In search of the optimal fiscal incentives to foster innovation: firm-level evidence from Poland

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Abstract

Tax breaks and government subsidies are two main tools in the financial support of innovation in firms. While both types of policy instruments are widely used in middle-income- and high-income countries with seemingly positive effects, relatively little is known about how their impacts differ, and how they depend on the capabilities of the firms. In this paper, we use a panel based on five runs of Polish CIS data from 2012 to 2020 to compare the relative success of these instruments in terms of inducing innovation. We find evidence for the effectiveness of both types of support schemes. Tax exemptions seem to have a stronger effect on the introduction of product innovation and manufacturing process innovation, while grants for R&D appear more effective in inducing innovation co-operation and patenting activities. Overall, firms with worse innovation records react stronger to policy instruments than firms with prior innovation experience. Given that more and more countries introduce R&D tax breaks in their tax systems, this finding may have significant policy implications.

JEL codes: C10, H23, H25, H59, O31, O38
Keywords: innovation performance, R&D tax breaks, R&D subsidies, Community Innovation Survey, panel data, machine learning

1. Introduction

The optimal architecture of government financial support for innovation in firms is one of the key questions of STI (Science, Technology and Innovation) policy. Both tax breaks and direct subsidies are widely used in middle- and high-income countries (Appelt et al., 2016). While the empirical literature indicates that these instruments seem to be effective in most cases (Castellacci and Lie, 2015; Dimos and Pugh, 2016; Pöschel, 2022; Dimos et al., 2022), several interesting questions remain. Does it make sense to apply both types of instruments in the same national innovation system? Which instruments are more effective for a given type of innovation? How do firms with different capabilities respond to different types of policy measures?

We address some of these puzzles by analysing panel data from five waves of the Polish edition of the Community Innovation Survey from 2012 to 2020. Poland is an interesting case to study, first, because it is still a catching-up country, while most of prior empirical work has been on developed countries, and second, because it is a country with a generous (EU-funded) subsidy-based innovation support policy, which quite recently added tax breaks to the policy portfolio.

Although the use of Community Innovation Survey data for this type of research is rather standard, it is not very common that several runs of CIS data form a panel. We exploit this unique aspect of our dataset to mitigate the endogeneity problem that plagues evaluation studies. Although the question about the use of tax breaks have only been included in the last two of the five CIS runs we analyse, we use the older editions to assess innovation capabilities of the firms.

The structure of the paper is as follows. We first give the background by reviewing the theoretical and empirical literature on innovation support, as well as by depicting the specific context of the Polish system. Then, we move on with empirical analysis, which consists of econometric and machine-learning parts. Next, we put our results to a number of robustness tests, and in the final section we offer conclusions.

2. Background

2.1.Conceptual framework

Government support for innovation in firms is well grounded in economic theory and, importantly, almost unanimously accepted by policy-makers in both developed and catching-up countries. Traditionally, neoclassical economics justified government intervention through the occurrence of market failures caused by the public good nature of scientific and technological knowledge, through the related externalities, the imperfect information of the agents that decide about the funding of innovation (and who are not the ones who introduce it), and through the risk aversion of individuals and firms (Nelson, 1959). More recently, scholars in mainstream economics, such as Aghion et al. (2016) and Acemoglu (2023), have acknowledged that government actions can actually guide companies towards innovating in certain technologies (a claim that has long been made in evolutionary economics and innovation studies, cf. Hekkert et al., 2007). By implication, government support for innovation activities of firms can also be motivated by some bigger goals, such as the economy-wide transition to certain technologies. Further arguments for innovation policies addressing firms have been supplied by evolutionary economics which regards firms as learning entities that have to develop their capabilities to innovate; this process can be unlocked or accelerated by policy intervention. Moreover, the systemic view of innovation (echoed by the open innovation concept in strategy research) implies that the government affects innovation practices of firms in many ways, from funding to regulation to policies affecting the science sector.

Despite the wide acknowledgement of the sensibility of innovation support in firms, the question of the right policy mix remains open in economics, and it has been addressed in very different ways in political practice. In particular the balance between direct measures, such as subsidies (or loans), as opposed to indirect support in the form of tax exemptions for R&D activities, is still quite country-specific (Figure 1).

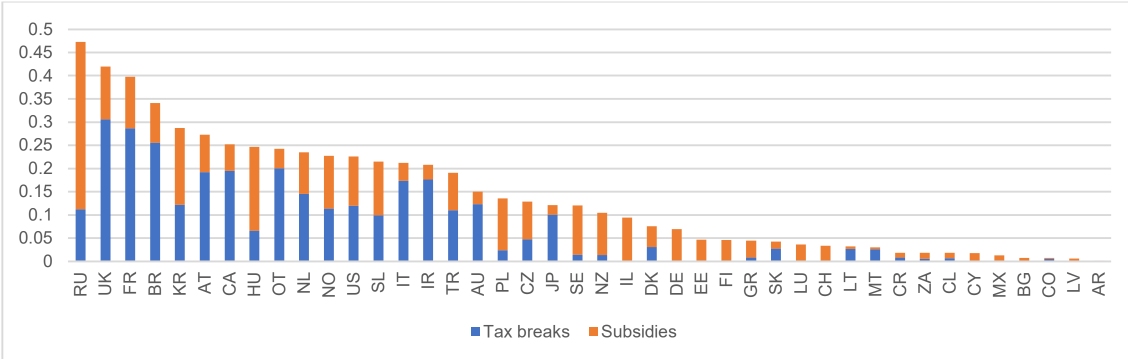

Figure 1. The amount of indirect support (tax breaks) and direct support (subsidies) for innovation in firms in 2019 (as percentage of GDP).
Source: OECD

From the academic perspective, both types of instruments have their advantages and weaknesses. The good thing about direct instruments (especially grants) is that they can be applied flexibly and targeted to specific technology fields or specific actions, for instance, taking up co-operation with universities or research institutes to obtain 'behavioural additionality'; they can also address specific types of recipients, defined by geography or socio-economic characteristics. These measures can also be launched and stopped relatively easily. Moreover, they are the preferred instrument for small and/or cash-constrained firms. On the other hand, grants can crowd out private innovation expenditures (thus fail to achieve 'input additionality'). They also require a skilled and reliable administration to be effective and to reduce the risk of fraud.

Tax breaks for R&D activities, for their part, do not carry a risk of crowding out and are simple to administer. However, they make the tax system more complicated and, in fact, there are numerous details of the design that should be considered (see Warda, 2002). They can also be ineffective if firms relabel their (routine) expenditures instead of incurring new R&D expenses. Also, they make more sense for profit-generating than loss-generating firms, although forward- or backward-carrying of unused tax deductions is usually possible, and some systems even provide cash refunds (this is the case in Germany and in Canada for SMEs). Another way of looking at this tradeoff is through aggregate spending. In this respect, grants offer a higher degree of discretion not only in terms of selection of beneficiaries, but also in terms of the total cost for the government; this can be planned with subsidies but not so much with tax breaks.

The judgement about the efficiency of a given policy instrument and the occurrence of unwelcome effects ultimately comes down to empirical studies. These have been reviewed and systematically analysed in recent meta-analyses of Castellacci and Lie (2015), Dimos and Pugh (2016), Pöschel (2022), and Dimos et al. (2022), who reported on both literatures: on R&D subsidies- and on tax breaks.

More than half of the empirical papers reviewed by Dimos et al. indicated the input additionality of R&D subsidies and the same was true for the set of studies on tax incentives. The metaregression analysis showed that the effects of both types of instruments were positive and statistically significant even when the possible publication bias was controlled for. On the other hand, these effects were rather modest. Focusing on the subset of studies that reported the elasticities of firm R&D expenditure with respect to government support, Dimos et al. calculated the average elasticities of subsidies and tax incentives: they were both about 0.015. That means that doubling the amount of funds the firm receives in the form of grants or foregone taxes increases the firm's own R&D spendings by 3%.

It is also worth noting that Pöschel (2022) obtained a different result, as in her study of the effects of tax incentives the publication bias rendered the average effect of tax incentives statistically insignificant. Her meta-analysis comprises a bigger set of primary studies (37) as compared to Dimos et al. (who review 25 sources). On the other hand, Pöschel shows that the publication bias is driven by the works published in scientific journals; once this factor is controlled for, the average effect of tax incentives becomes significant again.

The results from the study by Dimos et al. suggest that when defining their innovation policy mix, countries actually choose between the instruments of similar effectiveness. But let us not forget that most empirical evidence comes from developed countries. The similar efficiency of subsidies and tax breaks might be true for these countries because of their high administrative capacity. Countries with lower capacities might find it harder to administer efficient grant programs so the efficiency of subsidies can be relatively lower there. This is how one can interpret the findings of Szczygielski and Lewkowicz (2023), who analysed international differences in the generosity of tax incentives for R&D. Using the implied tax-subsidy ratio calculated by the OECD as their independent variable, they demonstrated that countries with higher government capabilities offer less generous tax breaks for R&D. Their analysis also suggests that there is a tradeoff between the generosity of tax incentives and the direct funding of R&D by governments.

2.2 Innovation policy mix in the national context

The case of Poland is quite an interesting one because the history of innovation policy is relatively short. Before the EU accession in 2004, there was virtually no support for innovation in firms. Thanks to the EU's structural policy, a system of grants was introduced that was quite generous and easily accessible. While the early programmes financed, to a large extent, investment in new equipment and machinery and showed little additivity in terms of innovation performance (Szczygielski et al., 2017), gradually the administrative capacity of the relevant government agencies improved to the extent that allowed for planning and execution of more elaborate R&D support schemes in the form of matching grants (Szczygielski, 2019). However, over time an increasing number of evaluation studies indicated that these instruments have approached their limits, in the sense of their inability to trigger R&D activities in the firms that have not applied for support. In particular, efforts to encourage a larger number of SMEs to apply for grants have not been successful (PAG Group, 2019, p. 65, PAG Group, 2021, pp. 58 and 103). In this context, the introduction of tax breaks for R&D in 2016 can be regarded as a welcome policy experiment, even if the motivation behind it was probably of a more political nature (a new government that wanted to show its initiative and support for a more "modern" economic model, cf. Ministry of Development of the Republic of Poland, 2017). The scheme allowed extra deductions of R&D costs from a firm tax base. Initially, in 2016, firms could deduct an extra 30% of R&D costs; in 2017 the rate was increased to 50%, and finally to 100% in 2018 and later years. Thus, since 2018, businesses in Poland can effectively count their R&D costs twice. It is worth noting that the Polish R&D tax breaks are relatively generous. According to the OECD data, the implied tax-subsidy rate for profit-making large firms in Poland was 0.17 in 2020, and it was higher than the respective rate in three-quarters of countries surveyed.[1]

In addition, since 2019, the Polish tax system has included an IP-box tax break. This type of tax exemption has been adopted by more and more countries in recent years, even if there are few theoretical arguments supporting it and a number of possible abuses, such as shifting profits to tax havens (Gaessler et al., 2021).

The total amount of tax exemptions for R&D granted for Polish firms has been increasing continuously since the instrument was launched (Figure 2), although subsidies continue to be the dominant support scheme. As of 2020, four times as much money was disbursed in the form of government grants and matching grants as there was tax foregone due to tax breaks for R&D. However, these OECD-based statistics ignore at least some of the subsidies that are funded by the EU. If we also count grants from international organisations, then grants are *eight* times as important as tax exemptions.

Furthermore, these differences are reflected in the microdata. According to a detailed evaluation study of the innovation support programmes co-funded from the 2016-2020 EU Financial Perspective, the median grant was 1.68 million PLN in the principal support scheme, i.e., the Smart Growth Operational Programme (PAG Group, 2021). The programme accounted for 75% of innovation support in Poland, while the remaining part was disbursed through 16 regional programmes. The median grant in the regional programmes was 820 thousand PLN. For a comparison, we estimate that the median tax

[1] The implied tax-subsidy rate is defined as one minus the B-index, where the B-index is "the present value of before-tax income that a firm needs to generate in order to cover the [on unit] cost of an initial R&D investment and to pay the applicable income taxes" (Warda 2002, p. 192).

deduction for the firms in 2020 did not exceed 75 thousand PLN for companies subject to Company Income Tax.[2] [3]

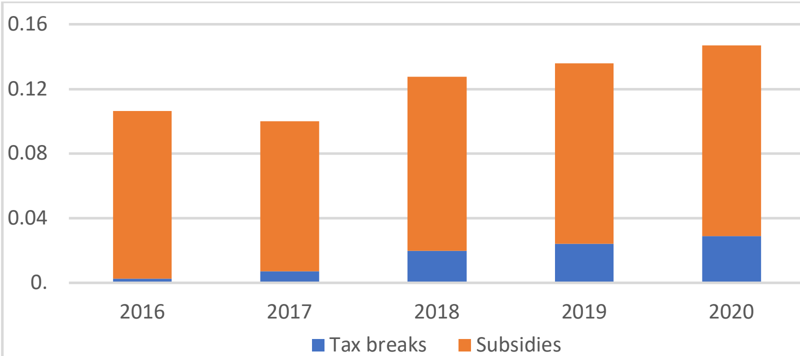

Figure 2. The amount of tax breaks for R&D granted in Poland vs. the amount of subsidies for R&D, as a percentage of GDP. Source: OECD

3. Dataset and descriptive statistics

Our analysis is based on five waves of the Polish edition of the Community Innovation Survey: 2012, 2014, 2016, 2018, and 2020. As it has always been the case with the CIS, since the inception of the study in the 1990s, respondents report their innovation activities (or the lack thereof) in the last three years, implying that we have data on innovation activities of Polish firms in the period 2010-2020.

Several features of our dataset are worth stressing. First, we have panel data, which is often not the case in the empirical works based on the CIS. For instance, the CIS data from different countries, made available for researchers in the Eurostat Safecentre in Luxembourg, are not structured as panels. On the other hand, due to the extremely strict confidentiality conditions imposed by Statistics Poland, we are missing several indicators from the survey, in particular any indicator that refers to revenue or expenditure. By implication, we have to base our empirical analysis, to a large extent, on binary variables. Finally, although we have data from five editions of the same survey, the questionnaire used in the last two waves of the study (2018 and 2020) is quite different from the one that was filled in by the firms participating in the previous three editions (2012, 2014, and 2016). This is because of the change in the CIS questionnaire following the revision of the Oslo manual (OECD, 2018). One of the key changes is that *all* the respondents answer *all* the questions in the survey, unlike the old version

[2] Our estimate is based on the median R&D cost being subject to the tax allowance, which was roughly 393 thousand PLN (Białek-Jaworska and Maruszewska, 2023). Assuming the 19% CIT rate pertaining to most firms in Poland, we obtain the tax allowance of 74 670 PLN. Small and micro-firms can apply for a reduced tax rate of 9%, implying a smaller absolute amount of foregone taxes. Therefore, the median did not exceed 74 670 PLN.
[3] The average euro official exchange rate in 2020 was 1 EUR = 4.4459 PLN, hence the respective numbers in euro were: the median OP Smart Growth grant – 377 876 euro, the median regional grant - 184 440 euro, and the median tax exemption - 16 795 euro.

where only firms that had some innovation activities answered. Another novelty is that since 2018 firms report their use of two types of “tax credits and allowances”: those pertaining to innovation activities, and those related to other types of activities. These variables are key to our study. Since they were only introduced in 2018, our econometric analysis is based on the 2018 and 2020 editions of the CIS, and we use the previous three editions to learn about the innovation history of the firm.

We would like to add one caveat here. While the CIS questionnaire refers to “tax breaks for innovation activities”, it does not specify the actual tax instrument. This makes our analysis a bit difficult, because of the IP-box tax break introduced in Poland in 2019: some of the beneficiaries of “tax breaks for innovation” from the 2020 edition of the CIS could be, in theory, the beneficiaries of IP-box and not of the R&D tax breaks. However, we have reasons to believe that such cases are very rare. Anecdotal evidence suggests that in Poland IP-box is mainly used by (individual) software developers, while CIS only includes companies that have at least 10 employees. To make sure our results are not distorted by this type of tax break, in Section 6 we repeat our calculations on a sample that excluded NACE industry 62 (Computer programming, consultancy and related activities).

In total, we have 74,218 observations from the five editions of the CIS. A total of 34,521 unique firms were surveyed (the panel is not balanced). Table 1 shows the breakdown of firms by the number of times they appear in the CIS.

Table 1: The number of firms in CIS by the number of times they were surveyed

Times in CIS	Number of firms
1	17,438
2	6,491
3	3,392
4	2,378
5	4,822

For the innovation survey, Statistics Poland only interviews firms that have 10 or more employees. While we do not have the exact number of employees, we know their size classes: small (10-49 employees), medium (50-249) and large (250 and more employees). As shown in Table 2, the share of large firms is quite stable, while the proportions of small and medium firms changed over time. However, the compositions of the 2018 and 2020 surveys – which are the two editions that are most important in our statistical analysis – are very similar.

Table 2. Composition of the sample by size classes

	small	medium	large
2012	40%	46%	14%
2014	44%	43%	13%
2016	30%	56%	14%
2018	38%	46%	16%
2020	37%	47%	16%

Foreign-owned firms tend to have distinct innovation patterns in Poland, as evidenced by many previous studies (Szczygielski et al., 2017; Szczygielski and Grabowski, 2014), so it is important to note that 12-17% of the sample, depending on the year, are firms that are members of business groups with the head company located abroad (Table 3). On the other hand, 6-11% of the sample are firms that are members of Polish business groups: such companies often perform relatively well in terms of innovation activities.

Table 3. Composition of the sample by membership in business groups

CIS	standalone	members of domestic groups	members of foreign groups
2012	78%	10%	12%
2014	79%	8%	12%
2016	76%	10%	14%
2018	77%	6%	17%
2020	77%	11%	12%

Table 4 shows the use of support schemes in 2018 and 2020. We distinguish four types of support for firms: tax breaks for innovations, other tax breaks, grants for R&D, and grants that support innovation activities but not R&D efforts. We do not know what specifically falls into the latter categories: it can be the purchase of equipment and machinery, but it can also be e.g. support in the commercialisation phase of new product development. Our main aim is to compare the effectiveness of tax breaks for innovation with the effectiveness of grants for R&D. Interestingly, in CIS 2020, these instruments benefited a similar number of companies (in fact 2.85% were both R&D grant recipients and beneficiaries of tax breaks for innovation). One cannot help but notice the major increase in the proportion of firms that received non-R&D grants in 2018-2020. This was likely caused by the ending of the EU-funded Operational Programmes in 2020 and the willingness of central and regional government agencies to disburse money as quickly as possible.

Table 4. The average number of firms in the sample benefiting from the support schemes

CIS	Tax breaks for innovation	Other tax breaks	R&D grants	Non-R&D innovation grants
2018	4.6%	3.5%	6.3%	9.1%
2020	7.1%	5.2%	7.5%	28.0%

Next, we focus on tax breaks for innovation and on the grants for R&D, and we examine the size distribution of the beneficiaries of these instruments (cf. Figure 3). Apparently, firms that take advantage of tax exemptions are larger than the firms that apply for and obtain R&D grants, which in turn are bigger than those that do not use any of these instruments.

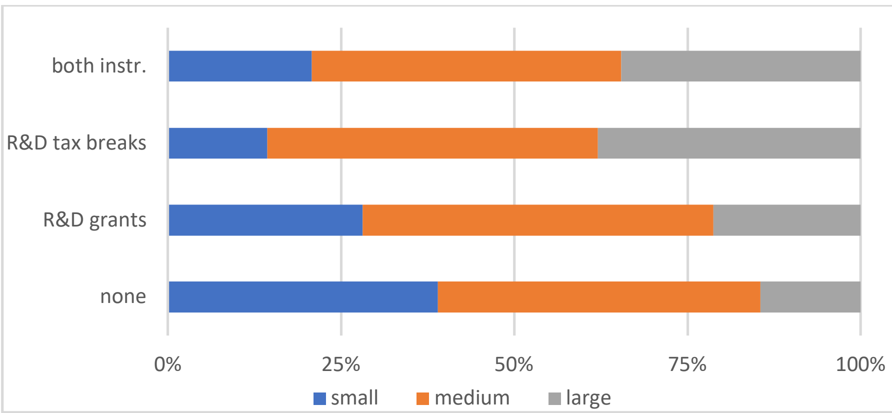

Figure 3. Beneficiaries of R&D tax breaks and R&D grant recipients in 2018-2020 by size category.

We perform a similar analysis for the three types of ownership we can observe in our dataset (standalone firms, members of domestic business groups, members of foreign business groups). We find that firms in Polish business groups are particularly likely to be beneficiaries of R&D grants, while foreign-owned firms seem to prefer the tax credits (Figure 4).

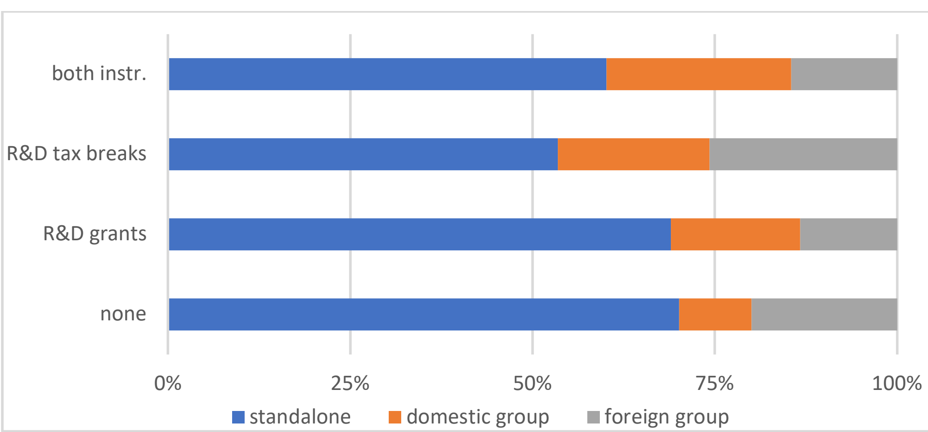

Figure 4. Beneficiaries of R&D tax breaks and R&D grant recipients in 2018-2020 by size category.

Finally, we look at our innovation performance variables. Regarding the innovation activities of firms, Table 5 would suggest that the average level of innovation activities of Polish companies was quite stable until 2016 and then it increased substantially. It is quite likely, however, that this outcome was related to the substantial changes in the CIS questionnaire we mentioned earlier.

Table 5. The incidence of different types of innovation

	product innovation	product innovation new to the market	production methods innovation	RD*	Innovation cooperation*
2012	19%	10%	14%	11%	11%
2014	18%	10%	13%	11%	10%
2016	19%	10%	14%	13%	11%
2018	25%	11%	18%	14%	11%
2020	27%	12%	23%	19%	16%

*) Percentages for the 2012, 2014, and 2016 editions of the CIS were obtained by dividing the number of firms that were innovators and declared a given activity – by the total numbers of firms in the sample.

As an alternative to the dummy variables we look at the number of patent applications. Unsurprisingly, this variable equals zero for more than 95% of observations (Table 6). The number of patent applications filed with foreign patent authorities has a distribution that is even more concentrated in zero. We regard these indicators as somehow worse than the number of domestic filings because many international filings can actually belong to the same patent family, i.e., refer to the same invention for which the firm sees protection in multiple countries; hence, we might be counting the same invention multiple times.

Table 6. The number of patent applications filed with domestic and foreign patent authorities.

Number of applications	Domestic		Foreign	
	CIS 2018	**CIS 2020**	**CIS 2018**	**CIS 2020**
0	14,075	13,401	14,460	13,754
1	344	304	110	118
2	127	150	53	42
3	66	59	18	29
4	36	33	17	17
5	28	24	16	15
6	9	9	5	3
7	5	7	1	4
8	6	5	4	1

9	5	5	1	3
10	2	3	3	3
11 and more	8	8	23	21

4. Methodology

For our binary variables we estimate the models of the following type

$$P(y_{it=1} = 1|x_{it}, \boldsymbol{z_{it}}, \boldsymbol{v_i}, t) = F(\beta_0 + \beta_1 x_{it} + \boldsymbol{\gamma z_{it}} + \boldsymbol{\theta v_i} + \lambda t), (1)$$

where y_{it} is the value of the innovation indicator of firm i in period t (we just have two time periods: ($t = 0$ for 2016-2018 and $t = 1$ for 2018-2020). We will discuss the innovation indicators in a moment. Variable x_{it} is our treatment dummy variable equal to one if the firm used tax breaks for R&D in period t, and zero otherwise. Vector $\boldsymbol{z_{it}}$ includes time-variable controls, specifically the share of workers with higher education in period t, if the firm is an exporter in period t and if the firm used other tax deductions. Vector $\boldsymbol{v_i}$ contains time-invariant control variables, such as the size category of firm i, whether it is a member of a domestic or a foreign business group and the industry to which the firm belongs (while these variables could in principle change over time, they practically never do, let alone in the course of two years: from 2018 to 2020). One key variable in $\boldsymbol{v_i}$ past *innovation experience*: here we will use the information from the 2012, 2014 and 2016 editions of the CIS. $F(\cdot)$ is the cdf of the logistic function, i.e., $F(s) = e^s/(1 + e^s)$.

We use five versions of variable y_{it}

- the incidence of product innovations in general,
- the incidence of product innovation new to the market on which the firm operates (as opposed to the innovations that are novel to the firm only),
- the incidence of the innovation in the methods of productions (a type of process innovation),
- the incidence of R&D activities,
- the incidence of co-operation in innovation activities.

We estimate model (1) by fixed effects, i.e., we apply the conditional logit model (cf. Cameron and Trivedi, 2005, pp. 796-797). The disadvantage of this method is that it only looks at the observations for which the *dependent* variable is not constant over time. To validate our results, in the robustness test section we re-estimate model (1) using fixed effects but applying a linear probability model.

Model (1) is estimated on the whole sample of firms (keeping in mind the restrictions of the conditional logit model) as well as on subsamples of firms differing in their innovation record. Given the nature of our dependent variables (binary indicators), it is more difficult to assess the efficiency of tax breaks for the firms that had good innovation history; since we lack the information on their innovation expenditure, we cannot tell if the use of tax breaks made them spend more. As a partial remedy, we analyse the patenting activities of such firms. We estimate two Poisson models: for the number of patent applications filed with the Polish patent authority, and for the number of patent applications filed with the foreign patent authorities. The respective formula is

$$P(y_{it} = y | x_{it}, \boldsymbol{z_{it}}, \boldsymbol{v_i}, t) = \frac{1}{y!} exp\{-exp(\beta_0 + \beta_1 x_{it} + \boldsymbol{\gamma z_{it}} + \boldsymbol{\theta v_i} + \lambda t + \varepsilon_{it})\} exp(\beta_0 + \beta_1 x_{it} + \boldsymbol{\gamma z_{it}} + \boldsymbol{\theta v_i} + \lambda t + \varepsilon_{it})^y.$$

As before, we estimate the above model using fixed effects (cf. Cameron and Trivedi, 2013, pp. 337-344), which implies the same restriction that we can only consider firms for which the dependent variable was not constant over time. By implication, we only consider firms that filed *some* patent applications in 2018 or 2020.

All the regressions are estimated on the full sample, and on the subsamples of firms defined by their innovation history. This is because we are particularly interested if the tax reduction encouraged firms that did not do so well before to become innovators. Also, since we use the fixed-effects model, this is the only way we can utilise the information on a firm's innovation record.

To obtain further insights and a more comprehensive perspective, we resort to machine-learning methods, and we run random forest models (Breiman, 2001). This class of models is able to handle non-linear relations relatively well as compared to standard linear models, which mitigates the problem of selecting an appropriate functional form. Tree-based machine learning models do not assume any particular distribution of independent variables. Random forest, which is a set of decision trees selected with adequate sampling methods or bootstrapping, addresses the issue of excessive variance and performs better in generalisation than simple decision trees. In our random forest models, we consider the same set of explanatory variables as in the econometric part.

To facilitate a transparent interpretation of the random forest models output, we opt for feature importance stemming from the mean decrease in model impurity (Breiman, 2001). The feature importance approach makes it possible to compare the relative influence of each factor on the dependent variable in the data. This is done by removing the given variable and inspecting the changes in model errors. It can also be interpreted as the contribution of a variable to the predictive power of the model.

5. Results

5.1. Conditional logit estimates

We start by estimating a range of conditional logit models. As explained, we can only use the observations for which the dependent variable changes over time. As a result, when the dependent variable is the incidence of product innovations, our sample is reduced more than tenfold to 2,382 observations (Table 7). Despite this, we obtain a quite compelling outcome, with three out of four support instruments statistically significant. Tax breaks for innovation activities and grants for R&D seem to be the two most important instruments, working both for firms with no innovation history and for firms that innovated before (by which we mean at least one of the earlier CIS editions, i.e., 2012, 2014 or 2016). However, the effect is stronger for new innovators, a pattern that will apply to all our results presented later. We note that, just like in a classical fixed-effect model, the explanatory variables that stay constant over time are excluded from the model, including the size, ownership and industry dummies.

Table 7. Conditional logit estimates of equation (1) with the incidence of product innovations as independent variable

	(1) All firms	(2) No prior product innovations	(3) Some prior product innovations	(4) No prior records
tax_break_inno	1.036***	1.528***	0.793**	1.039*
	(0.216)	(0.398)	(0.327)	(0.588)
tax_break_oth	0.108	0.0658	0.372	-0.0903
	(0.211)	(0.361)	(0.350)	(0.502)
support_RD	0.842***	1.097***	0.612*	0.787
	(0.190)	(0.314)	(0.316)	(0.508)
support_non_RD	0.333***	0.0858	0.483**	0.406
	(0.119)	(0.180)	(0.215)	(0.319)
high_ed	0.00176	-0.00516	-0.00315	0.0133
	(0.00541)	(0.00786)	(0.0125)	(0.0122)
exporter	0.0439	-0.211	0.0940	0.266
	(0.193)	(0.298)	(0.387)	(0.415)
Observations	2,382	1,234	786	362

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Time dummy included

Interestingly, when we estimate model (1) for the incidence of product innovations new to the market, the effects are quite different (Table 8). The effect of tax exemptions for innovation activities are clearly the strongest and they also pertain to firms with some innovation history. By contrast, we do not see a similar effect of R&D grants.

Table 8. Conditional logit estimates of equation (1) with the incidence of product innovations new to the market as the independent variable

	(1)	(2)	(3)	(4)
	All firms	No prior product innovations new to the market	Some prior product innovations new to the market	No prior records
tax_break_inno	0.889***	2.105***	0.692**	1.213*
	(0.223)	(0.651)	(0.291)	(0.686)
tax_break_oth	0.551**	0.0646	0.832***	0.518
	(0.234)	(0.516)	(0.320)	(0.642)
support_RD	0.231	0.526	0.171	-0.0430
	(0.184)	(0.374)	(0.265)	(0.502)
support_non_RD	0.115	-0.266	0.288	0.198
	(0.151)	(0.269)	(0.234)	(0.418)
high_ed	0.0175**	0.0219	-0.0104	0.0412**
	(0.00745)	(0.0142)	(0.0145)	(0.0191)
Exporter	0.0905	0.0340	-0.502	1.261
	(0.279)	(0.479)	(0.461)	(0.801)
Observations	1,518	534	766	218

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Time dummy included

Next, we analyse innovation in methods of production (Table 9). What seems to matter are only the instruments supporting R&D activities, both tax breaks and subsidies. However, the effect of the latter seems to be limited to the firms with no prior innovations, while tax incentives for R&D work across the board. On the other hand, other tax breaks and grants funding activities other than R&D do not increase the probability that a firm will introduce new methods of production.[4]

[4] We could not analyse process innovation new to the market because the respective question was discontinued after 2016.

Table 9. Conditional logit estimates of equation (1) with the incidence of production method innovations as the independent variable

	(1)	(2)	(3)	(4)
	All firms	No prior production method innovations	Some prior production method innovations	No prior records
tax_break_inno	0.720***	0.744**	0.770***	0.572
	(0.190)	(0.334)	(0.265)	(0.540)
tax_break_oth	0.175	0.375	0.127	0.687
	(0.178)	(0.315)	(0.247)	(0.550)
support_RD	0.605***	1.337***	0.103	0.782
	(0.167)	(0.309)	(0.231)	(0.604)
support_non_RD	0.167	0.193	0.178	-0.122
	(0.103)	(0.155)	(0.165)	(0.306)
high_ed	0.00345	0.00172	-0.00433	0.0238*
	(0.00519)	(0.00768)	(0.00965)	(0.0138)
Exporter	0.151	0.230	0.178	-0.440
	(0.190)	(0.265)	(0.363)	(0.524)
Observations	3,098	1,576	1,120	402

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Time dummy included

Both R&D tax incentives and the use of grants for R&D are correlated with the incidence of R&D activities (Table 10), which is of little surprise given the strings attached to these instruments; the recipients of direct subsidies have to report from their projects, while tax breaks, by definition, are possible only when R&D is performed. Interestingly, the parameters for the tax break dummies are significantly higher than those for the R&D grant dummy in columns (1) through (3). One possible explanation is that the tax incentives were more effective in triggering R&D in firms that had not innovated earlier. This hypothesis is supported by the fact that the difference between the respective estimates is particularly large in column (2).

Table 10. Conditional logit estimates of equation (1) with the incidence of RD activities as independent variable

	(1)	(2)	(3)	(4)
	All firms	No prior R&D activities	Some prior R&D activities	No prior records
tax_break_inno	1.374***	1.980***	1.049***	0.734
	(0.245)	(0.443)	(0.357)	(0.638)

tax_break_oth	0.0605	-0.0475	0.179	-0.0769
	(0.257)	(0.388)	(0.417)	(0.689)
support_RD	0.695***	0.926***	0.482*	0.905
	(0.193)	(0.314)	(0.275)	(0.632)
support_non_RD	0.0763	0.115	-0.0373	0.287
	(0.159)	(0.237)	(0.247)	(0.490)
high_ed	0.00229	0.000450	-0.00875	0.0244
	(0.00719)	(0.0102)	(0.0137)	(0.0178)
exporter	-0.369	-0.330	-0.508	-0.302
	(0.252)	(0.370)	(0.419)	(0.664)
Observations	2,000	992	786	222

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Time dummy included

Direct funding of R&D matters more for innovation co-operation than tax incentives do (Table 11). The latter are only effective in case of firms that have not co-operated before (cf. column (2)). The strong result for R&D subsidies is consistent with the findings of evaluation studies demonstrating that around 2/3 of beneficiaries of innovation subsidies forged co-operation with the R&D sector (PAG Group 2021, p. 79). Interestingly, while some support schemes did require that firms co-operate with research institutes or universities (or funded the acquisition of R&D services, so-called “innovation voucher programmes”), most of them did not; the observed linkages were voluntarily formed.

Table 11. Conditional logit estimates of equation (1) with the incidence of innovation co-operation

	(1)	(2)	(3)	(4)
	All firms	No prior co-operation	Some prior co-operation	No prior records
tax_break_inno	0.671***	1.155***	0.0687	1.155*
	(0.195)	(0.323)	(0.288)	(0.635)
tax_break_oth	0.207	-0.123	0.251	0.698
	(0.201)	(0.319)	(0.286)	(0.731)
support_RD	1.095***	1.104***	1.057***	1.309**
	(0.177)	(0.281)	(0.257)	(0.621)
support_non_RD	0.332**	0.262	0.251	1.090**

	(0.137)	(0.203)	(0.211)	(0.524)
high_ed	0.000367	-0.00696	-0.00886	0.0155
	(0.00675)	(0.0104)	(0.0143)	(0.0141)
exporter	-0.224	-0.712**	0.214	0.285
	(0.224)	(0.320)	(0.411)	(0.623)
Observations	2,352	1,154	928	270

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Time dummy included

5.2 The magnitude of estimated effects

Since the estimates of coefficients of the conditional logit model do not have a straightforward interpretation, we would like to obtain a measure of the magnitude of the observed effects. However, the marginal effects are problematic due to the inability to consistently estimate the individual effects in short panels (cf. Santos Silva and Kemp, 2016). The solution that has been suggested by Santos Silva and Kemp is to estimate the average semi-elasticities of the respective probabilities. We report these semi-elasticities in Table 12. For instance, the use of innovation tax breaks increases the probability that the firm introduces product innovations by 76.8 percent (recall that the mean probability of this type of innovation in 2020 was 0.27, cf. Table 5).

Table 12 shows that the semi-elasticities for the use of innovation tax breaks and for the R&D grants are quite high: between 0.5 and 1. For all dependent variables but innovation co-operation, the effects of tax incentives seem to be stronger, but the respective differences are not statistically significant.

Table 12. Average semi-elasticities of the probability of a given type of innovation indicator with respect to policy variables

	product inn.	product inn. new to the market	prod method inn	R&D activities	innovation cooperation
tax_break_inno	0.768***	0.784***	0.573***	1.147***	0.583***
support_RD	0.624***	0.203	0.482***	0.580***	0.950***

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

If we compare the effects of the two policy instruments in the subsamples of firms that had not innovated earlier with the firms that had, we obtain an interesting pattern (Table 13). Apparently, tax breaks are relatively more effective in the group of firms with poor innovation history. This is true for all independent variables except for production method innovations. This observation has important policy implications that we discuss in the final section of the paper.

Table 13. Average semi-elasticities of the probability of a given type of innovation indicator with respect to policy variables: by innovation history

	product inn.	product inn. new to the market	prod method inn	R&D activities	Innovation cooperation
no prior innovation					
tax_break_inno	1.308***	1.990***	0.637**	1.819***	1.060***
support_RD	0.939***	0.497	1.145***	0.851***	1.014***
some prior innovation					
tax_break_inno	0.768***	0.784***	0.573***	1.147***	0.583***
support_RD	0.624***	0.203	0.482***	0.580***	0.950***

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

5.3 Effects on patenting activity

We estimate the fixed-effects Poisson models of the number of patent applications with fixed effects (Table 13). Unfortunately, as was the case with conditional logit, we can only rely on observations that vary over time. With our sample vastly reduced, and much lower estimated coefficients, we can confirm the effect of tax breaks on patenting for all firms, and for firms with no patenting history, but not for firms that have filed for patents in the past. For patenting activities, the R&D subsidies seem to have a stronger effect than tax breaks for innovation.

Table 13. Fixed-effects Poisson estimates of equation (1) with the number of domestic and foreign patent applications as independent variables

	(1)	(2)	(3)	(4)	(5)	(6)
		Domestic applications			**Foreign applications**	
VARIABLES	All firms	No filings 2012-2016	Some filings 2012-2016	All firms	No filings 2012-2016	Some filings 2012-2016
tax_break_inno	0.174*	0.179	0.124	0.283***	0.397*	-0.0176
	(0.0995)	(0.154)	(0.133)	(0.0760)	(0.215)	(0.0997)
tax_break_oth	-0.0789	-0.337*	0.117	0.281***	0.498***	-0.0348
	(0.118)	(0.194)	(0.152)	(0.0911)	(0.149)	(0.135)
support_RD	0.239**	0.320**	0.226*	0.127	0.630***	-0.639***
	(0.0933)	(0.148)	(0.127)	(0.104)	(0.180)	(0.153)
support_non_RD	-0.0202	0.171	-0.140	0.250**	0.637***	-0.106
	(0.0927)	(0.147)	(0.123)	(0.119)	(0.150)	(0.237)
high_ed	-0.0110***	-0.00867	-0.0132**	0.0404***	0.0415***	0.0514***
	(0.00411)	(0.00612)	(0.00566)	(0.00419)	(0.00765)	(0.00601)

exporter	-0.566***	0.320	-1.023***	-0.197	1.163***	-1.572***
	(0.173)	(0.293)	(0.235)	(0.197)	(0.382)	(0.349)
2020.year	-0.0195	0.0774	-0.0798	0.0399	0.0922	0.0130
	(0.0438)	(0.0724)	(0.0558)	(0.0378)	(0.0713)	(0.0463)
Obs.	1,452	796	656	636	446	190
Number of id	726	398	328	318	223	95

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

Given that patenting is a lengthy process, it is likely that the effects of a given policy instrument are only visible with a time lag. To account for this, we re-estimate equation (1) with lagged values of policy variables. Unfortunately, we no longer can apply the panel model, because we only have data for one period. As a result, we estimate a regular Poisson model: the consideration of lagged effects comes at the cost of a higher endogeneity risk. The results in Table 14 show a strong correlation between past grants for R&D and present patent filings. The respective coefficients for tax exemptions are smaller, except for column (3). Interestingly, the estimate for *tax_break_inno* in column (4) is actually negative. We were not able to estimate the model for the foreign patent applications of firms with some prior filings.

Table 14. Poisson model estimates of equation (1) for the period 2018-2020 with the number of domestic and foreign patent applications as independent variables

	(1)	(2)	(3)	(4)	(5)
	Domestic applications			**Foreign applications**	
VARIABLES	All firms	No filings 2012-2016	Some filings 2012-2016	All firms	No filings 2012-2016
L2.tax_break_inno	0.600***	0.703***	0.573***	-0.252***	0.605***
	(0.189)	(0.126)	(0.0866)	(0.0626)	(0.108)
L2.tax_break_oth	-0.178	0.134	-0.231*	-0.508***	0.502***
	(0.190)	(0.157)	(0.123)	(0.0863)	(0.123)
L2.support_RD	0.970***	1.128***	0.444***	1.450***	1.246***
	(0.163)	(0.121)	(0.0968)	(0.0611)	(0.111)
L2.support_non_RD	1.139***	0.743***	0.818***	0.00259	0.708***
	(0.182)	(0.134)	(0.106)	(0.114)	(0.139)
high_ed	0.0193***	0.0148***	0.0188***	0.0633***	0.0296***
	(0.00469)	(0.00268)	(0.00229)	(0.00125)	(0.00240)
no_RD	0.465***	0.278***	0.0443	0.810***	0.0133

	(0.0639)	(0.0464)	(0.0411)	(0.0248)	(0.0381)
exporter	0.396	0.498***	0.137	1.382***	1.174***
	(0.264)	(0.164)	(0.178)	(0.215)	(0.222)
group_foreign	-0.598**	-0.862***	0.109	1.375***	-0.225*
	(0.256)	(0.143)	(0.127)	(0.0730)	(0.134)
group_dom	0.202	0.0846	0.0765	0.303***	0.922***
	(0.150)	(0.126)	(0.0943)	(0.0869)	(0.106)
medium	0.458**	0.147	0.591*	0.0967	-0.0807
	(0.210)	(0.173)	(0.325)	(0.154)	(0.166)
large	1.124***	0.768***	1.126***	1.855***	0.864***
	(0.244)	(0.194)	(0.334)	(0.157)	(0.181)
Constant	-4.609***	-4.451***	-1.920***	-10.20***	-6.532***
	(0.472)	(0.259)	(0.404)	(0.353)	(0.353)
Observations	8,596	8,000	596	8,596	8,305

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

5.4. Results of the Feature Importance Analysis

In Figures 5-11, we show the feature importance reported by the random forest models. To remain consistent with the econometric analysis, these models are estimated on the same respective datasets. Note that in the machine-learning framework we do not distinguish between policy variables and control variables, and we simply check to what extent each indicator contributes to the predictive power of the model. In all the models, the variable with the highest feature importance is the share of workers with tertiary education. As far as the relative importance of the fiscal incentives for innovation is concerned, the results of the econometric analysis are largely confirmed: tax incentives matter more for product innovations and R&D activity, while R&D grants are more important for innovation co-operation and patenting activity. In the model of process innovations, direct financing has a slightly higher predictive power than tax breaks. In the case of international patent filing, the feature importance of both instruments is very similar.

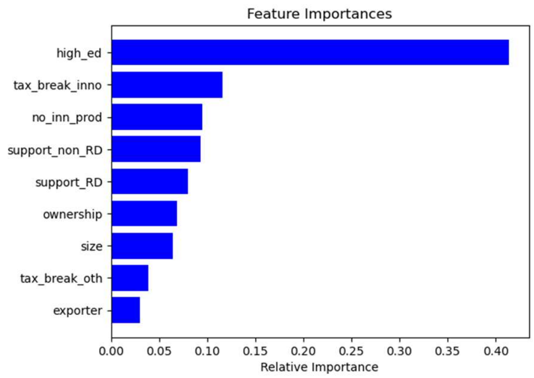

Figure 5. Feature importance, product inn. as dependent variables

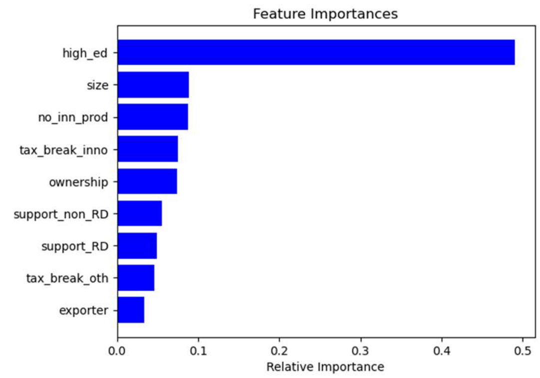

Figure 6. Feature importance, product inn. new to the market as dependent variables

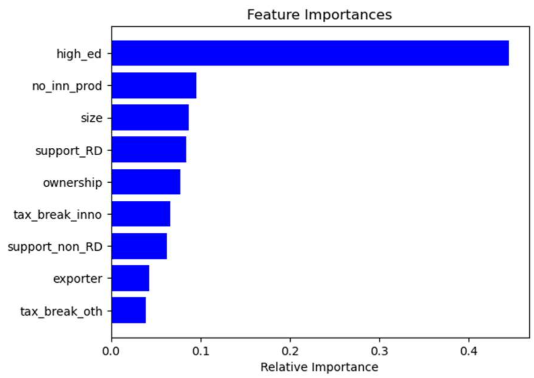

Figure 7. Feature importance, manufacturing process inn. as dependent variables

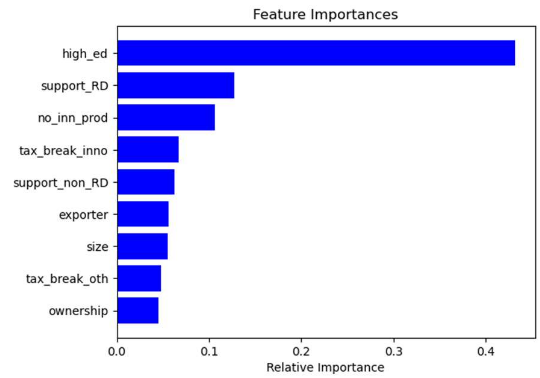

Figure 8. Feature importance, innovation cooperation as dependent variables

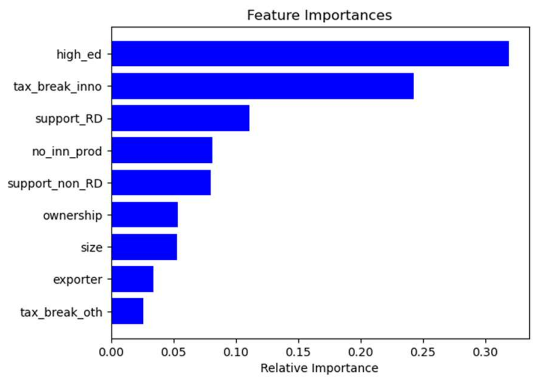

Figure 9. Feature importance, R&D activity as dependent variables

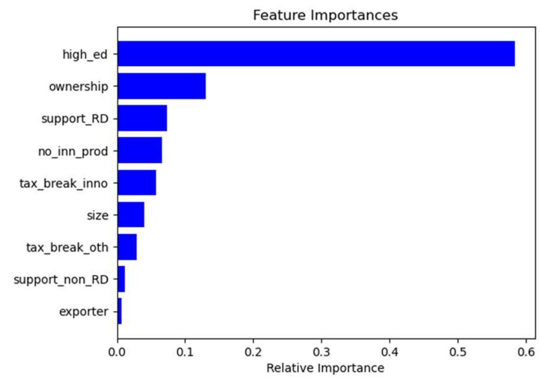

Figure 10. Feature importance, the number of domestic patent applications as dependent variables

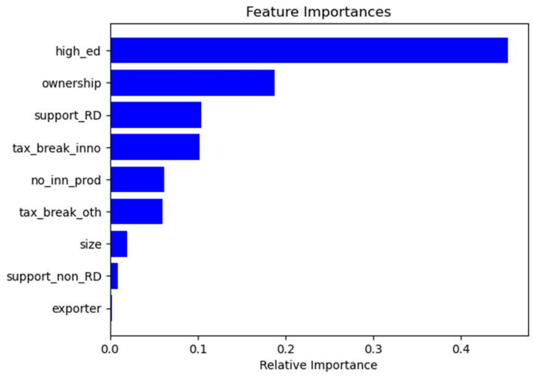

Figure 11. Feature importance, the number of foreign patent applications as dependent variables

6. Robustness checks

We put our results to three types of tests. First, we re-estimate our models on the full sample of firms surveyed in the CIS in 2018 or 2020 by applying a linear fixed-effects model. Second, we make sure that the effects we observe are those of tax breaks for R&D and not those of the IP-box tax break. Third, we want to verify that it is indeed innovation activity, and not the relabelling of expenditure that we see in the data.

We begin by estimating the fixed-effects linear probability model.[5] The results are reported in Tables A1-A5 in the Appendix and they are similar to the results of our baseline model, indicating that our findings were not sensitive to the reduced dataset. In particular, we obtain substantially stronger effects on firms that had not innovated earlier (i.e., in 2002-2016, bearing in mind that each edition of the CIS covers three years), and relatively strong effects for tax breaks in this group. Note that the coefficients of the linear probability model *can* be interpreted as marginal effects.

As explained in Section 2.2, the Polish tax system includes both an R&D tax deduction and an IP-Box tax break. However, the CIS questionnaire does not distinguish between the two. Instead, it only refers to the "tax breaks for innovation activities". Nevertheless, we argue that the effects identified above are the effects of the R&D tax breaks. As reported by Białek-Jaworska and Maruszewska (2023), the IP-box tax break is mostly used by software developers, and, almost exclusively by individual taxpayers (as opposed to the entities that are subject to the Company Income Tax). To account for this, we single out firms that are either in NACE section 62 ("Computer programming, consultancy and related activities") or are sole proprietorships or partnerships, i.e., not incorporated firms, and hence

[5] That is model (1) with $F(s) = s$.

exempted from CIT. There were 2,687 such firms (out of 14,010) in 2020.[6] We re-estimate the regressions for innovation activities when these firms are dropped. The results, reported in Table A6, are unaffected by this exclusion, making us confident that the effects we observed earlier were driven by the tax breaks for R&D activities.

Finally, to account for possible relabelling of expenditures, we re-estimate equation (1) on the subsample of firms that answered *negatively* to the question if the firm introduced "new or improved methods for accounting or other administrative operations". While this is admittedly a crude indicator of possible relabelling, it is also a restrictive condition, resulting in a reduction of our sample by almost one thousand observations. Yet, the findings shown in Table A7 are very much like the ones in the original estimation. Apparently, our results are also robust to changes in accounting practices.

7. Conclusions

Defining the right innovation policy mix is a challenge for every government, as it involves a number of factors, including the structural characteristics of the economy, the government capabilities and the priorities of public policy (which define the amount of funds available). Poland has had almost two decades of experience with EU-funded policy of direct innovation support in firms. The experience with indirect support in the form of tax exemptions is considerably shorter.

Our results suggest that both types of support schemes are effective in the sense that they encourage firms to perform more innovation activities than they would otherwise. Tax exemptions seem to have a stronger effect on the introduction of product- and manufacturing process innovation, while grants for R&D appear more effective in inducing innovation co-operation and patenting activities. These results are interesting given that the amounts of the tax benefits in Poland continue to be substantially smaller than the direct subsidies.

There are at least two questions that arise here. First, to what extent are these differences specific to the country context we studied? Is it also true for other countries that the relative effect of tax breaks for R&D versus direct subsidies varies with the type of innovation activity? As explained in Section 2, tax exemptions have been applied in more and more countries in recent years, so the question about their behavioral additionality certainly merits further studies.

Secondly, it is tempting to ask: what *is* the optimal tax-subsidy mix? The answer, however, will depend on the many different facets of the national innovation system. For instance, the results presented above would prima facie indicate that Poland should emphasize to a larger extent the indirect support

[6] This is a conservative estimate because there could be more firms that were, e.g., partnerships but for some firms Statistics Poland regarded this information as confidential and did not disclose it to us.

to innovation to the detriment of direct support. Policymakers would respond, however, that while the subsidies are organised around the EU-co-funded multiannual operational programmes, the tax breaks are run (and funded) by the national authority.[7] Still, tax exemptions could be the right instrument to active firms that for some reason would not apply for innovation support despite the continued efforts of funding agencies.

Although we worked with panel data, our dataset has considerable limitations. Most of all, we did not know the exact amount of grants or tax exemptions, nor could we access detailed data on firms' costs and revenues. As a result, we could not estimate the elasticity of R&D expenditure with respect to the amount of government support of each type. Hopefully, future studies on other countries will be able to fill this gap.

[7] Also, prior macroeconomic modelling has shown that the grants have contributed to an increase in the R&D spendings in Poland (PAG Group, 2021, pp. 65-69).

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Appendix

Table A 1. Estimates of the fixed-effects linear probability model of the incidence of product innovations

	(1) All firms	(2) No prior product innovations	(3) Some prior product innovations	(4) No prior records
tax_break_inno	0.125***	0.250***	0.0624***	0.158***
	(0.0164)	(0.0268)	(0.0229)	(0.0524)
tax_break_oth	0.0183	0.0148	0.0317	0.00912
	(0.0156)	(0.0230)	(0.0239)	(0.0480)
support_RD	0.0811***	0.134***	0.0523**	0.109**
	(0.0145)	(0.0226)	(0.0213)	(0.0451)
support_non_RD	0.0265***	0.00668	0.0487***	0.0338
	(0.00830)	(0.0105)	(0.0161)	(0.0226)
high_ed	6.74e-05	-0.000317	3.32e-05	0.000896
	(0.000404)	(0.000527)	(0.000947)	(0.000804)
exporter	0.00948	-0.00454	0.0151	0.0256
	(0.0144)	(0.0182)	(0.0308)	(0.0339)
Constant	0.226***	0.119***	0.629***	0.0979***
	(0.0162)	(0.0200)	(0.0415)	(0.0335)
Observations	28,721	13,539	6,100	9,082
R-squared	0.016	0.050	0.020	0.022
Number of id	20,124	8,767	3,481	7,876

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Time dummy included

Table A 2. Estimates of the fixed-effects linear probability model of the incidence of product innovations new to the market

	(1)	(2)	(3)	(4)
	All firms	No prior product innovations new to the market	Some prior product innovations new to the market	No prior records
tax_break_inno	0.0856***	0.155***	0.0463**	0.139***
	(0.0131)	(0.0178)	(0.0226)	(0.0406)
tax_break_oth	0.0345***	0.0124	0.0636***	0.0179
	(0.0125)	(0.0153)	(0.0236)	(0.0373)
support_RD	0.0269**	0.0597***	0.0226	-0.00372
	(0.0116)	(0.0150)	(0.0211)	(0.0350)
support_non_RD	0.00565	-0.00764	0.0265*	0.00394
	(0.00665)	(0.00698)	(0.0160)	(0.0176)
high_ed	0.000799**	0.000778**	-0.000651	0.00189***
	(0.000324)	(0.000350)	(0.000937)	(0.000624)
exporter	0.00536	0.00124	-0.0290	0.0464*
	(0.0116)	(0.0121)	(0.0304)	(0.0263)
Constant	0.0805***	0.0152	0.368***	-0.0268
	(0.0130)	(0.0133)	(0.0410)	(0.0260)
Observations	28,721	13,539	6,100	9,082
R-squared	0.008	0.031	0.016	0.023
Number of id	20,124	8,767	3,481	7,876

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Time dummy included

Table A 3. Estimates of the fixed-effects linear probability model of the incidence of production method innovations

	(1)	(2)	(3)	(4)
	All firms	No prior production method innovations	Some prior production method innovations	No prior records
tax_break_inno	0.0986***	0.129***	0.0945***	0.0682
	(0.0187)	(0.0277)	(0.0308)	(0.0549)
tax_break_oth	0.0387**	0.0456*	0.0205	0.105**
	(0.0178)	(0.0247)	(0.0314)	(0.0504)
support_RD	0.0777***	0.148***	0.0126	0.0903*
	(0.0165)	(0.0232)	(0.0292)	(0.0473)
support_non_RD	0.0167*	0.0106	0.0267	0.00237
	(0.00947)	(0.0112)	(0.0221)	(0.0237)
high_ed	0.000330	0.000134	-0.000248	0.00122
	(0.000461)	(0.000573)	(0.00127)	(0.000843)
exporter	0.0133	0.0141	0.0295	-0.0170
	(0.0164)	(0.0193)	(0.0437)	(0.0356)
Constant	0.153***	0.0924***	0.427***	0.0823**
	(0.0185)	(0.0222)	(0.0547)	(0.0352)
Observations	28,721	14,468	5,171	9,082
R-squared	0.016	0.034	0.006	0.032
Number of id	20,124	9,352	2,896	7,876

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Time dummy included

Table A 4. Estimates of the fixed-effects linear probability model of the incidence of R&D activities

	(1)	(2)	(3)	(4)
	All firms	No prior R&D activities	Some prior R&D activities	No prior records
tax_break_inno	0.220***	0.392***	0.0853***	0.220***
	(0.0146)	(0.0204)	(0.0278)	(0.0400)
tax_break_oth	0.00133	0.00486	-0.00462	-0.00977
	(0.0139)	(0.0161)	(0.0329)	(0.0367)
support_RD	0.101***	0.126***	0.0764***	0.138***
	(0.0129)	(0.0172)	(0.0264)	(0.0344)
support_non_RD	0.00335	0.00120	0.0194	0.00778
	(0.00740)	(0.00787)	(0.0229)	(0.0173)
high_ed	0.000168	0.000136	-0.000598	0.000903
	(0.000360)	(0.000413)	(0.00120)	(0.000614)
exporter	-0.0220*	-0.00824	-0.0973**	-0.000476
	(0.0128)	(0.0139)	(0.0424)	(0.0259)
Constant	0.127***	0.0468***	0.621***	0.0361
	(0.0145)	(0.0156)	(0.0569)	(0.0256)
Observations	28,721	15,423	4,216	9,082
R-squared	0.070	0.107	0.064	0.070
Number of id	20,124	9,886	2,362	7,876

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Time dummy included

Table A 5. Estimates of the fixed-effects linear probability model of the incidence of innovation co-operation

	(1)	(2)	(3)	(4)
	All firms	No prior innovation co-operation	Some prior innovation co-operation	No prior records
tax_break_inno	0.0993***	0.171***	-0.00428	0.178***
	(0.0161)	(0.0201)	(0.0341)	(0.0444)
tax_break_oth	0.0284*	0.0132	0.0306	0.0915**
	(0.0153)	(0.0182)	(0.0352)	(0.0407)
support_RD	0.161***	0.164***	0.169***	0.148***
	(0.0142)	(0.0177)	(0.0314)	(0.0382)
support_non_RD	0.0140*	0.00246	0.0386	0.0300
	(0.00815)	(0.00865)	(0.0260)	(0.0192)
high_ed	0.000149	-0.000166	-0.000806	0.00127*
	(0.000396)	(0.000448)	(0.00145)	(0.000682)
exporter	-0.0203	-0.0415***	0.0322	0.0175
	(0.0141)	(0.0151)	(0.0510)	(0.0288)
Constant	0.0998***	0.0794***	0.370***	-0.0130
	(0.0159)	(0.0169)	(0.0691)	(0.0285)
Observations	28,721	15,443	4,196	9,082
R-squared	0.041	0.057	0.028	0.057
Number of id	20,124	9,906	2,342	7,876

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Time dummy included

Table A 6. Estimates of equation (1) – firms that are not in NACE 62 and are not individual taxpayers (see text).

	(1)	(2)	(3)	(5)	(4)
VARIABLES	Product innovation	Product innovation new to the market	Production method innovation	R&D activities	Co-operation for R&D
tax_break_inno	1.150***	0.859***	0.627***	1.271***	0.593***
	(0.240)	(0.236)	(0.197)	(0.258)	(0.208)
tax_break_oth	0.0192	0.350	0.287	0.159	0.280
	(0.224)	(0.246)	(0.189)	(0.268)	(0.210)
support_RD	0.909***	0.254	0.677***	0.784***	1.124***
	(0.208)	(0.191)	(0.177)	(0.202)	(0.187)
support_non_RD	0.320**	0.128	0.195*	0.0556	0.293**
	(0.128)	(0.159)	(0.111)	(0.169)	(0.144)
high_ed	0.000399	0.0132*	0.00264	0.00267	0.00255
	(0.00578)	(0.00797)	(0.00555)	(0.00767)	(0.00691)
exporter	0.0605	-0.0557	0.218	-0.399	-0.196
	(0.214)	(0.316)	(0.209)	(0.280)	(0.240)
Observations	2,106	1,360	2,780	1,822	2,152

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

Table A 7. Estimates of equation (1) – firms that did not introduce innovation in accounting or organisational methods (neither in 2016-2018 nor 2018-2020).

	(1)	(2)	(3)	(5)	(4)
	Product innovation	Product innovation new to the market	Production method innovation	R&D activities	Co-operation for R&D
tax_break_inno	1.200***	0.868***	0.700***	1.214***	0.643**
	(0.305)	(0.318)	(0.255)	(0.315)	(0.259)
tax_break_oth	-0.0148	0.439	0.105	0.317	0.247
	(0.287)	(0.347)	(0.255)	(0.377)	(0.289)
support_RD	0.888***	0.529**	0.509**	0.708***	0.843***
	(0.238)	(0.259)	(0.223)	(0.247)	(0.231)
support_non_RD	0.415***	0.196	0.241*	0.0567	-0.108
	(0.149)	(0.199)	(0.144)	(0.214)	(0.191)
high_ed	-0.00217	0.0162	0.0101	0.00352	0.0155
	(0.00684)	(0.0106)	(0.00716)	(0.0105)	(0.0108)
exporter	0.0451	0.289	0.261	-0.339	-0.371
	(0.252)	(0.354)	(0.260)	(0.315)	(0.320)
Observations	1,474	838	1,564	1,150	1,126

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