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Complementarity of innovation policies in Brazilian industry: An econometric study ☆

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ABSTRACT

The paper aims to assess discrete complementarities in innovation policies in the context of Brazilian industry in 2003. We focus on complementarity and substitutability tests for obstacles to innovation (in the present application, lack of: finance sources, skilled personnel, cooperation opportunities, and information on technology or markets). The application, based on the Brazilian innovation survey (PINTEC-IBGE, 2003. Pesquisa Industrial de Inovação Tecnológica 2003. Retrieved October 23, 2013, from http://www.ibge.gov.br/home/estatistica/economia/industria/pintec/2003/pintec2003.pdf), avoids micro-aggregation of the data and explicitly considers sampling weights in the econometric estimation. The analysis highlights the two phases of the innovation process in terms of the propensity and intensity of innovation. We find evidence that firms subject to international competition have higher propensity to innovate. We also present some evidence that foreign ownership may be a driver to the propensity of innovation when companies actually innovate in the host countries. The evidence, unlike previous results, is not totally clear-cut in terms of contrasts of the two phases. Nevertheless, we can detect some substitutability and complementarity for specific pairs of obstacles regarding the propensity to innovate, and some evidence of complementarities in obstacles when considering intensity of innovation. Evidence is suggestive and favors the adoption of more targeted incentive policies for innovation.

1. Introduction

The role of active innovation efforts in fostering economic growth is largely recognized in the endogenous growth literature (see e.g. Romer, 1990). For developing countries, bridging the technological gap is paramount to long term growth. The nature of relationships between different types of innovation is relevant to defining appropriate incentives for innovative activities. The literature on industrial organization has emphasized inter-firm rivalry in terms of strategic complementarity or substitution as defined by Bulow et al. (1985). The former category refers to strategic decisions that mutually reinforce one another, whereas the latter considers choices that counteract one another. In an intra-firm context, it is also possible to conceive complementarity and substitution among groups of activities, as suggested by Milgrom and Roberts (1990). In the context of innovative activities, the existence of complementarities favors the adoption of packages of incentive policies instead of isolated policies for specific factors. For example, if access to information and labor skills are identified as complementary activities, innovation policies should favor joint initiatives.

There are two approaches for empirically testing complementary innovation factors: direct (Mohnen and Röller, 2005) and indirect (Arora and Gambardella, 1990; Arora, 1996; Ichniowski et al., 1997 and Miravete and Pernias, 2006), and neither is preferred, with differences related to issues of econometric estimation due to the availability of data. The evidence weakly indicates that the prevalence of complementarities depends on the phase of the innovation process.

However, there is much we still don't understand regarding innovation policies, because of the many interaction between innovation factors, phases, strategies, and types of countries. Doran (2012) recently considers complementarity strategies associated with indicators reflecting the output dimension of innovation in terms of activities that are new to firm and market product, process innovation and organizational innovation. The emphasis on the actual outcomes of the innovative activities contrast with

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the bulk of the literature that highlights the input dimension of the innovative activities often considered in terms of R&D efforts.

It is worth mentioning that the increasing empirical interest on innovation strategies reflects, in part, the more recent availability of detailed innovation surveys for different countries. Those surveys are often based on the European innovation surveys (Community Innovation Survey-CIS) (see Hong et al., 2012 for a discussion).

We try to contribute to the literature by considering a very favorable data scenario in which we are able to improve on the identification of complementary strategies for innovation policies. The motivation for the paper builds on at least three factors:

(a) The scarcity of related works in the context of developing economies. In the case of Brazil, a handful of studies (e.g. Resende and Hasenclever, 1998; De Negri, 2005 and Kannebley et al., 2005) point out the reduced level of technological effort prevalent in that country;
(b) The possibility of avoiding micro-aggregation of the data and the potential related biases that constitutes a shortcoming of the previous analogous application of the European survey data.
(c) The consideration of estimators that acknowledge the complex sampling of the innovation survey. In fact, the non-negligible heterogeneity of the Brazilian economy naturally motivates estimators that consider different probabilities of firm selection in the survey (see Pfeffermann, 1993 for an overview of the related statistical issues).

Our results indicate that firms subject to international competition have higher propensity to innovate. For a country that is shifting towards more trade barriers, the unintended consequence of less innovation is particularly important. We also find weak evidence that foreign ownership may be a driver to the propensity of innovation when companies actually innovate in the host countries.

The paper is organized as follows. The second section discusses some conceptual aspects associated with the assessment of complementarities in innovation policies and econometric strategies for assessing it. The third section discusses the data source, the empirical model and the obtained estimates. The fourth section provides some final comments.

2. Measuring complementarity in innovation factors

2.1. Conceptual aspects and main empirical results

There is a clear correlation between innovation and development. Countries have been pursuing innovation policies for a long time, but there are still marked differences between innovation patterns around the world. Innovation is a major goal of public policy, since most governments believe it is subject to more than market forces only (Aalbers et al., 2012). One does not know how to optimally allocate resources for innovation policies, even though models for innovation systems abound, both in terms of supply and demand sides. Tidd (2006) provides an introductory framework on the different aspects of national systems of innovation. Meanwhile, companies are striving to improve innovation outcomes and are searching for optimal strategies regarding assets allocation (Hess and Rothaermel, 2011).

Here we try to improve on the literature that analyses the supply side of innovation. Early models of innovation are based on a pull–push system (Tidd, 2006), and the literature has evolved beyond those simple models. However, there is still much we do not understand regarding how companies actually perform innovative activities.

One of the dichotomies related to how companies innovate is the one between complementary and substitute factors. The nature of the interrelationships among different types of innovation is relevant to defining appropriate incentives for innovative activities. In an intra-firm context, the notions of complementarity and substitution among a group of activities are suggested by Milgrom and Roberts (1990). In such cases, complementarities prevail when the increase in any subset of activities leads to an increase in the marginal return of the remaining activities. In the context of innovative activities, the existence of complementarities favors the adoption of incentive policies as a package that contemplates the relevant set of complementary activities rather than a focus on isolated incentive policies for specific innovation factors. For example, if access to information and labor skill are identified as complementary any incentive policy should consider joint initiatives on those aspects, but if a substitution relationship prevails, one should focus on a specific innovation input because each activity would tend to offset the other.

Understanding if relevant factors for innovative activities are complementary or substitutes is particularly relevant for deriving industrial policy and improving on managerial practices. Our work is closely related to the empirical literature that searches for evidence on the complementarity of innovation factors. (e.g. Athey and Stern, 1998; Mohnen and Röller, 2005 and Doran, 2012). Hess and Rothaermel (2011), for instance, analyse the pharmaceutical industry and present many interesting results based on an exploration of substitutability of factors relating to upstream and downstream parts of the value chain. One of their conclusions is the substitutive relationship between star scientists and upstream alliances, and they posit that performance effects of star scientists on firm innovation are contingent on their connections to other firm-specific resources.

Our work is not industry specific but follows an empirical strand that uses national surveys to gather insights into innovation factors pertaining to different industries. This strand of the innovation literature can be divided into two different empirical methodologies: direct and indirect. The indirect methodology can be further divided in the "correlation" and the so-called "reduced form" approaches.

The correlation indirect approach emphasizes the association between different choice variables with varying degrees of theoretical foundation (see e.g. Arora and Gambardella, 1990; Ichniowski et al., 1997 and Miravete and Pernias, 2006). The reduced form indirect approach focuses on exclusion restrictions and highlights similar effects of exogenous variables on complementary variables (see e.g. Holmström and Milgrom, 1994).

Galia and Legros (2004) undertake an indirect approach in the context of France over the period of 1994–1996 with innovation survey data (CIS2), and use both the correlation and the reduced form approaches. They consider indicators pertaining to obstacles to innovation, and use a smaller set of equations for 3 types of R&D. Besides usual controls pertaining firm size, they incorporate the importance of information sources and protection mechanisms, barriers to innovation activities, technology intensity and skilled labor. A distinctive feature of Galia and Legros (2004) is that they consider obstacles to innovation in postponed and abandoned projects and the detailed account of patent-related factors. Moreover, the study undertakes a multivariate Probit estimation for the nine types of obstacles for the postponed and abandoned projects, and considers explanatory variables that include firm size, type of ownership, group membership, internal and external R&D variables portraying technological intensity (low, medium or high), and qualitative variables related to cooperation and training. The approach for assessing complementarities is indirect because it seeks to evaluate correlations obtained upon the disturbances covariance matrix. They find that while adopting a package of policies increases the pace of innovation, a more targeted choice among policies is needed to encourage firms to persevere in their innovative efforts.

Schmiedeberg (2008) also considers an indirect approach based on CIS data, but in the context of a cross-section for the German manufacturing sector. The evidence indicates significant complementarities between internal R&D and R&D cooperation, but no clear pattern regarding the complementarity of internal and contracted R&D.

In contrast to the papers mentioned above, direct approaches consider special features of an innovation function in which complementarities or substitutability in innovation policy are associated to the supermodularity or submodularity of that function, respectively. Examples include Mohnen and Röller (2005), Leiponen (2005), Love and Roper (2009), Carree et al. (2011), and Doran (2012). We follow the direct approach literature.

Previous evidence (Love and Roper, 2009; Leiponen, 2005; Carree et al., 2011) shows that there are two distinct phases in the innovation process, based on the coefficients of the obstacle states. Mohnen and Röller (2005) observe few significant results in the propensity equation, but a larger number of significant coefficients for the intensity of innovation phase. Furthermore, the evidence for the propensity to innovate indicates a non-negligible substitutability across most obstacles that is also supported in terms of the supermodularity test that suggests the rejection of complementarity in the case of the four obstacles pairs. Altogether, the evidence indicates stronger substitutability in the case of propensity to innovate and salient complementarity in the case of intensity of innovation. Mohnen and Röller (2005) present relevant policy implications in terms of obstacles to innovation: complementarity suggests that specific targeted policies should be considered, but substitutability leads to the recommendation of simultaneous removal of obstacles by means of packages of innovation policies. Leiponen (2005) reinforces these results by investigating complementarities between employees' skills and firms' innovation activities in the Finish manufacturing industry from 1992 to 1996. The main point of the study pertains to the supporting role of internal competencies (as approximated by employees' technical skills) in facilitating product and process innovation. In fact, the literature on complementarities often highlights lack of skill as an important obstacle to innovation. The evidence indicates significant complementarities between technical skills and innovation, and between technical skills and R&D collaboration activities, but the latter result is not clear-cut.

Another direct approach results is found in Love and Roper (2009), who test for complementarities in the use of external networking between stages of the innovation process in the context of plants in Germany and in the U.K. Important contrasts emerge between the two countries. The evidence favoring complementarities is stronger for Germany, and in the U.K. substitutability in external networking appears to prevail in various stages. Finally, Doran (2012) undertakes a study of Irish firms from 2004 to 2006. A distinguishing feature of the analysis is that it does not rely on the input dimension of innovation. Indeed, formal tests for complementarities are considered for innovation as related to four categories: new to firm product, new to market product, process innovation and organizational innovation. An interesting result is the role of organizational innovation as a complement to technological innovation, and the author obtains initial evidence for the presence of scope economies among different innovation outputs.

Even though the direct approach is well established in the literature, Carree et al. (2011) provide a critique of this approach on different grounds, including the use of dichotomous variables and the possibility of inconclusive areas in the supermodularity and submodularity tests. The authors contend that an even more direct testing framework for supermodularity/submodularity is possible and that the restrictive case of dichotomous practices would be a particular case of continuous practices. However, actual empirical applications are likely to be limited by data availability made possible by current innovation surveys.

We contribute to the literature by presenting a more careful empirical estimation based on complex sampling, to mitigate issues raised by Carree et al. (2011), and exploring the results of innovation factors for a developing country. In particular, our data does not suffer from micro-aggregation data and by considering complex sampling we approximate an ideal data scenario as described in Carree et al. (2011).

2.2. A direct approach for measuring complementary among innovation factors

Formally, for an innovation function, the assessment of discrete complementarities requires imposing a lattice ordered structure in its domain and evaluating the possibility of supermodularity or submodularity.[1]

Let $I(a, \theta)$ represent a general innovation function where $a = (a_1,\ldots,a_k)$ denotes a set of policy variables and θ_I indicates other relevant control variables that might portray institutional and firm or sector-specific characteristics. Supermodularity of that function would prevail if for all combinations of actions a' and a'', it holds that:[2]

$$I((a' \wedge a''), \theta) + I((a' \vee a''), \theta) \geq I(a', \theta) + I(a'', \theta) \tag{1}$$

The previous definition is more readily understood if we consider an example with $\mathbf{A} = \{(0,0),(1,1),(0,1),(1,0)\}$.

Supermodularity would prevail if $I(1,0) + I(0,1) \leq I(1,1) + I(0,0)$ or yet $I(1,0) - I(0,0) \leq I(1,1) - I(0,1)$.

This inequality indicates that the reward for increasing a given activity is higher when the other activity is already undertaken. The analysis becomes more complex as the number of inequalities to be considered increases with the number of available policies. A convenient result is advanced by Topkis (1978). A pairwise analyses is supermodular over a subset of its arguments if, and only if, all pairwise components in the subset satisfy the previous definition.

In the general case of k policies there will be $2^{(k-2)} \sum_{i=1}^{k-1} i$ non trivial restrictions to be tested. In particular, in the application considered by Mohnen and Röller (2005), and in the present paper there, are 24 restrictions to be considered because $k=4$ in both cases.

In practice, governmental policies are often not observed in survey data, and we need to rely on indirect measures that indicate perceived obstacles to innovation. We define $C_k = -a_k$, where C_k ($k=1,\ldots$, K), indicate the innovation obstacles faced by firms. The innovation function in that case would be given by:

$$I(C, \theta) = f(C_1, \ldots, C_k, \theta) \tag{2}$$

In the case where we have inverse proxies for innovation, the interpretation should be more cautious. For barriers that have complementarities, specific targeted policies should be considered.

[1] Introductory overviews of the related concepts appear in Milgrom and Roberts (1995) and Vives (1999).

[2] A related relevant concept defines that a function f is said to submodular if $-f$ is supermodular.

However, the case of a substitution pattern between barriers would call for packages of innovation policies because the reduction of a given barrier exacerbates the effect of the remaining barriers.

3. Empirical analysis

3.1. Data and variables

The study relies on a comprehensive survey of technological innovation in the context of Brazilian industry [Pesquisa de Inovação Tecnológica-PINTEC, Instituto Brasileiro de Geografia e Estatística-IBGE]. The survey considers active firms that have their main revenues associated with extractive or manufacturing industries and with 10 or more employees. We are granted special access to the micro data of PINTEC-2003. This questionnaire closely follows the Community Innovation Survey (CIS 1) conducted for European countries and used by Mohnen and Röller (2005). However, in the Brazilian case we do not face a microaggregation limitation. The quantitative data and a few qualitative data refer to the current year of the survey. The majority of the qualitative data refer to the period of the current year and the two previous years (in the case of PINTEC-2003, from 2001 to 2003).

A stratified sampling procedure is adopted in which the first stratum is defined in accordance with the probability of the firm being an innovator. The allocation of a firm to a stratum depends on a set of indicators (primary and secondary). The first subset, the certain stratum, comprises large firms (with 500 or more employees) or firms that had declared to be innovators in the previous edition of the survey. Firms in this stratum are included with probability 1.

Two additional classes of stratum are considered in terms of eligible and non-eligible categories. The first one includes firms with reasonable chances of being innovators and the second one includes firms with slim or no chances of performing innovation. To guarantee reliable information for the different regions, an additional stratum has different cut-off points depending on the importance of the economic activity of each region. For example, in the case of the most important industrial state, São Paulo, the criterion is 80% of the industrial transformation value. The selection of the sample in the final stratum considers a selection probability that is proportional to the square root of the number of employees. Altogether, we arrive at a complex stratified sampling, and thus the maximum likelihood estimation incorporates firm-level sampling weights that aim at accounting for the aforementioned heterogeneities. Additionally, we consider aggregate controls for the Brazilian macro-regions, and dummy variables for the 16 industrial sectors (from the Classificação Nacional de Atividades Econômicas-CNAE-IBGE).

Prior to defining the sample, we exclude firms with R&D intensity above 50% as potential outliers. In fact, that order of magnitude largely extrapolates descriptive figures from previous studies.[3] Next we describe the variables used in the econometric estimation. The descriptive information pertains to the expanded sample that takes into account potentially distinct sampling weights for the various firms accruing from the stratified complex sampling. In fact, if the sample is selected with unequal selection probabilities, one should consider the referred weights in the estimation in order to avoid biased results (see e.g. Kreuter and Valliant, 2007). The importance of accounting for those weights later appears in terms of very distinct estimation results in the present study.

[3] It is also worth noting that some of the more R&D-intensive sectors typically have their innovative efforts carried out in their headquarters outside Brazil.

The variables are described in Table 1. For policy variables we focus on perceived obstacles to innovation, but consider the categories referring to risk and finance, knowledge-skill within enterprise, and knowledge-skill outside the enterprise. In the first category we have the lack of appropriate sources of finance. In the second category, the variable is related to lack of skilled personnel, of information on technology, or the market. In the third category, we focus on the lack of opportunities for cooperation with other firms/institutions. Tables 2 and 3 display some basic summary statistics and indicate substantial heterogeneity for the selected variables. The core of our empirical analysis is to assess the role of the joint perusal of distinct innovation policies (in terms of inverse proxies specified as obstacles to innovation) in determining the propensity to innovate and intensity of innovation. However, it is important to control for other relevant variables that may impact those two phases of the innovation process. We control for (other than size and R&D intensity, variables are binary):

- Size. Size variables are often considered in innovation studies and frequently proxied in terms of the number of employees. Here we define Log(*EMP*), the logarithm of the number of employees, as a proxy for size. The two main Schumpeterian hypotheses (based on the work Schumpeter (1942) on innovation) state that innovation is promoted by large firms and by the presence of imperfect competition (see Levin et al., 1985 and Cohen and Levin, 1989 for an overview). The underlying arguments for size advantages include: (i) capital market imperfections that would make funding more readily available for larger firms, (ii) scale economies for R&D, (iii) higher returns for R&D in the case of larger firms that can also explore important complementarities with other activities such as marketing (see Kay, 1988);
- Foreign ownership. The *foreign* variable explores distinct innovation patterns associated with foreign ownership. This can be particularly relevant for the Brazilian case, as many firms in R&D-intensive industries are multinational and carry out innovation in their headquarters. Emblematic examples are given by the pharmaceutical, chemical and electronic equipment industries;
- Diversification. The *group* variable aims to capture the possibility that firms that are a part of a diversified group are more able to conduct risky R&D activities. This variable also explores the size aspect, but in terms of degree of diversification of the firm (see Nelson, 1959);
- Organizational features. The *organizational* variable is based on a self-report answer to: did the firm observe a significant organization change in the last year? It indicates that the actual organizational features and related innovations may facilitate technological innovations;
- Export industries. The *exporting* variable is motivated by competitive pressures that are more likely to prevail in more globalized markets, and force firms to innovate. One example is Embraer, a leading firm in aircraft manufacturing;
- R&D intensity. A standard control in different innovations studies;
- Knowledge accumulation. The *continuous* variable is based on the cumulativeness of knowledge in certain industries. In more dynamic and mature industries learning effects spread over time (Breschi et al., 2000);
- Cooperation. The *cooperation* variable highlights complementarities with external organizations that can facilitate innovation. A common example is provided by synergetic effects accruing from the simultaneous undertaking of in-house R&D and external R&D (Cassiman and Veugelers, 2006);
- Dummies (for the Brazilian macro-regions) and for industries aim at capturing more aggregated heterogeneities.

Table 1
Definition of variables.

Endogenous variables	
Propensity to innovate	Dummy variable assumes value 1 if the firm has innovated in process or product, for the market or only for the firm, and 0 otherwise
Intensity of innovation	Revenues from innovating products divided by total revenues when the main market is national, and net exports of innovating products divided by total exports when the main market is abroad
Exogenous variables	
Log(*EMP*)—*size*	Logarithm of the number of employees
Foreign	Dummy variable assumes value 1 if the firm has dominant share of foreign capital and 0 otherwise
Group	Dummy variable assumes value 1 if the firm is part of a group and 0 otherwise
Organizational	Dummy variable assumes value 1 if the firm implemented a significant organizational change and 0 otherwise
Exporting	Dummy variable assumes value 1 if the firm exports and 0 otherwise
R&D intensity	R&D expenses divided by net sales revenues
Continuous	Dummy variable assumes value 1 if the firm makes continuous R&D expenditures and 0 otherwise
Cooperation	Dummy variable assumes value 1 if the firm cooperates with other institutions and 0 otherwise
Sectoral dummies	Dummy variables for the sectors listed in the appendix
Regional dummies	Dummy variables for the Brazilian macro regions (North, Midwest, Northeast, Southeast, South)
Obstacles to innovation (dummy variables constructed upon combinations)	
O1	Lack of appropriate finance sources
O2	Lack of skilled personnel
O3	Lack of opportunities for cooperation with other firms/institutions
O4	Lack of information on technology or on the market

Table 2
Summary statistics (expanded sample).
Source: PINTEC-IBGE, 2003. More detailed summary statistics are available upon request.

	Mean	Std. error	Confidence interval 95%	
Propensity to innovate	0.330	0.007	0.315	0.344
Intensity of innovation	0.088	0.004	0.080	0.096
Number of employees	49.08	0.690	47.71	50.44

Table 3
Summary statistics (expanded sample).
Source: PINTEC-IBGE, 2003.

	Did not innovate				Did innovate			
	Mean	Std. error	Confid interval 95%		Mean	Std. error	Confid interval 95%	
Foreign	0.014	0.002	0.011	0.017	0.030	0.002	0.025	0.034
Group	0.025	0.002	0.020	0.029	0.043	0.004	0.035	0.050
Organizational	0.584	0.010	0.565	0.603	0.834	0.010	0.813	0.854
R&D intensity	–	–	–	–	0.007	0.001	0.005	0.008
Continuous	–	–	–	–	0.071	0.005	0.062	0.080
Cooperation	–	–	–	–	0.029	0.003	0.022	0.036

Table 4
Relative frequency of obstacles to innovation (expanded sample).
Source: PINTEC-IBGE, 2003.

No obstacle was encountered	69.00%
Finance source	28.16%
Skilled personnel	12.80%
Opportunities for cooperation with other firms/institutions	7.88%
Information on technology or market	12.30%
High economic risks	24.74%
Scarcity of adequate technological services	6.67%

Table 4 provides a representation of the relative importance of the perceived obstacles to innovation. The final selection consists of four categories of obstacles: lack of finance sources, lack of skilled personnel, lack of cooperation opportunities, and lack of information on technology or markets.

3.2. Empirical implementation and econometric issues

After selecting the variables and innovation obstacles we need an empirical strategy. The innovation function can be empirically considered in terms of the expression below, as in Mohnen and Röller (2005):

$$I_i = \sum_{l=0}^{2^k-1} \gamma S_{ij} + \beta Z_{ij} + \eta_j + \varepsilon_i \tag{3}$$

I_i represents some outcome of the innovative activity by firm I; S_j refers to dummy variables indicating the prevalence of a given combination of policies; Z_t denotes the remaining exogenous variables; η_j and ε_i represent the sectoral fixed effects and the error term.

The first econometric issue refers to the consistent estimation of Eq. (3). To address it, we need to indicate the phase of the innovation process that is being considered. In the investigation of the propensity to innovate we have data from both innovating and non-innovating firms and therefore we can use standard models for limited dependent variables (for example, a probit model). However, the evaluation of the intensity of innovation is more complex, as we observe data on intensity only for innovating firms and we are therefore faced with a truncated distribution. A traditional approach to such an issue is to consider Heckman's two step procedure, known as Heckit (for more, see Greene, 2003). The intensity of innovation is observed only for innovating firms and thus the corresponding model must take into account the chances that a particular firm actually innovates. The correcting factor for the referred truncation is an additional regressor in the (second stage) OLS model, with robust standard errors, for explaining the intensity of innovation. We also need to deal with another aspect that has been neglected in the literature. It pertains to the consideration of a weighted estimation to account for a complex sampling design. In fact, survey respondents are selected in accordance with distinct sampling weights and various modern statistical and econometric packages already incorporate the related procedures (Kish, 1965 and Silva et al., 2002 provide useful discussions on complex sampling). Without taking into account sampling weights we would obtain erroneous interpretation of results in the case of more heterogeneous samples. The sampling weights lead to weighted objective functions and it is important to highlight the default correction for standard errors that is implemented by the complex sampling command svy in Stata.

The weighted estimator has variance based on a Taylor linear approximation method (see Binder, 1983 and Kreuter and Valliant, 2007). The linearization-based variance estimators are extensions of the variance estimator for totals. The resulting variance estimator for $\hat{\beta}$ after a first-order matrix Taylor-series expansion is:

$$\hat{V}(\hat{\beta}) = \left[\left\{ \frac{\partial \hat{G}(\beta)}{\partial \beta} \right\}^{-1} \hat{V}\left\{ \hat{G}(\beta) \right\} \left\{ \frac{\partial \hat{G}(\beta)}{\partial \beta} \right\}^{-T} \right] \Bigg|_{\beta = \hat{\beta}} = D\hat{V}\left\{ \hat{G}(\beta) \right\} \Bigg|_{\beta = \hat{\beta}} D' \tag{4}$$

In which $\hat{G}(\beta)$ is the weighted sample estimating equation that defines the objective function; $D = (X_S' WX_S)^{-1}$ in the case of linear regression (as in the estimation for the intensity of innovation); W is a diagonal matrix of the sampling weights; and X_S is the matrix of sampled explanatory variables. In the case of a pseudo-maximum likelihood estimation (as in the estimation of the propensity to innovate), D stands for the inverse of the negative Hessian matrix.[4]

A second econometric issue relates to the implementation of the tests for supermodularity of the innovation function that is considered for pairs of policies. Assuming a total of 4 policies, for policies 1 and 2 we face restrictions associated with 4 inequalities (where $XX = \{00,01,10,11\}$):

$$\gamma_{10XX} + \gamma_{01XX} \le \gamma_{00XX} + \gamma_{11XX} \tag{5}$$

whereas for pairs 1 and 3 one would have:

$$\gamma_{1X0X} + \gamma_{0X1X} \le \gamma_{0X0X} + \gamma_{1X1X} \tag{6}$$

and for polícies 2 and 3:

$$\gamma_{X10X} + \gamma_{X01X} \le \gamma_{X00X} + \gamma_{X11X} \tag{7}$$

to prevail complementarity among policies 1, 2 and 3, it is necessary not to reject the validity of the null hypothesis relating to those restrictions in all tests. Similarly, the same follows in the case of inclusion of the fourth incentive policy.

The hypothesis test needs to consider multiple linear restrictions. Letting, with a slight abuse of notation, the k coefficients be represented by the vector $\mathbf{b}(kx1)$, the inequality test assesses the null hypothesis $H_0 = \mathbf{Rb} \le 0$, against the alternative hypothesis $H_1 = \mathbf{Rb} \ge 0$. Also, $\mathbf{R}$ is a pxk matrix, in which p is the number of restrictions, and under the null hypothesis a strict inequality holds for at least one of the restrictions. The relevant test statistic is provided by Kodde and Palm (1986)):

$$c_W = (\mathbf{R}(\mathbf{b} - \bar{\mathbf{b}}))^{\mathbf{T}} (\mathbf{R}\Omega\mathbf{R}^{\mathbf{T}})^{-1} \mathbf{R}(\mathbf{b} - \bar{\mathbf{b}}) \tag{8}$$

in which $\mathbf{b}$ indicates a consistent estimator for the parameter vector and $\bar{\mathbf{b}}$ refers to the estimator that minimizes the previous expression subject to the null hypothesis. Gouriéroux et al. (1982) and Wolak (1989, 1991) show that the appropriate statistic for such a test follows a mixture of chi-square distributions. The probability of the test statistic exceeding c under the null hypothesis is given by $\sum_i Pr(\chi_i^2 \le c) \times w_i$, in which w_i is the relevant weight (see Shapiro, 1985 and Wolak, 1989.[5] The relevant critical values appear in Table 1 from Kodde and Palm (1986), with the lower and upper bounds (c_l and c_u) at significance levels ranging from 0.25 up to 0.001, and degrees of freedom from 1 to 40 for tests involving multiple equalities and inequalities.[6] If the test statistic lies between c_l and c_u it is not conclusive. It is important to stress that consistent estimation of the coefficients is required for implementing the test, and potential endogeneity could pose an important challenge. We argue, as do Mohnen and Röller (2005), that such caveat does not directly jeopardizes the analysis, as even with inconsistent estimates the error term would be correlated with the interaction terms, and not with the practices themselves.

Mohnen and Röller (2005) also consider four types of obstacles to innovation (lack of appropriate sources of finance, lack of skilled personnel, lack of opportunities for cooperation with other firms and technological institutions, and legislation, norms, regulations, standards, and taxation). The first stage of their analysis is a probit model for assessing the propensity to innovate with control variables reflecting firm size and group membership in addition to the combinations of obstacles to innovation that constitute the focus of the analysis. The equation for assessing the intensity of innovation relies on a generalized Tobit estimation to correct for the sample selection problem. We diverge from the literature by using different variables and presenting a more complete estimation strategy, using complex sampling to get more robust standard errors. We show that disregarding complex sampling actually changes our results.

3.3. Empirical results

We use a generalized Tobit model to estimate Eq. (3) with robust errors based on the variance of the estimator in Eq. (4). We then test for sub and supermodularity with Wald tests. Variables are as described in Section 3.1.

The related results appear in Tables 5 and 6. For conciseness, we report the results regarding the sectoral and regional dummies in the appendix, but important differences emerge when comparing estimates that incorporate complex sampling to those that do not. We use the results with sampling weights as our preferential results because those acknowledge the distinct probabilities of a firm belonging to the sample that reflect regional and sectoral heterogeneities. The main advantage of using complex sampling is that we have more robust standard errors.

As we can see from Tables 5 and 6, results are different if we compare estimations with and without sampling weights. For instance, size, as measured by the log of the number of employees, is significant for both phases of innovation if we use sampling weights, but it is not significant for the intensity of innovation phase without it.[7] Coefficients for log(EMP) in the model using sampling weights are 0.091 and -0.034 for the propensity and intensity of innovation, respectively. Results are as expected for the Schumpeterian hypothesis, with propensity of innovation increasing with size, but intensity being higher for smaller companies.

Surprisingly, *foreign* is marginally significant, and even then only so for the intensity of innovation phase. The coefficient, 0.052, indicates that foreign ownership may increase the intensity of innovation, but the result is not significant for the propensity of innovate phase. We would expect that if companies with foreign ownership would take their innovation abroad, results for both phases would be different. However, it indicates that foreign ownership may be a driver to the propensity of innovation when companies actually innovate in the host countries, in this case Brazil. It is weak evidence, but it helps to corroborate the

[4] Additional details are provided in the Stata Survey Data Reference Manual.

[5] Shapiro (1985) shows that those weights add to 1.

[6] Following Kodde and Palm (1986), the degrees of freedom equal one plus the number of equalities tested for the lower bound and the total number of equalities and inequalities for the upper bound.

[7] Although with a criterion that is slightly over the 5% confidence level in the case of the intensity equation.

Table 5
Regression results (models using sampling weights).

Variables	Propensity to innovate			Intensity of innovation		
	Coef.	Std. error	*p*-Value	Coef.	Std. error	*p*-Value
Log(*EMP*)	0.091*	0.021	0.000	−0.034	0.018	0.059
Foreign	0.087	0.089	0.332	0.052	0.029	0.061
Group	0.097	0.093	0.297	0.072	0.040	0.074
Organizational	0.649*	0.052	0.000	−0.145*	0.033	0.000
Exporting	0.205*	0.054	0.000	−0.044	0.023	0.055
R&D intensity	–	–	–	0.504	0.267	0.059
Continuous	–	–	–	0.023	0.024	0.342
Cooperation	–	–	–	0.035	0.038	0.348
States:						
0001	−0.742	0.444	0.095	0.288	0.167	0.087
0010	−0.150	0.692	0.828	0.676*	0.274	0.014
0011	1.650*	0.715	0.021	0.291	0.169	0.085
0100	−0.021	0.472	0.964	0.398*	0.162	0.014
0101	0.318	0.474	0.503	0.362*	0.155	0.020
0110	−0.759	0.725	0.295	0.286	0.220	0.193
0111	0.342	0.677	0.613	0.442*	0.211	0.036
1000	−0.808*	0.341	0.018	0.473*	0.154	0.002
1001	−0.699*	0.356	0.050	0.426*	0.156	0.006
1010	−0.739	0.380	0.052	0.531*	0.168	0.002
1011	−0.488	0.372	0.189	0.429*	0.167	0.010
1100	−0.916*	0.353	0.009	0.503*	0.160	0.002
1101	−0.323	0.350	0.356	0.453*	0.155	0.004
1110	−0.459	0.384	0.231	0.511*	0.172	0.003
1111	−0.198	0.353	0.574	0.404*	0.155	0.009
0000	−1.073*	0.336	0.001	0.489*	0.152	0.001
Lambda				0.0249	0.0143	0.041

Note:
* Indicates significance at the 5% level.

Table 6
Regression results (models not using sampling weights).

Variables	Propensity to innovate			Intensity of innovation		
	Coef.	Std. error	*p*-Value	Coef.	Std. error	*p*-Value
Log(*EMP*)	0.138*	0.013	0.000	0.007	0.015	0.650
Foreign	0.122*	0.059	0.037	0.085*	0.029	0.003
Group	−0.010	0.051	0.851	0.036	0.025	0.148
Organizational	0.679*	0.035	0.000	0.176*	0.080	0.027
Exporting	0.249*	0.035	0.000	0.051	0.030	0.088
R&D intensity				0.386	0.202	0.056
Continuous				0.047*	0.017	0.005
Cooperation				0.042	0.024	0.070
States:						
0001	−1.600*	0.290	0.000	−0.680*	0.335	0.043
0010	−1.156*	0.481	0.016	−0.226	0.341	0.508
0011	−0.481	0.585	0;411	−0.342	0.307	0.266
0100	−0.632*	0.306	0.039	−0.372	0.264	0.159
0101	−0.621	0.326	0.057	−0.471	0.265	0.076
0110	−1.349*	0.498	0.007	−0.231	0.370	0.533
0111	−0.810	0.437	0.064	−0.269	0.301	0.371
1000	−1.503*	0.218	0.000	−0.626*	0.314	0.047
1001	−1.364*	0.229	0.000	−0.564	0.304	0.064
1010	−1.418*	0.241	0.000	−0.532	0.312	0.088
1011	−1.232*	0.245	0.000	−0.529	0.297	0.077
1100	−1.435*	0.228	0.000	−0.542	0.310	0.080
1101	−1.086*	0.225	0.000	−0.472	0.280	0.092
1110	−1.239*	0.252	0.000	−0.530	0.299	0.076
1111	−0.964*	0.228	0.000	−0.452	0.272	0.097
0000	−1.868*	0.215	0.000	−0.722*	0.349	0.038
Lambda				0.531	0.1576988	0.001

Note:
* Indicates significance at the 5% level.

analogous result obtained by Guadalupe et al. (2012), who provide an explanation for the salient fact that multinational subsidiaries generally outperform domestic firms.

Organizational change and exporting performance also present interesting results. Both variables present positive coefficients for the propensity to innovate phase (0.649 and 0.205, respectively) and negative coefficients (−0.145 and −0.044, respectively) for the intensity of innovation phase. This indicates that changing organizations and those which are subject to international competition are more likely to innovate, but not with higher intensity. This makes sense in the context of a developing economy such as Brazil, in which innovation tends to be more incremental than for more dynamic countries.

Altogether, in the equation referring to the propensity of innovation regional dummies exert no significant effect. We observe marginally significant coefficients for regional dummies in the propensity equation in one case, but not for any of the coefficients of the intensity equation. Moreover, firm-level sampling weights appear to be relevant given the large size and heterogeneity of Brazilian industry compared to more developed and homogeneous economies.

As for the variables indicating a combination of obstacles we do not emphasize the discussion of individual coefficients, because we discuss complementarity tests later in this section. Interesting results emerge in terms of positive and significant coefficients for the firm size variable, the organizational change variable, and the exporting variable. When we consider the intensity of innovation, the previous results essentially prevail, but additionally there is a clearly significant positive coefficient for organizational change. Moreover, if a significance level slightly above 5% is considered, we can detect important positive effects accruing from ownership, participation in groups and R&D intensity.

This helps us build a case for a relation between openness and innovation. The Brazilian economy is particularly closed compared to most countries—in 2003 the sum of exports and imports is less than 25%, a value comparable to the poorest countries in the world (Cuba has a more open economy than Brazil if we judge openness just by export and import ratios to GDP). It is a well-known fact that the Brazilian economy is closed, with a high degree of oligopolies and other imperfect markets, and with few indicators of competitiveness pressure. This reinforces the evidence that in the few cases in which industries are faced with external competition they turn to be more innovative. It is a salient result, because the country still faces policies that look for bringing less international competition to local markets—since the mid-nineties there is no significant opening of the Brazilian economy to foreign trade.

Next, we consider the testing for the presence of complementarities in innovation policies (or obstacles to innovation) in Table 7.[8] The null hypothesis for the left side of the table is that there is (weak) supermodularity, while the alternative is no supermodularity in the innovation function. For submodularity, the acceptance of the null hypothesis signals the presence of substitutability in obstacles to innovation. Values above the upper bound critical value at a 10% confidence level, as given by 7.094, indicate a rejection of the null hypothesis. Values below lower bound critical value of 1.642 favor acceptance of the null hypothesis. Intermediate values between these bounds would indicate that the test is inconclusive.

Mohnen and Röller's (2005) results are clear-cut, in the sense that substitutability in obstacles to innovation generally prevails when considering the propensity to innovate, and complementarity is salient when considering the intensity of innovation. These authors find a large number of pairwise complementarities that are statistically significant, both for the probability of being an

[8] We thank Pierre Mohnen for kindly providing the Gauss code for implementing the inequality restrictions tests.

Table 7
Wald tests for inequality restrictions (at the 10% significance level, the lower bound is given by 1.642 and the upper bound is given by 7.094)—Obstacles to innovation.

Pair of obstacles	Propensity to innovate						Intensity of innovation					
	1–2	1–3	1–4	2–3	2–4	3–4	1–2	1–3	1–4	2–3	2–4	3–4
Supermodularity test:	12.826	10.766	4.238	9.148	0.321	1.555	1.145	0.918	1.26	1.593	0.002	1.038
Submodularity test:	4.178	2.545	0.266	1.79	5.755	3.366	3.367	0.337	3.847	0.151	5.2	0.694

Definition of obstacles: 1—Lack of appropriate finance sources; 2—Lack of skilled personnel;3—Lack of opportunities for cooperation with other firms/institutions; 4—Lack of information on technology or on the market.

innovator as well as for the intensity of innovation. In the present investigation the results are less clear.

We have evidence of complementarity of obstacles between the lack of technological or market information (OBS4) and the lack of skilled personnel (OBS2) and cooperation opportunities (OBS3) for the propensity to innovate. For example, for the pair of obstacles 2–4 the test statistic is 0.321 and favors supermodularity (complementarity). On the other hand, the test for submodularity only favors the acceptance of the null hypothesis of substitutability between lack of finance sources and lack of information (pair 1–4).

When we consider the intensity of innovation, results are stronger. In the case of the test for supermodularity we cannot reject the null hypothesis for any of the pairs (the largest value for the test statistics is 1.593 for pair 2–3). As for the test of submodularity evidence indicates substitutability between a lack of cooperation opportunities and both a lack of finance sources and a lack of skilled personnel (respectively pairs 1–3 and 2–3). Pair 2–3 shows ambivalent evidence and given the generous confidence level adopted we refrain from a strong conclusion in that case. Finally, submodularity appears to prevail between a lack of cooperation opportunities and lack of information (pair 3–4).

Altogether, the evidence contrasts somewhat with previous studies for European counties. In particular, there is only limited evidence for substitutability or complementarity for few pairs of obstacles. However, when we consider the intensity of innovation evidence indicates the presence of complementary obstacles. In this sense, once the firm is able to innovate, targeted policies seem to be effective to increase the intensity of innovation.

Despite the differences with previous studies on complementarities, some categories appear to play a decisive role in the different countries, e.g. a lack of skilled personnel and lack of access to finance.

4. Final comments

The paper aims to investigate the presence of complementarities in innovation policies in Brazilian industry in terms of inverse proxies for innovation (obstacles). The paper benefits from micro-data that are not subject to limitations related to micro-aggregation. We explicitly consider sampling weights in the estimations, and have variables for some organization characteristics of companies, such as foreign ownership, organizational changes, and others. The analysis considers tests for supermodularity and submodularity of an innovation function taking as references obstacles to innovation such as the lack of adequate finance sources, lack of skilled personnel, lack of opportunities for cooperation with other firms/institutions, and lack of technological or market information. The study highlights the different phases of the innovation process in terms of the propensity of innovation (in terms of a Probit model) and the intensity of innovation (in terms of a generalized Tobit model).

Results are relevant for policy makers, especially to improve the design of industrial policies regarding innovation and international trade. In fact, in the Brazilian case historically one has not observed careful coordination among different public institutions.

We find weak evidence that foreign ownership may be a driver for the propensity of innovation when companies actually innovate in host countries. We also find that changing organizations and those which are subject to international competition are more likely to innovate, but not with higher intensity. This makes sense in the context of a developing economy such as Brazil, in which innovation tends to be more incremental than for more dynamic countries. It also provides support for industrial policies that are in favor of opening up the Brazilian economy, at least relative to the low level of openness that the country presently enjoys.

Results do not indicate clear distinct patterns in the two phases of the innovation process, in contrast with previous results for developed countries. In fact, we find limited evidence favoring substitutability and complementarity in obstacles in the case of the propensity to innovate. Specifically, there is some evidence that suggests the relevance of a package of policies relating to finance sources and technological or market information.

If we consider the intensity of innovation evidence is stronger and indicates complementarities of obstacles and the need for more targeted policies. Thus, implications for policy makers relate to whether incentive policies should be implemented in terms of coordinated packages or isolated actions. If the substitution and complementarity effects appear to be pervasive, they could also provide firm-level guidance on types of information relevant for innovation that should be gathered together or separately. In the present study, however the results are not particularly salient.

Especially relevant is the result that firms subject to international competition have higher propensity to innovate. For a country that is currently implementing more trade barriers, the unintended consequence of less innovation is particularly important.

Even though results are suggestive, stronger policy recommendations would be clearer if the evidence was stronger and further research combined different years of that survey in the future. The perception that innovation has been curbed by some particular obstacle can be subjective, as one is not sure that an innovation would actually occur if that barrier did not prevail. A relevant extension should consider direct measures reflecting actual incentive policies for innovation, but that would require better data. Doran (2012) use the complementary role of organizational innovation with respect to other types of innovation. In fact, the supporting role of the organization configuration for technological innovation has been recognized at least since Schumpeter (1934). Thus, a relevant line of research would involve assessment of complementarities on innovation with more specific organizational practices. Unfortunately, the currently available innovation surveys do not provide such detailed data. Moreover, the present paper focuses on discrete complementarities and the investigation of continuously defined policy variables would also yield interesting results.

Finally, it is worth mentioning that if the previous evidence is representative it would indicate that programs funded by the Ministry of Science and Technology [both in terms of sectoral funds and its main R&D funding agency (Financiadora de Estudos e Projetos-FINEP)] or yet through the large public development bank (Banco Nacional de Desenvolvimento Econômico e Social-BNDES) should undertake more coordinated efforts and be aware of possible complementarities and substitutability patterns. In any case, it appears that extremely bureaucratic procedures characterize Brazilian institutions and that public policy could be more proactive in mitigating the lack of relevant information on different aspects of innovative activities.

Appendix. Estimates for dummy variables.

	Propensity to innovate	Intensity of innovation
Regional dummies		
Southeast	−0.493 (0.094)	−0.134 (0.315)
South	−0.296 (0.316)	−0.146 (0.273)
Midwest	−0.388 (0.211)	−0.022 (0.878)
North	−0.214 (0.498)	−0.055 (0.699)
Northeast	−0.391 (0.193)	−0.165 (0.224)
Sectoral dummies		
Extractive	0.150 (0.349)	0.083 (0.252)
Food, beverages and tobacco	0.131 (0.478)	0.390* (0.000)
Textiles	0.042 (0.795)	0.168* (0.026)
Clothing	−0.059 (0.743)	0.333* (0.000)
Leather	0.035 (0.842)	0.328* (0.000)
Wood products	0.017 (0.092)	0.129 (0.109)
Cellulose, paper and printing	−0.114 (0.665)	0.042 (0.575)
Coke and fuel	0.321 (0.060)	0.078 (0.277)
Chemicals	0.152 (0.371)	0.168* (0.032)
Pharmaceuticals	−0.171 (0.323)	0.189* (0.032)
Non-metallic minerals	0.169 (0.298)	0.059 (0.423)
Metallurgy and metal products	0.320 (0.058)	0.154* (0.041)
Machinery and equipments	0.389 (0.024)	0.213* (0.006)
Electric machinery and equipment	0.122 (0.518)	0.095 (0.256)
Transport vehicles	0.007 (0.965)	0.263* (0.001)

Note: *p*-values are reported in parentheses.

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