Complementarities in Innovation Policy

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by

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Abstract

This paper develops a framework for testing discrete complementarities in innovation policy using European data on obstacles to innovation. We propose a discrete test of supermodularity in innovation policy leading to a number of inequality constraints. We apply our test to two types of innovation decisions: to innovate or not, and if so, by how much. We find that the evidence regarding the existence of complementarity in innovation policies depends on the phase of innovation that is targeted (getting firms innovative or increasing their innovation intensity) as well as on the particular pair of policies that is being considered. The two phases of the innovation process, i.e. the probability of becoming an innovator and the intensity of innovation, are subject to different constraints. Interestingly, there seems to be a need to adopt a package of

policies to make firms innovate, while a more targeted choice among policies is necessary to make them more innovative.

1. Introduction

The question as to whether policy variables are interrelated is important. Changing one policy variable may have little effect if other policy variables remain unchanged. Understanding these interlinkages is central for policy makers in order to achieve the desired objectives. In this context, this paper asks a simple question, namely to what extent there is empirical evidence for complementarities in some innovation policy[1]. In answering this question we develop a framework for testing complementarities in a discrete setting and apply it to a data set on European firms.

A group of activities is complementary if doing more of any subset of them increases the returns from doing more of any subset of the remaining activities. In a standard (differentiable) framework, complementarity between a set of variables means that the marginal returns to one variable increases in the level of any other variable, or more formally that the cross-partial derivatives of the payoff function are positive. However, complementarity can also be present when the decision variables are discrete. The notion of complementarities per se requires only that some order relation be put on the objects under consideration. This observation has lead to the actual formalization of the concept within the mathematical theory of lattices, which is the basis for the development of monotone optimization problems pioneered by Arthur Veinott and Donald Topkis (see, for instance, Topkis (1978)).

The formalization of complementarities to discrete structures permits the analysis of such complex and discrete entities as organizational structures, institutions, and government policies. It provides a way to capture the intuitive ideas of synergies and systems effects, i.e. that "the whole is more than the sum of its parts." Furthermore, it constitutes the starting point for an understanding of the failure of piecemeal approaches to policy: if elements of a given organization are complementary, then adopting only

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[1] We do not consider all potentially relevant innovation policies. Still, the analysis is valid as it is possible to study complementarities amongst a subset of variables regardless of whether the objective function is supermodular on the remaining variables or not.

some of the features of a better performing organization may not yield as good a performance as if all features are adopted.

The study of complementarity has since been introduced into economics. The first full-fledged application in economics to the optimization in complementary problems and oligopoly problems is by Xavier Vives 1990[2]. There have been many subsequent contributions; like the work by Paul Milgrom and John Roberts (1990)). For a recent reference on the theory of supermodularity and complementarity, as well as a comprehensive reference list, the interested reader is referred to Topkis (1998).

A prominent arena where such interlinkages are frequently claimed is in the study of innovation, which is the topic of this paper. It is often argued that innovation is a complex outcome, influenced by many factors that are interrelated. Moreover, an innovation system is often said to have discrete characteristics encompassing a set of institutions, laws, incentives, and customs. More importantly, the interrelatedness of those factors is often described as one that is complementary, i.e. the factors act together and reinforce each other (Dosi, 1988). A consequence of this is that piecemeal policy may not be successful, as one-dimensional policy prescriptions in isolation will not produce the desired outcomes.

This paper develops a framework for testing complementarities in innovation policy. Our approach is based on governments choosing a set of parameters (policies) at the national level in order to maximize innovation activities. Within this framework we ask whether policy decisions are complementary. If so, policy actions would tend to occur together in order to maximize the impact on innovation activities.

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[2] The paper was first published in 1985, as a CARESS working paper at the University of Pennsylvania.

Testing for complementarity can be achieved in a number of different ways (for a thorough overview of these different approaches see Athey and Stern (1998))[3]. One approach is based on revealed preferences, assuming optimization behavior. Given the complementarity in the choice variables (in our case the government's policies), they would tend to be correlated. Using the "correlation approach" one can start by computing simple correlations, which would not control for any other characteristics. More sophisticated analysis would entail controlling for other factors (observed and unobserved) as well as deriving explicit first-order conditions (see, for instance, Arora and Gambardella (1990), Ichniowski et al. (1997), or Miravete and Pernìas (2000)). Note that this approach requires availability of the choice variables, but no data on the objective.

A second approach, the so-called reduced form approach, is based on exclusion restrictions (see, for instance, Holmström and Milgrom (1994)). The idea is that a factor that has an effect on one action will not be correlated with another action unless the actions are complementary. As noted by Arora (1996) this approach is unable to disentangle interactions between more than two variables.

The final approach is the one taken in this paper[4]. We consider the objective function directly, in our case the innovation function. Recall that whenever actions are complementary then the innovation function is supermodular. The direct way of testing for complementarity is thus to investigate whether the innovation function is supermodular in the policy action (see also Ichniowski et al. (1997)). Consequently, we

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[3] They show that unobservable heterogeneity can introduce a bias into the estimation of complementarity. Having cross-sectional data, our analysis only controls for observed heterogeneity through exogenous control variables (see below). To the extent that there are omitted variables, which are correlated with others, a bias in the estimates does occur. However, this does not automatically imply that complementarity will be inconsistently estimated. To see this, consider the following simple model: $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2 + \varepsilon$. Complementarity exists whenever $\beta_3 > 0$, which implies that we need a consistent estimate of β_3. Suppose that the omitted variable is correlated with x_1, such that $\text{plim}(x_1, \varepsilon) \neq 0$. In this case β_1 is inconsistently estimated by OLS. However, β_3 may still be consistently estimated, unless we also have that $\text{plim}(x_1 x_2, \varepsilon) \neq 0$. That is despite the correlation between the omitted variable and the included variables, complementarity can still be consistently estimated, unless the omitted variable is correlated with the interaction of $x_1 x_2$.

[4] Another recent paper using this approach is Cassiman and Veugelers (2002). However, they estimate complementarity between two innovation activities only (internal R&D and external technology acquisition). By contrast, our approach allows for multiple dimensions.

directly estimate the innovation function and develop tests for both super- and submodularity.

We apply our test to a data set on European firms and consider four types of obstacles to innovation that are affected by policies: (i) lack of appropriate sources of finance, (ii) lack of skilled personnel, (iii) lack of opportunities for cooperation with other firms and technological institutions, and (iv) legislation, norms regulation, standards, and taxation.

For two reasons, we like to differentiate between two phases of the innovation process: the decision to innovate or not and the intensity of innovation conditional on doing any innovation at all. The first reason for considering the two innovation decisions separately is an empirical one. We only observe innovation activities, *conditional on doing any innovation at all*. In other words, we may have a censoring problem. In order to control for possible censoring biases we estimate a generalized Tobit model. The second reason is that the complementarities may differ substantially across the two phases of innovation. Policy impacts as well as complementarity in policy may be rather different for the intensity of innovation, as compared to the likelihood of becoming an innovator.

We find that the evidence regarding the existence of complementarity in obstacles depends on the phase of the innovation process (decision to innovate and intensity of innovation) as well as the particular pair of policies. While the evidence regarding the propensity to innovate points towards a number of substitutable relationships, complementarity exists for a number of obstacles as far as the intensity of innovation is concerned. This points towards a possible difficulty in designing optimal policies for innovation, since the impact may pan out very differently across innovation activities. Interestingly, there seems to be a need to adopt a package of policies to make firms innovate (propensity to innovate), while a more targeted choice among policies is necessary to make them more innovative (intensity of innovation).

The paper is organized as follows. Section 2 develops the framework, while Section 3 defines supermodularity in innovation. Section 4 specifies the test and section 5 discusses the results. Section 6 concludes.

2. A Framework for Innovation Policy

In this section we present a framework in which complementarity in innovation policy can be identified. We begin by assuming that innovation is affected by *K* national policy variables chosen by governments denoted by $a_j = (a_{1j}, a_{2j}, ..., a_{Kj})$, where *j* is the country. Innovation occurs in each country and is characterized by the innovation function $I(a_j, \theta_{ij})$, where θ_{ij} are country and industry-specific pre-determined factors. The problem of the government is to choose a set of national policies $a_j = (a_{1j}, a_{2j}, ..., a_{Kj})$ that maximize innovation, i.e. $\max_{a_j} I(a_j, \theta_{ij})$.

Even though the maximization problem is analogous for all countries, this does not imply that all countries will choose the same set of policies, due to the country and industry-specific factors θ_{ij}. For instance, countries or industries might differ because of their institutional endowments. According to North (1994, page 360):

> "Given that these institutions are likely to be different across countries and industries, such as institutions, laws, incentives, customs, etc., they will translate into country-specific and firm-specific heterogeneity, which in turn may lead to different outcomes."

These pre-determined factors θ_{ij} thus represent institutions, history, customs, norms, technologies, etc. and are responsible for different national policy choices.

Using the direct approach, complementary in government actions can in principle be tested by asking whether $I(a_j, \theta_{ij})$ is supermodular in a_j, assuming that data on government actions are available. Unfortunately, the available data on innovation do not report government actions. Instead, we have a number of measures of the obstacles to

innovation. To the extent that the relationship between actions and obstacles is monotone, we are able to measure complementarity in actions through data on obstacles. Accordingly, we define $C_{kj} = -a_{kj}$, where C_{kj}, ($k=1,...,K$), denote the innovation obstacles faced by firms in country j. We then write the innovation function as,

$$I(C_j, \theta_{ij}) = f(C_{1j}, C_{2j}, ..., C_{Kj}, \theta_{ij}) \qquad [1]$$

and test whether [1] is supermodular in the obstacles.

3. Supermodularity of the Innovation Function

Since obstacles are discrete variables, one cannot introduce interaction terms in the regression framework and test for the sign of the interaction parameters. Instead we need to derive a set of inequality constraints as implied by the theory of supermodularity and test whether the constraints are accepted by the data.

Let the innovation function be given by [1], where the obstacle set C ($C_j \in C$) is a set of elements that form a lattice and the θ's are pre-determined parameters. We define complementarity of the innovation function as follows (see for example Milgrom and Roberts 1990, page 516).

Definition: *Let C'_j and C''_j be two elements in the obstacle set. Then the industry innovation function $I(C_j, \theta_{ij})$ is supermodular if and only if $I(C'_j, \theta_{ij}) + I(C''_j, \theta_{ij}) \leq I(C'_j \vee C''_j, \theta_{ij}) + I(C'_j \wedge C''_j, \theta_{ij})$.*

A useful result for the empirical analysis below is that it suffices to check *pairwise complementarities* in case there are more dimensions than two in the lattice (Topkis, 1978). In other words, a function is supermodular over a subset of its arguments, if and only if all pairwise components in the subset satisfy the above definition.

A Simple Example:

A simple example might be useful for illustrative purposes[5]. Suppose there are two binary decision variables, which implies that the set C consists of four elements $C = \{\{00\}, \{01\}\{10\}, \{11\}\}$. For example, a country may adopt flexible labor markets and a market-based financial system (corresponding to $C_j^1 = 00$) or choose less flexible labor markets and less market-based finance (corresponding to $C_j^4 = \{11\}$), as well as the mixed cases. Using the above definition of supermodularity implies that there is only one nontrivial inequality constrain $I(10) + I(01) \leq I(00) + I(11)$ or equivalently $I(10) - I(00) \leq I(11) - I(01)$. The intuition from the last inequality is that increasing the first activity is more effective when the second activity is high. In other words, the impact of less flexible labor markets is higher whenever we have less market-based finance. Or alternatively, more flexible labor markets are effective whenever finance is market-based.

Note that the above example ignores the institutional endowments (θ_{ij}). Whenever the institutional endowment is the same for two countries, it follows that the countries will optimize by choosing the same actions. In the example above this would imply that countries with identical θ's either choose $\{00\}$ or $\{11\}$ whenever the innovation function is supermodular. Thus, the only source of variation in the observed outcomes stems from differences in θ. This has been formalized by Milgrom and Shannon (1994), who show that the comparative statics on the maximizers $C_j^*(\theta)$ are unambiguous, whenever $I(C_j, \theta_{ij})$ is supermodular with respect to the lattice C. In other words, the set of choice variables in C are complementary, moving up or down together in a systematic, coherent fashion, depending on the institutional endowments θ_{ij}.

We now derive the inequality constraints that need to be satisfied for the industry innovation function to be supermodular. Let the K obstacles to innovation be binary, i.e. they take on the value of either 1 (high) or 0 (low). Define an element of the set C ($C_j \in C$) as a string of K binary digits, where the individual binary components of each

element of the set C represent the obstacles to innovation. Thus, there are 2^K elements in C. In terms of our data set below we have chosen 4 obstacles, which implies that $K=4$. The elements in C are therefore (0000), (0001), (0010),……,(1111), a total of 16 elements. Define the ordering of the elements in the set C as the component-wise order under the "max" operation. This implies that the set C is a lattice. Finally, define the innovation function [1] over the set C.

Using the definition of supermodularity, and the fact that we only need to check pair-wise elements, it can be shown that the number of *nontrivial*[6] inequality constraints implied by the definition of supermodularity is equal to $2^{(K-2)}\sum_{i=1}^{K-1} i$, where K is the number of obstacles and $i=2$ (binary). Since $K=4$, we have a total of 24 nontrivial inequality constraints.

In particular, using the above definition of supermodularity we can write the 4 nontrivial inequality constraints for obstacle 1 and 2 to be complementary in innovation as,

$$I\left(10XX,\theta_{ij}\right)+I\left(01XX,\theta_{ij}\right)\leq I\left(00XX,\theta_{ij}\right)+I\left(11XX,\theta_{ij}\right), \qquad [2]$$

where $XX=\{00,01,10,11\}$. Similarly, the 4 nontrivial inequalities necessary to hold for obstacles 1 and 3 to be complementary are,

$$I\left(1X0X,\theta_{ij}\right)+I\left(0X1X,\theta_{ij}\right)\leq I\left(0X0X,\theta_{ij}\right)+I\left(1X1X,\theta_{ij}\right),$$

where $XX=\{00,01,10,11\}$ again. The remaining 16 constraints corresponding to complementarity between obstacles 1 and 4, 2 and 3, 2 and 4, and 3 and 4 are analogous. Complementarity over all actions is given, whenever all the 24 inequality constraints are satisfied.

We next turn to the empirical analysis, which will test for complementarity by checking whether these constraints are accepted by our data on innovation.

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5 We drop the subscript and the institutional endowment for convenience.

4. Testing for Complementarity

As we discussed above, one way to test for complementarity is to test whether the choice variables are correlated. For instance, within the context of our simple example above, if the two countries are located at $\{11\}$ and $\{01\}$, there is little evidence of complementarity. By contrast, evidence of one country being at $\{11\}$ and the other at $\{00\}$ would be indicative of complementarity. An alternative approach is to test for complementarity in innovation policy by directly testing whether the objective function is supermodular, i.e. testing whether the inequality constraints [2] are satisfied. This is the approach followed in this paper, which we turn to after a brief description of the data.

4.1 The CIS data

In 1992, the statistical agency of the European Union - Eurostat - directed a coordinated effort to collect firm-level data on innovation in the EU member countries. The Community Innovation Survey (CIS 1) data were collected using a similar questionnaire and comparable sampling procedures. To date, there has been relatively little econometric analysis of this data set, but given the information it offers, it is ideally suited for tackling the research tasks described here.

The data set comprises individual firm data on some general characteristics of the firm (main industry of affiliation, sales, employment, export sales), various innovation measures, numerous perceptions of factors hampering or fostering innovation, and some economic impact measures of innovation. We use the CIS 1 survey data from four

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[6] The remaining constraints are equalities.

countries: Ireland, Denmark, Germany, and Italy.[7] The data are made publicly available at a micro-aggregated level, i.e. continuous variables are averaged over three observations of consecutive rank within an industry. Non-aggregated individual responses can be used for empirical studies at the Eurostat site in Luxemburg. However, the micro-aggregation procedures chosen by Eurostat allow us in principle to apply the full set of micro-econometric techniques even with the aggregated data. The possibility of a micro-aggregation bias in the presence of nonlinear estimation techniques is an interesting topic in itself, but we shall not pursue it here.[8]

In terms of our dependent variables we use two variables for equation [3] and [4] below. The innovation surveys provide an output measure of innovation, which is the share in sales of innovative products. In addition, the survey also provides information on whether a firm innovates at all, which is the dependent variable in the probit equation [4].

Of particular importance is a survey question in which firms were asked to evaluate the importance of potential innovation obstacles. These obstacles can be categorized into four groups (see Appendix 2): factors relating to risk and finance, factors relating to knowledge-skill within the enterprise, factors measuring the knowledge-skill outside the enterprise, and finally regulation. The complementarity between these potential impediments is the focus of this paper.

Aggregating the obstacles in each group would be inconsistent with our assumption of obstacle-specific functions linking constraints to government actions. Therefore we have decided to analyze four specific obstacles, one from each group: lack of appropriate sources of finance, lack of skilled personnel, lack of opportunities of cooperation with other firms and technological institutions, and legislation, norms,

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[7] France had no questions on innovation obstacles, Portugal and the Netherlands had missing values for some innovation obstacles, Greece and Norway had too few observations, and the Belgian survey was actually the result of three regional surveys and therefore not considered homogeneous enough.

[8] Mairesse and Mohnen (2001) compare the raw and the microaggregated CIS2 data for France on a model similar to the one used in this paper. They do not find any aggregation bias.

regulations, standards, taxation (see Appendix 2)[9]. The respondents answered these questions on a Likert scale (one to five).

There may very well be a country specific response bias, which could, for instance, be due to differences across countries in survey methods or questionnaires. In order to control our estimates for such country effects in responding to the questionnaire, we have transformed the responses into binary responses, according to whether or not the response to each question was above or below the *average* country response (for all obstacles and industries), which was 1.87 in Ireland, 2.04 in Denmark, 2.15 in Germany and 1.93 in Italy.

The data have been cleaned for outliers, missing observations, and inconsistencies. In particular, we eliminated all enterprises with less than 20 employees, with missing industry affiliation, and with an R&D/sales ratio higher than 50%. We put to zero R&D/sales ratios positive but lower than 0.1%. As the Italian sample resulted from a census and not a survey, the Italian sample was ten times greater than the second largest country sample, Germany. We therefore took for Italy a random subsample (after cleaning) of 5% of all enterprises with 20 to 49 employees, 10% of all enterprises between 50 and 99 employees, 10% of all enterprises between 100 and 249 employees, and all enterprises with more than 250 employees. This sampling is consistent with the sampling frame adopted by the other countries. In the end we were left with 572 observations in Denmark, 715 in Ireland, 1910 in Germany and 2254 in Italy.

We divided total manufacturing into 11 sectors, whose description, abbreviation and related NACE codes are listed in Appendix 1. In defining the sectors we were guided by the industry aggregation Eurostat (1997) uses in presenting the descriptive statistics of the CIS 1 survey.

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[9] We have also experimented with alternative specific obstacles from each group. The basic results are the same.

4.2 Complementarity Tests

To test the inequality constraints implied by complementarity, we need consistent estimates of the effects of obstacles on innovation. Recall from [1] that the innovation function depends on obstacles as well as other pre-determined industry and country specific effects θ_{ij}.

In this spirit we specify the following innovation function,

$$I_{ij} = \sum_{l=0}^{2^k-1} \gamma_l s_{lj} + \alpha \cdot Z_{ij} + \mu_j + \delta_i + \varepsilon_{ij} \qquad [3]$$

where j is the country and i is the industry (note that [3] will be estimated with firm level data, and that we have suppressed the firm subscript).

The innovation variable I will be the percentage in sales of innovative products. In accordance with the previous section, we include a set of state dummy variables denoted by s_{lj}, which correspond to state l in country j. In particular, we define the 16 dummy variables by following the convention of binary algebra[10]. The coefficients on these state dummy variables (γ_{li}) allow us to test for complementarity in innovation policies.

In line with [1], we allow for industry and country specific pre-determined factors (θ_{ij}) by including country fixed effects, μ_j, and industry fixed effects, δ_i.

Finally, we also include a number of firm-level control variables related to innovative activities that are available in the CIS data set, which we denote by Z_{ij} in [3]. Note that these variables are not explicitly mentioned in [1], for notational convenience. Specifically, we use size dummies as measured through employment, a dummy for whether the firm belongs to a group, the R&D per sales ratio, a dummy for continuous

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[10] In other words, s_0 corresponds to state 0000, s_1 to 0001, ... , s_{15} to 1111. We drop the *i* and *j* subscripts for convenience.

R&D, and a dummy for whether the firm is engaged in cooperative R&D. Summary statistics of all variables used in [3] are provided in Table 1. [11]

Using specification [3] and the definition of the state dummies, we write the inequality constraints for supermodularity as a set of restrictions on the coefficients on the state variables[12]. Using [2] and [3], the four constraints that need to be satisfied for obstacles 1 and 2 to be complementary can be compactly written as,

$$\gamma_{8+s} + \gamma_{4+s} \leq \gamma_{0+s} + \gamma_{12+s} \ , \quad \text{where} \quad s = 0,1,2,3 \qquad \text{(comp12)}$$

Similarly, the other complementarity conditions can be written as,

$$\gamma_{8+s} + \gamma_{2+s} \leq \gamma_{0+s} + \gamma_{10+s} \ , \quad \text{where} \quad s = 0,1,4,5 \qquad \text{(comp13)}$$

$$\gamma_{8+s} + \gamma_{1+s} \leq \gamma_{0+s} + \gamma_{9+s} \ , \quad \text{where} \quad s = 0,2,4,6 \qquad \text{(comp14)}$$

$$\gamma_{4+s} + \gamma_{2+s} \leq \gamma_{0+s} + \gamma_{6+s} \ , \quad \text{where} \quad s = 0,1,8,9 \qquad \text{(comp23)}$$

$$\gamma_{4+s} + \gamma_{1+s} \leq \gamma_{0+s} + \gamma_{5+s} \ , \quad \text{where} \quad s = 0,2,8,10 \qquad \text{(comp24)}$$

$$\gamma_{2+s} + \gamma_{1+s} \leq \gamma_{0+s} + \gamma_{3+s} \ , \quad \text{where} \quad s = 0,4,8,12 \qquad \text{(comp34)}$$

Note that complementarity over the entire set will involve all 24 constraints to jointly hold for a given industry. Testing 24 joint inequality constraints is computationally very burdensome (see below). Given that pairwise complementarity between any subset

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[11] As we have mentioned above, omitted variables may bias the estimates. However, this does not automatically imply that complementarity will be inconsistently estimated. An example of this is as follows. Let x_1 be "lack of appropriate sources of finance" and x_2 be "lack of opportunities for cooperation", which are variables that we include in our analysis. Consider now a possible omitted variable such as firms' willingness to "risk taking". When risk taking is positively correlated with x_1, then the estimate of β_1 is inconsistent. By contrast, β_3 is not inconsistently estimated, unless we also have that $\text{plim}(x_1 x_2, \varepsilon) \neq 0$, which implies that risk taking is higher whenever both the "lack of appropriate sources of finance" and the "lack of opportunities for cooperation" exist. In other words, complementarity between two policies is inconsistently inferred when the omitted variable is correlated with the interaction.

[12] It is worth mentioning that the above specification [3] can also be equivalently written in terms of obstacle dummies instead of state dummies. In this case, intuitively, the conditions for complementarity concern interaction effects between obstacles. Note that this is not equivalent to the cross-partials between those two obstacles, since the derivative w.r.t. a discrete variable is not defined.

of obstacles implies supermodularity over the subset, we are able to proceed by testing each pair of obstacles separately. This implies the joint testing of four inequality constraints. For completeness, it is worth emphasizing that the innovation function could be *submodular*, that is the obstacles could be *substitutes*. In this case, the above inequality constraints would be analogous, however the inequalities would have the opposite signs.

Assuming that we have consistent estimates of the γ_i's from [3], we can test for super- and submodularity between any two obstacles. In both tests we will specify as the null hypothesis that the constraints are met. As should be clear from the above inequality constrains, the tests for sub- or supermodularity are *joint, one-sided* tests of the four constraints.

We begin with a test for *strict* complementarity. Consider the hypothesis that the four constraints for obstacles 1 and 2 are complementary (i.e. the innovation function is supermodular)[13], that is,

$$H_0 : h_0 < 0 \text{ and } h_1 < 0 \text{ and } h_2 < 0 \text{ and } h_3 < 0 \qquad \text{[Test 1 – strict Supermodularity]}$$
$$H_1 : h_0 \geq 0 \text{ or } h_1 \geq 0 \text{ or } h_2 \geq 0 \text{ or } h_3 \geq 0$$

where $h_s = -\gamma_{0+s} + \gamma_{4+s} + \gamma_{8+s} - \gamma_{12+s}, s = 0,1,2,3$. The test accepts H_0 (strict complementarity of the two obstacles) whenever the constraints are jointly negative. By contrast, rejection of the null hypothesis does not imply that the two obstacles are substitutes. Note that H_1 includes an "or", which implies that some constraints may have mixed signs. In this case, neither complementarity nor substitutability is present.

Similarly, we can specify a test for *strict* substitutability. Consider the null hypothesis that the four constraints for obstacles 1 and 2 to be substitutes are met, that is

$$H_0 : h_0 > 0 \text{ and } h_1 > 0 \text{ and } h_2 > 0 \text{ and } h_3 > 0 \qquad \text{[Test 1 – strict Submodularity]}$$
$$H_1 : h_0 \leq 0 \text{ or } h_1 \leq 0 \text{ or } h_2 \leq 0 \text{ or } h_3 \leq 0$$

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[13] The specification of the tests for the other 5 complementarity relationships are analogous.

The test accepts H_0 whenever the constraints are jointly positive. As before, rejection of the null hypothesis does not imply that the two obstacles are complements.

To test this set of inequality conditions (4 for each pair of innovation policies) we apply the distance or Wald test, which minimizes the distance between $S\hat{\gamma}$ and $S\tilde{\gamma}$, where $\hat{\gamma}$ is a consistent estimate of γ and $\tilde{\gamma}$ is the closest to $S\gamma$ under H_0.[14] We follow Kodde and Palm (1986) who have computed lower and upper bound critical values for this test. Values of the Wald test below the lower bound imply that the null hypothesis is accepted. By contrast, values above the upper bound yield a rejection of the null hypothesis. Values in between the two bounds imply that the test is inconclusive.

Before we report on our empirical test results, we must return to the issue of consistent estimation of [3]. Recall that our modularity tests are based on consistent estimates of the γ_l's.

4.3 Econometric Issues and Estimation

An important consideration is to obtain consistent and efficient estimates of the γ_l's. A potentially significant issue is that we observe a firm's innovation activity only if this firm in fact innovates. Many firms in our sample do not innovate at all, i.e. we have that $I_{ij} = 0$, which may give rise to censoring.

Besides the econometric problem of censoring, we may also be interested to test for complementarity in the likelihood that firms innovate. As we mentioned above, there are potentially two separate effects obstacles may have on innovation activities: a change in the obstacles to innovation may have an impact on the probability of innovating as well as on the intensity of innovation.

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[14] In other words, $\tilde{\gamma}$ minimizes $(S\tilde{\gamma} - S\hat{\gamma})'S\operatorname{cov}(\hat{\gamma})S'(S\tilde{\gamma} - S\hat{\gamma})$, s.t. $S\tilde{\gamma} \leq 0$.

In order to also test for complementarity in the probability of innovating (the intensity is tested through [3]) and to correct for censoring, we specify a probit model (suppressing firm subscripts again):

$$PI_{ij} = \sum_{l=0}^{2^k-1} \lambda_l s_{lj} + \beta \cdot Z_{ij} + \eta_i + \phi_j + v_{ij} \tag{4}$$

where PI_{ij} is the latent variable corresponding to the probability of innovating, Z_{ij} are pre-determined variables (size and group dummies in this case), and s_{lj} are the states of obstacle perception defined above. Innovating firms have positive values for PI_{ij}, non-innovating firms have negative values. A firm is considered as innovative if it reports a positive share in sales of innovative products.[15] In addition, we allow for industry and country specific pre-determined factors by including country fixed effects, ϕ_j, and industry fixed effects, η_i.

The error terms ε_{ij} and v_{ij} are assumed to be jointly normally distributed with mean zero and variance-covariance matrix Σ.[16] The constraints and hypothesis tests for complementarity in becoming an innovator are analogous to the previous section with the γ_l's replaced by the corresponding λ_l's.

Consistent estimates of the parameters in [3] and [4] are obtained by maximum likelihood estimation of a generalized tobit. In order to get initial values we estimated a probit equation for the probability to innovate and an ordinary least squares regression for the intensity of innovation, with the inverse Mill's ratio to correct for censoring[17]. The Mill's ratio was significant, suggesting that censoring is a problem.

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[15] Few firms declare to be innovative in processes and not in products. By focusing on shares in sales of innovative products, we actually capture process innovations as well.

[16] Where for reasons of identification $\sigma_{11} = 1, \sigma_{22} = \sigma_2^2, \sigma_{12} = \rho\sigma_2$.

[17] The correlation coefficient between the two equations of the generalized tobit model was not significant. Nevertheless, we have decided to report the generalized tobit results (as opposed to estimating a simple probability to innovate and a separate equation for the intensity of innovation) as the former nests the latter.

5. Empirical Results

We begin by presenting descriptive evidence in the form of simple count statistics. The idea is to infer something about complementarity by inspecting occurrences. For instance, if obstacle one occurs more often together with obstacle two, rather than separately, we may interpret this in favor of complementarity between the two obstacles. Table 2 reports the frequency of occurrences of the 16 states in the four countries, as well as in a sub-sample of innovating firms.

5.1 Descriptive Statistics

As can be seen in Table 2, it is clear that the most frequent responses are the two extremes - zero everywhere and one everywhere - as well as lack of appropriate sources of finance and zero for the other obstacles. It appears that the data contain some evidence in favor of complementarity. In terms of pairwise complementarity, there are a large number of possible counts to consider. For example, obstacle 3 (external knowledge) and obstacle 4 (regulation) appear complementary: the occurrence of (0000) plus (0011) is more frequent than (0001) plus (0010). In addition, (1111) plus (1100) occurs more often than (1101) plus (1110). The remaining two constraints for obstacles 3 and 4 are also met. Note that this holds for both data sets, i.e. ALL FIRMS (top of Table 2) as well as INNOVATORS (bottom of Table 2). We therefore have some descriptive evidence in favor of pairwise complementarity of obstacles 3 and 4.

Checking all the other constraints for all other obstacle pairs is tedious, yet it appears that there is considerable descriptive evidence in favor of complementarity for other obstacle pairs as well. Nevertheless, concluding from this that the innovation function is supermodular is premature. Count statistics can only be considered suggestive evidence of complementarity, since they do not control for any other factors. We now turn to a more systematic approach.

5.2 Econometric Evidence

Consistent estimates of the parameters in [3] (i.e. intensity of innovation) and [4] (i.e. propensity to innovate) are obtained by maximum likelihood estimation of a generalized

tobit. Table 3 reports the tobit estimates. As can be seen, the probability to innovate depends on firm size (as measured by number of employees) with large firms (over 1000 employees) having the highest likelihood of being an innovator. Given data restrictions, we are able to include only one other control variable into the propensity equation, namely whether the firm is part of a conglomerate group. As can be seen we find that the firms that are part of a group are significantly more likely to be an innovator. As far as the intensity of innovation is concerned, we find again that size matters. However, the estimates in Table 3 suggest that smaller firms have a higher intensity of innovation. There are also a number of other control variables that are significant. In particular, whether a firm did R&D cooperatively as well as the R&D/sales ratio had a significant and positive impact on the intensity of innovation.

Turning to the obstacles, we find that several obstacle states in the propensity equation are not significant, while the intensity of innovation equation displays a larger number of significant states (see Table 3 again). At this point, it is important to emphasize that the individual significance and signs of the coefficients on the obstacles do not directly reveal whether the innovation function is complementary or substitutable for two reasons. First, complementarity involves testing linear restrictions of several coefficients, like $-\gamma_0 + \gamma_4 + \gamma_8 - \gamma_{12} < 0$. Second, complementarity requires testing the joint distribution of several of these linear restrictions. For both reasons, it is possible that all coefficients are statistically insignificant, even though the joint hypothesis for supermodularity is accepted.

Consistent with the view that obstacles to innovation are perceived highest when a firm is in fact innovating, we find that when firms report no obstacles (state 0000) the propensity to innovate is lowest (see Table 3). This suggests an endogeneity problem, as there may be reverse causality from innovation activities to the reported obstacles by the firms. By contrast, the coefficient associated with state 0000 in the intensity equation is the largest coefficient of any state (see Table 3 again), suggesting no reverse causality. In other words, obstacles are associated with lower levels of innovation.

To partially investigate the reverse causality issue, we have estimated a simultaneous system, where in addition to [3], we also estimate a second equation that allows for the states to depend on innovation. When we estimate by 2SLS the intensity of innovation, we find that reverse causality is not statistically significant, i.e. we find no significant impact of innovation intensity on any of the states (at the 5% level).[18] However, many of the instruments used in the 2SLS are likely to be endogenous. Obtaining better instruments is difficult in this context. Since we only have micro-aggregated data, we cannot merge the firm data in our sample with observations on the same firms from other data sets and are therefore constrained in the choice of instruments to variables collected in the same innovation surveys. If we could merge the innovation surveys with data on production, organizational change, or matched employers-employees surveys, other instruments could be used such as the capital intensity of the firm, the educational background of the CEO, the skill level of the managers, the financial structure of the firm, the legal status, or the type of ownership. Alternatively, with the appearance of new waves of innovation surveys it will become possible to have a longitudinal data set and to use lagged variables as instruments.

Using the estimated $\hat{\gamma}_l$ and $\hat{\lambda}_l$, we now turn to the complementarity and substitutability tests described above for both the probability of becoming an innovator (through $\hat{\lambda}_l$) as well as the intensity of innovation (through $\hat{\gamma}_l$). Table 4 presents the Wald statistic for both the super- and sub-modularity tests. The upper bound critical value at a 10% significance level is 7.094, which implies that the null hypothesis is definitely rejected when the Wald statistic is above 7.094. The lower bound critical value is 1.642, which implies that the null hypothesis is definitely accepted for values below this level. The test is inconclusive for values in between the two bounds.

As can be seen in Table 4 the results regarding the supermodularity of the innovation function depends on whether one is concerned with the propensity or the intensity to

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[18] Since we do not have enough information on firms that do not innovate (only innovators need to fill out the whole questionnaire), we cannot estimate the simultaneous system for the propensity equation (equation [4]) due to lack of instruments. In this sense, our results below regarding the propensity of innovation have to qualified.

innovate. In particular, the probability of becoming an innovator displays considerable substitutability in obstacles. For instance, the null hypothesis that obstacles 2 ("internal human capital") and obstacle 3 ("external human capital") are substitutable is accepted by our test (Wald statistic of 0.353). In other words, the lack of skilled personnel is less of a problem, when there is also a lack of external human capital. More generally, obstacles 2 ("internal human capital"), obstacle 3 ("external human capital"), and obstacle 4 ("regulation") are all jointly substitutable factors in determining whether a firm is innovative or not (the Wald statistic is below 1 for all these pairs, see Table 4). This indicates that the probability of innovating is submodular in obstacles 2, 3 and 4. Finally, there is also substitutability between obstacles 1 ("lack of finance") and obstacle 3 ("external human capital").

Overall, the results regarding the probability to innovate suggest that there is considerable substitutability across most (but not all!) obstacles. This finding is further supported by the results of the supermodularity test, which soundly rejects complementarity for 4 obstacle pairs. In the two cases where we cannot accept a relationship of substitutability between pairs of obstacles (the test being inconclusive), we can definitely reject complementarity.

By contrast, the results regarding the intensity of innovating suggest a significant complementarity over several obstacles. In particular, as can be seen in Table 4, obstacle 1 ("lack of finance") is complementary with all other obstacles (the highest Wald statistic of any obstacle pair is 1.53). In other words, insufficient finance lowers the intensity of innovation by more whenever there is insufficient internal human capital, or there is lack of cooperation with other firms or when regulatory obstacles exist. A relationship of substitutability shows up between obstacles 2-3 ("lack of skilled personnel" and "lack of opportunity to cooperate") and 3-4 ("lack of opportunity to cooperate" and "regulations"). Moreover, in three out of six cases, the results of the complementarity test get reinforced by the results of the Wald test for submodularity. Obstacle pairs 1-2 and 1-3 are accepted as complements and rejected as substitutes,

whereas obstacles 3 and 4 are accepted as substitutes and rejected as complements. In the other three cases, one of the two tests is inconclusive.

The previous findings indicate that the evidence regarding the existence of complementarity in obstacles depends on the phase of innovation (propensity or intensity) as well as the particular obstacle pair. While the evidence regarding the propensity to innovate points towards a number of substitutable relationships, complementarity comes out strongly for a number of obstacles as far as the intensity of innovation is concerned.

While some obstacle pairs – such as 2-3, 3-4 – are substitutable across both dimensions of innovation, others – such as 1-3 – display strong evidence of substitutability in the propensity to innovate, and at the same time significant complementarity in the intensity of innovation. This points towards a possible difficulty in designing optimal policies for innovation, since the impact may pan out very differently across the two innovation phases. Lack of access to finance is complementary to all other obstacles for the intensity of innovation, while complementarity is rejected for the propensity to become an innovator.

What implications do complementarities (substitutabilities) in innovation obstacles have for innovation policy. If obstacles are substitutes, the presence of one obstacle relieves the pressure from the other one. In that case removing one obstacle will exacerbate the other one. Both should be removed jointly. If obstacles are complements, however, the two obstacles reinforce each other. Removing one will attenuate the other one. There might be less reasons to remove both at the same time. Submodularity (supermodularity) in innovation obstacles means supermodularity (submodularity) in innovation policies.

Subject to the endogeneity issue raised above our results lead to the following preliminary policy recommendations. When it comes to turn non-innovators into innovators, it is important to remove a bunch of obstacles at the same time. Governments should adopt a mix of policies, for instance easing access to finance and

allowing firms to cooperate with other firms and technological institutions, or increasing the amount of skilled personnel and reducing the regulatory burden. When it comes to increasing the amount of innovation, one or the other policy will do: easing access to finance, making more skilled labor available, or allowing for more collaborations.

6. Conclusion

This paper develops a framework for testing complementarity in innovation policies based on estimating the objective function directly. We specify and estimate an innovation function using European firm data from the first Community Innovation Survey (CIS1) and test the implied inequality conditions for supermodularity. Innovation obstacles serve as negative proxies of innovation policies. We investigate two phases of the innovation process: the decision to innovate or not, and the intensity of innovation, conditional that a firm does any innovation at all.

Our results are preliminary insofar that they are based on cross-sectional evidence which significantly reduces our ability to fully address the endogeneity of perceived obstacles to innovation. With this qualification we find that the evidence regarding the existence of complementarity in innovation policies depends on the phase of innovation (propensity or intensity) as well as the particular pair of economic policies. While the evidence regarding the propensity to innovate points towards a number of substitutable relationships in innovation policy, substitutability among policies seems more often the norm as far as the intensity of innovation is concerned. This indicates that these two phases of innovation, i.e. the probability of becoming an innovator and the intensity of innovation, are subject to different constraints.

Moreover, some obstacle pairs are substitutable in the propensity to innovate, while complements in the intensity of innovation. This points towards a possible difficulty in designing optimal policies for innovation, since the impact may pan out very differently across innovation phases. For example, the "lack of finance" and the "lack of

opportunity to cooperate" are complements for the intensity to innovate, but substitutable for the propensity to become an innovator, which implies that policies should be put in place to remove both obstacles in order to make firms innovative, but only one policy is needed to make them more innovative.

Table 1
SUMMARY STATISTICS
CIS I, micro-aggregated data, 1992 (sample mean)

Variable	Mean
Percentage of innovators	61.1
% in sales of innovative products for innovators	27.6
% of enterprises with 20-49 employees	26.2
% of enterprises with 50-99 employees	18.8
% of enterprises with 100-249 employees	17.3
% of enterprises with 250-499 employees	19.5
% of enterprises with 500-999 employees	9.6
% of enterprises with >999 employees	8.7
% of enterprises that are part of a group	47.2
Average number of employees	654.3
% of enterprises doing R&D among innovators	55.2
% of innovators doing R&D continuously	43.4
% of innovators doing cooperative R&D	21.1
Average R&D/sales ratio for innovators	3.1
Number of observations	5451

Table 2
OBSTACLE OCCURRENCES IN %
(SEE APPENDIX 2 FOR OBSTACLE DEFINITIONS)

Obstacle State	0000	0001	0010	0011	0100	0101	0110	0111	1000	1001	1010	1011	1100	1101	1110	1111
ALL FIRMS	23.5	3.1	1.3	1.0	4.0	2.7	1.8	2.3	11.8	5.6	2.4	3.8	6.0	7.7	4.8	18.3
INNOVATORS	17.0	3.8	1.5	1.2	4.7	3.3	2.2	2.7	12.1	6.5	2.7	4.3	6.6	9.2	5.1	17.2

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Table 3

MAXIMUM LIKELIHOOD ESTIMATES OF THE GENERALIZED TOBIT MODEL

Variables	Propensity to innovate	Intensity of innovation
Size dummies		
50-99 employees	0.24 (.057)	-0.11 (.109)
100-249 employees	0.41 (.062)	-0.21 (.114)
250-499 employees	0.68 (.064)	-0.55 (.124)
500-999 employees	0.81 (.082)	-0.66 (.143)
over 1000 employees	0.90 (.094)	-0.58 (.151)
Being part of a group	0.30 (.046)	-0.10 (.078)
R&D/sales	-x-	0.16 (.029)
Doing R&D on a continuous basis	-x-	0.03 (.076)
Doing cooperative R&D	-x-	0.24 (.078)
States		
0000	-0.49 (.087)	0.76 (.230)
0001	0.13 (.141)	0.20 (.244)
0010	0.13 (.200)	0.12 (.320)
0011	0.35 (.234)	0.20 (.341)
0100	0.07 (.127)	0.33 (.243)
0101	0.02 (.148)	0.73 (.259)
0110	0.14 (.172)	0.40 (.287)
0111	-0.07 (.151)	0.44 (.276)
1000	0.08 (.097)	0.61 (.210)
1001	0.12 (.113)	0.43 (.222)
1010	-0.01 (.151)	0.45 (.272)
1011	0.23 (.129)	0.40 (.239)
1100	0.10 (.113)	0.43 (.227)
1101	0.28 (.106)	0.50 (.207)
1110	0.12 (.118)	0.35 (.234)
1111	0.14 (.093)	0.44 (.204)
Standard error	1	1.83 (.03)
Percentage of correct predictions	0.45	-x-
Squared corr (obsv'd and pred'd values)	-x-	0.31
Estimated ρ	-0.13 (0.32)	

Standard errors in parentheses under estimated coefficients. There are also country and industry dummies in both equations. A prediction is considered to be correct when an innovator gets a prediction above the average observed propensity to innovate.

Table 4

COMPLEMENTARITY/SUBSTITUTABILITY TETS IN INNOVATION POLICY
Wald test of inequality restrictions based on generalized Tobit estimates
(at 10% significance level: lower bound=1.642, upper bound=7.094[*])

Obstacle Pairs	Probability 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												
	13.443	7.908	10.998	6.752	11.952	3.028	0.00	0.00	1.529	3.341	3.730	14.090
Submodularity Test												
	2.690	0.000	2.215	0.353	0.772	0.871	18.653	9.984	5.215	0.335	8.156	0.403

Obstacle definitions: 1= Lack of appropriate sources of finance, 2= Lack of skilled personnel, 3= Lack of opportunities for cooperation with other firms and technological institutions, 4= Legislation, norms, regulations, standards, taxation.
* see Kodde and Palm (1986)

Appendix 1

INDUSTRY DEFINITIONS

Industry	NACE code	Description of Industry
FOOD	15-16	food, beverages and tobacco
TEXTILE	17-19	textiles, wearing apparel, dressing and dyeing of fur, tannings, and dressing of leather, luggage, handbags, saddlery, harness and footwear
WOOD	20-22	wood and products of wood and cork, except furniture, straw and plaiting materials, pulp, paper, and paper products, publishing, printing, and reproduction of recorded media
CHEM	23-24	refined petroleum products and nuclear fuel, chemicals and chemical products
PLASTIC	25	rubber and plastic products
NON-MET	26	other non-metallic mineral products
METAL	27-28	basic metals, fabricated metal products, except machinery and equipment
M&E	29	machinery and equipment
ELEC	30-33	office machinery and computers, electrical machinery and apparatus, radio, television and communication equipment and apparatus, medical, precision and optical instruments, watches and clocks.
VEHIC	34-35	motor vehicles, trailers, semi-trailers, and other transport equipment
NEC	36	furniture

Appendix 2

OBSTACLES TO INNOVATION[*]

Category 1: Risk and finance

- Excessive perceived risk
- ***Lack of appropriate sources of finance***   *=> Obstacle 1*
- Innovation costs too high
- Pay-off period of innovation too long

Category 2: Knowledge-skill within enterprise

- Enterprises's innovation potential too small
- ***Lack of skilled personnel***   *=> Obstacle 2*
- Lack of information on technologies
- Lack of information on markets
- Innovation costs hard to control
- Resistance of change in the enterprise

Category 3: Knowledge-skill outside the enterprise

- Deficiencies in the availability of external technical services
- ***Lack of opportunities for cooperation with other firms and technological institutions***   *=> Obstacle 3*
- Lack of technological opportunities
- No need to innovate due to earlier innovations

Category 4: Regulations

- Innovation too easy to copy
- ***Legislation, norms, regulations, standards, taxation***   *=> Obstacle 4*
- Lack of customer responsiveness to new products and processes
- Uncertainty in timing of innovation

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[*] The obstacles used in the analysis of this paper are in bold.

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