations; they allow firms to acquire knowledge more quickly and generate learning (Capozza and Divella, 2018; Milan et al., 2020). We define qualified employees in Table 3 and the results indicate only an increase in the probability of choosing innovation strategies, including organizational and product innovation (semi-complex and complex strategies). These results are consistent with the fact that organizational innovations involve knowledge management, which requires a higher level of training for developing specific tasks or greater technical knowledge (Damanpour and Aravind, 2011; Gallego et al., 2012; Sapprasert and Clausen, 2012). This result differs from previous studies showing the relevance of firms' human capital for innovation decisions. For example, Karlsson and Tavassoli (2016) showed that human capital can determine the choice of semi-complex and complex strategies, and Du et al. (2007) indicated that qualified employees decrease the probability of process innovation while increasing the likelihood of product innovation (when analyzing only technological innovations). Furthermore, Tavassoli and Karlsson (2015) showed that human capital positively affects the propensity to innovate.

Regarding firms' environment, some authors suggested that firms competing in domestic markets and are open to international trade should focus on product innovation (Bhattacharya and Bloch, 2004; García-Piqueres et al., 2020). In contrast, our results for the environment variable in Table 3 suggest that competition in foreign markets increases the probability of choosing simple and semi-complex strategies involving product innovation and semi-complex nontechnological strategy. Our results are similar to Crespi and Zuniga (2012) on Chilean exporting firms and Aboal and Garda (2016) on Uruguayan manufacturing firms; they found that these types of firms are less likely to develop technological innovations (including process innovation) and nontechnological innovations. Furthermore, Agwu et al. (2019) showed how African exporting firms choose among the four types of innovations. As shown, the literature has mixed results. Others suggested that exporting firms should innovate in product and marketing (García-Piqueres et al., 2020) or process innovation (Carboni and Russu, 2018).

Karlsson and Tavassoli (2016) showed that belonging to a group of firms shows few significant results. Conversely, we observed that firms belonging to a group are more likely to develop semi-complex and complex strategies that include organizational innovation and the complex strategy of all innovations. Firms belonging to groups tend to be larger, which can be explained by Schumpeter's proposal that larger firms have greater access to financing and capabilities to replicate and complement innovation strategies across multiple companies within the group. García-Piqueres et al. (2020) showed that firms belonging to a group of companies are more likely to innovate in products than in marketing; however, Agwu et al. (2019) found that they are more likely to engage in organizational innovation and are less likely to innovate in products.

Manufacturing firms are generally characterized as capital-intensive firms that produce goods generally opt for innovation in products and marketing (Evangelista and Vezzani, 2010; Geldes et al., 2017; Mothe and Nguyen-Thi, 2012, 2013); however, our results in Table 3 show a lower probability of developing process innovation and nontechnological innovation. All the same, other authors showed that manufacturing firms are more likely to choose a complex strategy. Karlsson and Tavassoli (2016) found that manufacturing firms are generally more likely to select complex strategies. In contrast, our results showed that manufacturing firms are more likely to choose only the complex strategy that combines all four types of innovation. Firms in the service sector are more likely to choose a nontechnological innovation strategy plus process innovation (Szczygielski et al., 2017), allowing them to be more efficient in internal processes and improve responsiveness to customers.

Finally, this paper's novel result indicates that the higher the strategy's complexity, the higher the sales per employee. As it is possible to see in column 3 of Table 3 these coefficients increase monotonically from simple to semi-complex to complex strategies. Table 5 complements this result and shows that firms that innovate have an increase in sales higher than the increase in employment. Monotonic growth is noted when differentiating by type of strategy. No other papers have evaluated these strategies to compare our results.; the closest articles found very implausible results. Crespi and Zuniga (2012) and Aboal and Garda (2016) found a negative impact of nontechnological innovations. In the specific case of Chile our results differ from those of Crispi. Appendix H shows the results obtained by replicating Crespi's estimation and we obtained positive and significant results for all innovation, because we have included all possible combinations of innovations and we do not differentiate only between technological and nontechnological innovation.

5.2. Limitations

This study has some limitations that should be considered when interpreting and applying its findings. First, similar to how Eurostat's CIS has been utilized in innovation strategy research, the Chilean Innovation Survey has limitations, such as single firm responses, potential inaccuracy in survey answers, and availability of control variables. Future research can use more granular data on innovation strategy to enrich this paper's results, including the capital variable in the productivity equation. Second, our sample only includes Chilean firms; however, our results are primarily aligned with previous studies based on European country samples. Confirmations on data from countries (after considering endogeneity issues) outside this study are recommended. Finally, further examinations of firm characteristics on innovation strategy from a dynamic lens could reveal changes in the type of innovation combinations that firms choose to implement over time.

6. Conclusions

Extensive literature has analyzed the determinants of innovation decisions at the firm level. This study extended this discussion to explore the determinants of product, process, organizational, and marketing innovations; however, given the heterogeneity of firms, especially in the level of access to resources available for the development of innovations, it is relevant to analyze the possibility of joint development of innovations.

We consider the possibility of complementarity in the use of resources, and the resulting joint development of innovations, to analyze the firms' choice of innovation strategy from the 16 possible combinations with the 4 innovation types. This discussion used a set of variables that characterize a firm's resources and environment to analyze their impact on the choice of innovation strategy, including agricultural, manufacturing, and service firms.

Using a multinomial logit model, we analyzed the characteristics of the firms that determine the probability of choosing an innovation strategy compared to the baseline scenario of no innovation. The main result shows that regardless of the strategy (simple, semi-complex, or complex), the expenditure in R&D per employee is relevant for deciding on any possible innovation strategies.

Considering the heterogeneity of firms' resources, firms that have more skilled employees opt for innovation strategies that include organizational innovation. Medium-sized firms tend to choose strategies that include organizational innovation and process innovation. Large firms tend to choose complex innovation strategies given their ability to generate economies of scale in the utilization of resources. A firm facing large external markets must focus on a product strategy to adapt to external customers' requirements and does not seek internal efficiency with a process innovation strategy.

A novel result of this paper is that the higher the complexity of the strategy is, the higher the sales per employee are; these coefficients increase monotonically from simple to semi-complex to complex strategies. Our results are more plausible than those found in previous literature.

For managers, these results imply that firm heterogeneity should not be a constraint for developing innovations. Instead, it should be an opportunity to focus decision-making efforts on innovations that can obtain a higher return given the resources used. Despite the relevance of R&D activities, firms should not necessarily focus on only one type of innovation (often either product or process innovation) but consider complementarity decisions, which can occur given the firm's resources or growth stage. By reducing the possibility of imitation, combining innovation strategies also contributes to developing a competitive advantage.

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A. Appendix A

We ran an auxiliary regression for R&D expenditure using using three instruments: cooperation in R&D with other firms, patent protection, and their product of them. We used these instruments to estimate a multinomial logit model using the prediction of the endogenous variables, similar to a 2SLS approach, and the multinomial logit using the control function approach.

Variable	**Parameter**
Age	0,03
	(0,024)
Qualifield employment	0,46 ***
	(0,04)
Small	0,26***
	(0,05)
medium	0,57***
	(0,04)
Large	0,53 ***
	(0,05)
Export	0,45 ***
	(0,05)
Group	0,17***
	(0,04)
Manufacturing	0,06
	(0,06)
Service	0,06
	(0,05)
Patent	2,55 ***
	(0,12)
Cooperation	3,67 ***
	(0,08)
Patent*cooperation	-2,23 ***
	(0,22)

Notes: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The control function (Guevara and Ben-Akiva, 2006, 2012) indicates that it is possible to perform a linear projection between the errors of the auxiliary regression and the primary regression as follows:

$$\mu_{ijt} = \varepsilon_{ijt}^{'}\alpha + e_{ijt}$$

where μ_i is the error in the estimation of the multinomial logit model and, under the use of instrumental variables, must be satisfied that $E(Z_i\mu_i) = 0$. Endogeneity is given by the variable in the set X_i, R&D expenditure per employee, but it is not correlated with e_i; therefore, the estimation error obtained in the auxiliary regression can be incorporated into the main equation as an explanatory variable (Hansen, 2022). Since the panel fixed-effect multinomial logit model is robust to endogeneity, the three approaches should provide similar results.

Once we have estimated the RD function (equation (6)), we obtain the predicted of the dependent variable ($\widehat{RD}$) and then the residual of equation (6). We use this residual ($\widehat{e_{ijt}}$) as the explanatory variable in equation (5).

B. Appendix B

Table B1: *Result multinomial logit with predict R&D expenditure per employee*

Strategy	P	Pr	O	M	P+O	P+Pr	P+M	Pr+O	Pr+M	O+M	P+Pr +O	P+Pr +M	P+O +M	Pr+O +M	P+Pr +O+M
	343	742	614	397	133	354	94	492	149	278	395	146	139	453	865
Age	-0.14***	0.01	-0.04	-0.06	0.20	-0.05	0.15	-0.06	-0.01	-0.06	0.01	0.01	-0.05	-0.10	-0.06
	(0.06)	(0.05)	(0.05)	(0.07)	(0.12)	(0.007)	(0.14)	(0.06)	(0.11)	(0.08)	(0.07)	(0.11)	(0.11)	(0.06)	(0.05)
Qual. Employ	0.45***	0.12	0.65**	0.26*	1.00***	0.40**	-0.02	0.21	0.35	0.57	0.69***	0.02	0.56***	0.60***	0.64***
	(0.14)	(0.11)	(0.12)	(0.14)	(0.26)	(0.16)	(0.32)	(0.14)	(0.24)	(0.17)	(0.15)	(0.25)	(0.25)	(0.14)	(0.11)
Small	0.21	0.46***	0.57***	0.08	0.56*	0.15	0.40	0.61***	0.61**	0.39	0.49**	0.27	0.54	0.31*	0.41***
	(0.15)	(0.13)	(0.15)	(0.15)	(0.33)	(0.18)	(0.41)	(0.20)	(0.29)	(0.20)	(0.21)	(0.30)	(0.34)	(0.17)	(0.14)
Medium	0.07	0.54***	0.90**	0.04	0.69**	0.14	0.52	1.12***	0.63**	0.47	0.83***	0.05	0.57***	0.41***	0.34***
	(0.14)	(0.11)	(0.13)	(0.14)	(0.30)	(0.16)	(0.35)	(0.17)	(0.27)	(0.18)	(0.18)	(0.27)	(0.30)	(0.15)	(0.12)
Large	0.09	0.66***	1.32***	0.14***	0.90***	0.39***	0.68*	1.49***	0.88***	0.62	1.19***	0.49	1.34***	0.68***	0.88***
	(0.17)	(0.14)	(0.15)	(0.17)	(0.34)	(0.19)	(0.39)	(0.18)	(0.31)	(0.21)	(0.20)	(0.30)	(0.32)	(0.17)	(0.13)
Exp. R&d per	0.74***	0.64***	0.62***	0.62***	0.78***	0.84***	0.91***	0.73***	0.72***	0.72***	0.96***	0.99***	0.92***	0.82***	1.04***
employee	(0.04)	(0.03)	(0.04)	(0.05)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.05)	(0.03)	(0.05)	(0.05)	(0.03)	(0.03)
Export	0.72***	0.29***	-0.08	0.58***	0.62***	0.55	0.75***	-0.19	0.32	0.49***	0.07	0.91***	0.47*	0.22*	0.28***
	(0.12)	(0.10)	(0.12)	(0.14)	(0.21)	(0.13)	(0.25)	(0.13)	(0.22)	(0.16)	(0.14)	(0.20)	(0.22)	(0.13)	(0.10)
Group	-0.24***	0.06	0.10	-0.005	-0.27	-0.05	0.11	0.24**	-0.18	-0.05	-0.23**	-0.30	0.11	0.16	0.15***
	(0.11)	(0.08)	(0.09)	(0.11)	(0.19)	(0.12)	(0.22)	(0.10)	(0.19)	(0.13)	(0.11)	(0.19)	(0.18)	(0.10)	(0.08)
Manuf	0.55***	-0.38***	-0.04	0.99***	0.34	0.26	0.65	-0.11	0.75**	1.03***	0.10	1.49***	2.54**	0.38*	1.18***
	(0.19)	(0.11)	(0.15)	(0.27)	(0.33)	(0.19)	(0.44)	(0.15)	(0.36)	(0.35)	(0.18)	(0.47)	(1.01)	(0.20)	(0.19)
Service	-0.30	-0.55***	-0.06	1.32***	0.25	0.018	0.98***	-0.34**	0.61*	1.48***	0.006	1.60***	3.24***	0.62*	1.28***
	(0.19)	(0.11)	(0.15)	(0.27)	(0.34)	(0.19)	(0.44)	(0.15)	(0.36)	(0.34)	(0.18)	(0.47)	(1.02)	(0.20)	(0.19)

Notes: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B2: *Result multinomial logit with control function*

Strategy	P	Pr	O	M	P+O	P+Pr	P+M	Pr+O	Pr+M	O+M	P+Pr +O	P+Pr +M	P+O +M	Pr+O +M	P+Pr +O+M
	343	742	614	397	133	354	94	133	149	278	395	146	139	453	865
Age	-0.513**	-0.006	-0.05	-0.06	0.16	-0.08	0.11	-0.10	-0.03	-0.07	-0.02	-0.01	-0.12*	-0.91	-0.10*
	(0.07)	(0.05)	(0.05)	(0.07)	(0.12)	(0.07)	(0.14)	(0.06)	(0.11)	(0.08)	(0.07)	(0.12)	(0.07)	(0.29)	(0.05)
Qual. Employ	0.26*	-0.11	0.53***	0.09	0.82***	-0.13	-0.29	-0.008	0.10	0.41***	0.45***	-0.30	0.37**	0.85	0.37***
	(0.15)	(0.12)	(0.12)	(0.15)	(0.27)	(0.17)	(0.33)	(0.15)	(0.26)	(0.18)	(0.17)	(0.27)	(0.15)	(0.41)	(0.12)
Small	0.26*	0.055***	0.60***	0.10	0.63	0.28	0.49	0.70***	0.70**	0.42***	0.61***	0.41	0.40**	0.62*	0.55***
	(0.16)	(0.14)	(0.16)	(0.16)	(0.34)	(0.19)	(0.41)	(0.20)	(0.30)	(0.21)	(0.22)	(0.30)	(0.18)	(0.81)	(0.15)
Medium	0.08	0.59***	0.9***	0.03	0.72***	0.23	0.57	1.18***	0.68**	0.47***	0.92***	0.17	0.64**	0.48***	0.48***
	(0.15)	(0.12)	(0.14)	(0.14)	(0.30)	(0.17)	(0.36)	(0.17)	(0.27)	(0.18)	(0.19)	(0.28)	(0.15)	(0.97)	(0.14)
Large	0.17	0.81***	1.34***	0.16	1.02***	0.64***	0.84**	1.65***	1.04***	0.66***	1.43***	0.72***	1.53***	0.86***	1.19***
	(0.18)	(0.15)	(0.15)	(0.18)	(0.35)	(0.20)	(0.41)	(0.19)	(0.32)	(0.22)	(0.21)	(0.31)	(0.18)	(1.05)	(0.15)
Exp. R&d per	1.12***	1.04***	0.94***	0.97***	1.17***	1.28***	1.33***	1.12***	1.13***	1.07***	1.39***	1.45***	1.33***	1.24***	1.50***
employee	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)	(0.04)	(0.07)	(0.04)	(0.07)	(0.05)	(0.04)	(0.06)	(0.04)	(0.05)	(0.03)
Residual exp. Per	0.625***	0.65***	0.52***	0.56***	0.64***	0.73***	0.68***	0.65***	0.68***	0.57***	0.71***	0.76***	0.69***	0.69***	0.76***
employee	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Export	0.55***	0.08	-0.20	0.44***	0.45***	0.32***	0.55**	-0.39***	0.12	0.35***	-0.13	0.68***	0.27	0.01	0.04
	(0.13)	(0.11)	(0.12)	(0.14)	(0.22)	(0.14)	(0.25)	(0.14)	(0.22)	(0.17)	(0.14)	(0.21)	(0.14)	(0.67)	(0.11)
Group	-0.15	0.0005	0.17*	0.08	0.20	0.008***	0.17	0.30***	0.11	0.02	-0.17	-0.27	0.17	0.24**	0.20**
	(0.12)	(0.009)	(0.09)	(0.12)	(0.20)	(0.13)	(0.23)	(0.10)	(0.19)	(0.14)	(0.12)	(0.19)	(0.11)	(0.44)	(0.09)
Manuf	0.72***	-0.21	0.13	1.12***	0.49	0.49***	0.83*	0.02	0.93**	1.16***	0.27	1.73***	2.70***	0.57***	1.38***
	(0.2)	(0.13)	(0.16)	(0.28)	(0.34)	(0.20)	(0.45)	(0.16)	(0.36)	(0.35)	(0.19)	(0.47)	(0.21)	(1.2)	(0.20)
Service	0.5**	-0.34***	0.17	-1.48***	0.43	0.27	1.21***	-0.15	0.83**	1.64***	0.21	1.88***	3.45***	0.84***	1.52***
	(0.20)	(0.13)	(0.15)	(0.27)	(0.34)	(0.20)	(3.71)	(1.16)	(0.37)	(0.02)	(0.19)	(0.48)	(0.21)	(1.4)	(0.20)

Notes: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The results in Table B1 show the positive and significant effect of spending on R&D activities for any innovation strategy developed by the firm. Medium and large firms are more likely to engage in semi-complex and complex strategies involving process and organizational innovations, while small firms are more likely to engage in simple semi-complex strategies. Employees have a positive and significant effect on simple and semi-complex strategies involving organizational innovation and on developing complex innovations. Exporting firms are more likely to develop strategies involving product and marketing innovation, while firms in the manufacturing and service sectors are more likely to engage in simple marketing or complex strategies.

When we look at the results of the multinomial logit with control function we see changes in the significance of firm age, which now has an effect on the decision of a complex innovation strategy. While for skilled employees the changes are presented in that now the significance is maintained in those strategies that involve technological innovations with organizational innovation. In the situation of exporting firms, they develop product innovations with marketing and organizational innovation.

C. Appendix C

Table C1: *Tobit model*

ID (probability of investing in innovation IE>0)	**Parameter**
Exporting	0.05
	(0.05)
Patent protection	0.34***
	(0.08)
Small	0.05
	(0.07)
Medium	0.24***
	(0.06)
Large	0.30***
	(0.07)
IE (ln innovation expenditure per employee)	
Exporting	0.30***
	(0.11)
Patent	0.23
	(0.17)
Cooperation in R&D	0.56***
	(0.12)
Market information sources (INFO 1)	7.72***
	(0.18)
Scientific sources (INFO 2)	-0.79***
	(0.15)
Other spillovers (INFO 3)	3.66***
	(0.19)

Notes: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The results of the tobit model show that medium and large firms and those that use patents are more likely to spend on R&D activities. While the highest spending on R&D activities occurs in firms that export, develop R&D cooperation activities and use market information sources with respect to those that do not carry out this type of activities, the results of the tobit model show that medium and large firms are more likely to spend on R&D activities.

D. Appendix D

Table D1: *Impact on Labor Productivity—Log Sales per Employee – by type of strategy*

Y = LN sales per employee	
Product	-0.049
	(0.48)
Process	0.18***
	(0.00)
Organizational	0.19***
	(0.00)
Marketing	0.31***
	(0.00)
Product + Organizational	0.15
	(0.21)
Product + Marketing	0.55***
	(0.00)
Process + Organizational	0.31***
	(0.00)
Process + Marketing	0.16
	(0.18)
Product + Process	0.17**
	(0.02)
Marketing + Organizational	0.16*
	(0.06)
Product + Organizational + Marketing	0.23*
	(0.06)
Process + Organizational + Marketing	0.38***
	(0.00)
Product + Process + Organizational	0.12*
	(0.08)
Product + Process + Marketing	0.23*
	(0.05)
Product + Process + Organizational + Marketing	0.30***
	(0.00)
Small	-0.45***
	(0.00)
Medium	-0.46***
	(0.00)
Large	-0.54***
	(0.00)
Observations	19,095

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

E. Appendix E

For the definition of the innovation strategy of a firm, we have followed the work of Karlsson and Tavassoli (2016). Given the possibility of developing 4 types of innovations: product, process, organizational and marketing, innovation strategies are defined according to the possible combinations of these types of innovations. Given this, firms have 16 possible strategies to decide on and this includes the option of not innovating (which in our paper is the base decision for comparison). After that we have defined as simple strategy when a firm develops only one type of innovation, semi complex strategy when the firm develops 2 types of innovation and a complex strategy is when the firm develops 3 or 4 types of innovation.

F. Appendix F

Table F1: *Multinomial logit results for aggregated strategies*

Strategy	**Single Strategies**	**Semi-complex Strategies**	**Complex Strategies**
Firm ´s characteristics			
Ln age	-0.26*	-0.33*	-0.49***
	(0.13)	(0.18)	(0.17)
Qual. Employ	0.33*	0.15	0.60***
	(0.18)	(0.22)	(0.23)
Small	0.77**	0.94*	0.48
	(0.34)	(0.49)	(0.44)
Medium	1.02***	1.39***	1.27***
	(0.32)	(0.51)	(0.47)
Large	1.11***	1.81***	1.86***
	(0.38)	(0.55)	(0.52)
Ln(R&D)	0.57***	0.63***	0.71***
	(0.03)	(0.03)	(0.03)
Firm ´s environment			
Export	0.32	0.71*	0.21
	(0.28)	(0.35)	(0.33)
Group	0.30*	0.52**	0.68***
	(0.17)	(0.21)	(0.22)
Economic activity			
Manuf	-0.95*	-0.78	-0.40
	(0.51)	(0.67)	(0.75)
Service	-0.85*	-1.40*	-0.03
	(0.51)	(0.77)	(0.81)

G. Appendix G

Table G1: *Relative Risk Ratio for single strategy*

Strategy	**Variable**	**RRR**
Product	Large	7.33**
		(0.02)
	Ln(R&D)	1.91***
		(0.00)
	Export	3.55**
		(0.04)
Process	Ln(R&D)	1.94***
		(0.00)
	Service	0.21**
		(0.03)
Organizational	Qual. Employment	2.08**
		(0.01)
	Medium	6.9***
		(0.00)
	Large	5.6**
		(0.01)
	Ln(R&D)	1.66***
		(0.00)
Marketing	Ln(R&D)	1.68***
		(0.00)

Notes: In parenthesis p-value *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table G2: *Relative Risk Ratio for semi-complex strategy*

Strategy	**Variable**	**RRR**
Process + Organizational	Large	15.7**
		(0.02)
	Gasto	1.74***
		(0.00)
	Export	5.49***
		(0.00)
Product + Marketing	Ln(R&D)	1.75***
		(0.00)
Process + Organizational	Medium	6.9**
		(0.03)
	Large	7.7**
		(0.03)
	Ln(R&D)	1.95***
		(0.00)
Process + Marketing	Ln(R&D)	2.11***
		(0.00)

Strategy	**Variable**	**RRR**
Product + Process	Medium	57.3***
		(0.00)
	Large	92.2***
		(0.00)
	Ln(R&D)	1.96***
		(0.00)
	Group	3.6***
		(0.00)
Organizational + Marketing	Qual. Employ.	3.07***
		(0.03)
	Ln(R&D)	1.8***
		(0.00)
	Export	4.16**
		(0.03)
	Group	0.04**
		(0.03)
Product + Organizational + Marketing	Ln(R&D)	2.2***
		(0.00)
Process + Organizational + Marketing	Age	0.39***
		(0.00)
	Ln(R&D)	2.23***
		(0.00)
Product + Process + Organizational	Medium	13.06***
		(0.00)
	Large	28.31***
		(0.00)
	Ln(R&D)	2.07***
		(0.00)
Product + Process + Marketing	Ln(R&D)	2.27***
		(0.00)
Product + Process + Organizational + Marketing	Age	0.57**
		(0.01)
	Ln(R&D)	2.09***
		(0.00)
	Group	4.2***
		(0.00)

H. Appendix H

Table H1: *Impact en labor productivity – log sales per employee*

	(1)	(2)
Tech innovation	0.95***	
	(0.00)	
Expenditure per employee		0.07***
		(0.00)
Size	-0.10***	-0.11***
	(0.00)	(0.00)
No-tech innovation	0.089**	0.031
	(0.04)	(0.47)
obs	19025	19,025
R2	0.0043	0.024

In parenthesis p-value. *** sig. al 1%, ** sig. al 5%, * sig al 10%