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## Start-Up 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 on Venture Capital (VC), through providing certification and early-stage liquidity. Building on the attention-based view, we argue that the various sources of VC value public start-up subsidies differently. This study is the first to differentiate between distinct types of investors who pursue different investment strategies. We show for a large sample of knowledge-intensive start-ups that there is indeed a correlation between subsidies and all sources of VC (Government VC, Independent VC, Corporate VC, and Business Angels). However, when accounting for firm characteristics that drive both selection into public subsidies as well as into VC financing through econometric matching techniques, subsidies are no longer linked to all types, but only to Government VC and Business Angel financing. We discuss possible explanations for this finding and implications for entrepreneurial finance.

**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

Access to managerial and financial resources is crucial for the success of entrepreneurial firms. Yet, uncertainty about their technological viability, managerial capacity as well as their ability to compete with competitors (Ostgaard and Birley, 1994) makes it challenging for them to secure external resources. Public support programs for entrepreneurial firms aim to help them to overcoms such constraints (Wilson and Silva, 2013; Duruflé, Hellmann and Wilson, 2018; Hellmann and Thiele, 2019). Research suggests that in addition to direct access to seed funding through subsidies, there are also indirect positive effects of public start-up subsidies on (followon) financing provided by other lenders (Hottenrott, Lins and Lutz, 2018; Li, Chen, Gao and Xie, 2019) or investors (Lerner, 1999; Feldman and Kelley, 2006; Cumming, 2007; Conti, 2018; Söderblom, Samuelsson, Wiklund and Sandberg, 2015; Howell, 2017; Islam, Fremeth and Marcus, 2018; Giraudo, Giudici and Grilli, 2019; Hottenrott and Richstein, 2020; Zhao and Ziedonis, 2020).

The evidence on the link between start-up subsidies and access to external resources is not limited to specific countries, as these studies show similar patterns for several knowledge-based economies. In these studies, a special focus has been put on VC investments. VC investors not only provide financing to start-ups, but also managerial support (Hellmann and Puri, 2002), which is an important driver of success for entrepreneurial firms (Ewens and Marx, 2018; Conti and Graham, 2020). As such, VC investors are considered to be an important characteristic of ecosystems conducive to the birth and growth of new firms (Samila and Sorenson, 2011; Popov and Roosenboom, 2013).

Existing research studying the link between public subsidies and VC has regarded VC as a generic financing type. This resulted in the notion that public start-up subsidies are an initiator and facilitator for start-ups' success in raising private sector VC per-se. However, VC providers are a heterogeneous class of investors and the sources of VC differ substantially in their investment approaches (Bottazzi, Da Rin and Hellmann, 2008). Importantly, the are significant performance differences of entrepreneurial firms across different investor types in terms of innovation performance (Chemmanur, Loutskina and Tian, 2014; Bertoni and Tykvová, 2015; Dutta and Folta, 2016) and exits (Brander, Du and Hellmann, 2014; Colombo and Murtinu, 2017; Cumming, Grilli and Murtinu, 2017; Cumming and Zhang, 2019). Yet, we know little about the role of public subsidies in the decision making of different types of VC.

This study aims to contribute to our understanding of the link between start-up subsidies and VC, focusing on the heterogeneity of VC investors. Conceptually, we build on insights by Bianchi, Murtinu and Scalera (2019) suggesting that public subsidies carry information - both about technological prospects and initial resource endowments - and the value of this information depends on the nature of the signal receiver. Drawing on the attention-based view, Bianchi et al.

<sup>&</sup>lt;sup>1</sup>While entrepreneurial firms financed by independent venture capital (IVC) investors and corporate venture capital (CVC) show very similar performance patterns in terms of sales growth and exits (Colombo and Murtinu, 2017), those financed by Business Angels (BA) and Governmental Venture Capital (GVC) investors differ substantially (Brander et al., 2014; Cumming et al., 2017; Cumming and Zhang, 2019). Performance differences also emerge for innovations (Chemmanur et al., 2014; Bertoni and Tykvová, 2015; Dutta and Folta, 2016).

(2019) show that the relative salience of subsidy-related signals varies depending on the type of signal receiver. Building on these insights, the goal of this study is to re-examine the previously documented link between public subsidies and follow-on financing in the context of newly founded firms. We analyze the extent to which public support affects the likelihood to attract different sources of venture capital (VC) financing. We differentiate between Government Venture Capital (GVC), Independent Venture Capital (IVC), Corporate Venture Capital (CVC), and Business Angels (BA).

Using detailed data from 9,743 start-ups founded between 2005 and 2018 in knowledge-intensive sectors in Germany that are potentially of interest to venture capital investors, we show that there is indeed a positive correlation between public subsidies and all sources of VC. However, when we apply an econometric matching approach that combines propensity score matching (PSM) with coarsened exact matching (CEM) to achieve comparability between subsidized and non-subsidized ventures based on founder and firm characteristics that likely drive both public funding and VC, the follow-on financing effect can only be linked to GVC and BA financing. This result suggests that public start-up subsidies do not per-se facilitate follow-on financing and that IVC and CVC providers do not appear to rely on the information value carried by public subsidies.

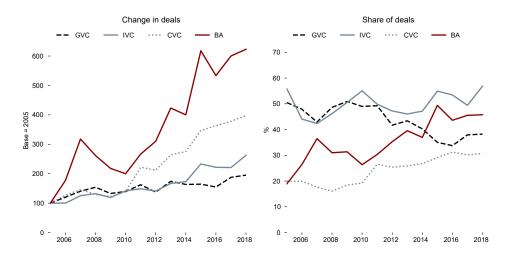
Our results have important implications for both entrepreneurial firms and public policy. By participating in public funding programs, founders may initialize further funding, but not with the same likelihood for all sources. The type of VC, however, may determine the extent to which entrepreneurial firms have access to managerial, financial and social capital in the long-run.

## 2 Public Subsidies and Venture Capital

Venture Capital has become increasingly important in the financing of new firms including in countries that traditionally had comparably low levels of VC (OECD, 2011; Caselli and Negri, 2018). The empirical setting for the following study is Germany for which Figure 1 shows that VC financing increased substantially from 2006 to 2018 (left panel). It also illustrates that there is a mix of VC providers and that the difference sources of VC became equally important over time (right panel). The importance of BA and CVC increased more than financing provided by GVC and IVC and while IVC remained the most frequent source of VC, BA financing caught up from the least (in 2005) to the second most frequent source of VC in 2018. This development is not specific to Germany, but similar trends have been witnessed in other countries (OECD, 2011; Wilson and Silva, 2013).

Research on the decision making of VC investors shows that they base their funding decisions on objective and verifiable indicators of venture development (Shepherd, 1999; Lerner, 2002; Eckhardt, Shane and Delmar, 2006; Bapna, 2019) and initial resource endowments affect the likelihood that new ventures attract VC financing (Shane and Stuart, 2002). Public start-up subsidies also provide such objective and verifiable information as well as they contribute to a firm's initial endowment.

Figure 1: Sources of VC



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

Indeed previous research documents that new firms that receive subsidies are more likely to also successfully raise VC funding in a wide range of countries and for different policy designs. Lerner (1999), Howell (2017) and Islam et al. (2018) study firms funded by the United States' Small Business Innovation Research (SBIR) program and Feldman and Kelley (2006) focus on firms that received public financial support from the Advanced Technology Program (ATP) at the National Institute of Standards and Technology (NIST). Cumming (2007) shows similar effects for an Australian program and Conti (2018) shows that public start-up support in Israel comes with higher likelihood of VC. Giraudo et al. (2019) confirm this also for Italian start-ups and Söderblom et al. (2015) provide evidence for young firms in Sweden. Zhao and Ziedonis (2020) and Hottenrott and Richstein (2020) show that participating in loan-based programs in the United States and Germany increases the likelihood of VC. While both Howell (2017) for the U.S., and Söderblom et al. (2015) for Sweden state that their measure for VC contains various sources of VC (including BA), the heterogeneity of sources of VC is not part of their analyses.

This line of research suggests publicly financed start-ups appeal to VC investors. There may be at least two reasons for this. First, public subsidies provide quality certification. Second, they finance risky early stage activities. Bianchi et al. (2019) refer to the former as a pointing signal which indicates a quality attribute that distinguishes the recipient firm from its competitors. In addition, the monetary amount raised through a subsidy may serve as an activating signal in the sense that it activates the quality attribute of the recipient. Drawing on the attention-based view, they show that the relative salience of these signals varies depending on the type of signal receiver. Thus, although all 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 little is known about the true selection criteria of funding agencies, most programs claim to support firms with high innovation potential and those whose innovations create knowledge spillovers and social returns. The information value could also be related to aspects of regulatory uncertainty and societal returns to the firms' activities. Public funding agencies that award subsidies base their funding decisions on expert reviews and assessments, which may convey valuable information these firms' technologies, their regulation, as well as their longer-run prospects (Lerner, 1999). Such information should be more valuable to investors who acquire less information about start-ups ex-ante. Maxwell, Jeffrey and Lévesque (2011), for example, show that BA base their investment decisions on heuristic assessments, which is in line with earlier findings that BA are less likely to acquire information through formal due diligence or networks (Fiet, 1995; Van Osnabrugge, 2000). 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, Haynie, Simmons and McKelvie, 2014).<sup>2</sup> Especially GVC and BA may therefore understand the award of a public subsidy as a signal of these prospects.

In line with the second channel in which subsidies affects VC investments through the provision of seed financing, Howell (2017) argues that firms in the energy sector use the awarded money to advance their project thereby reducing technological uncertainty. Thus, they reach a proof-of-concept stage which makes 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 certification alone, but it is also the funding amount that attracts investors. The importance of this channel, however, may depend on the relative size of the subsidy compared to the overall investment amount. Since GVC and BA are known to typically invest smaller amounts (Lerner, 1998; Cumming and Zhang, 2019), the initial endowment may matter more to them.

IVCs spend a great deal of their time screening investment projects (Kaplan and Stromberg, 2001; Kaplan and Strömberg, 2004; Gompers, Gornall, Kaplan and Strebulaev, 2020), not least to fulfill their due diligence obligations to their limited partners. General partners and investment managers typically come from various backgrounds including science, engineering and finance (Bottazzi et al., 2008). From there, IVC should be able to arrive at an informed assessment regarding complex technological and market related questions, and for them the information value of public subsidies should be relatively low. Also societal returns may matter less for IVC investors, as their main goal is to maximize the return on investment (Hsu et al., 2014). The cash inflow from the subsidy may still increase firms' attractiveness as it allows financing of uncertain early stage investments.

The decisions of CVC funds typically rely to a large extent 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 value of uncertainty reducing early stage investments (Bianchi et al., 2019).

Previous analyses, however, do not distinguish between the sources of VC leaving the question

<sup>&</sup>lt;sup>2</sup>BAs prefer investment proposals characterized by the moderate use of positive language, moderate levels of promotion of innovation, supplication and blasting of competition, and high levels of opinion conformity which differs from preferences of other investors (Parhankangas and Ehrlich, 2014).

open whether the observed link between the subsidy and VC is driven by a specific type of investor. We hypothesise that there may be differences depending on the information value that the subsidy provides for the respective investor and the relative importance of the financial resources attached to it. Understanding this phenomenon has implications for assessing the overall impact of start-up subsidies and for funding strategies of entrepreneurial ventures.

#### 3 Data

For the analysis we use detailed firm-level and transaction-level data for start-ups founded in Germany in the years from 2008 to 2018. The information comes from four primary databases. In the following we briefly describe the databases and our data collection.

Data on start-ups. Our primary data source is the IAB/ZEW Startup Panel,<sup>3</sup> which is based on a representative annual survey among start-ups in Germany, administered by the Institute for Employment Research and ZEW - Leibniz Centre for European Economic Research. The sample of start-ups that enter the survey are drawn as a stratified random sample from the Mannheim Enterprise Panel (MEP),<sup>4</sup> a comprehensive database of the universe of German firms. When start-ups enter the survey, they are at least one year and at most three years old, and remain in the sample until a maximum age of seven years. By 2019 the panel contained information on more than 28,000 start-up companies. The IAB/ZEW Startup Panel covers information on both the founders and the activities of the company. Importantly for our analysis, it contains detailed information on public subsidies in start-up companies. Founders are asked to indicate whether they have received public subsidies in the form of grants, subsidized loans, or guarantees. For the purpose of this paper, we consider these three forms of subsidies jointly.

To control for founder and firm characteristics, we use information on founders' gender, educational background, founding experience 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 which have been shown to be a signal to investors (Conti, Thursby and Thursby, 2013; Haeussler, Harhoff and Mueller, 2014), as well as a variable indicating whether founders were opportunity driven, i.e. firms were founded based on a concrete business idea.

Venture capital transactions. To identify start-ups 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, 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

<sup>&</sup>lt;sup>3</sup>See Fryges, Gottschalk and Kohn (2009) for details.

<sup>&</sup>lt;sup>4</sup>The MEP is based on data from credit reform - 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).

identify i.a. German venture capital transactions (Bertoni, Colombo and Quas, 2015). 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.<sup>5</sup> 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 (start-ups) with the MEP based on names and adresses. We identified 99% of firms from the Zephyr database and 98% from Majunke's data applying a fuzzy string matching algorithm on company names and addresses.<sup>6</sup> Once the transaction information is merged to the MEP, we can link the data to the survey information in the IAB/ZEW Startup Panel based on a unique company identifier.

Classification of investors. We classified investors into categories based on the main origin of their funds. Specifically, we differentiate between Business Angels (BA), i.e. individuals, who invest their own money, independent venture capital funds (IVC) whose sources come from a pool of wealthy individuals, institutional investors and other private sector sources, government venture capital (GVC) where funds are provided by the public sector, and corporate venture capital (CVC), where the fund is operated by a corporation. For the classification we used information from the primary data bases when available. If not available, we manually researched this information using investors' websites, crunchbase, Bloomberg as well as ownership information from the MEP.

Figure 2: VC Investments by Founding Cohorts

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

**Sample.** We focus on firms that are potentially relevant for venture capital investors. Research on the venture capital market shows consistently that venture capital investments are concentrated in certain sectors and focus on certain types of start-ups (Lerner and Nanda, 2020). Therefore, we restrict the sample to knowledge-intensive sectors. That is, we discard start-ups that are operating in construction, retail and consumer oriented services industries.

<sup>&</sup>lt;sup>5</sup>The DACH region comprises Germany (D), Austria (A) and Switzerland (CH).

<sup>&</sup>lt;sup>6</sup>For the fuzzy string matching we used Thorsten Doherr's SearchEngine: https://github.com/ThorstenDoherr/searchengine

We also exclude start-ups that are operating as franchise companies or joint-ventures, and keep only start-ups that are either limited liability companies or incorporations. After the elimination of observations with missing values, the final sample covers information from 9,743 firms of which 35% received start-up subsidies and 2.7% some form of VC. Tables 1 provide descriptive statistics and A.1 describes the variables. Table A.2 shows the distribution of subsidies and VC investments over sectors illustrating that both are most common in high-tech manufacturing, but also occur in other industries.

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). At the same time the importance of VC types - in particular Angel financing - that we hypothesized to be more sensitive to start-up subsidies increased as well (Figure 1), suggesting a link between these two trends. Table 2 presents 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 pointing to the importance of accounting for these differences in the following analysis.

## 4 Empirical methodology

**Estimation.** 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 start-ups 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 start-ups receive their first public subsidy,  $X_{it}$  is a set of control variables and  $\tau_t$  and  $\phi_i$  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. Firms that seek subsidies typically have less internal funds and constrained access to external capital, which is arguably the main reason why they apply for subsidies. Firms that are more innovative may select both into subsidy schemes and are at the same time more attractive targets for VCs.

Matching. To address the selection into the group of subsidized firms, we perform matching techniques suited for causal analysis in non-experimental research designs (Rubin, 2005). In particular, we employ a matching procedure that combines propensity score matching (PSM) and coarsened exact matching (CEM) (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 re-weighting observations. The goal is to

quasi-randomize the treatment assignment by ex-post balancing treatment and control group in terms of all relevant characteristics that explain selection into treatment. 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 some down-sides. Most notably exact matching often leads to small estimation samples due to empty cells, as it discards any observation that is not within the set of strata defined by coarsened pretreatment covariates of treated observations. This may lead to inefficient estimations. PSM does not have this constraint, but used alone it is often insufficient to ensure balancing in terms of all covariates between groups.

Our matching algorithm therefore 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 2, 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 exact matching requirements. We want to strictly match observations that are from the same founding cohort, the same industry, and are located in a similar region. For those variables we employ an exact matching algorithm.

The advantage of this empirical approach is that it is applicable to different data structures and has relatively modest data requirements. Furthermore it allows us to make a more general statement about an average treatment effect of start-up subsidies on follow-on financing from different sources of VC, and is not confined to specific program designs, which are typically limited to the estimation of local average treatment effects. The limitation of this approach is that it is based on the selection on observables assumption, which does not rule out the possibility of omitted variable bias. However, if observed variables are highly correlated with our unobserved variables that affect the outcome, the bias arising from omitted variables is reduced (Lechner and Wunsch, 2013). Given VCs place a high weight on founding team characteristics when making their investment decisions (Gompers et al., 2020), and we have plenty of information about founding teams in our data set, we are confident that we can reduce potential bias from omitted variables substantially. In addition, firm fixed-effects (included in estimations based on the matched sample) will account for the remaining time-invariant unobservable characteristics. If the matching procedure reduces the difference of the covariate distribution between treatment and control firms, our results can be interpreted as an average treatment effect. Figure A.1 shows the distributions of propensity scores after matching and Table 2 shows that the differences between treated and control firms in terms of the key characteristics are significantly reduced after matching.

<sup>&</sup>lt;sup>7</sup>This is the case for studies that use instrumental variables, or regression discontinuity designs (RDD). Furthermore RDDs often require detailed information about the evaluation process of the firms that apply for support programs. Such information is often not available or not comparable across schemes. Especially, in the case of public support schemes the names of rejected applicants are often not provided by funding agencies to protect unsuccessful applicants from experiencing negative consequences from their rejected application.

#### 5 Results

Table 3 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 coefficient of the subsidy variable gives the percentage point change in the probability to receive VC. In all three panels, the results confirm the previously reported link between public start-up subsides and VC. The first column in Panel B indicates that this relationship is robust to accounting for the non-randomness of the subsidy receipt as it persists also in the matched sample. In particular, receiving a public subsidy more than doubles the probability to receive VC to 0.0050 relative to the baseline probability of receiving VC for non-recipients which is 0.0024 in any given period.<sup>8</sup>

Looking at the different sources of VC in Panel B, 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 (Panel A) in which we observe positive correlations with all four different sources of VC. This result is also robust to the within estimation (Panel C) which additionally accounts for unobserved heterogeneity among firms (Tables A.5-A.3 shows the full estimation results with and without matching). Since the four VC-types may co-occur, we also estimate the four equations jointly in seemingly unrelated regression (SUR) models and find that the previous results are robust to this alternative specification (see Tables A.8 and A.9 for regression results and Table A.10 for error correlation across equations). In this specification, we test whether the coefficients for subsidy receipt are significantly different in the GVC versus the BA equation and find that the coefficients are not statistically different ( $\chi^2(1) = 1.21$ , p-value = 0.27). See Table A.11 for all pair-wise comparisons.

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 start-ups that receive a subsidy, receive it in their year of business activity. For the group of firms 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 therefore conduct robustness tests 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. The results from these models confirm the initial results (see Table A.7).

<sup>&</sup>lt;sup>8</sup>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 1: Summary Statistics 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					
High-tech manufacturing	9743	0.201	0.401	0	1
High-tech services & Software	9743	0.455	0.498	0	1
Low-tech 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 2: Difference in Means of Control Variables (before and after matching)

February 1.5 matched $10^{-1}$ and		Devel A						
No			Pa	anel A: u	ınmatched			
Controls         Std. Err.         Mean         Std. Err.         Δ         t           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         -0.04         -0.52           Industry experience         0.498         0.500         0.666         0.349         0.107         10.20           Failure experience         0.175         0.380         0.211         0.408         0.03         4.35           Opportunity driven         0.493         0.500         0.403         0.500         0.403         0.500         -0.010         -0.117         -11.11           Patent         0.520         0.500         0.403         0.491         -0.117         -11.11           Patent         0.522         0.500         0.403         0.491         -0.117         -11.11           Patent         0.522         0.500         0.403         0.491								
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         0.498         0.500         0.606         0.489         0.107         10.20           Failure experience         0.498         0.500         0.606         0.489         0.107         10.20           Failure experience         0.175         0.380         0.211         0.049         0.30         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         0.512         0.520         0.500         0.403         0.491         -0.117         -11.11           Patent         0.520         0.500 <t< th=""><th></th><th>N=</th><th>=3422</th><th>N=</th><th>=6321</th><th></th><th></th></t<>		N=	=3422	N=	=6321			
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         -0.010         -0.99           &&D         1.520         0.520         0.500         0.403         0.491         -0.117         -11.11           Patent         1.522         8         N=1756         Mean         Std. Err.         Δ         t           Controls         1.528         1.522         0.051		Mean	Std. Err.	Mean	Std. Err.	Δ	t	
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         0.520         0.500         0.403         0.491         -0.117         -11.11           Patent         0.520         0.500         0.501         0.522         -0.020         -3.87           Controls         S         S         S         S         S         L         E	Controls							
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         0.403         0.491         -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           Controls         Industry experience         New Propertion of Std. Err.         Mean         Std. Err.         \(Delta \)         \(Delta \)         -0.001         -0.075           Team         0.518         0.500         0.506         0.500         0.012         0.619           Academic <td>Founder age (log)</td> <td>3.680</td> <td>0.216</td> <td>3.710</td> <td>0.252</td> <td>0.029</td> <td>6.05</td>	Founder age (log)	3.680	0.216	3.710	0.252	0.029	6.05	
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           Controls         Founder age (log)         3.691         0.214         3.691         5td. Err.         Δ         t           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<	Team	0.537	0.499	0.440	0.496	-0.097	-9.19	
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           Mean         Std. Err.         Mean         Std. Err. $\Delta$ t         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	Academic	0.716	0.451	0.682	0.466	-0.034	-3.49	
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           N=Experience           N=208         N=1756	Female	0.170	0.375	0.166	0.372	-0.004	-0.52	
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         Patent         Expent B: matched           Controls         N=2208         N=1756         Mean         Std. Err.         Mean <td rowspa<="" td=""><td>Industry experience</td><td>12.950</td><td>9.290</td><td>13.739</td><td>10.309</td><td>0.789</td><td>3.85</td></td>	<td>Industry experience</td> <td>12.950</td> <td>9.290</td> <td>13.739</td> <td>10.309</td> <td>0.789</td> <td>3.85</td>	Industry experience	12.950	9.290	13.739	10.309	0.789	3.85
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           Paret B: matched           N=2208         N=1756         N=1756         Δ         t           Mean         Std. Err.         Mean         Std. Err.         Δ         t           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 <th< td=""><td>Founding experience</td><td>0.498</td><td>0.500</td><td>0.606</td><td>0.489</td><td>0.107</td><td>10.20</td></th<>	Founding experience	0.498	0.500	0.606	0.489	0.107	10.20	
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           Parel B: matched           N=208         N=1756         N=1756         Mean Std. Err.         Mean Std. Err. $\Delta$ 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 <td>Failure experience</td> <td>0.175</td> <td>0.380</td> <td>0.211</td> <td>0.408</td> <td>0.036</td> <td>4.35</td>	Failure experience	0.175	0.380	0.211	0.408	0.036	4.35	
Patent         0.071         0.257         0.051         0.220         -0.020         -3.87           Parel B: matched           N=208         N=1756         N=1756         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	Opportunity driven	0.493	0.500	0.483	0.500	-0.010	-0.99	
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$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Patent	0.071	0.257	0.051	0.220	-0.020	-3.87	
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$			F	Panel B:	matched			
Controls         Section 1         Control 2         Control 3         Control 3 <th< td=""><td></td><td>N=</td><td>=2208</td><td>N=</td><td>=1756</td><td></td><td></td></th<>		N=	=2208	N=	=1756			
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		Mean	Std. Err.	Mean	Std. Err.	Δ	t	
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Controls							
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Founder age (log)	3.691	0.214	3.691	0.242	-0.001	-0.075	
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 $0.066$ $0.248$ $0.063$ $0.243$ $0.003$ $0.290$		0.518	0.500	0.506	0.500	0.012	0.619	
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 $0.066$ $0.248$ $0.063$ $0.243$ $0.003$ $0.290$	Academic	0.711	0.454	0.711	0.453	-0.000	-0.027	
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	Female	0.162	0.369	0.173	0.378	-0.010	-0.698	
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	Industry experience	13.591	9.304	13.675	10.233	-0.084	-0.220	
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	Founding experience	0.521	0.500	0.529	0.499	-0.009	-0.451	
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	Failure experience	0.183	0.386	0.170	0.376	0.012	0.884	
Patent 0.066 0.248 0.063 0.243 0.003 0.290	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	
Propensity score         0.255         0.151         0.254         0.149         0.001         0.215	Patent	0.066	0.248	0.063	0.243	0.003	0.290	
	1 atent							

Notes: Panel B shows the means, and differences in means ( $\Delta$ ) 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. The standard errors and t-values are calculated under the assumption of heteroskedasticity.

Table 3: Estimation Results

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

Notes: 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. Panel C includes year and firm fixed effects.

#### 6 Conclusion

Understanding how venture capitalists make decisions is an important topic in entrepreneurship and management research (Gompers et al., 2020). Recent research suggests that start-up subsidies play an important role in their decision making. A number of studies show that firms that receive public seed funding are more likely to raise VC. This holds for different policy programs, countries and industries. So far, however, studies have not taken into account the heterogeneity of investor types in the subsidy-VC link, although their objectives, screening processes, and investment strategies differ substantially (Brander et al., 2014; Bertoni et al., 2015).

Using detailed transaction-level data, we classify investors by the source of their funds into government VC (GVC), independent VC (IVC), corporate VC (CVC), and business angels (BA), and re-examine the subsidy-VC link, explicitly distinguishing between these investor types. Our results confirm the positive relationship between public start-up subsidies and subsequent VC financing documented in earlier studies. This relationship also holds when accounting for selection effects and common drivers of both subsidies and VC financing. Yet, the results show that the notion that subsidies facilitate follow-on financing by VC investors does not hold for all investor types. We show that the positive relationship is driven by GVC and BA financing and not by CVC or IVC.

We propose several explanations for this finding. In line with the attention-based view, the information value attached to the subsidy may depend on the degree of ex-ante information acquisition of the signal receiver. Higher engagement in ex-ante information acquisition should

reduce subsidies' information value. Information attached to the subsidy pertains to both start-ups' technological aspects as well as to their initial endowment. As an alternative explanation for the case of GVC, there could be an inherent link between a subsidy and GVC investment. Subsidies could be provided with the explicit invitation of the funder to seek GVC. In addition, when pitching for GVC, firms that have previously dealt with public agencies may have an advantage either through learning about their expectations or simply through (personal) connections.

These results have implications for both entrepreneurs and policy makers as the investor type affects longer-run firm performance. Relative to IVC, both GVC and BA (but not CVC) show smaller performance effects in terms of innovation (Chemmanur et al., 2014; Bertoni and Tykvová, 2015; Dutta and Folta, 2016) and exits (Brander et al., 2014; Cumming et al., 2017; Colombo and Murtinu, 2017; Cumming and Zhang, 2019). However, there is some evidence that initial financing from GVC increases the likelihood of receiving IVC (Guerini and Quas, 2016), but for initial BA financing the evidence is mixed. There may be substitution effects resulting in less IVC (or other VC) financing raised later on (Hellmann, Schure and Vo, 2013; Kerr, Lerner and Schoar, 2014) or a crowding-in of further VC (Lerner, Schoar, Sokolinski and Wilson, 2018).

Thus, public start-up subsidies may or may not initiate a funding cascade. We strongly encourage further research on the interplay between private and public sources of start-up financing and in particular the role of public subsidies as triggers for financing cascades.

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## Appendices

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

## A Additional Tables

Table A.1: Description of Variables

Variable Name	Variable Description
Subsidy(T)	The start-up has received a subsidy as a grant or loan in any year.
VC(T)	The start-up received at least one investment by any venture capital investor in any year.
GVC(T)	The start-up received at least one investment by an governmental venture capital investor
	in any year.
IVC(T)	The start-up received at least one investment by an independent venture capital investor in any year.
CVC(T)	The start-up received at least one investment by an corporate venture capital investor in any year.
BA(T)	The start-up received at least one investment by an angel investor in any year.
Start-up age at VC (1)	Age of the start-up at first VC financing round.
Start-up age	Age of the start-up in years.
Founder age	Age of the founders at foundation, for teams it is the average founder age.
Team	The star-tup was founded by more than one person.
A cademic	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 start-up was founded to realize a business idea.
$R \mathcal{C}D(T)$	The start-up has conducted research and/or development activity in any year.
Patent	The start-up held a patent at foundation.
Founding year	The start-up's year of foundation.
Industry	The main industry the start-up operates in.
Region	The start-ups business location (West Germany, East Germany, Berlin).

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.

Table A.2: Distribution of Subsidies and VC by Industry

	Subsidized	VC
High-tech manufacturing	45.8	3.8
High-tech services & Software	32.7	3.7
Low-tech manufacturing	45.7	0.7
B2B & Knowledge-int. services	23.8	0.6
N	9743	

Notes: The table shows the shares in the total number of firms receiving a subsidy and some type of VC.

Table A.3: 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

<sup>\*</sup> p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

Table A.4: 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

<sup>\*</sup> p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

Table A.5: 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	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.  $\,$ 

Table A.6: 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

<sup>\*</sup> p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

<sup>\*</sup> p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

Table A.7: Robustness Test: Timing assumption

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

Standard errors in parentheses, clustered at the firm level.

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

The sample includes only start-ups that enter the sample in their first year of operation.

Table A.8: 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.

<sup>\*</sup> p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

<sup>\*</sup> p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

Table A.9: 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.

Table A.10: Correlations of Seemingly Unrelated Regression Results (After Matching)

$GVC \times CVC$	$(0.0733)$ $0.2283^{***}$
$\mathrm{BA}  imes IVC$	$(0.0694)$ $0.2739^{***}$
$BA \times CVC$	$(0.0753)$ $0.4054^{***}$
	(0.0999)
$IVC \times CVC$	$0.2490^{**}$ $(0.1117)$
Obs.	25410

<sup>\*</sup> p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

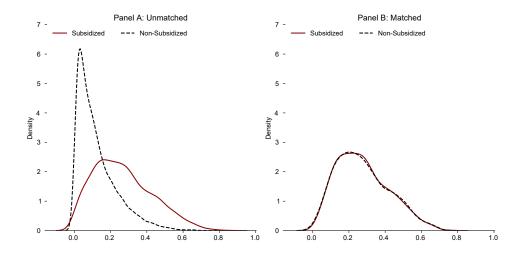
<sup>\*</sup> p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

Table A.11: Chi<sup>2</sup>-tests for Equality of Subsidy Coefficients

	$\mathrm{Chi}^2$	df	p-value
GVC:Subsidy(t) vs. BA:Subsidy(t) GVC:Subsidy(t) vs. IVC:Subsidy(t)	1.21 7.43	1 1	0.27 0.01
GVC:Subsidy(t) vs. CVC:Subsidy(t)	5.09	1	0.02
	Chi <sup>2</sup>	df	p-value
BA:Subsidy(t) vs. IVC:Subsidy(t) BA:Subsidy(t) vs. CVC:Subsidy(t)	$3.80 \\ 3.71$	1 1	$0.05 \\ 0.05$

## **B** 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 start-ups 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. 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.