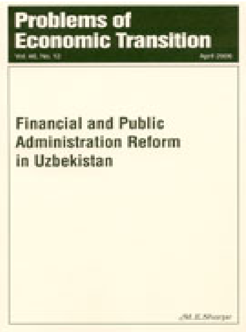

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Analysis of the Innovation Activities of Firms Using the CDM Approach

The innovation factors at work at companies and the estimation of the effectiveness of innovation remain pressing topics in the study of the modern economy. The specific nature of the innovation process has led to the growing popularity of structural modeling under the CDM [Crepon, Duguet, and Mairesse, 1998—Ed.] approach in academic research. It allows us to study the effect of the company's innovative efforts on its bottom line. This article analyzes empirical research that has been carried out using the CDM approach.

Keywords: *CDM model, innovations, productivity analysis*

Jel Classification: *O31, O32, D22, D24*

It is quite difficult to measure the cost-effectiveness of the investments made by firms in innovation. For example, how can we estimate the effectiveness of research and development at Apple? The easiest way is to compare the company's research and development costs with its expected cash flows. However, this approach is more suitable for the analysis of investments in physical capital: buildings, equipment, and

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so on. Investments in innovation are of a different nature. First, it makes sense at a minimum to distinguish two stages in the innovation process: the creation of new knowledge (for example, the development of a new iPad or software) and the direct commercialization of this knowledge leading to an increase in sales of new products or a reduction in the company's costs. Second, each of these stages is characterized by high uncertainty about the length of time they will take and the size of the effect that they will have. Third, it is difficult to determine the causality of investment processes as well as whether new knowledge is created or an economic effect is created at the firm. They are dependent on each other. Finally, a firm can be innovative without making formal investments in research and development by outsourcing, conducting informal studies, acquiring intellectual property, advanced equipment, and so forth. If these factors are not taken into account, the evaluation of the effectiveness of the firm's investments in innovation will be distorted.

All these difficulties in analyzing innovation at the micro level are considered in the CDM [Crepon, Duguet, and Mairesse, 1998—Ed.] approach, which makes it possible to study the process of how new knowledge is created in a comprehensive fashion. This article examines the most notable empirical studies through the lens of this approach and briefly describes the genesis of the approach and the results that it can produce. The strengths and weaknesses of the CDM approach have been identified together with its place and importance in modern academic studies of the innovative activity of companies.

The study of the innovative activity of firms across the history of economics

Since the early 1960s a large number of academic studies have explored the relationship between innovation and company performance. These works have studied how the innovative efforts of companies have affected their economic performance indicators as expressed in the form of research and development expenses (R&D expenditures). Historically, this was the first indicator used to estimate "knowledge capital." Zvi Griliches (1964), Edwin Mansfield (1965), Jora Minasian (1969), and others have used it in their research. The effectiveness of innovative activity is usually analyzed on the basis of the production function of companies with regard to their "innovation capital," which is calculated on the basis of a series of investments in R&D made over time.

R&D expenses as a financial indicator allow direct investments in innovations. Another advantage of the indicator is the openness of the data. Nevertheless, R&D expenditures as a measure of innovation have been criticized for a number of shortcomings, including the uncertain relationship between investments and real economic effects, a large time lag between investment and return, and various levels of effectiveness by which firms are able to create innovations (Antonelli and Colombelli, 2011; Griliches, 1979, 1998). Griliches (1979) notes that R&D costs should be understood as a kind of input in the firm's innovative activity and not as a kind of output.

The work of Pakes and Griliches (1984) represents an important step in the study of innovation at the micro level. The authors analyze the innovative efforts of firm R (R&D expenses) and the outcomes of these efforts in the form of the growth of knowledge capital $dK = f_1(R)$. R&D expenses are realized as innovations that affect economic performance $Z = f_2(dK)$. The new knowledge cannot be measured directly, but it can be estimated through any innovation outcome indicator, such as, for example, the number of patents $P = f_3(dK)$.

Articles published from the 1980s to the 1990s that further developed the concept of Pakes and Griliches do not as a rule contain enough quality results. The reason is largely due to the absence of a reliable knowledge indicator at present. Patents reflect only part of the newly created knowledge. Their value is very heterogeneous, and sometimes the number of patents provides a worse rating of the firm's performance than R&D expenditures (Griliches, 1998, pp. 287–343).

Another complicating factor in the analysis is endogenous R&D costs. Firms decide to invest in innovations on the basis of expected returns (Griliches, 1979; Jefferson et al., 2006). In addition, the Pakes–Griliches model excludes firms that do not invest in R&D. However, these companies that are not innovative according to formal criteria can in fact generate new knowledge or acquire it on the market in the form of technologies, rights, licenses, and so forth. The exclusion of these companies at the level of empirical analysis can lead to a significant sampling error (Griffith et al., 2006).

The CDM model

Crepon, Duguet, and Mairesse's (1998) study represents a milestone in the field. In the scientific community their approach is called the "CDM approach" (an abbreviation formed from the first letters of the authors' last names).

The model proposed by Crepon, Duguet, and Mairesse (1998) is novel for a a number of reasons (Hall and Mairesse, 2006; Loof and Heshmati, 2006). First, the authors combined different lines of research into innovation: innovation factors, the knowledge production function, and the company production function by taking knowledge capital into account. This comprehensive model considers the firm's decision about innovations, the amount of investment in innovations ("innovative input"), the innovative outcome ("innovative output"), and the economic effect on the company's bottom line. The inclusion of the firm's investment decisions in the analysis makes it possible to consider firms that are not innovative according to formal criteria and to avoid bias due to sampling error. The authors used a comprehensive approach to the econometric analysis of their model, which is able to take into account the sampling error and simultaneity that can lead to the endogeneity of certain variables (e.g., R&D expenses and innovation proxies), as well as the fact that the indicators may vary in their statistical nature (they may be continuous, integral, or ordinal). Finally, the creation and empirical analysis of the model has been largely made possible by the Community Innovation Surveys that have been conducted in the European Union since the 1990s. The surveys provide a number of previously unavailable sources and indicators of company innovation activity.

The original CDM model is a system of four equations. The authors consider two very similar versions of the model that differ in the last two equations.

The first two equations determine the size of the investments that firms make in innovations. Equation (1) (sampling equation) describes the company's decision to pursue innovation, where g_i* is the latent dependent variable. If g_i* exceeds a certain threshold value d, the firm invests in innovation. Equation (2) determines the latent innovation intensity k_i*. For firms that have decided to invest, it coincides with the actual intensity, that is, $k_i^* = k_i$ if $g_i^* > g_i^*$. The authors measured k_i as the logarithm of the accumulated costs of innovations per employee. Subsystems (1) and (2) are the Tobit II model[1]:

$$g_i^* = x_{0i}b_0 + u_{0i}. \tag{1}$$

Equation (3) is the innovation function (or knowledge production function). It links the latent innovative efforts k_i* and the innovative outcome. Crepon, Duguet, and Mairesse (1998) propose two proxies for the innovation outcome: the number of filed patents per employee n_i* and the share of innovative sales t_i*. Depending on the indicator that is used, they consider two options for the innovation function (3a) and (3b):

$$n_i^* = E\left(n_i | k_i^*, x_{2i}, u_{2i}, a_k, b_2\right) = \exp\left(a_k k_i^* + x_{2i}b_2 + u_{2i}\right), \tag{3a}$$

$$t_i^* = a_k k_i^* + x_{2i}b_2 + u_{2i}. \tag{3b}$$

Equation (4) is the q_3 employee productivity equation, which depends on the result of latent innovation. In fact, this is a Cobb–Douglas transformed production function with a knowledge capital factor. Depending on the innovation proxy, it is also evaluated in two ways (4a) and (4b):

$$q_i = a_i \ln\left(n_i^*\right) + x_{3i}b_3 + u_{3i}, \tag{4a}$$

$$q_i = a_i t_i^* + x_{3i}b_3 + u_{3\mathrm{i}}. \tag{4b}$$

In the proposed system x_{0I}, x_{1i}, x_{2i}, x_{3i} are the vectors of the explanatory variables; a_k, a_I, b_I, b_1, b_2, b_3 are the vectors of coefficients; u_{0i}, u_{1i}, u_{2i}, u_{3i} are errors in the equations. The model is schematically presented in Figure 1.

Errors in the system of Equations (1)–(4) can be correlated so that they are linked to strong endogeneity and simultaneity in the model. The authors solve this problem by carrying out their assessment in two stages. During the first stage the system equations are estimated in reduced form by disclosing the parameters of the preceding equations. In addition, each equation is solved using the most relevant method, which takes into account the type of dependent variable: (1) and (2)—Tobit II, (6a)—quasi-maximum likelihood method (quasi-MLE) with negative binomial remnants, (3b)—ordinal probit model, (4a) and (4b)—method of ordinary least squares (OLS) with a robust covariance matrix. During the second stage the obtained auxiliary parameters are

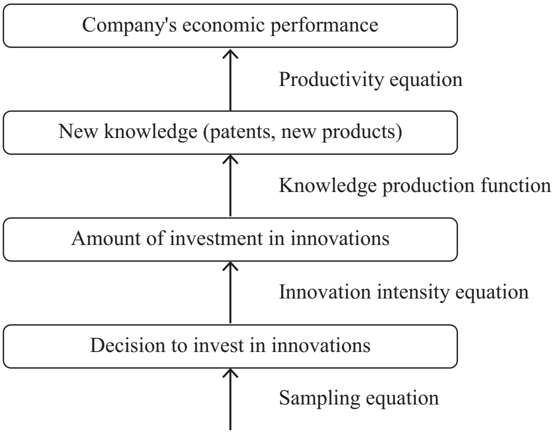

Figure 1. **The CDM Model.**
Source: Crepon, Duguet, and Mairesse (1998)

used for the simultaneous estimation of the structural model using the asymptotic method of least squares (ALS).

The empirical estimation by the authors of models (1)–(4) using data on French firms from 1986 to 1990 has revealed the presence of a significant chain of links: investments in R&D affect the emergence of new knowledge in the form of patents and products that, in turn, affect the firm's productivity. Crepon, Duguet, and Mairesse (1998) found that the likelihood of investment in R&D is determined by the size of the firm, its market share, and the influence of shifts in demand and technology. The total volume of investments for firms that have decided to fund R&D depends on the same factors except for size. An analysis of the two versions of the model (with patents and shares of innovative sales) showed that the creation of new knowledge depends on demand and technology. The firm's productivity above and beyond innovation also depends on the quality of labor and capital intensity.

To confirm whether the use of an econometric tool (ALS) is justified, Crepon, Duguet, and Mairesse (1998) evaluated the model using simpler methods (MLE, 2SLS, OLS).[2] A comparison of the assessments showed that the system (1)–(4) contains a big problem in which the simultaneity and sampling errors are correlated, so they can reinforce each other. The use of alternative methods makes it possible to offset the coefficients due to the endogeneity of R&D expenditures and sampling bias.

Furthermore, the proposed method is computationally simple, particularly compared with GMM.[3]

Structural modeling under the CDM approach

A number of studies have been devoted to CDM models. They share a close systematic vision of the innovation process. Articles using this approach are based on a certain structure that links several stages of innovative activity at the company into a single model. The Table 1 provides a brief list and description of the most famous and notable studies that have been conducted using the CDM approach.

All these studies use the systematic approach to the analysis of innovation proposed by Crepon, Duguet, and Mairesse (1998), but they differ significantly in terms of the structure of the model, estimation methods, and the analyzed sample. The results of the studies also vary.

Structure of models using the CDM approach

The CDM model provides ample opportunities for the analysis of companies. Subsequent studies conducted using the CDM approach considered options for systems of innovation equations that modified the original model (1)–(4). They differ in aspects such as:

- equations chosen to be used in the system;
- the relationship between equation indicators; and
- indicators that measure the intensity of innovation, the creation of new knowledge and the company's bottom line.

Many studies repeat the original system of four elements: sampling equations, innovation intensity, the function of innovations, and the productivity equation. The system becomes complicated two innovative functions are included at once for different types of new knowledge, such as, for example, the creation of new products and processes (Griffith et al., 2006; Mairesse and Robin, 2009; Masso and Vahter, 2008). Raymond et al. (2013) detail the knowledge production function, dividing it into two consecutive equations: does the firm create new products, and if so, then what is the proportion of its innovative sales? Some scientists, on the contrary, simplify the model by considering only two equations related to innovative efforts (Johansson and Loof, 2008; Mairesse and Mohnen,

Table 1

Studies Conducted Using the CDM Approach

Authors	Country and sample size (number of firms)	Sector	Analysis period
Crepon, Duguet, and Mairesse (1998)	France (4,164)	Industry (18 branches and about 600 market segments)	1986–1990*
Loof and Heshmati (2002)	Sweden (619)	Industry	1996*
Mairesse and Mohnen (2002)	Belgium (182), Denmark (223), Germany (1,070), Ireland (259), Italy (845), Netherlands (666), Norway (150)	Industry	1992*
Loof et al. (2003)	Finland (1,062), Norway (1,315), Sweden (746)	Industry (17 branches)	1994–1996*
Janz, Loof, and Peters (2004)	Germany (575), Sweden (474)	Industry sectors with high demand for research	1998–2000*
Benavente (2006)	Chile (488)	Industry	1997–1998*
Chudnovsky, Lopez, and Pupato (2006)	Argentina (718)	Industry, service sector, mining (20 branches)	1992–1996, 1998–2001** (2 surveys)
Duguet (2006)	France (4,085)	Industry (around 20 branches)	1985–1990*
Griffith et al. (2006)	France (3,625), Germany (1,123), Spain (3,588), Great Britain (1,904)	Industry (10 branches)	1998–2000*

Jefferson et al. (2006)	China (5,451)	Industry, (large- and medium-size enterprises)	1997–1999**
van Leeuwen and Klomp (2006)	Netherlands (2,985)	Industry, services sector	1994–1996*
Loof and Heshmati (2006)	Sweden (3,190)	Industry, services sector, housing and utilities	1996–1998*
Parisi, Schiantarelli, and Sembenelli (2006)	Italy (465)	Industry	1992–1994, 1995–1997** (2 surveys)
Roud (2007)	Russia (3,408)	Industry sectors with high demand for research	2005*
Johansson and Loof (2008)	Sweden (2,094)	Industry, services sector	1998–2000*
Masso and Vahter (2008)	Estonia (1,467 and 992)	Industry	1998–2000, 2002–2004 (2 surveys)*
Mansury and Love (2008)	United States (206)	Services sector	2000–2003*
Heshmati (2009)	Sweden (1,694)	Industry, services sector	1996–1998*
Mairesse and Robin (2009)	France (3,518 and 4,831—industry, 3,467—services sector)	Industry, services sector	1998–2000 (1 survey), 2002–2004 (2 surveys)*
Musolesi and Huiban (2010)	France (416)	Innovative sectors in business services (Knowledge Intensive Business Services, KIBS)	1998–2000*
Vakhitova and Pavlenko (2010)	Ukraine (792)	Industry	2004–2006*

(Continued)

Table 1
(*Continued*)

Authors	Country and sample size (number of firms)	Sector	Analysis period
Damijan, Kostevc, and Rojec (2012)	Slovenia (1,454, 1,777, 2,518, and 2,564)	Industry	1996, 1998, 2000, 2002 (4 surveys)*
Raymond et al. (2013)	France (1,091, 1,920, and 1,416), the Netherlands (917, 1,228, and 722)	Industry	1994–1996, 1998–2000, 2002–2004 (3 surveys)**
Teplykh (2014)	Great Britain, France, Germany, Spain, Italy (429 in all countries)	Industry	2004–2011**

*Cross-sectional data.
**Panel data, including an unbalanced panel.

2002), or they consider only the function of innovation and company productivity (Damijan, Kostevc, and Rojec 2012; Duguet, 2006; Musolesi and Huiban, 2010; Parisi, Schiantarelli, and Sembenelli, 2006). Jefferson et al. (2006) do not consider the sampling equation in their analysis and examine only those firms that carry out R&D.

The key chain of ties "innovative efforts–new knowledge–company result" can be found in the majority of works based on the CDM approach, since it relates to the theoretical foundation of innovative research. Some authors take into account the direct effect of R&D on the firm's bottom line (Heshmati, 2009; Teplykh, 2014). This can be explained by the fact that even in the absence of concrete results, R&D can help company employees acquire informal knowledge. To account for the reverse effect, the final index of firm performance can be included in the equation of innovation intensity or innovation functions (Heshmati, 2009; Loof et al., 2003; Loof and Heshmati, 2002, 2006; Roud, 2007). This effect is manifested in the fact that any increase in the firm's productivity provides greater opportunities and incentives for R&D, and it also affects the company's ability to create new knowledge. Some researchers take into account the dynamic nature of the innovation process by taking advantage of the time lags between the equations in the system (Jefferson et al., 2006; Raymond et al., 2013).

The firm's investments in R&D are most often used to measure innovative activity. They can be expressed either in absolute terms or per employee ("innovation intensity"). The company's general innovation costs are used less commonly than R&D (Chudnovsky, Lopez, and Pupato, 2006; Masso and Vahter, 2008) because they represent a broader concept, which includes the costs of purchasing external knowledge (technologies). Instead of a set of quantitative indicators, Musolesi and Huiban (2010) use a set of dummies for the different sources of innovation, thereby distinguishing the firm's own R&D costs, the R&D costs of third parties, and the costs of acquiring technologies.

The authors of studies that use the CDM approach consider various indicators of generated knowledge: the share of innovative sales (Jefferson et al., 2006), the volume of sales of new products per employee (Janz, Loof, and Peters, 2004), the number of patents (Crepon, Duguet, and Mairesse, 1998), or dummies that reproduce the creation of innovations (Duguet, 2006; Parisi, Schiantarelli, and Sembenelli, 2006). In the latter case, the innovation function reproduces the creation of new products or processes (Masso and Vahter, 2008; Musolesi and Huiban, 2010; Parisi, Schiantarelli, and Sembenelli, 2006) or the creation of incremental and radical innovations (Duguet, 2006). This makes it possible to separate the processes that are responsible for the creation of different types of knowledge, which allows us to conduct a deeper analysis of innovation activity.

Value-added labor productivity (Benavente, 2006), revenue (Janz, Loof, and Peters, 2004), production volume (Parisi, Schiantarelli, and Sembenelli, 2006) or profit (Jefferson et al., 2006) are usually considered as final indicators of company economic performance. Productivity growth indicators (Duguet, 2006; Heshmati, 2009; Loof and Heshmati, 2006) make it possible to assess the effect of innovation on company economic growth as well as smooth out the influence of fixed (permanent) effects.

Analysis tools

The CDM model requires the use of relevant tools for econometric estimation. It is necessary to take into account the sampling error, statistical type of dependent variables, endogeneity of a series of indicators, and correlation of errors in the system equations.

There are different methods for estimating the model. It is possible to distinguish two major approaches to analyzing the model: simultaneous and staged estimation.

Simultaneous estimation of the system makes it possible to take the correlation of errors between equations into account to the maximum degree possible and provides higher-quality results. The disadvantage of this approach is the need for a priori and rather strict assumptions about the joint distribution of remainders. It is also computationally complex. The CDM model is rarely assessed using a fully simultaneous procedure. For example, Mairesse and Robin (2009) as well as Raymond et al. (2013) apply this method using the maximum-likelihood estimation.

Crepon, Duguet, and Mairesse (1998) and Benavente (2006) have used an ALS procedure consisting of two stages. During the first stage each equation is estimated separately based on the type of dependent variable, and during the second received auxiliary parameter values are used to estimate the entire system. Crepon, Duguet, and Mairesse (1998) use both theoretical and empirical arguments in favor of the fact that their method provides more reliable and unbiased results than the MLE or staged estimate tool.

In the second approach, the equations are estimated in stages. Thus, in order to account for the endogeneity of the “input” and “output” of innovations and sampling bias, each successive step in the system can use the predictive values ??of indicators of the previous equations. However, some equations from the system can be estimated simultaneously. As a result, the approach to estimates becomes essentially an “intermediate” stage. Most researchers apply either staged or intermediate approaches.

To estimate the first two equations that define the innovative activity of firms (Tobit II), the MLE or Heckman two-step approach are commonly used.[4] The innovation function is estimated while taking into account the statistical type of dependent variable. When using innovative dummies, the probit (Griffith et al., 2006; Musolesi and Huiban, 2010), two-dimensional probit (Masso and Vahter, 2008), logit, logit with random effects or conditional logit (Parisi, Schiantarelli, and Sembenelli, 2006) can be used. Ordinal probit (Benavente, 2006; Crepon, Duguet, and Mairesse, 1998), ordinal logit (Duguet, 2006), or multiple logit (Chudnovsky, Lopez, and Pupato, 2006) are used for ranking variables. A quasi-MLE with various error distribution options can be used for integral indicators (such as the number of patents) (Crepon, Duguet, and Mairesse, 1998). The following estimation tools are used to assess the innovative function and productivity equation: 2SLS (Janz, Loof, and Peters, 2004; Jefferson et al., 2006), 3SLS (Loof and Heshmati, 2006; Roud, 2007),[5] GMM (Duguet, 2006), and so on. These two equations can be estimated both simultaneously on the basis of MLE (Musolesi and Huiban, 2010), and according to the stage by substituting the endogenous forecast variable from previous equations (Duguet, 2006; Heshmati, 2009; Masso and Vahter, 2008).

Analyzed sample

Innovation is typically studied under structural modeling using the Community Innovation Survey and other surveys that are based on a comparable methodology.[6] Many studies have investigated the innovative activities of firms in EU countries: France, Italy, Sweden, the Netherlands, Slovenia, Estonia, and others. A number of studies have investigated data from emerging economies: Chile, Argentina, China, Russia, Ukraine, and others. The unified methodology of the

Community Innovation Survey made it possible to conduct cross-country comparisons (Mairesse and Mohnen, 2002; Loof et al., 2003; Janz, Loof, and Peters, 2004; Griffith et al., 2006). Due to the lack of relevant surveys, studies until recently rarely touched on companies in the United States (e.g., Mansury and Love, 2008). However, since 2008, American firms have been surveyed using the Business R&D and Innovation Survey (BRDIS) methodology,[7] which is broadly comparable with the Community Innovation Survey (Hall, 2011).

Studies that use the CDM approach are based mainly on a broad sample of companies in various industries. Some studies have carried out cross-industry comparisons based on a separate analysis of production and the services sphere (Loof and Heshmati, 2006; Mairesse and Robin, 2009). Sometimes researchers limit themselves to the most innovative sectors of the economy (Musolesi and Huiban, 2010; Roud, 2007).

Since 1992, several waves of the Community Innovation Survey have been conducted, allowing for an analysis of innovation over time. Nevertheless, very few studies have been conducted under the CDM approach that examine changes over time. Chudnovsky, Lopez, and Pupato (2006) used a model that took account of fixed-effects on the basis of panel data from two surveys (CIS2 and CIS3). Masso and Vahter (2008) separately estimate the models for two waves of surveys in Estonia and compare them. Jefferson et al. (2006) used a balanced panel of Chinese firms to analyze a dynamic model. Raymond et al. (2013) also constructed a dynamic model, but on the basis of unbalanced panel data. Parisi, Schiantarelli, and Sembenelli (2006) estimated a dynamic model of productivity growth with random effects. We estimate the model on the basis of one sample over two periods in order to detect a shift caused by the economic 2008 crisis (Teplykh, 2014).

Most researchers are limited to the study of cross-sectional data, or they deliberately, as in the case of Damijan, Kostevc, and Rojec (2012) transform data from different survey waves into a single pooled sample. A diachronic analysis is hampered by the fact that usually a small number of firms falls into the list of different waves of survey respondents. In addition, there is an unverifiable sampling error due to the fact that only the “surviving” firms participate in every following survey.

Key findings

Company analysis results that are based on innovative enterprises surveys in different countries and sectors are broadly comparable and reflect a close link between R&D expenses, new knowledge, and an economic result. Different researchers (Griffith et al., 2006; Hall, 2011; Janz, Loof, and Peters, 2004; Loof and Heshmati, 2006; Mairesse and Robin, 2009; Musolesi and Huiban, 2010) on the whole provide very similar estimates of the coefficients of the key variables in the model (R&D intensity in the function of knowledge production and an innovative result in the productivity equation). Loof et al. (2003) stand out from the average study in being able to reveal a significant difference in the models of the Scandinavian countries. Benavente (2006) shows that in Chile R&D costs and the volume of innovative sales are insignificant, but this can be explained by the specific nature of the developing Chilean economy.

The set of exogenous factors in structural model equations usually include the following firm characteristics: size, market share, form of ownership, competition level in the industry, the influence of demand and technology, and so on. For these variables the results are usually very different due to regional and industry-specific factors.

Research shows that the creation of new products and processes depends on various factors. The innovative efforts of the company itself have a stronger influence on the creation of new products rather than processes. Process innovations significantly depend on the company's investments in fixed assets and expenditures to purchase new foreign technology and innovations (Chudnovsky, Lopez, and Pupato, 2006; Mairesse and Robin, 2009; Masso and Vahter, 2008; Musolesi and Huiban, 2010; Parisi, Schiantarelli, and Sembenelli, 2006).

Most researchers believe that the creation of new products has the most significant effect on the company's productivity (Griffith et al., 2006; Mairesse and Robin, 2009; Musolesi and Huiban, 2010). According to Hall (2011), process innovations are only relevant in determining the market power of firms. The author offers two explanations for this phenomenon: (1) firms with market power are active in an inelastic area of the demand curve, and the implementation of effective process innovations can reduce their productivity; (2) lack of precision of dummy indicators. In analyzing the model into linear differences (this form is more resistant to measurement errors), Parisi, Schiantarelli, and Sembenelli (2006) reach the opposite conclusion: process innovations have a stronger influence on productivity growth. According to Masso and Vahter (2008), the importance of new products and processes in Estonia changes over time depending on macroeconomic conditions.

Duguet (2006), who classifies innovations by virtue of their strength into radical and incremental (insignificant, but gradual) categories, considers that only radical innovations can significantly increase total factor productivity. At the same time, the determinants underlying the creation of these innovations are different: radical innovations mainly arise from complex knowledge in the course of the firm's innovative activities, and incremental ones are based on informal studies and the adaptation of technologies from other companies.

Notably many authors believe that in addition to innovation indicators of personnel quality are a significant factor in the productivity equation (Benavente, 2006; Crepon, Duguet, and Mairesse, 1998; Loof and Heshmati 2002, 2006; Roud, 2007). In other words, a firm requires adequate high-quality human resources in order to successfully transform new knowledge into economic benefit.

The importance of the CDM approach to economics

The CDM model, in developing the theoretical ideas of Griliches (1979) and Pakes and Griliches (1984), is a more complex and detailed vision of the process of company innovative activity. Considered together with other approaches, it covers all stages of production and the use of new knowledge: from making investment decisions to obtaining economic benefits. Innovation surveys have allowed researchers to gather a large and sufficiently representative sample that covers medium and small firms. This makes it possible to project the results of the analysis to the level of industries and countries as a whole. Modeling under the CDM approach has made it possible to actively apply more advanced econometric procedures that take into account the peculiarities of this field to the analysis of innovations.

Despite the advantages of the approach, studies that use it have limitations associated with these characteristics. The vast majority of articles are based on survey results, often in conjunction with data from company financial statements and patent offices. A few studies (e.g., Teplykh, 2014) do not use survey data. Most CDM models are limited to cross-sectional analyses, since surveys do not provide a well-balanced panel for particular firms (Hall, 2011). This complicates the study of innovative trends. Surveys are based on subjective self-assessments, and they are poor measures of the influence of innovation (Antonelli and Colombelli, 2011). Innovative dummies do not measure the novelty of created knowledge. In general, this is an inaccurate and noisy indicator. The share of innovative sales makes it possible to estimate the importance of new products for firms, but surveys do not contain the same indicator for the outcome of process or organizational innovations (Hall, 2011). Survey indicators are closely correlated. Therefore, causation is not always clear, and as a result the estimation of the model cannot completely cope with endogeneity in the model (Chudnovsky, Lopez, and Pupato, 2006; Jefferson et al., 2006). It takes a long time to collect and process Community Innovation Survey data, so studies that rely on this information markedly lag behind economic reality.

Modern microeconomic studies of innovations are not limited to the CDM approach. Some researchers continue to directly assess the relationship between investments in R&D and the performance of firms, often as part of the modeling of the production function (Bond, Harhoff, and van Reenen, 2005; Griffith, Redding, and van Reenen, 2004; Wakelin, 2001). Other researchers analyze patent data (Jaffe and Trajtenberg, 1999; Ramani, El-Aroui, and Carrère, 2008). In particular, they try to identify the relationship between innovation efforts and the creation of new knowledge.

Data on R&D and patents as objective quantitative indicators of innovation are available across a range of time periods for a wide range of companies. In this they have a significant advantage in comparison with surveys. Instead of current economic performance, authors have also resorted to the analysis of the market value of companies (Blundell, Griffith, and van Reenen, 1999; Hall, Jaffe, and Trajtenberg, 2005). The advantage of stock market data is that they allow us to estimate the expected future effect of the current innovation activities of firms. Finally, even studies that are based on survey data do not always follow the CDM approach (Koch and Strotmann, 2008; Ornaghi, 2006). The applied method of analysis depends largely on the objectives of the study and the issues raised, and the overly broad scope of the CDM approach may be inappropriate.

Overall, however, the CDM approach has an important place in modern empirical studies of innovation at the micro level along with more traditional approaches, such as the modeling of the production function. The potential of the approach has yet to be exhausted. It could be developed in a number of promising directions: the development of dynamic versions of the model; the incorporation of investment expectations based on stock market data into the model; the seeking out of more objective proxies for innovation efforts and created knowledge; and so on. Further improvements will make the CDM model more comprehensive, detailed, and accurate in terms of reflecting the specific nature of the innovation activities of firms.

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Notes

1. Tobit models are used when the dependent variable is continuous and bounded. In this case, these are investments in innovation that cannot take a negative value. Tobit II (or generalized Tobit) is a system of two equations: the sampling equation, which is estimated across the entire sample, and the second equation, which is estimated only in the case of positive sampling in the first equation. In this case, the sampling Equation (1) indicates whether the firm is investing in innovation, and the expression (2) indicates how much, if so.
2. MLE—maximum likelihood method, 2SLS—two-stage least squares method.
3. GMM—generalized method of moments.
4. The Heckman procedure involves the alternate estimation of equations in the Tobit II model.
5. 3SLS—three-stage least squares method.
6. See www.epp.eurostat.ec.europa.eu/portal/page/portal/microdata/cis.
7. See www.nsf.gov/statistics/industry/.

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