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Publication Date
2014-10-08

Innovation Output Choices and Characteristics of firms in the U.S.

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October 8, 2014

Abstract

This paper uses new business micro data from the Business Research and Development and Innovation Survey (BRDIS) for the years 2008-2011 to relate the discrete innovation choices made by U.S. companies to features of the company that have long been considered to be important correlates of innovation. We use multinomial logit to model those choices. Bloch and Lopez-Bassols (2009) used the Community Innovation Surveys (CIS) to classify companies according dual, technological or output-based innovation constructs. We found that for each of those constructs of innovation combinations considered, manufacturing and engaging in intellectual property transfer increase the odds of choosing innovation strategies that involve more than one type of categories (for example, both goods and services, or both tech and non-tech) and radical innovations, controlling for firm size, productivity, time and type of R&D. Company size and company productivity as well as time do not lean the choices in any particular direction. These associations are robust across the three multinomial choice models that we have considered. In contrast with other studies, we have been able to use companies that do and companies that do not innovate, and this has allowed to rule out to some extent selectivity bias.

Keywords Innovation, R&D, productivity, intellectual property, generalized logistic regression, choice models 031, 032, 033, 034.

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†The research in this paper was conducted while the author was Special Sworn Status researcher of the U.S. Census Bureau at the Center for Economic Studies. Research results and conclusions expressed are those of the author and do not necessarily reflect the views of the Census Bureau. This paper has been screened to insure that no confidential data are revealed.

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1 Introduction

How firms innovate matters. Product innovating firms put new goods or services onto the market. A process is changed to solve a problem in order to get a product to the market (Gault, 2010). The innovation choices firms make are at the core of firms‘ and nations‘ strategies for growth (Foster and Grim, 2010; Archibugi and Michie, 1995). But our understanding of how firms make those choices is far from perfect (Mairesse and Mohnen, 2010; Freeman and Soete, 2009; Grupp and Schubert, 2010; Carayannis and Grigoroudis, 2014). Measuring the choices with adequate metrics appears equally challenging (Freeman and Soete, 2009; Grupp and Mogee, 2004; Grupp and Schubert, 2010; Gault, 2010). There has not yet been a connection between the line of research on innovation indicators and the econometric research on the determinants of innovation. Our paper is a unique attempt at reconciling the two with new U.S. micro data.

The objective of this paper is to explain the choices that U.S. companies make between polytomous innovation output based on company behavior. Most efforts to model the determinants of innovation using survey data have used simple indicators of the frequency of the response to a single question, for example product innovation or process innovation, as dependent variables. But companies often choose more than one way of innovating. The indicators that we use to represent their polytomous choices were introduced by Bloch and Lopez-Bassols (2009) to gain greater insigh into innovation for European Union (EU) and non-EU countries with Community Innovation Survey (CIS) data (Eurostat, 2010). The U.S. was excluded from their study because at the time there was no comparable survey data on U.S. companies. But that is no longer the case. The U.S. Business Research and Development and Innovation Survey (Census-Bureau/NCSES, 2010), henceforth denoted as BRDIS, opened doors not only to the creation of alternative indicators like those proposed by Bloch and Lopez-Bassols (2009) but also to new micro-based research linking individual U.S. firms‘ innovation choices to other firm level performance data (Wolfe, 2010; Boroush, 2010; Jankowski et al., 2010). Assessing the empirical evidence regarding the extent to which some widely studied theoretical arguments are related to firms‘ polytomous innovation choices is now feasible.

The first indicator considered involves goods and services innovation. Bloch and Lopez-Bassols (2009) found that a significant share of firms implement both goods and services innovation in both the manufacturing and the service sectors. Thus they proposed an indicator that defines a company as a dual innovator if it is active

Table 1: Dual innovation status of U.S. firms, BRDIS 2008-2011 (weighted percentage). A star indicates that the manufacturing sector has higher share of that category than the non-manufacturing sector.

Status	**Percent of all companies**
Dual innovation	13%(∗)
Goods innovation/no services innovation	22% (∗)
No innovation in goods or services	60%
Services innovation/no goods innovation	5%

Table 2: Technological innovation status of U.S. firms. BRDIS 2008-2011 (weighted percentage). A star indicates that the manufacturing sector has higher share of that category than the non-manufacturing sector.

Status	**Percent of all companies**
Neither technological or non-technological innovation	53%
Non-tech only	3%
Non-technological and technological innovation	19%(∗)
Technological innovation only	25%(∗)

in both goods and services innovation, what Howells (2004) calls 'encapsulation.' As we can see in Table 1, 13% of all U.S. companies studied in this paper chose the dual innovation path in 2018-2011, with higher share of dual innovators in the manufacturing sector than in the service sector.

BRDIS asks companies to report four types of innovation: product (good or service); methods of manufacturing; logistics or distribution methods for inputs, goods or services; supporting activities for process. The first two are often considered technological innovations while the last two are thought of as non-technological. Based on these types of innovation Bloch and Lopez-Bassols (2009) proposed another indicator described in Table 2.

As we can see in Table 2 the U.S. presents a relatively larger share of firms with technological innovations only or both technological and non-technological innovation, particularly in the manufacturing sector.

The third indicator considered represents firms' choices in more detail. It is based on the fact that a product innovation that is new to the market for an enterprise that operates on international markets may be considered more novel than a product innovation that is new only to the domestic market. On the other hand, a product innovation that is new to domestic markets may or may not be more novel than an

Table 3: Output-based innovation status of U.S. firms, BRDIS 2008-2011 (weighted percentage). A star indicates that the manufacturing sector has higher share of that category than the non-manufacturing sector.

Status	**Percent of all companies**
Domestic modifier	8%(∗)
International modifier	2% (∗)
Neither	68%
New-to-market domestic innovators	17%(*)
New-to-market international innovators	5%(*)

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innovation that already exists on international markets. In the period 2009-2011, more than 50% of the innovations in the U.S. were new-to-the market or new-to-the-company. That percentage was higher for companies active in R&D. Companies in the service sector and active in R&D attributed an average of 24 percent of their sales to new-to-market innovations, and 16% to new-to-company innovations (Sanchez, 2014). The indicator captures all these dimensions of innovation output choice by characterizing the firms as:

- New to market international innovators. Process and product innovators that operate in international markets.

- New to market domestic innovators. Process and product innovators that operate only in domestic markets.

- International modifiers. New-to-enterprise product or process innovation that already exists in international markets. Enterprise operates international markets. The innovation may be new or not to domestic markets.

- Domestic modifiers. Firms that operate only on domestic markets. Product and or process innovation already exists in the market. Adopters able to adopt and implement the new technologies.

Table 3 shows that U.S. companies‘ choose the new-to-market domestic innovation category over other categories. Only a small percentage of U.S. companies operate in international markets.

In this paper, we model the innovation choices under each of the three indicators based on firm characteristics using multinomial logistic models.

The rest of the paper is organized as follows. First, we do a bibliographic review. Then the review continues while describing the data and presenting the results of the discrete innovation choices of firms estimated with multinomial logistic models. We consider the three polytomous innovation output metrics described above as dependent variables in those models. We finish the paper with some conclusions and recommendations for further research.

2 Literature Review

At the microeconomic level, innovation is linked to firm's performance and competitiveness. Not surprisingly, as a result, the 1970s and the 1980s witnessed an increasing interest on the development of analytic models and measuring tools to study the determinants of innovation. Innovation was measured on the input side by the fact of having pursued innovation activities, such as R&D or other input proxies for innovation (Stadler, 1992; Gonzalez and Pazo, 2004; Buck and Stadler, 1992; Negassi, 2004; Lee, 2003; Zemplinerova and Hromadkova, 2012; Lederman, 2010; Ding, 2006; Demirel and Mazzucato, 2012; Bilbao-Osorio and Rodriguez-Pose, 2004; AlAzzawi, 2012; Guloglu and Tekin, 2012; Akinwale et al., 2012; Pessoa, 2010; Frantzen, 2000; Guellec and van Pottelsberghe de la Potterie, 2001; Aiello and Cardamone, 2005). That is understandable, given the emphasis on technological innovation and the lack of appropriate survey data until recently. Many models on what determines R&D and patents were designed. Meanwhile many national statistical agencies and independent researchers attempted to develop reliable indicators of the output of innovative activity (Freeman and Soete, 2009) that could replace input side indicators in the models.

R&D was soon found to be a too restrictive measure of innovation (Freeman and Soete, 2009), a measure that does not necessarily have any link to tangible innovation output. The introduction of the Oslo manual in 2005 extended the definition of innovation to encompass non technological characteristics of product and process innovation (such as organizational, logistic and marketing changes).

> 'An innovation is the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations.' OECD/Eurostat (2005)p. 46.

Surveys based on the Oslo Manual were implemented in the early 1990s to directly measure innovative activity beyond what can be found in other science and technology statistics such as surveys of R&D, patent data or bibliometric indicators (Cohen, 2010; Bloch and Lopez-Bassols, 2009; OECD/Eurostat, 2005; Eurostat, 2010). The surveys confirmed that there can be what Freeman and Soete (2009) called "innovation without research." Many companies have an interest in increasing innovation without research by using open innovation collaboration. Today, innovation can not be said to depend only on R&D (maybe technological innovation is) but rather on collaboration mechanisms, formal or informal and other factor.

Progress made in the development of indicators, and availability of data, opened the door for microeconomic studies of the determinants of innovation using the new direct metrics of innovation output (Horbach et al., 2013; Arvanitis, 2008; Dotzel et al., 2013; Mairesse and Mohnen, 2010; Carvalho et al., 2013; Hollenstein, 2003; Jensen et al., 2007; Frenz and Lambert, 2009; Geroski et al., 1993). Some researcher have tried to explain why a firm innovates or not by explaining a dichotomous measure of innovation (pertaining to a particular type of innovation output such as process innovation, product innovation, organizational innovation or marketing innovation) (Carvalho et al., 2013). Others have used a measure of the intensity of innovation or sales turnover as dependent variables. Studies have found that R&D effort and company size, two factors that have interested researched for half a decade, play a role in innovation thus measured.

3 Data and Methodology

The data analysis is based on items in the 2008, 2009, 2010 and 2011 BRDIS questionnaires (Census-Bureau/NCSES, 2010) for about 67000 companies. The target population consists of for-profit businesses that have 5 or more paid employees in the United States, have at least one establishment that is in business during the survey year, are located in the United States, and are classified in select industries based on the 2007 North American Industry Classification System (NAICS), with a particular focus on those companies that perform R&D in the United States. To account for missing values and possible errors in the Business Register employment data, companies with fewer than 5 employees but with annual payroll of at least $250,000 are also included in the frame Wolfe (2010) Boroush (2010) Jankowski et al. (2010).

BRDIS is more than an innovation survey. It also contains information on total R&D expenditures. These are disaggregated by R&D performed by the company and R&D spent in having others perform the R&D. Separately, there is a section on intellectual property reporting the importance of different ways of appropriating returns to innovation (patents, trademarks, copyrights, mask works, secrets), levels of patents and license income and intellectual property transfer (patent pools, cross-licensing, among them).

The sample used in this paper includes active companies that have sales and employment larger than 0 and which may or may not report expenditures in R&D. In 2008, only companies that reported positive R&D were asked about their sales, thus those companies which do not are excluded from the analysis. Some companies (no more than 5000) receive the long form of BRDIS each year. In order to include all kinds of R&D levels and companies that innovate even though they do not have R&D, the variables included in the models are strictly those that have received the largest attention in the literature and we can also find in BRDIS. We determine the relation between each of the three new innovation output indicators described and a set of explanatory variables considered in the literature regarding determinants of innovation also found in BRDIS. The methodology common to the three models studied is weighted generalized logistic regression model because the dependent variable, the innovation indicator, is categorical with more than two unordered responses.

Logistic regression is often used to investigate the relationship between discrete responses and a set of explanatory variables (Hosmer and Lemeshow, 2000; Roberts et al., 1987). When there are more than two categorical responses without order, the logit model is also called generalized logit model, discrete choice model or multinomial model. The model for $D+1$ possible responses has the form:

$$\log\left(\frac{Pr(Y=i \mid x)}{Pr(Y=D+1 \mid x)}\right) = \alpha_i + x\beta_i, \qquad i = 1, ..., D,$$

where the $\alpha_1, ..., \alpha_D$ are intercept parameters and the $\beta_1, ..., \beta_D$ are D vectors of parameters (McFadden, 1974). This type of model has been used to model firm's innovation strategies choices, complementarities in innovation, and innovation and competition (Crepon and Duguet, 1997; Fares, 2014; Autant-Bernard et al., 2007). We use SAS Proc Surveylogistic procedure to conduct the analysis. The results are presented in the form of odds ratios.

The variables included in our models as explanatory variables are dictated by widely studied theoretical arguments on the determinants of innovation and availability of the data in BRDIS. They are described below.

Dichotomous variable for manufacturing or service sector . Our sample spans multiple industries but we control only for the fixed effect of sector of the economy where the firm lies. By pooling observations across industries within a sector the assumption made is that the same elasticity for all industries, which probably lowers the effect of this variable. Pooling observations and ignoring industry level differences in technological opportunities, demand and appropriability conditions, economies in production, market structure and other factors

Table 4: Odds ratio interval estimates for dual innovation multinomial model. Base of comparison is the no-innovation category.

Indep. Variable	**Dep. Variable**	**Odds ratio**	**Lower odds ratio**	**Upper odds ratio**
manufacturing	dual	1.659	1.542	1.784
manufacturing	good only	3.448	3.215	3.698
manufacturing	service only	0.286	0.259	0.315
year	dual	0.862	0.836	0.887
year	good only	0.897	0.874	0.921
year	service only	0.891	0.858	0.926
IP transfer	dual	3.490	3.258	3.739
IP transfer	good only	2.429	2.277	2.592
IP transfer	service only	2.471	2.243	2.722
R&D spent/R&D performed	dual	3.210	2.630	3.917
R&D spent/R&D performed	good only	3.316	2.677	4.108
R&D spent/performed	service only	2.784	2.352	3.295
Extramural R&D/intramural R&D	dual	0.084	0.045	0.157
Extramural R&D/intramural R&D	good only	0.179	0.093	0.345
Extramural R&D/intramural R&D	service only	0.090	0.035	0.236
World R&D employees/total World employees	dual	8.331	6.763	10.264
World R&D employees/total World employees	goodon	7.432	5.968	9.255
World R&D employees/total World employees	servon	1.840	1.450	2.335
Log world employment	dual	1.085	1.066	1.105
Log world employment	good only	1.038	1.019	1.058
Log world employment	service only	0.947	0.926	0.967
Log world sales/World employees	dual	1.076	1.052	1.101
Log world sales/World employees	good only	1.183	1.156	1.210
Log world sales/World employees	service only	0.951	0.928	0.974

could bias estimates of the effect of the other variables on innovation (Cohen, 2010). Usually technological opportunity and these other factors are captured by industry dummies (Mairesse and Mohnen, 2010). Given that the empirical evidence regarding market structure and R&D remains problematic, it would be interesting to assess the evidence with more disaggregation by industry, but this is not the purpose of our paper.

Time is measured by the year in which the survey data was collected to account for the few companies that report more than one year and possible variability across time.

Dichotomous variable for intellectual property exchange . In addition to the enterprise R&D effort, inter-firm networks play an increasingly important role as sources of new technical knowledge, particularly as innovation becomes more cooperative and global (OECD, 2013). They are only indirectly linked with any formal R&D process (Love and Roper, 1999; Freeman, 1991) They are explicit arrangements which do not include the informal information-sharing arrangements that often exist between companies (von Hippel, 1987). BRDIS contains a section on Intellectual property that asks companies whether they engage in intellectual property transfer activities such as technical assistance or transfer of know-how, patent pools, cross-licensing and transfers due to acquisitions or spin offs, open source community, open source IP. The hypothesis that inter-firm networks or what is the same formal IP transfer is a substitute, not a complement of R&D has been contemplated in the literature (Love and Roper, 1999). However, not much comparison can be made between studies as each research paper defines network and transfer differently.

R&D paid by company over total R&D performed by the company . This reflects how much of the total performed R&D is paid by the company. A decrease in this quantity reflects an increase in inter-firm R&D partnerships in the direction from others to the firm observed. The smaller this quantity, the more the company is doing research for others. We include this variable instead of plain R&D expenditures to distinguish companies that may be conducting research for others from companies that are conducting intramural research. This is not a variable too studied in the literature. We would expect that companies with higher ratio will be more innovative.

About 88% of worldwide R&D expense of U.S. companies in 2008 was for company performed R&D. Manufacturing companies conduct the largest percent of total R&D expense (71%) Wolfe (2010). Some authors Tingvall and Karpaty

(2011) mention that the form of the relation between competition (industry structure) and R&D depends on whether the R&D is intramural or extramural. There is a debate as to the relative importance of intramural vs extramural R&D for firm performance. According to Ebersberger and Herstad Ebersberger and Herstad (2013) this depends on the size of the company, with SMEs being more likely to rely only on intramural R&D due to organizational costs of international collaboration.

R&D performed by others over domestic R&D paid and performed . This is the ratio of extramural R&D to company-funded, company-performed R&D. An increase in this quantity reflects an increase in inter firm R&D partnerships in the direction of from the firm observed to other firms. In 2011, U.S.-located companies spent $29.6 billion for extramural (purchased and collaborative) research and development performed by domestic and overseas organizations Moris and Shackelford (2011). This amount includes contract or otherwise purchased R&D ($24.0 billion) and payments to R&D collaborators ($5.6 billion). Most of these extramural R&D expenditures involve domestic providers and partners. The ratio varies considerably across industries, and it is expected to have a significant effect on the propensity to have any type of innovative choices. R&D cooperation is motivated by cost and risk sharing (Mairesse and Mohnen, 2010). Companies collaborate R&D expenses with universities and other companies. The extent of doing so depends on the appropriability of returns. More appropriability, more collaboration Cohen (2010).

Much has been debated about the internal versus external R&D. This has to do with the R&D strategy of the firm. Empirical results support the notion that the probability of a firm becoming innovative increases with internal R&D input, understood as R&D expenditures that are used for research performed by the company (Hall et al., 2009; Crepon et al., 1998; Segarra and Teruel, 2011). According to this literature, R&D performed by the firm affects innovation and also the absorptive capacity of companies. A question investigated has been whether there is complementarity between internal and external R&D. This refers to the fact that more of one increases the return from the other (Cassiman and Veugelers, 2006). Much of this research has been based on a question in CIS that separates innovation activities into: internal R&D; acquisition of R&D; acquisition of machinery, equipment and software; acquisition of external knowledge; training; all forms of design; marketing expenditures. (p.5, question 5.2 of the CIS-4 survey).

World R&D employment over total world employment . This variable represents the importance of tacit knowledge.

Log productivity level, measured as world sales over world employment.

Log world employment, to measure company size. The Schumpeterian tradition implies that a positive link exists between firm size and monopoly power and innovative activity, the latter usually measured by R&D. Although doubts have been cast on that link by empirical evidence (Love and Roper, 1999), Cohen (2010) highlights the longstanding, robust finding that there is a relation between firm size and R&D. Others assert the same (Mairesse and Mohnen, 2010). In the Schumpeterian tradition, firm size can be measured by the amount of R&D, proportion of workers in R&D, or number of employees Lejarraga and Martinez-Ros (2014). Company size needs to be considered because smaller and medium sized firms may exhibit different patterns of behavior to those of large firms. However, the evidence regarding a Schumpeterian effect associated with monopoly power is mixed (Mairesse and Mohnen, 2010).

This concludes the description of the variables that we found to be significant explanatory variables for the three indicators. In the three models for innovation indicators that we are about to present below, additional variables were not significant and we removed them from the model. We describe those variables now. The management of technology, i.e., whether the company did more or less basic research, was not significant. Neither was the propensity to patent, the propensity to license, the level of dollars spent in extramural research, or source of funds for R&D performed that was not paid by the company (no evidence of crowding out effect,or technology push effect).

There is overwhelming evidence that companies in most industries appear to use a combination of different appropriation mechanisms (Hall et al., 2012). Available empirical evidence strongly suggests that only a small fraction of innovative companies relies on patents to protect their inventions (Hall et al., 2012; Nicholas, 2011) and more businesses report that trademarks, trade secrets, and copyrights are important forms of IP protection than report that patents and mask works are important (Jankowski, 2012). Thus, the non significance of patent-related variables was not surprising. Survey-based evidence indicates that companies report heavier reliance on alternative mechanisms, such as lead time and secrecy. On the other hand, perhaps patenting activity is not significant in our model, because the effect of patents is best noticed when there is persistent patenting behavior Demirel and Mazzucato (2012).

Table 5: Odds ratio interval estimates for technological innovation multinomial model. Base of comparison is the no-innovation category.

Indep. Variable	**Dep. Variable**	**Odds ratio**	**Lower odds ratio**	**Upper odds ratio**
manufacturing	non tech only	0.615	0.545	0.694
manufacturing	both tech non tech	1.804	1.686	1.930
manufacturing	tech only	2.255	2.114	2.406
year	non tech only	0.963	0.918	1.010
year	both tech non tech	0.827	0.806	0.849
year	tech only	0.921	0.899	0.944
IP transfer	nontech only	1.725	1.495	1.991
IP transfer	tech and nontech	3.297	3.085	3.524
IP transfer	tech only	2.431	2.275	2.598
R&D spent/R&D Performed	non-tech only	1.847	1.418	2.406
R&D spent/R&D performed	both tech non tech	3.634	2.983	4.428
R&D spent/R&D performed	tech only	3.671	3.005	4.484
Extramural R&D/Intramural R&D	nontech only	0.471	0.330	0.672
Extramural R&D/Intramural R&D	tech and nontech	0.133	0.075	0.234
Extramural R&D /Intramural R&D	tech only	0.133	0.076	0.234
World R&D employees/Total World employees	non tech only	0.521	0.319	0.850
World R&D employees/Total World employees	tech and non tech	4.631	3.718	5.769
World R&D employees/Total World employees	tech only	6.247	5.042	7.740
Log world employment	non tech only	1.030	1.003	1.057
Log world employment	tech and non tech	1.094	1.075	1.113
Log world employment	tech only	0.978	0.960	0.995
Log world sales/world employees	non tech only	1.074	1.032	1.117
Log world sales/world employees	tech and non tech	1.078	1.055	1.100
Log world sales/world employees	tech only	1.087	1.066	1.108

4 Results

In this section we describe the odds of choosing the innovation outputs that we described earlier.

4.1 Dual innovation

We used a weighted generalized logistic regression (or multinomial) model to investigate what characteristics of companies lead them to be in any of the following categories: (i) neither goods nor services innovation, (ii) goods innovation but not services innovation, (iii) services innovation but not goods innovation or both service and product innovation. The base of comparison is no innovation of these two kinds at all. Note that the companies could be active in other forms of innovation. Using the neither category as base, we estimate odds ratios of being a product innovator against a non innovator, a service innovator against a non-innovator and a dual innovator against non-innovator for several binary characteristics of companies controlling for non binary variables. The results can be seen in Table 4.

The results indicate that manufacturers have almost twice the odds of being a dual innovator than a non innovator compared to the service industries. Manufacturers have more than three times the odds of being good only innovators than non innovators compared to the service industries. Engaging in technology transfer is associated with three and a half higher odds of being a dual innovator than a non innovator.

Higher R&D spent over R&D performed is associated with 3 times higher odds of being a dual or good only innovator than a non-innovator. The opposite association is seen with higher extramural R&D. These two effects combined suggest that intramural and extramural R&D are substitutes rather than complements as some authors have suggested.

Tacit knowledge embedded in the R&D workers is eight and a half more likely to result in dual innovation. Company size and productivity on the other hand have odds ratios very close to one, indicating that although significant they are equally likely to result in any of the types of innovation.

To summarize, firms that hire R&D workers and engage in informal IP trading and do intramural R&D are more likely to be dual innovators other things constant.

4.2 Technological innovation

Controlling for other variables, an industry in the manufacturing sector has almost twice the odds of choosing both tech and non tech or tech only over non innovation than a company in the service sector. Engaging in associated IP trading is associated with over three times higher odds of being dual innovators and almost two times higher odds of being technological innovators only.

Higher level of intramural R&D is associated with higher technological and non-technological innovation only. The opposite effect can be seen for extramural R&D, suggesting again that when it comes to technological innovation output intramural and extramural R&D are substitutes.

Higher employment of R&D workers translates into higher odds of being both tech and non-tech or tech only innovators. Again, company size and productivity do not make much difference as reflected by their odds ratios being close to one.

According to Bloch and Lopez-Bassols (2009), Japan has the largest share of non-technological innovators followed by Brazil and Luxembourg and Denmark have the highest shares.

4.3 Output-based indicators

This is an indicator that uses information on product (good or service) and process innovation, on whether the good or service was new to the market or new to the company and on whether the company sells or not in international markets. *Innovation new-to-the-company* refers to good or services innovation that is new to the company but not new to the market. *Innovation new-to-the-market* refers to good or services innovation that is new to the market.

This important distinction between 'new to company' or 'new to market' has to do with the difference between tacit knowledge (or absorptive capacity) to imitate and assimilate the discoveries of others, also known as the imitative role of R&D or diffused and embedded technology, and innovation per se. Innovative enterprises are companies that actively create new knowledge. If the company uses the technology of others, or new to the firm innovation, then this indicates diffusion. Theoretical models have been proposed in which R&D has both an innovative and imitative role Aiello and Cardamone (2005) Hall et al. (2009) Griffith et al. (2004).

Block and Bassols found that in most countries, a much larger share of innovators operating internationally have introduced new to market innovations than of those operating on domestic markets only. They interpret that as suggesting that exposure to international markets has a strong positive effect on firms' incentives to develop novel products.

Companies that engage in IP transfers have twice the odds of being international modifier and three times higher odds of being new-to-market international innovators than being non-innovators. Manufacturers are more likely than non manufacturers to

Table 6: Odds ratio interval estimates for output based innovation multinomial model. Base of comparison is the no-innovation category. Domestic modifier=dm; international modifier=im; new-to-market domestic inn=ntmdi; new-to-market international innovator=ntmii

Indep. Variable	**Dep. Variable**	**Odds ratio**	**Lower odds ratio**	**Upper odds ratio**
manufacturing	dm	1.735	1.599	1.882
manufacturing	im	1.785	1.540	2.068
manufacturing	ntmdi	2.074	1.934	2.224
manufacturing	ntmii	2.579	2.318	2.870
year	dm	1.675	1.620	1.732
year	im	1.918	1.808	2.034
year	ntmdi	1.672	1.625	1.720
year	ntmii	1.917	1.844	1.993
IP transfer	dm	1.491	1.362	1.632
IP transfer	im	2.194	1.890	2.547
IP transfer	ntmdi	1.992	1.860	2.134
IP transfer	ntmii	2.983	2.712	3.281
R&D spent/R&D performed	dm	2.039	1.651	2.518
R&D spent/R&D performed	Im	2.028	1.641	2.507
R&D spent/R&D performed	ntmdi	2.047	1.653	2.535
R&D spent/R&D performed	ntmii	2.026	1.640	2.503
Extramural R&D /intramural R&D	dm	0.124	0.055	0.281
Extramural R&D /intramural R&D	im	0.301	0.121	0.750
Extramural R&D /intramural R&D	ntmdi	0.182	0.108	0.307
Extramural R&D %	ntmii	0.245	0.125	0.478
World R&D employees/Total world employees	dm	2.251	1.752	2.892
World R&D employees/Total world employees	im	7.922	5.862	10.705
World R&D employees/Total world employees	ntmdi	7.077	5.789	8.652
World R&D employees/Total world employees	ntmii	9.015	7.129	11.401
Log employment	dm	0.884	0.864	0.905
Log employment	im	1.545	1.503	1.588
Log employment	ntmdi	0.865	0.847	0.883
Log employment	ntmii	1.642	1.610	1.675
Log sales/employees	dm	1.046	1.020	1.072
Log sales/employees	im	1.107	1.048	1.170
Log sales/employees	ntmdi	1.060	1.039	1.082
Log sales/employees	ntmii	1.159	1.118	1.202

be new-to-market international or domestic innovators. Tacit knowledge is associated with much higher odds of being international or domestic innovator and international modifier.

As in the other two models, company choices regarding innovation types could go either way with size and productivity.

5 Conclusions

This paper has presented an empirical study of the significant associations between a set of variables that have long been considered to be important correlates of innovation and the innovation choices that firms make. The micro-level data comes from the BRDIS of 2008-2011. We found that for the three types of innovation combinations considered, manufacturing and engaging in intellectual property transfer increase the odds of choosing innovation strategies that involve more than one type of categories (for example, both goods and services, or both tech and non-tech) and radical innovations, controlling for firm size, productivity, time and type of R&D. Company size and company productivity as well as time are not clear determinants of firms choices. The odds are equally likely to lean on any type of innovation. These associations are robust across the three multinomial choice models that we have considered. In contrast with other studies, we have been able to use companies that do and companies that do not innovate, and this has allowed to rule out to some extent selectivity bias.

The management of technology, i.e., whether the company did more or less basic research, was not significant. Neither was the propensity to patent, the propensity to license, the level of dollars spent in extramural research, or source of funds for R&D performed that was not paid by the company (thus we found no evidence of crowding out effect, of government funds or technology push effect).

We have not considered directly the effect of cash flow (Murro, 2012), diversification, type of firm, and other firm characteristics for which operational definitions are not as clearcut in BRDIS. Technological opportunity and demand conditions were proxied by a dichotomous variable distinguishing between the manufacturing and service sectors. Perhaps because of these omissions, the variability in the responses explained by the significant variables selected is close to 40%. Controlling for the effects of those variables not considered here could result in higher R-square.

By aggregating across industries in the manufacturing and the service sector, we made the strong assumption that the effects are the same for all industries within those aggregate sectors. In addition to that, most variables in the innovation surveys, at a particular date are codetermined and jointly influenced by other variables. Few studies, apart from those that adopt the CDM framework (Crepon et al., 1998), take the mutual dependence and the dependence on third factors explicitly into account Mairesse and Mohnen (2010). This is partly because of the lack of long time series and because of the lack of other variables than those collected in the surveys. In a future paper, we plan to break down the results by industry to account for industry-level variation and to model the structural relations between all the variables considered.

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