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Heterogeneous effects of financial constraints on innovation: Evidence from Chile

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In this paper we study the effect of financial constraints on innovation using data from a 2007 survey of more than 10,000 Chilean firms. In contrast with other surveys, this dataset allows for the construction of a direct indicator of constraints on credit for investment in innovation and sheds light on how these restrictions affect firm's innovation outcomes heterogeneously. In our empirical approach, we deal with several econometric problems associated with the endogeneity of the credit constraint indicator and the binary nature of the innovation variable. We find that financial constraints are quantitatively important barriers for innovation in Chile. These constraints are particularly severe in the case of small firms and firms operating in the service sectors. We also find that these constraints are specific to innovation-related investments and particularly with regard to the accumulation of intangible assets.

Keywords: financial constraints; innovation; size of firm.

1. Introduction

In the knowledge-based economy, the capacity of firms to generate and assimilate new technology is unanimously recognized as the main engine of growth in productivity. Despite that, important gaps persist in the innovation performance of Latin American firms. They not only invest less on innovation than firms in developed countries, but they also invest significantly less in R&D. Thus, it is not surprising that there are also persistent gaps in innovation outcomes such as patents or the technological content of exports (Inter-American Development Bank 2010a,b).

However, the presence of innovation gaps is not enough to justify policy interventions. Indeed, the fundamental premise for innovation policies is that government intervention would be necessary if profit-driven actors underperform with regards to the production and/or exchange of technological knowledge from a social welfare perspective (Steinmueller 2010). From this perspective, policy intervention emerges from the need to correct market failures. Despite the fact that the majority of regional policy frameworks recognize the presence of different market failures that might hinder innovation, surprisingly little progress has been made to properly account for such failures.

In this paper we move a step in this direction by trying to understand whether access to credit is an important driver of the low propensity to innovate in developing countries. We use a novel dataset covering all industries and sizes of firms in the Chilean economy which allow us to investigate the heterogeneous effects of financial constraints by size of firm, industry and type of innovation. Following previous works on this issue, we employ a direct and self-reported measure of financial obstacles for innovation as our key focus and deal with this variable's endogeneity.

Our results show consistent evidence that financial constraints reduce innovation in Chile. Moreover, we find that dealing with this variable's endogeneity is crucial for uncovering the negative relationship between innovation and access to credit. Our evidence complements previous findings for some developed economies (Savignac 2008; Mohnen et al. 2008), and is one of the first studies to use this empirical approach for a developing country.

We extend the previous studies in several dimensions. First, we exploit the richness of our dataset to analyze the relationship between innovation and finance across the size of firms and the industries. We find that financial constraints are very important for innovation in Chile, and that they are particularly severe in the case of small firms and those operating in the non-traditional service sectors. Second, we analyze whether self-reported financial constraints are specific to innovation or if they are capturing overall problems of access to credit. We find that these constraints are specific to innovation-related investments, particularly with regards to the accumulation of intangible assets. Third, we look at heterogeneous effects across types of innovation outcomes and inputs. Our results show that financial constraints have more impact on product innovation and R&D investment.

The remainder of this paper is organized as follows: Section 2 discusses the theoretical background and main questions addressed in this literature. Section 3 presents the dataset and the main facts about innovation and financial constraints in the Chilean economy. Section 4 develops the theoretical framework and our empirical methodology. Section 5 presents the main results and those across firms, industries and alternative measures of innovation. Finally, Section 6 draws our conclusions.

2. Theoretical background

That constraints on credit could severely harm innovation is well established in the field of the economics of innovation.[1] Innovation is the result of investment in knowledge, and there are several specific attributes of knowledge that might have important impacts on the financing of innovation. First, since the seminal work by Nelson (1959) and Arrow (1962), scientific and technological knowledge has been defined as a durable (semi) public good (i.e. non-excludable and non-rival). This means that firms may be unable to exclude others from using the innovations they create. Although the (semi) public-good nature of knowledge is the primary reason why firms underinvest in innovation, it also plays an important role in the financing of innovation.

A second attribute is that knowledge investments produce an intangible asset that may be very difficult to use as collateral. Indeed, the wages of the engineers and technicians working in a firm are an important share of the investment in knowledge. Banks prefer to use physical assets to secure loans and may be reluctant to lend when the project involves the accumulation of intangible assets that are partially embodied in the firm's human capital since such investments can be lost whenever employees quit the organization or are fired.

A third attribute of knowledge investments is that they have tacit components that are very idiosyncratic to the firm. That means that a potentially substantial share of these investments is sunk and cannot be easily deployed in other activities (Sutton 1991).

A fourth and final attribute of knowledge investment is the uncertainty associated with its outputs. This is related to the lack of a well-defined probability distribution of potential impacts. In this context, knowledge investment has an option value, implying that some projects with very small probabilities of success may be worthy of pursuit even if they do not pass an *ex-ante* cost–benefit analysis (Hall and Lerner 2010).

The above-mentioned knowledge attributes have very important impacts at the moment of financing innovation because they exacerbate the resources gap that normally exists whenever the investor and financier are different entities. There are two conceptual reasons for this gap. Both are a result of the asymmetric information that mediates the relationship between innovators and external investors: adverse selection and moral hazard.

The information economics literature clearly shows that the problem of asymmetric information is generated by the fact that an inventor frequently has better information about the quality of an innovative project than do the external investors (Stiglitz and Weiss 1981). In this case investors will charge a premium to provide access to external financing because of the difficulty in distinguishing between good and bad projects and the need to use the returns from good projects to pay for losses made on funding bad ideas. This leads to a problem of adverse selection because increasing interest rates worsen applicant quality. This prevents the interest rate from clearing the market, thus producing credit rationing.

Although the asymmetric information problem can harm access to credit for all types of investment, it is expected that impacts will be higher in the case of knowledge investments. For example, because of the problem of incomplete appropriability, innovators are reluctant to share information about their projects with outside investors. This, together with the intangible nature and extreme uncertainty of knowledge investments, exacerbates problems of access to credit. In summary, asymmetric information drives a wedge between the opportunity cost that private innovators require of their innovation investments and the capital cost that external investors are willing to lend to finance innovative projects, which eventually leads to credit rationing. The result will be that private (and eventually social), profitable innovation projects will not materialize.

The second conceptual issue is the moral hazard problem that emerges from the separation between investors and managers (Hall and Lerner 2010). The manager's effort determines the likelihood of an innovation project's success, but this effort is unobservable to the bank. In this scenario, the manager has the incentive to expend effort up to the point where its marginal cost equals its marginal benefit, which is given by the marginal increase in the innovation project's expected net returns on interest payments. As the firm's debt increases and more of the gains go to the bank, the net marginal benefit of the effort falls. Knowing this, the bank will set a ceiling on the firm's capacity to obtain external financing. In the case of innovation projects, the typical uncertainty that surround these investments makes the moral hazard problem worse, which can result in innovation strategies that do not maximize share value. For example, managers may be willing to pursue technological trajectories that will increase their reputation but not the company's profits.

The implication that the adverse selection and the moral hazard problems lead to constraints on credit has led to a straightforward test for their presence.[2] If internal funds have lower capital cost than external funds, it should be expected that investment in knowledge will be responsive to the availability of internal funds. In other words, a natural test for constraints on credit would be to estimate the elasticity of innovation to cash flow. This theory predicts that in the presence of constraints on credit, the elasticity should be positive and higher than in the case of normal investments. However, one problem with this approach is that cash flow is also correlated with future productivity and growth in demand. These two variables are unobservable and their positive correlation with cash flow might overstate the relative importance of constraints on credit. For this reason, instrumental variables are needed to identify the causal effect of cash flow on investment.

Several empirical implementations of this test have been undertaken. The majority of them show a positive and significant correlation between cash flow and knowledge investments (particularly R&D), and that this correlation tends to be stronger for new and technology-based firms. However, the same results also show that there is very little evidence of the extent to which R&D investment is more severely credit constrained than normal investments (Mulkay et al. 2001). The same literature also shows that cash flow predicts R&D investment strongly in the UK and the USA, but not in other European countries or Japan, suggesting the importance of differences in the institutional factors that regulate financial markets (Hall and Lerner 2010). Evidence about differences across countries is also provided by Cincera and Ravet (2010), showing that the sensitivity of R&D investments to cash flow variations are important for European firms but not for US firms.

Evidence of the impacts of constraints on credit on investments in innovation in developing countries is very scarce mainly due to a lack of available data. Previous empirical approaches suffer from two serious limitations. First, the identification of the impact of constraints on credit depends strongly on model specification and the availability of instrumental variables correlated with cash flow shocks. Second, the identification is even more problematic due to the strong persistence of R&D investments.[3] This requires having access to panel data and also using econometric techniques that take the time series characteristics of R&D investments into consideration (Blundell and Bond 1998). Unfortunately this kind of data is not normally available for developing countries.[4]

Given the identification problems with the standard approach and the increasing availability of innovation survey data, several papers have exploited an alternative approach based on direct measures of the credit constraints. Savignac (2006) estimated the importance of constraints on credit for innovative projects in a sample of French manufacturing firms by using a qualitative indicator based on firms' own assessment of the existence of financial constraints. Combining this qualitative information with balance sheet data of the firm's financial structure, she found that firms with innovative projects face financial constraints that significantly reduce the likelihood that they will implement their innovative investment.

Savignac (2008) examined the impact of financial constraints on innovation for the same sample of French firms. She used the same qualitative indicator based on firms' self-assessment of the credit constraint problem and found that financial constraints significantly reduce the likelihood that firms undertake innovative activities. More recently, Mancusi and Vezzulli (2010), using a sample of Italian small and medium-sized enterprises (SMEs), found that, when controlling for endogeneity, there are significant negative effects from credit constraints on the probability of setting-up R&D facilities. This effect on this variable is far more important that the impact on R&D investment levels.

With regards to developing countries, Gorodnichenko and Schnitzer (2010) used data from the Business Environment and Enterprise Performance Survey for a broad array of sectors and countries in Eastern Europe and the Commonwealth of Independent States. They found that financial constraints restrain the ability of domestically owned firms to innovate and export and thus to catch up technologically. They also found that innovative firms are more likely to be affected by financial constraints, thus instrumental variable techniques are used to identify the impacts of such constraints.

Our approach is also based on the use of a qualitative indicator of constraints on credit. The main research questions that we address in our empirical sections are:

(i) Whether constraints on credit hinder innovation in a developing country such as Chile.
(ii) Whether these effects are higher for SMEs.
(iii) Whether the severity of constraints on credit vary across different economic sectors.
(iv) Whether financial constraints are relatively more important for intangible investments.

3. Data source

The data for this empirical analysis come from the first version of the Enterprise Longitudinal Survey with information for 2007 (see Table 1). In contrast with other surveys used in the innovation literature, the sample in that survey is stratified according to both industry and size for all formal firms. The number of firms surveyed was 10,011, which is much larger than available information in other innovation surveys in Chile. Table 1 shows the distribution of firms according to industry and size using population weighting factors. The most important sector is retail with almost 38% of the observations, followed by real estate, community services, and agriculture, each with around 10–12% participation. A small percentage of firms (less than 1%) are in mining and utilities. Regarding size, micro-firms represent more than 80% and small firms around 15% of the sample. Medium and large firms account for 2.2% and 1.1%, respectively.[5]

The survey has a special module that asks about innovation activities, public support for these activities, and the identification of the main obstacles to innovation. We define a firm as innovating by using the answers to five types of innovations (products, services, process, organization management, and marketing). A dummy variable for innovation takes the value 1 if the firm says it has introduced at least one of these five types of innovation during 2007.[6] Table 1 shows the average of this variable by industry and size of firm. The probability of innovation is about 15–30% across industries, with higher percentages in the manufacturing industries (30.6%) and lower percentages in the transportation and communications sectors (15.3%). In the case of size, we find a positive relationship with innovation. Large and medium firms have a propensity to innovate of 61.3% and 46.0%, respectively. In contrast, innovating micro- and small size firms represent 18.4% and 30.9%, respectively.

Table 1. Firms' distribution, propensity to innovate and incidence of financial constraints by industries and size

Industry/size of firm	Number of firms (%)	Propensity to innovate (%)	Financial constraints (%)
Agriculture	10.3	22.1	42.1
Mining	0.4	18.8	39.4
Manufacturing	7.8	30.6	46.9
Utilities	0.3	25.8	30.7
Construction	5.6	19.9	44.0
Retail	37.9	18.5	41.2
Hotels and restaurants	4.5	22.0	39.0
Transportation and communications	7.3	15.3	44.2
Financial services	1.5	19.8	16.2
Real estate	12.6	22.0	30.9
Community services	12.0	26.5	42.8
Micro	82.0	18.4	42.1
Small	14.8	30.9	34.7
Medium	2.2	46.0	27.8
Large	1.1	61.3	19.3

Source: Enterprises Longitudinal Survey (2007).

This survey allows us to define a direct measure of constraints on credit for innovation. Firms are asked to identify the main two factors (from a specific list of eight closed and one open alternatives) that they perceive as obstacles or disincentives to innovation. We define a firm to be credit constrained if the factor: 'difficulty for obtaining adequate financing' is one of their two main obstacles to innovation. Table 1 shows the incidence of credit constraints across industries and sizes of firms. Around 40% of the firms have experienced significant obstacles to financing innovation. The incidence is higher in the manufacturing industry (46.9%) and lower in financial services (16.2%). The evidence across size shows a negative relationship with financial constraints. The incidence of this obstacle to innovation is 19.3% for large firms and 42.1% for micro-firms.

Table 2 summarizes the main variables used in the analysis. Our main dependent variable is a firm's propensity to innovate, which is 21% for the total sample. We also present the propensities for a more narrow definition of innovation: technological products and/or process innovation. About 10% of the firms have product innovations, and only 7% have process innovations. We also show information on innovation investments, which include tangible investments (machinery and equipment), information and telecommunication technologies (ICTs), and R&D. Table 2 shows that, although 13% of the firms invested in machinery and equipment, fewer than 5% invested in ICTs and only 0.2% invested in R&D.

We present information for two variables related to constraints on credit. One is our preferred variable regarding financial obstacles to innovation. This variable indicates that about 40% of the firms report suffering from financial constraints which are directly related to innovation. We also define an alternative and more standard definition for financial constraint from a question in the survey asking whether the firm had recently been denied credit by the banking system. This was the case for 14% of the firms surveyed.

The bottom half of Table 2 shows the descriptive statistics for the main covariates. For our empirical specification we selected those variables that the previous literature suggests are the most relevant for explaining both the decision to innovate and the probability that the firm is credit constrained with regards to innovation. Among the first set of covariates we include: firm's market share, manager's age, firm's age,[7] the manager's educational level (a dummy equal to 1 for a university degree) and the firm's human capital measured as the percentage of workers with higher education. We also incorporate variables related to technological opportunities and demand-pull factors. With regards to the technological opportunity

Table 2. Variable definition and descriptive statistics

Variable	Obs	Mean	Std Dev	Min	Max
Dependent variables					
Innovation (0/1)	10011	0.2127	0.4092	0.0000	1.0000
Product innovation (0/1)	10011	0.1074	0.3097	0.0000	1.0000
Process innovation (0/1)	10011	0.0764	0.2657	0.0000	1.0000
Credit constraint (a) (0/1)	10011	0.4048	0.4908	0.0000	1.0000
Credit constraint (b) (0/1)	10011	0.1459	0.3530	0.0000	1.0000
Tangible investment (0/1)	10011	0.1320	0.3385	0.0000	1.0000
Technology investment (0/1)	10011	0.0497	0.2174	0.0000	1.0000
R&D investment (0/1)	10011	0.0022	0.0478	0.0000	1.0000
Covariates					
Market share (%)	10011	0.0039	0.1202	0.0000	46.636
Firm's age (Ln)	10011	2.0927	0.9389	0.0000	5.0625
Manager's age (Ln)	10011	3.9047	0.2558	2.9957	4.5325
Manager's education (1/0)	10011	0.2529	0.4343	0.0000	1.0000
Tech. opportunities (0/1)	10011	0.4949	0.7332	0.0000	4.0000
Future sales growth (0/1)	10011	0.3221	0.4673	0.0000	1.0000
Future sales stable (0/1)	10011	0.3568	0.4790	0.0000	1.0000
Financial group (0/1)	10011	0.0246	0.1549	0.0000	1.0000
Human capital (%)	10011	0.0803	0.1911	0.0000	0.99953
Collateral (Ln)	10011	4.5076	4.5570	0.0000	22.803
Debt (ratio)	10011	5.1557	429.90	0.0000	36128.
Retained profits (%)	10011	0.9636	8.794	0.0000	100.00
Micro (0/1)	10011	0.8196	0.3845	0.0000	1.0000
Small (0/1)	10011	0.1481	0.3552	0.0000	1.0000
Medium (0/1)	10011	0.0214	0.1449	0.0000	1.0000
Large (0/1)	10011	0.0107	0.1032	0.0000	1.0000
Potentially innovative firms	$N = 7261$, % = 72.5				

we created an index for technological intensity calculated as the number of ICTs-related applications that are used by the firm. These are: internet connection, having a web page, online sales and online purchases. For demand factors, we use the expectations of the chief executive officer (CEO) about future sales codified by two dummy variables based on whether the CEO expects increased or stable demand.

In addition to these variables, we include four others that the previous literature suggests are closely correlated with access to finance: the amount of collateral that the firm has, measured as fixed assets, the debt–sales ratio, the percentage of dividends that are distributed each year, and whether or not the firm is a member of a financial group.

4. A simple model of innovation under financial constraints

In order to motivate our empirical strategy, we built on work by Evans and Jovanovic (1989) and assumed that the firm's knowledge production function (I) depends on its investment in innovation (R) and the firm's innovativeness (θ). This last variable depends on characteristics (X_1) such as the firm's human capital, CEO's experience and ability, expected demand push, and access to external knowledge. The firm's knowledge production function is given by:

$$I_i^* = \theta(X_{1i})R_i^{\alpha}\varepsilon_{1i} \tag{1}$$

Where $\alpha \in (0, 1)$.

Each firm faces a budget constraint that depends on its success in innovation and its balance sheet. This budget constraint is given by:

$$I_i^* \leq (1+\rho)(\omega_i - R_i) \tag{2}$$

Where ρ is the interest rate and ω is the firm's wealth. If $\omega < R$, the firm is a net borrower. In order to avoid default, and following the arguments in Section 3, banks and external investors set a limit on how much a firm can borrow. This limit is set as a proportion $(\lambda - 1)$ of the firm's total wealth (with $\lambda > 1$). So the amount borrowed cannot exceed $(\lambda - 1)\omega$, and the maximum amount that a firm can invest in innovation is given by $\omega + (\lambda - 1)\,\omega = \lambda\omega$. Thus, the firm either invests in innovation R or the ceiling $\lambda\omega$ if the optimum investment is more than $\lambda\omega$. In the empirical model λ is a function of variables that capture a firm's ability or intention to repay the loan. The firm's innovation investment decision is given by R_i^* that solves the following profit function:

$$\pi_i = \theta(X_{1i})R_i^{\alpha} + (1+\rho)(\omega_i - R_i) \tag{3}$$

This leads to the following solution for the optimal innovation investment:

$$R_i^* = \left(\frac{\alpha\theta(X_{1i})}{1+\rho}\right)^{\frac{1}{(1-\alpha)}} \tag{4}$$

Equation (4) is a valid solution as long as the right-hand side is not greater than $\lambda\omega$ (i.e. the firm is not financially constrained). However, if the right-hand side of Equation (4) is higher than $\lambda\omega$, the firm is financially constrained. Hence, in order to be financially unconstrained $\theta(\cdot)$, the firm's innovativeness must be:

$$\theta(X_{1i}) \leq \left(\lambda(Z_{2i})\omega\right)^{(1-\alpha)} \frac{(1+\rho)}{\alpha} \tag{5}$$

A good feature of Equation (5) is that, given wealth, only firms with a relatively low level of innovativeness will be financially unconstrained. Firms with a high level of innovation productivity will want to invest more in innovation and thus will hit the ceiling given by the limit on debt. Hence, whether a firm is financially constrained for innovation is indeed endogenous to the firm's innovativeness. This justifies our empirical approach outlined below.

Finally, although our data shows if a firm has invested in innovation and whether it has actually innovated, we do not have good quality data on investments in innovation. Given this, we have two possible innovation functions depending on whether or not the firm is financially constrained:

$$I_i = \theta(X_{1i})^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{1+\rho}\right)^{\frac{1}{1-\alpha}} \epsilon \tag{6a}$$

or

$$I_i = \theta(X_{1i})\left(\lambda(Z_{2i})\omega\right)^{\alpha} \epsilon \tag{6b}$$

We estimate either Equation (6a) or Equation (6b), respectively, depending on whether the firm is financially constrained or unconstrained. Given that we do not actually know if a firm is financially constrained, a natural way to start the empirical approach is by specifying Equation (6b) and exploring the extent to which variables that capture the financial balance sheet of the firm, its wealth/collateral, and the firm's willingness to pay are significant predictors of the firm's innovation output. For this we follow the methodology applied by Savignac (2008) in estimating a qualitative simultaneous model. Consider the following two general equations for the unobserved firm's innovation output (I_i^*) and the severity of financial constraints (FC_i^*), respectively:

$$I_i^* = X_{1i}\beta_1 + \delta FC_i + \varepsilon_{1i} \tag{7a}$$

$$FC_i^* = Z_{2i}\beta_2 + \theta I_i + \varepsilon_{2i} \tag{7b}$$

Given that I_i^* and FC_i^* are latent variables, we define:

$$I_i = 1 \text{ if } I_i^* \geq 0 \text{ and } I_i = 0, \text{ otherwise}$$

$$FC_i = 1 \text{ if } FC_i^* \geq 0 \text{ and } FC_i = 0, \text{ otherwise}$$

For reasons of coherence and completeness, it is required that neither of the two endogenous variables affects the other (Lewbel 2007).[8] Thus, we assume that financial constraints affect innovation, but innovation, after controlling for observable determinants of access to credit, does not have an impact on financial constraints, so we set $\theta = 0$. In addition, for identification purposes, we adopt the standard normalization of the variance of the errors. Specifically, we assume that the error terms are independently and identically distributed as a bivariate normal as follows:

$$\begin{matrix}\varepsilon_{1i}\\ \varepsilon_{2i}\end{matrix} \sim \Phi\left(\begin{matrix}0\\0\end{matrix}, \begin{bmatrix}1 & \rho\\ \rho & 1\end{bmatrix}\right)$$

The vector X_1 (see Equation (7a) includes the traditional determinants of innovation, such as the firm's size and age, market share, CEO's age and education, firm's human capital, and the proxies for demand-pull and technological opportunities. The vector Z_2 (see Equation (7b)) contains determinants of the probability of being affected by financial constraints in innovation based on previous studies of financial constraints on investment. We include the collateral value and a dummy variable if the firm belongs to a financial group. For both variables, we expect a negative effect on the probability of being financially constrained. We also include the debt–sales ratio, which we expect to be positively correlated to experiencing constraints on credit due to moral hazard problems. Finally, we include the percentage of retained profits since this variable operates as signal of efforts by a firm to mitigate moral hazard problems.

Our identification strategy assumes that these four variables affect financial constraints, but not innovation. Nevertheless, in some regressions we also include the financial group variable in the innovation regression to test whether firms belonging to a group also have higher access to knowledge and thus to increased opportunities for innovation. In general, we do not find evidence for this.

5. Econometric results

5.1 Basic results

Table 3 presents the results for two different groups: the full sample and a sample of potentially innovative firms. With regards to the results for the full sample, the first two columns are probit regressions that do not deal with the endogeneity of financial constraints. The financial constraints variable is not included in the innovation equation in the first column, but is in the second column. This shows that most of the explanatory variables have

Table 3. Basic results

	All of sample			Potentially innovative sample		
	(1)	(2)	(3)	(5)	(6)	(7)
Innovation						
Financial constraints		0.2956***	−1.0526**		−0.2858***	−1.2829***
		(0.0554)	(0.3831)		(0.0608)	(0.3332)
Market share	0.0298	0.0273	0.0161	0.0059	0.0077	0.0041
	(0.0339)	(0.0357)	(0.0326)	(0.0349)	(0.0333)	(0.0301)
Firm’s age	0.0056	0.0073	0.0027	−0.0038	−0.0060	−0.0102
	(0.0344)	(0.0339)	(0.0316)	(0.0387)	(0.0392)	(0.0383)
Manager’s age	−0.3685**	−0.3304**	−0.5003***	−0.2430	−0.2720	−0.3208*
	(0.1235)	(0.1236)	(0.1141)	(0.1393)	(0.1409)	(0.1375)
Manager’s education	0.0844	0.1029	0.0182	0.0991	0.0762	−0.0150
	(0.0665)	(0.0663)	(0.0748)	(0.0750)	(0.0758)	(0.0827)
Tech opportunities	0.4695***	0.4616***	0.3403***	0.4625***	0.4671***	0.3991***
	(0.0406)	(0.0401)	(0.0834)	(0.0448)	(0.0455)	(0.0608)
Expected sales growth	0.1855**	0.1934**	0.1451*	0.1727*	0.1585*	0.1374*
	(0.0667)	(0.0663)	(0.0631)	(0.0732)	(0.0740)	(0.0676)
Expected sales stable	−0.0731	−0.0625	−0.0391	−0.0395	−0.0450	−0.0316
	(0.0688)	(0.0685)	(0.0530)	(0.0768)	(0.0775)	(0.0679)
Financial group	0.0106	0.0386	−0.1194	0.2368	0.2123	0.0973
	(0.1218)	(0.1197)	(0.1305)	(0.1292)	(0.1313)	(0.1380)
Human capital	0.1518	0.1455	0.1862+	−0.0011	−0.0170	−0.0685
	(0.1245)	(0.1246)	(0.1112)	(0.1463)	(0.1493)	(0.1488)
Small	0.1260*	0.1514**	0.0053	0.1792**	0.1522**	0.0158
	(0.0497)	(0.0504)	(0.0801)	(0.0561)	(0.0569)	(0.0785)
Medium	0.2360**	0.2847***	0.0352	0.3124***	0.2613**	0.0178
	(0.0732)	(0.0744)	(0.1321)	(0.0824)	(0.0841)	(0.1288)
Large	0.4691***	0.5372***	0.1776	0.5594***	0.4877***	0.1366
	(0.0883)	(0.0898)	(0.1816)	(0.0977)	(0.1001)	(0.1730)
Financial constraints						
Financial group			−0.3261**			−0.2098
			(0.1032)			(0.1167)
Collateral			−0.0111*			−0.0171**
			(0.0050)			(0.0065)
Debt ratio			0.0274*			0.0373
			(0.0126)			(0.0422)
Retained profits			−0.0054*			−0.0063**
			(0.0021)			(0.0022)
Firm’s age			−0.0013			−0.0068
			(0.0303)			(0.0361)
Manager’s age			−0.4691***			−0.2241
			(0.1067)			(0.1324)
Manager’s education			−0.1028+			−0.2052**
			(0.0608)			(0.0697)
Human capital			0.1527			−0.1342
			(0.1165)			(0.1396)
Small			−0.1405**			−0.2107***
			(0.0460)			(0.0555)
Medium			−0.2386***			−0.3802***
			(0.0718)			(0.0840)
Large			−0.3286**			−0.5545***
			(0.1023)			(0.1023)
N	10011	10011	10011	7261	7261	7261
Log likelihood	−4680.4041	−4632.6812	−8.182e+05	−4075.9769	−4038.5219	−6.034e+05
chi2	1126.1047	1153.6942	1951.5571	957.8369	959.5139	2051.1854
P	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rho			0.8174			0.6408
chi2_c			2.8398+			4.0283+

Standard errors in parentheses *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, +$p < 0.10$.

the expected effects and are generally not affected by the inclusion of the financial constraint variable. To start with, market share and firm's age affect the probability of innovation, positively and negatively, respectively. However, neither effect is significant. Second, the positive and significant parameters for an expected increase in sales and technological opportunities indicate that innovation is driven by both pull and push factors. Third, size is positively and significantly correlated with the probability of innovating. This positive effect of size can be explained because larger firms can have better access to financial resources, but it can also be due to the fact that larger firms have greater access to other complementary resources such as tacit knowledge or experience or that they are more diversified, so enjoying the benefits of economies of scope (they could pursue more research projects in the same or related fields than smaller firms and hence could also have a higher probability of achieving at least one successful innovation outcome).[9] Fourth, the manager's age is negatively related to the probability of innovation, suggesting that, conditional on other covariates, younger managers are more innovative. Finally, although both human capital variables have a positive sign, neither is statistically significant.

The results in column (2) of Table 3 show that financial constraints are positively related to innovation and their inclusion as an explanatory variable does not change the basic results.[10] This positive association between innovation and financial constraints is mainly explained by the endogeneity of financial constraints. Several authors have shown that obstacles to innovation tend to be more important for innovators than for firms that are not undertaking these activities (Savignac 2008; Mohnen et al. 2008; Iammarino et al. 2007; Galia and Legros 2004). In other words, only those who try to innovate discover that they are constrained in obtaining innovation financing.

Column (3) of Table 3 shows the results for the simultaneous model. It should be noted that the parameter for financial constraints changes from positive to negative, indicating that once we control for this variable's endogeneity, we find that financially constrained firms are less likely to innovate. Another interesting result is that larger firms are less likely to be financially constrained, and the positive effect of size on innovation in the simple probit estimation disappears in the simultaneous model. This is consistent with the idea that the positive effect of size is mainly driven by the fact that larger firms have better access to financial markets.

Our results for the determinants of financial constraints are those that are expected theoretically. We find that firms belonging to a holding company, with higher collateral value, and with more retained dividends are less likely to be financially constrained. On the other hand, firms with higher debt are more likely to report financial constraints. We also find that older and more educated managers are more likely to gain access to external finance for innovation. It may be that older managers are less affected by the asymmetric information problem, and that more educated managers have a greater ability to formulate higher quality investment projects. Finally, the correlation coefficient between these two equations is positive and significant, suggesting that simultaneous estimation is the correct empirical strategy.

As has been argued by Savignac (2008), the previous results may still have a bias considering that all the firms surveyed, even those who did not wish to innovate, were asked about obstacles to innovation. This sample includes firms that do not innovate and declare that they do not face any obstacles to innovation. When we exclude these firms from the sample, we have a group of firms defined as potentially innovative.[11] It may be relevant to explore whether the wrong correlation of financial constraints in the naïve model is due to a pure endogeneity problem, is driven by a sample selection problem, or both.

The results of our estimations for these firms are in the last three columns in Table 3. It can be seen in the simple probit model in column (5), that the effect of financial constraints is negative and significant, and that there are no relevant changes in the main determinants of innovation. However, dealing with endogeneity reveals that the negative effect of financial constraints is larger than that estimated by the probit model. As shown by the simultaneous equation system, the parameter for financial constraints is more than four times the value in the probit estimation. Thus, the estimation using the sample of potentially innovative firms reinforces our previous finding that financial constraints are important for understanding innovation performance.

In sum, and consistent with evidence for other countries, our basic results support the idea that financial constraints are a significant deterrent to innovation for Chilean companies. However, this finding only appears when we deal with the endogeneity of access to external financial resources for innovation. In what follows, we study the relationship between innovation and finance across the size of the firms and the industry.

5.2 Results by size and sector

To look at differential effects across the size of the firms, we divide the sample into two main groups: micro/small firms and medium/large companies.[12] These results are shown in the first two columns of Table 4. The evidence suggests that the constraints on credit for innovation are mainly binding for micro- and small firms. In the case of medium or large firms, the coefficient for credit constraints is negative but not significant. Furthermore, in the case of medium and large firms, there is no evidence of endogeneity for financial constraints because the correlation between both equations' error terms is not significant. With regards to the remaining explanatory variables,

Table 4. Results by size and sector. Potentially innovative sample

	Micro/small	Med/large	Production	Trad services	KIBS
Innovation					
Financial constraints	−1.4603***	−0.3514	−1.1412***	−1.1876	−1.6280***
	(0.2585)	(0.5574)	(0.3232)	(0.9156)	(0.0891)
Market share	0.7187	0.0318	0.0346	−0.0342	0.0695
	(1.7755)	(0.0511)	(0.0466)	(0.0513)	(0.0728)
Firm's age	−0.0123	0.1092*	−0.0871	−0.0465	0.0868
	(0.0382)	(0.0535)	(0.0576)	(0.0515)	(0.0736)
Manager's age	−0.3226*	0.0535	−0.2473	−0.3534+	−0.3180
	(0.1386)	(0.1853)	(0.2030)	(0.2074)	(0.2623)
Manager's education	−0.0475	0.1659	0.0480	0.0509	−0.2228+
	(0.0847)	(0.0881)	(0.1075)	(0.1631)	(0.1262)
Tech opportunities	0.3812***	0.3911***	0.3580***	0.3459***	0.3656***
	(0.0638)	(0.0499)	(0.0745)	(0.0886)	(0.0599)
Expected sales growth	0.1285+	0.1649+	0.0943	0.1815	0.1406
	(0.0658)	(0.0888)	(0.1016)	(0.1146)	(0.0932)
Expected sales stable	−0.0227	−0.1263	0.0246	0.0058	−0.0562
	(0.0654)	(0.1049)	(0.1072)	(0.0973)	(0.1037)
Financial group	0.0448	0.1760*	0.0175	0.1043	−0.1531
	(0.1901)	(0.0893)	(0.1890)	(0.3365)	(0.1284)
Human capital	−0.1175	0.2204	0.0439	0.3448+	−0.4259
	(0.1555)	(0.1173)	(0.1741)	(0.1916)	(0.2509)
Small			0.1756	−0.1141	−0.1070
			(0.1152)	(0.1618)	(0.0977)
Medium			0.1393	0.0406	−0.2813*
			(0.1588)	(0.3113)	(0.1294)
Large			0.3798+	0.1081	−0.1365
			(0.2183)	(0.4242)	(0.1491)
Financial constraints					
Financial group	−0.3235+	−0.1495+	0.0220	−0.0935	−0.4563**
	(0.1685)	(0.0815)	(0.1788)	(0.2243)	(0.1482)
Collateral	−0.0221***	−0.0292*	0.0019	−0.0035	−0.0373***
	(0.0058)	(0.0139)	(0.0101)	(0.0116)	(0.0088)
Debt ratio	0.0507	−1.6460	−2.6929+	0.0492	0.0220
	(0.0434)	(2.3097)	(1.5110)	(0.0659)	(0.0252)
Retained profits	−0.0077**	−0.0031+	−0.0033	−0.0100*	−0.0032+
	(0.0027)	(0.0017)	(0.0033)	(0.0040)	(0.0018)
Firm's age	−0.0140	−0.0683	−0.1296*	−0.0241	0.0537
	(0.0368)	(0.0520)	(0.0567)	(0.0515)	(0.0724)
Manager's age	−0.2067	−0.3934*	0.1078	−0.4006*	−0.1959
	(0.1350)	(0.1732)	(0.2060)	(0.1822)	(0.2624)
Manager's education	−0.2241**	−0.1295	0.0179	−0.2667**	−0.2675*
	(0.0721)	(0.0844)	(0.1083)	(0.0967)	(0.1254)
Human capital	−0.2275	0.0283	0.2605	0.0115	−0.4408+
	(0.1434)	(0.1166)	(0.1783)	(0.1646)	(0.2524)
Small			−0.2990**	−0.3312***	−0.0877
			(0.1009)	(0.0841)	(0.1043)
Medium			−0.4934***	−0.5617***	−0.1998
			(0.1454)	(0.1307)	(0.1422)
Large			−0.7664***	−0.7954***	−0.2178
			(0.1785)	(0.1592)	(0.1651)
N	4760	2501	1830	3059	2372
Ll	−5.817e+05	−2.210e+04	−1.309e+05	−2.851e+05	−1.854e+05
chi2	906.9185	211.8636	553.0273	880.0298	434.0308
P	0.0000	0.0000	0.0000	0.0000	0.0000
Rho	0.7641	0.0436	0.5859	0.5061	0.9740
chi2_c	5.2169**	0.0167	4.1257**	0.4578	21.2758***

Standard errors in parentheses $*p < 0.05$, $**p < 0.01$, $***p < 0.001$, $+p < 0.10$.

we find that the effect of technological opportunities and expected sales increases are positive and statistically significant for both groups. We also find that collateral, being part of a financial group, and retained profits reduce the likelihood of financial constraints for small and large firms.

One of the advantages of this dataset is the availability of information on several industries. We exploit the richness of this information by looking at the relationship between innovation and finance, grouping firms into three main sectors: production (agriculture, mining and manufacturing), traditional services (construction, retail, and hotels and restaurants), and knowledge-intensive business services (KIBS) sectors (transportation and communications, financial services, and real estate). The results are presented in last three columns of Table 4.

Our main finding is that financial constraints have a heterogeneous impact across sectors. The coefficient for financial constraint is negative and statistically significant for the production and KIBS sectors. Although negative, the impact of credit constraints on traditional services is not statistically significant. This coefficient is in line with those of other sectors and the correlation coefficient between the error terms is significant. Thus, it can be argued that the lack of significance for traditional services is more of a lack of precision in the estimates, rather than a signal of a complete absence of constraints on credit. Finally, an important result is that the impact of credit constraints is particularly high in the KIBS sectors where the coefficient of the credit constraint variable is about 40% higher than for the other two sectors. This could be due to the more intangible nature of the innovation carried out in these sectors.

5.3 Robustness checks

We now present a summary of the different robustness checks on the whole sample in order to confirm that we are really identifying the impacts of credit constraints and not some other situation. We carried out the following three tests:

- *Credit constraints on innovation or just credit constraints in general?* Our first test is to explore whether our credit constraints variable is really capturing effects on innovation or is capturing the effects of general credit constraints. We replace our credit constraint variable with an alternative credit constraint definition that does not discriminate, based on the objective of the financial need. We use information on whether or not the firm was rejected for a loan in the past year. The results of this experiment are in the first column of Table 5. This alternative variable is not significant and, in fact, has the wrong sign. In other words, by using our preferred variable of credit constraints we are correctly identifying the effects of these constraints on innovation investments.
- *Tangible versus intangible innovation outputs*. Our conceptual framework places a strong emphasis on the fact that financial constraints are more severe due to the intangible nature of many investments in innovation. In order to explore this issue, we replace our dependent variable, which identifies any sort of innovation, with two new dependent variables: product innovation and process innovation. Previous research on innovation suggests that while process innovation is strongly related to the acquisition of tangible assets such as machinery and equipment, this is not the case for product innovation which, in principle, is more based on R&D efforts (Crespi and Zúñiga 2012). Given its more intangible nature, we expect that credit constraints will be more binding for the outputs of product innovation. The results of this exercise are summarized in the second and third columns in Table 5. In line with our previous reasoning, the results show that credit constraints indeed have heterogeneous impacts across innovation outputs. We found that credit constraints are clearly binding for the case of product innovation. On the other hand, these constraints do not seem to be relevant in explaining process innovations.
- *Tangible versus intangible innovation inputs*. We extend our previous reasoning to explore whether financial constraints impact innovation inputs differently. We expect that the impacts of credit constraints would increase with the intangibility of the investments in innovation. We explore the impacts of credit constraints on three types of innovation investments: tangible (mostly machinery and equipment), ICTs (including hardware and software), and R&D. The results are summarized in the last three columns of Table 6. Credit constraints are particularly important in the case of R&D, which is the most intangible of the investments in innovation. The effects are 20% higher than for normal tangible investments.

Summarizing, these robustness checks confirm that we are capturing activities related to credit constraints on innovation and not overall difficulties in financial access. Indeed, when we use a different indicator of credit constraints that is not necessarily aligned with credit constraints on innovation, we find that its effect on innovation is not significant. However, we do find that constraints on credit for innovation are critically important for product rather than for process innovations, which is consistent with the more intangible nature of the investments needed for the former type of innovation output. In a similar vein, we find that credit constraints on innovation are more significant for R&D investment compared to other, more tangible, innovation investments.

The results in Section 5.2 refer to the coefficients of a nonlinear model and as such are not very useful when evaluating the impacts of constraints on credit for

Table 5. Robustness checks

	Alternative measure of financial constraints	Product	Process	Tangible	Tech innovation	R&D
Innovation						
Financial constraints	0.3978	−0.8176+	0.2258	−1.3278***	−1.2067***	−1.5753*
	(0.5130)	(0.4643)	(0.9868)	(0.1030)	(0.3047)	(0.7029)
Market share	0.0316	0.0080	0.0672+	0.0472	0.0331	0.0275
	(0.0350)	(0.0187)	(0.0368)	(0.0377)	(0.0254)	(0.0196)
Firm's age	0.0084	0.0262	−0.0331	−0.0301	−0.0202	0.0300
	(0.0339)	(0.0404)	(0.0389)	(0.0320)	(0.0408)	(0.0570)
Manager's age	−0.3435**	−0.4691**	−0.4380	−0.6424***	−0.3817*	−0.5257**
	(0.1287)	(0.1442)	(0.2355)	(0.1081)	(0.1508)	(0.1899)
Manager's education	0.1214	0.1131	0.1646+	−0.1967**	0.0544	−0.1973
	(0.0729)	(0.0898)	(0.0941)	(0.0659)	(0.0819)	(0.2020)
Tech opportunities	0.4607***	0.2818***	0.3251***	0.0605*	0.5251***	0.5046***
	(0.0409)	(0.0579)	(0.0471)	(0.0308)	(0.0741)	(0.1092)
Expected sales growth	0.2001**	0.1775*	0.1332	0.1063*	0.1313	−0.2559+
	(0.0669)	(0.0737)	(0.0849)	(0.0470)	(0.0841)	(0.1517)
Expected sales stable	−0.0566	−0.0384	−0.0122	0.0278	−0.0275	−0.3449+
	(0.0688)	(0.0725)	(0.0868)	(0.0524)	(0.0861)	(0.2065)
Financial group	0.0031	−0.0721	0.1080	−0.2282**	−0.1907+	−0.2958*
	(0.1133)	(0.1486)	(0.1680)	(0.0819)	(0.1001)	(0.1339)
Human capital	0.1734	0.0853	0.2044	0.5161***	0.1397	0.0176
	(0.1235)	(0.1359)	(0.1685)	(0.1121)	(0.1516)	(0.2248)
Small	0.1488**	−0.0178	0.2464**	0.1302*	0.1284	−0.3100
	(0.0554)	(0.0730)	(0.0920)	(0.0549)	(0.0810)	(0.1757)
Medium	0.2765***	−0.0272	0.4818***	0.3757***	0.4047**	−0.1173
	(0.0838)	(0.1176)	(0.1433)	(0.0896)	(0.1381)	(0.2201)
Large	0.5130***	0.0593	0.7265***	0.6079***	0.5875***	0.0893
	(0.1005)	(0.1621)	(0.1895)	(0.1120)	(0.1775)	(0.2844)
Financial constraints						
Financial group	0.0540	−0.3124**	−0.3032**	−0.2697**	−0.2902**	−0.3034**
	(0.2304)	(0.1022)	(0.1018)	(0.0990)	(0.1007)	(0.1019)
Collateral	−0.0024	−0.0086	−0.0094	−0.0190***	−0.0122*	−0.0094
	(0.0077)	(0.0058)	(0.0061)	(0.0049)	(0.0058)	(0.0060)
Debt ratio	−1.1142	0.0188*	0.0164+	0.0197**	0.0218**	0.0168*
	(0.9798)	(0.0075)	(0.0087)	(0.0074)	(0.0074)	(0.0076)
Retained profits	0.0055	−0.0062***	−0.0053*	−0.0043**	−0.0047*	−0.0054*
	(0.0041)	(0.0019)	(0.0024)	(0.0014)	(0.0021)	(0.0023)
Firm's age	−0.0431	−0.0024	−0.0013	0.0045	0.0006	−0.0014
	(0.0366)	(0.0301)	(0.0299)	(0.0296)	(0.0298)	(0.0298)
Manager's age	−0.2788*	−0.4704***	−0.4736***	−0.4909***	−0.4735***	−0.4750***
	(0.1316)	(0.1059)	(0.1060)	(0.1056)	(0.1054)	(0.1059)
Manager's education	−0.3232***	−0.1045+	−0.1032+	−0.0891	−0.0977	0.1032+
	(0.0794)	(0.0607)	(0.0610)	(0.0608)	(0.0611)	(0.0607)
Human capital	−0.1362	0.1425	0.1437	0.1632	0.1355	0.1445
	(0.1368)	(0.1172)	(0.1183)	(0.1174)	(0.1164)	(0.1173)
Small	−0.2359***	−0.1508**	−0.1496**	−0.1130*	−0.1381**	−0.1502**
	(0.0606)	(0.0464)	(0.0470)	(0.0457)	(0.0464)	(0.0468)
Medium	−0.4758***	−0.2626***	−0.2639***	−0.2039**	−0.2445***	−0.2640***
	(0.1110)	(0.0730)	(0.0747)	(0.0702)	(0.0731)	(0.0743)
Large	−0.8581***	−0.3892***	−0.4115***	−0.3139***	−0.3869***	−0.4120***
	(0.1606)	(0.0863)	(0.0900)	(0.0832)	(0.0864)	(0.0881)
N	10011	10011	10011	10011	10011	10011
Ll	−6.331e+05	−7.093e+05	−6.537e+05	−7.417e+05	−5.858e+05	−4.906e+05
chi2	1411.8693	1364.3470	1241.6172	2284.1364	2000.4981	1989.0787
P	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rho	−0.0589	0.6221	−0.0297	0.8893	0.7425	0.8066
chi2_c	0.0477	2.7190+	0.0025	22.5140***	8.0090**	3.4600+

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

Table 6. Marginal effects of financial constraint on innovation and investment. Potentially innovative sample

Variable	Marginal effects	Mean	Normalized marginal effects
Innovation: all	0.321	0.311	1.03
Innovation: micro/small	0.381	0.298	1.28
Innovation: medium/large	0.040	0.653	0.06
Innovation: production	0.271	0.330	0.82
Innovation: traditional services	0.289	0.278	1.04
Innovation: KIBS	0.422	0.350	1.20
Product innovation	0.119	0.157	0.76
Process innovation	0.038	0.112	0.34
Tangible investment	0.249	0.156	1.60
ICTs investment	0.057	0.062	0.93
R&D investment	0.014	0.003	4.34

Marginal effect measures impact of discrete change of a dummy variable 1 (with financial constraint) to 0 (without financial constraints) on probability of innovation and investing. Mean is sample average of dependent variable and normalized marginal effect is ratio between marginal effect and mean.

innovation. For this we need to compute the variable's marginal effects, which are summarized in Table 6. Together with reporting the marginal effects, evaluated at sample means, we also report the corresponding dependent variable's mean for the sample of innovative firms. This mean is also useful to normalize the marginal effects across comparable denominators. The last column of Table 6 reports the ratio between the marginal effects and the sample mean of the dependent variable. In other words, the normalized marginal effects report the innovation shortfall (evaluated at the sample means) that can be attributed to the financial constraints on innovation. The actual definition of the last column of Table 6 (normalized marginal effects) is given by:

$$(-1)\frac{\partial P(I=1, FC=1, X)/\partial FC}{P(I=1, FC=1)} \tag{8}$$

The marginal effects suggest that financial constraints are quantitatively important to currently explain Chilean shortfalls in innovation. In particular, we found that an innovative firm without financial constraints has a 32% increase in its probability to innovate. This is about the same magnitude as the currently observed propensity to innovation. In other words, a complete lifting of financial constraints in Chile might well double its innovation rates. A significant part of this effect would come from micro- and small firms. Indeed, the absence of financial constraints increases the probability of innovation by 38% for these firms, while the effect for medium and large firms is only 4%. These results also show that the innovation shortfall generated by financial constraints is relatively more important in the KIBS sectors. Eliminating financial constraints to innovation increases the probability of innovation by KIBS firms by 42%, while the increase in traditional services and production activities is about 30%.

In terms of the remaining variables, we find that relaxing financial constraints would be particularly relevant for increasing product innovations (with an 11% increase) than for process innovation. Finally, financial constraints are particularly bad for intangible components of innovation investments. Specifically, if there were no financial constraints, the likelihood of R&D investment would increase by 1.4%. Considering that the average innovative firm only has a 0.3% chance of investing in R&D, reducing financial constraints would increase the proportion of firms investing in R&D by nearly fourfold.

6. Conclusions

In this paper we use a novel dataset covering all industries and the size of the firms in the Chilean economy to provide empirical evidence for the importance of financial constraints on innovation. Chile is an interesting setting for studying this phenomenon since very little is known regarding the extent to which financial constraints affect innovation in less developed countries. We follow the literature and employ a direct and self-reported measure of financial obstacles for innovation while dealing with this variable's endogeneity.

The results for all firms and for those defined as potentially innovative show consistent evidence that financial constraints reduce Chilean innovation. Moreover, we find that dealing with the variable's endogeneity is needed to uncover the negative relationship between innovation and access to credit. The naïve approach would show that the relationship is positive since only those firms that have good innovation perspectives discover the financial problems. Our evidence complements findings for certain developed economies (Savignac 2008; Mohnen et al. 2008) and even extends them in several dimensions.

First, we study the relationship between innovation and finance across the size of the firm and type of industry. We find that these constraints are particularly severe for micro- and small firms and those operating in the KIBS sectors. These effects are quantitatively important: in the absence of financial constraints, small firms would increase their probability of innovating by 38% and KIBS firms by 42%.

Second, we analyze whether self-reported financial constraints are specific to innovation or capture overall problems of access to credit. Our results show that these constraints are specific to innovation-related investments, particularly with regards to the accumulation of intangible assets. In fact, we find that a measure of overall financial constraint does not affect innovation. We also find that financial constraints are more important for product innovation than for process innovation and that they are more relevant for R&D investment rather than for other more tangible investments. All of these results confirm our basic findings that difficulties in gaining access to credit have an important negative impact on innovation.

Our results suggest several policy implications for enhancing innovation in developing countries. Given that overall credit constraints do not affect innovation, policy efforts should be oriented to improving access to credit for innovation-specific investments. Our findings also indicate that these interventions need to be focused on small firms, on the intangible component of the innovation projects, and should place special emphasis on product innovation projects. Our results suggest that direct interventions such as subsidies might have a higher impact than indirect interventions, such as R&D tax credits. Indeed, although well-designed tax credits can relax financial constraints, their effects depend on the firm's effective tax rate and its tax position. Given that, particularly in developing countries, both the tax rate and the fiscal pressure is higher in the case of large firms, it seems that tax credits are not beneficial to those firms more severely affected by financial constraints. Large firms can take advantage of tax credits but are not the most seriously affected by credit constraints.

Many options are still open for further research. For example, the future availability of panel data would allow us to use econometric techniques that can achieve better control of the firms' heterogeneity. It is also important to extend the same analysis to other developing countries to check the external validity of our findings. Finally, it is relevant to explore how important these findings are for the performance (sales, productivity, etc), survival, and employment growth of the firms.

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Notes

1. See Hall and Lerner (2010). This section borrows heavily from their work. See also Hall (2005).
2. There are, of course, other reasons that might lead to a premium on external financing. The capital structure of the firm along with differences in the tax treatments of external capital costs, retained earnings and dividends might also drive a wedge between internal and external financing.
3. Due to the fact that innovation investments are mainly formed by human capital costs, firms try to smooth these investments in order to avoid the turnover of human capital that could lead to knowledge leaks.
4. Although several developing countries have already collected several waves of innovation surveys, the sampling methodologies are not typically set to build firm level, time series data. A large fraction of firms, normally the smallest or youngest ones, which are those more likely to be affected by credit constraints, changes from one cross-section to the next.
5. We follow the classifications used in the survey, where micro-firms are those with annual sales up to 2.400 UF (Unidad de Formento (UF), approximately US$95,000 in 2007), small firms with annual sales in the range 2,400–25,000 UF, medium firms with annual sales in the range 25,000–100,000 UF, and large firms with annual sales above 100,000 UF (approximately US$4 million).
6. We use an alternative definition for innovation in Section 5.3.
7. Age is the number of years (in logs) since a firm initiated activities with the Internal Revenue Service, which is, strictly speaking, the year in which it entered the formal economy.
8. The problem of completeness refers to the issue that for certain values of the parameters, the model predicts both success and failure at the same time. The problem of coherence refers to the fact that for certain values of the parameters the model predicts neither success nor failure at the same time.
9. For a detailed review of the literature about the relationship between size and innovation see Cohen (2010).
10. Tables 3 and 4 show the results for innovation-related financial constraints.
11. The number and percentage over the total sample of potentially innovative firms are shown in Table 2.
12. Due to space considerations, we focus on results for the sample of potentially innovative firms. Estimations for the whole sample are available upon request.

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