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A Pooled Overview of the European National Innovation Systems Through the Lenses of the Community Innovation Survey

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Abstract

In this paper, we perform a detailed pooled cross-sectional analysis on the innovation performance in nine European countries by using data stemming from the Community Innovation Survey. The temporal dimension of our dataset includes three waves of CIS surveys from 2008 until 2014. As such, it allows us to evaluate the changes in the innovation processes within the countries in a more profound way. Our findings suggest that there are no significant differences among the countries regarding the firms' determinants to enter the innovation process. However, the effect of innovation output over labor productivity varies among economies: there is a positive relationship in the more developed economies compared to a negative or neutral relationship in the less developed. We use these results to speculate that the national innovation system in developing economies becomes more vulnerable in periods of the financial crisis.

Keywords CIS · European countries · National innovation systems · Pooled cross-sectional studies · Labor productivity

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Introduction

Productivity, defined as the output per unit of input, and its growth, relies on a combination of investment in physical and human capital, knowledge, and technical progress. In this aspect, the dynamics of innovative processes may directly impact productivity through complex channels and interconnections that drive the ability of firms to turn R&D efforts into high entrepreneurial profits (Calcagnini et al., 2021).

A standard methodological framework that is used for analyzing the relationship between R&D, innovation, and productivity is the well-known Crépon et al. (1998) (CDM) structural econometric model. In Europe, the estimation of this model is usually based on innovation statistics, published by Eurostat, and is gathered via the Community Innovation Survey (CIS). Interestingly, despite the growing body of empirical studies that analyze the statistics from single waves of CIS (see, for example, Mairesse et al., 2005; Miguel Benavente, 2006; Griffith et al., 2006; Lööf & Hesmati, 2006b; Jefferson et al., 2006b; Van Leeuwen and Klomp (2006); Hall et al., 2009; Kijek & Kijek, 2019; Hashi & Stojčić, 2013; Ballot et al., 2015), investigations combining multiple years of CIS versions have been largely neglected. The potential of pooled cross-sectional studies which evaluate the differences between the innovation activities and characteristics between and within countries, to the best of our knowledge, is yet to be exploited. This effectively hinders the application of CIS for developing policies aimed at improving the innovation processes as the resulting analyses do not look at the past firms' behavior.

To bridge this gap, in this paper, we perform a detailed pooled cross-sectional analysis on the innovation performance in selected nine European countries by using data for three waves of the survey: CIS 2010, CIS 2012, and CIS 2014. The temporal dimension of our dataset includes period from 2008 to 2014, during the financial crisis as well as the period after the crisis. The countries that are included in the analysis are Bulgaria, the Czech Republic, Germany, Hungary, Norway, Portugal, Romania, Slovakia, and Spain. By estimating the CDM model separately for each country in our sample, we try to evaluate the changes in the innovation processes both within and between the countries during and after the crisis.

The innovation systems in these countries experience disparities in terms of the absorption capacity, the presence of human capital, quality of the human capital, size of the enterprise, infrastructure, business environment, size of the local economy, etc. This allows us to deliver more profound conclusions regarding the structure, innovation strategies, and innovation performance of the firms for specific institutional settings in Europe. Heterogeneity among EU countries is evident particularly in the intensity of business R&D, a key component of innovation capacity reflecting the capabilities and the incentives of the business sector to invest in innovation. Also, there are significant differences in the public R&D expenditures as a percentage of GDP.

The countries that are leading are all in the North: Sweden, Denmark, Finland, Germany, and the Netherlands. Most other EU15 countries are also above the EU average, like Belgium, the UK, Austria, and France. However, not all the EU15 are above EU average. Particularly noteworthy is the weak score of Italy and the former cohesion countries: Portugal, Spain, and Greece.

As such, our contribution can be seen as a generalization to previous studies that explore the relationship between innovation and productivity in a single wave of CISs (Tevdovski et al., 2017; Toshevska-Trpchevska et al., 2019; Disoska et al. 2020).

The paper is structured into four sections. In the second section, we discuss the literature that is relevant to our research. The third section describes the data and the methodology used for the creation of the econometric model. Subsequently, in the fourth section, we present and interpret the results obtained from the model. The final section provides conclusions.

Literature Review

For Schumpeter (1982), economic growth was related to the innovation of products and the continual development of the existing ones. The extent to which an economy can grow depends on both the favorable terms of trade and the degree of specialization in knowledge-intensive products with higher value-added (OECD (2017). These characteristics, in turn, are determined by the ability of the policymakers to develop coherent economic policies which stimulate spending on R&D activities and increase the efficiency of the innovation process. Before the development of policies, the policymakers are required to investigate the current and past structural features of the innovation activities, thereby unfolding the innovation system in the economy.

Although there are different approaches to evaluate the national innovation system, we chose to observe in a standard micro-approach. A standard micro-approach for performing this step is utilizing cross-sectional microdata capturing the innovation activities of the firms in the country. Firms' growth dynamics can help explain differences between countries in aggregate productivity growth (Van Ark et al., 2008).

The growth of high and medium technology manufacturing industries in the EU lagged the performance of the USA. However, the EU is the largest global producer in pharmaceuticals (26%) and the second-largest global producer in aircraft and spacecraft (22% global share) and testing, measuring, and control equipment (19% global share) (National Science Board, official website, 2022). In commercial knowledge-intensive services (such as banking, finance, insurance, R&D services), over the last decade, the EU's global share has declined from 29 to 21% due to faster growth in the USA and China and other developing countries.

Therefore, it is very important to explore the link between small and large firms, private and public actors in the production, diffusion, and commercialization of knowledge because it is evident that the EU is losing its dominant position on the global market. Despite decades of technological progress, productivity had been growing at a much slower pace in the EU. Although it was expected that membership in the EU will create converges to a unique economic model among countries, there are highly different innovation systems in Europe. They vary in terms of institutions, regulatory framework such as intellectual property legislation, patent and copyright protection, education, employment, quality of human resources, specialization in high and medium-tech sectors, and financial systems (Pinto & Pereira, 2013).

The creators of the CDM model, Crépon et al. (1998), were among the first ones to explore the relationship among R&D, innovation, and productivity empirically and estimated that firm productivity correlates positively with innovation output. R&D intensity has a positive and significant effect on the probability to introduce product innovations, process innovations, or both innovations together (Medda, 2020; Aschhof & Schmidt, 2008; Eom & Lee, 2010). Furthermore, many other expert studies conclude that innovation leads to a better productivity performance (Lööf & Hesmati, 2003; Mairesse et al., 2005; Miguel Benavente, 2006; Griffith et al., 2006; Lööf & Hesmati, 2006b; Jefferson et al., 2006; Hall et al., 2009; Peters et al., 2017; Kijek & Kijek, 2019; Aldieri et al., 2021).

Hashi and Stojcic (2013) and Stojčić and Hashi (2014) also claim that productivity increases with innovation output although the relationship is stronger in Western European countries compared to Central Eastern European (CEE) countries. Also, a recent study (Aspara et al., 2018) points to issues of reverse causality, according to which more productive firms are associated with stronger innovation activities. Therefore, if firm productivity is persistent over time, innovations that raise productivity have long-lived effects on firm value (Peters et al., 2017). However, some studies confirm a negative relationship between different types of innovation and productivity (especially when innovation intensity is controlled for).

The inverse relationship between process innovation and productivity is estimated in the study of Lööf & Heshmati (2003) for the Swedish firms for the period 1994–1996; Janz et al. (2003) for German firms in the period 1998–2000; Van Leeuwen and Klomp (2006) for the firms in the Netherlands for the period 1994–1996; and in the study of Criscuolo (2009) for 17 OECD countries for the period 2002–2004. The coefficient for process innovation on productivity in Griffith et al. (2006) is negative but statistically non-significant in Spain. Furthermore, Lööf & Heshmati (2006a) find a negative relationship between process innovations and productivity in both the manufacturing and the service sector. According to Hall (2011), product innovations create a market power effect that increases the revenue measure of output, whereas efficiency improvements from process innovations may not show up in the revenue figures if they result in lower prices without corresponding increases in output (at least in the short run). Also, the joint effect of product and process innovations is the most visible since they usually go together. The negative relationship between innovation output and productivity is especially evident in the CEE countries (Disoska et al., 2020 and Toshevska-Trpchevska, 2019) and Southern Europe (Toshevska-Trpchevska et al., 2020). These countries were the most severely hit by the recession, and this is affecting the process of convergence in innovation performance in the EU (Archibugi & Filippetti, 2011).

However, despite an abundance of studies that use various versions of the CIS survey and different countries, most of the estimates lie somewhere between these two extremes. The variation in the outcome is a result of wide measurements of the R&D variable and different model specifications. To draw consistent conclusions, we try to explain productivity growth by using long-term series. An explanation for this is that R&D is likely to yield productivity improvements over longer time horizons (Vancauteren et al., 2017).

In the paper of Balcombe et al. (2005), the time-series data for the period 1955–2000 on agricultural innovation show that R&D is likely to yield productivity improvements over longer time horizons. Raymond et al. (2015) confirm this statement and evidence that continuously undertaken R&D activities in the previous 2 to 4 years significantly affect the occurrence and the intensity of product innovations and therefore productivity in French and Dutch firms. However, the inverse relationship was not demonstrated in their study.

Methodology and Data

Methodology[1]

To provide a pooled cross-sectional overview of the European national innovation systems, we utilize a modified pooled version of the CDM model. The analytical framework of the CDM model consists of two general stages, while each of them can be divided into two sub-stages. In the first general stage, we estimate the factors that drive firms' decisions to innovate, as well as innovation investment, using a Heckman correction model. In the second stage, we perform the three-stage least squares (3SLS) methodology to simultaneously estimate the innovation output and the productivity of the firm. Because we study the differences between countries in their innovation systems, we estimate the CDM model separately for each country in our sample.

Under this model, we first simultaneously estimate the effect of R&D engagement and intensity on innovation outcome and then quantify the effectiveness of the innovative efforts leading to productivity gains for each country separately and account for the temporal property of the data. In other words, to surpass the issue of estimating the effects with a hugely unbalanced dataset, we create a pooled dataset and resort to individually applying the CDM methodology for each entity and account for the time effects through dummy variables.

Concretely, the developed model controls for the possible time-specific effects that may drive the within-country differences, such as political and/or economic cycles. Moreover, a limited degree of correlation is allowed between the two parts of the model through the inclusion of the inverse Mills ratio in the innovation output equation.

The two general stages are divided into two additional sub-stages. In the first stage, we implement a Heckman correction model to estimate the innovation input constrained on a variable that models the decision to innovate. Mathematically, this stage can be explained with the following equations.

[1] The methodology was implemented using Stata, and the code to replicate the findings can be found at the following link.

$$Prob\left(d_{it} = 1 \middle| x_{it}^{0}\right) = \Phi\left(\beta_0 x_{0it} + z_{0t}\right) + u_{0it}, \tag{1}$$

$$w_{it}^{*} = \alpha d_{it} + \beta_1 x_{1it} + z_{1t} + u_{1it}. \tag{2}$$

Equation (1) models the unobserved decision to innovate d_{it} of a firm i in period t as a probit regression (with Φ denoting the cumulative standard normal distribution) dependent on a vector x_{0it} of covariates and their parameter vector β_0. In the equation, z_{0t} is the time-specific that may impact the final decision of the firm of whether to innovate or not. With Eq. (2), we estimate the unobserved innovation input w_{it}^{*}, measured as "the log of the amount (in euro) of expenditure on intramural or extramural R&D, acquisition of machinery, equipment and software or acquisition of other external knowledge in year of survey," using a vector x_{1it} of covariates, weighted by parameters β_1, adding d_{it} as an additional explanatory variable that helps us to "correct" for the potential selection bias which arises due to using only data for firms that decided to invest in innovation and again including a time-specific effect z_{1t}.

The second stage utilizes the three-stage least squares (3SLS) methodology to simultaneously estimate the innovation output and the productivity of the firm. This stage is specified as

$$r_{it} = \beta_{w^*} w_{it}^{*} + \beta_q q_{it} + \beta_2 x_{2it} + z_{2t} + u_{2it}, \tag{3}$$

$$q_{it} = \beta_r r_{it} + \beta_3 x_{3it} + z_{3t} + u_{3it}. \tag{4}$$

In Eq. (3), r_{it} is the innovation output measured as "the logarithm of the firm's percentage of turnover in year of survey coming from goods or services that were new to market or to enterprise in 3 years prior to survey," z_{2t} is the time-specific effect, and u_{2it} is the error term. Together with this equation, we estimate Eq. (4) — the productivity q_{it} of the firm, "quantified as the log of the firm's turnover divided by the y number of employees in year of survey," as a linear function of the innovation output r_{it} and a vector of exogenous explanatory variables x_{3it} with parameter vector β_3. As in the previous equations, z_{2t} is a time-specific effect, and u_{3it} is the error term.

Empirical work that uses long-run time series is subjected to a major drawback, i.e., the likely presence of a large discontinuity. The potential of pooled cross-sectional studies which evaluate the differences between innovation activities and characteristics between countries is yet to be exploited since there is not much done in this area. In the recent contribution of Mairesse and Robin (2017), the authors use CIS data on French firms capturing three different waves of the survey (CIS3, CIS4, and CIS 2008) to assess the measurement errors in the CDM research–innovation–productivity relationships. Bogliacino (2009) and Bogliacino and Pianta (2010) also highlight the importance of lagged effects on innovation and economic performance concerning industries (Raymond et al., 2010) and countries. This paper also uses a pooled dataset of three waves of CIS survey data and assesses biases in all three equations of the CDM model and the magnitude of the underlying measurement errors.

Data

We implement our econometric model on firm-level data taken from three waves of the Community Innovation Survey (CIS) for 9 countries. The CISs represent harmonized surveys aimed at collecting microdata on innovation activities conducted in 2 years from firms belonging to countries that are part of the Eurostat network. In this analysis, we utilize three waves of CIS surveys, namely CIS10 (conducted between 2008 and 2010), CIS12 (conducted between 2010 and 2012), and CIS14 (conducted between 2012 and 2014) for Bulgaria, the Czech Republic, Germany,[2] Hungary, Norway, Portugal, Romania, Slovakia, and Spain. We create unbalanced samples for every country, i.e., for each country, we have data for three different periods but the set of firms in each period is not necessarily the same. To be more specific, we added Table 7 in the Appendix that summarizes the dataset structure of the three waves of CIS surveys, divided by country and year. The detailed description of the used variables in the model is presented in Table 5 in the Appendix, while Table 6 presents the summary statistics of the innovation and productivity variables included in the analysis for every country during the three periods. It can be easily noticed that there are significant discrepancies in the observed average values of the variables that are included in the analysis between the countries, therefore suggesting that the innovation process is not the same between countries.

Interpretation of the Results

In this section, we interpret the results in four sub-sections corresponding to the four stages of the model and separately by each country. We thereby emphasize once more that we estimate the CDM model parameters for each country individually. With this procedure, we can differentiate between the magnitudes of the estimates between countries and highlight their differences. We also note that we do not conduct statistical tests for the differences between parameter estimates as we already have a very large dataset, implying that all coefficient differences tests will be significant.

Decision to Innovate

The first stage of the CDM model gives results on the factors that drive firms' decisions to innovate. It models the decision to innovate as a function of firm size measured as the natural logarithm of employment; three dummy variables for market

[2] The CIS10 dataset does not include reliable data for Germany, and therefore only for this country the dataset is constituted of combining the CIS12 and CIS14 dataset.

orientation, representing the presence of the firm on national, EU, or/and other markets; a dummy variable for a firm being part of an enterprise group; a dummy variable for a firm having ongoing or abandoned innovations in the previous 3 years; and two dummy variables for a firm undertaking organizational (introduced new or improved knowledge management system, changed management structure, integrated different activities or introduced changes in its relations with other enterprises or public institutions) or marketing innovation (introduced significant changes to the packaging of goods or services or changed its sales or distribution methods) in the previous 3 years. The results are given in Table 1.

The results confirm the fact that the probability of a firm engaging in the innovation process increases with its size. Firms with more employees have a higher probability to engage in the innovation process in all nine countries. However, the sizes of the estimated coefficients show that an increase in the firm size has a different marginal effect on the probability to innovate across countries. It is highest in Hungary and Portugal, while lowest in Norway and Spain. Audretsch et al., (2020) state that innovation activities of micro or small firms enhance firm productivity and ultimately economic growth through knowledge-intensive services. This outcome is important for economies suffering from low shares of large firms such as in Southern Europe.

The results also confirm the fact that the intensity of competition motivates firms to innovate. Firms that are oriented towards national, EU, and other foreign markets are more likely to innovate than firms oriented towards local/regional markets. The participation of all surveyed countries in the joint EU market may be an explanation for the non-existence of the differences in the decision to innovate between the national and EU markets. A firm being a part of an enterprise group increases the probability to innovate in all surveyed countries, except in Norway, while the marginal effect of this influence is strongest in Germany. From a political economy perspective, based on the Hall and Soskice typology, this can be explained by the existence of the coordinated market economy whose poorest form is in Germany. The results also show that the existence of an innovation process in a current or past period increases the probability to innovate in all countries. The high values of the coefficients for this explanatory variable imply that persistence is important for the decision to innovate, showing also that a firm needs to achieve some level to enter innovation activities and that acquired knowledge is important.

In the end, the firm's decision to innovate in all countries is influenced by organizational or marketing innovations. The probability of an innovation-decision increases with improvements in the management system, changes in management structure, changes in its relations with other firms and institutions, changes in the packaging of goods or services, or changes in distribution methods.

Innovation Input

In the second stage of the model, we analyze the innovation input that represents innovation expenditure measured by the natural logarithm of the overall amount spent on innovations in a firm. We are modeling innovation input by the same

Table 1 Decision to innovate (Eq. (1))

Variable	Bulgaria	Czech Republic	Hungary	Romania	Slovakia	Germany	Spain	Norway	Portugal
Firm size	0.183***	0.156***	0.192***	0.093***	0.131***	0.184***	0.015***	0.049***	0.206***
	(0.011)	(0.012)	(0.014)	(0.012)	(0.023)	(0.012)	(0.005)	(0.013)	(0.012)
Market participation									
National	0.249***	0.243***	0.202***	0.185***	0.122**	0.310***	0.376***	0.317***	0.164***
	(0.022)	(0.030)	(0.045)	(0.027)	(0.050)	(0.032)	(0.013)	(0.028)	(0.03)
European	0.271***	0.211***	0.146***	0.087***	0.255***	0.389***	0.231***	0.430***	0.195***
	(0.024)	(0.028)	(0.033)	(0.029)	(0.047)	(0.038)	(0.013)	(0.032)	(0.027)
Others	0.233***	0.338***	0.259***	0.322***	0.340***	0.438***	0.430***	0.411***	0.214***
	(0.027)	(0.031)	(0.032)	(0.034)	(0.052)	(0.038)	(0.014)	(0.034)	(0.026)
Part of a group	0.134***	0.164***	0.110***	0.169***	0.238***	0.241***	0.197***	0.01	0.075***
	(0.026)	(0.028)	(0.031)	(0.033)	(0.044)	(0.031)	(0.011)	(0.03)	(0.027)
Abandoned or ongoing innovations	3.712***	2.542***	8.113***	7.585***	6.979***	0.704***	0.712***	1.997***	2.881***
	(0.300)	(0.172)	(0.046)	(0.485)	(0.105)	(0.04)	(0.016)	(0.079)	(0.206)
Innovations									
Organizational	0.778***	0.861***	0.885***	0.776***	1.004***	0.477***	0.687***	0.671***	0.909***
	(0.030)	(0.030)	(0.035)	(0.033)	(0.050)	(0.031)	(0.011)	(0.03)	(0.025)
Marketing	0.648***	0.886***	0.699***	0.697***	0.863***	0.430***	0.534***	0.887***	0.832***
	(0.029)	(0.030)	(0.035)	(0.033)	(0.053)	(0.031)	(0.013)	(0.031)	(0.025)
Constant	−2.720***	−2.105***	−2.454***	−2.080***	−2.246***	−1.703***	−1.528***	−1.672***	−1.943***
	(0.048)	(0.057)	(0.073)	(0.056)	(0.109)	(0.057)	(0.024)	(0.057)	(0.055)
Observations	39,039	15,555	15,783	24,308	7,718	11,806	96,082	15,076	18,076
Pseudo-R^2	0.198	0.324	0.196	0.229	0.265	0.239	0.222	0.321	0.278
Chi-square statistic	5454.03***	3558.34***	2841.75***	3628.49***	1628.88***	3195.27***	22,094.00***	3695.32***	4669.51***

The coefficients were estimated using a Heckman selection model. Each regression includes period fixed effects. For each regression, we also include the pseudo-R^2 as a measure of the model performance and the chi-square statistic for overall model significance. Robust standard errors in brackets. Asterisks denote statistical significance: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

explanatory variables as in the first stage, plus we add three dummy variables that intend to determine the influence of subsidies on the innovation process. The three different sources of subsidies received by a firm are observed: local, national, and EU level.

The results are presented in Table 2. As expected, investment in innovation increases with the firm's size in all observed countries, except in Romania. The marginal effects of the firm size for innovation investment are different across countries. It is highest in Germany and lowest in Spain.

Firms that are oriented towards national, EU, and other foreign markets, in general, invest more in innovation than firms oriented towards local/regional markets, but there are exceptions. Firm orientation to the national market or EU market does not increase innovation investment in the Czech Republic, Romania, and Slovakia, while in Bulgaria, only orientation to the national market does not increase innovation investment. Also, firm orientation to other markets outside to joint EU market is important for the firms in all countries, except in Romania. One possible explanation for these results can be the situation that R&D activities are not made in many firms operating in Bulgaria, the Czech Republic, Romania, and Slovakia, but in their mother firms or headquarters outside of the borders of these countries. Also, this argument for Bulgaria and the Czech Republic is confirmed by the significant coefficient in front of the variable for the firm being part of the enterprise group. Investment in innovation is higher in firms that are part of groups in all countries, except in Romania and Slovakia. Similarly, persistence in investment in innovation is increasing innovation input in all countries, except in Hungary, Romania, and Slovakia. The presence of organizational innovations is increasing innovation investment in all countries, except in Romania, while marketing innovations do not have importance in firms in the three countries (Hungary, Romania, and Slovakia) that have no persistence in innovation investment. This result suggests that investment in marketing in these three countries is not made in parallel with more innovation investment.

In terms of funding, local subsidies have a positive and significant effect on investment in innovation only in Hungary, Germany, Spain, and Norway, while national and EU subsidies increase innovation input in all countries. One possible explanation for these results can be the low level or non-existence of local subsidies for the innovation activities in Bulgaria, Romania, the Czech Republic, Slovakia, and Portugal.

The results across all explanatory variables give us intuition to differentiate the countries in two groups regarding the investment in innovation. In the first group, we could differentiate Bulgaria, Romania, the Czech Republic, and Slovakia, while in the second group, Germany, Spain, and Norway. Hungary and Portugal are found in the middle, with characteristics of both groups. What is interesting is the fact that the countries from the first group are EU member countries that joined the Union after 2004 or even later. According to the varieties of capitalism argument, the countries in the first group belong in the dependent market model (Nölke & Vliegenhart 2009). It is the third typology of capitalism that emerged in the post-communist countries, where firms are managed through hierarchy within transnational corporations and they are used mostly as assembly platforms, while innovations are made in

Table 2 Innovation inputs (Eq. (2))

Variable	Bulgaria	Czech Republic	Hungary	Romania	Slovakia	Germany	Spain	Norway	Portugal
Firm size	0.409***	0.329***	0.268***	0.012	0.338***	1.210***	0.024**	0.132***	0.342***
	(0.043)	(0.026)	(0.045)	(0.112)	(0.066)	(0.027)	(0.01)	(0.025)	(0.023)
Market participation									
National	−0.011	0.085	−0.445***	−0.081	−0.138	0.170**	0.335***	0.231***	0.217***
	(0.092)	(0.079)	(0.160)	(0.231)	(0.177)	(0.079)	(0.078)	(0.073)	(0.067)
European	0.197**	0.059	0.257**	0.164	0.085	0.207***	0.124***	0.488***	0.101*
	(0.091)	(0.068)	(0.107)	(0.146)	(0.155)	(0.077)	(0.048)	(0.069)	(0.055)
Others	0.470***	0.497***	0.347***	0.085	0.441***	0.406***	0.297***	0.633***	0.153***
	(0.090)	(0.060)	(0.092)	(0.352)	(0.144)	(0.071)	(0.067)	(0.064)	(0.052)
Part of a group	0.548***	0.386***	0.395***	0.287	0.136	0.771***	0.434***	−0.146**	0.398***
	(0.088)	(0.055)	(0.081)	(0.213)	(0.122)	(0.062)	(0.035)	(0.063)	(0.047)
Abandoned or ongoing innovations	1.547***	0.234***	0.266	-0.788	0.165	0.272***	0.527***	0.419***	0.155**
	(0.306)	(0.083)	(0.215)	(1.863)	(0.240)	(0.074)	(0.09)	(0.095)	(0.074)
Innovations									
Organizational	0.717***	0.350***	0.373***	-0.11	0.423**	-0.480***	0.362***	0.290***	0.352***
	(0.130)	(0.065)	(0.124)	(0.928)	(0.170)	(0.065)	(0.105)	(0.063)	(0.06)
Marketing	0.370***	0.221***	0.179	−0.314	0.179	-0.123*	0.265***	0.125*	0.164***
	(0.123)	(0.066)	(0.110)	(0.836)	(0.155)	(0.064)	(0.076)	(0.074)	(0.057)
Funding									
Local	0.285	0.175	0.883***	0.063	-0.251	0.640***	0.571***	0.297***	0.105
	(0.331)	(0.115)	(0.311)	(0.235)	(0.604)	(0.070)	(0.023)	(0.093)	(0.119)
National	0.742***	0.851***	0.797***	1.006***	0.863***	0.703***	1.069***	1.027***	0.804***
	(0.114)	(0.061)	(0.090)	(0.148)	(0.224)	(0.055)	(0.022)	(0.072)	(0.048)

Table 2 (continued)

Variable	Bulgaria	Czech Republic	Hungary	Romania	Slovakia	Germany	Spain	Norway	Portugal
EU	1.044***	0.713***	1.048***	1.004***	0.826***	0.815***	0.878***	0.851***	0.771***
	(0.101)	(0.063)	(0.083)	(0.147)	(0.197)	(0.072)	(0.038)	(0.154)	(0.061)
Constant	−8.490***	−7.322***	−7.169***	−4.722	−6.919***	6.373***	−5.872***	−5.302***	−6.964***
	(0.519)	(0.226)	(0.509)	(3.830)	(0.584)	(0.314)	(0.426)	(0.248)	(0.195)
Observations	39,039	15,555	15,783	24,308	7,718	11,806	96,082	15,076	18,076
ρ	0.46	0.16	0.06	-0.26	0.09	0.08	0.35	0.07	0.03
Chi-square statistic	31,292.63***	82,935.39***	66,650.83***	39.261.91***	19,286.00***	8137.57***	547,843.00***	82,648.63***	120,971***

The coefficients were estimated using a Heckman selection model. Each regression includes period fixed effects. For each regression, we also include the correlation ρ between the errors of the decision to innovate and innovation input regressions. Robust standard errors in brackets. Asterisks denote statistical significance: *$p<0.1$, **$p<0.05$, ***$p<0.01$

headquarters outside their territories and transferred within transnational corporations' hierarchy. On the other side, the second group of countries consists of countries that have been EU members before 2004 and Norway which can also be considered as highly developed country. For these countries, most of the analyzed variables are significant and have a positive influence over the innovation investment.

Innovation Output

In the third and fourth stages of the model, we analyze only the firms that have reported innovation activities in the second stage. This is the reason for the decreased number of observations in comparison with the previous two stages. In this stage, we measure the innovation output, i.e., the results from the innovation activities undertaken by the firms. More precisely innovation output is the natural logarithm of the share of sales of new products and services (new to the firm and new to the market) in the total turnover of the company. The summary statistics of the innovation output per country in the analyzed period are presented in Table 6 in the Appendix. The data in the show that innovation output is higher in the countries from the new EU members group rather than the old EU members. The three countries with the highest innovation output are Romania, Slovakia, and Bulgaria. This can be explained by the productivity gap in the firms from new EU member countries in comparison with the firms from old EU members.

In the third stage, we measure the impact of firms' size, innovation input from the second stage, the natural logarithm of firms' labor productivity, organizational and marketing innovations, and funding (from local authorities, the national government, or EU) on the innovation output. In Table 3, we present the results of the third stage of the model. The data show that there are great differences among countries on the significance and influence of the analyzed variables over innovation output. In this stage, we also included the inverse Mill's ratio, calculated from the first stage of the model, to control for potential selectivity bias. The coefficient of Mill's ratio is significant at 1% in the case of Slovakia, Germany, and Spain. The insignificance of the Mill's ratio for the rest of the countries is suggesting the absence of selectivity.

The estimated coefficients on firms' size point out that in six of the analyzed countries (Czech Republic, Hungary, Germany, Spain, Norway, and Portugal), there is a significant and negative effect of firms' size over innovation output. This means that bigger firms are less efficient than smaller firms in converting the innovation input to innovation output, i.e., the marginal effect of the innovation input is lower in smaller firms than in bigger firms. This finding we have also discovered in our previous analysis (Toshevska-Trpchevska, et al., 2020), where the focus is only on CIS2014, and it is in the line with stylized observations first documented by Cohen and Klepper (1996). Vyas and Vyas (2019) explained this negative effect of firms' size on innovation output by the increasing influence of entrepreneurs and small firms in innovation in modern economies. We note that for the other three analyzed countries, the firms' size is not significant for the innovation output, but for two of them (Bulgaria and Slovakia), it is also with a negative sign.

Table 3 Innovation output (Eq. (3))

Variable	Bulgaria	Czech Republic	Hungary	Romania	Slovakia	Germany	Spain	Norway	Portugal
Firm size	−0.021	−0.224***	−0.326***	0.001	−0.183	−0.767***	−0.110***	−0.363***	−0.172***
	(0.048)	(0.029)	(0.059)	(0.053)	(0.119)	(0.088)	(0.025)	(0.04)	(0.056)
Mills's ratio	−0.735	0.353	−2.506*	1.585	5.042**	0.683**	−0.857**	0.294	0.192
	(0.565)	(0.221)	(1.442)	(1.816)	(2.369)	(0.287)	(0.363)	(0.378)	(0.231)
Innovation input	−0.387***	0.220**	0.353*	0.787*	0.588*	0.417***	−0.475**	0.254***	0.21
	(0.128)	(0.096)	(0.208)	(0.443)	(0.352)	(0.104)	(0.197)	(0.066)	(0.222)
Labor productivity	−0.002	0.056	−0.367*	−0.776***	0.086	0.001	0.043	0.300**	−0.467***
	(0.108)	(0.090)	(0.212)	(0.293)	(0.181)	(0.103)	(0.154)	(0.145)	(0.133)
Innovations									
Organizational	0.476***	0.095**	−0.201	0.527**	0.837***	0.458***	0.135***	−0.111*	0.146***
	(0.067)	(0.045)	(0.203)	(0.257)	(0.322)	(0.066)	(0.043)	(0.057)	(0.056)
Marketing	−0.004	−0.075*	−0.22	0.464*	0.688**	0.031	0.130***	0.132**	−0.095**
	(0.062)	(0.045)	(0.176)	(0.280)	(0.307)	(0.056)	(0.039)	(0.066)	(0.047)
Funding									
Local	0.431**	−0.089**	−0.09	0.109	0.366	−0.175***	0.344**	0.049	−0.059
	(0.177)	(0.042)	(0.170)	(0.217)	(0.391)	(0.067)	(0.142)	(0.099)	(0.079)
National	0.516***	−0.191**	−0.314	−0.583	−0.274	−0.297***	0.571**	−0.114	−0.159
	(0.129)	(0.077)	(0.215)	(0.519)	(0.357)	(0.081)	(0.235)	(0.113)	(0.175)
EU	0.309**	−0.181**	−0.430*	−0.823*	−0.363	−0.172***	0.501**	−0.079	−0.169
	(0.137)	(0.078)	(0.240)	(0.458)	(0.338)	(0.064)	(0.205)	(0.164)	(0.18)
Constant	−3.573**	−0.432	6.826*	9.326*	−2.174	−4.760***	−3.789	−3.299**	4.512*
	(1.732)	(1.354)	(4.091)	(5.275)	(2.847)	(0.472)	(2.439)	(1.634)	(2.63)
Observations	3,199	3,586	1,502	683	565	2,224	11,363	2,893	3,832
R2	0.01	0.06	−0.31	−0.16	0.04	0.08	−0.00	−0.34	−0.368
Chi-square statistic	173.15***	271.69***	−43.66***	135.48***	46.61***	250.52***	1152.86***	165.62***	278.48***

The coefficients were estimated using a 3-stage least squares. Each regression includes period fixed effects. For each regression, we also include the R^2 and the chi-square statistic for overall model significance. Robust standard errors in brackets. Asterisks denote statistical significance: $*p<0.1$, $**p<0.05$, $***p<0.01$

We find a positive and statistically significant relationship between innovation input and output in six out of nine countries. Romania is the country with the highest marginal effect of the innovation input, where a 1% increase in innovation investment would yield to 0.787 increase in innovation output. In the analyzed period, we observe a negative marginal effect of innovation input only in Bulgaria and Spain.

The effect of labor productivity on innovation output is significant on a 1% level only in three countries, while in two of them (Romania and Portugal) is negative. The negative relationship between labor productivity and innovation output implies that more efficient firms have a lower proportion of sales from new products in their total revenue. The same finding was previously documented by Hashi and Stojčić (2013) for the sample of Central and Eastern European countries using CIS4. They explained it by possibly risk-aversion of more efficient firms in these countries, arguing that the introduction of new products or services increases the risk of failure which is why these firms transform improvements in efficiency into competitive advantages in the production of existing products. Another complementary explanation can be found in the variety of capitalism typologies, where the firms in the dependent market model do not innovate but are used as production platforms, based on cheap labor. Contrary to this finding is the situation in Norway, where the effect of labor productivity on innovation input is significant and positive.

The organizational innovations are statistically significant and positive in most of the countries, except in Norway. This implies that firms in these countries can achieve higher sales from new products by improvements in organizational efficiency. The results concerning marketing innovations are rather ambiguous. The effect is positive only in four countries (Slovakia, Spain, Norway, and Romania), suggesting that differentiation in terms of design, packaging, or delivery can enable firms to achieve higher sales from new products.

Regarding funding, we find a statistically significant and negative effect of subsidies from different levels on innovation output in many cases. These results question the ability of existing subsidies to adequately support the innovation process. On the other side, Bulgaria and Spain are two countries with positive effects of subsidies from all three levels (local, national, and EU) on innovation output.

Labor Productivity

In the final stage of the model, we estimate the effect of firm size, innovation output from the third stage, and organizational and marketing innovations on labor productivity. Exploring the relationship between innovation and productivity has been the main driving force of the CDM model and motive for many types of research in this field. Although most of the conducted analyzes have found a positive relationship between innovation and labor productivity, there are also studies that documented a negative relationship. In this paper, we try to analyze the innovation–productivity relationship through a pooled cross-sectional perspective

Table 4 Labor productivity (Eq. (4))

Variable	Bulgaria	Czech Republic	Hungary	Romania	Slovakia	Germany	Spain	Norway	Portugal
Firm size	−0.03	0.516**	1.642	0.177***	0.235***	0.936***	−0.173**	0.120**	−0.384**
	(0.076)	(0.205)	(1.390)	(0.063)	(0.070)	(0.075)	(0.067)	(0.052)	(0.152)
Innovations									
Organizational	0.430***	−0.192	−1.189	0.194*	0.265	−0.625***	0.149*	0.128***	0.558***
	(0.090)	(0.205)	(1.230)	(0.115)	(0.161)	(0.133)	(0.09)	(0.045)	(0.144)
Marketing	0.01	0.237	−0.344	0.093	0.237*	−0.043	0.177**	−0.004	−0.236*
	(0.067)	(0.198)	(0.563)	(0.111)	(0.132)	(0.125)	(0.086)	(0.046)	(0.138)
Innovation output	−0.642*	2.248	7.313	−0.066	−0.558	1.868***	−2.970***	−0.229	−3.034***
	(0.342)	(1.467)	(6.925)	(0.360)	(0.490)	(0.333)	(0.382)	(0.168)	(0.589)
Constant	8.942***	12.532***	22.009*	9.482***	8.826***	12.972***	6.641***	10.970***	5.598***
	(0.301)	(1.932)	(11.627)	(0.291)	(0.712)	(0.614)	(0.496)	(0.201)	(0.906)
Observations	3,199	3,586	1,502	683	565	2,224	11,363	2,893	3,832
R^2	−0.015	−4.409	−25.76	0.05	−0.06	−1.47	−9.37	0.09	−6.67
Chi-square statistic	260.58***	150.75	9.67	41.63***	74.38***	443.69***	154.10***	207.20***	104.59***

The coefficients were estimated using a 3-stage least squares. Each regression includes period fixed effects. For each regression, we also include the R^2 and the chi-square statistic for overall model significance. Robust standard errors in brackets. Asterisks denote statistical significance: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

and diagnose potential problems with certain countries and their national innovation systems.

We present the estimated results from the fourth stage of the model in Table 4. The size of the firm has a positive and significant effect on labor productivity in the case of the Czech Republic, Romania, Slovakia, Germany, and Norway. This means that in these countries, the same level of innovation output has a larger impact on productivity in larger firms than in smaller firms. The coefficients are significant but with negative sign in Spain and Portugal which imply that in these countries, the same level of innovation output has a smaller impact on productivity in larger firms. This illustrates the increasing role of entrepreneurs and small firms in innovation in modern economies (Vyas & Vyas 2019).

The effect of innovation output is positive and significant only in the case of Germany, where is confirmed that a firm's productivity increases with innovation output. On the other side are Bulgaria, Spain, and Portugal, where the effect of innovation output is significant but with a negative sign. This implies that more innovation output does not lead to higher labor productivity. These results are in line with our previous studies. We found a negative relationship between innovation output and productivity for Central and Eastern European countries in 2010, 2012, and 2014 and for Southern European countries (Spain, Portugal, and Greece) in 2014 (Toshevska-Trpchevska et al., 2019; Disoska et al., 2020; Toshevska-Trpchevska et al., 2020). A possible explanation for this result may be the decreased innovation activity in most of the countries, especially in the aftermath of the 2008 financial crisis. Another explanation could be the fact that the higher innovation output registered in Romania, Slovakia, and Bulgaria with the third stage of the model could mean that the firms in these countries have started to introduce new products, but it does not necessarily mean that they are innovative.

For the other countries in the sample, innovation output is not significant for labor productivity in the whole analyzed period.

As expected, organizational innovations have a significant and positive effect on labor productivity in most of the analyzed countries. On contrary, the effect of marketing innovations is insignificant in the case of six out of nine countries. One likely explanation for the results on marketing innovations can be that these activities involve a considerable number of financial means, and the results are not visible in the short term.

Conclusion

In this paper, we provide a pooled cross-sectional analysis of different types of innovations and their influence over labor productivity in selected nine European countries for the period of six years (2008–2014). In the analysis, we have representatives which are highly developed European countries (Germany and Norway), some of which had problems with the macroeconomic stability in the aftermath of the financial crisis (Spain and Portugal) and representatives from the new EU member countries from Central and Eastern Europe (Bulgaria, the Czech Republic, Hungary, Slovakia, and Romania). The application of the four-stage CDM model enabled us to see and differentiate the influence of different variables among different national innovation systems during the longer period. CDM is a structural model that describes the link between R&D expenditure, innovation output, and productivity and allows for the fact that some firms may undertake innovation efforts but do not report them as R&D.

This four stages model has led us to gradually observe the determinants of the innovation process and their influence over increasing labor productivity. We found that the factors that drive firms' decisions to innovate are almost the same among all analyzed countries. These results indicate that all analyzed variables are significant and have a positive relationship with the firms' decisions to start to innovate. In the first general stage, we find that all analyzed factors that drive firms' decisions to innovate have positive and high statistically significant magnitude. Those are firms' size, orientation towards national, European, or other markets, being part of an enterprise group, having ongoing or abandoned innovations in the previous 3 years; applying organizational and marketing innovations. Then to measure the innovation input, we apply the same explanatory variables as in the first stage, plus we add three dummy variables that intend to determine the influence of three types of subsidies for the innovation process. In this stage, the results start to differentiate among the countries, and they can be observed into three categories: the first group is Bulgaria, Romania, the Czech Republic, and Slovakia; the second group is Germany, Spain, and Norway; and Hungary and Portugal are found in the middle, with characteristics of both groups.

In the second general stage, we analyze only the firms that have reported innovation activities in the previous stage. The results show that there are great differences among countries on the significance and influence of the analyzed variables over innovation output. In the final stage, we measure the influence of firm size, innovation output from the previous stage, and organizational and marketing innovations on labor productivity. The results show that the impact of the innovation output on labor productivity varies between economies: there is a positive relationship in the more developed economies compared to a negative or neutral relationship in the less developed (though Portugal appears an outlier). We use these results to speculate that the national innovation system in developing economies becomes more vulnerable in periods of economic crisis.

Policy Options

The most important result from the analysis comes from the last stage where we test the influence of innovation over productivity. Once again, the results in this paper confirm the findings from our previous research. The positive impact of innovation over productivity is confirmed only in Germany as a highly developed economy with a stable national innovation system. In all the other countries, we have found either insignificant (in most CEE countries) or significant and negative influence (Bulgaria, Spain, and Portugal) of innovations over labor productivity. This indicates that the national innovation systems of these countries appear to be vulnerable and cannot properly transfer innovation into increased productivity. The studies of Toshevska-Trpchevska et al. (2019) and Disoska et al. (2020) indicate that the national innovation systems of the Central and Eastern European countries were unsustainable especially after the period of the financial crisis 2008–2012. The effects of the crisis were negative on the innovation process and on productivity in general.

In this aspect, we believe that there is an urgent need for the reconstruction of the national innovation systems in these countries. We believe that the inverse relationship between innovation output and labor productivity may be explained by the low absorption capacity of the firms operating in these country settings (presence of human capital, size of the enterprise, infrastructure, business environment, and size of the local economy, among others). The countries should focus on strengthening of the institutional framework by increasing the cooperation between companies, universities, and public institutions at both the national and EU level. Also, there is a need to eliminate the barriers to knowledge by fostering competitive business environment, upgrading public infrastructure, lessening the bureaucratic burdens on the firms, and encouraging the adoption of best management techniques and organizational structures (European Central Bank, 2021). Apparently, there is more to be done so that the European Single Market could more smoothly enable diffusion of knowledge among the different European countries.

Limitations of the Research

The main limitation of our previous research on innovation and the relationship with productivity, Tevdovski et al. (2017), Toshevska-Trpchevska et al. (2019); Disoska et al. (2020); Toshevska-Trpchevska et al. (2020), was the grouping of the countries and the averaging of the results. Because of that, we could not obtain clearer picture about what happens with the innovations in the analyzed countries and why the innovation did not transfer into increase of productivity. With this paper, we performed pooled overview of nine countries from the territory of Europe which are all part of the European Single Market, and we increased the time to six years and three consecutive CIS data. Again, we think that the obtained results give us only a comparative perspective between the countries on several aspects: the level of innovation, innovation output, and the influence of innovation on productivity. But again, we could not obtain clearer picture about the reasons why there are big differences especially in the influence of innovation on productivity. We consider that this is the biggest limitation of our research, and our further research should focus on analysis of certain country and its concrete national innovation system in order to analyze the specifics of this whole process.

Outlook

From the analysis that we have undertaken, we cannot recognize improving and strengthening of the innovation systems in Europe or convergence between the different parts of Europe. The results have confirmed our previous grouping of the countries into Western European countries, Southern European countries, and Central and Eastern European countries. Regarding the Western European countries (presented by Germany), the financial and economic crisis did not have negative effects on the innovation system as innovation activity there has resulted in a higher level of labor productivity. The Sothern European countries (represented by Spain and Portugal) have experienced a lower level of productivity and weakening of their innovation systems. Since the beginning of the crisis, the attention in these countries was shifted from innovation policies toward macroeconomic stabilization due to budget constraints and financial restrictions. An additional problem due to the low investments in science, spending, and salary cuts concerns the outmigration of talented young people. This can cause an irreversible weakening in these countries' research and innovation systems (Izsak et al., 2015). When it comes to the CEE countries, on the other hand, the effects of the crisis negatively influenced the innovation process and labor productivity in general. To avoid a further widening of the productivity gap, CEE countries should focus on strengthening their institutional frameworks by increasing the cooperation between companies, universities, and public institutions on both the national and EU level.

However, the post-crisis period shows that the overall innovation performance of the EU is reduced and there are serious drawbacks in the innovation performance of most of the countries. That would mean that to foster productivity growth, boost competitiveness, and strengthen the interdependence of innovation outputs and productivity in Europe, there is a need to eliminate the barriers to knowledge diffusion by fostering a competitive business environment, upgrading public infrastructure, lessening the bureaucratic burdens on firms, and encouraging the adoption of best management techniques and organizational structures (European Central Bank 2021; Jungmittag 2004). Also, to enable productive firms to grow, the EU needs to establish well-functioning capital, product, and labor markets since the mobility of human resources are fundamental mechanism of the diffusion of knowledge (Barca 2009). To obtain a more precise explanation of the problems of the national innovation systems and offer a possible solution for reconstruction a more detailed analysis is needed, taking into consideration the specific situation and conditions in separate countries. This might be a sufficient challenge for future research in this area.

Appendix

Table 5 Definition of variables

Dependent variables	Definition
Equation (1): Decision to innovate	Dummy variable: 1 if firm in 3 years before survey engaged in intramural or extramural R&D, purchased new machinery, equipment, software or other external knowledge, engaged in training of personnel, market research or did any other preparations to implement new or significantly improved products and processes
Equation (2): Innovation input (natural logarithm)	Amount (in euro) of expenditure on intramural or extramural R&D, acquisition of machinery, equipment, and software, or acquisition of other external knowledge in the year of the survey
Equation (3): Innovation output (natural logarithm)	Percent of firm's turnover in year of survey coming from goods or services that were new to market or enterprise in 3 years prior to the survey
Equation (4): Labor productivity (natural logarithm)	Turnover divided by number of employees in the year of survey
Independent variables	
Firm size (natural logarithm)	Number of employees
Market participation	
National market	Dummy variable: 1 if firm in past 3 years sold goods on the national market
EU Market	Dummy variable: 1 if firm in past 3 years sold goods on EU, EFTA or EU candidate countries markets
All other countries	Dummy variable: 1 if firm in past 3 years sold goods on markets of other countries
Part of a group	Dummy variable: 1 if firm is part of an enterprise group
Abandoned or ongoing innovations	Dummy variable: 1 if firm in past 3 years had any abandoned or ongoing innovations
Organizational innovation	Dummy variable: 1 if firm in past 3 years introduced new or improved knowledge management system, changed management structure, integrated different activities or introduced changes in its relations with other enterprises or public institutions (alliances, partnerships or subcontracting)
Marketing innovation	Dummy variable: 1 if firm in past 3 years introduced significant changes to the packaging of goods or services or changed its sales or distribution methods
Funding	
Local	Dummy variable: 1 if firm in past 3 years received financial support for innovation activities from local/regional authorities
Government	Dummy variable: 1 if firm in past 3 years received financial support for innovation activities from central government
EU	Dummy variable: 1 if firm in past 3 years received financial support for innovation activities from EU authorities
Inverse Mill's ratio	Inverse Mill's ratio from selection equation

Table 6 Summary statistics for the dependent variables

	Mean	Std. Dev	min	p25	Median	p75	max
Bulgaria							
Decision to innovate	0.177	0.395	0	0	0	0	2
Innovation input	5.955	6.993	−11.745	−2.21	8.876	11.203	18.132
Innovation output	−1.707	1.296	−4.605	−2.303	−1.609	−0.693	0
Log of productivity	9.8	1.428	2.613	8.85	9.789	10.715	17.066
Czech Republic							
Decision to innovate	0.477	0.577	0	0	0	1	2
Innovation input	6.668	7.759	−12.352	−2.681	10.277	12.547	20.122
Innovation output	−2.034	1.235	−4.605	−2.996	−1.897	−1.204	0
Log of productivity	10.936	1.316	−0.389	10.081	10.849	11.658	18.221
Germany							
Decision to innovate	0.553	0.589	0	0	1	1	2
Innovation input	13.198	2.761	6.906	11.29	12.729	14.914	22.747
Innovation output	−2.51	1.124	−4.605	−2.996	−2.526	−1.609	0
lProductivity	11.828	1.430	4.536	10.86	11.645	12.489	18.504
Hungary							
Decision to innovate	0.336	0.508	0	0	0	1	2
Innovation input	6.509	7.735	−13.117	−2.714	10.749	12.562	20.466
Innovation output	−1.816	1.345	−4.605	−2.813	−1.609	−0.693	0
Log of productivity	11.199	1.241	−0.545	10.441	11.172	11.951	18.402
Norway							
Decision to innovate	0.388	0.487	0	0	0	1	1
Innovation input	8.046	7.828	−12.366	−1.614	11.998	13.639	22.829
Innovation output	−2.073	1.244	−4.605	−2.996	−2.303	−1.204	0
Log of productivity	12.105	1.230	1.897	11.424	12.091	12.789	17.939
Portugal							
Decision to innovate	0.545	0.567	0	0	1	1	2
Innovation input	6.16	7.465	−12.371	−2.86	9.723	11.898	18.886
Innovation output	−2.399	1.158	−4.605	−2.996	−2.303	−1.609	0
Log of productivity	10.908	1.192	0.365	10.102	10.816	11.585	19.105
Romania							
Decision to innovate	0.129	0.341	0	0	0	0	2
Innovation input	2.474	8.489	−14.379	−5.289	−1.709	11.058	18.036
Innovation output	−1.611	1.199	−4.605	−2.303	−1.386	−0.693	0
Log of productivity	10.247	1.366	2.097	9.294	10.171	11.099	17.318
Slovakia							
Decision to innovate	0.227	0.447	0	0	0	0	2
Innovation input	5.828	8.215	−11.684	−3.436	9.993	12.502	19.093
Innovation output	−1.788	1.317	−4.605	−2.659	−1.609	−0.693	0
Log of productivity	10.69	1.454	3.108	9.771	10.681	11.624	15.878

Table 7 Dataset structure: by country and by year

Country	Year	Count
Bulgaria	**2010**	14,617
	2012	14,296
	2014	14,255
Czech Republic	**2010**	5151
	2012	5449
	2014	5198
Germany	**2010**	5817
	2012	6328
	2014	6282
Hungary	**2010**	4638
	2012	5152
	2014	6817
Norway	**2010**	5320
	2012	5083
	2014	5045
Romania	**2010**	8625
	2012	7670
	2014	8206
Slovakia	**2010**	2363
	2012	2897
	2014	2790
Spain	**2010**	34,550
	2012	32,120
	2014	30,333
Portugal	**2010**	6160
	2012	6840
	2014	7083

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