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# Is there a Connection between Finance and Innovation?

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**ABSTRACT**

Within the current macroeconomic environment, innovation activity, especially a radical one, is developed under extreme uncertainty conditions. A number of studies have proven the existence of severely asymmetrical information generated by innovation activities. Our research objective focuses on whether or not the development of financial systems influences the level of innovation, also analyzing the real impact of several features of the financial system on the overall innovative process of a country. In this respect, we propose a two-fold contribution. First, we address the impact on innovation which is exercised by the financial intermediation entities granting credits to the private sectors of the economy. Such a 'financial resources availability' view excludes the role played by financial markets or by the firms' internal resources. Second, we employ a Bayesian nonparametric empirical framework that can deal with various types of uncertainty about the 'true model' governing the relationship between finance and innovation. Our findings show that, at an empirical level, finance does matter in explaining the status of innovation processes and outcomes. However, this conclusion should be nuanced by adding that different features of the financial system have a non-uniform importance: while the global supply of financial resources through credit granted to the private sector is putting forth a positive and robust influence on innovation, the expansion of commercial banks network appears to play a more ambiguous and less robust role. Additionally, the existence of geographically spread specific mechanisms clearly influences the amplitude and shape of financial variables' impact on innovation. It is our view that the paper may contribute to proving that the development, as well as the functional capabilities of the financial systems, are highly relevant for the status of innovation processes in modern 'knowledge-based' economies.

**Keywords:** *finance, innovation, Bayesian nonparametric 'infinite-probits mixture linear' regression model*

**JEL Classification:** C11, C58, G20, O00

## INTRODUCTION

As with anything else in the economy, innovation is not a 'free lunch'. Instead, it might require a substantial amount of human, material, financial and informational resources in order to generate significant economic and social effects. Our main question of interest here is the following: Among such critical resources, how important are those with a financial nature? How can the status of financial systems development and efficiency impact the inputs and outputs of innovative processes?

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In his 1934 book, "*The theory of economic development*", Schumpeter came up with the idea that innovative activities may sometimes be very difficult to finance, especially within competitive economic environments, because of their specific characteristics. In such contexts, he states the idea that financial intermediaries have a very important role in technological innovation if they have the capacity to select the most promising and challenging projects in order to subsequently finance them. Schumpeter's idea was later developed by Dosi (1990), whose paper exhibits that different financial setups induce different levels of industrial innovation. Practically starting from Schumpeter's theory, King and Levine (1993) describe in an argumentative manner the actual implication of the financial system on overall economic growth. They present a four-direction approach on that subject and conclude that better financial systems lead to economic growth by accelerating productivity and innovation.

The problem of financing innovative activities should, in fact, be considered from a double perspective. In the first place, the real dependency of innovative activities on the financial system should be searched for from a macroeconomic point of view, and secondly, the microeconomic implications should be accounted for. Innovation is currently interfering with a multitude of fields, including social sciences and humanities. A current growing body of literature suggests that finance is relevant for differentiating countries with better innovation performances, both through micro and macro mechanisms.

From a microeconomic point of view, an essential part of the innovation literature has focused mainly on technological aspects of innovation. As Callegari (2018) states, recent attempts by some authors to reintegrate missing financial elements have been tempered by this theoretical lack. The new approach identifies innovation's economic role as dependent on financial constraints. Financial constraints reduce the appetite for innovation, especially for radical innovation, as firms prefer to use the classic, usually inexpensive, solutions for their businesses. Both microeconomic theory and empirical evidence have recognized the potential hurdles in the innovation financing process, as in Giordani (2015), which suggests that inventors may have financial constraints. The arguments proposed to explain the imperfections of the financial market in the innovation sector vary from transaction costs and tax advantages to agency costs due to the information asymmetries between the innovator and the funding body. As shown in Pyka and Andersen (2012), innovation in the public sector and entrepreneurship are fundamental elements that show the complex nature of creating the future orientation of economic systems. Le Corre and Mishchke (2005) consider that research and innovation are an inherently risky investment. This investment may or may not be profitable, depending on the results obtained and on the costs of financing. The higher the cost of financing or the more difficult access to financing, the riskier the innovation process becomes.

According to Laperche and Uzunidis (2008), companies, especially the large ones, use their financial strength to create convergence between science and technology centers, stimulating the development of the innovation processes. Under these conditions, finance has become a very powerful, results-based innovation regulation tool. Finance monitors the applications of science up to the details of the production process, and profit becomes the main criterion for selecting appropriate research programs to be implemented. Thus, taking into account only the financial criteria, the companies can weaken their potential for radical innovations. Amendola et al. (2003) suggest that the existence of financial constraints is a threat to competition, as innovative companies facing financial problems may be eliminated from the market. The stronger the financial constraint, the greater the threat to competition, except in companies where the innovation process is very intensive. As a result, there is a complex causal relationship between financial constraint and the frequency of innovation, which allows companies to stay on the market.

**THEORETICAL BACKGROUND**

In order to analyze the restrictions existing in the financing of innovation, it is necessary to look at the process of finding and matching between the entrepreneurs who propose their innovative activities and the financial entities that select and finance the most profitable projects, as in Giordani (2015). In this sense, the amount of resources dedicated to innovation must be estimated to ensure a balanced growth of companies, with a reasonable financing cost. Financing constraints limit the innovation activities of companies, especially the hard type. On the contrary, financial constraints do not impede the implementation of easy innovation. Differential impacts are explained in Qi and Ongena (2019) by the fact that hard innovation requires greater capital, so greater credit is needed, while this is not the case with soft innovation.

Financial constraints are a serious obstacle to business innovation, especially in times of crisis, and offer new perspectives on the role of lending relationships, especially for small and medium-sized enterprises, as Brancati (2015) states. However, not only do small and medium-sized enterprises have a lower chance of innovation and a greater probability of coping with financial constraints, but innovative behavior is also more sensitive to financial conditions, even for large companies. Good relationships with the financing bodies and long-term trust can help overcome financial barriers to innovation.

From a macroeconomic perspective, Takalo and Tanayama (2010) highlight the idea that government programs that give grants to innovative applicants can provide valuable information to funding agencies. Public subsidies in the field of research and development can reduce the financing constraints of innovating entrepreneurs. Mainly, the subsidy helps the innovation projects by reducing the necessary capital on the market, and, on the other hand, if an entrepreneur has received a grant for an innovation project, it gives a positive signal to the funding bodies, which will be more willing to finance the future projects of that entrepreneur.

In a recent article, Fagiolo et al. (2019) studied the effects that finances have on the innovation activities of companies, as well as on the long-term performance of the economy. The results of their study show that banks, by granting advantageous loans for research activities, are able to encourage technological innovation and dissemination, thus improving long-term economic growth. Reasonable credit conditions allow for a better balance between technological exploration and business operations. They suggest that a more in-depth study of the relationship between innovation and financing will play a much more important role in economic development in the future. In the same direction, Glabiszewski and Zastempowski (2018) attempted to evaluate the absorptive potential of the financing companies in terms of their efficiency in the transfer of innovative technologies. The accomplishment of this potential confirms that the more developed the financial absorption capacities of companies, the stronger the effects of innovative activities based on external sources.

Also, in the intention to analyze the relationship between finance and innovation, Caiani et al. (2015) highlight the cyclical characteristic of the development process and emphasize the relevance of the relation between finance and innovation, analyzing the real and financial flows from the economy. The relationship between innovation and financing is studied, creating a multi-sectorial model of the economy based on consumption industries and capital goods, the banking sector and the household sector, which is divided into businessmen and employees. This model is framed from the perspective of structural change initiated by technological innovation. Another finding in the literature, as noted by Becchetti (1995), stipulates that in countries where financial markets are well developed and various financial intermediaries exist, but information is still imperfect and expensive, large and innovative firms benefit more from the advantages of the system and face fewer financial problems. Therefore, the assertion that larger companies with significant financial possibilities are more inclined to invest in research and innovation is reinforced. However, the role of financing in the development of innovation processes remains a matter of debate with theoretically ambiguous forecasts and empirically mixed results.

Based on this literature, we propose a two-fold contribution. First, we focus on the impact on innovation, which is exercised by the financial intermediation entities granting credits to the private sectors of the economy. Such a 'financial resources availability' view excludes the role of financial markets or firms' internal resources. Nonetheless, it has the intended advantage of more precisely identifying the sources of attracted financial resources and better emphasizing their relevance. Second, we employ a Bayesian nonparametric empirical framework capable of handling various types of uncertainty about the 'true model' governing the relationship between finance and innovation.

The next section describes this framework as well as the international data involved, while Section 3 reports and comments on the results.

## METHODOLOGY AND INTERNATIONAL DATA

### Bayesian Nonparametric 'Infinite-Probit Mixture Linear' Framework

Since most research questions in the field of social sciences can be described in terms of dependent variables responses to shocks occurring in explanatory covariates' levels or variances, regression models are perhaps the most common tool in applied modeling. Nonetheless, empirical applications often provide cases where the specific set of normal linear models' assumptions are, for one reason or another, not fully applicable. Thus, recent developments in modeling tools have focused on alternative approaches. Among these, one of the most flexible views is provided by the Bayesian frame. The starting point in building up such a frame is the idea that the model parameters' uncertainty can be depicted in terms of probability distributions. By providing a robust framework for estimation, Bayesian nonparametrics can be used to handle large parameter spaces as well as unknown density and regression functions. Hence, as Karabatsos (2017: 336) notes, Bayesian nonparametric (BNP) regression models "can provide a more robust, reliable, and rich approach to statistical inference, especially in common settings where the normal linear model assumptions are violated". Our argument for using this approach here is backed up by the idea that different violations of normality assumptions can easily occur whenever highly heterogeneous data about fast and significant time-varying processes of the international spread of innovation are involved. Among the various available BNP models, we choose the 'infinite-probit mixture linear' one. Infinite-mixture models exhibit a mixture distribution assigned a (BNP) prior on the entire space of probability measures and provide posterior-based clustering of subjects into distinct homogeneous groups (see Ghahramani, 2013; Karabatsos and Walker, 2012a, 2012b; Karabatsos, 2017; Müller et al., 2015).

More exactly, with a given covariate (x) dependent, discrete mixing distribution $G_x$, kernel (component) densities $\left(y|x;\psi,\theta(x)\right)$ ( with component indices j = 1, 2, . . ., respectively), fixed parameters $\psi$ and with component parameters $\theta_j(x)$having sample space $\Theta$ and given mixing weights $\omega_j(x)^{\infty}{}_{j=1}$ that sum to 1 at every $x \in \aleph$ ($\aleph$being the covariate space), a Bayesian Non-Parametric (BNP) infinite-mixture regression model can be represented in the following the general form (see Karabatsos, 2017 for details):

$$f_{G_x}(y|x;\zeta) = \int f\left(y|x;\psi,\theta(x)\right)dG_x(\theta) = \sum_{j=1}^{\infty}\left(y|x;\psi,\theta_j(x)\right)\omega_j(x) \tag{1}$$

For such a model, the covariate-dependent mixing distribution is a random probability measure that has the general form:

$$G_x(B) = \sum_{j=1}^{\infty}\omega_j(x)\delta_{\theta_{j(x)}}(B), \forall B \in B(\Theta) \tag{2}$$

Thus, such a model can be viewed as a case of a species sampling model (Pitman, 1995).

Further, the mixture model from (1) is completed by the specification of a prior distribution $\Pi(\zeta)$on the space $\Omega_\zeta = \{\zeta\}$ of the infinite-dimensional model parameter, given by:

$$\zeta = \left(\psi, \theta_j(x), \omega_j(x)\right)^{\infty}_{j=1}, x \in \aleph \tag{3}$$

For the infinite-probits model, with prior $\Pi(\zeta)$, the mixture distribution (2) is defined by a dependent normalized random measure (Karabatsos and Walker, 2012a). More exactly, for a dataset $D_n = \{(y_i, x_i)\}^n{}_{i=1}$ a Bayesian infinite-probits mixture model can be defined by (see, for more details, Karabatsos, 2015, 2017):

$$y_i|x_i \sim f(y|x_i; \zeta), i = 1,2,\ldots, n \tag{4}$$

$$f(y|x;\zeta) = \sum_{j=-\infty}^{\infty} n\left(y|\mu_j + x^T\beta, \sigma^2\right)\omega_j(x) \tag{5}$$

$$\omega_j(x) = \Phi\left(\frac{j - x^T\beta_\omega}{\sigma_\omega}\right) - \Phi\left(\frac{j - 1 - x^T\beta_\omega}{\sigma_\omega}\right) \tag{6}$$

$$\mu_j|\sigma^2{}_\mu \sim N\left(0, \sigma^2{}_\mu\right) \tag{7}$$

$$\sigma^2{}_\mu \sim U\left(0, \sigma^2{}_\mu\right) \tag{8}$$

$$\beta_0|\sigma^2 \sim N\left(0, \sigma^2 \upsilon_{\beta_0} \to \infty\right) \tag{9}$$

$$\beta_k|\sigma^2 \sim N(0, \sigma^2\upsilon), k = 1,2,\ldots, p \tag{10}$$

$$\sigma^2 \sim IG\left(\frac{a_0}{2}, \frac{a_0}{2}\right) \tag{11}$$

$$\beta_\omega|\sigma^2{}_\omega \sim N(0, \sigma^2\upsilon_\omega I) \tag{12}$$

$$\sigma^2{}_\omega \sim IG\left(\frac{a_\omega}{2}, \frac{a_\omega}{2}\right) \tag{13}$$

Here $y_i$can be a proxy for country *i* level of innovation efforts and outcomes while $x_i$is a set of specific determinants of innovation status; $\Phi(.)$ denotes the normal $N(0,1)$ cumulative distribution function. For model parameters $\zeta = \left((\mu_j)^{\infty}{}_{j=1}, \sigma^2{}_\mu, \beta, \sigma^2, \beta_\omega, \sigma_\omega\right)$ a prior $\Pi(\zeta)$ is assigned with cumulative distribution function being described by (with $J_p$denoting a *p X 1*vector of *1*s and $u\left(\sigma_\mu|0, b\right)$ referring to probability density function of the uniform distribution with minimum 0 and maximum $b$):

$$\pi(\zeta) = \prod_{j=-\infty}^{\infty} n\left(\mu_j|0, \sigma^2{}_\mu\right) u\left(\sigma_j|0, b_{\sigma_\mu}\right) n\left(\beta|0, \sigma^2 diag\left(\upsilon_{\beta_0} \to \infty, \upsilon J_p\right)\right) \tag{14}$$
$$\times\, ig(\sigma^2|a_0/2, a_0/2) n\left(\beta_\omega|0, \sigma^2{}_\omega \upsilon_\mu I_{p+1}\right)$$
$$ig(\sigma^2{}_\omega|a_\omega/2, a_\omega/2)$$

## Geographical Spread Effects in Innovation

A key issue in the design of innovation models is the existence of a global spread process for their leading mechanisms and policies. Such spread can be driven by convergence tools implying cooperative harmonization of domestic practices or interdependent but uncoordinated diffusion of practices using cross-national imitation, emulation or learning (Busch and Jörgens, 2007). Indeed, the literature provides a large body of evidence suggesting that innovation diffusion is spatially variable (Baptista, 2001; Asheim and Gertler, 2016). Of course, geographical segmentation is not the only possible segmentation criteria: clusters of countries that share similar levels of development or even similar social, historical and cultural features might also be considered. Nonetheless, geographical proximity can be viewed as one of the most direct mechanisms for the existence of different layers in international data related to innovation spread. Thus, a robustness analysis of the results provided by any model of the innovation explanatory frame should include an assessment of potential diffusion effects at regional/international levels. With this aim, in addition to the BNP 'infinite-probits mixture linear' analysis, we also employ an 'ANOVA-linear DDP model' (see De Iorio et al., 2004, Karabatsos, 2017). These models can account for the existence of different data strata formed by countries with (relatively) homogenous levels of innovative processes and outcomes.

The first task for carrying out the analysis of the potential connection between financial resource accessibility and the status of innovative processes, mechanisms and institutions consists of a proper choice of the involved descriptors.

First, in order to capture the level of both input and output factors leading to the emergence of an innovation-based economy and society, we employ the 2019 data for the *Global Innovation Index* (GII) (Cornell University, INSEAD, and WIPO, 2019) for 114 countries, including developed, emerging and frontier economies, with a world-wide geographical spread. Data represents the overall GII score, which is the simple average of the Input and Output Sub-Index scores and is based on around eighty indicators.

Second, we employ a) Domestic credit to the private sector (% of GDP) and, b) Commercial bank branches (per 100,000 adults) as proxies for financial resource availability in the economy. The first variable includes all gross credit to various sectors, except for credit to the central government, which is net. The second variable accounts for retail locations of resident commercial banks and other resident banks that function as commercial banks. These locations provide financial services to customers, are physically separated from the main office, but are not organized as legally separated subsidiaries. The data are collected from the World Bank's *World Development Indicators* database (World Bank, 2019) and are computed as averages of all available data between 2005 and 2018. By expressing the data as long-run values, we aim to avoid potential endogeneity issues in our analysis.

In addition, several control variables are considered. The core model includes proxies for financial accessibility alongside GDP per capita (measured in Purchasing Power Parity, constant 2011 international dollars) as a proxy of economic development. An extended model will incorporate additional variables identified in the literature as innovation enhancement factors including: foreign direct investment net inflows (% of GDP) (Walz, 1997; Erdal and Göçer, 2015; Cheung and Qian, 2009); international migrant stock (% of population) (Bahar et al., 2019; Miguélez, 2018); the quality of logistic services, proxied by the *Logistics Performance Index* (Competence and quality of logistics services component) (Yang, 2009) and the age dependency ratio for the elderly (% of working-age population) (Henseke and Tivig, 2009). To capture the long-run effects potentially exercised by these control variables, the corresponding data are collected as averages of all available values between 2005 and 2018.

Finally, to eliminate scale effects, all the involved variables are transformed to their *Z*-scores by removing their mean and dividing the result by their standard deviation. The main statistics for the transformed data for the key-dependent and explanatory variables are shown in Table 1.

**Table 1:** Main statistics for the Global Innovation Index (GII) and availability of financial resources (Z-scores)

| | Global Innovation Index | Domestic credit provided by financial sector (% of GDP) | Commercial bank branches (per 100,000 adults) |
|---|---|---|---|
| Mean | 0.000 | 0.000 | 0.000 |
| Median | -0.223 | -0.331 | -0.235 |
| Standard deviation | 1.000 | 1.000 | 1.000 |
| Skewness | 0.626 | 1.108 | 1.634 |
| Kurtosis | 2.385 | 3.442 | 6.093 |
| Interquartile range | 1.532 | 1.283 | 1.105 |

*Source: own computations*

According to the empirical values of distribution parameters, it appears that, even after their transformation, these variables exhibit signs of deviation from normality. Thus, any involved estimation methodology used to analyze possible linkages between these variables should be able to deal with potential violations of the normality assumption.

## RESULTS AND DISCUSSION

A key choice for performing a Bayesian inference is the selection of the involved priors. Such choice lies around the decision of using a noninformative prior versus a *weak* informative or a complete informative one. As Gelman and Hill (2007:347) explain: "Noninformative prior distributions are intended to allow Bayesian inference for parameters about which not much is known beyond the data included in the analysis at hand… we consider noninformative prior distributions to be "reference models" to be used as a standard of comparison or starting point in place of the proper, informative prior distributions". Since our data does not appear to follow a standard distribution and are affected by a rather high degree of uncertainty related to implied reciprocal relationships, we choose to use a noninformative prior as a starting point.

The marginal posterior parameter estimates of the core model are reported in Table 2. The largest (and positive) posterior point estimate corresponds to the development levels followed by the provision of domestic credit, while the weakest impact on innovation status seems to stem from the territorial expansion of commercial banks. Meanwhile, the largest standard deviation of the estimates relative to their mean are occurring for commercial bank branches variable, while the lowest relative standard deviation is the one which corresponds to domestic credit provided by financial sector.

**Table 2:** Marginal posterior parameter estimates of the infinite probits mixture core model

| Parameter | Mean | Standard deviation | 25% | 75% | 2.50% | 97.50% |
|---|---|---|---|---|---|---|
| $\beta$ parameters for: | | | | | | |
| $\beta_0$ | -0.101 | 0.283 | -0.231 | 0.073 | -0.818 | 0.392 |
| Domestic credit provided by financial sector (% of GDP) | 0.254 | 0.067 | 0.209 | 0.296 | 0.125 | 0.396 |
| GDP per capita, PPP (constant 2011 international $) | 0.566 | 0.167 | 0.454 | 0.672 | 0.262 | 0.911 |
| Commercial bank branches (per 100,000 adults) | 0.06 | 0.064 | 0.013 | 0.107 | -0.056 | 0.185 |
| $\sigma^2$ | 0.06 | 0.031 | 0.034 | 0.085 | 0.017 | 0.124 |
| ${\sigma^2}_\mu$ | 0.509 | 0.68 | 0.24 | 0.53 | 0.122 | 1.962 |
| $\beta_\omega$ parameters for: | | | | | | |

| **Parameter** | **Mean** | **Standard deviation** | **25%** | **75%** | **2.50%** | **97.50%** |
|---|---|---|---|---|---|---|
| $\beta_{0_\omega}$ | -2.512 | 1.43 | -3.62 | -0.838 | -4.924 | -0.538 |
| Domestic credit provided by financial sector (% of GDP) | -0.199 | 0.192 | -0.312 | -0.079 | -0.628 | 0.156 |
| GDP per capita, PPP (constant 2011 international $) | 2.461 | 0.998 | 1.347 | 3.318 | 1.003 | 3.96 |
| Commercial bank branches (per 100,000 adults) | -0.287 | 0.283 | -0.449 | -0.095 | -0.935 | 0.153 |
| $\sigma^2{}_\omega$ | 0.335 | 0.27 | 0.075 | 0.494 | 0.029 | 0.971 |

*Notes:* The dependent variable is the corresponding Z-score of the Global Innovation Index (GII), while the covariates are expressed through their Z-scores having mean 0 and variance 1. A rather non-informative prior distribution is specified for the model parameters with: $b_{\sigma\mu} = 5, \upsilon = 100, a_0 = 0.01, \upsilon_\omega = 10, a_\omega = 0.01$ .

In order to estimate the model's posterior distribution, 20,000 MCMC sampling iterations were run, using an initial burn-in of 2,000 and a thinning interval of 5. The model obtained a *D(m)* statistic of 14.899, with an R-squared of 0.972, and had no outliers according to standardized residuals that ranged within −2 and 2.

*Source: own computations*

**Table 3:** Ninety-five percent MCCI half-widths of the marginal posterior point estimates of the intercept and slope parameters of the infinite-probits mixture from Table 2 (core model)

| **Parameter** | **Mean** | **Standard deviation** | **25%** | **75%** | **2.50%** | **97.50%** |
|---|---|---|---|---|---|---|
| $\beta$ parameters for: | | | | | | |
| $\beta_0$ | 0.1 | 0.042 | 0.121 | 0.093 | 0.157 | 0.087 |
| Domestic credit provided by financial sector (% of GDP) | 0.012 | 0.004 | 0.011 | 0.014 | 0.011 | 0.017 |
| GDP per capita, PPP (constant 2011 international $) | 0.053 | 0.013 | 0.051 | 0.057 | 0.049 | 0.073 |
| Commercial bank branches (per 100,000 adults) | 0.01 | 0.003 | 0.011 | 0.012 | 0.01 | 0.01 |
| $\sigma^2$ | 0.013 | 0.002 | 0.012 | 0.014 | 0.01 | 0.015 |
| $\sigma^2{}_\mu$ | 0.131 | 0.229 | 0.033 | 0.146 | 0.014 | 0.646 |
| $\beta_\omega$ parameters for: | | | | | | |
| $\beta_{0_\omega}$ | 0.683 | 0.074 | 0.708 | 0.667 | 0.736 | 0.62 |
| Domestic credit provided by financial sector (% of GDP) | 0.031 | 0.033 | 0.047 | 0.028 | 0.089 | 0.054 |
| GDP per capita, PPP (constant 2011 international $) | 0.468 | 0.052 | 0.452 | 0.493 | 0.399 | 0.516 |
| Commercial bank branches (per 100,000 adults) | 0.069 | 0.048 | 0.106 | 0.049 | 0.136 | 0.05 |
| $\sigma^2{}_\omega$ | 0.103 | 0.034 | 0.08 | 0.122 | 0.054 | 0.183 |

*Source: own computations*

Additionally, Table 3 reports the 95 % Monte-Carlo confidence interval (MCCI) half-widths of the (marginal) posterior coefficient point estimates for the core model from Table 2. Almost all half-widths are nearly 0.10, and thus, these posterior point estimates are quite accurate in terms of Monte Carlo standard error.

The core model seems to support the idea that there is empirical evidence in favor of a positive role played by the supply of financial resources for innovation processes. However, in order to check the robustness of such evidence, we turn to an extended model that includes a supplementary set of control covariates. Table 4 shows the marginal posterior parameters for such an extended model. Interestingly, with the additional control variables, the level of development no longer appears to be the main driver of innovation. Instead, the largest positive effects relate to logistic performance, the age dependency ratio, the importance of high technology in international trade flows and domestic credit, while international migrant stock and the number of commercial bank branches show a lower impact. Perhaps the most ambiguous result is associated with low posterior point estimates and a relatively significant standard deviation of these estimates for the net inflows of foreign investment. Their expected positive spillovers do not seem to be manifested in a non-ambiguous manner in this analytical frame.

**Table 4:** Marginal posterior parameter estimates of the infinite probits mixture extended model

| **Parameter** | **Mean** | **Standard deviation** | **25%** | **75%** | **2.50%** | **97.50%** |
|---|---|---|---|---|---|---|
| $\beta$ parameters for: | | | | | | |
| $\beta_0$ | -0.132 | 0.174 | -0.259 | -0.013 | -0.467 | 0.194 |
| Age dependency ratio, old (% of working-age population) | 0.181 | 0.085 | 0.122 | 0.238 | 0.021 | 0.357 |
| Domestic credit provided by financial sector (% of GDP) | 0.102 | 0.045 | 0.073 | 0.133 | 0.015 | 0.191 |
| Foreign direct investment, net inflows (% of GDP) | 0.038 | 0.036 | 0.014 | 0.062 | -0.032 | 0.11 |
| GDP per capita, PPP (constant 2011 international $) | 0.044 | 0.079 | -0.005 | 0.098 | -0.118 | 0.185 |
| High-technology exports (% of manufactured exports) | 0.178 | 0.045 | 0.147 | 0.207 | 0.094 | 0.272 |
| International migrant stock (% of population) | 0.063 | 0.041 | 0.034 | 0.09 | -0.013 | 0.15 |
| Logistics performance index: Competence and quality of logistics services | 0.444 | 0.059 | 0.404 | 0.484 | 0.332 | 0.561 |
| Commercial bank branches (per 100,000 adults) | 0.08 | 0.047 | 0.048 | 0.111 | -0.012 | 0.174 |
| $\sigma^2$ | 0.058 | 0.01 | 0.051 | 0.064 | 0.041 | 0.08 |
| ${\sigma^2}_\mu$ | 0.191 | 0.306 | 0.06 | 0.202 | 0.02 | 0.895 |
| $\beta_\omega$ parameters for: | | | | | | |
| ${\beta_0}_\omega$ | -0.037 | 0.088 | -0.088 | 0.019 | -0.22 | 0.128 |
| Age dependency ratio, old (% of working-age population) | 0.557 | 0.091 | 0.504 | 0.609 | 0.379 | 0.76 |
| Domestic credit provided by financial sector (% of GDP) | -0.09 | 0.105 | -0.157 | -0.024 | -0.293 | 0.126 |
| Foreign direct investment, net inflows (% of GDP) | 0.085 | 0.153 | 0.021 | 0.183 | -0.28 | 0.328 |
| GDP per capita, PPP (constant 2011 international $) | 0.131 | 0.185 | 0.002 | 0.267 | -0.266 | 0.444 |
| High-technology exports (% of manufactured exports) | -0.095 | 0.11 | -0.159 | -0.025 | -0.343 | 0.122 |
| International migrant stock (% of population) | -0.004 | 0.09 | -0.065 | 0.059 | -0.183 | 0.164 |
| Logistics performance index: Competence and quality of logistics services | -0.134 | 0.132 | -0.213 | -0.057 | -0.385 | 0.135 |
| Commercial bank branches (per 100,000 adults) | 0.254 | 0.099 | 0.183 | 0.317 | 0.088 | 0.473 |
| ${\sigma^2}_\omega$ | 0.009 | 0.006 | 0.005 | 0.01 | 0.003 | 0.024 |

*Notes:* Same specifications as in Table 2. The model obtained a *D(m)* statistic of 13.907, with an R-squared of 0.952.

*Source: own computations*

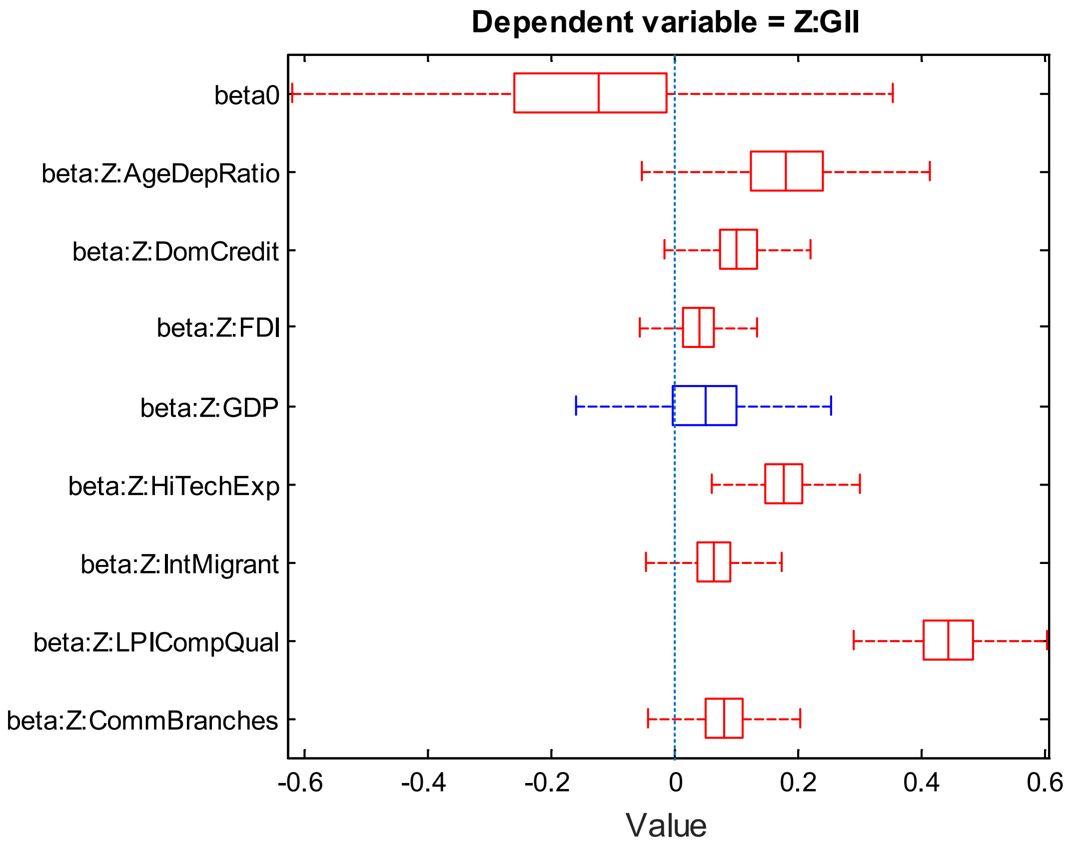
Table 5 supplementary reports the 95 % Monte Carlo confidence interval (MCCI) half-widths of the (marginal) posterior coefficient point estimates for the extended model from Table 4. All half-widths are nearly 0.05, indicating that these posterior point estimates are reasonably accurate regarding Monte Carlo standard error.

**Table 5:** Ninety-five percent MCCI half-widths of the marginal posterior point estimates of the intercept and slope parameters of the infinite-probits mixture (extended model from Table 4)

| **Parameter** | **Mean** | **Standard deviation** | **25%** | **75%** | **2.50%** | **97.50%** |
|---|---|---|---|---|---|---|
| $\beta$ parameters for: | | | | | | |
| $\beta_0$ | 0.048 | 0.018 | 0.05 | 0.052 | 0.053 | 0.05 |
| Age dependency ratio, old (% of working-age population) | 0.015 | 0.004 | 0.015 | 0.016 | 0.015 | 0.021 |
| Domestic credit provided by financial sector (% of GDP) | 0.004 | 0.001 | 0.004 | 0.004 | 0.005 | 0.007 |
| Foreign direct investment, net inflows (% of GDP) | 0.004 | 0.001 | 0.004 | 0.004 | 0.004 | 0.006 |
| GDP per capita, PPP (constant 2011 international $) | 0.019 | 0.005 | 0.021 | 0.019 | 0.029 | 0.019 |
| High-technology exports (% of manufactured exports) | 0.009 | 0.003 | 0.008 | 0.009 | 0.008 | 0.012 |
| International migrant stock (% of population) | 0.006 | 0.002 | 0.006 | 0.006 | 0.006 | 0.008 |
| Logistics performance index: Competence and quality of logistics services | 0.01 | 0.002 | 0.01 | 0.012 | 0.011 | 0.012 |
| Commercial bank branches (per 100,000 adults) | 0.006 | 0.002 | 0.007 | 0.006 | 0.009 | 0.007 |
| $\sigma^2$ | 0.002 | 0 | 0.001 | 0.002 | 0.002 | 0.002 |
| $\sigma^2{}_\mu$ | 0.022 | 0.04 | 0.008 | 0.026 | 0.003 | 0.154 |
| $\beta_\omega$ parameters for: | | | | | | |
| $\beta_{0_\omega}$ | 0.02 | 0.008 | 0.025 | 0.016 | 0.032 | 0.02 |
| Age dependency ratio, old (% of working-age population) | 0.018 | 0.009 | 0.016 | 0.02 | 0.023 | 0.036 |
| Domestic credit provided by financial sector (% of GDP) | 0.021 | 0.012 | 0.022 | 0.022 | 0.043 | 0.028 |
| Foreign direct investment, net inflows (% of GDP) | 0.055 | 0.019 | 0.062 | 0.051 | 0.078 | 0.05 |
| GDP per capita, PPP (constant 2011 international $) | 0.059 | 0.018 | 0.069 | 0.055 | 0.074 | 0.054 |
| High-technology exports (% of manufactured exports) | 0.026 | 0.016 | 0.03 | 0.027 | 0.041 | 0.036 |
| International migrant stock (% of population) | 0.017 | 0.01 | 0.02 | 0.02 | 0.027 | 0.025 |
| Logistics performance index: Competence and quality of logistics services | 0.034 | 0.016 | 0.033 | 0.038 | 0.061 | 0.047 |
| Commercial bank branches (per 100,000 adults) | 0.025 | 0.01 | 0.023 | 0.029 | 0.021 | 0.043 |
| $\sigma^2{}_\omega$ | 0.001 | 0.001 | 0 | 0.001 | 0 | 0.004 |

*Source: own computations*

Figure 1 is a box plot of the (marginal) posterior quantile point estimates of the intercept and slope coefficient parameters for the covariates (including the constant term). Clearly, with the exception of GDP per capita, all the coefficient parameters of the extended model look significantly different than zero.




*Notes:* Center vertical line: posterior median. Thick box: inter-quartile range (50 % interval). Horizontal lines (whiskers): 95 % credible interval (.025 and .975 marginal posterior quantiles). A red box (blue box, resp.) flags a coefficient parameter that is (not, resp.) significantly different than zero, according to whether or not the 50 % (marginal) posterior interval (box) includes zero.

**Figure 1.** *Box plots* of the marginal posterior distributions of the intercept and slope coefficients of the infinite probits mixture model (extended model)

*Source: own representation*

The Markov Chain Monte Carlo (MCMC) convergence is evaluated in Figure 2. The trace plots appear to support good (although not a “perfect” one, especially in the case of foreign direct investment and high-technology exports) mixing for these parameters, since each trace plot appears to be reasonably stable.

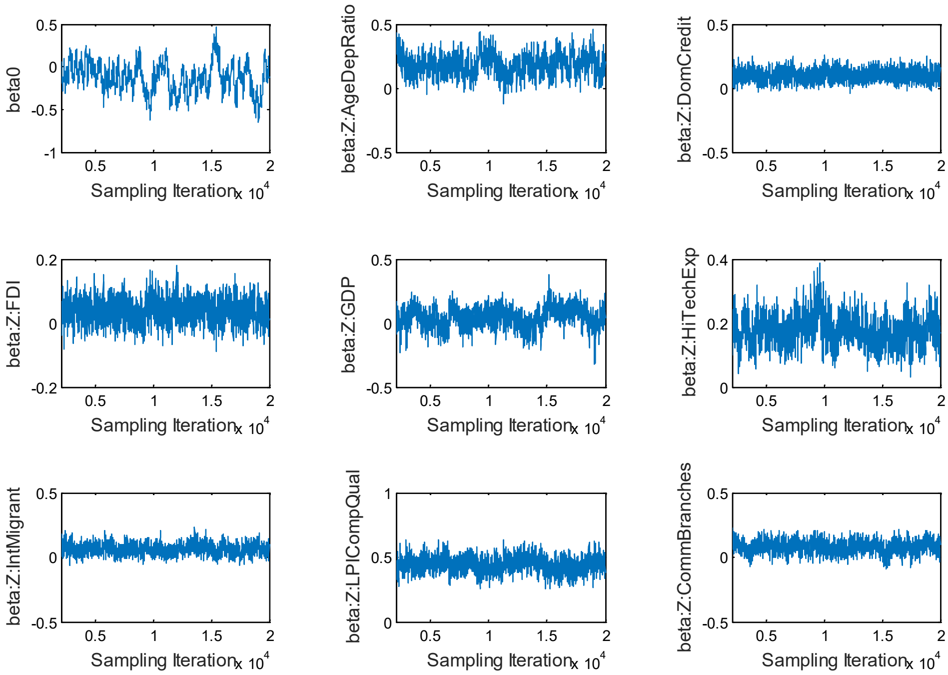



**Figure 2.** Trace plots of MCMC samples of the intercept and slope coefficients for the infinite probits mixture model (extended model)

*Source: own representation*

Figure 3 provides a quantile and mean regression analysis, by showing the estimates of the mean, and the .1, .25, .5 (median), .75, and .9 quantiles of the model's posterior predictive distribution of the Global Innovation Index, conditionally on selected values of the domestic credit covariate, and on zero for all the other covariates (using the zero-centering method). This figure suggests that there might be some small non-linear effects of domestic credit on innovation for high values of financial resources supply while for its 'middle' values the impact is relatively a 'flat' one.

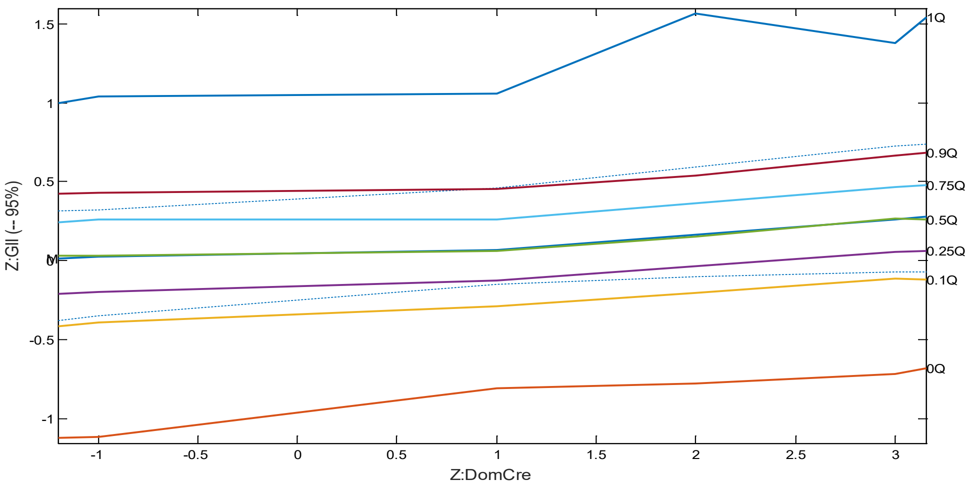



**Figure 3.** The posterior predictive mean and quantiles of the Global Innovation Index, over chosen values of the covariate domestic credit provided by financial sector (% of GDP) (extended model)

*Source: own representation*

In correlation with this, Figure 4 shows a three-dimensional plot of (Rao-Blackwellized) estimates of the model's posterior predictive probability density function (p.d.f.) of the Global Innovation Index (conditionally on the same values of the covariates). These results show that the location and shape of this index distribution change as a function of domestic credit.

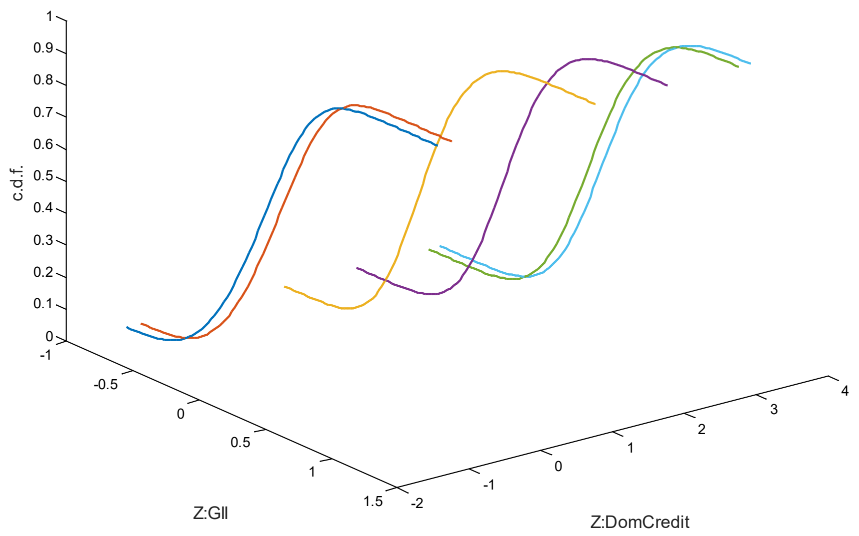



**Figure 4:** The Rao-Blackwellized estimate of the posterior predictive probability density function (p.d.f.) of the Global Innovation Index as a function of domestic credit provided by the financial sector (% of GDP) (extended model)

*Source: own representation*

A final analytical step is to check for the potential effects of geographical distribution in the levels of innovation. Indeed, as the results of the BNP 'ANOVA-linear DDP model' with a regional dummy as a grouping variable from Table 6 show, the geographical factor induces significant heterogeneity in the effects exercised by domestic credit supply and banking development. While in most regions, a higher level of credit granted to various sectors seems to clearly support better innovative performances, this influence is displaying a 'wrong' negative sign in the case of Europe, Northern Africa and Western Asia. Regarding the number of commercial banks, this is important in explaining the status of innovation in all regions. However, there are quite significant differences with lower estimated impacts in Central and Southern Asia, Latin America and the Caribbean and Sub-Saharan Africa compared to a much higher impact in the other regions.

**Table 6:** Marginal posterior parameter estimates of the intercept and slope parameters of a Dirichlet process mixture of homoscedastic linear regressions (ANOVA-linear DDP) model

| **Parameter** | **Mean** | **Standard deviation** | **25%** | **75%** | **2.50%** | **97.50%** |
|---|---|---|---|---|---|---|
| $\beta$ parameters for domestic credit provided by financial sector (% of GDP): | | | | | | |
| Region =1 | 0.276 | 0.342 | 0.314 | 0.396 | -0.491 | 0.903 |
| Region=2 | -0.219 | 0.133 | -0.286 | -0.128 | -0.286 | 0.182 |
| Region=3 | 0.311 | 0.192 | 0.314 | 0.396 | -0.402 | 0.399 |
| Region=4 | 0.311 | 0.187 | 0.314 | 0.396 | -0.402 | 0.399 |
| Region=5 | 0.276 | 0.178 | 0.314 | 0.396 | -0.193 | 0.396 |
| Region=6 | -0.174 | 0.224 | -0.286 | -0.128 | -0.286 | 0.509 |

| Parameter | Mean | Standard deviation | 25% | 75% | 2.50% | 97.50% |
|---|---|---|---|---|---|---|
| Region=7 | 0.31 | 0.184 | 0.314 | 0.396 | -0.402 | 0.399 |
| $\beta$ parameters for commercial bank branches (per 100,000 adults): | | | | | | |
| Region =1 | 0.146 | 0.458 | -0.109 | 0.426 | -0.706 | 1.018 |
| Region=2 | 0.265 | 0.082 | 0.293 | 0.293 | -0.03 | 0.298 |
| Region=3 | 0.041 | 0.358 | -0.109 | 0.426 | -0.564 | 0.426 |
| Region=4 | 0.026 | 0.34 | -0.109 | 0.426 | -0.564 | 0.426 |
| Region=5 | 0.185 | 0.268 | -0.109 | 0.426 | -0.109 | 0.528 |
| Region=6 | 0.214 | 0.232 | 0.293 | 0.293 | -0.638 | 0.298 |
| Region=7 | 0.032 | 0.343 | -0.109 | 0.426 | -0.564 | 0.426 |

*Notes:* The grouping variable is a regional dummy taking values of 1 for Northern America, 2 for Europe, 3 for Central and Southern Asia, 4 for Latin America and the Caribbean, 5 for South East Asia, East Asia, and Oceania, 6 for Northern Africa and Western Asia and, respectively, 7 for Sub-Saharan Africa. To estimate the model's posterior distribution, 100,000 MCMC sampling iterations were run. 5,000 initial burn-in and a thinning interval of 5 were considered. A non-informative prior distribution is specified for the model parameters. The full model is based on all the explanatory variables of the extended model. Only the corresponding values for domestic credit and commercial bank branches are reported here.

*Source: own computations*

As Table 7 reports, for these results, the MCMC convergence is confirmed by the results of small 95 % MCCI half-widths for (marginal) posterior point estimates (nearly all less than .1 or around this level).

**Table 7:** Ninety-five percent MCCI half-widths of the marginal posterior point estimates of the intercept and slope parameters of a Dirichlet process mixture of homoscedastic linear regressions (ANOVA-linear DDP) model from Table 6

| Parameter | Mean | Standard deviation | 25% | 75% | 2.50% | 97.50% |
|---|---|---|---|---|---|---|
| $\beta$ parameters for domestic credit provided by financial sector (% of GDP): | | | | | | |
| Region =1 | 0.046 | 0.043 | 0.078 | 0.054 | 0.1 | 0.151 |
| Region=2 | 0.047 | 0.011 | 0.045 | 0.051 | 0.042 | 0.054 |
| Region=3 | 0.058 | 0.033 | 0.077 | 0.058 | 0.098 | 0.034 |
| Region=4 | 0.058 | 0.034 | 0.077 | 0.059 | 0.093 | 0.02 |
| Region=5 | 0.055 | 0.03 | 0.067 | 0.053 | 0.087 | 0.053 |
| Region=6 | 0.056 | 0.039 | 0.055 | 0.068 | 0.048 | 0.112 |
| Region=7 | 0.058 | 0.033 | 0.077 | 0.06 | 0.081 | 0.02 |
| $\beta$ parameters for commercial bank branches (per 100,000 adults): | | | | | | |
| Region =1 | 0.085 | 0.057 | 0.111 | 0.096 | 0.221 | 0.166 |
| Region=2 | 0.028 | 0.01 | 0.033 | 0.026 | 0.035 | 0.023 |
| Region=3 | 0.121 | 0.04 | 0.131 | 0.122 | 0.138 | 0.15 |
| Region=4 | 0.121 | 0.033 | 0.131 | 0.122 | 0.138 | 0.109 |
| Region=5 | 0.095 | 0.034 | 0.099 | 0.101 | 0.097 | 0.106 |
| Region=6 | 0.062 | 0.034 | 0.077 | 0.061 | 0.099 | 0.053 |
| Region=7 | 0.122 | 0.034 | 0.13 | 0.122 | 0.144 | 0.122 |

*Source: own computations*

**CONCLUSIONS**

Our findings provide empirical support for the idea that finance *matters* in explaining the status of innovation processes and outcomes. However, this overall conclusion should be nuanced by adding that different features of the financial system have a non-uniform importance: while the global supply of financial resources through credit granted to the private sector is putting forth a positive and robust influence on innovation, the expansion of commercial banks network appears to play a more ambiguous and less robust role. Additionally, the existence of geographically spread specific mechanisms clearly influences the amplitude and shape of financial variables' impact on innovation.

Several clarifications can be provided for a better understanding of these results. First, one can argue that the idea according to which 'finance matters for innovation' is somehow too general and, in fact, covers a full spectrum of empirical cases. The essential facts in this respect are actually the degree of financial system development, its sophistication, efficiency and stability, as well as the structural characteristics of financial intermediation processes. For instance, there might be some substantial differences between the cases in which firms are financing their innovations through internal cash flow and external equity markets and the cases in which they depend almost entirely on the loans granted by commercial banks or on the financial resources from venture debt or other non-bank lenders. Broadly, as Acharya and Xu (2017) found, public firms in external finance-dependent industries tend to spend more on research and development than their private counterparts. It should also be added that the effects of financial resource availability may further vary depending on the architecture and status of their providers, including factors such as market concentration, regulations and prudential supervision, specific efficiency and risk management mechanisms. For an extended discussion of these issues, see Kerr and Nanda, 2015).

Second, it is not enough to establish that 'finance supports innovation'; it should also be explained *what types* of innovation are promoted by changes in financial resource availability. For instance, Nanda and Nicholas (2014) provide historical evidence that bank distress periods were associated with a shift away from high-risk R&D projects toward more incremental innovation activities. Thus, not only the *level* but also the *structure* of innovation might be affected by changes in the financial conditions of the economy.

Third, the influence of geographical factors on the relationship between finance and innovation might highlight the role of the international flows of capital goods - especially those that incorporate technological advances. However, considering that our findings do not provide strong support for the positive impact of foreign direct investment (and, by extension, its associated technology, knowledge, skills and abilities) on the innovation status of host countries, further analysis is required at this point.

Fourth, it should be noted that, in a dynamic framework, the availability of financial resources in the economy may also influence the innovation *conditions*, such as the R&D frame, infrastructure, or innovation risk management systems. Thus, one can draw a distinction between the possible *direct* effects of finance on innovation (which are explicitly considered in this analysis) and the *indirect* effects that are not accounted for here.

Fifth, the explanation should be completed by integrating other explanatory variables explicitly considered in this analysis from the much-extended set of possible direct enhancers of innovation. For example, the positive and significant impact of demographic factors identified in this analysis aligns with the literature supporting the hypothesis that the scope of start-up activities is positively associated with two types of instrumental family support: financial and social capital (Edelman et al., 2016). Thus, the extent of finance's impact on innovation might be conditioned by the presence of other key determinants that could either amplify or compensate for the lack of such impact.

Nevertheless, even with such clarifications, there is still a list of open questions regarding these results. What are the specific mechanisms that differentiate the roles of different financial system components in providing support for innovation? If the distinction between heavily dependent and less dependent sectors is neither fixed nor permanent, what factors drive the variation in the impact of financial resource availability over time? Do banks modulate the structure of innovation exclusively during their periods of financial distress, or is this intervention in the typology of innovation projects a constant characteristic of their financial support? How can our finding - that geographical proximity is relevant for discerning the impact of finance on innovation - be correlated with the effects of trans-regional globalization processes? What specific factors can compensate for (or, conversely, exacerbate) the existence of some ‘hard restrictions’ on the supply of financial resources? This list of questions could easily be extended.

Despite its limitations, this study points toward the fact that the development and functional capabilities of the financial systems are highly relevant for the status of innovation processes in modern ‘knowledge-based’ economies.

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