INNOVATION AND FIRMS' PRODUCTIVITY GROWTH IN SLOVENIA
Does estimation method influence the result?*

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Abstract

The paper analyses the impact of innovation on firms' productivity growth by combining information on firm-level innovation (CIS) with accounting data for a large sample of Slovenian firms from 1996-2002, and applying three different empirical methods: simple OLS, matching techniques, and the Crépon-Duguet-Mairesse (CDM) approach. The three parallel approaches serve to provide a robustness check for our primary results. In addition, we explicitly distinguish between product and process innovations, on the grounds that process innovations may have a labor displacement effect and are expected to result in significant productivity growth. However, due to demand effect, product innovations may likely cause employment growth and, thus, may not result in significant productivity improvements. The results of the exercise are not robust to different econometric approaches. Simple OLS indicates that a firm's innovation activity may contribute substantially to its total factor productivity growth. However, by applying both the propensity-score matching techniques and the asymptotic least squares on a system of simultaneous equations describing research activities, innovation, and productivity, we find a strong correlation between innovation and productivity levels, but no support for the importance of innovation on productivity growth. Furthermore, none of the three methods show a significantly different impact of product and process innovations on productivity growth.

Keywords: Research and development, innovation, knowledge spillovers, FDI, trade, productivity growth
JEL Classification: D24, F14, F21

1. Introduction

The primary aim of the paper is to analyze the impact of firms' innovation activity on their productivity growth. Endogenous growth theory suggests, firstly, that technological progress is endogenous and driven by the deliberate investment of resources by profit-seeking firms (Smolny, 2000) and, secondly, that a firm's innovation activity is central to its technological progress and productivity growth.

Griliches (1979) was the first to introduce R&D capital stock as a factor of production into the residual computation framework pioneered by Solow (1957). In his approach, R&D activities add to the existing stock of accumulated knowledge of firms, leading to productivity growth through product and process innovation. Romer's (1990) model also predicts a link between R&D activity and productivity growth. Along these lines, early models developed by economists affiliated with the NBER focused mainly on the relationship between R&D activity and productivity growth within a production function framework. While studies of the direct relation between R&D and firm performance give mixed results, there is sufficient evidence to suggest a strong and positive relationship between R&D expenditures and the growth of output or total factor productivity. They

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also tend to claim that firms accrue spillover benefits from R&D activity in other firms, inter-industry spillovers being more important than intra-industry ones.

One of the most influential studies on innovation and productivity growth is that of Crepon, Duguet, and Mairesse (1998), who combine a knowledge-production function, relating R&D activity to patenting or innovative activities, with economic performance as measured by labor productivity. The paper by Crepon et al. (1998) has influenced a new and burgeoning literature on the relationship between innovation output and firm performance. The main finding of these studies is that, regardless of how performance is measured, innovation output positively and significantly affects firm performance. The exception to this is the study by Klomp and van Leeuwen (2001) that finds a negative but insignificant effect of innovation output on employment growth. Studies have been done on developing countries as well. Two of these, Benavente (2006) on Chile and Mohnen (2006) on Tanzania, show that innovation output (or R&D activity) does not influence firm performance. The findings of Jefferson et al. (2002) for China are more optimistic.

Some of the studies distinguish between product and process innovations. The findings of Harrison et al. (2005), Griffith et al (2006), Parisi et al. (2006), and Hall et al. (2007) tend to demonstrate that process innovations have labor displacement effects and are expected to result in significant productivity growth, while, due to the demand effect, product innovations may likely cause employment growth and, thus, may not result in significant productivity growth.

Based on the above mentioned theoretical concepts and empirical evidence, and by combining firm-level innovation (CIS) and accounting data for a large sample of Slovenian firms from 1996-2002, we test two main hypotheses. First, a firm's innovation activity should have a positive and significant impact on both productivity levels and productivity growth. Second, process innovations are more likely to have a positive impact on productivity growth than product innovations. We apply three different methods in analyzing the impact of innovation on firms' productivity growth: simple OLS, matching techniques, and the Crépon-Duguet-Mairesse (CDM) approach. Three different methods are used to check for the robustness of the results. In formulating the OLS model of the effect of innovation on productivity, one needs to formulate the research capital function, containing the determinants of firms' innovation activity. Here we use the estimation approach of Damijan et al. (2006), who estimate the impact of firms' internal R&D capital, various types of external R&D spillovers, and absorption capacity on firms' innovation activity within an integrated dynamic model while using a dataset very similar to ours.

Our main findings are the following. First, the results of the estimations are not robust to different econometric approaches. Simple OLS indicates that a firm's innovation activity may contribute substantially to its total factor productivity growth. However, by applying both the matching techniques after the propensity score and the asymptotic least squares on a system of simultaneous equations describing research activities, innovation, and productivity, we find a strong correlation between innovation and productivity levels, but no support for the importance of innovation on productivity growth. Second, none of the three methods shows a significantly different impact of product and process innovations on productivity growth.

The remainder of the paper is structured as follows. Section two provides the theoretical background on R&D, innovation, and firm performance. Section three briefly discusses the extent and determinants of the innovation activity of Slovenian firms. Section four provides estimations of the effect of innovation activity on firms' productivity growth by three different empirical methods. The last section presents the conclusions.

2. Theoretical background: R&D, innovation activity, and firm performance

Griliches (1979) was the first to introduce R&D capital stock as a factor of production into the residual computation framework pioneered by Solow (1957). In this approach, R&D activities add to the existing stock of accumulated knowledge of firms, leading to productivity growth through product and process innovation. Romer's (1990) model predicts a link between R&D activity and productivity growth, and Cohen and Leventhal (1989) point to the importance that R&D activity can have in absorbing technology produced in other firms. Studies of the relationship between knowledge creation and productivity appear at different levels of aggregate (economy, sector, firm) depending on the objective of the analysis.[5]

Early models developed by economists affiliated with the NBER incorporate a variable that captured the 'economically valuable technological knowledge', or what Griliches (1979) termed 'knowledge capital' and said very little regarding what knowledge is, or regarding how it becomes important for innovation and growth. These models focused mainly on the relationship between R&D activity and productivity growth within a production function framework (Wieser, 2005) that includes 'knowledge capital' in addition to the traditional inputs. It is the elasticities of output with respect to each of the inputs that will matter most for the analysis. Studies of the direct relation between R&D and firm performance give mixed results.[6] These include Schankerman (1981) and Griliches (1980, 1986) on the value-added of U.S. firms in selected industries in 1963 and 1972, respectively, Griliches and Mairesse (1984) on sales of U.S firms from 1966 to 1977, Cuneo and Mairesse (1984) on French scientific firms from 1972 to 1977, Hall and Mairesse (1995) and Mairesse and Hall (1996) on sales and value-added in U.S. and French firms in the 1980s, Bartelsman, et al. (1998) on value-added in Dutch firms in the late 1980s, Cincera (1998) with regard to the world from 1987 to 1994, O'Mahoney and Vecchi (2000) on sales of U.S., European, and Japanese firms in the mid-1990s. Wieser (2005) carries out a meta-analysis of these studies and provides five conclusions:

1. Despite considerable variation across studies, the analysis suggests a strong and positive relationship between R&D expenditures and the growth of output or total factor productivity.
2. Studies confirm that firms accrue spillover benefits from R&D activity in other firms. They also suggest that spillovers between industries are more important than those within industries.
3. There is considerable variation in the rates of return on R&D activity within firms, but no apparent trend across industries.
4. It is not clear whether the relationship between R&D activity and firm performance is strengthening or weakening over time.

5 Relevant reviews of the literature include Nadiri (1991), Griliches (1992), Mairesse and Mohnen, (1995), Cincera (1998), and Wieser (2005).

6 There is also group of studies that focus on the rate of return on R&D activity at the firm level. These include Mansfield (1980) and Link (1981, 1983) on the United States, Griliches and Mairesse (1983, 1984, 1990) on the United States, France, and Japan, Hall and Mairesse (1995) on France, and Cincera (1998) on the world.

5. The rates of return on R&D activity are similar across countries.

Pakes and Griliches (1984) developed a variant of this framework in which changes in knowledge capital, defined as the level of economically valuable technological knowledge, are unobservable, which allows for the inclusion of several interrelated innovation inputs. Crepon et al. (1998) extended this model to explore the channels through which R&D activity influenced innovation and productivity growth for a cross-section of firms in the French manufacturing sector for 1992. The model combines a knowledge-production function, relating R&D activity to patenting or innovative activities, with economic performance as measured by labor productivity. It contains a system of three simultaneous equations where R&D activity and other factors generate new knowledge, which then propels innovation (output) and finally productivity growth. Other supply and demand factors as well as sectoral differences and unobserved heterogeneity are also included in the model to improve its explanatory power. One novel aspect of the model is that the authors incorporated indicators derived from a French innovation survey into the framework. They found evidence in support of a positive effect on R&D activity and innovation output measured by patent numbers, as well as a positive and significant effect on the value-added per employee of French firms.

The paper by Crepon et al. (1998) has influenced the growing literature on the relationship between innovation output and firm performance. Firm performance variables may include value-added, sales or exports per worker, sales per worker, and the growth rate of value-added, sales, profitability, or employment, and sales margin, profit before and after depreciation (in level and growth rates). The main finding of these studies is that, regardless of how performance is measured, innovation output positively and significantly affects firm performance, with the exception of the study by Klomp and van Leeuwen (2001), which found a negative but insignificant effect of innovation output on employment growth (Hall and Mairesse, 2006; Raymond et al., 2006). Lööf and Heshmati (2006) performed a sensitivity analysis of the different measures of firm performance and found the same pattern of positive and significant effect of innovation output on firm performance.

Similar results are found in other papers. Mohnen et al. (2006) estimated the relationship between innovation output and firm performance by using micro-aggregated data from seven countries (Belgium, Denmark, Ireland, Germany, the Netherlands, Norway, and Italy) for 1992. They also observed that firm productivity correlates positively with higher innovation output, even when correcting for the skill composition of labor and capital intensity, but they also found that simultaneity tends to interact with selectivity, and that both sources of biases must be taken into account together.[7] Griffith et al. (2006) estimated a variation of the model for four European countries (France, Germany, Spain, and the UK), using firm-level data from CIS3 carried out in2000. This model differentiates between the labor displacement effect of process innovation and the compensation effect caused by higher demand. They found that job loss due to process innovation is partly compensated for by the displacement effect and that there is no evidence of a displacement effect when there is product innovation, even when old products are no longer produced. Although they find that the results are similar across these four countries, the employment effects are different. For example, there is no sign of a displacement effect from process innovations in Spain, whereas product innovation

[7] Mohnen, et al. (2006) use a generalized tobit model together with a variation of the production accounting framework and include size, industry, ownership type, continuous R&D, cooperative R&D, R&D intensity, proximity to basic research, and perceived competition as independent variables.

generates more employment in Germany and less in the UK. Similarly, Parisi et al. (2006) found that process innovations significantly impacted the productivity growth of Italian firms in the late 1990s, while product innovations had a much less significant effect. A common explanation for this may be the different displacement and compensation effects of product and process innovations. As shown by Harrison et al (2005) and Hall et al. (2007), due to demand effect, product innovation may likely result in employment growth, while process innovation is likely to have labor saving effects.

Other papers, including Lööf et al. (2002), showed that there was considerable variation between Finland, Norway, and Sweden in the early 1990s. They argue that this variation may be due to data errors, the econometric model (3 SLS), model specifications, or unobservable country effects. Using CIS data from France in 1993, Duguet (2000) shows that strongly innovative firms are much more likely to improve their TFP than weaker firms, and that the return on innovation increases with the degree of innovation opportunities that firms have. The model also shows that the Solow residual at the industry level is linked to radical innovations at the firm level. Janz et al. (2004) pooled observations from Germany and Sweden to show that there is a strong link between innovation output and sales per employee in knowledge intensive manufacturing firms independent of the country. Using data on the Netherlands from 1997, van Leeuwen and Klomp (2006) show that the impact of innovation differs between measures of firm performance and that additional information on the technological environment of the firm can improve the estimation. Mohnen and Therrien (2003) compared Canada with selected European countries in the late 1990s and found Canadian firms were more innovative as a whole, but with a lower share of sales from innovative products for its innovative firms. These results led the authors to suggest that the national samples may not be representative and that differences in the questionnaire or perceptions of the questionnaire matter. Criscuolo and Haskel (2002) used a matched innovation survey and Census data to investigate the link between innovation and productivity growth in the UK. They found a statistically significant association between (process) innovations and TFP growth.

Lately, there have also been studies looking at the impact of innovative activity in less developed countries. Benavente (2006) applied the Crepon et al. (1998) model and estimating procedures to Chile during the period 1995 to 1998. He found that R&D and innovative activities are related to firm size and market power, but that innovation output (or R&D activity) does not influence firm performance. By contrast, Jefferson et al. (2002) showed that there is a strong relationship between R&D intensity and new product sales and returns on R&D expenditure after correcting for size, industry, profitability, and market concentration. Using data from the World Bank Investment Climate Survey covering the years 2000 to 2002, Mohnen (2006) showed that innovation output (or R&D activity) did not influence firm performance in Tanzania, but that the institutional arrangements had an important impact.

These robust conclusions suggest there might be a persistence of innovation which is important to many of the neoclassical endogenous growth models (Romer, 1990; Aghion and Howitt, 1992) and the Schumpeterian inspired evolutionary models (Malerba and Orenigo, 1996). Studies of input measures by Manez Castillejo et al. (2004) and Peters (2005) and of output measures by Duguet and Monjon (2002) found the persistence in innovation activities to be high between R&D and innovation survey data, whereas they tend to be lower with patent and major innovations (Raymond et al., 2006). Raymond et al. (2006) tested the persistence of innovation using Dutch firm data from three waves of innovation surveys, covering the periods 1994-1996, 1996-1998, and 1998-2000. Using a dynamic panel data type 2 tobit model that accounts for individual effects and handles the initial conditions problem, they found that there is no evidence of true persistence in achieving technological product or process innovations, while past shares of innovative sales condition, albeit to a small extent, current shares of innovative sales.

3. The extent and determinants of firms' innovation activity in Slovenia

Firms' innovation activity in the European Union member states is measured in a standard manner by the so called Community Innovation Surveys (CIS). In Slovenia, CIS surveys are conducted by the Slovenian statistical office every even year, starting in 1996. We have at our disposal four waves of innovation surveys, covering the periods 1994-1996, 1996-1998, 1998-2000, and 2000-2002). These innovation surveys are carried out among a wide sample of manufacturing and non-manufacturing firms with no restrictions put on the actual R&D activity by these firms. The number of firms covered by the innovation survey constantly increased during the 1996-2002 period (stratified random sampling, see Table 1). Hence, these surveys allow for a broad picture of determinants of innovation activity and its impact on the performance of Slovenian firms.

Table 1: R&D expenditures and innovation activity of Slovenian firms by type of ownership, 1996-2002 (%)

	N	R&D/Sales (Innovative firms)	R&D/Sales (Non-Innovative firms)	Fraction of Innovative firms
All firms				
1996	1,454	1.5	0.026	21.7
1998	1,777	1.6	0.003	23.0
2000	2,518	6.0	0.021	21.2
2002	2,564	6.5	0.015	20.6
Domestic				
1996	1,148	1.4	0.027	18.6
1998	1,371	1.5	0.003	19.5
2000	1,923	7.1	0.023	17.5
2002	1,935	6.4	0.004	17.3
Foreign				
1996	306	1.8	0.023	33.3
1998	406	1.9	0.003	34.7
2000	595	4.1	0.012	32.9
2002	629	6.6	0.055	30.5

Source: Statistical office of Slovenia; own calculations.

Table 1 reveals that the rate of innovation activity, which captures both product innovation and process innovation, is comparatively low in Slovenia. Only about 20% of Slovenian firms innovate, i.e. claimed to have conducted at least one innovation regarding products and services or regarding the innovation of processes in the respective 2-year period. What is striking is the negative trend of the innovation activity of Slovenian firms, which shows that the share of innovative Slovenian firms shrunk from 1998 to 2002.[8] This is predominantly due to the low innovation activity of domestic firms (only 17% of firms with domestic owners are innovative). Among foreign owned firms (firms with 10% or higher foreign equity share) the share of innovative firms is twice as high as in domestic firms. This indicates a more competitive and innovation conducive environment in foreign owned firms. Still, higher innovation activity by foreign owned firms is not necessarily backed by their higher own R&D expenditures (relative to total sales). The fact is that in the 2000 innovation survey foreign owned firms show proportionally less R&D expenditures compared to domestically owned firms, and in the 2002 survey

[8] The share of innovative firms is shrinking in spite of the fact that total R&D expenditure is increasing.

approximately the same. Hence, their higher propensity to innovate must be driven by other factors, such as a constant transfer of technology and other knowledge spillovers from their parent companies.

Determinants of innovation activity by Slovenian firms were extensively studied by Damijan et al. (2006) by using the same dataset. Table 1 reveals the basic descriptive statistics of the innovation activity of Slovenian firms, showing that innovative firms are on average larger in terms of employment, have higher R&D expenditures, receive more R&D subsidies, are more export oriented, and are more likely to be foreign owned. At the same time, Table 1 shows also that the innovation activity of firms is persistent over time.

Table 2: Determinants of firms' innovation in Slovenia, 1996-2002 (in %)

	No.	INOV_ t-2[1]	rVA/ Emp[2]	Employ -ment	R&D/ Sales[3]	R&D/ VA[4]	Total sub./ R&D[5]	Public sub./ R&D[6]	Foreign sub./ R&D[7]	Exports / Sales	IFDI[8]
Innovative firms											
1996	316	-	1.26	346.7	1.55	5.39	5.39	3.12	0.27	43.9	0.388
1998	409	0.643	0.84	312.9	1.62	5.96	4.07	2.42	0.85	43.1	0.397
2000	533	0.554	1.11	278.5	6.02	19.22	4.33	3.42	0.59	38.1	0.368
2002	527	0.694	1.09	283.6	6.47	18.42	4.98	3.14	1.08	43.7	0.364
Non-Innovative firms											
1996	1138	-	1.19	122.8	0.026	0.101	0.180	0.066	0.054	25.7	0.254
1998	1368	0.095	1.11	96.5	0.003	0.006	0.004	0.004	0.000	27.3	0.237
2000	1985	0.122	1.01	68.5	0.021	0.047	0.013	0.013	0.000	21.6	0.201
2002	2037	0.113	0.99	67.5	0.015	0.038	0.016	0.000	0.001	22.8	0.215

Source: Damijan, Jaklič and Rojec (2006). *Notes:* 1/ Past innovation activity, lagged one period, that is two years; 2/ Relative productivity; firm value added per employee relative to the average productivity of particular sector; 3/ R&D expenditures as a share of sales; 4/ R&D expenditures as a share of value added; 5/ The share of total R&D subsidies in R&D expenditures; 6/ The share of public R&D subsidies in R&D expenditures; 7/ The share of foreign R&D subsidies in R&D expenditures; 8/ Foreign ownership.

Based on these data, Damijan et al. (2006) estimated the impact of firms' internal R&D capital, external R&D spillovers, firms' absorption capacity, and other structural indicators (such as firm size and productivity) on firms' innovation activity within an integrated dynamic model. They find that the probability of a firm innovating depends on the following factors:

(i) a firm's own R&D expenditures have a highly significant and positive impact on the probability of it innovating;
(ii) a firm's current innovation activity is heavily dependent on its previous innovation activity;
(iii) a firm's size positively affects its ability to innovate;
(iv) public R&D subsidies as well as R&D subsidies received from abroad significantly improve a firm's ability to innovate,
(v) foreign ownership stimulates firms to innovate, while exporting is not shown to have a significant impact on a firm's innovation activity;
(vi) horizontal knowledge spillovers seem to drive firm innovation activity, while vertical knowledge spillovers are shown to not be important;
(vii) contrary to expectations, the labor productivity and technological intensity of sectors in which a firm operates do not determine its innovation activity.[9]

[9] In addition to the above estimations, Damijan et al. (2006) also ran a separate estimation for product and process innovations. Results are almost identical for both types of innovation activity. There are only minor differences in estimation results in the sense that process innovations require a slightly larger firm size, while product innovations seem to be more pronounced in foreign owned firms and seem to give slightly higher return on public subsidies.

4. The impact of innovation activity on firms' productivity growth

This section is aimed at exploring the efficiency of innovations regarding firms' total factor productivity (TFP) growth. We apply different empirical and econometric approaches in order to verify the robustness of the link between firms' innovation and productivity growth. First, we estimate the growth accounting model including the R&D capital by applying the OLS approach. In the second approach we use the matching techniques and propensity score to discriminate between innovating and non-innovating firms and to explore whether innovation activity is the decisive factor driving firm productivity growth. In the third approach we apply the estimation algorithm introduced by Crépon, Duguet, and Mairesse (1998) and asymptotic least squares on a system of simultaneous equations describing research activities, innovation, and productivity.

4.1. The effect of innovation on productivity growth using OLS estimations

In the OLS estimations we follow a great body of literature on the contribution of R&D to firms' TFP growth. Typically, a growth accounting approach in the form of a standard Cobb–Douglas production function is used in this type of analysis (see section 2). We start from the following production function:

(1) $$Y_{it} = Ae^{\lambda t} K_{it}^{\alpha} L_{it}^{\beta} R_{it}^{\gamma} e^{\varepsilon_{it}} \ ,$$

where Y_{it} is value added in firm i at time t, and K, L, and R represent the capital stock, employment, and research capital used in production, respectively. A is a constant and λ represents the rate of disembodied technical change; e is the error term capturing all firm specific disturbances as well as measurement errors, etc. The production function is homogenous of degree r in K, L, and R, such that $g = \alpha+\beta+\gamma \neq 1$, which implies that Y may have non-constant returns to scale. α, β, and γ are the elasticities of production with respect to capital, labor, and R&D capital. Our main focus is placed on the estimated elasticity γ, which reflects the marginal productivity or rate of return of output to R&D capital.

By log-linearizing one can easily rewrite (1) in the form of first differences:

(2) $$\Delta y_{it} = \lambda + \alpha \Delta k_{it} + \beta \Delta l_{it} + \gamma \Delta r_{it} + \Delta \varepsilon_{it} \ .$$

Note that after controlling for standard inputs (labor and capital), the estimate of γ returns the contribution of R&D capital to total factor productivity (TFP) growth. We assume that R&D capital contains a set of factors that enhance innovation activity and are either internal or external to the firm. Hence, one can write R as a function of a firm's internal R&D capital $\mathbf{F}_{it}$ and of various spillover effects $\mathbf{Z}_{it}$:

(3) $$R_{it} = f^{i}(\mathsf{F}_{it}, \mathsf{Z}_{it})$$

where $\mathbf{F}_{it}$ contains the firm's own R&D expenditures, measured as a share of R&D expenditures relative to the firm's total sales. $\mathbf{Z}_{it}$ captures all spillover effects that enhance the firm's ability to innovate, such as foreign ownership, learning by exporting (exports to sales ratio), public R&D subsidies received either from national or international sources, as well as innovation spillovers received from other firms within the same sector or from other sectors.

We employ the same formulation of the research capital function (3), i.e. elements of F_{it} and Z_{it}, following the determinants of firms' innovation activity as identified by Damijan et al. (2006) for the same dataset of Slovenian firms.

Note that in a panel data framework, equation (1) is typically subject to firm-specific time invariant disturbances, which one can control for by using one of the standard panel data estimation techniques (within or between estimators). Alternatively, one can get rid of firm-specific effects by estimating the equation as in (2), where by first-differencing the time invariant, firm-specific effects are simply eliminated. Another problem with the time-series cross-section specification of (1) is a potential endogeneity between the inputs and the output, which may lead to a biased estimation of input coefficients. However, in such a short and unbalanced panel dataset with mostly two to three observations per firm, there is little one can do about it. Correcting for this endogeneity, by using both the Olley-Pakes method and general method of moments (GMM) requires longer time series of input and output data in order to be efficiently used as lagged instruments for a firm's present performance.

Table 3: Impact of R&D and innovation on firm's TFP growth of Slovenian firms, 1996-2002 [OLS estimations]

	(1) R&D	(2) Inov All	(3) Inov Product	(4) Inov Process	(5) Inov All	(6) Inov Product	(7) Inov Process
ΔCapital	0.141	0.138	0.138	0.138	0.139	0.138	0.138
	[8.20]***	[7.92]***	[7.92]***	[7.93]***	[8.10]***	[7.93]***	[7.94]***
ΔLabor	0.434	0.429	0.429	0.430	0.433	0.430	0.430
	[13.02]***	[12.77]***	[12.75]***	[12.80]***	[13.05]***	[12.79]***	[12.79]***
Δ R&D/Sales	0.150						
	[1.14]						
INOV		0.072	0.063	0.069			
		[2.12]**	[1.75]*	[1.83]*			
p[INOV]					0.085	0.083	0.087
					[2.51]**	[1.94]*	[1.80]*
IFDI		0.059	0.051	0.065			
		[1.84]*	[1.63]	[2.15]**			
INOV * IFDI		-0.026	0.001	-0.048			
		[0.46]	[0.02]	[0.77]			
EX/Sales		0.070	0.071	0.075			
		[1.94]*	[1.97]**	[2.10]**			
HS_INOV		-0.001	-0.001	-0.001			
		[1.07]	[1.07]	[1.05]			
VS_INOV		0.001	0.001	0.001			
		[0.64]	[0.64]	[0.60]			
Medium low tech		0.006	0.007	0.006	0.004	0.014	0.014
		[0.15]	[0.16]	[0.15]	[0.13]	[0.46]	[0.48]
Medium high tech		0.107	0.108	0.113	0.112	0.105	0.111
		[2.45]**	[2.47]**	[2.58]***	[2.94]***	[2.68]***	[2.86]***
High tech		0.047	0.047	0.051	0.057	0.049	0.054
		[0.95]	[0.95]	[1.03]	[1.67]*	[1.40]	[1.55]
Const.	0.076	0.056	0.06	0.058	0.079	0.081	0.082
	[6.34]***	[1.42]	[1.53]	[1.47]	[2.73]***	[2.70]***	[2.69]***
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs	4192	4046	4046	4046	3931	4046	4046
Adj R-sq.	0.07	0.07	0.07	0.07	0.08	0.07	0.07

Dep.var.: ΔValue added.
*, ** and *** denote significance of coefficients at the 10%, 5% and 1%, respectively.

In the first specification we follow other empirical studies and estimate (2) by including only R&D expenditures (relative to sales) as a measure of R&D capital. This estimate gives us the upper bound of the possible return of output on R&D capital. Indeed, as shown in Table 3 (see column 1), the estimated elasticity of R&D capital with respect to output growth for Slovenian firms in the period 1996-2002 is about 0.15 (but insignificant). This estimate is closer to the lower boundary of returns – which is between 0.04 and 0.56 - found by other empirical studies with a similar model specification.[10]

In our second specification (see column 2 in Table 3) we go one step further by estimating the impact of innovations which is the effective result of R&D on firm TFP growth. This is our preferred estimation, returning an estimate of the rate of return on innovation of 0.072. It demonstrates that in an average Slovenian firm innovation results in an annual TFP growth of 7.2%. In addition to this, foreign ownership enhances a firm's TFP growth by an additional 5.9%, but our results also show that innovations have the same impact on TFP growth both in foreign owned and domestic firms (no significant difference found for the interaction term INOV*IFDI). Hence, foreign ownership has a double impact on a firm's TFP growth. It first enhances a firm's ability to innovate that was demonstrated already in the previous section, but then it also contributes additionally to a firm's TFP growth via superior organizational techniques, and so on. In addition, export propensity is shown to contribute significantly to TFP growth.

Interestingly, in spite of the hypothesized different impact of product and process innovation on firm productivity growth, we find no difference between the two. Both – product and process innovation – seem to have a similar positive impact on TFP growth (0.63 and 0.69, respectively; see columns 3 and 4).

Other external spillover variables included in our specification in columns 2 - 4, such as vertical and horizontal innovation spillovers, do not seem to have any direct impact on a firm's TFP growth. Using the same dataset, Damijan et al. (2006) claim that it is very likely that many external knowledge spillovers, such as export propensity as well as horizontal (intra-industry) and vertical (inter-industry) knowledge spillovers do enhance a firm's ability to innovate but do not affect a firm's TFP growth *per se*. Damijan et al. (2006) do indeed find a positive impact of horizontal spillovers on firms' ability to innovate but no significant impact of vertical knowledge spillovers and of export propensity on innovation output was found.

As a robustness check we replicated the estimation of the research capital function (3) above using the probit model where the dependent variable is innovation output and innovation determinants, including R&D expenditures, foreign ownership, learning by exporting (exports to sales ratio), public R&D subsidies received either from national or international sources, as well as innovation spillovers received from other firms within the same sector or from other sectors. In the second step, we then include the so obtained predicted value of innovation into our basic growth accounting model (2). The results of including this predicted innovation variable (see columns 5 - 7 in Table 3) returns a slightly higher estimate of the return on innovation (the estimate of γ increases to 0.85). However, again we do not find a significantly different impact of product and process innovation on firm productivity growth (estimates of γ amount to 0.83 and 0.87 for product and process innovations, respectively).

[10] See, for instance, Mansfield (1980), Griliches and Mairesse (1983), Clark and Griliches (1984), Sassenou (1988), Lichtenberg and Siegel (19891), Fecher (19890), Griliches and Mairesse (1990), and Griliches (1998).

According to the above findings, we can draw the conclusion that for Slovenian firms innovation activity as a result of a firm's R&D seems to contribute substantially to their total factor productivity growth.

In the remainder of the paper we focus on analyzing the impact of innovation activity on productivity growth. Using different empirical approaches, we explore the robustness of the above positive correlation of measures of innovation with changes in firm productivity.

4.2. The effect of innovation on productivity using the nearest neighbor matching and average treatment effects

The results presented so far indicate that innovation and R&D expenditure may be of crucial importance as determinants of firm productivity dynamics. However, our approach so far did not control strictly enough for the inherent differences between innovative and non-innovative firms. In order to determine the actual effect innovative activity has on firm productivity growth the effect of innovative activity on firm performance must be estimated by comparing otherwise similar firms. A way of doing this is to employ matching techniques to construct something akin to a controlled experiment. We use firm propensity to innovate to match innovating firms with otherwise similar non-innovating firms in order to evaluate the importance of innovation on productivity growth. Firms' probability to innovate is calculated by running the following probit regression:

$$\text{(4)} \qquad \Pr(INOV_{it}=1)=\alpha+\beta_1 INOV_{it-2}+\beta_2 Size_{it}+\beta_3 \frac{rVA}{Emp}_{it}+\beta_4 \frac{RD}{Sales}_{it}+\beta_5 \frac{EX}{Sales}_{it}+\beta_6 IFDI_{it}+\varepsilon_{it}$$

Conditional on satisfying the balancing property of the propensity score, the fitted values obtained from estimating the above equation (the probit estimation) are used to pair up innovators with non-innovators and those matched pairs are subsequently used to estimate the average treatment effect of innovation on firm productivity growth. The balancing property ensures that once the observations have been stratified into blocks according to the propensity score, the right hand side variables of (4) do not differ significantly between the groups of treated and non-treated observations within a block. The more closely the firms are matched with respect to regressors in (4), the more likely it is that the observed productivity differences result purely from the fact that some firms managed to innovate while others did not. We match innovating firms with their non-innovating counterparts using nearest neighbor matching (with random draws) which pairs up the treated with the closest, with respect to the propensity score, non-treated observations. Given that our sample size is very small in some instances, all the standard errors reported were generated by bootstrapping with 100 repetitions.

Tables 4-6 present the results of average treatment effects estimates of innovation on different specifications of growth in value added per employee. In each of the tables we differentiate between manufacturing and service firms, and as well take explicit account of firm size classes. The top panel of Table 4 presents the average treatment effects of innovation on labor productivity growth in the first two years after the innovation has been introduced, where productivity growth is accounted for as:

(5) $$growth[(t+2)-t] = \ln\left(\frac{VA}{Emp}\right)_{t+2} - \ln\left(\frac{VA}{Emp}\right)_{t}$$

where *VA* is value added and *Emp* is employment. In contrast to the subsequent results, here we do not discriminate between product and process innovation and consider any form of determinant of productivity growth.

Table 4: Average treatment effects estimates of innovation on growth in VA/Emp (difference in logs)

	Productivity growth in first two periods after innovation (*t+2*) - *t*					
Firm size	Manufacturing (NACE 15-37)			Services (NACE 45-90)		
	ATT	SE	No. of obs. treatm.(control)	ATT	SE	No. of obs. treatm.(control)
Emp ≤ 10	-0.106	0.079	87 (68)	0.037	0.056	131 (116)
10 < Emp ≤ 50	-0.121*	0.072	172 (126)	0.024	0.066	69 (57)
50 < Emp ≤	-0.029	0.027	545 (311)	-0.102	0.083	47 (41)
Emp > 250	-0.035	0.038	380 (137)	-0.050	0.067	31 (21)
	Productivity growth between periods 4 and 2 after innovation (*t+4*) - (*t+2*)					
Firm size	Manufacturing (NACE 15-37)			Services (NACE 45-90)		
	ATT	SE	No. of obs. treatm.(control)	ATT	SE	No. of obs. treatm.(control)
Emp ≤ 10	-0.168	0.146	87 (55)	-0.090	0.080	131 (92)
10 < Emp ≤ 50	0.033	0.084	172 (86)	-0.120	0.109	69 (44)
50 < Emp ≤	-0.047	0.044	545 (215)	-0.013	0.179	47 (32)
Emp > 250	-0.054	0.060	380 (94)	-0.144	0.099	31 (18)

Note: *,** and *** denote statistical significance at 10%, 5% and 1% level. The number of observations is given in terms of both the number of treatment and control observations (the latter in parentheses). SE-bootstrapped standard errors.

Contrary to our expectations, no significant positive effects of innovation on labor productivity growth are revealed in the top panel of Table 4. Moreover, small manufacturing firms (between 10 and 50 employees) even experienced a significant negative "treatment" effect of innovation on labor productivity growth (significant at 10 per cent only). It remains to be seen in the later specification whether this result is robust.

One possible explanation for the lack of finding more conclusive results may be that we are not capturing the relevant growth period. It may take longer than two years after the initial innovation for firms to internalize all the benefits of it. To control for this we redefined productivity growth so that we explore the growth in labor productivity between the second and fourth year after the innovation:

(6) $$growth[(t+4)-(t+2)] = \ln\left(\frac{VA}{Emp}\right)_{t+4} - \ln\left(\frac{VA}{Emp}\right)_{t+2}$$

The bottom part of Table 4 presents estimates of the average treatment effect of innovation on labor productivity growth between the second and fourth years after the innovation was initially made. By changing the period of observation we hope to capture the effects of innovation on productivity that were not apparent in the first two years after the time of innovation. As before, we find that innovating firms did not grow significantly faster (in terms of productivity) than comparable non-innovating firms. We no longer find negative impacts of innovation on productivity growth in small manufacturing firms.

Table 5: Average treatment effects estimates of innovation on growth in VA/Emp (difference in logs) two periods after innovation $(t+2) - t$ [Process innovation]

	PROCESS INNOVATION					
Firm size	Manufacturing (NACE 15-37)			Services (NACE 45-90)		
	ATT	SE	No. of obs. treatm.(control)	ATT	SE	No. of obs. treatm.(control)
Emp ≤ 10	-0.041	0.064	51 (47)	0.005	0.081	65 (62)
10 < Emp ≤ 50	-0.151***	0.059	114 (99)	0.111	0.073	39 (35)
50 < Emp ≤	0.000	0.024	404 (285)	-0.129	0.087	22 (19)
Emp > 250	-0.054	0.044	318 (142)	-0.031	0.062	12 (10)
	PRODUCT INNOVATION					
Firm size	Manufacturing (NACE 15-37)			Services (NACE 45-90)		
	ATT	SE	No. of obs. treatm.(control)	ATT	SE	No. of obs. treatm.(control)
Emp ≤ 10	-0.190	0.112	77 (53)	-0.053	0.078	121 (87)
10 < Emp ≤ 50	0.153	0.111	153 (83)	0.049	0.111	64 (35)
50 < Emp ≤	0.005	0.063	502 (193)	-0.319***	0.114	42 (28)
Emp > 250	0.019	0.079	357 (98)	-0.075	0.101	30 (15)

Note: *,** and *** denote statistical significance at 10%, 5% and 1% level. The number of observations is given in terms of both the number of treatment and control observations (the latter is in parentheses). SE- bootstrapped standard errors.

To further disentangle the cause of this lack of evidence on the effects of innovation on productivity growth, we opt for a more specific definition of innovation by explicitly discriminating between product and process innovations in Table 5. This is based on the findings that process innovations have labor displacement effects and are expected to result in significant productivity growth, while, due to the demand effect, product innovations may likely cause employment growth and, thus, may not result in significant productivity growth (Harrison et al, 2005; Hall et al, 2007). Evidence on changes in employment after a firm has carried out some innovation, however, do not confirm these expectations (see Table C1 in Appendix). Notwithstanding what kind of innovation a firm has conducted, both process and product innovating firms seem on average to decrease their employment levels. This is true for virtually all size classes with only few exceptions. Decreases in employment levels should therefore result in positive changes in productivity growth in both groups of innovating firms.

Table 5 presents estimates of the average treatment effect separately for process and product innovation on labor productivity growth.[11] In line with the evidence on employment changes, results for separate sets of process and product innovating firms do not differ substantially from those presented for aggregate innovations. Again, little evidence is found in favor of innovations positively affecting productivity growth. As was the case before, most of the estimates are not significantly different than zero, whereby small manufacturing firms (between 10 and 50 employees) in the case of process innovations and medium sized (between 50 and 250 employees) in the case of product innovations, are found to experience a significant negative "treatment" effect of innovation on labor productivity growth. These negative effects disappear when taking into account productivity growth between the second and fourth years after the innovation (see Tables B1 and B2 in Appendix).

Possibly, the reasons for the lack of results may be that the effects of innovation are not adequately captured by labor productivity and that total factor productivity should have

[11] Note that we only show results for the first two years after the innovation has been introduced, while the results for productivity growth between the second and fourth years after the innovation was initially introduced are shown in the Appendix (Tables B1 and B2).

been used instead. Additionally, our productivity proxy may fail to control for contemporaneous growth in inputs which may conceal the actual productivity dynamics. In order to control for this we use a TFP measure of productivity estimated by the Levinsohn-Petrin (2003) method. For obvious reasons this is done for manufacturing firms only. The results shown in Table 6 again indicate that there is no significant relationship between innovation activity and subsequent increase in productivity after two or four years. The only exception are micro firms (less than 10 employees) in the period of four years after innovation, where a negative relationship is found, but this result is not repeated in any other alternative specification.

Table 6: Average treatment effects estimates of innovation on growth in Levinsohn-Petrin specification TFP/Emp (difference in logs)

Productivity growth in the first two periods after innovation (*t+2*) - *t*			
Firm size	Manufacturing (NACE 15-37)		
	ATT	SE	No. of obs.
Emp ≤ 10	-0.188	0.122	87 (33)
10 < Emp ≤ 50	-0.110	0.085	172 (74)
50 < Emp ≤ 250	0.193	0.170	545 (200)
Emp > 250	-0.012	0.039	380 (98)
Productivity growth between second and fourth period after innovation			
Firm size	Manufacturing (NACE 15-37)		
	ATT	SE	No. of obs.
Emp ≤ 10	-1.792***	0.616	87 (3)
10 < Emp ≤ 50	-0.192	0.158	172 (32)
50 < Emp ≤ 250	0.021	0.052	545 (114)
Emp > 250	-0.083	0.110	380 (63)

Note: *,** and *** denote statistical significance at 10%, 5% and 1% level. The number of observations is given in terms of both the number of treatment and control observations (the latter is in parentheses). SE-bootstrapped standard errors.

4.3. The effect of research on innovation and productivity using the Crépon-Duguet-Mairesse (1998) approach

In order to provide an additional robustness check, we examine the links between productivity, innovation, and research by applying the estimation algorithm introduced by Crépon, Duguet, and Mairesse (1998) (hereinafter CDM). Given that our dataset differs in certain aspects from the one originally used by CDM, we adapted their estimation approach to the available data.

The three stage estimation approach proposed by CDM is based on a structural model that explains productivity by innovation output and innovation output by research investment. The applied econometric methods take into account several key statistical features of the available data: the fact that only a portion of the of firms engage in research and development activities, the endogeneity of productivity, innovation, and research activity, as well as the fact that research investment and (research) capital are truncated variables, while innovative activity is binomial data. The availability of innovation survey data in addition to the usual firm-level accounting information allows us to separate different aspects of the innovation process and directly measure the effects this process has on productivity. Following CDM, we model three simultaneous relationships: the research equation, which links research to its determinants, the innovation equation relating research to innovation output measures, and, finally, the productivity equation relating innovation output to productivity.

4.3.1. The estimation approach

Following CDM, we present our version of the estimation algorithm to estimate the effects of R&D activity and expenditures on innovation and productivity. The system of equations is split into three sets: the research equation, innovation equation, and productivity equation.

Research equation. Firm research activities are depicted by two equations accounting separately for a firm's decision to engage in research and the magnitude or intensity of these activities. For the research decision, CDM assume that there exists a latent dependent variable g_i^* for firm *i* given by the following equation:

$$g_i^* = x_{0i} b_0 + u_{0i} \tag{7}$$

where g_i^* expresses the decision criterion (such as the expected present value of firm profit accruing to research investment), x_{0i} is a vector of explanatory variables, b_0 the associated coefficient vector, and u_{0i} an error term. Firms with g_i^* above some threshold value (overall or industry specific) choose to invest in research. As was the case for French firms studied by CDM, only a portion of Slovene firms actually invest in R&D.

The intensity of research k_i^* is determined by the second "research" equation:

$$k_i^* = x_{1i} b_1 + u_{1i} \tag{8}$$

where k_i^* is the research capital per employee of firm *i* when this firm does research, x_{1i} is again a vector of explanatory variables, b_1 the associated coefficient vector, and u_{1i} an error term.[12] Even though it needs not be the case[13], we follow CDM and assume that both equations have the same explanatory variables ($x_0 = x_1$). The explanatory variables we employ in the estimation of equations (8) and (9) differ somewhat from those employed by CDM due to the restrictions of the dataset. The regressors we use are:

$$x_{0i} = x_{1i} = (l_i, s_i, a_i, T_i, S_i)$$

where l_i is employment, s_i is the market share (based on NACE 3-digit markets), a_i is firm age, and *T* and *S* are time and industry dummies. Unfortunately, the innovation survey does not include information on demand pull and technology push factors, nor do we have access to product-level sales information.

Innovation equation. We proxy innovation output with an indicator variable of innovation, which takes the value 1 if a firm has innovated in the past year and 0 if it has

12 We use both logarithm of research capital per employee and logarithm research investment per employee in the estimation. Construction of the research capital variable follows the approach suggested by CDM.

13 There do not seem to be many theoretically convincing choices of variables that could serve to explain the choice to invest in R&D but not the magnitude of the investment, and vice versa.

not. Furthermore, we are able to differentiate between product and process innovations.[14] On the other hand, we do not observe patent data nor do we have information on the share of sales coming from newly launched products. The innovation equation we estimate is:

$$p_i^* = \alpha_k k_i^* + x_{2i} b_2 + u_{2i} \tag{9}$$

where p_i^* is the latent probability to innovate, k_i^* is the latent research variable, x_{2i} is a vector of other explanatory variables, and u_{2i} is the heterogeneous error term. We assume that the error term is normally distributed with zero mean and constant variance. In contrast to CDM, in two innovation equations, where the regressants are patents and share of innovative sales, respectively, we estimate (9) using a probit model.[15] The exogenous variables x_{2i} used in the actual estimation are:

$$x_{2i} = (l_i, a_i, T_i, S_i)$$

with the notation the same as above. As suggested by CDM, the market share variable is not included directly into the innovation equation, but only indirectly through research capital. This also helps impose structure on the model and allows us to use market share as an instrument.

Productivity equation. Lastly, we use the results of the previous two stages to augment the standard Cobb-Douglas production function with innovation output. Given the specification of the innovation equation, innovation output will be measured by the probability that firm *i* will innovate in the current period. The productivity equation to be estimated is:

$$q_i = \alpha_I p_i^* + x_{3i} b_3 + u_{3i} \tag{10}$$

where q_i is the logarithm of labor productivity (log value added per employee), while the factors of productivity (other than innovation output) captured in x_{3i} are:

$$x_{3i} = (l_i, c_i, T_i, S_i)$$

where c_i is the logarithm of physical capital per employee. Again, our choice for the regressors in the productivity equation differs from the one suggested by CDM as we do not have data on the shares of engineers and administrators in the total number of employees.

4.3.2. Estimation issues

In estimating the above system of equations (7)-(10), we first have to take into account the nature of available data: research investment and hence research capital are truncated variables, while innovative outcome is binomial. Furthermore, there are possible

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[14] In the regressions presented here we do not discriminate between product and process innovations, but include both forms in the indicator variable. As a robustness check, we ran regressions on product and process innovation dummies individually and found no appreciable difference in the results.

[15] CDM estimate their two innovation equations with pseudo maximum likelihood and ordered probit, respectively.

selectivity and simultaneity biases stemming from the endogeneity of research capital in the innovation equation, while innovation output is endogenous in the productivity equations.

The setup of the model and the endogeneity issues argue for the use of a simultaneous equations system estimator. CDM find that the joint distribution of observable variables does not have a closed form, while numerical integration seems intractable due to the number of integrals involved and the size of the sample. Although a generalized method of moments estimator (GMM) could have been used, CDM propose using an asymptotic least squares (ALS) estimator[16]. ALS has been shown (Lee, 1981), firstly, to be more efficient than GMM in large samples. Secondly, there is a smaller computational cost (in terms of lost observations) of the estimator. Thirdly, ALS can be easily generalized to more complicated systems, which helps provide a unified and tractable framework for estimating limited dependent variables systems.

4.3.3. The results

First of all, we attempt to replicate the CDM results by estimating the above system of equations for a single period of observation. These results also serve as a benchmark for further estimation. In the presentation of results, following the first two columns of each table will show estimates of the two research equations, followed by estimates of the innovation equation and, in the last column, the productivity equation.

Table 7: Impact of R&D spending and innovation on productivity in Slovenia for 1996 [asymptotic least squares estimations]

Model	Research equations		Innovation and productivity equations	
	Probit[a]	Tobit[b]	Innovation[c]	Productivity[d]
R&D investment per employee (k_i)			0.250*** (0.007)	
Probabilty to innovate (p_i)				1.897*** (0.125)
Market share (s_i)	2.081*** (0.544)	8.084*** (1.729)		
Number of employees (l_i)	-0.032 (0.036)	-0.087 (0.139)	0.046 (0.029)	-0.008 (0.006)
Firm age (a_i)	0.0002 (0.002)	0.008 (0.008)	-0.001 (0.002)	-0.004*** (0.001)
Physical capital per employee (c_i)				0.733*** (0.012)
Sectoral dummies (S_i)	YES	YES	YES	YES
Number of observations (N)	804	804	804	804

Notes: [a] dependent variable is an indicator variable taking on value 1 if firm *i* invests in research and 0 if it does not
[b] dependent variable is the logarithm of investment in research and development per employee
[c] dependent variable is an indicator variable taking on value 1 if firm *i* has innovated and o if it has not (we include both product and process innovation)
[d] dependent variable is logarithm of value added per employee
Robust standard errors in parentheses. *,** and *** denote statistical significance at 10%, 5% and 1% level.

Table 7 presents estimates of equations (7)-(10) on Slovenian data for 1996 only. Although a direct comparison between these results and the findings of CDM is not possible as different specifications were employed, we find that our results are broadly consistent with those in French manufacturing firms. Market share of a firm positively affects both the probability of a firm to engage in research activities as well as the actual

[16] For more on asymptotic least squares, see CDM and Gourieroux and Monfort (1989).

intensity of research. The impact of firm size and age[17] is less conclusive in the research equations. Furthermore, we find that R&D investment per employee has a positive impact on innovative activity, while higher probability to innovate is associated with higher firm productivity levels. The probability to innovate coefficient is approximately ten times larger than the comparable CDM estimates, but this can be attributed to the fact that our innovation variable was a simple indicator variable (innovation dummy variable), while CDM use either patents or share of innovative sales.

Table 8: Impact of R&D spending and innovation on productivity in Slovenia for 2002 [asymptotic least squares estimations]

Model	Research equations		Innovation and productivity equations	
	Probit[a]	Tobit[b]	Innovation[c]	Productivity[d]
R&D investment per employee (k_i)			0.225** (0.103)	
Probability to innovate (p_i)				4.042*** (0.422)
Market share (s_i)	0.993** (0.425)	3.979** (1.726)		
Number of employees (l_i)	0.046 (0.038)	0.312 (0.193)	-0.017 (0.060)	-0.093 (0.001)
Firm age (a_i)	0.002 (0.002)	0.006 (0.008)	0.00004 (0.002)	-0.004*** (0.001)
Physical capital per employee (c_i)				0.630*** (0.009)
Sectoral dummies (S_i)	YES	YES	YES	YES
Number of observations (N)	756	756	756	756

Notes: [a] dependent variable is an indicator variable taking on value 1 if firm *i* invests in research and 0 if it does not
[b] dependent variable is the logarithm of investment in research and development per employee
[c] dependent variable is an indicator variable taking on value 1 if firm *i* has innovated and o if it has not (we include both product and process innovation)
[d] dependent variable is logarithm of value added per employee
Robust standard errors in parentheses. *,** and *** denote statistical significance at 10%, 5% and 1% level.

Our data spans all even years between 1996 and 2002, and for the sake of brevity we only present the results for the first and last year of the sample. For the remaining years the results prove to be robust regarding the choice of year in the sample. The estimates presented in Table 8 are based on observations for the year 2002 only.

The results presented in Table 8 correspond very closely to those presented in Table 7. While the sign and significance of the coefficients remain largely the same, the size of the coefficients differs significantly. Comparing results in the last column, the absolute effect of innovation on productivity is twice as large in 2002 as in 1996. Interestingly, the market-share coefficients in the first two columns (research equations) of Table 8 are only half the size of those in 1996.

Finally, estimates on the complete sample of firms are presented in Table 9. The only difference between the results presented here and those in Tables 7 and 8 is the fact that time dummies are added to the regressions. In contrast to CDM, our sample spans multiple years, allowing an increase in the size of the sample we performed our estimate on. Again, results remain consistent with those for individual years, and are as well in line with the findings of CDM. We find no statistically significant effect of market share or

[17] The age variable is specific to our approach and was not used by CDM. Instead, they use the number of activities a firm engages in, which we do not have information on.

firm size on the probability to engage in research[18], but the size of R&D expenditures is found to be positively affected by both variables.

Table 9: Impact of R&D spending and innovation on productivity in Slovenia for the whole sample 1996-2002 [asymptotic least squares estimations]

Model	Research equations		Innovation and productivity equations	
	Probit[a]	Tobit[b]	Innovation[c]	Productivity[d]
R&D investment per employee (k_i)			0.118*** (0.020)	
Probability to innovate (p_i)				1.832*** (0.085)
Market share (s_i)	0.429 (0.329)	5.932*** (0.728)		
Number of employees (l_i)	0.509 (0.038)	0.514*** (0.080)	0.408*** (0.014)	-0.102*** (0.010)
Firm age (a_i)	-0.0002 (0.0005)	-0.0004 (0.005)	-0.0009 (0.0013)	-0.0004*** (0.0006)
Physical capital per employee (c_i)				0.698*** (0.008)
Sectoral dummies (S_i)	YES	YES	YES	YES
Time dummies (T_i)	YES	YES	YES	YES
Number of observations (N)	3391	3391	3391	3391

Notes: [a] dependent variable is an indicator variable taking on value 1 if firm *i* invests in research and 0 if it does not
[b] dependent variable is the logarithm of investment in research and development per employee
[c] dependent variable is an indicator variable taking on value 1 if firm *i* has innovated and o if it has not (we include both product and process innovation)
[d] dependent variable is logarithm of value added per employee
Robust standard errors in parentheses. *,** and *** denote statistical significance at 10%, 5% and 1% level.

The innovation equation reveals that firms with larger R&D investment per employee tend to be more successful at innovating, which is line with the conclusions of CDM. On the other hand, we find that firm size has a beneficial effect on innovative activity, which contradicts the CDM finding that size has no impact on innovation intensity (which they measure by patents or share of innovative sales). The effect of innovation on productivity is again positive and significant. A novelty of our approach is the inclusion of firm age in the analysis. Where in most instances different estimations do not yield conclusive results with respect to the effects of age on either research or innovation, we find that younger firms, other things considered, are more productive than older ones.

Lastly, we use the CDM framework to test whether research and innovation impact productivity growth. Although we analyzed the issue in the first part of this paper, we believe that the framework proposed by CDM is well suited to test for the effect of innovation on productivity improvements. The only changes we implement from the estimation presented in Table 9 is that the dependent variable is replaced by growth (in logarithm) of value added per employee, while the physical capital per employee variable is also replaced by its growth equivalent. Since the first three columns of the regression remain unchanged, we only present estimates of the productivity equation in Table 10.

[18] This is in contrast to the cross-section results presented earlier, where market share positively impacted the probability to research/ propensity to R&D.

Table 10: Impact of R&D spending and innovation on productivity growth in Slovenia for the whole sample 1996-2002 using asymptotic least squares

Productivity equation	
Probability to innovate (p_i)	0.064 (0.052)
Number of employees (l_i)	-0.008 (0.021)
Firm age (a_i)	0.0002* (0.0001)
Growth in physical capital per employee (gc_i)	0.323*** (0.067)
Sectoral dummies (S_i)	YES
Time dummies (T_i)	YES
Number of observations (N)	3391

Notes: [a] dependent variable is growth in the logarithm of value added per employee
Robust standard errors in parentheses. *,** and *** denote statistical significance at 10%, 5% and 1% level.

In contrast to the robust evidence of a positive impact of research and innovation on productivity, the effect on actual productivity improvements is less evident. Although positive, the effect of innovative ability is not significantly different than zero.[19] This is in line with the estimates from the matching techniques, where an effect of innovation on productivity growth was found, but it was by no means robust.

5. Conclusions

The paper analyses the impact of innovation on firms' productivity growth using firm-level innovation (CIS) and accounting data for a large sample of Slovenian firms from 1996-2002, and applying three different methods: simple OLS, matching techniques, and the Crépon-Duguet-Mairesse (CDM) approach. Three different methods are used to check for the robustness of the results. We also distinguish between product and process innovations.

OLS estimates provide three important conclusions for Slovenian firms. First, a firm's own R&D, as well as innovations as a result of a firm's R&D seem to contribute substantially to the firm's total factor productivity growth. Second, foreign ownership has a dual impact on a firm's TFP growth - it enhances the firm's ability to innovate, but then it also contributes additionally to the firm's TFP growth via superior organization techniques, and so on. Third, other channels of external knowledge spillovers do not affect a firm's TFP growth *per se*, although some of them may enhance a firm's ability to innovate. Separate estimations for product and process innovations show only some minor differences.

Estimates arrived at by the matching techniques do not reveal any significant positive effects of innovation on labor productivity, regardless of the period after the innovation was made. The results also do not show any different effects for product and process innovations. Both types of innovations bring about a reduction of employment, however, little evidence is found in favor of innovations – be it product or process – positively affecting productivity growth. The result is no different if we use a TFP instead of a VA/emp as a measure of productivity.

[19] In several different specifications the impact was revealed to be positive, but not statistically significant.

As regards the CDM approach, we find a positive effect of innovation on the level of productivity but not on productivity growth. R&D investment per employee has a positive impact on innovative activity, and higher probability to innovate is associated with higher firm productivity levels. The market share of a firm also seems to positively affect both the probability that a firm engages in research activities (in two of three specifications) as well as the actual intensity of research (in all specifications). The impact of firm size in the case of the 1996 and 2002 samples is not significant, while for the whole sample from 1996-2006 it is significant, positive in the case of innovation activity but negative in the case of productivity level. A novelty of our approach is the inclusion of firm age in the analysis, where in most instances different estimations do not yield conclusive results. In contrast to the robust evidence of the CDM approach regarding a positive impact of research and innovation on productivity, the effect on actual productivity improvements is less evident. Although positive, the effect of innovative ability is not significantly more than zero.

The overall conclusion is that the results of the exercise are not robust to different econometric approaches. While by applying a simple OLS we find some evidence of the positive impact of innovation on productivity growth, these results are not confirmed when using alternative empirical approaches. A significant impact of innovation activity on firm productivity growth has not been found, neither by the matching techniques nor by the CDM approach. On one hand, there is conclusive evidence that firms that are involved in R&D and those that invest more in R&D are more likely to invent and that, in addition, innovative firms are, on average, more productive. On the other hand, there is no conclusive evidence that more innovative firms have higher productivity growth. While some recent research suggests that product and process innovation may have an opposite impact on employment levels and thus differently affect innovating firm labor productivity, for Slovenian firms we find no divergent effects for both groups of innovating firms. These results are robust also to the use of TFP measures (instead of value added per employees), which eliminates the employment effects of innovation.

There are several possible reasons why our analysis has not yielded the expected positive relationship between innovative activity and productivity growth in the case of matching techniques and the CDM approach. In our opinion, the primary reason for these results lies in the quality of the survey data, primarily with regard to the definition of innovation. Secondly, we do not have available information on the exact time of innovation, as innovative activity could happen in either of the two years between surveys. Finally, it may be the case that a longer time series is required to capture the full effects of innovation.

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Appendix A

Table A1: Firms' probability to innovate products and processes in Slovenia, 1996-2002
(Results of a probit model)

	Product innovation				Process innovation			
	1		2		3		4	
	Coef.	z	Coef.	z	Coef.	z	Coef.	z
INOV_t-1	1.136	18.5	1.137	18.5	0.868	13.1	0.866	13.1
Size	0.438	9.9	0.442	10.0	0.532	12.1	0.531	12.0
rVA/Emp	0.003	0.4	0.003	0.4	0.007	1.0	0.007	1.0
R&D/Sales	18.842	18.0	19.217	18.4	18.489	17.4	18.504	17.5
Total sub./R&D	4.413	6.9			2.851	7.3		
Public sub./R&D			5.115	6.4			3.268	6.2
Foreign sub./R&D			4.771	2.5			2.273	3.5
IFDI	0.146	2.4	0.140	2.3	0.106	1.7	0.103	1.7
EX/Sales	0.241	2.8	0.228	2.6	0.175	2.0	0.171	1.9
HS_INOV	0.007	3.4	0.008	3.4	0.011	5.0	0.011	5.1
VS_INOV	-0.008	-1.5	-0.008	-1.5	0.002	0.3	0.001	0.3
ML tech	-0.030	-0.3	-0.035	-0.4	-0.206	-2.1	-0.214	-2.2
MH tech	0.144	1.5	0.135	1.4	-0.150	-1.5	-0.158	-1.6
H tech	0.188	1.6	0.177	1.5	-0.184	-1.6	-0.183	-1.6
Const.	-2.426	-19.8	-2.424	-19.8	-2.612	-21.2	-2.596	-21.2
Number of obs	4166		4166		4166		4166	
LR chi2(12)	1931.6		1938.3		1536.4		1527.5	
Prob > chi2	0.00		0.00		0.00		0.00	
Pseudo R2	0.438		0.440		0.382		0.380	

Dep.var.: $INOV_t$

Appendix B

Table B1: Average treatment effects estimates of innovation on growth in VA/Emp (difference in logs) between two and four periods after innovation (*t+4*) - (*t+2*) [Process innovation]

Firm size	Manufacturing (NACE 15-37)			Services (NACE 45-90)		
	ATT	SE	No. of obs. treatm.(control)	ATT	SE	No. of obs. treatm.(control)
Emp ≤ 10	-0.084	0.140	52 (43)	-0.019	0.103	65 (47)
10 < Emp ≤ 50	0.003	0.083	114 (70)	-0.062	0.133	39 (28)
50 < Emp ≤ 250	-0.044	0.040	404 (194)	0.027	0.096	22 (16)
Emp > 250	0.042	0.066	318 (106)	0.027	0.136	13 (9)

Note: ***,**,* denote statistical significance at 10%, 5% and 1% level. The number of observations is given in terms of both the number of treatment and control observations (the latter is in parentheses). SE-bootstrapped standard errors.

Table B2: Average treatment effects estimates of innovation on growth in VA/Emp (difference in logs) between two and four periods after innovation (*t+4*) - (*t+2*) [Product innovation]

Firm size	Manufacturing (NACE 15-37)			Services (NACE 45-90)		
	ATT	SE	No. of obs. treatm.(control)	ATT	SE	No. of obs. treatm.(control)
Emp ≤ 10	-0.084	0.140	52 (43)	-0.019	0.103	65 (47)
10 < Emp ≤ 50	0.003	0.083	114 (70)	-0.062	0.133	39 (28)
50 < Emp ≤ 250	-0.044	0.040	404 (194)	0.027	0.096	22 (16)
Emp > 250	0.042	0.066	318 (106)	0.027	0.136	13 (9)

Note: ***,**,* denote statistical significance at 10%, 5% and 1% level. The number of observations is given in terms of both the number of treatment and control observations (the latter is in parentheses). SE-bootstrapped standard errors.

Appendix C

Table C1: Changes in employment in firms conducting product and process innovations in 1996 – 2002, by size classes*

		Product and process innov.				Process innovators only				Product innovators only			
		-1	0	1	2	-1	0	1	2	-1	0	1	2
0<x<10	change in employ.	1.0	0.4	0.1	-27.0	1.0	0.7	-10.4	-1.2	0.9	-4.1	-0.6	-8.5
	number of firms	38	82	7	10	5	3	5	5	41	23	12	16
10<x<50	change in employ.	2.5	2.0	-2.9	-6.3	1.4	0.3	1.7	-6.2	1.2	1.4	-2.4	0.2
	number of firms	216	204	99	121	45	43	22	28	176	173	105	126
50<x<250	change in employ.	2.8	1.1	-8.0	-0.8	-0.3	0.7	-25.0	-1.8	0.3	-1.9	0.9	-2.2
	number of firms	401	264	148	278	52	78	31	36	185	162	119	148
x>250	change in employ.	-8.5	-10.8	-12.9	-13.2	-5.4	-34.0	-6.2	-9.2	-1.3	-11.8	-1.2	-9.5
	number of firms	302	171	70	215	30	25	16	21	94	81	57	68

Notes: *Change in number of employees calculated as mean of changes at the firm level in respective size class.Source: SURS, own calculations.