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R&D subsidies and productivity in eastern European countries

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ABSTRACT

This paper shows that R&D subsidy policies at the European Union (EU) and national levels stimulated labor productivity in Central and Eastern European countries (CEEC) in the years after their entry to the EU. However, the average impact of national funding on labor productivity was higher for countries in the Western control group than in the CEEC sample. EU R&D subsidies compensated the CEEC in part for the greater innovation impact of Western economies. Although they crowded out some R&D subsidies by local governments at the country level, the EU subsidies crowded in many national and local subsidies at the firm level. Local/regional state innovation aid to enterprises encouraged no increase in labor productivity in all but one of the sample CEEC countries. These impacts are assessed in a sequential structural econometric model estimated using Eurostat's collection of Community Innovation Surveys covering the years 2006–2014.

1. Introduction

In 2005, several Central and Eastern Europe countries (CEEC), plus Cyprus, became members of the European Union (EU).[1] These countries' reorientation from central planning to market innovation–supporting policies presented them with special challenges, as the European Commission (EC) recognized (European Commission (2003); Hölscher et al., (2017); Kornai, 2010). The CEEC inherited structural weaknesses in their innovation systems, and any beneficial legacy effects of central planning disappeared in the years leading up to the global financial crisis in 2008 (Carlin et al., 2013; Piech and Radosevic, 2006: 47; Surubaru, 2021).

In compensation, the EU's early stimulus for innovation in CEEC has been judged as highly positive, reorienting economic policies generally toward more sustainable growth (Suurna and Kattel, 2010). However, initiatives also supposedly exposed problems in innovation: inadequate networking, together with weak administrative capacity, coordination, and cooperation. None of the CEEC had developed system-oriented innovation policy evaluation practices by 2016–2017 (Borrás and Laatsit, 2019). But the transition economies had accumulated a wide variety of experience, with some in North and Central Europe seen as successful in their transition whereas others in Southeastern Europe viewed as laggards (Uberti, 2018).

This paper assesses the productivity impact of enterprise R&D subsidies from the EU, national, and local governments on some of the new EU members, at both the firm and the economy level. Economy-wide effects depend not only on firm-level effects but also on how many national firms are subsidized. We compare performance in the CEEC to that of selected Western European economies that had joined the EU earlier with Eurostat's Community Innovation Surveys covering the period 2006–2014. We quantify the extent to which public money for innovation has had an innovation impact by modeling the process, from the decision to subsidize research

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[1] On May 1, 2004, Estonia, Latvia, Lithuania, Czech Republic (now Czechia), Slovakia, Poland, Hungary, and Slovenia entered the EU. On the same date, Cyprus became a full EU member state. Romania and Bulgaria joined the EU on January 1, 2007.

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activities to the use of the resulting innovation in productive activities. The model structure realistically recognizes that it is not innovation input (R&D) but, rather, innovation output that boosts enterprise productivity.

Previous research with this type of model has not usually linked R&D subsidies with the final outcome (Griffith et al., 2006; Hashi and Stojcic, 2013; Tevdovski et al., 2017). Researchers typically evaluate the impact of policy on innovation expenditure without integrating this finding with the influence of the innovation spending on productivity at the firm level. We quantify the cumulative impact on the sample countries of subsidies on firms' labor productivity over the period 2006–2014.

We find that EU-funded marginal effects on productivity were, on average, greater for the new members than for the control group of prior members (old members), which can be attributed to the proportionately greater resources allocated to the East.[2] This was true of both firm-level and economy-wide effects. But the marginal effects of policy innovation funded by central and local governments were generally larger for old members. Lithuania and Slovakia were extreme cases of large firm-level EU marginal effects and small central or national government policy impacts. Given the administrative and other resources of the new members, the pattern is consistent with the crowding out of locally supported innovation at the country level by EU-funded innovation initiatives. By contrast, at the enterprise level, EU innovation projects encouraged the awarding of national and local innovation funding.

Our estimates show considerable heterogeneity among the 2005 new members' innovation policy impacts, which prevents a clear distinction between flagging economies in the South and successful "transitioners" in the North. Czechia and Romania implemented the national innovation firm-level policies for new members with the greatest impact. They experienced a greater effect than Portugal (one of the old member countries) did from its national innovation policy, though this was not true for the economy-wide impact. In extensions, we show that our baseline estimates of the marginal effects of innovation policy are credible because they are higher than obtained with less complete innovation specifications but lower than those with a model that ignores feedback.

The paper contributes to the literature on transition innovation policy by quantifying the labor productivity impact of R&D subsidies on formerly centrally planned economies. It identifies recent persistent differences in the subsidy-induced innovation performance between Eastern and Western Europe. The analysis controls for the possible endogeneity of R&D subsidies while employing a sequence of data cross sections in a common framework for eleven countries. The study finds that EU subsidies crowded out some R&D subsidies of local governments at the country level, but they crowded in many national and local subsidies at the firm level.

Following this introduction, Section 2 briefly surveys the background and key concepts, Section 3 summarizes some of the previous model-based research on innovation support in Eastern Europe. Section 4 discusses our model and the estimation procedures, Section 5 describes the data, Section 6 presents the results, Section 7 offers some extensions, and Section 8 concludes.

2. Background

Innovation policy is intended to stimulate productive innovation, but some innovations can be harmful, some beneficial, and others may be of only minor use. How do we measure the value of the average innovation? One approach is to use patents as a proxy for the value of innovations (Griliches, 1990). But in services and for small firms, patents are rarely used, so this indicator understates innovation in these sectors (Jaumotte and Pain, 2005: 25). Another method is to identify and count "significant" innovations (Tether et al., 1997). However, there is no obvious way to compare the relative importance of the innovations, and therefore the count measure of innovation output may be misleading. An increasingly common measurement of innovation comes from asking firms about their behavior. For instance, the Community Innovation Survey (CIS) of enterprises offers self-assessed innovation indices—primarily binary measures of process and product innovation – though these in themselves provide no indication of the value or effect. The impact of an innovation depends on how widespread it is, within an enterprise as well as outside it. The CIS also supplies an enterprise level measure of the diffusion of innovation: the (self-assessed) proportion of new product revenue in total sales.

Many innovation measures are included in the EU's European Innovation Scoreboard (EIS).[3] In 2020 the EIS measurement framework distinguished four main types of activities: capturing 10 innovation dimensions and using a total of 27 different indicators. The resulting EIS innovation index is the unweighted average of normalized scores for all these indicators.[4] The appropriateness of some indicators is questionable when used in this way. For instance, the proportion of employment in high-tech industries might be a misleading indicator if one country has a larger proportion of less-efficient workers in these industries than another country. In view of the finding that CEEC had lower productivity than might be expected given their research and development (R&D), innovation, and production capabilities (Kravtsova and Radosevic, 2012), a simple aggregation of inputs and outputs for innovation indices could be misleading.

Linking the innovation measure at the enterprise level to enterprise performance is the most appropriate measure of the value or impact of innovations. The CIS definition of innovations does not require them to be profitable or accepted by the market; quality enhancement or cost reduction could come at the expense of each other, so change can be damaging. So, in principle, it is possible that innovations, as measured, have an adverse impact on business performance.

[2] For the period 2007–2015, EU funds allocated to the eleven CEEC averaged 14.8% of the gross domestic product (GDP) and EUR 1848 per capita (KPMG, 2016: 10).

[3] https://ec.europa.eu/commission/presscorner/detail/en/QANDA_20_1150/.

[4] To calculate normalized scores, we first deduct the lowest value of an indicator across all countries and all years from the value in a specific year for each country. This recalculated value is then divided by the difference between the highest and lowest values across all countries and all years.

In a multi-equation context, evaluations of subsidies are typically only partial; they measure the policy impact only on an intermediate variable, such as R&D or innovation. An innovation policy may be fully additive at one stage but totally ineffective if later stages lack additivity. A full evaluation assesses the ultimate consequences of the policy intervention for the policy objective, whether employment, output, or productivity. The multi-equation approach is more persuasive in the sense that it attempts to identify structural parameters of the innovation process. But it makes the assessment of policy statistical significance (addressed in this paper) more challenging.

3. Literature survey

The EU's CIS is the most widely used firm-level data source for innovation effectiveness and related studies for groups of countries (Mairesse and Mohnen, 2010). In a survey of the innovation activities of enterprises across Europe, the CIS data consist of enterprises that employ over ten people. The survey is conducted by the national statistical authorities using a harmonized questionnaire developed by Eurostat to ensure comparability across countries. Comparative studies that include CEEC are rarer than single-country analyses or comparisons of Western European economies. More recently, Orbis, an alternative business database, has been used for cross-country firm-level analysis (Bureau van Dijk, Bachtrögler, and Hammer, 2018). The firm-level Business Environment and Enterprise Performance Survey (BEEPS), a joint initiative of the European Bank for Reconstruction and Development and the World Bank, does not cover the wealthier economies in the EU and so cannot be used for the comparisons possible with the CIS and Orbis.

More aggregated datasets have recently been employed, such as Tunali and Fidrmuc (2015), using a panel dataset covering 27 EU countries over the period 1992–2011, to estimate the macroeconomic effects of industrial policy for these countries on economic growth and investment. Their results suggest that a policy of state assistance is not an effective tool for achieving higher rates of economic growth and investment. But this result might be a consequence of a high level of aggregation of the data. Alternatively, as maintained in another NUTS-2 aggregated study (Rodríguez-Pose and Ketterer (2020)) without explicit policy variables, it was government quality that mattered for European regional growth. However, not all state assistance can be classified as support for innovation, and it cannot be assumed that none subsidized innovation merely because assistance is classified as, say, "regional." In 2008 Lithuania recorded spending no state assistance on R&D but 73% on regional development (out of a total of 0.82% of the gross domestic product [GDP]). Yet 6.1% of Lithuanian enterprises in the CIS (2008) claimed to have received R&D subsidies from the EU, 3.4% from the national government, and just under 1% from a local or regional government.

The Crépon, Duguet and Mairesse model (CDM) has been very influential, especially for users of the CIS (Crépon et al., 1998; Lööf et al., 2017). The CDM framework introduced a structural model that explains productivity by innovation output and innovation output by research investment. It indicates a method of correcting for the endogeneity inherent in the model. Janz et al. (2003) explore the comparability and pooling of CIS datasets between Germany and Sweden. Using a slightly modified CDM model to examine the innovation-productivity link, they found that innovation strongly affects productivity and that knowledge-intensive manufacturing firms are rather similar in the two countries. Griffith et al. (2006) compare innovation in France, Germany, Spain, and the UK with the CDM model. They conclude that the drivers of innovation and productivity are similar across these four countries, and government funding is important in all countries.

Many studies have been conducted on the contribution of public funding to innovation in the EU, but CEEC studies and comparisons are still in the minority.[5] For Eastern Europe, Masso and Vahter (2008) find a positive effect of government funding on innovation expenditure and infer that funds are used efficiently in Estonia. Like our paper, Hashi and Stojcic (2013) compare firm-level determinants of the innovation process in mature market economies in Western Europe and in the transition economies in Central and Eastern Europe that recently joined the EU. But they aggregate countries between the CEEC and Western European blocs and use the CIS for 2006–2008, in contrast to our country-level analysis and later sample. They highlight the role of national and EU subsidies that facilitate the transformation of innovation input into innovation output, but not into the final productivity stage. Their local subsidies variable has a significant negative sign with the old EU sample and is statistically insignificant for the new EU countries. They suggest that this result may reflect local decisions that target political objectives.

Tevdovski et al. (2017) find no impact of any public innovation funding on Romanian companies' R&D intensity. In Bulgaria, national funding had very little effect on R&D intensity, EU funding had no impact, and local funding had a slightly negative influence. Using an Orbis dataset, Bachtrögler and Hammer (2018) detect that firm-level innovation, the EU Framework Program for Research and Technical Development (RTD), and other EU business projects contributed to the additional positive impact of financial assistance in some cases but not others. Net job creation in Portugal grew, as did the capital stock in Czechia, Spain, Italy, and Portugal. Nevertheless, innovation and business projects were correlated with negative total factor productivity (TFP) growth at policy-supported firms in Czechia and Spain. Also using Orbis, Fattorini et al. (2020) evaluate the impact of the European Regional Development Fund spending on productivity across the EU NUTS-2 areas, finding that more targeted support for product and process innovation under RTD funding is significantly associated with an increase in TFP. The impact was highest for the least productive firms

[5] The final list of studies discussed by Dvouletý et al. (2020) includes nine of the 30 CEEC.

in the first quartile of the TFP distribution. Using the 2009 BEEPS, Mateut (2018) constructs a positive relation between public subsidies and the innovative activities of many firms in 30 Eastern European and Central Asian countries. A stronger positive association found for enterprises that are more likely to be financially constrained provides support for the EU market failure's justification for state intervention (although none of the EU's wealthiest economies are covered in the study).

The number of CIS-based studies of Eastern European innovation using CDM-based modeling has recently expanded, though none have attempted to find a net effect of R&D subsidies. Kijek and Kijek (2019) modify the CDM model by introducing information and communications technology as an intermediating variable in their analysis of Polish innovation using the CIS (2012). They estimated with Generalized Structural Equation Modeling (GSEM) – as does the present paper – and employ a variable for financial constraints, for which they find a significant coefficient in the labor productivity relationship.

In a comparison of Western European and CEEC enterprises, Toshevska-Trpchevska et al. (2019) use CIS 2010, finding that national and EU subsidies positively affect the innovation process at CEE companies, more so than did local subsidies. For innovation output of the CEEC group, they identify that more financial support for innovation activities leads to less innovation output. They doubt the effectiveness of existing schemes for R&D subsidies at the local, national, or EU level in CEECs.

In a comparable study, Disoska et al., (2020) use CIS 2012 and find that the influence of subsidies on innovation output in the period 2010–2012 is the opposite of that in 2008–2010. The financial crisis might be blamed for this difference. Pooling CIS cross sections for 2010–2014, Disoka et al. (2021) use a CDM analysis of innovation to show that local subsidies had positive and significant effects on investment in innovation only in Hungary, Germany, Spain, and Norway, whereas national and EU subsidies increased innovation input in all countries. They conjecture that the small size or nonexistence of local R&D subsidies in Bulgaria, Romania, Czechia, Slovakia, and Portugal was responsible. They find statistically significant and negative effects of subsidies from different levels on innovation output in many cases. On the other hand, Bulgaria and Spain achieve positive effects of subsidies on innovation output from all three levels (local, national, and EU).

4. Model

Governments attempt to subsidize innovating firms in the belief that doing so has substantial benefits for society. Firms invest in research to develop innovations that in turn might contribute to their economic performance. The achievements of innovation policy show the extent to which subsidies boost performance. This process, as modeled, is summarized in Fig. 1.

State funding allocators might assume that the innovative potential is greater in some industries than others or that some types of firms face greater handicaps. Regardless of what officials think, some firms may be less capable of completing formal funding applications because of bureaucratic impediments combined with their limited capacities. In any of these cases, funding is allocated selectively, not randomly, as econometric modeling requires. This implies that firms that are awarded one type of grant are more likely to be awarded another type of grant. We therefore expect to see EU funding crowding in innovation projects that are financed by other means. To capture this process, we estimate a probit equation to explain R&D subsidies with strictly exogenous variables, such as industry, market, and size. If the selection equation is statistically significant and plausible, then the hypothesis of endogeneity is not rejected. Although in Fig. 1 two arrows connect Subsidy and R&D, the goal here is not to estimate a structural subsidy equation

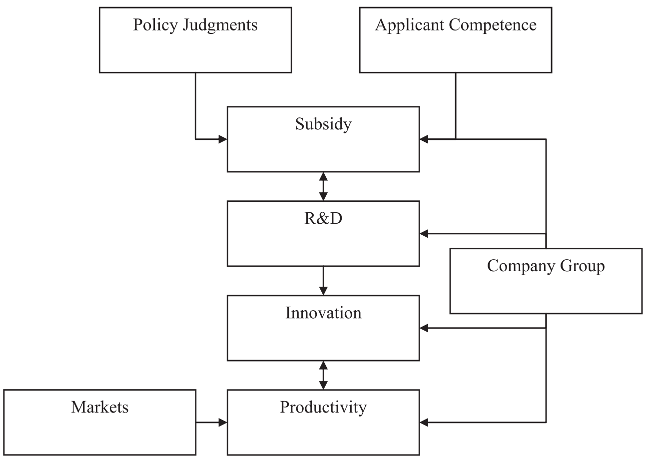

Fig. 1. Simplified Representation of the Enterprise R&D subsidy Model.

Table 1
Descriptive statistics for model variables, 2006–2014.

Variables	Old	New	Total
R&D internal (rrdin2)	0.2532	0.1016	0.1805
Innovation (inn)	0.3995	0.2375	0.3218
Process Innovation	0.2016	0.1219	0.1634
Product Innovation	0.2119	0.1271	0.1712
% of turnover from product inn (turnmar)	0.036	0.0218	0.0292
log Labor productivity	11.3396	10.3876	10.8842
EU funding inc. RTD (xfunrtd)	0.0324	0.0392	0.0356
National government funding (xfungmt)	0.1005	0.0379	0.0705
Regional government funding (xfunloc)	0.078	0.0065	0.0437
Enterprise group member (gp)	0.3042	0.2337	0.2704
10–49 employees	0.6012	0.6015	0.6013
50–249 employees	0.284	0.3035	0.2933
250 + employees	0.1148	0.0951	0.1053
Sales to other European markets (mareur)	0.4438	0.4513	0.4474
Sales to national market (marnat)	0.7511	0.6535	0.7041
Sales to local/regional markets (marloc)	0.9013	0.7327	0.82

Source: Eurostat CIS.
Note: German data for 2010 scaled up for consistency with other years. “New” refers to Bulgaria, Cyprus, Czechia, Estonia, Lithuania, Hungary, Romania, and Slovakia. “Old” refers to Germany, Portugal, and Spain.

influenced by R&D. Rather, we want to obtain a reduced-form equation for subsidies so as to estimate the complete impact of subsidies on R&D (allowing for a reciprocal effect).

Subsidies might encourage firms to increase their innovation effort; state assistance for innovation influences whether firms undertake intramural R&D. We do not attempt to model the intensity of a firm’s R&D, but we need to estimate endogeneity bias that affects R&D (Dimos and Pugh, 2016). We do not limit the modeling to manufacturing enterprises, as is done in some of the previous literature (Crépon et al., 1998; Griffith et al., 2006).

The output of this innovation effort is knowledge that leads to innovation. Here, “innovation” is broadly defined as new or improved goods or services or production methods or delivery or supporting activities. In principle, the coefficient on the innovation index for any sample can be negative, zero, or positive, depending on the average innovative success.

Innovation feeds into a firm’s’ production function, potentially raising the sales per employee (our proxy for labor productivity), in logs. A possible complication is the endogeneity of the innovation index. More productive firms may be more innovative. We control for this endogeneity with the inclusion of an inverse Mills ratio (IMR) derived from the innovation equation.

The proximity, nature and size of the market is likely to influence productivity on the demand side. In our model, we attempt to control for the major European macroeconomic shocks – the 2008 financial crisis and the 2010 debt crisis – to isolate the average policy effect. The economies in the sample are very heterogeneous, so it is important to distinguish individual country effects. In 2014 Czechia’s GDP per capita was almost three times that of Bulgaria; Cypriot GDP per capita was higher than Portugal’s; and Czechia’s GDP per capita was only about 6% less than Portugal’s. However, the poorer economies tended to expand; the post-communist economies converged to German levels of GDP per capita more rapidly than other European countries (Zoega and Phelps, 2019).

On the supply side, subsidiary or enterprise group member enterprises might benefit from the R&D and marketing of a larger group of which they are a member, boosting their innovation, R&D, and productivity. We allow all R&D subsidy coefficients to vary across countries and country intercepts to differ, but otherwise we employ a common model for the eleven sample countries. In all equations, we control for unobserved industry characteristics. We also control for firm size in all equations.

In the recursive structure, our model is similar to the classic CDM model (Crépon et al., 1998; Lööf et al., (2017)). But to correct for endogeneity, we exclusively use the control function approach.[6] We allow for the possible selection of innovative firms for funding by policy makers based on a previously earned reputation or application skill. We fit a probit selection equation for funding (S). If S_i^* is an unobserved decision variable for whether a firm i receives state assistance, and R_i^* is an unobserved firm’s investment in R&D, with S_i and R_i as their observable counterparts, the first two stages can be represented as follows:

$$\Pr\ (S_i = 1) = \Phi(S_i^*),\ \text{where}\ S_i^* = \boldsymbol{\beta}_0'\mathbf{x}_{0i} + u_{0i}\ \text{ and }\ \Phi(\cdot)\ \text{is the normal CDF.} \tag{1}$$

$$\Pr\ (R_i = 1) = \Phi(R_i^*)\ \text{ where }\ R_i^* = \alpha_S S_i + \beta_1' x_{1i} + u_{1i} \tag{2}$$

Equation (1), unlike Eq. (2), is a reduced form enabling the derivation of an IMR for Eq. (2). In Eqs. (1) and (2), x_{0i}, x_{1i}, β_0, and β_1 are vectors of independent variables and their corresponding parameters. They reflect the impact of influences on firms’ decisions to be awarded and receive state assistance and on the actual probability of engaging in R&D. α_S is a state assistance effect parameter. u_{0i} and

[6] For example, Heckman and Robb (1985). Previous literature uses a combination of both instrumenting and control functions: Heckman for the R&D intensity stage and an instrumental variable for the productivity stage. The control function is especially appropriate here because it is suitable for non-invertible models (e.g., discrete-choice models) and allows for heterogeneous effects.

Table 2
Baseline estimation results of the model.

	(1) Funding	(2) R&D	(3) Inn.	(4) Prod.
Funding: EU		0.4374***		
Funding: Central Gov		1.2909***		
Funding: Local Gov		0.22		
(1) R&D			1.6650***	
(2) Innovation (Inn.)				0.1651***
Inverse Mills ratio		0.8322***		-0.1236***
Part of enterprise group	0.1093***	0.3424***	0.1715***	0.7055***
Size 50–249	0.2273***	0.3733***	0.2508***	-0.3214***
Size 250+	0.4494***	0.8777***	0.3723***	0.7728***
Period ending 2010	0.0436***	0.0605***	-0.0409***	-0.0440***
Period ending 2012	0.0066	-0.0600***	-0.2588***	0.0304***
Period ending 2014	0.0466***	-0.0623***	-0.2810***	0.0338***
Sales to other EU or European Free Trade Association				0.4366***
Sales to national market				0.3167***
Sales to local market				-0.0410***
Industry	yes	yes	yes	yes
Country	yes	yes	yes	yes
Funding*Country	no	yes	no	no
No. of obs.	356032	356032	356032	356032

Notes: *** $p < 0.001$. “Funding” is a selection equation with a dependent variable that equals 1 if the firm receives any funding. Bulgaria is the country base case, and “All other countries” is the base case for Sales markets. “Prod” is log of labor productivity. “Inn” equals 1 if the enterprise records any one of five types of innovation; otherwise, zero. Size refers to the number of employees, and the base case is 10–49.

u_{1i} are random error terms with zero mean and constant variance that are uncorrelated with the explanatory variables. Specifically, x_{1i} includes an IMR (IMR1, which is a function of S_i^*) predicted from Eq. (1) to correct for endogeneity bias. Wooldridge (2002: 568) shows that, under these circumstances, the inclusion of the IMR controls for endogeneity.

The binary R&D equation has explanatory variables including 24 industry categories, size of employment (larger firms are more likely to engage in R&D, according to Cohen and Klepper’s [1996] stylized facts), government and EU support, CIS year, membership in an enterprise group, and 11 countries. The selection Equation (1) for policy uses variables similar to those in the R&D Eq. (2) (see Table 3).

The R&D outcome of Eq. (2) feeds into the innovation output Eq. (3), which explains whether the firm engages in innovation. We do not restrict the sample to nonzero R&D performers because lags or high R&D reporting thresholds can explain positive innovation sales despite the absence of recorded R&D at some firms. Eq. 3 includes other explanatory variables: industry, country, size, and membership in an enterprise group.[7] This third stage of the estimation is as follows:

$$\Pr(N_i = 1) = \Phi(N_i^*), \text{ where } N_i^* = \alpha_R R_i + \beta_2 x_{2i} + u_{2i} \tag{3}$$

where N_i represents the observed innovating and non-innovating enterprises, R_i is R&D from Eq. (2) and α_R its corresponding parameter, and x_{2i} is the vector of other explanatory variables. β_2 is the vector of corresponding unknown parameters, and u_{2i} is the random error term with a zero mean and constant variance, uncorrelated with the explanatory variables.

Table 3
Marginal effects of subsidy on productivity at the firm level, by source of funding.

	EU Membership	EU	Central Gov	Local Gov
BG	New	0.0025	0.0149*	0.0011
CY	New	0.0169***	0.0171***	0.0028**
CZ	New	0.0205***	0.0350***	0.0101***
EE	New	0.0319***	0.0315***	-0.000***
HU	New	0.0309***	0.0299***	0.0023
LT	New	0.0361***	0.0118**	-0.001*
RO	New	0.0180**	0.0344***	0.0076
SK	New	0.0288***	0.0229**	0.0009
DE	Old	0.0249***	0.0413***	0.0225***
ES	Old	0.0200***	0.0438***	0.0298***
PT	Old	0.0168***	0.0329***	0.0066***
	New	0.0232	0.0247	0.0030
	Old	0.0206	0.0393	0.0196

Note: Derived from regressions in Table 2 using Eq. (5). Country labels: BG Bulgaria, CY Cyprus, CZ Czechia, DE Germany, EE Estonia, ES Spain, HU Hungary, LT Lithuania, PT Portugal, RO Romania, SK Slovakia.

[7] State funding to boost innovation is also likely to raise R&D. So, including the funding in both stages would be double counting.

The final equation explains the labor productivity of the firm (performance) by whether it is innovative, by the country, market, size, and membership in an enterprise group.

$$Q_i = \alpha_N N_i + \beta_3 x_{3i} + u_{3i} \tag{4}$$

where Q_i is labor productivity, N_i is the actual value of innovation from the knowledge production function Eq. (3), x_{3i} is a vector of other determinants of labor productivity including an IMR derived from Eq. (3),[8] α_N and β_3 are associated coefficient vectors, and u_{3i} is random error. Therefore, the effect of state assistance on turnover growth can be written as a partial derivative using the chain rule:

$$\frac{\partial Q_i}{\partial S_i} \approx \frac{\partial Q_i}{\partial N_i} \times \frac{1}{N}\sum_{i=1}^{N}[Pr(N_i = 1|R_i = 1) - Pr(N_i = 1|R_i = 0)] \times \frac{1}{N}\sum_{i=1}^{N}[Pr(R_i = 1|S_i = 1) - Pr(R_i = 1|S_i = 0)] \tag{5}$$

In the baseline model, Eqs. (1)-(3) are probits, and Eq. (4) is a linear regression.

The model has measures of policy effectiveness that can be compared between CEEC and the Western sample countries. The coefficient size of this measure could reflect any or all of the efficiency with which the innovation funding is used, the amount of funding, or the type, of funding given to each firm. The country-level impact also depends on the proportion of enterprises in the country that receive support and the timing of that support.

5. Data

The model is estimated with Generalized Structural Equation Modeling on four pooled CISs covering three-year periods ending in 2008, 2010, 2012, and 2014, including eleven countries.[9] The “new arrivals” comprise Bulgaria, Cyprus, Czechia, Estonia, Hungary, Lithuania, Romania, and Slovakia. The Western reference group consists of Germany, Portugal, and Spain.

In our model, the state innovation assistance or subsidy measure is the binary response to the CIS 2008 question “During the three years … did your enterprise receive any public financial support for innovation activities from … levels of government?”. The three sources of subsidy funding that we can measure are the EU, national government, and local government.[10] The R&D measure is the same binary variable as used by Harris et al. (2021) from the CIS 2012 for estimating the effect of absorptive capacity on innovative potential. The measure is defined broadly as “Creative work undertaken within [an] enterprise to increase the stock of knowledge for developing new and improved products and processes (include software development in-house that meets this requirement.”

In addition to providing the necessary data on subsidies and R&D, we use information on the size of enterprise employment, enterprise membership in a wider group, industry, proportion of turnover from new products and on principal markets. Table 1 lists the descriptive statistics for the “old” Western members and “new” members comprising the CEEC plus Cyprus. The probability of an enterprise’s engagement in R&D or innovation is considerably lower in the new member states. Labor productivity is also lower among the new members; the likelihood of receiving EU innovation funding is slightly higher there as well, in contrast to the lower likelihood of receiving funding from the central and local government for innovation by the new members. The new members are less likely to have firms with more than 250 employees or that are members of a larger corporate group.

Labor productivity is calculated following Tevdovski et al. (2017). For the innovation variable of the baseline model (inn), any one of the five categories of innovation available in the CIS is sufficient to achieve a positive score. For the sensitivity tests of the model, the novel turnover variable is the answer to the question “Please give the percentage of your total turnover in [the prior year] from new or significantly improved goods and services introduced during [years of the CIS] that were new to your market.” Out of necessity, to achieve consistent data over all country and period surveys, we use fewer variables than many CIS studies, but we have detailed industry (24) and country (11) breakdowns.

6. Results

In Table 2 we give parameters of the core model run with data for 2006–2014 and with selection for funding, feedback from R&D to the subsidy process, and feedback from productivity to innovation. A change in funding first affects the dependent variable of the R&D Eq. (2) (rrdin), then is transmitted to the innovation equation, and finally influences the productivity equation. This effect takes place over the CIS period of up to three years. The coefficients linking the equations and capturing this transmission are highly significant (in the top section of Table 2). The IMRs to control for selection and feedback were also highly significant.

The year controls show the impact of the financial crisis followed by the debt crisis; the opportunities for R&D subsidies increased, but the probability of undertaking R&D fell after 2010 compared with 2008 and fell strongly compared with 2014. Opportunities for innovation declined markedly after 2008 and so did labor productivity. Consistent with Kijek and Kijek (2019) and Biagi et al. (2016), we found that firms in the ICT sector (which includes electronics and electrical manufacturing, as well as telecommunications and programming) tend to innovate more than those in other sectors. In our case, we identified this tendency based on the contribution of industry to chances of undertaking R&D (Appendix).

The size coefficients indicate that larger firms were more likely to receive R&D subsidies and to undertake R&D. They also show

[8] By the same control function logic as for the IMR in the R&D Eq. (2).

[9] Not all EU countries make their disaggregated CIS data available to Eurostat. Each survey covers three years.

[10] The CIS also distinguishes participation in the EU RTD program. We aggregate this with all other EU programs, even though a substantial number of German firms in the sample admitted to participation in the RTD program but not to funding by the EU.

Table 4
Cumulative marginal effects of R&D subsidy on productivity at the country level.

	EU Membership	EU	Central Gov	Local Gov
BG	New	0.02%	0.11%	0.00%
CY	New	0.20%	0.73%	0.02%
CZ	New	0.66%	1.27%	0.07%
EE	New	0.70%	1.00%	0.00%
HU	New	0.69%	0.65%	0.00%
LT	New	1.55%	0.21%	0.00%
RO	New	0.10%	0.18%	0.02%
SK	New	0.27%	0.16%	0.00%
DE	Old	0.59%	2.15%	0.70%
ES	Old	0.19%	1.63%	1.07%
PT	Old	0.36%	1.49%	0.04%
	New	0.52%	0.53%	0.01%
	Old	0.37%	1.75%	0.60%

Note: Table 3 firm-level and period innovation policy effectiveness times the proportion subsidized and cumulative.

that larger firms (over 250 employees) were generally more productive and, across the entire range above 49 employees, more likely to innovate. Membership in an enterprise group boosted all three dependent variables. Enterprises that sell to a local market were less productive than those with national sales and even less productive than those selling in other EU economies (the base case was "other markets"). International sales (here, "other EU") can measure a firm's exposure to international competition and specialization, which might boost productivity. Because the three funding effects interact with the 11 country effects across the three equations to generate the reduced-form coefficients in Table 3, in the interest of clarity we do not report all these policy structural parameters in Table 2.

The three policy coefficients in Table 3 are the effect on labor productivity (of each average firm in each country) of funding from local, national, and EU sources. All EU, national, and local innovation funding responses, except Bulgaria's, are significantly higher than zero. Lithuania has the largest EU coefficient, which means that if a Lithuanian firm has innovation funded by the EU, then its labor productivity on average was 3.6% higher than that of firms that did not receive this support over up to three years. The (unweighted average) marginal effect for the CEECs is 2.32%. For the three Western countries, the average was lower, at just over 2%, reflecting stronger EU support for the new members.

National funding was more effective for both groups on average, though this was not so for Hungary, Lithuania and Slovakia. The average effectiveness of national funding, compared with EU funding, was higher for the Western group than for the CEEC. This might imply that the long-term technological gap based on continuous innovation between East and West is likely to persist unless compensated for by EU funding. Alternatively, the high level of EU funding displaced CEEC national innovation policy effectiveness. We address these possibilities below.

The coefficients of the CEEC for local funding are much smaller. But they were comparable on average to the EU marginal effects for Germany, Portugal and Spain. This might be because a local government was typically smaller in CEECs and Cyprus than in Spain or Germany. The population of Portugal is similar in size to that of Hungary and Czechia, and the marginal local innovation policy effect is much smaller in Portugal than in Spain and Germany. But local policy effectiveness was statistically significant in Portugal, unlike in Hungary.

The three marginal effect rankings are not significantly different from those of the EU Innovation Scoreboard values for 2014.[11] Although the scoreboard indices are constructed with different data and for different purposes, they measure the innovation environment, which, in key respects, is similar to our innovation policy concerns. However, our ranking of policy marginal effects differs in some respects from those of the Scoreboard. In Table 2, Romania's innovation policy is always stronger than Bulgaria's, but in the 2020 Scoreboard Bulgaria is more innovative than Romania. In the scoreboard, Czechia is behind Estonia in 2008–2014, whereas in our national and local marginal effects Czechia is ahead. In 2019, the Czech GDP per capita is higher than Estonia's, and Romania's was greater than Bulgaria's. If innovation impact is a predictor of future GDP per capita, then our policy ranking is superior with respect to these economies.

Table 4 shows the cumulative impact on the national economies of these R&D subsidies in 2006–2014 by multiplying the policy effectiveness measure by the proportion of enterprises subsidized over each of the four periods of the CIS. The result is a different ranking. Lithuania, which has a 1.55% increase in labor productivity, is by far the top beneficiary of EU innovation funding in our sample. Among the new members, Czechia is first in central government innovation funding, with 1.27%, though this is far behind Germany's impact of 2.15%. Local subsidies have a minimal impact on new members, and Spain is the top performer in the full sample. Bulgaria has the weakest impact across all three sources of innovation funding, with Romania and Slovakia close behind. In the West, Portugal, the weakest of the three, has a larger central government impact than any of the new members. The comparison is the

[11] Using the 2016 Scoreboard and the Wilcoxon matched-pairs signed-rank test (Wilcoxon, 1945). However, the ranking of the Innovation Scoreboard uses a different metric from our marginal effects. We therefore standardize both by Z = (Z-mean(Z))/SD(Z) before applying the test. The null hypothesis is that "The two series are not significantly different from each other in rank." For EU marginal effects, the *p*-value of the null is 84.88%. For central government marginal effects, the *p*-value is 84.66%. For local government marginal effects, the *p*-value is 90.35%. The first two *p*-values are the same because the sum rank of the marginal effects for EU and central are the same.

Table 5
Selected coefficients for the baseline innovation model and variants.

Dep. Var.	Indep. Var.	Baseline	No Selection	Turnmar	Separate
R&D	Funding: EU	0.9360***	0.9353***	0.9360***	0.9360***
	Funding: central gov	1.1784***	1.1764***	1.1784***	1.1784***
	Funding: local gov	0.3355***	0.3353***	0.3355***	0.3355***
Inn	R&D	1.6650***	1.6650***	–	–
Process inn		–	–	–	1.1267***
Product inn		–	–	–	1.4300***
Turnmar		–	–	0.0922***	–
Log productivity	Inn	0.1651***	0.2069***	–	–
	Process inn	–	–	–	0.1351***
	Product inn	–	–	–	0.0671***
	Turnmar	–	–	0.0975 * **	–
	No. of obs.	356,032	356,032	37,509	356,032

Note: The coefficients of funding are based on averages of the coefficients of all countries, hence, the baseline parameters differ from those in Table 2, which are only for Bulgaria (base group). ***$p < 0.001$. The R&D equation is the same for all variants except for the no selection specification. “Baseline” from Table 2, “No Selection” abandoning control function terms. “Turnmar” uses the proportion of innovative products in turnover as a replacement innovation variable, “Separate” distinguishes separate product and process innovations.

Table 6
R&D subsidy marginal effects on productivity.

Funding	Membership	Baseline	No Selection	Turnmar	Separate
EU	New	0.0232	0.0289	0.0022	0.0178
	Old	0.0206	0.0258	0.0020	0.0169
Central Gov	New	0.0247	0.0307	0.0024	0.0187
	Old	0.0393	0.0494	0.0038	0.0318
Local Gov	New	0.0030	0.0036	0.0003	0.0023
	Old	0.0196	0.0246	0.0019	0.0154

Note: Derived from equations estimated in Table 5.

Table 7
Crowding out and in: Correlation coefficient matrixes at the firm and country level.

		EU	Central Gov.	Local Gov.
Firm level	EU	1		
	Central gov.	0.3043*	1	
	Local gov.	0.1500*	0.2581*	1
Country level	EU	1		
	Central gov.	0.2333	1	
	Local gov.	-0.3205*	0.1431	1

Note: *5% significance level. A negative coefficient indicates subsidy displacement or crowding out. Positive coefficients indicate crowding in.

opposite for EU funding: the old members experience a smaller impact than the new members. The two possibilities discussed for the firm-level impact estimates are also pertinent to the economy-wide impact.

7. Extensions

We test the robustness of the model and the outputs in ways that show that the baseline estimates of policy marginal effects are higher than those obtained by less complete innovation specifications, but lower than those with a model version that ignores feedback. Abandoning the two endogeneity corrections has little effect on the structural coefficients, except for the innovation variable in the productivity equation, which increases (No Selection, Table 5). The overall effect is to boost the size of the innovation policy marginal effect (Table 6). Because the IMR coefficients were statistically significant, indicating that there was endogeneity, the baseline marginal effects estimates are more acceptable.

We replace the aggregate innovation variable (Inn) with the proportion of turnover accounted for by innovative products (Turnmar, Table 5) – following the original CDM model (Crépon et al., 1998) and Hashi and Stojcic (2013). This replacement variable captures the extent of diffusion of the product innovation within the firm’s product range. However, it is unlikely to be an adequate measure of process innovation as well. As Table 6 shows, the implied innovation policy multipliers, as expected, are smaller than in the baseline model.

The final model (Separate, Table 5) modification is to introduce separate variables and equations for product and process innovations (e.g., following Griffith et al., 2006).[12] The sum of the product and process innovation coefficients in the productivity equation, 0.2 or 20%, is somewhat higher than the composite innovation coefficient of the baseline, 0.16 or 16%. But because of smaller coverage of innovations than the baseline measure (Inn), the specification results in lower policy marginal effects (Table 6). The relatively small product innovation coefficient is consistent with the small policy effects of the Turnmar equation model.

To summarize, the baseline results still hold: the average innovation policy subsidy generated around a 1% cumulative increase in labor productivity over the period 2006–2014 (country level), old EU members had central and local government innovation policies with more impact than did new EU members, and EU subsidies to some extent compensated, with greater impact in CEEC than in the Western group.

Crowding out can occur at the country level, for which administrative and other resources are largely fixed. But, at the same time, crowding might occur at the firm level—that is, an enterprise awarded an EU subsidy might have a higher chance of obtaining a national subsidy. The correlations between the number of subsidies granted are consistent with this interpretation (Table 7). Using country-level data (average percentages funded for each country each period) shows that EU and local funding are negatively correlated (consistent with crowding out), whereas the firm-level correlation coefficients among the three funding sources are all positive and significant (consistent with crowding in). A caveat is that the crowding refers only to the number of subsidies, not the total amount of funding.

8. Conclusion

Recognizing the importance of innovation for economic development, we focus not on explicit policies but on subsidies intended to trigger it. We estimate the R&D subsidy policy impact, at the level of the firm and the economy, for eight members of the EU that joined in the first decade of the twenty-first century and, for comparison, three western European economies. We find that the impact within each group varied substantially, with that of the Bulgarian EU subsidy being minimal (as also discovered by Tevdovski et al., 2017), especially compared with those of Hungarian, Lithuanian, and Estonian firms. The impact in Hungary found here contrasts with that of the evaluation by Maroshegyi and Nagy (2010) for an earlier period.

For nationally funded policies, again there was considerable heterogeneity within the groups, with Estonia, Czechia and Romania having bigger firm-level innovation policy effects among the new members. Estonia was especially effective when considering the impacts of EU and central government innovation policies together, as implied by the earlier evaluations by Hartsenko and Sauga (2012) and Masso and Vahter (2008). On average, the three western economies have higher innovation policy effectiveness (at the level of both individual enterprises and the economy) than the new members for subsidies from the central and local government. All new members have a lower economy-wide impact than Portugal, the poorest among the western sample countries. Czechia has the most effective local innovation policy among the new members here, contrary to Bachtrögler and Hammer (2018), though the marginal effect was nonetheless very small.

We find an inverse relationship between EU and national innovation policy impacts across the old and new EU members. For old members national policy impacts were greater than EU impacts and for new members EU innovation policy impacts were greater than national impacts. This is consistent with substantial external EU-funded innovation initiatives crowding out nationally supported innovation projects. The correlation pattern between the proportion of subsidies also supports this crowding-out pattern, which might be explained by the limited administrative and other resources in the new member states. By contrast, the subsidy correlation at the enterprise level indicates that the grant of an EU innovation project encouraged the awarding of national and local R&D subsidies: crowding in.

Our evaluation of innovation policy analysis complements the EU Innovation Scoreboard, which uses a wider range of innovation data in a less theoretically structured manner. If our innovation effectiveness (at both levels) and the scoreboard are compared as predictors of future GDP per capita, then our non-EU rankings are more accurate in terms of the relative positions of the economies of Romania and Bulgaria, and Estonia and Czechia.

A qualification to the marginal R&D subsidy effects reported here is that some firms receiving 'public financial support for innovation activities' (the CIS definition) may not regard their innovation input as R&D – as we have done- and may not record it as such. In this case, the impact of our 'R&D subsidy' on R&D would be understated and our chain of actions from subsidy to productivity could be incomplete. This implies that our policy effectiveness measure could be downward biased.

The CIS dataset employed in this paper is not a panel because the enterprise identities are not known (to us) and thus cannot be linked in successive CIS waves. This means that we can only use cross-sectional variation to identify causal relations, not the time-series variation of enterprises. At the same time, the cross sections have experienced different macroeconomic shocks, providing another source of variation that is absent from individual CIS studies, yielding more stable long-run parameter estimates than those derived from only a single cross section.

Another qualification is that the economies analyzed do not include all those that joined the EU between 2004 and 2007, nor are all the older members covered. Widening the coverage could increase the heterogeneity of policy results. We could not quantify the return to R&D subsidies because the CIS does not contain sufficient information. Additions to future surveys could provide opportunities to remedy this omission.

[12] Tevdovski et al. (2017) estimate equations for four binary innovation variables but use only two in the productivity equation.

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Appendix

See Tables A1-A3 here.

Table A1
Descriptive ratios of R&D and innovation across industries.

Industry	R&D	Inn
Agriculture, forestry, and fishing	0.147	0.248
Mining and quarrying	0.088	0.207
Manufacture of food, beverages, and tobacco	0.173	0.358
Manufacture of textiles, apparel, and leather	0.092	0.224
Manufacture of wood, paper, and media	0.110	0.308
Manufacture of fuel, chemical, and pharmaceuticals	0.311	0.461
Manufacture of metals	0.203	0.371
Manufacture of electronics, electrical machinery and appliances etc.	0.396	0.522
Manufacture of furniture and other	0.159	0.332
Electricity, gas, steam, and air conditioning	0.128	0.279
Water, sewage, and waste	0.113	0.253
Construction	0.110	0.197
Wholesale and retail	0.067	0.201
Transportation	0.039	0.162
Warehousing and courier services	0.081	0.242
Accommodations	0.021	0.127
Publishing, movies, and TV	0.164	0.346
Telecoms and programming	0.393	0.495
Finance and insurance	0.180	0.402
Real estate	0.058	0.207
Legal, accounting, and consulting	0.163	0.324
Research	0.386	0.420
Design, photography, translation, and veterinary	0.260	0.410
Administration	0.091	0.223

Table A2
Non-SME marginal effects of state assistance (baseline specification).

	EU	Central gov	Local gov
Bulgaria	0.0035***	0.0103***	0.0024***
Cyprus	0.0104***	0.0059***	0.0086***
Czechia	0.0076***	0.0133***	0.0000***
Germany	0.0055**	0.0082**	0.0038**
Estonia	0.0082**	0.0063**	0.0107*
Spain	0.0156**	0.0168***	0.0125***
Hungary	0.0150***	0.0139***	-0.000***
Lithuania	0.0118***	0.0059***	-0.001***
Portugal	0.0061*	0.0080*	0.0051*
Romania	0.0118***	0.0152***	0.0099***
Slovakia	0.0158***	0.0097***	-0.007***

Note: non-SME = more than 250 employees. Significance: *10%, ** 5%, ***1%.

Table A3
Marginal effects of state assistance on labor productivity with different models.

	Country	Membership	Baseline	No selection	Turnmar	Separate
EU Funding	BG	New	0.0025	0.0031	0.0002	0.0019
	CY	New	0.0169***	0.0213***	0.0016***	0.0149**
	CZ	New	0.0205***	0.0256***	0.0019***	0.0167**
	DE	Old	0.0249***	0.0313***	0.0023***	0.0191**
	EE	New	0.0319***	0.0399***	0.0031***	0.0271***
	ES	Old	0.0200***	0.0252***	0.0019***	0.0150*
	HU	New	0.0309***	0.0385***	0.0029***	0.0199*
	LT	New	0.0361***	0.0449***	0.0034***	0.0293***
	PT	Old	0.0168***	0.0210***	0.0017***	0.0166***
	RO	New	0.0180**	0.0222*	0.0017**	0.0129
	SK	New	0.0288***	0.0356***	0.0027***	0.0196*
		New	0.0232	0.0289	0.0022	0.0178
		Old	0.0206	0.0258	0.0020	0.0169
Central Government	**Country**	**Membership**	**Baseline**	**No Selection**	**Turnmar**	**Separate**
	BG	New	0.0149*	0.0184	0.0014*	0.0107
	CY	New	0.0171***	0.0216***	0.0017***	0.0152**
	CZ	New	0.0350***	0.0437***	0.0033***	0.0283***
	DE	Old	0.0413***	0.0518***	0.0039***	0.0312***
	EE	New	0.0315***	0.0394***	0.0030***	0.0268***
	ES	Old	0.0438***	0.0551***	0.0041***	0.0320**
	HU	New	0.0299***	0.0373***	0.0028***	0.0193*
	LT	New	0.0118**	0.0147**	0.0011**	0.0097**
	PT	Old	0.0329***	0.0413***	0.0034***	0.0322***
	RO	New	0.0344***	0.0425***	0.0033***	0.0242*
	SK	New	0.0229**	0.0280**	0.0022***	0.0157*
		New	0.0247	0.0307	0.0024	0.0187
		Old	0.0393	0.0494	0.0038	0.0318
Local Government	**Country**	**Membership**	**Baseline**	**No Selection**	**Turnmar**	**Separate**
	BG	New	0.0011	0.0013	0.0001	0.0008
	CY	New	0.0028**	0.0035**	0.0002*	0.0025
	CZ	New	0.0101***	0.0127***	0.0009***	0.0084**
	DE	Old	0.0225***	0.0282***	0.0021***	0.0173**
	EE	New	-0.000***	-0.000***	-0.000***	-0.000**
	ES	Old	0.0298***	0.0374***	0.0028***	0.0222**
	HU	New	0.0023	0.0029	0.0002	0.0015
	LT	New	-0.001*	-0.002*	-0.000*	-0.001
	PT	Old	0.0066***	0.0083***	0.0007***	0.0066***
	RO	New	0.0076	0.0097	0.0007*	0.0055
	SK	New	0.0009	0.0009	0.0000	0.0006
		New	0.0030	0.0036	0.0003	0.0023
		Old	0.0196	0.0246	0.0019	0.0154

Note: Significance: *10%, ** 5%, ***1%.

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