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R&D investment behavior during a crisis: what is the role of subsidies?

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Abstract

Investments in R&D are crucial for fostering technological development and hence growth (Schumpeter 1942; Grossmann/Helpman 1991; Aghion/Howitt 1998). Governments use public innovation grants to support private R&D activities. Public funding decreases the costs of private R&D projects thus facilitates the realization of innovation projects (for a literature review on the effects of public R&D subsidies see David/Hall/Toole 2000). The rationale for governmental R&D support can be justified by the notion that firms will underinvest in R&D activities due to their public good characteristic (Arrow 1962). Although recent studies (e.g., Czartnitzki/Hanel/Rosa 2011, Paunov 2012, and Hud/Hussinger 2015) find that public subsidies significantly supported R&D activities during the 2008-09 crisis, none has yet tried to disentangle specific firm's R&D behaviors as reaction to the crisis. This paper investigates whether access to public funds in crisis times impacts the firms' R&D investment behavior by distinguishing between four behaviors: canceling, anticipating, postponing or not changing the planned R&D investment after a crisis hit. R&D investment behavior can be pro-cyclical or anti-cyclical. A firm's decision to give up or postpone its R&D investments signals a pro-cyclical behavior. This practice can be the result of demand-side factors such as lower sales (Bernanke/Gertler 1989) or less external financing due to higher agency costs between investors and researchers (Hall 1992; Aghion et al. 2012). The again, a firm's decision to not change or anticipate its R&D investments due to cheaper input factor costs, e.g., labor costs, during downturns (Aghion/Saint-Paul 1998) reflects an anti-cyclical behavior. We use Swiss firm-level panel data from four waves (2005, 2008, 2011, and 2013) provided by the Konjunkturforschungstelle at the ETH Zurich. Our empirical strategy consists of two iterations. First, we analyze whether public subsidies have an impact on firms' R&D investments. We establish a counterfactual by matching subsidized firms (treatment group) to unsubsidized firms (control group). Second, we use specific questionnaire questions from the 2013 wave regarding the firms' reaction to the 2008-09 crisis to analyze whether public funding, external funds or engagement in new R&D cooperation affect the likelihood of choosing a specific R&D investment behavior. We use a multinomial probit model for our estimation due to the categorical of the

dependent variable. Our results show that public subsidies foster R&D expenditures for subsidized firms. The effect of public grants on unsubsidized firms is smaller but may indicate that the government could enhance those grants to not supported firms. Furthermore, we show that public funds may induce firms to anticipate R&D investments (i.e., they react anti-cyclically). In contrast, government funding does not alter the firms' likelihood of giving up on or postponing investments. In a complementary analysis, we also use analyze the effect of external funds (definition). We find that they increase the propensity to anticipate R&D projects. Finally, the engagement in new R&D cooperation influences the likelihood of postponing R&D projects (e.g., pro-cyclical behavior). Overall, our results point at the importance of subsidies as an effective instrument to counteract economic downturns. Bibliography Aghion, Philippe, Askenazy, Philippe, Berman, Nicolas, Cette, Gilbert, And Eymard, Laurent. "Credit Constraints And The Cyclicality Of R&D Investment: Evidence From France." Journal Of The European Economic Association 10, No. 5 (2012): 1001–1024. Aghion, Philippe, And Howitt, Peter. "A Model Of Growth Through Creative Destruction." Econometrica 60, No. 2 (1992): 323–351. Aghion Philippe, And Saint-Paul, Gilles. "Virtues Of Bad Times Interaction Between Productivity Growth And Economic Fluctuations." Macroeconomic Dynamics 2, No. 3 (1998): 322–344. Arrow, Kenneth. "Economic Welfare And The Allocation Of Resources For Invention." Pp. 609-625 in The Rate And Direction Of Inventive Activity: Economic And Social Factors. Princeton, NJ: Princeton University Press Czarnitzki, Dirk, Hanel, Petr, And Rosa, Julio Miguel. "Evaluating The Impact Of R&D Tax Credits On Innovation: A Microeconometric Study On Canadian Firms." Research Policy 40, No. 2 (2011): 217–229. Hall, Bronwyn. "Investment And Research And Development At The Firm Level: Does The Source Of Financing Matter?" NBER Working Papers Series, No. 4096 (1992). Howitt, Peter, And Aghion, Philippe. "Capital Accumulation And Innovation As Complementary Factors In Long-Run Growth." Journal Of Economic Growth 3 (1998): 111–130. Hud, Martin, And Hussinger, Katrin. "The Impact Of R&D Subsidies During The Crisis." Research Policy 44, No. 10 (2015): 1844–1855. Paunov, Caroline. "The Global Crisis And Firms' Investments In Innovation." Research Policy 41, No. 1 (2012): 24–35. Schumpeter, Joseph A. "Capitalism, Socialism and Democracy". New York: Harper & Row, (1942)

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Abstract

This study empirically investigates the effect of public subsidies on R&D investment behavior of Swiss firms during the financial crisis 2008. We analyze whether recipients of public R&D funds alter investment behavior by giving up, preponing, postponing or not changing their R&D investments. By disentangling specific firm behaviors, this study goes beyond previous research on the effectiveness of subsidies. Our results show that publicly subsidized firms do not engage in significantly higher R&D activity. This effect of public grants on subsidized firms might indicate partial crowding out of private R&D expenditures by public subsidies. Second, our results also show that public funds may induce firms to prepone R&D investments which can be interpreted as anti-cyclical investment behavior implying windfall gains by public innovation grants.

Keywords: subsidies, public grants, R&D investments, crowding out, cyclicality

JEL classification: C14, C23, G01, H20, H32, H50, O38

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1 Introduction

The role of the governments in subsidizing private R&D expenditure has been extensively discussed for the last decades. Acknowledging that technological development fosters growth (Schumpeter 1942; Grossmann and Helpman 1991; Aghion and Howitt 1998), the analysis of this research question is crucial for the design of policy instruments as well as its impact on firm behavior.

Many countries have adopted public innovation grants to support private R&D investments. Among them Switzerland through the Commission of Technology and Innovation put into place a nationwide grant for R&D investments allowing firms located in the country to apply for R&D project related funding. So far attention has been paid to the analysis of effectiveness of such public subsidies on private investment but only few studies investigate the impact of the crisis on the effectiveness of public subsidies on R&D activity (e.g., Hud and Hussinger 2015, Paunov 2012).

Understanding the impact of economic downturns is crucial to assess the interplay both between fiscal policy and economic growth and the interdependencies between technological change and economic growth. Few studies have disentangled the direct consequences of public funds during the crisis on firm R&D investment behavior (e.g., Paunov 2012).

This paper relates to different fields of empirical literature. First, we contribute to the field of innovation economics by analyzing the effect of public subsidies on R&D expenditure. Second, this paper relates to the literature analyzing the real effects of tax policy. Finally, this study contributes to the financial economics literature analyzing the interplay between governmental policy and firm investment behavior. We contribute to these three strands of literature by estimating the causal impact of public subsidies on R&D activity and intensity. Further, we document how firms differently cope with the crisis in terms of R&D investment behavior.

We use Swiss firm-level data from 2005 to 2013 comprising of four waves. The empirical strategy comprises of two steps. First, we analyze whether R&D public subsidies have an impact on R&D activity. This analysis consists of the estimation of a counterfactual setting in which subsidized firms (treatment group) and unsubsidized firms (control group) are compared. Second, we use a specific question in the 2013 survey in which firms indicated their reaction to the 2008 crisis in terms of R&D investment behavior. Firms could choose between four options: giving up, preponing, postponing, and not changing it. Using this unique data, we investigate in a multinomial probit model how public funding, external funds, and the engagement in new R&D cooperation affect the likelihood of choosing specific R&D investment behavior.

The rest of the paper is structured as follows. Section 2 reviews the literature. Section 3 illustrates the empirical strategy. Section 4 presents the empirical results. Section 5 concludes.

2 Literature review and institutional background

2.1 Public R&D support and crowding out

Although, technological development is an important driver of economic growth and vice versa (Schumpeter 1942; Grossmann and Helpman 1991; Aghion and Howitt 1992; Howitt and Aghion 1998; Schmookler 1966), firms have the incentive to underinvest in R&D due to the public good characteristic of new knowledge. A firm's decision to underinvest in R&D goes along with the fear of other firms free-riding, namely by imitating its innovations. This problem of incomplete appropriability of R&D returns finally leads to a socially suboptimal level of R&D investment (Arrow 1962). Yet, even in the absence of incomplete appropriability of R&D returns a socially optimal level of R&D investments cannot be reached due to information asymmetries between investors and innovating firms and the general risk associated with R&D investments (Griliches 1986).

These market failures justify the use of public innovation grants to foster private R&D activities. Public funding decreases the costs of private R&D projects by facilitating the realization of the innovation project. The term ‘additionality effect’ or ‘crowding in’ of private R&D expenditure refers to the positive effect of public subsidies. However, public R&D support can also lead to ‘crowding out’ of private R&D investments. This occurs when public R&D funds substitute private ones due to the fact that application costs for public R&D support are relatively low and in case of positive decisions, firms benefit from the grant (for literature review see David, Hall and Toole 2000).

Extant literature analyzed the effectiveness of public R&D subsidies. However, empirical findings do not provide conclusive and generally valid results due to the heterogeneity of institutional backgrounds, underlying data, variables used and empirical approaches (a recent survey is provided by Zúñiga-Vicente, Alonso-Borrego, Forcadell, and Galán 2014).

Studies such as Hussinger (2008) take potential bias by self-selection into public funding into consideration by applying a semi-parametric two-step selection model using German data. Her results reject full crowding out of private R&D by public subsidies. Aerts and Schmidt (2008) find similar results using data for Flanders and Germany using a nonparametric matching estimator combined with a difference-in-difference estimator, they reject the crowding out hypothesis. A more recent study such as Dai and Cheng (2015) refutes previous results using a generalized propensity score approach and hence, point to a partial or even a complete crowding out of private R&D investments for Chinese manufacturing firms.

2.2 The role of business cycles

In response to economic downturns, governments support the economy by loosening their fiscal policy (Romer 1993, Makkonen 2013). One fiscal response to recessions is the additional provision of subsidies such as public innovation grants. The firms' R&D investment behavior during recessions is ambiguous: R&D investment behavior is 'pro-cyclical' when investment effort is reduced; on the contrary, R&D investment behavior is 'counter-cyclical' when investment effort is increased (Filippetti and Archiburgi 2011). Theoretical and empirical studies show mixed cyclicality of R&D investments.

Demand-side driven factors can explain pro-cyclical R&D investment behavior when sales are positively related to the investment innovation activities (Schmookler 1966). Moreover, the availability of external financing is a function of agency costs between investors and firms which are pro-cyclical (Bernanke and Gertler 1989). However, the opportunity-cost argument implies that firms should undertake R&D investments when costs are low, i.e., during a crisis, in order to benefit from those investments in better times (Aghion and Saint-Paul 1998; Barlevy 2007). Supply-side driven factors can explain counter-cyclical R&D investment behavior since labor costs, for example are lower during downturns. In other words, it would be more cost-effective for firms to employ R&D personnel during downturns.

For all the reasons above, R&D investment behavior is largely affected during economic downturns as firms face important decisions. Instead of leaving the current R&D investment projects unchanged, firms could prepone them - which would reflect an anti-cyclical behavior. Also, firms could give up or postpone R&D investment projects which would reflect pro-cyclical behavior.

As stated in section 2.1, public R&D subsidies may result in a crowding out of private R&D investments. Recent studies, e.g., Paunov (2012) and Hud and Hussinger (2015) focus on the effect of public subsidies during the crisis and find that they support firms' R&D activities during the crisis. From a macroeconomic perspective, Brautzsch et al. (2015) also find positive effects of fiscal policy on the stabilization of the economy during recessions.

2.3 Public funding by the Commission of Technology and Innovation

Switzerland's 2010 overall investment in R&D was CHF 4.6 billion in 2010, corresponding to 0.81% of the national GDP. Compared to the other 31 OECD countries, Switzerland held the 11th rank regarding the ratio of R&D funding as a share of GDP. The Commission for Technology Innovation (CTI) and the Swiss National Science Foundation (SNSF) are the two main public agencies that promote innovation. The CTI and the SNSF differ mainly in one aspect: whereas the CTI focuses on the financing R&D projects with an immediate commercial objective in the private, the SNSF finances application-oriented basic research. The firms that make the subject of this study are mainly financed through CTI subsidies (FSO 2012, CTI 2011).

A peculiarity of the Swiss system is its bottom-up indirect approach of supporting innovation. Private firms can submit their R&D projects (without limitations in terms of technology area) to a committee. Upon approval, the CTI will directly fund the public partner (often universities of applied sciences or research institutes), whereas the recipient will contribute to at least 50% of the expected costs (CTI 2013).[1]

Figure 1 depicts the R&D activities over the period 2005-2010. As it can be seen, the number of applications has been steady between 400 and 600 until 2008, for then increasing to 1110 in 2011.

[1] This cooperation is intended to promote an active collaboration between the private and public sector. In the period 2005-2010, 51.6% of the R&D applications have been granted support (CTI 2013).

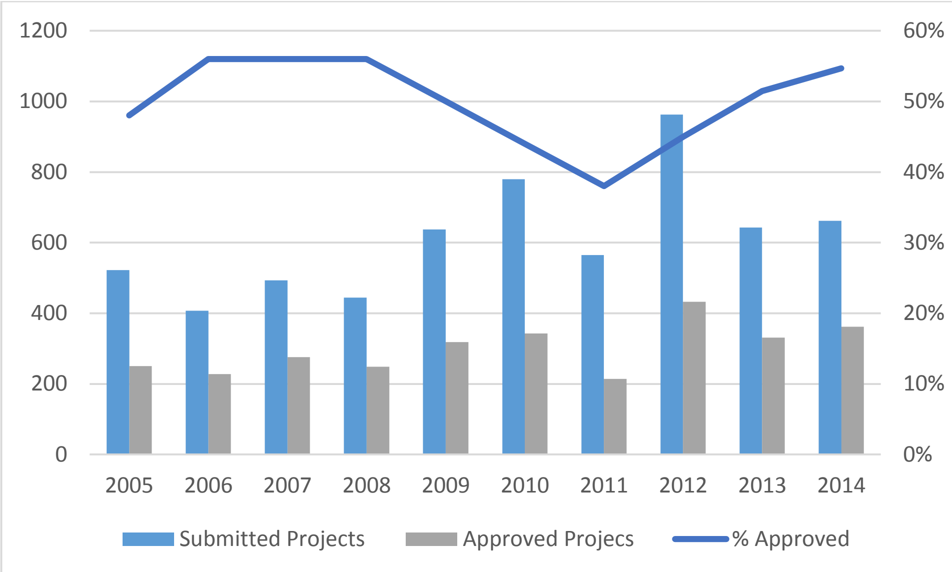

Figure 1: Times series of R&D project granting by the CTI, source: CTI (2013).

3 Data and empirical strategy

We use firm-level panel data from four waves (2005, 2008, 2011 and 2013) provided by the Konjunkturforschungsstelle (KOF) enterprise panel. The panel consists of about 6,500 firms in the official business register, roughly 2,000 firms reply to the questionnaire in each wave. The panel includes firms from various sectors such as the high-tech, traditional, modern and construction. As the panel provides longitudinal data on the micro-level including information on economic outcomes as well as firm-level characteristics, it is well-suited for the purpose of this study allowing the analysis of responses in the R&D investment behavior of firms. The 2013 questionnaire included a special section asking the firms about the consequences of the 2008 financial crisis.

Table 1: Firms receiving domestic public innovation grants (Datasource: KOF, 2015), own calculations

Year		2005	in %	2008	in %	2011	in %	2013	
Domestic public innovation grants	No	1,352	92.5%	1,108	92.4%	1,094	89.5%	813	85.9%
	Yes	109	7.5%	91	7.6%	128	10.5%	133	14.1%
Total		1,461		1,199		1,222		946	

We consider the aforementioned waves since information regarding receipt of public innovation grants have been collected only in these waves. Table 1 illustrates the number of Swiss firms in each wave and the percentage of publicly subsidized firms. Our treatment group consists of all subsidized firms, whereas the control group consists of the rest of unsubsidized firms.

Our empirical strategy comprises of two steps. First, we analyze whether R&D public subsidies have an impact on R&D activity. This analysis consists of the estimation of a counterfactual setting in which subsidized firms (treatment group) and unsubsidized firms (control group) are compared. Second, we use a specific question in the 2013 survey in which firms indicated their reaction to the 2008 crisis in terms of R&D investment behavior. Firms could choose between four options: giving up, preponing, postponing, and not changing it. Using this unique data, we investigate in a multinomial probit model how public funding, external funds, and the engagement in new R&D cooperation affect the likelihood of choosing specific R&D investment behavior.

3.1 Matching approach

By simply comparing the mean of R&D expenditure of both treatment and control groups, one ignores the incomparability by structural differences of firms in each group. To quantify the effect of public subsidies, this implies that one has to rely on the comparison of counterfactuals, i.e., how the firms in the control group would have invested if they were subsidized (see, e.g., Morgan and Winship 2010).

In order to quantify the average effect of public subsidies on subsidized firms, the parameter of interest can be formalized as the Average Treatment Effect on the Treated (ATT) where S_{it} is the treatment status:

$$ATT = E[Y_{it} \mid S_{it} = 1] = E[Y_{it}(1) \mid S_{it} = 1] - \underbrace{E[Y_{it}(0) \mid S_{it} = 1]}_{\text{unobserved counterfactual}}. \tag{1}$$

The ATT measures the difference between the level of outcome Y of firm i which benefits from public subsidies at time t ($S_{it} = 1$) and the outcome of the same firm if, hypothetically, it did not receive the subsidy at time t. As the counterfactual is unobserved, using observational data to compare the R&D investments of subsidized and unsubsidized firms would include a self-selection bias (Angrist and Pischke 2009, p.14):

$$\underbrace{E[Y_{it} \mid S_{it} = 1] - E[Y_{it} \mid S_{it} = 0]}_{\text{observed difference in R\&D investments}} = \underbrace{E[Y_{1it} - Y_{0it|} \mid S_{it} = 1]}_{\text{ATT}} + \underbrace{E[Y_{0it} \mid S_{it} = 1] - E[Y_{0it} \mid S_{it} = 0]}_{\text{self-selection bias}} \quad (2)$$

The naïve estimator (left-hand side of equation 2) would be equal to the ATT only if individual firm outcomes from the treatment and the control group would not differ in the absence of treatment (and thus, the self-selection bias would be zero).

Propensity score matching is a commonly used technique to reduce the potential self-selection bias (Rosenbaum and Rubin 1983). In order for this approach to be valid, the Conditional Independence Assumption (CIA) or unconfoundedness assumption has to hold. The CIA states that conditional on observed covariates X_i, potential outcomes $\{Y_{1i}, Y_{0i}\}$ are independent of the treatment status S_{it} : $\{Y_{1i}, Y_{0i}\} \perp S_i \mid X_i$. As a result, given the observed covariates X_i, assignment to treatment is almost randomly assigned.

Another assumption ensuring the consistent identification of treatment effects by matching estimators is called overlap or common support assumption. This assumption requires that the probability of treatment assignment is bounded away from zero and one

$$0 < \Pr(S_{it} = 1 \mid X_{it}) < 1. \quad (3)$$

With both assumptions of unconfoundedness and overlap holding, Rosenbaum and Rubin (1983) define the treatment to be strongly ignorable. This allows the estimation of the ATT of public R&D subsidies.

Depending on the combinations of X_{it}, we obtain different treatment effects. Since we are interested in a summary measure of all treatment effects, we use unconditional expectations.

$$\begin{aligned} ATE &= E_X\{E[Y_{it} \mid X_{it}, S_{it}=1] - E[Y_{it} \mid X_{it}, S_{it}=0]\} \\ &= E_X\{E[Y_{1it} - Y_{0it} \mid X_{it}]\} \\ &= E[Y_{1it} - Y_{0it}] \end{aligned} \quad (4)$$

This parameter can be calculated as the weighted average of any effects across all combinations of X. We can interpret it as the expected effect on the outcome variable if firms were randomly assigned to treatment, Average Treatment Effect (ATE). This estimand however is not relevant for us as it also includes the effect on persons for whom the subsidy was not intended (Heckman, 1997).

Similarly, by taking the conditional expectations for different combinations of X and by taking the weighted average of all X-specific effects across all treated individuals, we obtain a parameter for how much of the treated gain from treatment (ATT). This estimand provides us with the effect on those for whom the subsidy is intended.

$$\begin{aligned} ATT &= E_X\{E[Y_{1it} \mid X_{it}, S_{it}=1] - E[Y_{0it} \mid X_{it}, S_{it}=1]\} \\ &= E_X\{E[Y_{1it} - Y_{0it} \mid X_{it}, S_{it}=1]\} \\ &= E[Y_{1it} - Y_{0it} \mid S_{it}=1] \end{aligned} \quad (5)$$

Matching is a non-parametric technique which avoids misspecification of the expected outcome of observations in the control group given the conditioning sector and also allows for arbitrary heterogeneity in causal effects (Caliendo and Kopeinig 2008). By conditioning on the covariates

X_i and if the CIA holds, we assert that the variation in the outcome variable is only due to the treatment.

The implementation of the matching estimator is divided in two stages. In the first stage, we compute a balancing score representing functions of relevant observed covariates in the form of a propensity score by running a probit estimation that reflects the probability of receiving treatment determined by the covariates that determine selection into treatment (Rosenbaum and Rubin, 1983). We use different specifications[2] and then use an algorithm to test for meaningful choice of the covariates.

In a second stage, we look at the treatment effect on the outcome. By matching each treatment observation i with one or several control observations j, based on similar propensity scores and including a dummy for each block[3], we assure the comparability of treatment and control group. Using these matched pairs, we estimate the

$$ATT = \frac{1}{N^T} \sum_{i=1}^{N^T} (Y_{1i} - \sum_{j=1}^{N^C} w(i,j) Y_{0j}) \,. \tag{6}$$

with N^T being the number of treated firms and N^C being the number of control firms. The choice between different matching algorithms affects the number of control firms as well as the weighting $w(i,j) \in [0,1]$ of each control observation.

We apply the Kernel matching estimator as proposed by Heckman et al. (1998) and Smith and Todd (2005). Using the Epanechnikov kernel with a bandwith of 0.06, the counterfactual is

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[2] In more detail, we apply different bandwidths for the Kernel matching estimator (0.06, 0.03 and 0.01) and nearest neighbor matching with one and five neighbors as well as one-to-one matching.

[3] This controls for similarities within that group such that the absolute difference in propensity scores between i and j is minimized (min $|p_i - p_j|$).

calculated as the weighted average of all control units, the weight is higher for observations with similar propensity score. Furthermore, we apply a one-to-one matching which reduces the number of observations because each treated firm is matched only to one control firm due to no replacement in matching.

We include a large set of firm characteristics to support the CIA in our context. Nevertheless, since there might be some unobservables that cause a correlation between the subsidy receipt and R&D investments are possible, we also take into account time-invariant observed plant characteristics. The choice of covariates X_i determining the treatment status is determined such that the conditional independence assumption (CIA) holds. We need to include all variables that influence both the outcome variable as well as the treatment variable (subsidy receipt) (e.g. Sianesi, 2004; Smith and Todd, 2005; Caliendo and Kopeinig, 2008).

The set of covariates can be differentiated into four groups: structural firm traits, economic measures, innovativeness, and employment structure (see Table 2 for more details). Heckman et al. (1998) suggests that all observables determining the treatment and the outcome should enter the estimation of the propensity score.

Table 2: Description of matching covariates

Structural firm traits	Part of an enterprise group yes/no	Dummy indicating whether the firm an enterprise group
	Foreign owned yes/no	Dummy indicating whether the firm belongs to a foreign owned corporation
	SME	Dummy indicating whether the firm is a SME (below 250 employees)
	Exports yes/no	Dummy indicating whether the firm is engaged in exporting goods and services
	R&D co-operations yes/no	Dummy indicating whether the firm is cooperating in R&D with other institutions
	Log firm age	
Economic measures	Gross investments	Gross investments in real CHF
	Number of competitors <= 5 Number of competitors 6-10 Number of competitors 11-15 Number of competitors 16-50	Dummies indicating the number of competitors the firm is facing

	Share of exports in turnover	in %
Innovativeness	Number of patents	Number of patents registered at time t
	Technological potential	Self-reported technological potential on a five-scale with 1 as very low and 5 as very high technological potential
Employment structure	Share of trained employees	in %
	Share of untrained and partly trained employees	
	Share of apprentices	
	Share of employees with college/university degree	

The decision to apply for and receiving public innovation grants is non-random and can be determined by time-invariant firm characteristics such as dummies accounting for belonging to an enterprise group, being a foreign owned, being a SME, engaging in export activity. Other factors capturing the probability of subsidy receipt are related to economic measures such as gross investments, the share of exports on turnover, and number of competitors. With regard to the innovativeness of firms and its association with R&D subsidy receipt, we include a dummy for R&D co-operations, number of patents and technological potential. Also, the structure of employment in the firm can affect the probability of subsidy receipt. That is why we include the share of trained, untrained employees and the share of apprentices as well as employees with a tertiary degree. Since we expect differences in subsidy receipt depending on structural firm traits, we control for industry branches, year differences and industry-year differences.

3.2 Firms' R&D investment behavior during the crisis

As previously noted, the 2013 questionnaire provided a special section asking about the short and medium-term consequences of the financial crisis 2008; in which one question asks about the firm's decisions on R&D investments:

Which of the following investment decisions did your enterprise as a consequence of the financial crisis give up, postpone, prepone or not change?

R&D

The base category is no change in R&D investment behavior. Among 935 firms, 86 (9.2%) gave up on, 148 (15.8%) preponed, 55 (5.9%) postponed and 646 (69.1%) did not change R&D investment behavior (see Table 3).

Table 3: R&D investment behavior during the crisis (Datasource: KOF, 2015), own calculations

R&D investment behavior during crisis	No	in %	Yes	in %
Give up	849	90.8%	86	9.2%
Prepone	787	84.2%	148	15.8%
Postpone	880	94.1%	55	5.9%
No change	289	30.9%	646	69.1%
Total			935	

We use this unordered response variable as the outcome variable reflecting specific R&D investment behavior. We code the four possible outcomes as give up (R&D behavior = 1), prepone (R&D behavior = 2), postpone (R&D behavior = 3) and no change (R&D behavior = 4). In order to analyze the effect of being a recipient of public R&D subsidies, the access to extend funds, and the cooperation in R&D activities with external institutions, we include these as explanatory variables.

When working with unordered response outcome variables, one faces the important restriction on R&D investment decisions j. This restriction asserts that relative probabilities for any two alternatives depends only on the attributes of those alternatives. This is referred to as independence from irrelevant alternatives (IIA) assumption (Wooldridge 2002, p.501pp). As a consequence, the IIA assumption implies that including another decision outcome or modifying the characteristics of another alternative will not affect the relative odds of the first two decision alternatives. One way to cope with this problem is to apply a multinomial probit model. While a multinomial logit model assumes that the error term is independently distributed and a diagonal matrix covariance matrix, the multinomial probit model allows the error term to be autocorrelated by imposing error terms following a multivariate normal distribution with arbitrary correlations between a_{ij} and a_{ih} with $j \neq h$ (Wooldridge 2002, p.502pp).

The multinomial probit model is:

$$y_{ij}^{*} = X'_{ij}\,\beta_j + a_{ij}, \tag{7}$$

where the error term a_{ij} is multivariate-normally distributed, with $j = 0,1,2,\ldots,J$. Also, X'_{ij} is a $1 \times K$ vector that differs across investment decisions j and individuals i. Moreover, we control for firm age, number of employees and we include a dummy for foreign ownership, a dummy for export activity, a dummy for the high-tech sector, as well as regional dummies[4].

Using properties of the normal distribution, one obtains the probability distribution of firms' R&D investment decision j as follows:

$$\Pr(y_{ij} = j) = \frac{\exp(X_i'\beta_j)}{1+\sum_{s=1}^{J}\exp(X_i'\beta_s)}. \tag{8}$$

Each of the J regressions have a different error term and they potentially could be correlated to one another. This is due the multivariate normal distribution of the error term and hence allows for relaxation of the IIA assumption so that choices J do not have to satisfy the IIA. Hence, the multinomial probit model estimates J(J-1)/2 correlations.

[4] The regions are classified by the NUTS-2-level comprising of seven greater regions as defined by the Statistical Office of Switzerland.

4 Empirical Results

4.1 The effect of public grants on R&D activity

The first part of the propensity score matching comprises of the estimation of firm-individual propensity scores reflecting the predicted probabilities of receiving treatment on the basis on observable covariates. The results indicate that SMEs are less likely to receive public innovation grants. Also, engagement in R&D cooperation with external institutions increases the likelihood of subsidy receipt. Moreover, having a higher share of employees with a tertiary degree positively affects subsidy probability. Whereas the firm age positively affects the probability of receiving subsidies, a more competitive environment decreases it (Table 4).

With the previously estimated propensity scores and the chosen matching method explained in section 3.1, we are able ensure comparability of treatment and control group. Assessing the covariate balance between both groups and thus the appropriateness of the model is a crucial element of matching methods: we do this by looking at the overall statistics on covariate balance. Table 5 indicates a satisfying matching quality. The pseudo-R2 values indicate that the explanatory power of the covariates is lower in the matched sample (0.02) than in the unmatched sample (0.15) but also shzow that in the matched sample, systematic differences between treatment and control group are eliminated by the matching algorithm (Caliendo and Kopeinig 2008). Testing the hypothesis that all coefficients are zero with a likelihood test can be rejected in the unmatched sample while in the case of the matched sample, we cannot reject the hypothesis. This evidence confirms that using matching the probability to receive subsidies is unrelated to observable firm characteristics. Finally, the mean bias before matching 22% is reduced after matching to 5.1%.

Table 4: Probit estimation of domestic subsidy receipt, own calculations

	Coefficients	Std. err.
Part of an enterprise group yes/no	-.0807158	.1517293
Foreign owned yes/no	.3919164	.4155293
SME	-.5807441***	.168659
Exports yes/no	.478765	.3231751
R&D co-operations yes/no	.4558382***	.1513506
Gross investments	-1.98e-09	3.61e-09
Number of competitors <= 5	-.8427438***	.2727428
Number of competitors 6-10	-.5923377 **	.2726873
Number of competitors 11-15	-.8359864***	.3160239
Number of competitors 16-50	-.637354**	.3165173
Share of exports in turnover	.0008331	.0026099
Log firm age	.2460474**	.1136166
Number of patents	.0056334	.0037081
Technological potential	-.0317461	.0790321
Share of trained employees	-.0035927	.0062734
Share of untrained and partly trained employees	-.0016365	.0062867
Share of apprentices	-.0174592	.0166287
Share of employees with college/university degree	.0208227 **	.0095661
Constant	-.8207319	1.02455
Year dummies	Yes	
Branch dummies	Yes	
Year-branch dummies	Yes	
Observations	568	
LR Chi2	123.32	
p	0.0000	
Log-likelihood	-233.82998	
Pseudo R2	0.2087	

Note: *p < 0.1; **p < 0.05; ***p < 0.01

Table 5: Overall statistics on covariate balance

Sample	Pseudo R2	LR chi2	p>chi2	Mean bias
Unmatched	0.150	74.67	0.000	22.0
Matched	0.018	5.02	0.999	5.1

We assess the common support condition graphically by depicting the kernel plot for the propensity scores for plants with and without treatment (Figure 2). The propensity score lies between zero and one for treatment and control group and that both distributions share an area of common support so that identification of subsidized and unsubsidized firms featuring similar probabilities is achievable. The higher mass of distribution at the lower levels of the propensity score for firms without subsidy treatment indicate that firms receiving no subsidy are smaller firms which are unlikely to obtain public funds. Many firms that actually are able to benefit from the subsidy also have higher probability mass.

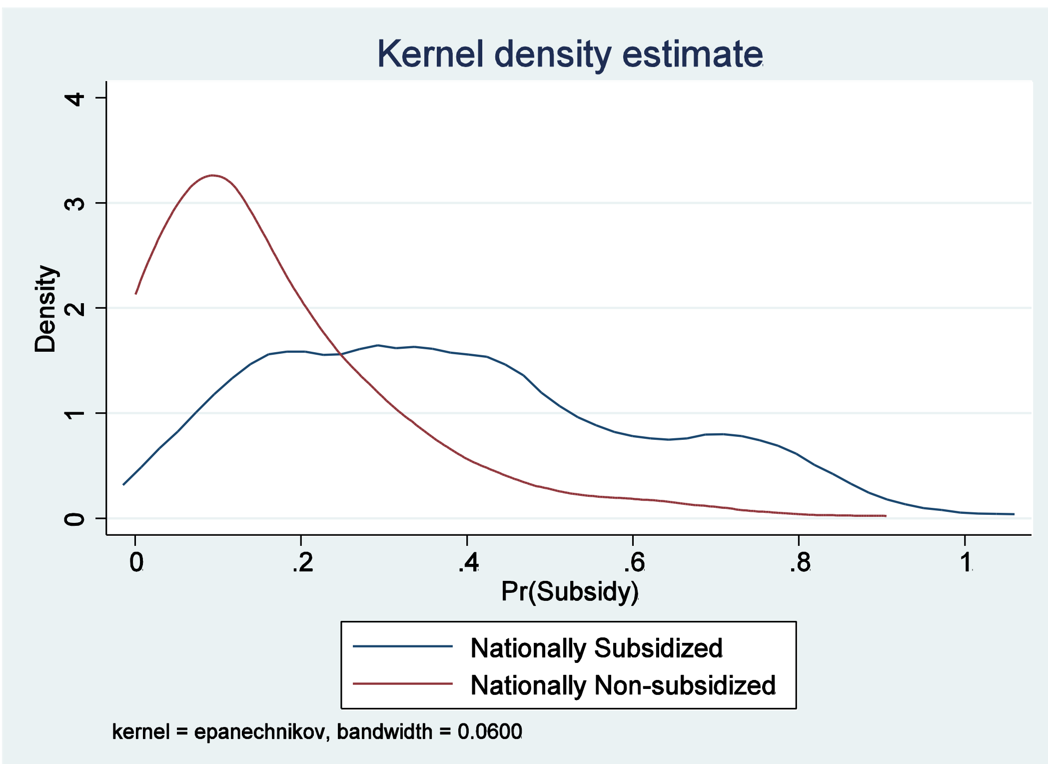

Figure 2: Kernel density plot, Source: KOF (2015), own calculations

After matching, the covariates reveal in a two-tailed t-test no difference between subsidized firms and unsubsidized firms which again confirms the matching quality (see Table 6). Overall, matching works sufficiently well in obtaining a control group similar to the treatment group. The observable determinants of subsidy receipt work well conditional on ruling out the influence of unobservables such that the remaining assignment to control and treatment group is as good as random, given the propensity score. Thus, we are able to compute the differences in our outcome variables while acknowledging that there is no bias from self-selection of firms into treatment.

Table 6: Sample descriptive statistics after kernel matching with bandwidth 0.06

	Unsubsidized (Control) N = 305 Mean	Subsidized (Treatment) N = 101 Mean	t-Test	p-Values
Covariates				
Part of an enterprise group yes/no	.57501	.58416	0.13	0.896
Foreign owned yes/no	.03739	.0396	0.08	0.935
SME	.54598	.51485	-0.44	0.659
Exports yes/no	.93723	.9604	0.74	0.458
R&D co-operations yes/no	.70923	.65347	-0.85	0.398
Gross investments	7.6e+06	8.1e+06	0.13	0.893
Number of competitors <= 5	.32421	.32673	0.04	0.970
Number of competitors 6-10	.32113	.33663	0.23	0.816
Number of competitors 11-15	.11937	.13861	0.41	0.685
Number of competitors 16-50	.10316	.09901	-0.10	0.923
Number of competitors >50	.13213	.09901	-0.73	0.464
Share of exports in turnover	60.274	62.574	0.47	0.641
Log firm age	3.9819	4.0733	0.86	1.06
Number of patents	9.8928	14.634	1.08	0.281
Technological potential	3.3967	3.3762	-0.16	0.876
Share of trained employees	39.263	39.99	0.29	0.773
Share of untrained and partly trained employees	23.994	23.788	-0.07	0.942
Share of apprentices	5.3179	4.7958	0.77	0.442
Share of employees with college/university degree	11.23	11.237	0.00	0.997

By using the probability of receiving public subsidies conditional on observable characteristics, we are able to obtain a matched sample in which to each subsidized firm, we find at least one other unsubsidized firm with a similar propensity score. Since the results might be driven by the chosen matching algorithm, we also apply a one-to-one matching as well as nearest neighbor matching with different specifications.

Table 7: ATTs on outcome variables by kernel matching with various bandwidths and nearest neighbor matching with one neighbor and five neighbors and one-to-one matching, own calculation

	Kernel matching			Nearest neighbor matching, caliper 0.001		One-to-one matching
	0.06	0.03	0.01	one neighbor	five neighbors	
	(1)	(2)	(3)	(4)	(5)	(6)
R&D expenditures						
ATT	0.4306 (0.2682)	0.4051 (0.2858)	0.3352 (0.3076)	0.1739 (0.4620)	-0.0429 (0.4093)	0.5483*** (0.2024)
t-stat	1.61	1.42	1.09	0.38	-0.10	2.71
N treatment	101	101	101	101	101	101
N control	305	305	305	305	305	101
N off-support	77	77	77	77	77	281
Median bias (%)	4.0	5.7	6.7	5.9	9.0	33.6
R&D intensity						
ATT	0.0681 (0.1833)	-0.01412 (0.1960)	-0.0862 (0.2116)	0.0659 (0.3073)	-0.0098 (0.2782)	.1735 (.1405)
t-stat	0.37	-0.07	-0.41	0.21	-0.07	1.23
N treatment	101	101	101	47	47	101
N control	305	305	305	77	77	101
N off-support	77	77	77	359	359	281
Median bias (%)	4.0	5.7	6.7	5.9	9.0	33.6

As table 7 shows, the average treatment effect on the treated on R&D expenditure reveals in almost all cases a positive sign (except for nearest neighbor matching with five neighbors, column 5) but no significance (only in case of one-to-one matching, column 6). The matching quality as previously discussed is sufficient to ensure comparability between treatment and control groups except in the cases of nearest neighbor matching with five neighbors and one-to-one matching where the bias after matching is nevertheless substantially high (column 5 and 6 of Table 7). This is due to the high loss on observations as a result of imposing the common support assumption.

Hence, across different specifications and different matching algorithms, subsidized firms do not reveal significant differences in R&D activity which points to partial crowding out of R&D public subsidies. Qualitatively similar results can be obtained when substituting the dependent variable with R&D intensity.

We interpret the partial crowding out as the result of the 2008 financial crisis which may have substantially affected R&D investment behavior and the allocation of funds. This setting gives rise to the question of how the firms adapted to the crisis with regard to different coping strategies.

4.2 Impact of coping strategies during the crisis on R&D investment behavior

Table 8 provides estimates of the effects of the effect of different strategies in coping with the financial crisis on R&D investment decisions using multinomial probit models. We estimate three models (baseline model 1), then we add some control variables (model 2) and regional dummies (model 3). The results of all three models indicate that giving up on R&D investments is not associated with any crisis-coping strategy such as applying for public funds, external funds, or engaging in new R&D cooperation activities.

However, public funds seem to be positively associated with the probability of preponing R&D investments. The positive coefficients in the second equation indicate that public funds and external funds have a positive effect on the utility difference between the different investment decisions. With a higher utility difference, firms are more likely to prepone R&D projects. We find that when firms apply for public R&D subsidies, then the probability to prepone compared to not changing behavior is increased ceteris paribus. Its marginal effect implies that firms applying for additional public funds during the crisis are more likely to anticipate their R&D investments projects at least by 22%. Similarly, applying for additional external funds also increases the probabilities of preponing investments by at least 12% (compared to not changing behavior).

Both results suggests the validity of the hypothesis that additional funding leads to anti-cyclical R&D investment behavior. In particular, this means that in the absence of the crisis, firms may not have applied for additional funding to prepone investments. However, as a result of the crisis and potential availability of funding, firms shift their R&D investment projects to earlier periods. This may result in windfall gains, i.e. gains that may not have occurred without access to additional funding. Having this in mind, the results also confirm possible crowding out of public subsidies, a result in line with the matching analysis (section 4.1).

Finally, the engagement in new R&D cooperation is associated with higher probability of postponing R&D investments. Similarly, the positive marginal effect implies that as a consequence of the crisis, firms that engage in additional R&D cooperation are at least 32% more likely to postpone R&D investment projects. Thus, cooperation leads to pro-cyclical R&D investment behavior by allowing firms to qualitatively revise R&D projects and subsequently realize them.

Table 8: Multinomial probit estimates of R&D investment behavior

R&D investment behavior	Model 1			Model 2			Model 3		
Marginal effects	Outcome: give up (=1)	Outcome: prepone (= 2)	Outcome: postpone (= 3)	Outcome: give up (=1)	Outcome: prepone (= 2)	Outcome: postpone (= 3)	Outcome: give up (=1)	Outcome: prepone (= 2)	Outcome: postpone (= 3)
Public funds	-0.0177	0.2702***	0.0193	-0.0301	0.2289***	0.0048	-0.0309	0.2247***	0.0025
	(0.0310)	(0.0663)	(0.0358)	(0.0261)	(0.0686)	(0.0288)	(0.0238)	(0.0698)	(0.0279)
External funds	0.0923**	0.1245**	0.0166	0.0827	0.1585***	0.0121	0.0737*	0.1677***	0.0163
	(0.0451)	(0.0543)	(.0340)	(0.0445)	(0.0579)	(0.0298)	(0.0424)	(0.0594)	(0.0304)
Cooperation	-.0161	0.0650	0.3181***	-0.0188	0.0503	0.3244***	-0.0127	0.0584	0.3220***
	(0.0452)	(0.0746)	(0.0872)	(0.0451)	(0.0713)	(0.0895)	(0.0459)	(0.0735)	(0.0887)
Firm age				0.0002	-0.0005	0.0000	0.0002	-0.0004	0.0000
				(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
N° of employees				-0.0002***	0.0001***	0.0000	-0.0002***	0.0001***	0.0000
				(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Foreign owned				0.0283	-0.0120	-0.0078	0.0262	-0.0151	-0.0046
				(0.0287)	(0.0341)	(0.0181)	(0.0279)	(0.0335)	(0.0189)
Export				-0.0347*	0.1036***	0.0354**	-0.0319	0.1155***	0.0326**
				(0.0204)	(0.0282)	(0.0163)	(0.0198)	(0.0281)	(0.0158)
Hightech				0.0202	0.1580***	0.0724***	0.0347	0.1690***	0.0672***
				(0.0270)	(0.0396)	(0.0259)	(0.0280)	(0.0406)	(0.0257)
Region dummies	NO			NO			YES		
Prob > chi2	0.0000			0.0000			0.0000		
Frequencies	75	142	53	69	136	50	69	136	50
Number of obs.	835			807			807		

Significance levels: * 0.05 < p < 0.10, ** 0.01< p < 0.05, *** p < 0.01; Notes: Base outcome (= 4): no change in R&D investment behavior, robust standard errors

5 Conclusion

This study analyzed the effects of public subsidies on R&D activity over the 2005 – 2013 period, when the 2008 financial crisis hit the global economy. We further disentangle R&D investment behavior when firms are coping with the crisis. First, the average treatment effect on the treated reveals no significant difference between subsidized and unsubsidized Swiss firms in terms of R&D activity and R&D intensity. Importantly, our results suggest a partially substituting effect of private funds by public funds in the decision to invest in R&D. This causal effect is robust to different specifications and matching methods. In the context of the crisis, partial crowding out may seem plausible if we consider that the time period covered by our dataset also includes the years of the crisis, a period when firms were adapting to the crisis by altering their investment decisions.

Second, building upon on the previous finding, we investigate the relation between different decisions on R&D investments as result of the crisis in order to understand the potential causes of the crowding out behavior. The results reveal that the search for public funds is positively related to preponing R&D investment projects, thus implying anti-cyclical R&D investment behavior. The same relation also holds for firms seeking external funds. Moreover, it may indicate that firms shift their R&D investment projects to earlier periods (during the crisis) to benefit from the public subsidies, i.e., from windfall gains. Related to the crowding-out result, the anti-cyclical R&D investment behavior emphasizes the substitution of private R&D investments by public ones during the crisis.

Our results have important implications for public policy. We show that the partial crowding out by firms is driven by firms' investment behavior in reaction to the crisis. Thus, we cannot rule out that public innovation grants failed to provide to the stabilization of the economy by setting false incentives. Ultimately, this market failure can be attributed to firms benefitting from easier access to public subsidies. Public policy should consider that firms do not necessarily select R&D investment projects with high success rates but projects of lower quality and therefore try to shift these R&D projects to earlier periods. While R&D projects which in response to

We are careful in interpreting the results as the empirical strategy applied bears several limitations that may affect inference and policy implications. First, matching approaches depend largely on the observable covariates chosen. In our case, we believe that the large set of covariates included should not raise this issue. Second, it may be interesting to include information on the "intensity" of public support measured by subsidy size, for example by using data by the subsidy granting institutions. This may provide deeper insights on the effectiveness of public policy on the economy.

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