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Public Subsidies and the Sources of Venture Capital

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Abstract

Research suggests that public subsidies for newly founded firms have a positive effect on follow-on financing, in particular, Venture Capital (VC). This study differentiates between Government VC, Independent VC, Corporate VC, and Business Angels and shows that public subsidies are not relevant for all of these sources. When accounting for firm characteristics that drive both selection into public subsidies as well as into VC financing through econometric matching techniques, we find that subsidies are only linked to Government VC and Business Angel financing.

Key words: Start-up Subsidies, Entrepreneurship Policy, Entrepreneurial Finance, Venture Capital, Business Angels

JEL codes: G24, L26, O25, O31

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1 Introduction

New firms play an important role in knowledge-based economies (van Praag and Versloot, 2007). They contribute to the introduction of new products as well as to the diffusion of new technologies (Audretsch, Link, Sauer and Siegel, 2016). In particular radical innovations are more likely to be implemented by new than by established firms (Acs and Audretsch, 1988; Caggese, 2019). New firms also create jobs (Haltiwanger, Jarmin and Miranda, 2013). The returns to new firm creation, however, are not fully appropriated by the entrepreneur. Social returns may exceed private returns through the value generated by new products or improved processes. Moreover, firms entering markets with novel, complex products are particularly prone to suffer from the liability of newness which can be a barrier to new firm success (Ostgaard and Birley, 1994).

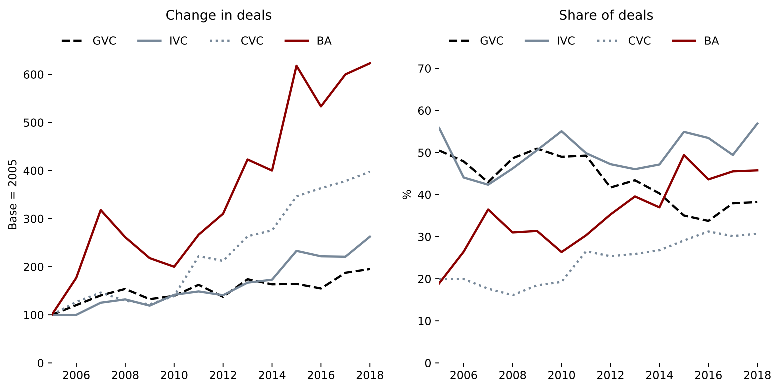
Public support of new firms therefore aims to help to overcome financing constraints. The effectiveness of subsidies for start-ups in achieving this goal has been examined in a series of studies suggesting that direct financial support fosters start-up innovation and growth (Colombo, Giannangeli and Grilli, 2012; Colombo, Grilli and Murtinu, 2011; Howell, 2017; Conti, 2018; Hottenrott and Richstein, 2020). Research further suggests that the effects go beyond direct financial aid by triggering second order effects in terms of access to (follow-on) financing provided by other lenders (Hottenrott, Lins and Lutz, 2018) or investors (Lerner, 1999; Söderblom, Samuelsson, Wiklund and Sandberg, 2015; Howell, 2017; Hottenrott and Richstein, 2020; Zhao and Ziedonis, 2020). These second order effects may explain why initially small amounts of public funding result in measurable effects.

This study contributes to understanding these second order effects by distinguishing the extent to which public support attracts different sources of venture capital (VC) financing. Different investor types pursue different goals and to some investors public support may be more valuable than for others (Hsu, Haynie, Simmons and McKelvie, 2014; Tykvová, 2018). We distinguish between Government Venture Capital (GVC), Independent Venture Capital (IVC), Corporate Venture Capital (CVC), and Business Angels (BA). Using data on 9,743 start-ups founded between 2005 and 2016 in knowledge-intensive sectors in Germany that are potentially of interest to venture capital investors, we show that there is a positive correlation between public subsidies and all sources of VC. When taking into account the selection into subsidy programs, however, the second order financing effect can only be linked to GVC and BA financing.

2 Public Subsidies and VC

VC has become increasingly important in the financing of new firms even in countries that traditionally had comparably low levels of VC. The empirical setting for the following study is Germany for which Figure 1 shows that VC financing increased substantially from 2006 to 2016 (left panel). Figure 1 also illustrates that there is a mix of VC providers that became equally important over time.

Figure 1: Sources of VC



Sources: IAB/ZEW Startup Panel, Bureau van Dijk, Majunke Consulting. Own calculations.

Previous research shows that new firms that receive subsidies are more likely to raise VC funding (Lerner, 1999; Howell, 2017; Conti, 2018; Hottenrott and Richstein, 2020; Zhao and Ziedonis, 2020). Publicly financed startups may appeal to VC investors for at least two reasons. First, public subsidies carry an information value. Second, they finance risky early stage activities. Although VC investors are typically well informed about industry prospects and perform own assessments (Shepherd, 1999), the information value that they extract from public subsidies may depend on the investor type. While it is often argued that subsidies may reveal quality-related information about a firm, the information value could also be related to aspects of regulatory uncertainty and societal returns to the firms' activities. Public funding agencies, that allocate subsidies may have an information advantage about new technologies, their regulation, and their longer-run prospects (Lerner, 1999). Such information should be more valuable to investors who acquire less information through formal due diligence processes or formal networks as is the case for BA (Fiet, 1995). For these investors the information value of subsidies should be relatively higher as they acquire less information ex-ante and often base their investment decisions on heuristic assessments (Van Osnabrugge, 2000; Maxwell, Jeffrey and Lévesque, 2011). Moreover, like GVC, BA may pursue goals other than pure economic profit by investing in firms that fit their mission and their desire to contribute to society (Hsu et al., 2014). Especially GVC and BA may therefore understand the award of a public subsidy as a signal of these prospects.

In addition, Howell (2017) argues that firms use the awarded money to advance their project thereby reducing technological uncertainty, and reach a proof-of-concept stage, making them more attractive to VCs. Similarly, Hottenrott and Richstein (2020) find that when firms receive grants combined with publicly backed loans, the VC probability is higher than in the case of grants alone. Therefore, it may not be the information value alone, but also the funding amount that attracts investors.

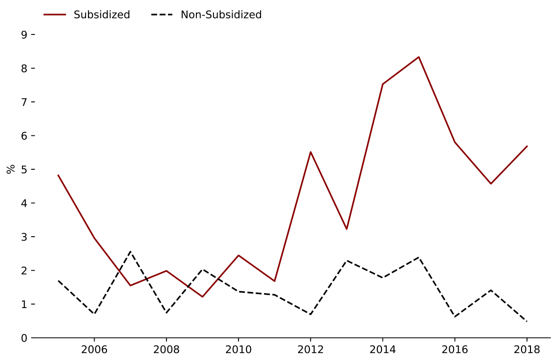
How much of these channels matter may depend on the source of VC. For IVC investors it is typically the return on investments that matters in the first place (Hsu et al., 2014) and their due diligence may allow them to collect sufficient information so that the subsidy carries little additional information value about technological market prospects, quality of the business model or founder characteristics. The cash inflow from the subsidy may still increase firms' attractiveness as it allows financing of uncertain early stage investments. CVC decisions may also rely on the corporate's own expert knowledge. Moreover, the economic profit of the venture may not be the most important aspect in the CVC objective function. The CVC may pursue strategic goals (Riyanto and Schwienbacher, 2006) which reduces both the information value of subsidies as well as of the uncertainty reducing early stage investment. Public subsidies may still serve as a talent and technology screening device. Corporations may observe grant competitions and participating startups may therefore be simply more visible to CVC funds compared to others.

Previous studies, however, do not distinguish between the sources of VC leaving the question open whether the observed link between the subsidy and VC is driven by a specific type of investor. Understanding this has implications for assessing the overall impact of start-up subsidies.

3 Data

The firm-level data for the analysis stems from the IAB/ZEW Start-up Panel (Fryges, Gottschalk and Kohn, 2009) for the founding cohorts 2008 to 2018, Bureau van Dijk's Zephyr data base as well as from transaction data published by Majunke Consulting. The final sample covers information from 9,743 firms of which 35% received start-up subsidies and 2.7% some form of VC. Subsidies include grants, subsidized loans and guarantees. When looking at VC-funding in subsidized versus non-subsidized firms, we see that in more recent founding cohorts, a larger share of subsidized firms received VC (Figure 2). See Appendix A for a detailed data description. Tables A.1 and A.2 summarize the variables. Table 1 present differences between the group of subsidized and non-subsidized start-ups in terms of founder and firm characteristics and shows that the groups differ considerable in their observable characteristics poiting to the importance of accounting for these differences in the following analysis.

Figure 2: VC investments by founding cohorts



Sources: Bureau van Dijk, Majunke Consulting, Mannheim Startup Panel. Own calculations.

4 Empirical methodology

To investigate the link between subsidies and venture capital, we estimate linear probability models such that:

$$XVC_{it} = \alpha + \beta Subsidy_{it} + \gamma X_{it} + \tau_t + \phi_i + u_{it},$$

where XVC_{it} is an indicator variable that switches to 1 in the year when startups receive their first venture capital investment from one of the investor types in $XVC = \{GVC, BA, IVC, CVC\}$. $Subsidy_{it}$ is an indicator variable that switches to 1 in the year when startups receive their first public subsidy, X_{it} is a set of control variables and τ_t and ϕ_i are year and company specific fixed factors, of which the latter are unobserved.
We estimate pooled models as well as a within estimator which accounts for unobserved time-constant firm characteristics. Yet, the key variable of interest - subsidy receipt - is not randomly assigned to firms. A correlation between subsidy receipt and VC financing could be due to common drivers of both outcomes rather than a causal link between the two.

To address the selection into the group of subsidized firms, we perform matching techniques (Rubin, 2005). We follow Hottenrott and Richstein (2020) and use a combination of propensity score matching (PSM) and exact matching (EM). See Appendix B for details. Table 1 shows the variables used in the PSM. Additionally, we match exactly on founding year, industry, and sector. The balance of the covariates improves through the matching so that there are no significant differences between treated and control firms anymore. Figure A.1 shows the distributions of propensity scores after matching and Table A.3 shows the balancing of the controls.

Table 1: Difference in Means of Controls

	Panel A: unmatched					
	Subsidized N=3422		Non-subsidized N=6321			
	Mean	Std. Err.	Mean	Std. Err.	Δ	t
Controls						
Founder age (log)	3.680	0.216	3.710	0.252	0.029	6.05
Team	0.537	0.499	0.440	0.496	-0.097	-9.19
Academic	0.716	0.451	0.682	0.466	-0.034	-3.49
Female	0.170	0.375	0.166	0.372	-0.004	-0.52
Industry experience	12.950	9.290	13.739	10.309	0.789	3.85
Founding experience	0.498	0.500	0.606	0.489	0.107	10.20
Failure experience	0.175	0.380	0.211	0.408	0.036	4.35
Opportunity driven	0.493	0.500	0.483	0.500	-0.010	-0.99
R&D	0.520	0.500	0.403	0.491	-0.117	-11.11
Patent	0.071	0.257	0.051	0.220	-0.020	-3.87
	Panel B: matched					
	N=2208		N=1756			
	Mean	Std. Err.	Mean	Std. Err.	Δ	t
Propensity score	0.255	0.151	0.254	0.149	0.001	0.215

5 Results

Table 2 shows the main estimation results. Panel A shows the results for the unmatched sample, Panels B and C show pooled OLS and fixed effects models on the matched sample, respectively. The first column in Panel B indicates that receiving a public subsidy more than doubles the probability to receive VC relative to non-recipients (109%).[1] Looking at the different sources of VC, we observe that subsidized firms are significantly more likely to receive GVC or BA investments, but not more likely to receive CVC and IVC. This is in contrast to the models on the unmatched sample in which we observe positive correlations with all sources of VC. This result is even more pronounced in the within estimation (Panel C) which additionally accounts for unobserved heterogeneity among firms (Tables A.6-A.4 shows the full estimation results with and without matching). Since the four VC-types may co-occur, we also estimate the four equations jointly and find that the results are robust to this alternative specification (see Tables A.9 and A.10 for regression results and Table A.11 for error correlation across equations). In this specification, we test whether the coefficients for subsidy receipt are significantly different in the GVC versus BA equation and find that the coefficients are not statistically different ($\chi^2(1) = 1.21$, p-value $= 0.27$). See Table A.12 for all pair-wise comparisons.

[1] The marginal effect of 0.0026 refers to the difference in the predicted probability of VC in both groups. The percentage increase is calculated as Prob(VC|Subsidy)/Prob(VC|No Subsidy) $= (0.0050/0.0024 - 1) \times 100 \approx 109$.

Table 2: Results

	Panel A: POLS (unmatched)				
	VC	GVC	BA	IVC	CVC
Subsidy(t)	0.0034^{***}	0.0029^{***}	0.0014^{***}	0.0010^{***}	0.0007^{**}
	(0.0006)	(0.0005)	(0.0004)	(0.0004)	(0.0003)
Obs.	55052	55321	55676	55599	55839
	Panel B: POLS (matched)				
Subsidy(t)	0.0026^{***}	0.0022^{***}	0.0015^{***}	0.0002	0.0005
	(0.0008)	(0.0007)	(0.0005)	(0.0006)	(0.0004)
Obs.	24978	25105	25285	25209	25327
	Panel C: Within (matched)				
Subsidy(t)	0.0058^{**}	0.0042^{**}	0.0031^{*}	0.0013	0.0012
	(0.0025)	(0.0020)	(0.0018)	(0.0017)	(0.0010)
Groups	3953	3955	3963	3961	3961
Obs.	24978	25105	25285	25209	25327

Standard errors in parentheses, clustered at the firm level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panels A and B include year, industry and region fixed effects, and firm controls.

Panel C includes year and firm fixed effects.

6 Conclusion

Previous research suggested that start-ups with public subsidies are more likely to receive VC. Our results confirm this even after accounting for selection effects. However, our results show that this positive relationship exists for GVC and BA financing, but not for VC from other investors. The result that GVC and BA funding is most sensitive to public start-up funding could have three reasons. First, to the extent that public funding agencies are considered knowledgeable, their start-up support may convey a valuable legitimizing endorsement. The information value of a subsidy award may, however, decrease with the degree of ex-ante information acquisition of the financier. Second, additional financial resources matter more to GVC and BA compared to other investors. Third, there is an inherent link between the two sources. In the case of GVC, subsidies could be provided with the explicit hint of the funder to seek GVC. There may also be advantages when pitching for GVC for firms that have previously dealt with public agencies either through learning about their expectations or simply through (personal) connections. Unlike for private VC, public subsidies and GVC could even be conditioned on one another. Yet, the data that we analysed here suggests that the increase in the share of VC in subsidized firms is largely driven by BA - a source of funding that became considerably more important.

Our results suggest that the second order effects of start-up subsidies are not guaranteed, but may depend on the active investor mix in a country. Finally, we strongly encourage research in other settings in order to understand the generalizability of this result.

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Appendices

Supplemental Material for 'Public Subsidies and the Sources of Venture Capital'

A Data description

We use information from four primary databases to conduct our analysis.

Data on startups. Our primary data source is the IAB/ZEW Startup Panel,[2] which is based on a yearly survey among startups in Germany, administered by the Institute for Employment Research and ZEW - Leibniz Centre for Europen Economic Research. The sample of startups that enter the survey are drawn as a stratified random sample from the Mannheim Enterprise Panel (MEP),[3] a comprehensive database of the population of German firms. When startups enter the survey, they are at least one and at most three years old, and remain in the sample until a maximum age of seven years. Importantly for our analysis, it contains detailed information on the use of public subsidies in startup companies. Startups are asked to indicate whether they have received public subsidies in the form of subsidized loans, grants, or guarantees. For the purpose of this paper, we consider all forms of subsidies jointly.[4] Note that only for companies first surveyed in their founding year we know the exact year of the first subsidy receipt. From these companies we know that 85% of startups that receive a subsidy, receive it in their year of foundation. For the group of startups for which the founding year and the first reference year are not equal, we assume that they receive their first subsidy in the founding year. We conduct robustness checks to check whether this assumption is material to the results and re-estimate all models only including firms that we observe from the first year onward (see Table A.8).

To control for founder and firm characteristics, we use information on founders' gender, educational background, founding and industry experience, as well as whether firms were founded by a team. In addition we include firms' founding year, their sector of activity and location. The innovation potential is proxied by an indicator for firms R&D activity and their Intellectual Property (IP) in terms of patents, as well as a variable indicating whether firms were founded based on a concrete business idea.

Venture capital transactions. To identify startups that receive venture capital investments, we use transaction data from two primary data sources. The first is Bureau van Dijk's Zephyr data base which contains information on worldwide M&A transactions,

[2] See Fryges et al. (2009) for details.

[3] The MEP is based on data from creditreform - Germany's largest credit raging agency - and maintained and administered by the ZEW - Leibniz Centre for European Economic Research in Mannheim. For more details on the MEP see Bersch, Gottschalk, Müller and Niefert (2014).

[4] Previous research suggest that there are differences between grants and loans with regard to incentivizing R&D versus tangible investments, but that in terms of their role for VC, both policy tools are quite similar (Hottenrott and Richstein, 2020).

including venture capital transactions. We use information on minority stake acquisitions through venture capital financing in the period from 2005 to 2018, where the target company is located in Germany. Zephyr has been used for a recent large scale research project on venture capital in Europe to identify i.a. German venture capital transactions (Bertoni and Martí, 2011). Zephyr has, however, a limited coverage for German venture capital transactions. We therefore complement the Zephyr data with information from Majunke Consulting, a private equity boutique that collects information on M&A, private equity, and venture capital transactions in the DACH region.[5] Majunke's venture capital data start in 2005 and the data set contains all information collected by Majunke up until 2018. We match information on acquirers (i.e. venture investors) and target companies (startups) with the MEP based on names and adresses. We identified 99% of startups from the Zephyr database and 98% from Majunke's data applying a fuzzy string matching algorithm on company names and addresses.[6] Once merged to the MEP, we can link the data to the IAB/ZEW Startup Panel. In a next step, we classified investors into categories, differentiating between independent and various types of captive venture capital investors using information from investors' websites, crunchbase, Bloomberg as well as ownership information from the MEP. For our analysis we distinguish between four different types of venture capital investors, government venture capital (GVC), independent venture capital (IVC), corporate venture capital (CVC), and Business Angels (BA).

Sample. We focus on firms that are potentially relevant for venture capital investments. Research on the venture capital market has shown consistently that venture capital investments are concentrated in certain sectors and certain types of start-ups (Lerner and Nanda, 2020). Therefore, we restrict the sample to knowledge-intensive sectors. That is, we discard startups that are operating in construction, retail and consumer oriented services industries. We also discard startups that are operating as franchise companies or joint-ventures, and keep only startups that are either limited liability companies or incorporations. After the elimination of observations with missing values, the final sample comprises information on 9,743 startups.

B Matching approach

Matching. We employ a matching procedure that combines propensity score matching and coarsened exact matching (Iacus, King and Porro, 2012). The idea of matching is to find observations that are reasonably comparable thereby adjusting the distribution of pretreatment covariates by either excluding and/or reweighting observations. While exact matching has several desirable properties, like an intuitive interpretation, and an upper bound on the level of imbalance in the matched sample (Iacus, King and Porro, 2011), i.e. the degree of variation between different specifications, it also has well known disadvantages. Most notably exact matching leads to small estimation samples, as it discards

[5] The DACH region comprises Germany (D), Austria (A) and Switzerland (CH).

[6] For the fuzzy string matching we used Thorsten Doherr's SearchEngine: https://github.com/ThorstenDoherr/searchengine

any observation that is not within the set of strata defined by coarsened pretreatment covariates of treated observations. This may lead to inefficient estimation.

Our matching algorithm proceeds in the following way: First, we narrow down a set of control observations that must have been active in the year when treated observations received their first subsidy. For those observations, we estimate the propensity score for being treated, i.e. the treatment probability, using the covariates displayed in the upper panel of Table 1, as well as indicators for industry, founding cohort and region. Second, we apply caliper matching on the estimated propensity score, on which we place an additional matching requirement. We only want to match observations that are from the same founding cohort, a similar industry, and are located in a similar region. For those variables we employ an exact matching algorithm. We implement the algorithm using the user written Stata command `ultimatch`,[7] which allows to blend different matching procedures.

C Additional Tables

Table A.1: Description of variables.

Variable Name	**Variable Description**
Subsidy(T)	The startup has received a subsidy as a grant or loan in any year.
VC(T)	The startup received at least one investment by any venture capital investor in any year.
GVC(T)	The startup received at least one investment by an governmental venture capital investor in any year.
IVC(T)	The startup received at least one investment by an independent venture capital investor in any year.
CVC(T)	The startup received at least one investment by an corporate venture capital investor in any year.
BA(T)	The startup received at least one investment by an angel investor in any year.
Startup age at VC (1)	Age of the startup at first VC financing round.
Startup age	Age of the startup in years.
Founder age	Age of the founders at foundation, for teams it is the average founder age.
Team	The startup was founded by more than one person.
Academic	At least one founder has a university degree.
Female	At least one founder is female.
Industry experience	Years of industry experience at foundation.
Founding experience	At least one founder has previously founded a company.
Failure experience	At least one founder has failed before.
Opportunity driven	The startup was founded to realize a business idea.
R&D(T)	The startup has conducted research and/or development activity in any year.
Patent	The startup held a patent at foundation.
Founding year	The startup's year of foundation.
Industry	The main industry the startup operates in.
Region	The startups business location.

Notes: All of the variables used are binary variables. Except for *Industry, Region* and *Founding Year*, which are categorical variables and industry experience and founder age which is measured in years.

[7] The command was developed by Thorsten Doherr: https://github.com/ThorstenDoherr/ultimatch

Table A.2: Summary of variables

	Firm Obs.	Mean	Std. Err.	Min.	Max.
Subsidy(T)	9743	0.351	0.477	0	1
Venture Capital					
VC(T)	9743	0.027	0.161	0	1
GVC(T)	9743	0.018	0.135	0	1
BA(T)	9743	0.012	0.111	0	1
IVC(T)	9743	0.012	0.108	0	1
CVC(T)	9743	0.006	0.079	0	1
Startup age at VC(1)	261	1.632	1.733	0	10
Founders					
Founder age	9743	41.573	9.744	17	95
Team	9743	0.474	0.499	0	1
Academic	9743	0.694	0.461	0	1
Female	9743	0.167	0.373	0	1
Industry experience	9743	13.462	9.969	0	59
Founding experience	9743	0.568	0.495	0	1
Failure experience	9743	0.198	0.399	0	1
Opportunity driven	9743	0.486	0.500	0	1
R&D(T)	9743	0.543	0.498	0	1
Patent	9743	0.058	0.234	0	1
Industry					
Hightech manufacturing	9743	0.201	0.401	0	1
Hightech services & Software	9743	0.455	0.498	0	1
Nontech manufacturing	9743	0.131	0.337	0	1
B2B & Knowledge-int. services	9743	0.213	0.409	0	1
Region					
West Germany	9743	0.824	0.381	0	1
Berlin	9743	0.062	0.240	0	1
East Germany	9743	0.114	0.318	0	1

Notes: Firm Obs. refers to the number of firms observed in the sample. The observation period per firm varies depending on the founding year and the corresponding years in which we observe the firm (the minimum number of observation periods is 1 year and the maximum is 12 years, the median is 5 years). Subsidy(T) comprises different types of public subsidies including grants (77% of subs. firms), subsidized loans (43% of subs. firms) and public guarantees (18% of subs. firms).

Table A.3: Difference in Means of Controls (before and after matching)

	Panel B: matched					
	Subsidized N=2208		Non-subsidized N=1756			
	Mean	Std. Err.	Mean	Std. Err.	Δ	t
Controls						
Founder age (log)	3.691	0.214	3.691	0.242	-0.001	-0.075
Team	0.518	0.500	0.506	0.500	0.012	0.619
Academic	0.711	0.454	0.711	0.453	-0.000	-0.027
Female	0.162	0.369	0.173	0.378	-0.010	-0.698
Industry experience	13.591	9.304	13.675	10.233	-0.084	-0.220
Founding experience	0.521	0.500	0.529	0.499	-0.009	-0.451
Failure experience	0.183	0.386	0.170	0.376	0.012	0.884
Opportunity driven	0.482	0.500	0.480	0.500	0.002	0.119
R&D	0.537	0.499	0.547	0.498	-0.010	-0.532
Patent	0.066	0.248	0.063	0.243	0.003	0.290
Propensity score	0.255	0.151	0.254	0.149	0.001	0.215

Notes: ***Panel B*** *shows the means, and differences in means (Δ) after balancing. Differences in means are the estimated coefficients of a weighted univariate regression of the control variable on the treatment status. The regression weights are the balancing weights obtained from the matching procedure described in section B. The standard errors and t-values are calculated under the assumption of heteroskedasticity.*

Table A.4: Unmatched pooled models results

	VC	GVC	BA	IVC	CVC
Subsidy(t)	0.0034***	0.0029***	0.0014***	0.0010***	0.0007**
	(0.0006)	(0.0005)	(0.0004)	(0.0004)	(0.0003)
Startup age (log)	-0.0044***	-0.0034***	-0.0017***	-0.0009***	-0.0007***
	(0.0004)	(0.0004)	(0.0003)	(0.0002)	(0.0002)
Founder age (log)	-0.0060***	-0.0034***	-0.0036***	-0.0026***	-0.0018***
	(0.0012)	(0.0010)	(0.0009)	(0.0009)	(0.0006)
Team	0.0039***	0.0029***	0.0013***	0.0016***	0.0007***
	(0.0006)	(0.0005)	(0.0004)	(0.0004)	(0.0003)
Academic	0.0030***	0.0021***	0.0013***	0.0013***	0.0004**
	(0.0004)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Female	-0.0013*	-0.0011*	0.0002	-0.0005	-0.0002
	(0.0008)	(0.0006)	(0.0006)	(0.0005)	(0.0003)
Industry experience	-0.0001***	-0.0001***	-0.0001***	-0.0000**	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Founding experience	-0.0008	-0.0010*	-0.0001	0.0006	-0.0000
	(0.0006)	(0.0005)	(0.0004)	(0.0004)	(0.0003)
Failure experience	0.0004	0.0012*	-0.0002	-0.0004	0.0001
	(0.0008)	(0.0007)	(0.0005)	(0.0006)	(0.0004)
Opportunity driven	0.0016***	0.0010**	0.0006	0.0006*	0.0002
	(0.0006)	(0.0005)	(0.0004)	(0.0004)	(0.0003)
R&D	0.0042***	0.0031***	0.0024***	0.0017***	0.0011***
	(0.0006)	(0.0005)	(0.0004)	(0.0004)	(0.0003)
Patent	0.0004	0.0011	0.0003	-0.0005	0.0001
	(0.0014)	(0.0013)	(0.0009)	(0.0008)	(0.0006)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
R2	0.010	0.008	0.005	0.004	0.003
Obs.	55052	55321	55676	55599	55839

Standard errors in parentheses, clustered at the firm level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Matched pooled models results

	VC	GVC	BA	IVC	CVC
Subsidy(t)	0.0026***	0.0022***	0.0015***	0.0002	0.0005
	(0.0008)	(0.0007)	(0.0005)	(0.0006)	(0.0004)
Startup age (log)	-0.0047***	-0.0035***	-0.0019***	-0.0006	-0.0008**
	(0.0007)	(0.0006)	(0.0004)	(0.0005)	(0.0003)
Founder age (log)	-0.0072***	-0.0044***	-0.0047***	-0.0036**	-0.0030***
	(0.0021)	(0.0017)	(0.0013)	(0.0016)	(0.0011)
Team	0.0023**	0.0019**	0.0003	0.0010	0.0006
	(0.0010)	(0.0008)	(0.0006)	(0.0006)	(0.0004)
Academic	0.0033***	0.0021***	0.0013***	0.0016***	0.0008***
	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0003)
Female	-0.0018	-0.0011	0.0000	-0.0014**	-0.0009**
	(0.0011)	(0.0010)	(0.0008)	(0.0006)	(0.0004)
Industry experience	-0.0001**	-0.0001*	-0.0000	-0.0000	-0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Founding experience	-0.0013	-0.0017**	-0.0009	0.0008	0.0000
	(0.0010)	(0.0008)	(0.0006)	(0.0007)	(0.0004)
Failure experience	0.0006	0.0011	0.0006	0.0007	-0.0000
	(0.0013)	(0.0011)	(0.0007)	(0.0014)	(0.0006)
Opportunity driven	0.0022**	0.0021***	0.0006	0.0004	0.0002
	(0.0008)	(0.0007)	(0.0005)	(0.0007)	(0.0004)
R&D	0.0040***	0.0032***	0.0025***	0.0013**	0.0004
	(0.0007)	(0.0005)	(0.0005)	(0.0006)	(0.0004)
Patent	0.0023	0.0028	0.0002	0.0005	0.0004
	(0.0023)	(0.0022)	(0.0011)	(0.0017)	(0.0008)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
R2	0.009	0.007	0.005	0.004	0.003
Obs.	24978	25105	25285	25209	25327

Standard errors in parentheses, clustered at the firm level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Unmatched within estimation results

	VC	GVC	BA	IVC	CVC
Subsidy(t)	0.0049**	0.0029	0.0025	0.0023	0.0006
	(0.0023)	(0.0018)	(0.0017)	(0.0017)	(0.0009)
Startup age (log)	0.0089***	0.0063***	0.0044***	0.0036***	0.0023***
	(0.0009)	(0.0007)	(0.0006)	(0.0006)	(0.0004)
R&D	0.0064***	0.0056***	0.0033***	0.0027***	0.0011
	(0.0015)	(0.0013)	(0.0011)	(0.0010)	(0.0007)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	
R2	0.006	0.005	0.003	0.003	0.002
Groups	9727	9731	9739	9738	9740
Obs.	55052	55321	55676	55599	55839

Standard errors in parentheses, clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Matched within estimation results

	VC	GVC	BA	IVC	CVC
Subsidy(t)	0.0058**	0.0042**	0.0031*	0.0013	0.0012
	(0.0025)	(0.0020)	(0.0018)	(0.0017)	(0.0010)
Startup age (log)	0.0092***	0.0068***	0.0051***	0.0036***	0.0026***
	(0.0016)	(0.0013)	(0.0011)	(0.0011)	(0.0008)
R&D	0.0014	0.0016	-0.0019**	0.0001	-0.0016***
	(0.0025)	(0.0023)	(0.0008)	(0.0013)	(0.0004)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R2	0.005	0.004	0.003	0.003	0.002
Groups	3953	3955	3963	3961	3961
Obs.	24978	25105	25285	25209	25327

Standard errors in parentheses, clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Robustness test: Timing assumption

	Panel A: POLS (unmatched)				
	VC	GVC	BA	IVC	CVC
Subsidy(t)	0.0022***	0.0020***	0.0009*	0.0002	0.0005
	(0.0008)	(0.0007)	(0.0005)	(0.0005)	(0.0004)
Obs.	30962	31128	31216	31212	31324
	Panel B: POLS (matched)				
Subsidy(t)	0.0029***	0.0025***	0.0013*	0.0005	0.0006
	(0.0009)	(0.0008)	(0.0007)	(0.0005)	(0.0004)
Obs.	19698	19798	19847	19865	19913

Standard errors in parentheses, clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Panels A and B include year, industry and region fixed effects, and firm controls.
The sample includes only startups that enter the sample in their first year of operation.

Table A.9: Unmatched seemingly unrelated regression results

	GVC	BA	IVC	CVC
Subsidy(t)	0.0031***	0.0015***	0.0010**	0.0007**
	(0.0006)	(0.0004)	(0.0004)	(0.0003)
Startup age (log)	-0.0033***	-0.0017***	-0.0009***	-0.0007***
	(0.0004)	(0.0003)	(0.0002)	(0.0002)
Founder age (log)	-0.0034***	-0.0040***	-0.0027***	-0.0019***
	(0.0012)	(0.0010)	(0.0009)	(0.0006)
Team	0.0031***	0.0014***	0.0016***	0.0007***
	(0.0005)	(0.0004)	(0.0004)	(0.0003)
Academic	0.0022***	0.0013***	0.0013***	0.0004**
	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Female	-0.0009	0.0002	-0.0005	-0.0002
	(0.0007)	(0.0006)	(0.0005)	(0.0003)
Industry experience	-0.0001***	-0.0001***	-0.0000**	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Founding experience	-0.0012**	0.0000	0.0007	-0.0000
	(0.0006)	(0.0005)	(0.0004)	(0.0003)
Failure experience	0.0016**	-0.0002	-0.0004	0.0001
	(0.0008)	(0.0006)	(0.0006)	(0.0004)
Opportunity driven	0.0011**	0.0006	0.0007*	0.0002
	(0.0005)	(0.0004)	(0.0004)	(0.0003)
R&D	0.0034***	0.0026***	0.0018***	0.0012***
	(0.0005)	(0.0004)	(0.0004)	(0.0003)
Patent	0.0012	0.0002	-0.0006	0.0001
	(0.0014)	(0.0009)	(0.0008)	(0.0006)
Obs.	55977			

Standard errors in parentheses, clustered at the firm level.
Year, industry and region fixed effects, and firm controls included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.10: Matched seemingly unrelated regression results

	GVC	BA	IVC	CVC
Subsidy(t)	0.0023***	0.0016***	0.0002	0.0006
	(0.0008)	(0.0006)	(0.0006)	(0.0004)
Startup age (log)	-0.0035***	-0.0018***	-0.0006	-0.0007**
	(0.0006)	(0.0004)	(0.0005)	(0.0003)
Founder age (log)	-0.0049**	-0.0053***	-0.0040**	-0.0032***
	(0.0019)	(0.0015)	(0.0018)	(0.0011)
Team	0.0022***	0.0004	0.0010	0.0007
	(0.0008)	(0.0006)	(0.0007)	(0.0004)
Academic	0.0021***	0.0013***	0.0016***	0.0009***
	(0.0005)	(0.0004)	(0.0005)	(0.0003)
Female	-0.0011	-0.0001	-0.0015**	-0.0009**
	(0.0010)	(0.0008)	(0.0007)	(0.0004)
Industry experience	-0.0001	-0.0000	-0.0000	-0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Founding experience	-0.0018**	-0.0008	0.0009	0.0000
	(0.0009)	(0.0007)	(0.0007)	(0.0005)
Failure experience	0.0020	0.0006	0.0006	0.0001
	(0.0013)	(0.0008)	(0.0014)	(0.0006)
Opportunity driven	0.0023***	0.0007	0.0005	0.0002
	(0.0007)	(0.0006)	(0.0007)	(0.0004)
R&D	0.0034***	0.0026***	0.0013**	0.0004
	(0.0006)	(0.0005)	(0.0006)	(0.0004)
Patent	0.0034	0.0004	0.0006	0.0004
	(0.0025)	(0.0013)	(0.0018)	(0.0008)
Obs.	25410			

Standard errors in parentheses, clustered at the firm level.
Year, industry and region fixed effects, and firm controls included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.11: Correlations of seemingly unrelated regression results (after matching)

GVC $\times BA$	0.4757***
	(0.0893)
GVC $\times IVC$	0.2934***
	(0.0733)
GVC $\times CVC$	0.2283***
	(0.0694)
BA $\times IVC$	0.2739***
	(0.0753)
BA $\times CVC$	0.4054***
	(0.0999)
IVC $\times CVC$	0.2490**
	(0.1117)
Obs.	25410

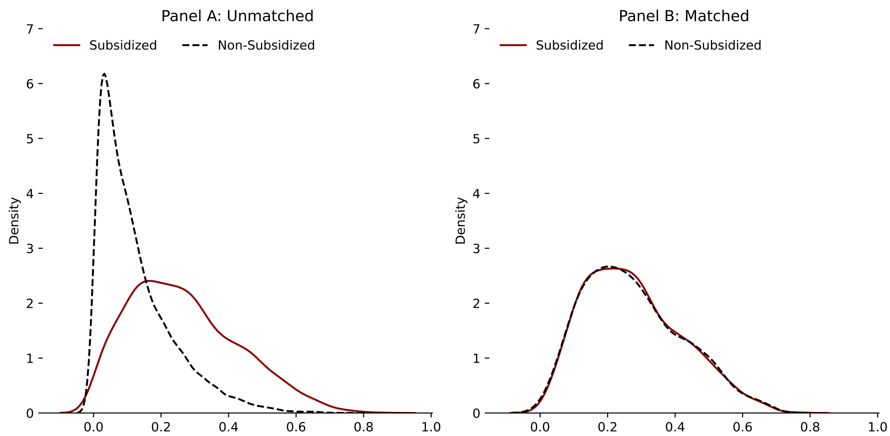
Standard errors in parentheses, clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.12: Chi^2-tests for equality of subsidy coefficients

	Chi^2	df	p-value
GVC:Subsidy(t) vs. BA:Subsidy(t)	1.21	1	0.27
GVC:Subsidy(t) vs. IVC:Subsidy(t)	7.43	1	0.01
GVC:Subsidy(t) vs. CVC:Subsidy(t)	5.09	1	0.02
	Chi^2	df	p-value
BA:Subsidy(t) vs. IVC:Subsidy(t)	3.80	1	0.05
BA:Subsidy(t) vs. CVC:Subsidy(t)	3.71	1	0.05

D Additional Figures

Figure A.1: Estimated probability for subsidy receipt before and after matching



Notes: ***Panel A*** *shows the kernel density estimates for the estimated probability of receiving a subsidy for the group of startups that have in fact received a subsidy (red line) and those that have not (black dashed line) before matching.* ***Panel B*** *shows the the same estimates weighted by the balancing weights obtained from the matching procedure described in section B. Kernel densities are estimated using a Gaussian kernel, the bandwidth is calculated using Scott's Rule, i.e $n(-1/(d+4))$, where n is the number of data points, and d the dimension of the data. For the weighted kernel density estimates, the effective number of data points $n_{eff} = \sum_i (w_i)^2 / \sum_i (w_i^2)$ is used, where w_i is the weight of data point i.*

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