RELATIONSHIP BETWEEN R&D, INNOVATION AND PRODUCTIVITY IN EMERGING ECONOMIES: CDM MODEL AND ALTERNATIVES[1]

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Abstract

CDM (Crépon, Duguet and Mairesse. 1988) is a workhorse model in the economics of innovation which explains productivity in three-stage procedure driven initially by R&D which then lead to patents and then to productivity improvements. Based on the logic of this model, there is increasing literature which applies it to emerging economies but which modifies the original model without being explicit about the nature and implication of this modification. We argue in this paper that in its original form, CDM cannot capture stylized facts of determinants of productivity in emerging economies and that we need alternative models. Accordingly, we are critical of literature that tries to maintain the validity of the model while actually changing it. For that purpose, we test the original CDM model and its two alternatives – investment and production capability driven models. Our research is based on a large sample of firms in Central and East Europe, former USSR economies and Turkey, and we show that the alternative models are much closer to stylized facts of innovation activities and technology upgrading in these and other emerging economies. Our conclusions have important policy implications, which we discuss.

1. Introduction

The CDM - Crépon, Duguet and Mairesse - model is considered a workhorse model in the economics of innovation. Crépon, Duguet and Mairesse (1998) initially proposed their model to explain productivity as driven by innovation output and innovation output as driven by investment in research. The main contribution of the model is methodological. It is regarded as a seminal attempt to explore the black box of the innovation process at the firm level (Loof et al., 2017) and is based on the concept of a 'knowledge production function'

[1] We grateful to anonymous reviewers for substantive and illuminating comments in revising this paper. All, remaining errors remain our responsibility.

(Griliches, 1989 1990), in which R&D capital stock determines the level of productivity indirectly via its impact on innovation output.

The CDM is designed as a four-stage sequential model, which includes, first, the decision to innovate (invest in R&D), second, the decision about how much to invest in innovation (R&D) activities, third, the relation between innovation expenditure and innovation output (patents, innovative sales) and fourth, the relation between innovation output and performance (productivity). Each of the four stages embeds different determinants of innovation such as firm characteristics, industry-specific factors and institutional background.

The CDM model has been used widely to explore the R&D-innovation-productivity link in the context of high-income economies (Benavente, 2006; Criscuolo and Haskell, 2003; Griffith et al., 2006; Janz et al., 2004; Jefferson et al., 2006; Loof and Heshmati, 2002, 2006; Mohnen et al., 2006; Parisi et al., 2006; Van Leeuwen and Klomp, 2006). These studies confirm the relevance of the model for developed economies and show that the marginal effects of innovation intensity are statistically and economically significant.

However, in the context of emerging economies, the evidence is less conclusive. Studies focusing on emerging economies are scarce, and the results are less robust and sometimes mixed. However, investigations based on innovation survey data confirm that innovative firms achieve higher labour productivity compared to other firms. Most studies report a positive relationship between innovation and firm performance, see, for example, Crespi and Pluvia (2010) for the Latin American case, De Fuentes et al. (2015) for Mexico, Lee and Kang (2007) for South Korea, Hegde and Shapira (2007) for Malaysia, Yan Aw et al. (2008) for Taiwan and Jefferson et al. (2006) for China. However, results for the relationship between R&D and innovation are mixed. For example, Chudnovski et al. (2006) and Arza and López (2010) for Argentina, Correa et al. (2005) and Raffo et al. (2008) for Brazil and Stoevsky (2005) for Bulgaria provide positive results for this relationship. However, Benavente (2006) and Benavente and Bravo (2009) for Chile, and Pérez et al. (2005) for Mexico suggest the relationship is negative or insignificant. The findings for the innovation-productivity link are similarly inconclusive. Raffo et al. (2008) provide positive results for Brazil and Mexico, but negative results for Argentina, while Perez et al. (2005) for Argentina, Chudnovsky et al. (2006) and Benavente (2006) for Mexico suggest the effect is not significant.

Since our data refer to Central and East European Countries (CEECs), former USSR economies (CIS) and Turkey, we draw on three papers that apply the CDM model approach to data on these economies. The main findings in Tevdovski et al. (2017), who use the CDM model for data on Romania, Bulgaria and Germany, are that the marginal effects of R&D

intensity are statistically and economically highly significant for product innovation in all three countries with the highest impact in Germany, followed by Bulgaria and then Romania. However, in terms of process innovation, R&D intensity is very significant for the companies operating in Germany, but negative for companies in Bulgaria and Romania (higher R&D expenses per employee lead to less process innovation). Tevdovski and colleagues also show that equipment investment is a fundamental driver of process innovation in all three countries.

Hashi and Stojcic (2013) study ‘old' and ‘new' EU member states, employing a modified CDM model based on a broad notion of innovation which includes all innovation expenditures. They provide three main findings. First, they show that the processes driving firms’ innovation activities in the two groups of countries are broadly comparable. Second, they show that investment in innovation activity has a positive influence on innovation output, measured as the proportion of sales attributable to new products. Third, firm productivity increases significantly with innovation output. In both regressions, the coefficients are statistically significant and positive. However, in CEECs, we observe a negative feedback effect from productivity to innovation output.

Masso and Vahter (2012) explore the link between innovation and productivity in Estonia’s services sector and find that the effects of innovation on productivity also work through the impact of innovation on exports as the determinant of the firm's productivity. Masso and Vahter (2008) find the changing importance of the type of innovation on productivity levels but not impact on productivity growth.

Most studies on emerging economies employ what we consider to be a ‘modified' CDM model, which is based not on R&D but on a ‘broad’ notion of innovation that includes R&D and expenditures on machinery and equipment (M&E). These papers show that a ‘modified’ CDM model, but not an R&D based CDM model, ‘works' for emerging economies. However, from our perspective, it is essential to recognise that a ‘broad’ notion of innovation combines expenditures on intangibles (R&D) with expenditure on tangibles (M&E). A lumping up together ‘exploration’ component (R&D) with ‘exploitation’ (physical investments) confounds the real nature of innovation in emerging economies which is about the acquisition of M&E and their effective absorption (Radosevic, 2017). The effective absorption of M&E requires developed production capability, which is a qualitatively different category of intangibles for which there is no direct proxy (Bell and Pavitt, 1993). By trying to accommodate the CDM to the context of the emerging economies, the ‘modified’ CDM model literature hides the essential distinction between the production and innovation capability. Our results show that innovation intensity does not explain productivity in emerging economies. Also, including investment and production capability as determinants of productivity better reflects the stylised facts of innovation activities in emerging economies. Compared to ‘modified’ CDM model literature, our results carry significantly different policy implications, which we discuss in conclusions.

In what follows, in Section 2, we discuss the stylised facts related to technological change and innovation in emerging economies and the CDM model. Section 3 presents the data and our econometric approach. Section 4 tests the original CDM model, sections 5 and 6 suggest two alternative specifications rooted in the stylised facts on innovation activities in emerging economies. Section 7 provides a discussion, presents some robustness checks, and compares the results from all three models. Section 8 concludes by summarising the results and discussing some policy-relevant issues from our analysis.

2. Technological change and innovation in emerging economies – the stylised facts - and the CDM model

Based on the main stylised facts of technological change and innovation in latecomer economies, we test the relevance of the R&D based CDM model and two alternative models in the context of emerging Euro-Asian (CEECs/CIS/Turkey) economies. In the first case, the original CDM model, we test the relationship between R&D, innovation and productivity. This model reflects R&D based growth, which is typical of economies operating close to the technology frontier. In the second case, the two-way model, we recognise the relevance of the original CDM model, but we also depict the sequence from production capability to innovation and productivity (Figure 1).

Figure 1: Two-way innovation–productivity model

Source: Authors

In emerging economies, non-R&D activities, such as production capability, are essential to firms' capabilities (Bell and Pavitt, 1993). Bell (2007) clarified the relationships among these categories as follows. Operating or production capabilities refer to using the knowledge embodied in or closely associated with existing production systems and facilities. Design, engineering and related management capabilities refer to the transformation of existing knowledge into new, often innovative, configurations for new or changed production systems. R&D capabilities refer to the creation of *new knowledge* and its translation into specifications for application in production (Bell, 2007). Based on this taxonomy, we argue that operating or production capabilities and design, engineering and associated management capabilities are mostly overlooked in CDM type models. However, in emerging economies, they are more significant as determinants of innovation and productivity than R&D [2].

We are not the first to highlight the limitations of the original CDM model in the context of emerging economies. Bartz et al. (2016) employ the CDM model but include management practices which is an appropriate indirect proxy of production capability. They acknowledge the limits of the R&D based CDM model and propose a modified version. This version includes management practices in a reduced form model that does not have R&D. Based on data from the BEEPS V survey, Bartz et al. (2016) show that high-quality management practices are more significant (twice the effect) for higher labour productivity than innovation. They show that performing R&D has no significant impact on labour productivity. We build on this insight and add several new proxies of the production capability concept. However, we also conceptually and empirically comprehensively explore the issue within the broader literature on technology catchup and productivity in emerging economies.

In the rest of this section, we provide descriptive and secondary evidence supporting an alternative –two-way – innovation model (figure 1). We base this section on data for the EU28, which includes both highly developed and broadly defined middle-income economies, the CEECs and southern European countries, which have similar technology upgrading issues to other emerging economies. The EU 28 serves as an excellent example of differences in the technology activities among countries of different levels of development.

Figure 2 depicts the share of enterprises involved in different innovation activities in three EU regions (north, south and east).[3] EU north has significantly higher involvement in various

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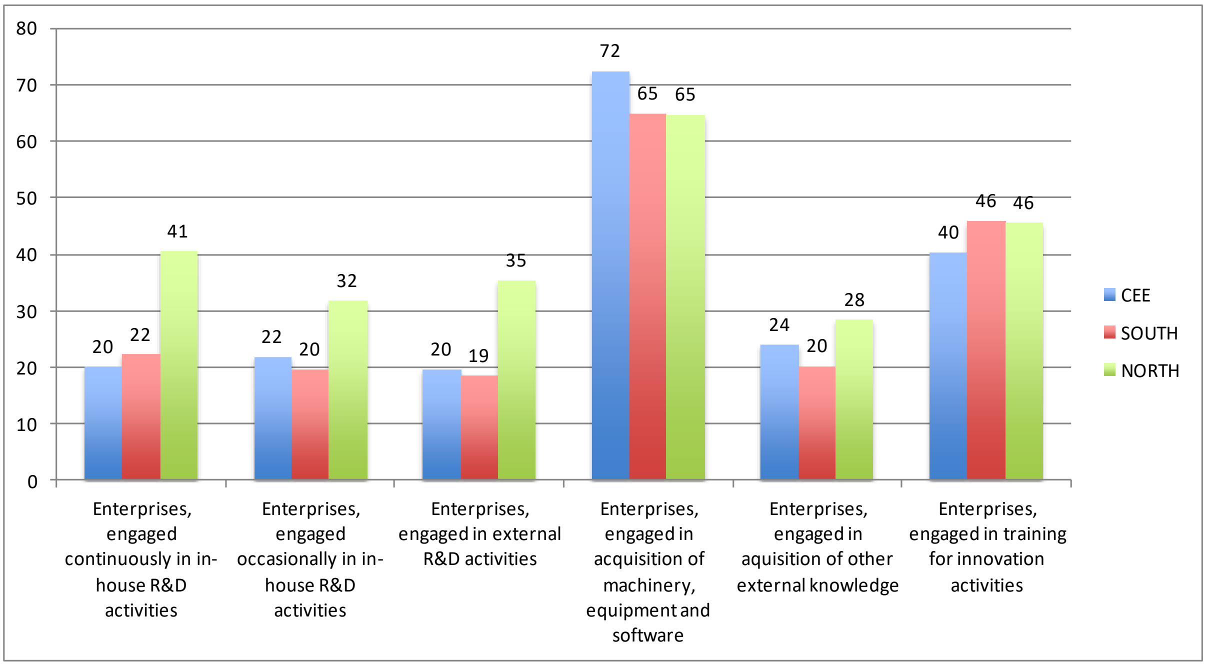
[2] We acknowledge the difficulty involved in capturing and defining variables or identifying appropriate proxies for production, design, engineering and management capabilities. However, this does not justify these critical areas of technology capabilities in emerging economies being ignored.

[3] EU South includes Greece, Portugal, Spain and Italy; EU East is 'new' EU member states from the CEECs; and EU North includes all other countries, except small island economies (Cyprus, Malta) and Luxembourg.

types of R&D activities and lower involvement in the acquisition of M&E compared to EU east/south. These differences suggest different nature of innovation processes in developed to comparatively less developed economies.

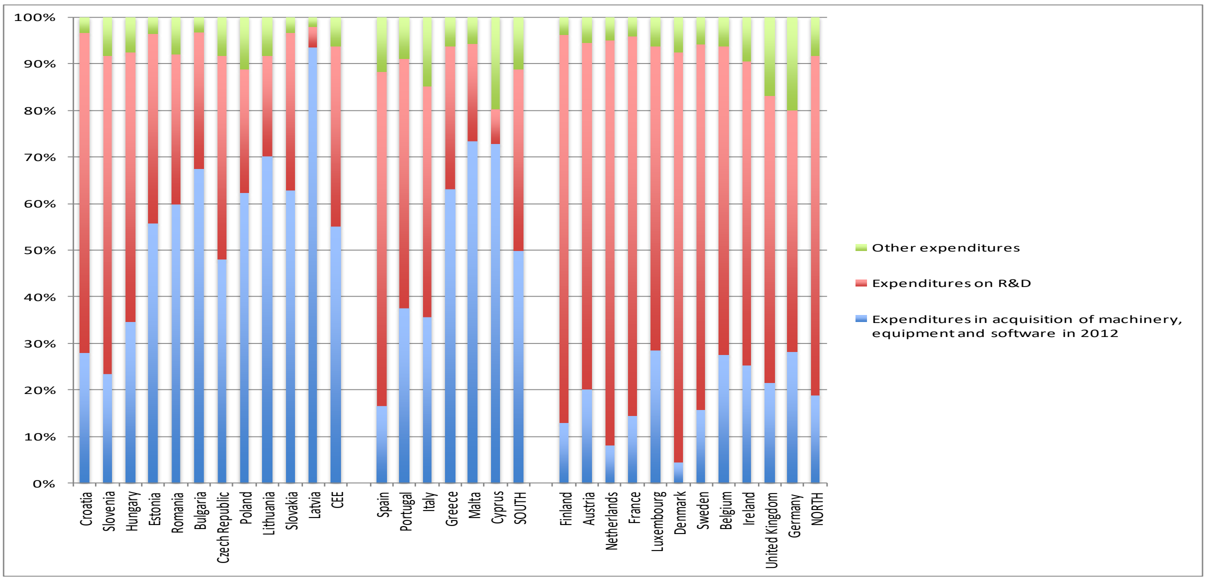
Figure 2: Share (as %) of enterprises involved in different types of innovation activities in 2012: EU



Source: Based on Eurostat Community Innovation survey 2014

Innovation activity in the EU periphery (east and south) is focused strongly on M&E, with a significantly larger share of this type of expenditure, ranging from 27% to 94% (Figure 3). On average, the EU north has a significantly higher share of innovation expenditure on R&D. These differences suggest that innovation in developed EU economies is focused more on knowledge generation. In contrast, in less developed economies, innovation is focused on knowledge exploitation.

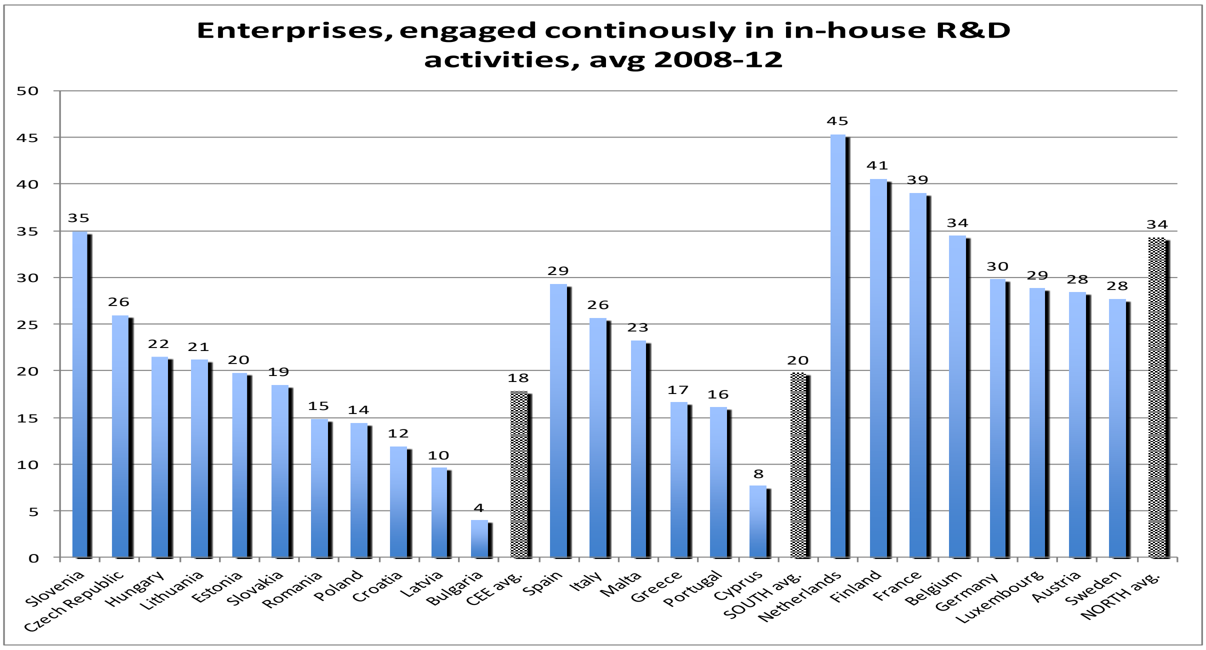
Figure 3: Structure of innovation expenditure 2010-2012



Source: Based on Eurostat Community Innovation survey 2014

Enterprises in countries in the EU periphery are significantly less involved in continuous R&D activity, ranging from 35% in Slovenia to only 4% in Bulgaria (Figure 4). Between 25% and 45% of EU north firms are engaged in continuous in-house R&D activities. The intermittent nature of R&D activity of firms in the EU periphery indicates very limited knowledge generation activities compared to developed parts.

Figure 4: Enterprises engaged in continuous in-house R&D activities, average 2008-12



Source: Based on Eurostat Community Innovation Survey 2104

Other authors have also noted qualitative differences in innovation activities between developed and emerging economies. Crespi and Pluvia (2010) compare R&D expenditures for five Latin American countries and a group of developed, mostly EU economies, and find similar differences with much higher shares of investment in M&E and lower shares in R&D in total innovation expenditure. Kravtsova and Radosevic (2011) show that productivity growth in CEECs/CIS is driven by production capability, not technology capability (patents). Their analysis is a macro level and explores the relationship between productivity, R&D, innovation (patents) and production capability proxied by ISO9001 certificates. A World Bank study (Cirera and Maloney, 2017) of innovation in developing countries shows that imitation and adoption are prevalent in low- and middle-income countries. A significant fraction of innovative firms does not perform R&D in-house. Innovation consists of marginal improvements to processes or products and seldom involves frontier research.

The descriptive evidence presented in figures, references in this section and innovation studies literature (Fagerberg et al., 2010; Bell and Pavitt, 1993) suggests three stylised facts related to innovation activity in broadly defined emerging economies: a) innovation is dominated by tangible assets (investment in M&E); b) macro-level productivity seems to be driven strongly by production (implementation) capability; and c) innovation in less developed economies refers more to successful adoption of a particular technology and less to new technology resulting from in-house R&D.

The focus of our paper is which innovation-productivity model best captures these stylised facts? The CDM model is an R&D based model which imposes a linear relationship between R&D, patents and productivity. Our alternative model(s) propose a link going from downstream activities, specifically investment in M&E, production capabilities, and management practices that directly or indirectly impact productivity improvements[4]. We also acknowledge the presence of R&D based growth in emerging economies and the causation from R&D to innovation and productivity (see figure 1). However, we consider it secondary and macroeconomically marginal compared to causation, which goes from production capabilities to innovation and productivity.

3. The Data and Econometric approach

To test our propositions, we use BEEPS V data[5]. BEEPS dataset is based on the stratified sampling of the whole non-agricultural sector, which gives us unbiased estimates for the entire population and its subgroups. We had to reduce the overall sample because of missing observations for two essential variables. First, the data on innovative sales (% of

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[4] For simplicity reasons we label these three activities as production capabilities

[5] EBRD-World Bank Business Environment and Enterprise Performance Survey (BEEPS)

annual sales accounted for by new or significantly improved products) are available only for 22% of observations. Second, data on R&D expenditures are available only for 9% of observations. As a result, our sample consists of 1,485 firms from 19 countries for 2012-14. We checked the representativeness of our sample only on the case of the Central and Eastern European economies (Czechia, Estonia, Croatia, Latvia, Romania, Slovenia and Slovakia, North Macedonia and Turkey), which is surprisingly high (see Annex 1). A difference regarding the lower average number of employees per firm in our sample compared to the population is probably due to the BEEPS survey, including only private and not also state-owned firms. Unfortunately, we cannot check representativeness for the former Soviet Union economies due to the poor availability of data available for only five out of nine economies of the former Soviet Union (Russia, Belarus, Ukraine, Armenia Kyrgyzstan). In addition, data are of questionable comparability due to methodological differences and uneven data quality.

Tables 1 and 2 present descriptive statistics for our sample of firms. Table 1 presents the list of variables, and Table 2 shows the distribution of observations by country and income groups.

Table 1: Descriptive statistics

Variable	**Definition**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Product innovators	New products/services introduced over the last 3 years	1,485	0.315	0.465	0	1
Process innovators	New production/supply methods introduced over the last 3 years	1,485	0.308	0.462	0	1
Organizational innovators	New organisational/management practices or structures introduced over the last 3 years	1,485	0.321	0.467	0	1
Patent	Applied/Granted a patent/trademark over the last 3 years	1,484	0.079	0.270	0	1

Innovation intensity (Innovative sales)	Annual sales accounted for by new or significantly improved products/services, %	1,485	7.836	18.023	0	100
R&D intensity	Expenditures for R&D over last 3 years to annual sales ratio	1,485	.0044	0.031	0	0.72
Internationally-recognized certification	Whether establishment has an internationally-recognized quality certification	1,485	0.195	0.396	0	1
New logistical or business support	New logistical or business support processes introduced over last 3 years	1,485	0.108	0.310	0	1
New organizational /management practices	New organisational/management practices or structures introduced over last 3	1,485	0.321	0.467	0	1
Employee training	Share of full-time employees received formal training in last year >10%	1,485	0.119	0.323	0	1
Production capabilities	Whether establishment has international quality certificate and share of full-time employee received formal training in last year>10%	1,485	0.276	0.447	0	1
Involvement of employees in R&D	Whether a firm gives employees time to develop or try out a new approach/idea about products/services	1,485	0.229	0.420	0	1
Productivity	Sales adjusted for national exchange rate, USD per employee, logarithm	1,483	10.399	1.625	0	20.141

Capital to labor ratio	Net book value of machinery vehicles and equipment in the last fiscal year adjusted by national currency exchange rate, USD per full time-employment	460	14.023	4.495	0.010	27.328
Size	No. permanent, full-time employees of firm at the end of last fiscal year, logarithm	1,485	3.256	1.270	0	8.343
Age	Number of years since the establishment began operations	1,485	13.670	10.818	1	89
Export intensity	Export to total sales ratio >10%	1,485	0.084	0.230	0	1
Foreign	Share of foreign ownership >10%	1,485	0.069	0.253	0	1
Investment intensity	Total annual expenditure for purchases of equipment adjusted by national currency exchange rates, USD per number of employees in the last fiscal year, logarithm	1,485	10.13	2.57	0	18.89

Table 2: Distribution of observations (number of firms) by country and income groups

High income	**231**	**Upper middle income**	**991**	**Lower middle income**	**263**
Czechia	6	Albania	30	Armenia	46
Estonia	83	Belarus	10	Georgia	2
Latvia	48	Croatia	115	Kyrgyzstan	31
Slovakia	19	North Macedonia	11	Mongolia	123
Slovenia	75	Romania	71	Tajikistan	38

		Russia	747	Ukraine	8
		Turkey	7	Uzbekistan	15
Total					**1,485**

We estimate the original CDM model (Crépon et al., 1998) in three steps. The first step is specified by a Heckman selection model and has two equations: equation (4.1) (selection equation) determines the firm's decision to engage in R&D, where $R\&D\ decision_i^*$ is the latent dependent variable, if it $R\&D\ decision_i^*$ exceeds a certain threshold, the firm engages in R&D[6]; equation (4.2) (outcome equation) determines R&D intensity for those firms that have decided to invest. The second step tests the determinants of patenting activity using the R&D intensity predicted in the first step with a simple probit (equation 4.3). The third step estimates the determinants of productivity using the predicted patenting intensity from step 2 with OLS (equation 4.4).

$$R\&D\ decision_i^* = X_{0i}\beta_0 + u_{0i} \tag{4.1}$$

$$R\&D\ intensity_i = X_{1i}\beta_1 + u_{1i} \tag{4.2}$$

$$Patent\ activity_i = \alpha_{2i} R\&D\ intensity_{1i}^* + X_{2i}\beta_2 + u_{2i} \tag{4.3}$$

$$Productivity_{3i} = \alpha_{3i} Patent\ activity_{2i}^* + X_{3i}\beta_3 + u_{3i}, \tag{4.4}$$

where $X_{oi}, X_{1i}, X_{2i}, X_{3i}$ are vectors of various explanatory variables respective to equations (4.1)-(4.4), $\alpha's\ and\ \beta's\ \ are\ the\ unknown\ parameters$, $u_{oi}, u_{1i}, u_{2i}, u_{3i}$ are the disturbances.

For the determinants of R&D performance, we include export intensity, foreign ownership, involvement of employees in R&D and investment intensity. Being an exporter or a foreign-owned company results in better firm performance. The involvement of employees in R&D refers to how much the firm's employees are involved in R&D activities. We use this rather than R&D expenditures or R&D employment which is an 'upstream' R&D activity, to proxy for 'downstream' R&D activity[7]. Given the importance of physical investment for emerging economies, we include investment intensity as a variable. Based on Peters (2008), we add

[6] Here and after: variables with a star are latent variables; all other variables are observable except the disturbances

[7] R&D employment assumes permanent R&D activity and thus refers to 'exploration' type of knowledge generation activity. The involvement of employees in R&D denotes the extent to which all employees are involved in R&D and thus reflects knowledge 'exploitation' activities. It is in this sense that we distinguish upstream (exploration) from downstream (exploitation) R&D activities. (Cohen and Levinthal, 1989)

size and age to the selection equation since they influence the decision to innovate, but not the intensity of innovation.

We test all the models on the full sample of innovators and three distinct types - organisational, product and process innovators. We consider this a necessary robustness check and the correct way to explore whether the determinants differ across different types of innovations. We control for country and industry fixed effects.

There are two major approaches to estimating the CDM model and its modifications. The first approach is based on the original paper (Crepon et al., 1998) and uses simultaneous ALS estimation to deal with selectivity and simultaneity biases. The major drawback of this approach is strong assumptions on the joint distribution of disturbances and complicated calculations. Only three papers follow simultaneous estimation techniques to the best of our knowledge. Benavente (2006) and Mairesse and Mohnen (2005) use ALS estimation technique, while Raymond et al.(2013) use maximum likelihood. The second approach uses stepwise techniques. The authors solve endogeneity issues by using predicted values of the dependent variable from the previous equation as an instrument for the successive equation in the CDM model. To estimate the innovation input (R&D intensity) equation, the authors usually use Generalised Tobit (FIML) (Griffith et al., 2006; Loof, Heshmati, 2001; Loof et al., 2001) or Heckman (Klomp and van Leeuwen, 2001; van Leeuwen and Klomp, 2006) approaches. To estimate innovation output equations, the authors use logit, logit with random effects of conditional logit (Parisi et al., 2006), probit (Griffith et al., 2006), ordered probit (Benavente. 2006) or OLS (Klomp and van Leeuwen, 2001; Jefferson et al., 2006). Finally, the authors use OLS to estimate the productivity equation (Jefferson et al., 2006; Criscuolo and Haskel, 2003; Klomp, van Leeuwen, 2001). Some authors introduce a simultaneous approach but only for some of the equations in the CDM model and 2SLS, 3SLS and FIML estimation techniques (van Leeuwen and Klomp, 2006; Griffith et al., 2006; Loof et al., 2003; Loof, Hechmati, 2001). This paper follows a conventional way to estimate the CDM model. To reduce the possible effects of selectivity bias, we correct for selectivity by applying Heckman's two-step procedure. We estimate the innovation output equation with probit and OLS and the productivity equation with OLS. The potential endogeneity of innovation input and output is considered by using its predicted values in innovation output and productivity equations, respectively.

Since we are working with a subsample of the BEEPS V database, which is in overall representative, we address the potential bias of the estimates and the use of weighted estimation procedures. According to (Solon et al., 2015), if the researchers are not concerned with the unbiased estimates for the whole population as in our study, the use of weights is more nuanced and might be less precise in some cases. Following their recommendations, we estimate the models using robust standard errors, which enables us to correct heteroscedasticity as an alternative to weights. However, we also estimate all the models with weightings when possible and discuss the comparability of weighted and unweighted results.

4. Testing the original CDM model

The results of this model are reported in Table 3 and show that export intensive firms have higher R&D intensity. The highest impact is for product innovators, and the lowest is for organisational innovators. R&D intensity does not increase for foreign-owned firms and only marginally for organisational and process innovators with higher investment intensity. Except for process innovators, higher involvement of employees in R&D does not increase R&D intensity. These results are intuitively plausible since we would expect exporters to be better performing firms. As expected, the lack of robust association of the other determinants to the intensity of R&D activities is a feature specific to the emerging economies in line with our core argument.

Our selection equations confirm that size is a significant differentiating variable for all innovators (Table 3). This is expected and reflects the stylised fact in innovation studies that large R&D performing firms are more frequent innovators. However, intensive exporters (although no process innovators) are not more significantly associated with the probability of being an R&D performer. It seems that size rather than export intensity *per se* is the dominant factor. Also, for all three types of innovators, higher investment intensity is associated with a higher probability of performing R&D, although not for the group of innovators in aggregate. In a nutshell, size and investment intensity are the dominant determinants of R&D activity in emerging economies.

Table 3. Determinants of R&D intensity. Heckman selection model

	(1)	(2)	(4)	(5)	(7)	(8)	(10)	(11)
VARIABLES	Innovators		Organizational Innovators		Product Innovators		Process Innovators	
	outcome	selection equation	outcome	selection equation	outcome	selection equation	outcome	selection equation
Export intensity	0.0193***	0.053	0.014***	0.023	0.030***	0.145	0.022***	0.190*
	(0.005)	(0.108)	(0.005)	(0.114)	(0.008)	(0.109)	(0.007)	(0.114)
Foreign	0.007	0.021	0.000	0.125	0.012	-0.114	0.015	-0.121

owned	(0.006)	(0.150)	(0.006)	(0.154)	(0.010)	(0.152)	(0.009)	(0.160)
Investment intensity	0.001	0.022	0.002**	0.058**	0.002	0.063***	0.004***	0.075***
	(0.001)	(0.022)	(0.001)	(0.023)	(0.002)	(0.023)	(0.001)	(0.023)
Involvement of employees	0.006		0.002		0.006		0.015**	
	(0.005)		(0.005)		(0.009)		(0.007)	
Size		0.142***		0.219***		0.103***		0.185***
		(0.033)		(0.034)		(0.033)		(0.034)
Age		0.007		-0.016**		0.010		0.0063
		(0.007)		(0.007)		(0.007)		(0.007)
Constant	0.002	-1.977***	-0.041	-2.979***	-0.019	-3.305***	-0.060	-3.858***
	(0.034)	(0.537)	(0.039)	(0.637)	(0.086)	(0.679)	(0.064)	(0.702)
Mills Ratio[8]	0.014 (0.014)		0.017 (0.009)		0.022 (0.025)		0.022 (0.014)	
Country FE	+	+	+	+	+	+	+	+
Industry FE	+	+	+	+	+	+	+	+
Observations	1,439	779	1,439	462	1,439	456	1,439	445

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

In the second model (Table 4), we use the R&D intensity predicted by the first model to test the determinants of innovation activity based on patents. We add the variables included in the previous regression (age, export, investment intensity). As in the original CDM model, we consider these variables as having an indirect impact on the dependent variable (Crépon et al., 1998, pp.123, 124). Also, as in the original CDM model, we test this relationship on the whole sample, not just on the sample of innovators.

In the regression that includes only predicted R&D intensity, this variable is significant for all innovators, including the aggregate group (Table 4). However, when we add the control variables, the coefficient of predicted R&D intensity loses its significance in all four equations. Only age and involvement of employees in R&D are significant in all the

[8] An insignificant lambda indicates no self-selection bias and suggests we could have used a linear (OLS) model. In a previous version of the paper, we used probit and OLS and obtained identical results.

equations. Age is marginally significant and suggests that the time taken to accumulate capabilities leads to a higher probability of patenting – an additional year of activity increases firms' probability of patenting by 0.3 percentage points. Also, if employees are involved in R&D firm's probability of patenting is higher by 9.7-10.1 percentage points, where a higher probability is for improvements to products/processes. Export intensity is not significant for organisational innovators or the aggregate group of innovators. Still, it is significant for product and process innovators, increasing the likelihood of patent activity by 5.6-6.0 percentage points. Being a foreign firm or having higher investment intensity does not increase the probability of patenting activity.

Estimation of patent activity determinants using weighted probit gives similar results in terms of variable significance and the size of the effects[9]. Age and employees' involvement in R&D are the only variables significant in all specifications. One additional year of activity increases patenting probability by 0,5 percentage points, involvement of employees in R&D increases patenting probability by 8.5-9.4 percentage points.

Table 4. Determinants of patent activity, probit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Innovators		Organizational Innovators		Product Innovators		Process Innovators	
Predicted R&D intensity	4.387***	0.075	8.825***	5.994*	2.271*	-0.743	2.822**	-0.593
	(1.611)	(2.428)	(2.672)	(3.068)	(1.295)	(1.694)	(1.421)	(1.581)
Age		0.003**		0.003**		0.003**		0.003**
		(0.001)		(0.001)		(0.001)		(0.001)
Export intensity		0.051		0.022		0.060**		0.056**
		(0.034)		(0.027)		(0.028)		(0.026)
Foreign		0.044		0.045		0.048		0.047
		(0.030)		(0.029)		(0.030)		(0.031)
Investment intensity		0.005		0.003		0.006		0.006
		(0.005)		(0.005)		(0.005)		(0.005)
Involvement of employees in R&D		0.099***		0.097***		0.100***		0.101***
		(0.025)		(0.025)		(0.025)		(0.025)

[9] Hereinafter due to space limit, results with weighted estimators are not shown in the paper

Industry FE	+	+	+	+	+	+	+	+
Country FE	+	+	+	+	+	+	+	+
Observations	1,342	1,342	1,342	1,342	1,342	1,342	1,342	1,342

Note: Average marginal effects are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

In the fourth step (Table 5), we include predicted patenting intensity as a determinant of productivity together with previously used variables that affect productivity indirectly. In the simple estimation, predicted patenting is significant for productivity in all four regressions. However, when we add the control variables, predicted patenting intensity as a proxy for innovation loses its significance or is significant only at the 10% level in the pooled regression and for product innovators. Overall explanatory power increases in the models that include the control variables, as shown by the higher R2. Only investment intensity is significant at the 1% level in all four regressions. An increase in investment intensity (total annual expenditure for equipment per employee) by 1% leads to an increase in productivity by 15.9-17.6%. This suggests that increased productivity is associated significantly with increasing investment intensity, while patent intensity is much less significant and is not linked consistently to increased productivity.

Foreign ownership is not associated with higher productivity except at a low significance level for organisational innovators. Age, export intensity and involvement of employees in R&D are not associated significantly with higher productivity.

Estimation of the determinants of productivity with weighted least squares is in line with unweighted results. Predicted patenting intensity as a proxy keeps significance in a simple model but loses significance in the pooled regression. Investment intensity is again a significant factor of productivity, and its increase by 1% increases productivity by 17.9-18.3%. Foreign ownership becomes a significant factor – foreign firms are more productive by 47.6-56.6%.

Table 5. Determinants of productivity. OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Innovators		Organisational		Product		Process Innovators	

			Innovators		Innovators			
Predicted patent	4.381***	3.850*	3.376***	1.128	4.536***	4.549*	4.431***	4.040
	(0.940)	(2.323)	(0.895)	(1.654)	(0.684)	(2.393)	(0.963)	(2.512)
Age		-0.008		-0.000		-0.0102		-0.009
		(0.009)		(0.008)		(0.009)		(0.010)
Export intensity		-0.020		0.135		-0.061		-0.031
		(0.179)		(0.149)		(0.183)		(0.186)
Foreign		0.209		0.377*		0.168		0.200
		(0.237)		(0.218)		(0.240)		(0.244)
Investment intensity		0.160***		0.176***		0.155***		0.159***
		(0.028)		(0.026)		(0.028)		(0.029)
Involvement of employees in R&D		-0.141		0.136		-0.212		-0.161
		(0.223)		(0.183)		(0.229)		(0.238)
Constant	8.362***	6.384***	8.500***	6.342***	8.347***	6.399***	8.364***	6.393***
	(0.293)	(0.428)	(0.294)	(0.429)	(0.465)	(0.424)	(0.292)	(0.425)
Country FE	+	+	+	+	+	+	+	+
Industry FE	+	+	+	+	+	+	+	+
Observations	1,342	1,342	1,342	1,342	1,342	1,342	1,342	1,342
R-squared	0.280	0.309	0.273	0.306	0.281	0.310	0.280	0.309

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

In summary, testing the original CDM model on the sample of firms from the emerging Euro-Asian (CEECs/CIS/Turkey) economies suggests that neither patents nor innovation sales are predictors of productivity once we control for other factors. This leads us to consider alternatives.

We test the alternative to the original CDM model; we leave the first two equations (4.1 and 4.2) with no change but use innovative sales instead of patents to measure innovation output and include predicted R&D as the determinant (equation (4.3'). Equation (4.4) includes predicted innovative sales as a determinant of productivity.

$$Innovative\ sales_i = \alpha_{2i} R\&D\ intensity^*_{1i} + X_{2i}\beta_2 + u_{2i} \qquad (4.3')$$

$$Productivity_{3i} = \alpha_{3i} Innovative\ sales^*_{2i} + X_{3i}\beta_3 + u_{3i} \qquad (4.4')$$

Like the model which uses predicted patents, predicted R&D intensity in the single estimation is significant in all four regressions (Table 6). Predicted R&D intensity loses significance when we add control variables except in the model with pooled all innovators at 5% level of significance. However, the involvement of employees in R&D as a proxy for downstream knowledge activities is associated significantly and positively with productivity. If employees are involved in R&D in a firm, its innovative sales are higher by 7.4-7.8%. Age and export intensity are insignificant while being a foreign firm decreases a firm's innovative sales by 3.5-3.8% although at the 5% level of significance and except for organisational innovators. Investment intensity is significant in all four models, although only at the 10% level. In addition, the overall significance of the model is low - R2 decreases to 10%.

Table 6. Determinants of innovative sales, OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Innovators		Organisational Innovators		Product Innovators		Process Innovators	
Predicted R&D intensity	272.4**	366.7**	387.5	265.8	224.5	259.2	261.7**	205.5
	(138.3)	(182.5)	(252.0)	(266.5)			(127.2)	(137.0)
Age		0.052		0.0453		0.053		0.0442
		(0.088)		(0.089)		(0.089)		(0.089)
Export intensity		-2.324		0.135		-1.097		-0.003
		(1.640)		(1.365)		(1.406)		(1.516)
Foreign		-3.769**		-2.510		-3.588**		-3.484**
		(1.805)		(1.816)		(1.798)		(1.673)
Investment intensity		0.511*		0.511*		0.540*		0.475*
		(0.290)		(0.301)		(0.288)		(0.288)
Involvement of employees in R&D		7.427***		7.819***		7.689***		7.567***
		(1.553)		(1.528)		(1.538)		(1.553)
Constant	4.318	-5.582	11.93*	4.435	6.442	-2.149	3.255	-1.535
	(7.452)	(8.434)	(6.172)	(7.419)	(7.285)	(7.992)	(7.742)	(8.399)
Country FE	+	+	+	+	+	+	+	+
Industry FE	+	+	+	+	+	+	+	+

Observations	1,439	1,439	1,439	1,439	1,439	1,439	1,439	1,439
R-squared	0.080	0.106	0.079	0.103	0.080	0.106	0.081	0.104

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 7 presents the determinants of productivity for an alternative CDM model; if we add the control variables, predicted innovative output measured by predicted innovative sales is insignificant. Both involvement of employees in R&D (proxy for downstream R&D activities) and firm age are insignificant. The variables that are significant overall are foreign ownership and investment intensity. Foreign ownership increases productivity by 49.5-59.4%. An increase in investment intensity by 1% increases firms' productivity by 17.4-20.1%, export intensity is significant at the 10% level for product innovators. The involvement of employees in R&D and firm age are both insignificant.

Table 7. Determinants of productivity. OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Innovators		Organisational Innovators		Product Innovators		Process Innovators	
Predicted innovative sales (innovation intensity)	0.061***	0.017	0.065***	0.028	0.058***	-0.006	0.066***	0.042
	(0.015)	(0.030)						
Age		0.005		0.004		0.006		0.004
		(0.007)		(0.007)		(0.007)		(0.007)
Export intensity		0.185		0.177		0.209*		0.164
		(0.125)		(0.124)		(0.123)		(0.126)
Foreign owned		0.543***		0.570***		0.495**		0.594***
		(0.194)		(0.209)		(0.193)		(0.191)
Investment intensity		0.188***		0.182***		0.201***		0.174***
		(0.029)		(0.036)		(0.029)		(0.029)
Involvement of employees in R&D		0.111		0.025		0.281		-0.076
		(0.241)		(0.422)		(0.246)		(0.270)
Constant	8.138***	6.044***	8.081***	5.972***	8.185***	6.176***	8.077***	5.902***
	(0.350)	(0.457)	(0.357)	(0.553)	(0.347)	(0.452)	(0.347)	(0.459)

Country FE	+	+	+	+	+	+	+	+
Industry FE	+	+	+	+	+	+	+	+
Observations	1,439	1,439	1,439	1,439	1,439	1,439	1,439	1,439
R-squared	0.253	0.292	0.253	0.292	0.251	0.291	0.254	0.292

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

In general, the alternative to the original CDM model provides only weak support for the R&D-innovation-productivity link, with investment intensity as the only highly statistically significant variable in both models.

The original CDM model assumes that innovation is promoted by R&D and that R&D will lead to patents and innovative sales, which will be significant determinants of productivity. A key result from testing the original CDM model on BEEPS data is that neither patents nor innovation sales are predictors of productivity. If we control for other factors, they become insignificant. This is expected based on the stylised facts on innovation in emerging economies, highlighted in section 2. In these economies, most firms operate well behind the technology frontier, and their innovation and growth are based more on investment, management and production capability than on R&D.

In the next section, we identify an alternative to the CDM model depicted on the right-hand side of figure 1 to explain productivity in emerging economies. We construct two alternative model types highlighting the two stylised facts of innovation activities in emerging economies: high share of physical investment in innovation activity and production capability as the major area of productivity improvements.

5. Alternative investment-driven model of the relationship between innovation and productivity

We test a model based on the investment in line with three stylised facts on emerging economies (section 2). Technological change in economies behind the technology frontier is based chiefly on imported technology, with expenditures on R&D being marginal. Innovation in emerging economies depends mainly on the adoption of imported technology to achieve world-class efficiency in its use. Our alternative model involves three steps, similar to the CDM model. In the first step, we test the determinants of investment intensity, then innovation intensity, and productivity.

Like in the estimation procedure of the original CDM model, we estimate investment intensity using Heckman's two-stage selection method. The first step has two equations (equations

(5.1) and (5.2)): the selection equation estimates the propensity to invest, and the second estimates investment intensity. Both equations include size, age, export intensity, foreign ownership and firm's capital intensity as determinants. In line with the CDM model, we add size and age to the selection equation since they influence the investment decision but not the investment intensity. The second step determines innovative sales (equation 5.3), and the third step identifies productivity determinants, estimated using OLS (equation 5.4). Again, we take the conventional stepwise approach and solve endogeneity issues by including predicted values as instruments.

$$Investment\ decision_i^* = X_{0i}\beta_0 + u_{0i} \qquad (5.1)$$

$$Investment\ intensity_i = X_{1i}\beta_1 + u_{1i} \qquad (5.2)$$

$$Innovative\ sales_i = \alpha_{2i} Investment\ intensity_{1i}^* + X_{2i}\beta_2 + u_{2i} \qquad (5.3)$$

$$Productivity_{3i} = \alpha_{3i} Innovative\ sales_{2i}^* + X_{3i}\beta_3 + u_{3i} \qquad (5.4)$$

where $X_{oi}, X_{1i}, X_{2i}, X_{3i}$ are vectors of various explanatory variables respective to equations (5.1)-(5.4), $\alpha's\ and\ \beta's\ \ are\ the\ unknown\ parameters$, $u_{oi}, u_{1i}, u_{2i}, u_{3i}$ are the disturbances.

Our results show that capital intensity is the only significant determinant of investment intensity both at the selection and outcome equations. Export intensity and foreign ownership are insignificant in both equations; size and age are included only in the selection equation and are insignificant. The Mills Ratio is positive and statistically significant, which indicates that there is potential for self-selection issues and that OLS estimation would have led to biased results[10].

In the second step, we use the predicted investment intensity from the first regression to test the determinants of innovation intensity, measured as the percentage of innovation sales. As additional explanatory variables, we use three different proxies for R&D and four different proxies for production and management capabilities. R&D intensity is measured by the share of expenditure above 1% of sales, defined as a dummy and as a percentage, and a dummy variable for employees' involvement in R&D. In line with the stylised facts, we include two proxies for production capabilities: dummy variables for international certifications and employee training.

Table 8 shows that innovation intensity is not significantly associated with predicted investment intensity. Innovation intensity is driven positively by the variables for R&D intensity, especially the involvement of employees in R&D. Increase in the share of

[10] Due to space limit, results for the estimation are not shown in the paper

expenditures for R&D in annual sales by one percentage point increases innovative sales by 1.040-1.07 percentage points (models 1 and 2). Employees' participation in R&D activities increases innovative sales by 5.6%-9.7%, and the introduction of new organisational and managerial practices increases innovative sales by 10.5%-10.9% (models 3 and 6). This suggests that investment intensity, on its own, cannot increase innovation intensity. Instead, this depends on knowledge activities specific to emerging economies related to R&D capabilities (upstream and downstream R&D activities) and management practices. Our proxies for production capabilities (international certifications and employee training) and support for new logistics are not significant, suggesting a non-linear relationship between innovation and production capability and that these activities are qualitatively different. They may sometimes be complements, but in most cases, they are parallel activities with different timing and sequence of adoption (Bourke and Roper, 2017).

Estimation of innovative sales determinants using weighted least squares produces similar results regarding the significance and the size of the effects. In particular, an increase in the share of expenditures for R&D in annual sales by 1% increases innovative sales by 1.02-1.06 percentage points. Employees' participation in R&D activities increases innovative sales by 5.2%-9.1%, introduction of new organisational and managerial practices - by 10.8%-11.1%.

Table 8. Determinants of innovative sales, OLS

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
Predicted investment intensity	0.554	0.623	0.408	0.464	0.563	0.363
	(0.887)	(0.901)	(0.877)	(0.882)	(0.895)	(0.870)
Share of expenditures for R&D	106.5**	103.700**	66.800			
	(42.840)	(42.020)	(41.320)			
Involvement of employees in R&D	9.689***	8.197**	6.089**	8.904***	7.554**	5.595*
	(2.886)	(3.222)	(3.075)	(2.891)	(3.274)	(3.122)
Internationally-recognised certification dummy		-2.167	-2.405		-1.785	-2.146
		(1.980)	(1.958)		(1.981)	(1.959)
New logistical or		5.041	0.647		4.787	0.482

business support dummy		(4.021)	(4.124)		(3.947)	(4.062)
Employee training dummy		-1.076	-1.815		-1.601	-2.201
		(2.211)	(2.135)		(2.181)	(2.115)
New organisational/management practices dummy			10.870***			10.500***
			(2.577)			(2.567)
Share of expenditures for R&D dummy				12.24***	12.03***	9.488**
				(4.253)	(4.166)	(4.315)
Constant	3.393	4.799	1.674	6.363	7.654	4.126
	(14.010)	(14.340)	(13.900)	(13.990)	(14.330)	(13.880)
Country FE	+	+	+	+	+	+
Industry FE	+	+	+	+	+	+
Observations	460	460	460	460	460	460
R-squared	0.146	0.152	0.196	0.159	0.164	0.206

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

In the third step (Table 9), we use the predicted innovation intensity from the previous equation and add patents to proxy for explicit technological activities and production capabilities which include international quality certification and employee training. We also control for firm size and capital intensity. The model shows first that productivity is explained by production capabilities which are significant in all five models. In models (3)-(5), production capabilities increase productivity by 22.9%-38.7% depending on the type of fixed effects controlled for. Second, innovation intensity has a mixed impact on productivity; it is insignificant in two of the estimations and positive, but significant at 10% in three out of the five. An increase in innovation intensity by 1% increases productivity by 1.2-1.7%. Third, the effect of production capability diminishes with country fixed effects, while innovation intensity is either insignificant or significant only at the 10% level. This, again, highlights the qualitatively different role played by production capabilities and innovation capabilities. They appear to be related non-linearly; improved production capability does not necessarily lead to improved innovation capability. These results align with micro-level studies that explore the relationship between quality improvements and innovation (Leavengood et al., 2012).

If we add the country fixed effects, the coefficient of determination improves significantly, although it is still quite low. If we include both country and industry fixed effects, predicted innovation intensity turns significant. Patents, which in the original CDM model are not significant, remain insignificant. Production capability captures manufacturing or implementation (exploitation) capabilities, while patents capture knowledge or technology generation (exploration) activities.

Estimation of productivity equation using weighted least squares produces similar results, and the sizes of the effects are close to those in OLS. First, predicted innovation intensity is insignificant in all five models with and without country and industry fixed effects. The only statistically significant determinant in weighted least squares is production capabilities (apart from the capital to labour in model 1); the effect size is 22.5-37.6%, which is very close to the size in the unweighted model.

Table 9. Determinants of productivity, OLS

	(1)	(2)	(3)	(4)	(5)
VARIABLES					
Predicted innovation intensity	0.012*	0.012*	0.012	0.011	0.017*
	(0.007)	(0.007)	(0.008)	(0.008)	(0.010)
Granted patents over last 3 years	0.147	0.141	0.260	0.278	0.282
	(0.196)	(0.198)	(0.200)	(0.198)	(0.214)
Size		-0.035	-0.011	0.037	0.057
		(0.043)	(0.044)	(0.041)	(0.045)
Production capabilities (international quality certificate and employee training)	0.513***	0.527***	0.387***	0.311**	0.229*
	(0.127)	(0.126)	(0.129)	(0.126)	(0.125)
Capital to labour	-0.030**				
	(0.015)				

Constant	10.200***	9.896***	10.720***	8.887***	9.304***
	(0.244)	(0.175)	(0.315)	(0.259)	(0.332)
Country FE	-	-	-	+	+
Industry FE	-	-	+	-	+
Observations	460	460	460	460	460
R-squared	0.053	0.044	0.128	0.211	0.266

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

The first alternative model explains innovation intensity based on a combination of R&D and production capability, with predicted investment intensity being an insignificant explanatory factor. Productivity is explained by the production capability variables and, in some specifications, by predicted innovation intensity, but at a low significance level (10%). This alternative case confirms the importance of production capability as a determinant of productivity and that physical investments do not significantly determine innovation or productivity. Based on these insights, we propose the second alternative to the original CDM model, starting from production capability, that is, from manufacturing (implementation) capability, which is considered the first step in the acquisition of technology and innovation capability (Lee et al., 2020; Bell and Pavitt, 1993).

6. Alternative production capability driven model of the relationship between innovation and productivity

The model starts by employing a probit estimation to test the determinants of production capability, considered essential for innovation intensity and productivity (equation 6.1). Then we estimate the determinants of innovation intensity measured by innovative sales (estimated by OLS) and the number of patents (estimated by probit) (equations 6.2 and 6.2’). The last step is an OLS regression to estimate the determinants of productivity (equation 6.3). As in the estimation of the original CDM model, we take a stepwise approach and take care of the endogeneity by using predicted values from the previous step as instruments for the subsequent step in the model.

$$Production\ capability_i = X_{1i}\beta_1 + u_{1i} \qquad (6.1)$$

$$Innovative\ sales_i = \alpha_{2i} Production\ capability^*_{1i} + X_{2i}\beta_2 + u_{2i} \qquad (6.2)$$

$$Patents_i = \alpha_{2i} Production\ capability^*_{1i} + X_{2i}\beta_2 + u_{2i} \qquad (6.2')$$

$$Productivity_{3i} = \alpha_{3i} Innovative\ sales^{*}_{2i} + X_{3i}\beta_3 + u_{3i} \qquad (6.3)$$

where $X_{oi}, X_{1i}, X_{2i}, X_{3i}$ are vectors of various explanatory variables respective to equations (6.1)-(6.4), $\alpha's\ and\ \beta's\ \ are\ the\ unknown\ parameters$, $u_{oi}, u_{1i}, u_{2i}, u_{3i}$ are the disturbances.

Estimation of equation 6.1 shows that production capabilities are affected positively by size, export intensity, age and investment intensity[11]. Foreign ownership is a significant contributing factor. Physical investment dominates innovation expenditure in emerging economies and significantly explains production capability. Larger firms are more likely to obtain quality certification and adopt better management practices, which is reflected in the significant coefficient of size on production capability. Also, firms with export intensity are 6.7% more likely, on average, to meet quality requirements. Age may be a proxy for accumulated organisational capabilities, which are reflected in the firm's higher production capabilities, although the size of this effect is small.

In the second step, we test the determinants of innovation intensity using predicted production capabilities from the first equation, including R&D and the control variables used in model 1 (Table 10). We also use patents as an alternative proxy for innovation (model 2). We find that innovation intensity is affected positively by R&D intensity and investment intensity. An increase in R&D expenditures to total sales ratio by one percentage point increases innovation intensity by 1.2 percentage points, an increase in investment intensity by 1% increases innovation intensity by 0.7 percentage points (Table 10). This confirms the stylised fact that innovation in emerging economies is about the acquisition of M&E. However, the joint significance of R&D and investment intensity suggest that R&D is required not only to generate new knowledge but also to absorb new technology. It confirms Cohen and Levinthal's (1989) notion of R&D as being about both the generation and absorption of existing knowledge. Predicted production capability is not a significant explanatory factor in innovation intensity, supporting our assumption about the qualitative difference between production capability and innovation capability.

The model includes patenting intensity, R&D intensity, and firm size are significant explanatory variables. This is as expected since patents refer to technology changing activities while R&D capabilities refer to both knowledge generation and knowledge absorption (Cohen and Levinthal, 1989). Also, size contributes significantly to patenting intensity, while investment intensity does not necessarily induce knowledge generation, proxied by patents.

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[11] Due to space limit, results of the regression are not shown in the paper

Estimation of the determinants of innovation intensity using weighted least squares and weighted probit, respectively, gives similar results. For innovative sales equations, all variables keep the significance levels and provide a similar size of the effects. An increase in R&D expenditures to total sales ratio by one percentage point increases innovation intensity by 1.2 percentage points, an increase in investment intensity by 1% - by 0.7 percentage points.

Table 10. Determinants of Innovation intensity

	(1)	(2)
VARIABLES	Innovative sales, OLS	Patents, probit
Predicted production capabilities	0.120	0.038
	(1.962)	(0.026)
R&D intensity	121.3***	0.994***
	(22.674)	(0.327)
Size	0.456	0.028***
	(0.462)	(0.007)
Age	0.008	0.000
	(0.095)	(0.001)
Export intensity	-0.486	0.016
	(1.343)	(0.021)
Foreign	-2.392	0.022
	(1.747)	(0.025)
Investment intensity	0.698**	0.007
	(0.256)	(0.005)
Constant	-0.959	
	(7.262)	
Country FE	+	+
Industry FE	+	+
Observations	1,439	1,293
R-squared	0.125	

Note: Average marginal effects for the probit model are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Finally, to explain productivity, we use predicted innovation intensity based on shares of innovative sales or patents. We add production capabilities and capital intensity as explanatory variables (Table 11). We find that neither predicted innovation sales nor patenting intensity explains productivity improvements. Patenting intensity is associated significantly with productivity only in models with industry fixed effects and at the 5% significance level. However, in six out of eight regressions, the production capabilities variable is highly significant for explaining productivity. Production capability is a positive but not significant factor in models that include both industry and country fixed effects. Production capabilities increase productivity by 37.2%-40.0%, controlling for innovation intensity, capital intensity and industry/country fixed effects. The insignificance or minor significance of innovation intensity and the high significance of production capability show qualitatively different activities. Innovation intensity refers to the generation of technological change, while production capability refers to the effective use of existing technology (Bell and Pavitt, 1993). We conclude that productivity is driven primarily by production capability in emerging economies.

Estimates of the productivity determinants using weighted least squares are in line with unweighted. We confirm that predicted innovation intensity does not explain productivity, while predicted innovation sales are again insignificant and predicted patents are significant only in 1 out of 4 models. Production capabilities are again significant in 6 out of 8 models and increase productivity by 46.2-46.3%, controlling for innovation intensity, capital intensity and industry/country fixed effects.

Table 11. Determinants of productivity, OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES								
Predicted innovation intensity (from eq. with innovative sales)	0.002	0.015	-0.000	0.012				
	(0.010)	(0.015)	(0.010)	(0.021)				
Predicted innovation					0.092	0.388**	0.188	0.362**
					(0.130)	(0.166)	(0.122)	(0.165)

intensity (from equation with patents)								
Capital to labour	-0.020	-0.025	0.001	-0.010	-0.019	-0.027*	0.009	-0.001
	(0.015)	(0.016)	(0.046)	(0.049)	(0.015)	(0.016)	(0.044)	(0.046)
Production capabilities	0.773***	0.541***	0.483***	0.259	0.748***	0.372**	0.400**	0.068
	(0.163)	(0.177)	(0.162)	(0.176)	(0.159)	(0.185)	(0.159)	(0.177)
Constant	9.824***	10.870***	8.984***	10.380***	9.804***	11.800***	8.773***	10.10***
	(0.303)	(0.261)	(1.090)	(1.302)	(0.292)	(0.205)	(1.048)	(1.225)
Country FE	-	-	+	+	-	-	+	+
Industry FE	-	+	-	+	-	+	-	+
Observations	457	457	457	457	460	460	460	460
R-squared	0.058	0.135	0.204	0.252	0.058	0.140	0.204	0.254

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

7. Discussion and robustness checks

We tested three models of the determinants of the relationship between R&D-investment-production capability, innovation and productivity (the original CDM model, investment intensity and production capability driven models). We believe that the two alternative models significantly better reflect the stylised facts of innovation in emerging economies. The original CDM model cannot explain productivity based on innovation in emerging economies by using patents or innovation intensity as proxies. Investment intensity emerges as the only significant and consistent explanatory factor.

Therefore, to explain productivity, we first employ an investment-driven model, which shows that when we control for fixed effects, productivity is explained in part by innovation intensity and production capability. In the production capability driven model, productivity is explained mainly by production capability and only weakly and inconsistently by predicted patent intensity.

The relationship between production capability and innovation is not straightforward because innovation does not arise automatically from production capability. Instead, production and innovation should be seen as qualitatively different activities: innovation is about generating technological change while production capability refers to the exploitation of the given technology. Table 12 summarises the results.

Table 12: Summary of results

Original CDM model	*R&D intensity*	*Patents*	*Innovation intensity*	*Productivity*
	Involvement of employees in R&D (sig, +) **Export intensity (sig, +)** **Investment intensity (sig, +)**	**Predicted R&D intensity (sig, +/ns)** Involvement in R&D (sig,+)	Predicted R&D intensity (sig, +/ns) **Involvement in R&D (sig,+)** **Investment intensity (sig, +)**	Predicted patents (ns) Predicted innovative sales (ns) **Investment intensity (sig, +)** Involvement employees in R&D (sig, +/ns)
Investment driven model	*Investment intensity*	*Innovation intensity*		*Productivity*
	Size (sig, -) **Capital intensity (sig, +)**	Predicted investment intensity (ns) **R&D expenditures (sig, +)** **Involvement of employees in R&D (sig, +)** Logistic/business support (ns, +) **Management practices (sig, +)** Quality certificates (ns)		**Predicted innovation intensity (sig, +/ns)** Patents (ns) **Production capability (sig, +)**
Production driven model	*Production capability*	*Patents*	*Innovation intensity*	*Productivity*
	Size (sig, +) Export intensity (sig, +) **Investment intensity (sig, +)**	Production capability (ns) **R&D exp. (sig, +)**	Production capability (ns) R&D exp. (sig, +)	Predicted innovation intensity (ns) **Predicted patents (sig,+/ns)**

		Size (sig, +)	Size (ns) **Investment intensity (sig, +)**	**Predicted production capability (sig, +)**

Note: ns – not significant

Thus, strict application of the CDM model to emerging economies does not yield the expected results since the model does not reflect the stylised facts of innovation activities in these economies. The two alternative models provide a more accurate picture of the determinants of productivity where production capability plays a critical role.

Robustness checks

We checked the robustness of our findings by decomposing the sample based on different criteria. The results are available at the request from the authors. Here, we briefly describe the checks conducted. First, we tested the model without controlling for endogeneity. The results show that production capabilities and investment intensity are positive and statistically robust determinants of productivity and that patents are significant, but less so, for productivity. When we control for firm size, age, export intensity and foreign ownership, only investment intensity emerges as a positive and strongly statistically significant determinant of productivity, with patents weakly significant.

Second, we divided the sample into low- and high-tech industries. The original CDM model shows that predicted innovation intensity is significant for the full sample, but insignificant for the low and high-tech groups. The only significant determinant of productivity for both the low- and high-tech industry groups is investment intensity. In the high-tech industries group, companies with foreign ownership show higher productivity. In the investment-driven model, predicted production capability is a significant determinant of productivity in the case of both groups, confirming its relevance for emerging economies. Patents are significant only for the high-tech group, confirming the specificity of productivity improvements in high-tech industries. If we split the full sample into industry groups, predicted innovation intensity becomes insignificant. In the production capabilities driven model, the only significant determinant of productivity is predicted production capability. The results for the separate low- and high-tech group samples are similar to the results for the full sample.

Third, we conducted robustness checks splitting the sample into low-income, upper-middle-income and high-income groups. Results are broadly in line with the results for the full sample. However, we are reluctant to consider it as a fully-fledged robustness check test for two reasons. First, our sample contains data only on emerging economies and testing whether there is a strong relationship between income levels and innovation – productivity links on quite an unbalanced sample within emerging economies may be pushing our propositions too far. Second, a proper robustness check on this dimension would require a comparable BEEPS type of data for upper high-income OECD economies, which are not available.

Fourth, a direct comparison of our results with other papers on emerging economies that apply the CDM model is not possible due to differences in definitions of variables and research designs. This reinforces the need for a more systematic meta-analysis of CDM results. It also reiterates our argument that researchers have been trying to fit the original CDM model by modifying it in two ways: blurring the distinction between exploitation (M&E) and exploration (R&D) innovation expenditures and ignoring the important distinction between production vs technological capability. Still, in the case of some regression models where direct comparisons could be tentatively acceptable, our results fall well within those of Hashi and Stojcic (2013) and Tevdovski et al. (2017). For example, in our original CDM model an increase in investment intensity is somewhat higher but close to those by Tevdovski et.al., 2017. The effects of exporting on productivity are very similar to those reported by Masso and Vahter (2008a, b). On the other hand, our estimates of impact of exporting on R&D are much lower than those of Hashi, Stojcic (2013) primarily due to different definitions of exporters.

Unfortunately, due to different specifications of models and different definitions of R&D, innovation intensity and output variables direct comparisons between our and other models are not possible. However, if we disregard these differences comparisons of the effects of innovation intensity on productivity are of similar order of magnitude as those reported by Hashi and Stojcic (2013), i.e. 0.6%-1.4% vs 1.2-1.7%. This suggests that differences in our results are not due to differences in samples but due to differences in model design and factors ignored by the previous models.

In summary, the extensive robustness checks confirm the robustness and greater empirical relevance of our alternative models of the relationship between innovation and productivity in the emerging Euro-Asian economies.

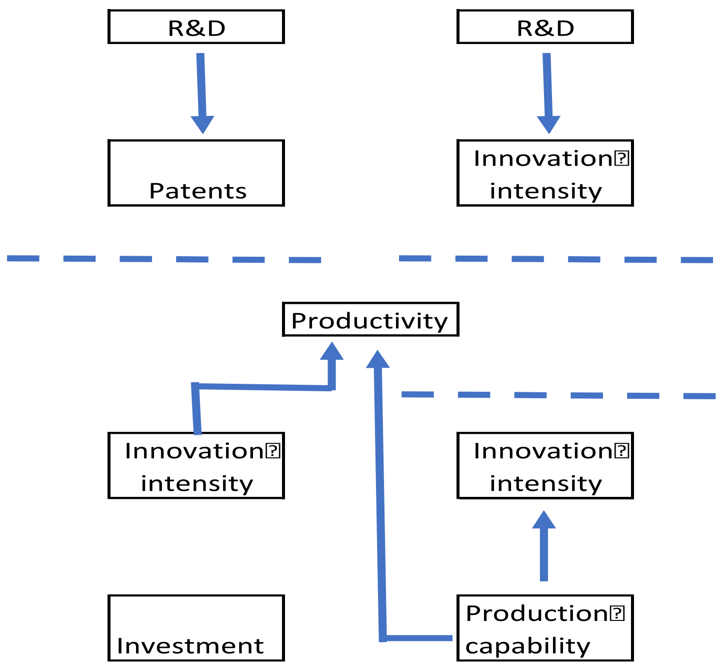
8. Conclusions and policy implications

In contrast to most applications of the CDM model to emerging economies, we show that the original (R&D based) model is not well-grounded in establishing the link between innovation and productivity. Adopting a 'broad' notion of innovation, the widely adopted 'modified' CDM models hide the critical distinction between the ‘exploration’ (R&D) and ‘exploitation’ (investment) components of innovation and fail to consider production capabilities. These approaches also hide the essential distinction between two different modes of technology acquisition - via R&D (intangibles) and via the acquisition of M&E (tangibles). Also, they ignore the crucial distinction between production and innovation capabilities as two qualitatively different types of capabilities.

We tested the original (R&D based) CDM model on BEEPS data. The results support our hypothesis that predicted innovation intensity does not explain productivity in emerging economies. Including investment and production capability better reflects the -stylised facts related to innovation activities in emerging economies. This alternative model goes beyond only R&D based growth as depicted in the original CDM model, which is relevant mainly to economies where most firms operate close to the technology frontier.

Figure 5 depicts the significant linkages between the three stages in the CDM and the alternative investment and production capability models. The arrows represent statistically significant links, and the dotted lines denote non-significant linkages. Thus, productivity is affected only by production capabilities, which, both directly and indirectly, via innovation intensity, affect productivity. The original CDM model does not explain productivity levels in emerging economies.

Figure 5: Summary of significant linkages in the CDM and the alternative models



Our results support the proposition that production capability and innovation intensity are not related linearly and that these aspects represent two different types of capabilities. Production capability refers to manufacturing and implementation capability, while innovation intensity refers to knowledge or technology generation capability (Bell and Pavitt, 1993). We found no evidence of a linear relationship between accumulation of production capability and high innovation intensity, that is, accumulation of production capability does not lead automatically to high innovation intensity.

In general, our evidence suggests that there is a threshold involved in the transition from production capability-based growth to technology-based growth, which has significant policy implications. Lee et al. (2020) refer to the transition from 'implementation' to 'design' capacity as a critical bottleneck in the process to becoming a broadly defined middle-income economy.

The original CDM model and its 'modified' forms provide a skewed picture of technology upgrading in emerging economies that does not reflect the stylised facts of innovation in these economies. The picture that emerges emphasises conventional linear R&D driven growth model and obscures the diversity in the patterns of technology upgrading and, especially, the importance of physical investment for the innovation process, the role of production capability, and the non-linear relationship between R&D, innovation and production capability.

Schumpeterian growth theory (Aghion, 2004; Aghion et al., 2013) suggests that R&D plays a different role in economies at different levels of development. Our econometric evidence is broadly in line with this proposition; we show that drivers of productivity in emerging economies are linked closely to production and manufacturing capabilities. Our results are supported by Reinstaller and Unterlass (2011). They use CIS micro-data for 17 EU countries (including CEECs) and show that European firms' determinants of successful product innovation vary across countries depending on how far they are from the technological frontier. The farther from the technological frontier, technology transfer and manufacturing capability are the more critical compared to R&D.

Underlying the original CDM model is the linear view of innovation based on the research>innovation>productivity sequence. The logic of this model rests on the crucial role of R&D, its 'commercialisation' and what prevents R&D from producing commercial applications. The stylised facts related to innovation in emerging economies and the results of our proposed models, suggest that for these economies, the alternative production capability>innovation>productivity sequence (figure 1) is equally or more relevant. The policy implication is that there should be a focus on both manufacturing and implementation capability, and the transition from production to innovation capability.

Our overall contribution is that we have identified the specificities of technology upgrading in middle-income economies. We adhered as closely as possible to the original CDM model approach to test its relevance to emerging economies. We tested alternative models that better reflect stylised technology innovation features in emerging economies. Further research should employ advanced estimation methods (particularly simultaneous estimation techniques), panel data and dynamic models. However, this will require new internationally comparable longitudinal data on emerging economies.

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Annex 1: Representativeness of our BEEPS sample compared to the population

	Our sample used for regressions	Population for the CEECs	Source for population data	Population for fSU	Source for population data
Employment per firm (avg 2012-14)	3.3	5.7	Eurostat for the CEECs	n.a.	
Share of innovative firms 2014	31.5%[12]	33.5%	Eurostat CIS for the CEECs plus Turkey and North Macedonia	12.2%	Data are available for Russia[13], Belarus[14], Kyrgyzstan[15], Armenia[16], and Ukraine[17][18]
Share of R&D expenditures in annual sales 2014	0.4%	0.3%	Eurostat for the CEECs[19]	n.a.	
Innovative sales	7.8%	11.9%	Eurostat (CIS) (inn_cis11_prodt, inn_cis11_bas)	10.5%	Data[20] are available for Russia, Belarus, and Ukraine

[12] Average of three types of innovators (product/process/organisational)

[13] https://rosstat.gov.ru/folder/14477

[14] https://www.belstat.gov.by/ofitsialnaya-statistika/realny-sector-ekonomiki/nauka-i-innovatsii/

[15] http://www.stat.kg/media/publicationarchive/b87cca0c-6199-43ee-88a9-09041f4986a0.pdf

[16] Data are average for 2013-15 https://armstat.am/file/article/rep_inov_2017_eng.pdf

[17] http://ukrstat.gov.ua/

[18] Only for industry sector

[19] BERD by NACE Rev. 2 activity/ Turnover of the non-financial business economy

[20] Sources as above