Non-technological and Mixed Modes of Innovation in the United States. Evidence from the Business Research and Development and Innovation Survey, 2008-2011

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Abstract

This paper presents a novel empirical study of innovation practices of U.S. companies and their relation to productivity levels using new business micro data from the Business Research and Development and Innovation Survey (BRDIS) for the years 2008-2011. The paper follows the work of Frenz and Lambert, who use factor analysis to reduce a set of inputs and outputs of innovation activities into four latent unobserved innovation modes or practices for OECD countries using Community Innovation Surveys (CIS). Patterns obtained with BRDIS data are very similar to those found by those authors in some OECD countries. Companies are grouped according to their scores across the four factors to see that in large, small and medium companies more than one mode of innovation practices prevails. The next step in the analysis links different types of innovation practices to levels of productivity using regression analysis. The four innovation modes have a statistically significant positive relation with the level of productivity, other things constant. The paper demonstrates the possibility of taking into account the multidimensionality of innovation without the use of composite indicators.

1 Introduction

The purpose of this paper is to use new Business Research and Development and Innovation Survey (BRDIS) (8) micro data to characterize the innovation practices of U.S. companies according to a combination of their inputs and outputs. Some authors claim that it is

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Table 1: New to market or new to company innovations among innovators in the U.S. 2009-2011

R&D Status	Sector	Percent new to market	Percent new to company
Not active	Service	52%	67%
Not active	Manufacturing	54%	68%
Active	Service	71	64
Active	Manufacturing	70	73

innovation output, and not innovation input (R&D) what increases productivity (15), while a large number of studies have found mixed results when considering the direct effect of R&D on productivity (12). In this paper, a new metric that takes into account the complex web of factors entering the innovation process is found to be a significant contributor to the productivity level of companies. Using this new metric we also conclude that a wide variety of innovation practices can be found in medium, small and large companies. More importantly, characterizing companies with this new metric allows us to compare the innovation practices across countries that may be using very different data specifications in their analyses.

The need for new innovation metrics that include inputs and outputs of innovation has been felt by many stakeholders (26) (27), as questions about where the U.S. stands in innovation compared to other OECD countries have been raised (14). According to new data from the BRDIS, about 9% of the estimated 1.5 million for-profit U.S. companies are active product innovators and about 9% are process innovators (7). That incidence varies substantially by industry sector, is much higher among R&D active companies, and refers to technological and non technological innovations. In the period 2008-2011, more than 50% of the innovations were new-to-the market or new-to-the-company. As we can see in Table 1, 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. As indicated in Table 2, that rate was smaller for other companies.

If we relied solely on innovation figures like those presented in Tables 1 and 2, which reflect the output of technological and non-technological innovative activity of U.S. companies, we would be concluding that other OECD economies fair much better than the U.S. The survey data available for those other economies, the Community Innovation Survey (CIS) (20), relies on voluntary responses and is highly populated by innovative companies, thus giving higher figures (6).

Luckily, an increasing interest in measuring innovation and its effects on the economy using broader metrics has led to some alternatives (26) (22) (6). With the latter, comparison across countries can be conducted according to their innovation practices, which are not as dependent on data specifications as univariate indicators are. Until 2008, there was

Table 2: Sales due to new-to-market (ntm) and new-to-company (ntc) innovations and sales due to the usual line of business.

R&D Status	Sector	N	Variable	mean	sd
Not active	Service	4700	% sales due to ntm	13	29
			% sales due to ntc	14	27
			% sales due to usual	73	38
Not active	Manufacturing	4600	% sales due to ntm	10	23
			% sales due to ntc	12	23
			% sales due to usual	78	32
Active	Service	6500	% sales due to ntm	24	39
			% sales due to ntc	16	29
			% sales due to usual	60	42
Active	Manufacturing	11100	% sales due to ntm	13	24
			% sales due to ntc	12	22
			% sales due to usual	75	32

no government survey data in the U.S. comparable to CIS data to do that. However, the introduction of new metrics of innovation by the BRDIS in 2008 (51) (7) (34) has changed the situation: we can now compare the modes of innovation of U.S. companies to the ones found by Frenz and Lambert (22).

We follow closely the methodology proposed in Frenz and Lambert (22), because we want to be able to compare our findings with those pertaining to other OECD economies. First we identify innovation modes or practices using factor analysis. A regression model is used to determine the relevance of the innovation practices for firm-level performance by examining their association with productivity. Combinations of innovation practices used by groups of firms are found based on clustering techniques.

The rest of the paper is organized as follows. First, we do a bibliographic review and discuss the potential of new BRDIS data to shed new light on innovation in the United States and compare it with its counterpart in other OECD countries (CIS). After that, we discuss the variables used in our analysis and the methodology used to extract mixed modes of innovation and grouping firms according to those and their effect on productivity. We finish the paper with some conclusions and recommendations for further research.

2 Metrics of innovation in the literature.

Innovation-related research on the determinants and effect of innovation usually emphasizes technological activities, measured by R&D or patents. That is understandable, given the lack of appropriate survey data until recently. Empirical and theoretical work traditionally follows the Schumpeterian definitions of innovation (48): the introduction of a new product and the introduction of a new production process, whether this is just to maximize profits or other more general goals such as consumer surplus (47). This is now known as the 'narrow definition of innovation.'

We highlight that R&D and patent activity are inputs to innovation (17) (5) (3) (30). Some have questioned their role as fundamental contributors to the economic growth and competitiveness of the economy (17) (2) (46) and others have found a change in the nature of the contribution of R&D to productivity (21) (24), or have found a dependence of the effect on the source of R&D (28) (29) (1).

The importance of other dimensions of innovation not related to technology, brought about by the need to cover appropriately innovation in services, which now dominate OECD and the U.S. economies, has been a major force behind the growing acknowledgment of a wider definition of innovation. With the introduction of the Oslo manual in 2005, the definition was extended 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.' (44)p. 46.

Innovation surveys based on the Oslo Manual increase knowledge about broad innovation beyond what can be found in other science and technology statistics such as surveys of R&D, patent data or bibliometric indicators (12). For example, Carvalho et al. (10) found that both input and output innovation variables have an effect on organization innovation; intramural R&D has an effect on innovation; but the effect of extramural R&D is not so clear. These authors, however, look at a small economy using CIS4 survey data, with models that consider one innovation variable at a time.

To capture the multidimensionality of innovation practices, a number of studies based on CIS have used factor and cluster analysis to group companies into categories with specific ratings in terms of their technological and non-technological innovative activities. Several of them confirm that companies that engage in both types of innovation outperform firms that do not. Hollenstein (33) , Jensen et al (36), Frenz and Lambert (22) and others find that firms that engage in both types of knowledge generation and acquisition outperform in terms of product innovation. Geroski et al. (23) suggest that firms that engage in both product and process innovations and, at the same time, introduce organization changes outperform firm that do either one or the other.

In comparing results obtained in this paper based on BRDIS to those of others based on CIS, we must keep in mind the differences between the two surveys (43): (i) CIS is strictly a innovation survey whereas the BRDIS is still a R&D survey with a few questions on innovation adopted from the CIS; (ii) CIS is a voluntary survey, thus participation rates are extremely low and participants are usually innovative firms, while BRIDS is a title 13 mandatory survey and has over 70% response rate; (iii) sectoral coverage, size thresholds, length of reference periods, sampling methods and units of analysis are also different; (iv) questions in the CIS are very direct. For example, in CIS IV, if a firm reports that she introduced a new or significantly improved good or service, she is asked who developed the product innovations (the enterprise, the enterprise in collaboration with others or mainly other enterprises). In contrast to that, in BRDIS one would have to deduce from the R&D expenses in collaboration whether the company collaborated with others.

Because of those differences, any comparison between results derived from BRDIS and CIS data can only be qualitative. In particular, Frenz and Lambert(22) analyze only innovative firms, whereas in this paper non-innovators are included to avoid the selectivity bias problem.

Although we address the multidimensionality of innovation, our research differs from the composite innovation literature. We do not attempt to summarize the many dimensions of innovation into a single real-valued metric derived from a set of indicator components by some aggregation method that may be sensitive to the weighting scheme (27) (9). In our approach, the single indicators that form part of the modes of innovation are transparent.

3 Data and Methodology

The data analysis is based on the items in the 2008, 2009, 2010 and 2011 BRDIS questionnaires (8). The target population consists of all 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 (51) (7) (34).

3.1 Characterizing Modes of Innovation Practices using Factor analysis

A number of studies have used factor and cluster analysis to group companies into categories with specific ratings in terms of their technological and non-technological innovative activities. Our analysis is closest to that of Frenz and Lambert (22), who fed the factor analysis several questionnaire items of CIS that are grouped under more or less the same headings as those in Table 3. The BRDIS does not contain some of the variables in the CIS, thus we did the best we could to have the questionnaire items that feed into the factor analysis grouped under the same broad headings as in Lambert.

We use exploratory factor analysis to reduce the set of observable variables in Table 3 above into a small set of latent unobserved factors which summarize combinations of inputs and outputs to innovation. These concepts identify innovation modes or practices.

Table 3: Factor Analysis based on BRDIS data, years 2008-2011.

Variable	Wider Innovation	Intramural Mixed Innovation	Extramural Mixed Innovation	Extramural Process Modernizing
Innovation new-to-company	0.61	0.22	0.4	−0.38
Innovation new-to-market	0.65	0.18	0.3	−0.43
Technical process innovation	0.61	0.43	0.31	0.28
Non-technical innovation	0.51	0.44	0.34	0.51
In house R&D	0.8	0.05	−0.17	−0.13
Patents	0.65	−0.04	−0.35	−0.04
R&D performed by others	0.62	−0.71	0.22	0.13
Capital equipment	0.73	−0.03	−0.17	−0.14
External knowledge	0.50	−0.73	0.22	0.15
Design Patents	0.60	0.11	−0.49	0.10
Copyright	0.61	0.13	−0.46	0.11
Variance explained by factor	45.1%	15.3%	12%	7.8%

A factor is a latent continuum along which we can locate data points according to the varying amounts of the construct that they posses.

Following Frenz and Lambert (22), four factors solutions are computed in order to maximize the comparability of results. This corresponds to the number of factors with eigenvalues greater than one. The results of the factor analysis are based on unweighted data, principal component analysis and varimax rotation method, also to maximize the comparability of our results. The patterns are very similar to the structures presented in Frenz and Lambert(22)

We next introduce the variables used to identify modes of innovation practices and fed into the factor analysis are introduced, along with an indication of the role of the variable in the innovation practice.

Innovation outputs

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 (1) (31) (24).

Technical process innovation refers to new or significantly improved methods of manufacturing or producing goods and services and new or significantly improved logistics, delivery or distribution methods for the company's inputs, goods, or services.

Non technical innovation refers to new or significantly improved supporting activities for the company's processes, such as maintenance systems or operations for purchasing, accounting, or computing.

Innovation inputs

Own technology

In house R&D **or** *Intramural R&D* are expenditures for research and development (R&D) performed within the company, whatever the source of funds. Expenditures made outside the statistical unit or sector but in support of intramural R&D (e.g. purchases of supplies for R&D) are included. Internal or intramural R&D is only one source of innovativeness (16). 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%) (51). Some authors (49) mention that the form of the relation between competition and R&D depends on whether the R&D is intramural or extramural.

Patents. Our model utilizes a zero versus nonzero patenting dummy variable. A firm is defined as patenting if it applied for at least one patent from the U.S. Patents and Trademark office in the United States or in foreign jurisdictions or if it was issued a patent. The patent or patent application could be for inventions that originated within the company's organized R&D activities, or from inventions considered for patenting. A firm has propensity to patent if any of the above is true.
The patent system, in principle,is designed to serve the dual role of providing incentives to inventions and facilitating diffusion of technology that in turn will have an impact on economic performance. However, its effects vary by industry (50). Some innovation surveys suggest that patents are a relatively unimportant means by which firms seek to protect their knowledge assets (41). Firms could patent to practice patent pooling with collaborators and for cross-licensing, or to obtain revenue (appropriation of returns). The former would be indicated by the number of agreements that the firm entered into to license patents to others not owned by the company.

Diffused and embedded technology

Extramural R&D refers to expenditures spent outside the statistical unit, or R&D performed outside but paid by the company. In 2011, U.S.-located companies spent $29.6 billion for extramural (purchased and collaborative) research and development performed by domestic and overseas organizations (39). 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.

There is a debate as to the relative importance of intramural vs extramural R&D for firm performance. According to Ebersberger and Herstad (19) 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.

Capital expenditures dedicated to R&D refers to the capacity of the firm to use its own technology to innovate.

Purchased R&D services refers to the use of external knowledge.

The latter are considered technological activities even though they are generated outside the firm and transferred to the company

Design

Design Patents and copyrights reflect whether these two forms of intellectual property protection are very important or somewhat important to the company. Design patents refer to the looks of the product or service. Registration of a design or copyright is used as a proxy for design-related activities, which are partly non-technical but also an important component of new and applied technologies.

New survey findings from the National Science Foundation (NSF) and the U.S. Census Bureau (Census) indicate that trademarks and trade secrets are identified by the largest number of businesses as important forms of IP protection, followed by copyrights, and then patents. However, the level of reliance on each of these forms of IP protection varies considerably across industry sectors (35).

Table 3 gives the matrix of factor loadings for four distinct innovation practices or modes of innovation based on BRDIS data. Factor loadings represent the correlations or linear association between a variable entered into the factor loading and the latent factor computed by the analysis. For example, the variable 'capital equipment' has correlation 0.73 with factor 1. The analysis of modes of innovation incorporates measures of innovation outputs, such as new product, together with innovation inputs, such as R&D activities or a patent application. The final row in Table 3 gives the amount of variation in the data

Table 4: Cluster analysis based on BRDIS data 2008-2011.

Cluster and n	**Variable**	**Mean**	**Standard Deviation**
Cluster 1 (N=117400)	Sales	70601	3562576
	Employment	778.83	8349.16
	Factor 1	−0.16	0.84
	Factor 2	−0.18	0.15
	Factor 3	−0.31	0.26
	Factor 4	−0.32	0.22
Cluster 2 (N=14000)	Sales	211466	2963191
	Employment	540	5971
	Factor 1	0.53	1.31
	Factor 2	−0.57	0.49
	Factor 3	2.19	0.97
	Factor 4	−0.34	0.97
Cluster 3 (N=18000)	Sales	561078	5558428
	Employment	1438	18541
	Factor 1	0.29	1.21
	Factor 2	−0.40	0.39
	Factor 3	0.08	1.47
	Factor 4	2.31	0.81
Cluster 4 (N= 9600)	Sales	1259655	7361213
	Employment	2111	11419
	Factor 1	0.70	1.17
	Factor 2	3.77	0.55
	Factor 3	0.43	1.43
	Factor 4	0.17	1.43

data explained by each factor. For example, factor 1 explains 45% of the variation in the data. The first factor explains the highest common variation and the last factor the least amount of variation, at 7.8%.

The first column of Table 3 gives the factor loadings with respect to the first factor. Factor 1 resembles a mode of innovation based on both technological and non technological activities, as it links own, diffused technologies with design activities. We call this *wider innovation.*

Factor 2 attaches high value to non technological and process innovation without technological activities. We call this the *intramural mixed innovation.*

Factor 3 represents a mode of innovation based on diffused and embedded technological and non technological components, called *extramural mixed innovation.*

Factor 4 is called *extramural process modernizing* as there is no new-to-market or new-to-firm innovation.

Frenz and Lambert draw out common patterns derived from the factor analyses of several countries as the following modes of innovation practices: i) Factor 1: new to market innovating (linked to own generation of technology, as indicated by the high loadings associated with in-house R&D and patenting, and linked to formal and informal methods of protecting); ii) marketing-based imitating; iii) process modernizing (acquisition of machinery, equipment and software, i.e., the use of embedded technologies, along with training of staff); and iv) wider innovating (factor 1). In general, the innovation modes process modernizing and wider innovating showed relatively high consistency across the nine countries they studied and we can see that they are prevalent in the U.S. as well.

The U.S. is closer to the innovation practices of Austria, Canada, and Denmark. However, these comparisons must be taken with a grain of salt. As was pointed out earlier in this paper, there is not as many details on innovation practices in the BRDIS as in the CIS. Based on the variables that they share, it appears that the U.S. is closer to innovation modes of European countries than to the practices of Asian or South American countries.

3.2 Companies with mixed modes of innovation. Cluster Analysis

As in Frenz and Lambert (22), 'based on the factor analysis and more precisely on the four factors derived from the factor analyses,' we grouped companies according to their factor scores. Factor scores can quantify individual companies on a latent continuum using a z score scale which ranges from approximately -3 to 3. A company with a factor score of 3 in factor 1 is strongly characterized by the mode of innovation represented by factor 1, that is, it performs above average in relation to factor 1. By using these factor scores, it is possible to conclude that companies are practicing more than one mode of innovation.

To group companies according to their factor scores we use cluster analysis. This is a generic term for a large number of methods which attempt to place objects into groups or clusters suggested by the data, not defined a priori, such that objects in a given cluster tend to be similar to each other in some sense, and objects in different clusters tend to be dissimilar (18).

After the grouping is obtained, we look at the average and standard deviation of the factor scores in each cluster, and the average size and sales of the companies in each group. As we can see in Table 4 we may identify the following groups of companies:

- Companies grouped in Cluster 1, the largest group, are the smallest companies and perform below average in relation to all the factors.
- Companies grouped in cluster 2, with the next higher volume of sales, apply innovation strategies linked to extramural mixed innovation jointly with some wider innovation..
- Companies in the next size, in cluster 3, have strategies linked to extramural process modernizing jointly with some wider innovation.

Table 5: Regression results based on company level data. BRDIS data 2008-2011. Dependent variable=log productivity.

Variable	Parameter estimate	Standard error	t-statistic	p-value
Intercept	4.67	0.016	287.76	< 0.0001
Factor 1 score	0.06	0.003	16.42	< 0.0001
Factor 2 score	0.05	0.003	16.83	< 0.0001
Factor 3 score	0.03	0.003	9.11	< 0.0001
Factor 4 score	0.01	0.003	3.66	0.0002
Log employment	0.10	0.002	50.56	< 0.0001
Formal collaboration	0.06	0.016	3.42	0.0006
Intellectual property transfer	0.06	0.010	5.73	< 0.0001
Manufacturing	0.08	0.006	11.91	< 0.0001
International	0.51	0.01	49.6	< 0.0001
R&D active	0.10	0.090	10.14	< 0.0001
Year 2009	-0.08	0.014	-5.87	< 0.0001
Year 2010	-0.01	0.014	-0.96	0.3383
Year 2011	0.05	0.014	3.41	0.0006
Rsquare	0.15			
Number of companies	91000			
F-statistic	1232.54	($p < 0.0001$)		
Root MSE	0.94			

- The largest companies in cluster 4 adopt innovation strategies linked to intramural mixed innovation, wider innovation and extramural mixed innovation. They are the largest and most innovative companies.

It is relevant that although each group of companies are strong in one particular mode of innovation (as indicated by factor scores larger than 2), they can be characterized by more than one, suggesting that companies of all sizes in the U.S. use mixed modes of innovation. This is consistent with the pattern found by Frenz and Lambert (22).

3.3 Modes of innovation and productivity. Regression analysis.

The next step in our analysis links different types of innovation practices to levels of productivity. Table 5 summarizes the regression results.

Table 5 suggests that the four modes of innovation have a statistically significant positive association with productivity levels, other things being equal.

There are no universally accepted approaches for measuring innovation and productivity (9). Assessment of the effect of innovation on productivity thus depends on the specification used in addition to the characteristics of the firm (17) (11), other economic variables and the methodology used. Two methodological approaches to the study of innovation and productivity can be found in the literature. One is based on indicators, while the second one is based on econometric models (26). Among the latter, there are widely varying estimates of the contribution of innovation, approximated by many by R&D, to productivity across samples, model specifications, and estimation methods. A few empirical studies show that R&D is successful in boosting company performance (17). Yet others disagree (4). On the other hand, an increasing number of studies use the CIS and introduce both product and process, technological and non-technological innovation and R&D as independent variables in the models (45). Some authors have found that the small effect that R&D has on productivity declines once innovation variables are included (16). Inputs to R&D, expenditures in labor, capital, and value added have been other variables included in the models (40) (25).

Because we want to compare our regression results to those found by Grenz and Lambert (22), we study the relation of innovation to productivity using a regression model approach and the innovation practices found earlier. As in their paper, the relative importance of innovation modes on productivity is measured by the factor scores of each individual company. We conduct regression analysis for all companies in BRDIS that have positive sales in the years 2008-2011, whether they conduct R&D or not.

The variables included in the model and the interpretation of their relation to productivity level can be described as follows:

International represents the openness of the company to international markets, whether the company sells in international markets or not. Companies that do have 51% higher productivity level.

Log employment is a proxy for company size. 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 (37). Of these three, only employees was found to be significant. Company size is important because smaller and medium sized firms may exhibit different patterns of behavior to those of large firms. Size elasticity is 0.1% however.

Manufacturing controls for industry fixed effects. How much of variability is within industry and how much is between industries is an important question in the literature. Our analysis controls only for whether the company is in the manufacturing or non manufacturing sector, thus market concentration is not really measured. By pooling observations across industries the assumption made is that the same elasticity for all industries, which probably lowers the effect of this variable.

R&D active , whether the company is R&D active, is significant and translates into 10% higher productivity levels for R&D active companies.

Intellectual Property Transfer refers to informal (not in the accounting books) mode of collaboration among firms that involves transfer of know-how, patent pools, cross-licensing and transfers due to acquisitions or spin offs. Markets for the informal exchange of technology play an increasingly important role in the economy, particularly as innovation becomes more cooperative (50).

Formal collaboration refers to the R&D expenditures in the accounting books of companies paid or received from collaborators, not patent licenses. Not all collaboration is expected to lead to higher productivity. Collaborative research with universities may not stimulate productivity (38) while publicly-financed R&D may lead to private sector total factor productivity growth (32).

Patents are believed to have an important effect on economic performance. However patenting activity is not significant in our model, perhaps because the effect of patents is best noticed when there is persistent patenting behavior (17). Companies that are R&D active have higher propensity to patent and that is higher in the manufacturing sector than in the service sector of the economy. Incorporating those variables in the model probably accounts for their effect. The surge in patenting in the last two decades has not translated into a significant effect on economic performance.

The regression model explains only 15% of the variability in productivity, which is low, but similar to the models described by Frenz and Lambert (22). Numerous studies have noticed the relatively small effect of R&D and technological factors on productivity (13) . Some have found exogenous demand to be the largest contributor (42). There are multiple factors other than R&D that can boost the growth of firms. That is probably why the R square is so low.

4 Conclusions

This paper has presented an empirical study of innovation practices of U.S. companies and their relation to company productivity levels. The data used is new and comes from BRDIS surveys for the years 2008-2011. The paper has used the methods of Frenz and Lambert (22) in order to be able to compare our results to those found by those authors for other OECD countries. This could not be done until the BRDIS was inaugurated. We used factor analysis to reduce a set of inputs and outputs of innovation activities into four latent unobserved innovation modes or practices. We then grouped companies according to their scores across the four factors and noticed that in large, small and medium companies more than one mode of innovation practices prevails. The next step in the analysis linked different types of innovation practices to levels of productivity using regression analysis. The four innovation modes have a statistically significant positive relation with the level of productivity, other things constant. In our study we did not account for endogeneity of the variables or their simultaneity because we wanted to keep our results comparable to those of Frenz and Lambert.

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 selectivity bias.

By aggregating across industries, we made the strong assumption that all industries have similar effects, but that is far from the truth. In a future paper, we plan to break down the results by industry to account for industry-level variation.

BRDIS is not as complete a survey of innovation as CIS is. Thus, the variables used are not exactly comparable. However, the methodology used suggests that it is possible to account for the multidimensionality of innovation and still carry out the analyses that help us answer the usual questions in the economics of innovation. Moreover, we found that the U.S. innovation modes are closer to those of European countries than Asian or South American ones. And we also found that like most OECD economies studies in Frenz and Lambert (22), U.S. companies within a given size adhere to a mixture of innovation practices.

In future analyses, this study will allow for the effect of competition,by doing the analysis at a more disaggregated level, industry by industry. This will allow to pinpoint which industries within each company-size group adhere to specific innovation modes.

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