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Start-up Subsidies: Does the Policy Instrument Matter?

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Abstract

New knowledge-intensive firms contribute to innovation, competition, and employment growth, but externalities like knowledge spillovers can prevent entrepreneurs from appropriating the full returns from their investments. In addition, uncertainty and information asymmetry pose challenges for financing. Public policy programs therefore aim to support start-ups. This study evaluates the effects of participation in such programs on the performance of start-ups in high-tech and knowledge-intensive sectors that were founded in Germany between 2005 and 2012. Distinguishing between grants and subsidized loans and after matching recipients and non-recipients based on a broad set of founder and company characteristics, we find that both grants and subsidized loans facilitate tangible investment, employment and revenue growth. Grants are, however, better suited to increasing R&D investments than loans are. Combined with grants, subsidized loans facilitate turning research results into marketable products by means of investments in tangible assets. Start-ups that participate in both types of programs outperform grant-only recipients in terms of innovation performance, employment and future revenues. Finally, program participation does not crowd out private venture capital.

Keywords: *financing constraints, subsidies, R&D, high-tech start-ups, innovation policy*

JEL Classifications: *G32 • H25 • O38*

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1. Introduction

The impact of newly established firms on economic development has interested scholars and policymakers for years (Acs and Audretsch, 1988; Haltiwanger et al., 2013; Audretsch et al., 2016). Particularly, young innovative companies produce positive externalities that create social returns, and knowledge spillovers facilitate follow-on innovations and their diffusion (Acs et al., 2009). Previous research therefore stresses the important role played by new technology-based firms in generating radical innovations and in exerting pressure on incumbents to innovate (Henderson, 1993; Schneider and Veugelers, 2010). However, research also points out the challenges that entrepreneurs face with regard to the financing they need to sustain and grow their businesses (Cassar, 2004). These challenges arise from start-ups' initially high investment requirements combined with the incomplete appropriability of the returns due to intangible outcomes from early-stage research and development (R&D) efforts as well as from overall technological and market uncertainty. Limited availability of financing may result in unpursued innovation opportunities, lower start-up performance and slower growth.

Consequently, public funding programs for new, potentially innovative start-ups have emerged in many countries (Storey and Tether, 1998), among which the Small Business Innovation Research (SBIR) program in the US is the most prominent example (Lerner, 1999; Howell, 2017). The rationale behind such funding programs is that providing seed funding to new companies reduces the consequences of financial market frictions and compensates the entrepreneur for the social benefits his or her activities create. Typically, such programs target start-ups with a high potential for innovation. By focusing on certain technology areas, these programs' support can also be directed at technological fields that promise societal returns (Mazzucato, 2018).

Despite the support programs that have been put in place, Decker et al. (2016) report a decline in young, high-growth firms for the US in the post-2000 period, a development that can also be observed in continental Europe during the 2008–2014 period (EFI - Commission of Experts for Research and Innovation, 2017). In addition, sceptics of subsidies for start-ups argue that public funding may crowd out financing from private investors[1]. For the case of public venture capital there is indeed some evidence that it might replace private venture capital (Leleux and Surlemont, 2003; Cumming and MacIntosh, 2006) and that it is minimally effective in supporting high-tech start-ups' growth (Grilli and Murtinu, 2014).

[1] See Dimos and Pugh's (2016) Figure 2 for an illustration of crowding in versus crowding out in the context of R&D subsidies.

Whereas the literature that evaluates innovation-support policies for established companies concludes that treatment effects are heterogeneous with regard to the size of the recipient firms and that a program's effectiveness depends on the nature of the projects it sponsors (e.g., Hottenrott and Lopes-Bento, 2014; Hottenrott et al., 2017; Nilsen et al., 2018)[2], fewer studies investigate support that is targeted at start-ups. The few existing studies generally conclude that these programs foster performance (Lerner, 1999; Grilli and Murtinu, 2012; Colombo et al., 2013; Cantner and Kösters, 2015; Söderblom et al., 2015; Howell, 2017; Conti, 2018). Their results suggest that support programs indeed reach firms that are constrained below their optimal investment level and that access to financing reduces these constraints. Despite these insights, what we know about the role of the support instrument's design in program effectiveness is limited. The programs that have been studied are typically grant-based, so insights from these studies may be specific to this type of policy tool.

In addition to grants, however, subsidized loans are a popular policy tool. For instance, in the US the Department of Energy provides subsidized loans for clean energy projects and Advanced Technology Vehicles Manufacturing (ATVM) through its Loans Program Office (LPO). Similarly, Germany and the UK offer start-up loans with conditions in terms of fees, interest payments, and required securities that are more favorable than those of standard loans (e.g., the KfW-ERP Start-up Loan or the British Business Bank's Start-up Loans). Several other countries, such as Canada, France, Finland, and Israel, offer support for start-ups that has a grant-based design but that must be paid back if the start-up sees commercial success. This makes these grants comparable to low-interest loans for which the failure risk is borne by the public funding agency. Although debt-based support instruments play an important role in practice, we still know little about their effectiveness in facilitating innovation efforts and improving start-up performance. Bertoni et al. (2019), the first to study participation in a government-sponsored participative loan (PL) program in Spain, find substantial growth effects but no effects on the probability of survival.

This study contributes to research on the effectiveness of public start-up support by addressing start-ups in knowledge-intensive industries on which policy makers focus because of their innovation and growth potential (Shane, 2009)[3]. Moreover, we explicitly differentiate

[2] While meta studies on programs particularly designed for start-ups are lacking, Dimos and Pugh's (2016) meta regression analysis of studies on the effectiveness of R&D subsidies in mainly established firms finds that crowding out—that is, displacement of privately financed R&D by subsidies—can be ruled out. However, they also conclude that the magnitude of overall crowding in—that is, additional R&D investments induced by the subsidy—is relatively small.

[3] Hurst and Pugsley (2011) discuss how the vast majority of new businesses do not intend to bring a new idea to the market or to create new markets so much as to serve existing markets with existing product and services. By

between grants and subsidized loans and investigate their impact on a broad range of outcomes, such as R&D investment, investment in tangible assets, innovation success, employment and revenues. Furthermore, we test the crowding-out hypothesis with regard to venture capital funding and investigate the effect of subsidies on outcomes that are highly relevant to the context of start-ups: the probability of merging with another firm, acquisition by another company, and business failure.

We derive expectations regarding the effects of public support from grants and loans based on a simple model of financing constraints that goes back to Howe and McFetridge (1976) and Hall (2002). The model's predictions are that through the liquidity channel both grants and loans facilitate start-up growth by providing funding that would not be available otherwise. In addition, the type of policy tool matters for the type of investment it triggers, i.e. there is a policy instrument channel through which program participation affects investment incentives. In the case of grants, risky R&D becomes attractive because the loss in the event of project failure is limited to the lost opportunity costs of having used the grant for a failed idea. However, loans rather increase investments in tangible assets that are necessary to bring new products to the market and to implement process innovations.

To test these predictions, we estimate treatment effects models that account for the selectivity of these support instruments for a large sample of start-ups in high-tech manufacturing sectors and knowledge-intensive services founded between 2005 and 2012 in Germany. The results suggest that both types of support increase tangible investment, employment and revenues while grants – and not subsidized loans – also lead to additional R&D spending and R&D employment. Moreover, when a start-up receives a subsidized loan along with a grant, the start-up is more likely to introduce a new product or service to the market than if it receives only a grant because of higher investments in complementary tangible assets. The finding that loans complement grants extends the findings of Huergo and Moreno (2017), who study the effects of R&D subsidies in a sample of established Spanish companies, to the context of newly founded firms. Finally, our results suggest a crowding-in of venture capital for recipients of loans and loans combined with grants.

These results have important implications for innovation policy, as they confirm the concern that innovation efforts in new technology-based firms are below their potential optimum and that, by carrying part of the risk, public funding institutions may encourage

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studying high-tech manufacturing and knowledge-intensive service sectors, we focus on these minority types of entrepreneurs rather than on new businesses in general.

innovations that would not be pursued otherwise. However, the results also suggest that a policy mix that combines grants with loans might be more effective in turning research outcomes into marketable innovations than loans or grants alone. Therefore, funding agencies may view both policy tools as essential parts of public business support rather than considering the two instruments as substitutes. The result that public subsidies increase the likelihood that a start-up will raise venture capital later in its life cycle suggests that public subsidies support potentially valuable start-ups at stages when they are not yet attractive to external investors, thus facilitating venture capital investments rather than substituting for them.

The remainder of the article proceeds as follows. Section 2 reviews the research on high-tech start-up financing and the role of subsidies, while Section 3 presents the theoretical framework that underlies our empirical study. Section 4 introduces the econometric identification strategy, Section 5 presents the data, Section 6 discusses the results, and Section 7 concludes.

2. High-tech start-up financing and the role of subsidies

In technology-driven industries, start-ups' business models typically build on scientists' and engineers' specific knowledge (Braguinsky et al., 2012), and the start-ups' success depends on their ability to finance cutting-edge research that allows them to stay at the knowledge frontier. They must also finance the development of products and processes to turn their research into new products and services. Unlike established companies with cash inflows, the extent to which start-ups can finance such R&D internally is limited, and the indivisibility of investments results in a large ratio between investment requirements and equity. Thus, if the entrepreneur cannot provide all necessary funds from private assets, external financing is required (Evans and Jovanovic, 1989).

The entrepreneurial finance literature has long stressed the challenges that are associated with external fundraising because of the uncertainty that R&D projects will yield usable results or eventual financial success. In addition, information asymmetries between entrepreneurs and capital providers are especially high in knowledge-intensive sectors (e.g., Carpenter and Petersen, 2002), where the complexity and novelty of products and services often means that founders have far greater insight into the technology than the potential financier does. Moreover, founders are typically reluctant to share their proprietary information for fear of it finding its way to imitators and larger competitors (Anton and Yao, 2002; Hellmann and Perotti, 2011). The unequally distributed information leaves external capital providers with two problems: a hidden-information problem because they cannot fully assess the quality of the potential investment ex-ante, and a hidden-action problem after the founder receives the capital.

To counteract these problems and attract capital, founders can pledge collateral to signal their quality (Bester, 1985; Berger and Udell, 1990; Boot et al., 1991) and ensure that they do not engage in opportunistic behavior after receiving funding (Stiglitz and Weiss, 1981; Elitzur and Gavious, 2003). However, technology start-ups' ability to provide collateral is typically limited, as much of their assets are intangible and company-specific. Therefore, asset specificity—that is, "the degree to which an asset can be redeployed by alternative uses or alternative users without sacrificing productive value" (Williamson, 1991, p. 281), poses particular constraints on high-tech start-ups that conduct R&D. Since highly specific assets lose value rapidly if the business fails, they are seldom considered suitable collateral (Berger and Udell, 2006).

Capital providers in the debt and equity markets face similar uncertainties, so start-ups may suffer from financial constraints that negatively influence their investment decisions and hinder their ability to pursue risky R&D (Hubbard, 1998; Colombo et al., 2013). Debt providers are especially disadvantaged in coping with the uncertainties that come with high-tech venture financing because of the structure of debt contracts. Since creditors do not participate in the returns, interest payments are unlikely to compensate for the unbalanced risk-return profile (Carpenter and Petersen, 2002; Denis, 2004; Brown et al., 2012). In addition, banks, which are by far the most frequent providers of debt, may lack the monitoring processes that could equalize the information asymmetries. While investors in the equity capital market gain specific experience and monitoring skills when they specialize in certain industries (Norton and Tenenbaum, 1993), banks typically specialize less, have little say regarding the company's strategic decisions, and have no upside potential in terms of returns. Banks may therefore rely on quality signals for lending decision to new firms in complex industries (Hottenrott et al. 2018).

Supporting these considerations, Carpenter and Petersen (2002) show that none in their sample of 2,400 US high-tech firms received any (or negligible) debt financing prior to their initial public offering. Colombo and Grilli (2007) find that only a minority of the Italian high-tech start-ups in their sample used outside financing, especially bank debt. Brown et al. (2012) find for start-ups in Germany that those that were active in high-tech sectors were less likely than low-tech start-ups to use bank loans and that they faced more difficulties in raising bank financing. Although equity providers' business models do not tend to be as risk-averse as those of banks, they still appear to avoid investments in R&D projects whose outcomes and commercial benefits are uncertain (Gompers, 1995). Howell (2017) shows that new firms that obtained public funding in the form of SBIR grants attracted venture-capital funding after they went beyond the failure-prone prototyping stage. Howell's result stresses the importance of public start-up support, particularly early in a start-up's life cycle.

To reduce financial constraints as a hindrance to the creation of radical innovation, employment, and economic growth, direct, grant-based financial support for technology start-ups have become a popular policy instrument. While there are several comprehensive reviews of the literature on the impact of subsidies on R&D activities in established firms (e.g., David et al., 2000; Cerulli, 2010; Zúñiga-Vicente et al., 2014; Becker, 2015), insights on public support for young, high-tech companies are scarcer. Lerner (1999) and Howell (2017) find that recipients of SBIR grants perform better than others in attracting follow-on financing and outperform others in terms of innovation success. Söderblom et al. (2015) find that a Swedish government program helps to attract human capital. They also find that grants facilitate access to follow-on equity investments mainly through business angels and that grants affect employment and sales growth. Colombo et al. (2012), Grilli and Murtinu (2012) and Colombo et al. (2013) show for Italian new-technology firms that subsidies have a positive impact on R&D spending and employment. Adding to these insights by looking at outcomes rather than inputs, Cantner and Kösters (2015) find that subsidized nascent firms have 2.8 times as many patents as unsubsidized firms and 66 percent higher growth in employment. Conti (2018) finds that the design of an Israeli support program affected its efficacy: As restrictions on transferring know-how away from a given geographic region undermined the value of program participation, abolishing these restrictions increased the program's benefits in terms of start-up survival, the ability to attract external investment, and innovation performance.

With regard to the policy instrument itself, studies either consider only grants or loan-like grants or do not differentiate among the types of policy tools. Bertoni et al. (2019) are the first to investigate performance effects of a government-sponsored participative loan program explicitly. Their results suggest that these loans are indeed beneficial for start-up growth but do not increase the probability of survival.

Both grants and subsidized loans provide funding to overcome financial market frictions, but their designs differ which may have implications for their effectiveness. Huergo and Moreno (2017) are the first to consider grants and loans in a unified framework and to test for possible complementarities between them. In a sample of companies in Spain they find that both types of policy tools are effective and that, for smaller firms, receiving both grants and loans comes with higher participation effects. However, their analysis is based on a sample of enterprises among which only about 3 percent of the firms can be classified as start-ups.

As we discuss in the next section, grants and subsidized loans may support start-up activities by giving them access to financing allowing investments in R&D or in production facilities (liquidity channel). In the case of subsidized loans, government institutions take on part of private lenders' credit default risk, thus improving the risk-return profile for lenders. Still, the two types of policy instruments may not be equally effective in triggering start-ups' R&D investments, which are an important determinant of innovation success, because of differences in the underlying incentive structures (policy instrument channel). Therefore, the choice of a policy instrument can affect the programs' effects on specific outcomes.

Moreover, it is of central interest to understand whether subsidies for start-ups affect only inputs by making them more affordable or whether there are follow-on effects on outcomes that have particular relevance for start-ups such as gaining initial market success with innovations, changes in ownership through equity investments, mergers and acquisitions, or bankruptcy.

3. Theoretical Framework

We build on the simple investment model initially presented by Howe and McFetridge (1976) and later developed further by Hall (2002) and Hottenrott and Peters (2012) to examine the effect of grants and subsidized loans on high-tech start-ups' investments and outcomes. We transfer the model to the context of start-up financing and extend it to the analysis of the differential impact of grants versus loans. We assume that a high-tech start-up *i* has several innovative project ideas but lacks the internal financial resources to fund them all. Aware of this financial constraint, the founder ranks the ideas *k* according to their expected rate of return (ROR_k), deriving the ROR_k for each idea from the expected benefits (B_k) minus implementation costs (C_k). A start-up's ROR_k profile is determined by the quality of its ideas and its innovative capability such that, the greater the innovative capability, the greater the individual project's value and the total value of all project ideas.

The descending order of ideas results in a downward-sloping demand function for financing of start-up *i* (D_i) that reflects *i*'s marginal rate of return (MRR_i). The MRR_i depends on the total level of investment (I_i) and on founder, firm, and industry characteristics (X_i), such as the technological opportunities in a sector:

$$MRR_i = f(I_i, X_i). \tag{1}$$

Assuming that the start-up follows a profit-maximizing strategy, it invests until the MRR_i equals the marginal cost of capital (MCC_i) needed to finance the investment. The MCC_i depends on I_i, the amount of internal funds (IF_i) available, creditworthiness (W_i), and the opportunity costs of the invested capital (R_i):

$$MCC_i = f(I_i, IF_i, W_i, R_i). \tag{2}$$

Pecking order theory suggests that the start-up exhausts internal sources of funds (e.g., the founders' own savings) before it attempts to finance investments externally (Myers and Majluf, 1984). The marginal opportunity costs of internal funds (c_{int}) are constant[4] (Fazzari et al., 1988), and the external capital supply curve is upward-sloping because of capital market imperfections. The slope of the capital supply curve that represents external funds increases with the gap between internal and external sources of financing. In the setting of high-tech start-ups, information asymmetries are likely to be high because of the complexity of the business activity, the risk associated with new technologies, and the comparatively high probability of default. Creditworthiness is often low because of the start-ups' limited internal funds and lack of re-deployable tangible assets with which to secure loans. Therefore, we expect the slope to be steep or even vertical.

Figure 1 shows both the MRR_i and the MCC_i. Equating MRR_i and MCC_i yields the optimal investments (I_i^*):

$$I_i^* = f(X_i, IF_i, W_i, R_i). \tag{3}$$

– Figure 1 about here –

3.1 The effects of grants versus subsidized loans

We use this simple model to derive expectations regarding the effects of grants and subsidized loans on a start-up's investments. These investments are expected to affect start-up performance through their impact on innovativeness and, hence, on revenues and employment growth. Therefore, a start-up's value function can be described as:

$$V_{i,t} = f\left(\sum_{k=1}^{n} \text{Investment}_{i,k}, \text{founder characteristics}, \text{startup charactistics}\right) \tag{4}$$

[4] Assuming increasing or decreasing internal costs of capital does not fundamentally affect how the model functions. For instance, increasing internal costs of capital suggest that a given project's expected return should be higher if it is to be profitable, whereas decreasing returns suggest a lower profitability threshold. Thus, this assumption affects the likelihood that additional funding will result in additional investments for different ROR_k profiles.

with $\frac{\partial V_t}{\partial Investment} > 0$. However, there is uncertainty about the success of the start-up, as we outline in more detail below. In the longer term, the performance $V_{i,t}$ determines outcomes like receipt of venture capital, merger with another company, acquisition by another company or bankruptcy.

A grant's impact via the liquidity channel on investments can be interpreted as an extension of internal funds as the grant is considered a 100 percent subsidy without repayment obligation (Figure 2). $I_i^{*\prime}$ represents the optimal investment after receipt of a grant. The extent to which additional financial resources affect investment – that is, whether there is a crowding-in-effect – depends on the amount of the grant and whether the start-up was financially constrained in the first place. In outlining the model, as depicted in Figure 1, we assume the presence of financial constraints and that the start-up has investment options on the shelf. In the absence of constraints, that is, if the start-up can finance all projects internally because, for example, there are no good project ideas or it has a low *ROR* profile, an influx of money leads to partial or full crowding out in the sense that the subsidy amount is partially or fully consumed in other activities and not invested. See Figure A.1 for an illustration. In such cases, we expect that the receipt of a subsidy has no effect on investment and, hence, no effect on firm value.

The fundamental difference between grants and subsidized loans is that grants do not come with repayment obligations whereas subsidized loans do. Moreover, in contrast to grants, subsidized loans affect the slope of the external capital supply curve rather than representing an extension of internal financing. A public institution taking over the risk that is inherent in every loan increases the start-up's W_i and so reduces its external cost of capital. Increased W'_i flattens the slope of the capital supply curve (Figure 3). In all financially constrained start-ups, a shift in the capital supply curve determines a new optimal investment $I_i^{*\prime}$. If the shift is large enough, subsidized loans, like grants, increase investments through the additionally available funds. Note that the amounts may differ between grants and loans resulting in different liquidity shocks. While loans may initially come with a larger cash inflow than grants, the actual subsidy amount is more complex to calculate in the case of loans compared to grants because of the repayment obligation. It consists of the interest rate difference between a standard loan and the subsidized loan as well as some value that stems from a potentially delayed repayment period and the availability of the loan in the first place.

However, these considerations are still incomplete, as projects may fail, in which case their benefits (B_k^f) approach zero. Therefore, an entrepreneur will assess a project's ROR_k by taking into account the possibility of failure as probability *1-p*, with *p* the probability of success.

If an internally funded or grant-funded project fails, the maximum loss equals the project's C_k, but if it is financed by debt, the entrepreneur has more "skin in the game" since he or she must repay the loan or lose the associated collateral. This repayment obligation (*RPO*) is assumed to prevail at least in part even if the loan is backed by a government institution (Huergo and Moreno, 2017); the *RPO* would reduce to zero only if the start-up files for bankruptcy as a result of the project's failure. Therefore, the entrepreneur will incorporate this additional risk component ex-ante and adjust the project's ROR_k:

$$ROR_k^{grant} = p(B_k - C_k) + (1-p)(B_k^f - C_k) \tag{5}$$

$$ROR_k^{loan} = p(B_k - C_k - RPO_k) + (1-p)(B_k^f - C_k - RPO_k). \tag{6}$$

Based on equations (5) and (6), we can show that, for any $p < 1$ and any $RPO > 0$ for a given project idea with characteristics $B_k > B_k^f$ and C_k, the start-up will find $ROR_k^{grant} > ROR_k^{loan}$. The greater the difference in the *ROR* – that is, if the project is high-risk – the larger we expect the stimulating effect to be so that optimal investment levels will be higher for grants than for loans through the policy instrument channel (Figure 4).

– Figures 2, 3, and 4 about here –

3.2 The nature of investment

So far, we did not distinguish the type of investment required to pursue the project idea. In the following, we differentiate between investments in R&D and investments in tangible assets, as the nature of the investment has implications for our previous considerations. For investments in tangible assets like production facilities, the default probability matters less because some of these assets may be sold, taken over by the debtor or can be redeployed. Unlike R&D investments, which are usually entirely sunk[5], investments in tangible assets have at least some value that can be used to reduce the *RPO*. Therefore, the higher initial cash inflow combined with the lower risk of tangible investment may result in subsidized loans being used for investments in fixed assets rather than for R&D.

These considerations lead to the hypothesis that grants are more likely to trigger additional R&D than subsidized loans are and that loans are used to finance early-stage tangible investments.

3.3 The joint receipt of grants and subsidized loans

[5] A large share of R&D expenditures are typically wages for R&D employees.

A start-up may apply for more than one type of support, as founders can receive both types of subsidy simultaneously thereby increasing the overall subsidy amount. Grants may be used to cover costs like wages for an R&D employee, while loans are used to acquire equipment. Thus, the receipt of both grants and loans may result in additional R&D spending initiated through a grant, as well as investment in tangible assets financed through a loan (liquidity channel). Moreover, it seems plausible to assume that R&D and tangible investments are complements in generating value for a start-up. Holding founders' and start-up characteristics constant, that is:

$$\mathrm{V}_{\mathrm{i,t}} = \sum_{k=1}^{n} \mathrm{R\&D}_{i,k} \times \sum_{k=1}^{n} \text{Tangible Investment}_{i,k}. \tag{7}$$

We can therefore expect that the combination of grants and subsidized loans is more likely to facilitate the successful market introduction of an innovation than are grants alone. If such is the case, a combination of grants and subsidized loans may be more effective in generating sales and employment growth than either one alone.

Besides the increased employment and sales growth that come with successful innovation, we may expect effects on follow-on venture capital financing. If there were a crowding in of investments, public support would increase $\mathrm{V}_{\mathrm{i,t}}$, making the start-up more attractive to investors. Sceptics of governmental financing of start-ups, however, refer to the crowding out of private capital, which would prevent a venture capital culture from flourishing in Europe. However, theoretical arguments work both ways. On the one hand, venture capital funding that comes with voting rights and influence may no longer be attractive to founders if they also have access to grants and inexpensive loans with few strings attached. On the other hand, public funding may fill a need early in a firm's life cycle, when investment is not attractive for venture capitalists, thus helping firms overcome the "valley of death" without compromising (or even facilitating) their chances to acquire venture capital funding later on. Whether grants or subsidized loans are crowding out private equity investments is therefore an empirical question. More innovative start-ups are also more likely to be targets for mergers and acquisitions (Henkel et al., 2015).

Regarding the risk of bankruptcy, the model leads to two opposing expectations. By facilitating additional investments, public support through both loans and grants may increase the likelihood of innovation success thus reducing the risk of failure. However, if funding agencies choose high-risk start-ups, failure rates may be higher among those that are subsidized. We could also expect a higher likelihood that a start-up that receives a loan will file for bankruptcy as it is the only way to get rid of the *RPO*.

Therefore, in addition to R&D activities and investments in tangible assets, the following analysis considers innovation success, overall employment, sales, mergers and acquisitions, venture capital financing and bankruptcy as outcome measures that may be affected by the receipt of subsidies.

4. Econometric method

The following analysis estimates the treatment effect of a subsidy on a set of outcome variables *Y* to determine whether and to what extent the subsidy impacts R&D investment, tangible investment, employment, revenues, innovation performance, and ownership. The average treatment effect on the treated can be written as:

$$\alpha^{TT} = \frac{1}{N^T}\sum_{i=1}^{N^T}\left(Y_i^T - \hat{Y}_i^c\right), \tag{8}$$

where Y_i^T is the outcome of treated firms and $\hat{Y}_i^c$ is the counterfactual situation – that is, the outcome that would have been realized if the treatment group ($S=1$) had not been treated. S ϵ $\{0,1\}$ is the receipt of a subsidy and N^T is the number of treated firms. We define three variants of $S = 1$: the receipt of a grant, the receipt of a subsidized loan, and the simultaneous receipt of a grant and a subsidized loan.

The challenge of such an analysis is that $\hat{Y}_i^c$ cannot be observed, so it must be estimated. Using the average values of untreated firms would lead to invalid conclusions because of the endogeneity of the subsidy receipt. In other words, firms that receive subsidies differ from those that do not in important characteristics that correlate with the outcome variables. The selection problem and the subsequent non-random composition of the group of subsidized start-ups must be considered with two possibilities in mind. If the granting institution follows a picking-the-winners strategy, the pool of subsidized firms may consist of over-performers (Cantner and Kösters, 2012). If the granting institution follows a backing-the-losers strategy by targeting start-ups with grave financial problems or because high-potential firms self-select out in favor of other funding options, the pool may consist primarily of underperforming firms. Therefore, we use an econometric evaluation technique that is suitable for estimating causal treatment effects when the available observations of firms are subject to a selection bias (see Heckman et al., 1999; Imbens and Wooldridge, 2009).

Suitable estimation strategies include the (conditional) difference-in-difference estimator, control function approaches (selection models), instrumental variable (IV) estimation, regression discontinuity designs, and non-parametric (matching) techniques that are based on, for instance, propensity scores (Athey and Imbens, 2017). In the case of a firm that receives the treatment early in its life cycle, differences in differences before and after the treatment cannot be used because of the lack of an ex-ante period for comparison. Figure A.3 shows that a large share of firms received treatment in their first or second years of activity. Control function approaches and IV models, on the other hand, require identification of valid exclusion restrictions, which in our case would require exogenous variables that explain the receipt of a subsidy but not the outcome variables R&D, employment, and innovation, which are notoriously difficult to find. Regression discontinuity designs require information about how the applicants to the support programs were evaluated, information that is often, as in our case, not available or not comparable across programs and rounds of funding. Moreover, funding agencies often avoid revealing details about rejected applicants to protect the firms.

Therefore, we adopt a variant of the propensity-score-matching (PSM) approach, combined with exact matching (EM) to determine the causal effects of program participation on a start-up's activities while taking into account the selective nature of public subsidies. Matching approaches have the advantage of making no assumptions about the functional form or error distribution, so they have gained momentum in the recent policy-evaluation literature (e.g., Czarnitzki and Lopes-Bento, 2013; Huergo and Moreno, 2017). The matching estimator builds on the conditional independence assumption (CIA) introduced by Rubin (1977); that is, we must observe what drives a start-up's selection or at least have proxy variables for these drivers.

Then, after being conditioned on a large set of founder and firm characteristics X, the setting comes close to an experimental design in which we have no a priori judgment about whether a firm receives the treatment[6]. Based on the CIA, we can estimate the counterfactual situation for any outcome Y using a matched group of non-subsidized firms that have similar characteristics in X:

$$E(Y \mid S = 1, X) = E(Y \mid S = 0, X) \qquad (9)$$

In our case, we must either observe or proxy all characteristics that determine selection by a grant or subsidized loan program. Huergo and Trenado (2010) provide support for the congruency of private and public funding criteria and the dependence of funding awards on observable factors. Given the detailed survey data, which provides a large set of founder and company characteristics, we are confident that our dataset provides sufficient information with which to conduct a matching approach.

[6] See Lechner and Wunsch (2013), who show that the inclusion of a large set of appropriate control variables substantially reduces bias in propensity score applications.

We construct a score based on the probability that a start-up receives a treatment (obtained from a probit regression), conditional on a set of observable characteristics *X*. This propensity score is an index function that summarizes in a single number a wide set of observable characteristics that affect the probability of receiving treatment. In particular, we use a variant of the nearest-neighbor matching approach pioneered by Czarnitzki et al. (2007) and Czarnitzki and Lopes-Bento (2013) in applications on R&D subsidies. By matching using the propensity score, we ensure that we compare subsidized start-ups with other start-ups that are similar in their propensities to receive the respective treatment. To ensure the validity of the matching estimators, we check the overall homogeneity of the subsidized and non-subsidized groups by identifying the highest and lowest propensity scores in the non-subsidized groups and eliminating all observations from the two subsidized groups that have higher or lower propensity scores. That is, we require "common support". In addition, we incorporate a threshold (caliper) to avoid bad matches, which restricts the maximum distance allowed between the a subsidized and a non-subsidized start-up's propensity scores. If the predefined distance is exceeded, we delete the subsidized observation from our sample. See Smith and Todd (2005) and Czarnitzki and Lopes-Bento (2013) for a similar approach. As Lechner and Wunsch (2013) argue, this approach has the advantage of reducing not only differences in observable characteristics between groups, but also likely reducing differences in unobservable characteristics by discarding highly dissimilar firms from the respective control group.

Finally, to ensure balancing of the propensity score and all of the covariates, we incorporate elements of EM by requiring the matched firms to be in the same region (East Germany or West Germany). In addition, we match firms only if observed in the same year which renders macroeconomic developments (i.e. inflation or unemployment levels) irrelevant to the comparison between treated and control firm. Finally, treated and control firms have to be active in the same sector and to stem from the same cohort.

After the matching process, we calculate the treatment effect on each outcome *Y* as:

$$\alpha^{TT} = E(\mathrm{Y}^{T} \mid S = 1, X = x) - E(\mathrm{Y}^{C} \mid S = 0, X = x)\,. \tag{10}$$

We test the validity of the estimator by confirming that no significant differences in variable means between groups remain after matching (for each of the variables *X)*. We account for the sensitivity of the mean comparisons to the skewed distributions of the outcome variables (particularly R&D expenditures, investment, employment and turnover) by considering logged versions of *Y* and intensities (ratios).

5. Data and variables

We build on the IAB/ZEW Start-up Panel (formerly the KfW/ZEW Start-up Panel), which the Center for European Economic Research (ZEW), the KfW Bankengruppe[7], and Creditreform[8] established in 2008 to create a comprehensive and representative dataset for the examination of newly founded firms in Germany. Every year, about 6,000 independent firms from various sectors[9] complete a computer-aided telephone survey. The dataset explicitly excludes de-mergers (spin-offs) and subsidiaries of other firms. This exclusion is an important strength in our research context, as non-independent firms may reflect the R&D activities of their related institutions. The firms to be contacted for each survey wave are drawn as stratified random sample from firms in the Creditreform database, which covers the overall population of newly registered businesses in Germany. Firms are re-contacted in the following waves, resulting in an unbalanced panel of new entrants and previously interviewed firms. Fryges et al. (2010) provide a detailed description of the survey method and the resulting data set. Information on sector affiliation is based on the description of business activity that the founder(s) provide when they register their businesses. Because our research question focuses on knowledge-intensive start-ups, we extract a subsample from the initial panel that includes four industries: cutting-edge technology manufacturing, high-technology manufacturing, technology-intensive services, and software supply and consultancy. See Table A1 for details. After observations with missing information are eliminated, the final data set comprises 5,267 firm-year observations.

5.1. Treatment variables

The data provides yearly information about whether a start-up received a grant, a subsidized loan, or both. Figure A.2 shows that the share of subsidized firms increased in the years following the global financial crisis (2009, 2010, and 2011) and fell back to lower levels in 2012 and 2013. The relative shares of grants, loans, and both types of subsidies remained similar over the whole period, with grants constituting by far the most frequent type of support.[10] The data captures support from several national and subnational programs that can be classified into grant-based and loan-based. The latter are predominantly administered by the KfW Banking Group, although regional banks also have special loans in place, typically with

[7] The KfW Bankengruppe is Germany's largest state-owned promotional bank.
[8] Creditreform is Germany's largest credit rating agency.
[9] Excluded sectors are agriculture, electricity, gas and water supply, health care, mining and quarrying, and the public sector.
[10] Fryges et al. (2010) report that due to stratification, subsidized firms are overrepresented in the panel, so the shares presented in this study should not be interpreted as shares in the population of start-ups.

support from the state governments. The groups of entrepreneurs that grant-based programs target differ from those targeted by loan-based programs, with some, such as the support provided through the Federal Employment Agency, addressing all founders and others, such as the *EXIST* program, focusing on entrepreneurs with university backgrounds. The overall awarded amount is substantial with the *EXIST* program alone supporting 875 projects with more than €70 million between 2007 and 2012[11]. Because the exact amounts of the grants and loans that firms in the sample received and the conditions attached to the loans are unavailable, we rely on binary information about program participation. However, based on information about popular funding programs, we can reasonably assume that the variance in treatment size within a program is relatively small. For instance, the *EXIST* program offers grants that are typically between 70,000 and 80,000 Euros, depending on the founder's or founding team's qualifications.[12] Subsidized loans are typically capped at 100,000 or 500,000 Euros and have a term of five to ten years during which the loans have to be repaid. Such loans are offered at interest rates that are more favorable than is typical for a conventional bank loan, may have some repayment-free years, and often require little to no collateral ex-ante.[13]

5.2. Outcome variables

We use the logarithms[14] of R&D expenditures [*ln(R&D Expenditures)*] and R&D employees [*ln(R&D Employees)*] as outcome variables and calculate the ratio of internal R&D expenditures per employee *(R&D Expenditures/Employees)* and the ratio of R&D employment over total employment (*R&D Employees/Employees*). Previous studies that examine the impact of public support measures (e.g., Colombo et al., 2013; Czarnitzki and Lopes-Bento, 2013; Huergo and Moreno, 2017) use similar ratios. The variable ln(*Tangible Investment*) captures the acquisition of tangible assets.

In addition to these input-related outcome variables, we use innovation output as a binary variable based on whether the start-up introduced a new product (i.e., a market novelty) or implemented a process innovation (*Innovation*) in the first three years following receipt of the subsidy. We use total revenue as an additional indicator of market success [*ln(Revenue)*] and the number of employees [*ln(Employees)*] as an indicator of overall firm size.

11 https://www.exist.de

12 This funding typically covers employees' wages (about 2,500€-3,000€ per month) for a twelve-month period, in addition to materials costs (about 30,000€) and training expenses (5,000€). Source: http://www.exist.de.

13 Source: www.kfw.de/inlandsfoerderung/Unternehmen/Gründen-Erweitern.

14 In cases of zeros in the expenditure or investment variables, we added a unit to be able to take the logarithm.

As for the event-based outcome variables, the variable *Venture Capital* takes the value of one if the firm received equity financing from a (non-public) venture capital fund, and zero otherwise. Information on changes in ownership through a *Merger* with another company or through *Acquisition* by another company is also obtained from dedicated questions in the survey. Finally, we measure *Bankruptcy* following the definition by Gottschalk et al. (2017) and base the determination that a firm declared bankruptcy on information from Creditreform. Thus, we count bankruptcy events independent from a start-up's participation in the survey.

5.3. Founder and start-up characteristics

The selection of control variables is based on documented funding criteria from public funding agencies but also on those of banks and other capital providers, which are presumably linked to expectations about a firm's chances of success and its riskiness. We construct a large set of founder-related and start-up related control variables to reduce omitted variable bias in the analysis. A main factor in entrepreneurial success that is also a key factor in funding agencies' decisions is the entrepreneur's human capital (Colombo and Grilli, 2005; Gimmon and Levie, 2010; Stucki, 2016), that is, his or her stock of knowledge and capabilities. An argument for including the entrepreneur's formal education as a control comes from Marvel and Lumpkin (2007), who find in a sample of 145 US technology entrepreneurs that innovation is positively associated with formal education. Therefore, we incorporate several control variables that capture entrepreneurs' human capital. *Uni* takes the value of one when at least one founder has a university degree, and zero otherwise. *Master craftsman* takes the value of one for founders who have obtained a "Master rank" license, the highest rank among non-university degrees, and zero otherwise. *Vocational training* indicates that a person has completed vocational training. In addition, we include the oldest founder's age (*Age*) as a control for accumulated human capital or, more simply, life experience.

Lerner et al. (1997) show that founders' industry experience increases the probability that a start-up will receive external financing and that it positively affects their ventures' performance. In addition, Colombo and Grilli (2007) suggest that industry experience is a proxy for private wealth, which reduces the start-up's default risk and reliance on external financing. Therefore, we include the variable *Industry experience* as the most experienced founder's number of years working in the start-up's industry.

In addition to industry experience, which may have been gained through dependent employment, external capital providers appreciate entrepreneurial experience (e.g., Wright et al., 1997), as experienced entrepreneurs have a stock of skills, knowledge, and social networks with which to address the challenges of founding, and the capacity to exploit business opportunities (Delmar and Shane, 2006). To control for entrepreneurial experience, we use the binary indicator *Entrepreneurial experience*, which takes the value of one when at least one founder had founded a company before, and zero otherwise. However, as Hsu (2007) shows, external capital providers look not just for entrepreneurs with entrepreneurial experience but for those with successful experience, so we anticipate that negative entrepreneurial experience, such as the failure of a previous start-up, might be penalized. Moreover, Metzger (2006) points out that re-starters differ substantially from first-time entrepreneurs in terms of performance-related characteristics. Therefore, we use the binary variable *Bankruptcy experience* to capture whether the founder experienced bankruptcy with a previous venture. We also distinguish between necessity-driven and opportunity-driven start-ups (*Opportunity driven*), which may proxy for the desire to grow, thus possibly explaining differences in our performance measures.

Whether the firm is founded by a team or by a single entrepreneur may be another important criterion. Eisenhardt and Schoonhoven (1990) argue that a large founding team comes with more diverse kinds of human capital than a small team or a single founder does, which facilitates multiple perspectives on the technology innovation and better decisions. Other reasons to control for team founders include that multiple founding team members can specialize and tasks like applying for public support, which is often bureaucratic and time-consuming, can be portioned out, making an application more likely. Another reason to control for an entrepreneurial team is the amount of internal funds the venture is likely to have, as internal funds can directly affect investment in R&D. The dummy variable *Team* takes the value of one if the firm was founded by more than one person, and zero otherwise. Finally, we control for the entrepreneur's gender with the variable *Female*, which takes the value of one if at least one founding team member was female, and zero otherwise. Although we do not expect that gender is a formal criterion for the allocation of public support, studies like that of Lins and Lutz (2016) indicate that the founder's gender does influence the receipt of external capital.

We also incorporate firm-specific information into the model. With the number of employees [*ln(Employees)*], we control for possible effects of size, as we assume that firm size is likely to impact whether a start-up will apply for and receive public support since larger firms have more resources for managing the application process. Another firm-specific control variable is the age of the firm (*Start-up age*). As younger start-ups tend to be more financially constrained than older ones, they may see a greater need to apply for subsidies and may also be more likely to receive public support that targets new companies, and the firm's age may also capture how much the team has learned since its founding. As an indicator of the start-ups' legal form, we include a variable that takes the value of one if the firm is a *limited liability* company, and zero otherwise. To reflect the firms' ex-ante financing structure, we include measures for the pre-subsidy use of *bank financing* and for the receipt of *equity financing*, such as venture capital, prior to the receiving a subsidy. Both variables are based on information on the financing profile provided in the survey and are measured as shares in the financing mix.

Because funding institutions that grant public support may follow a picking-the-winners or backing-the-losers strategy, we control for ex-ante *Revenue*, *R&D activities*, *Investment*, *Profit* (in thousands of euros) and *Tangible Assets* (in logs). Higher values in these indicators may reflect the degree to which a business idea is working, and start-ups with higher revenues and (especially) profits are likely to be able to finance some of their R&D efforts internally, complementing the public money and increasing its efficacy.

We also include three control variables that reflect the start-ups' technological and innovation profiles. *Patent stock* indicates the number of patents at the time of founding, as we associate a higher number of patents with a higher innovative potential and with greater R&D experience and success. *Export activity* controls for export activities, which may serve as proxy for a set of otherwise unobservable firm characteristics. For instance, Stucki (2016) finds a strong correlation between founders' human capital and export activities. Regarding unobserved competition that a firm may face, Czarnitzki and Lopes-Bento (2013) argue that firms that are engaged in foreign markets may face stronger pressure to innovate than others, which increases their need for financing and the chance that they will apply for subsidies. Huergo and Moreno (2017) also state that exporters face lower application costs, as they are more experienced with bureaucracy.

We also incorporate a variable for the use of production capacity (*Capacity utilization*) to capture the founders' desire for expansion and, hence, the likelihood that they will seek public support. In addition, we include a control variable for location (*East*), which takes the value of one if the venture is located in eastern Germany and zero if it is located in western Germany. This variable takes into account the German government's initiatives in support of structural development in the eastern states, which may increase the likelihood that firms located there will receive support (e.g., Liu and Rammer, 2016). We also include more fine-grained measures for the start-ups' local environment (i.e., the district) using *GDP per capita* as a measure of local purchasing power and a district-level *bankruptcy index*.

Finally, the propensity score estimation includes sector variables to account for differences in the sectors' technological opportunities and public funding agencies' preferences for certain technology fields, as well as year dummies that capture macroeconomic trends during the period of analysis.

5.4. Timing of the empirical model

We model the selection into each one of the three types of treatment in period *t* as a function of the founder's and the start-up's characteristics prior to *t* whenever possible. While most founder characteristics and some firm characteristics are time-invariant, we use time-varying indicators in the period prior to the subsidy receipt. However, as Figure A2 shows, a comparatively large share of start-ups received subsidies in their first year of business activity. In these cases, we set the values of time-varying variables to zero in the pre-period in which the start-up was not yet active[15].

The design of the selection stage is such that it resembles the start-up's condition at the time of the subsidy decision. We consider outcome variables in both *t* and strictly after *t*; that is, we forward the outcome variables to account for public subsidies' lagged "impulse effect" (if any) on firms' activities.[16] We refer to effects on outcome variables in the year of the subsidy receipt as "immediate", effects in t+1 as "short-term", and effects in years later than t+1 as "medium-term" effects. We allow up to three periods for innovation success and the event outcome variables *Venture Capital*, *Merger*, *Acquisition* and *Bankruptcy* to happen at some point after *t*, as long as we observe the firm in the panel. Because of the structure of the data, we model the firm's decision to apply for a subsidy and the funding agency's decision to grant support as a single step, thereby incorporating variables that affect both decisions simultaneously. See Colombo et al. (2013) and Czarnitzki and Lopes-Bento (2013) for similar approaches. Both conceptually and technically, this procedure does not affect the matching estimator that is used to match firms that are similar in their propensities to receive treatment. Differences in the outcome variables may then be attributed to participation in the respective subsidy program(s).

5.5. Descriptive statistics

Tables 1a and 1b show the descriptive statistics for the treatment groups and the potential control group. The groups of subsidized start-ups differ substantially from the group of non-

[15] See section 6.3 for tests without this assumption.

[16] The observation of lagged and future values requires that we observe a venture in more than one year, but the exclusion of ventures that appear only once burdens our data with a survivorship bias. While we had to keep this bias in mind when we interpreted the results, we matched strictly within cohorts, so the treatment effects that we estimated based on matched pairs should not be biased, as both treated and control group were equally affected.

subsidized ones in several of the founder profiles and firm characteristics (Table 1a). These differences may also explain differences in the outcome variables that we observe before conducting the matching between the groups (Table 1b).

Figure A.3., which depicts employment growth for firms from the 2008-founding cohort, illustrates two issues: A large share of subsidized firms were subsidized in the first or second year after founding, and the difference in firm size, measured by the number of employees, became more pronounced over time. This second observation may not be due only to the subsidy but also to the result of differences between the characteristics of firms that were selected for support and those that were not. For instance, t-tests of mean differences show that founders who received grants were, on average, less experienced than founders who did not receive a grant. The treatment groups also differ with regard to firm- and location-specific characteristics. For example, start-ups that received subsidies were, on average, significantly younger and had lower revenues ex-ante. However, there were few differences between the treatment types based on the start-ups age, suggesting that both grants and loans were received at similar stages of the firms' life cycles. These differences between subsidized and unsubsidized firms stress the importance of matching based on founders' profiles and firm characteristics to obtain comparable groups of start-ups.

– Table 1a and 1b about here –

6. Econometric results

6.1. Estimation of the propensity scores

To apply the matching estimator described in section 3, we first estimate probit models to obtain the probability that a start-up will receive a grant, a subsidized loan, or both during a particular period, given the control variables. Table 2 shows that, in all three models, the coefficients of several of the founder-, start-up-, and location-specific characteristics are significantly different from zero. Since these characteristics drive firms' selection into the funding programs, accounting for them in the selection stage reduces bias in the evaluation stage.

The likelihood ratio tests of the models' overall predictive power are significant at the 1% confidence level in all three cases [$chi^2(33) = 467.28$ for grants, $chi^2(33) = 201.32$ for loans, and $chi^2(33) = 217.05$ for grants and subsidized loans]. The rates of correct classifications observations are 83.19 percent for grants, 94.52 percent for subsidized loans, and 96.37 percent for grants and subsidized loans.

For the dependent variable subsidized loan (and for the combination of both a grant and a loan), we find that some of the variables that impact the funding decision are the same as those that impact grants, but we also see differences. For instance, a start-up's size in terms of assets correlates with the likelihood that it received a loan, whereas variables that reflect the start-ups R&D profile do not. Overall, there is no clear pattern of a "picking-the-winners" or a "backing-the-losers" policy reflected in these models. However, in the case of grants, it appears that more risky start-ups are more frequent among those selected for grants, as not only are these founders less experienced but their firms are also more export- and R&D-intensive, had fewer tangible assets at the time of founding, and collect smaller revenues.

– Table 2 about here –

6.2. Estimation of treatment effects

Tables 3a, 3b, and 3c show the outcome variables after matching. After matching, the propensity score and the founder- and start-up-related characteristics are balanced, so we conclude that the matching was successful in making the groups comparable. See Tables A2a-A2c for the balancing tests for the control variables. Therefore, differences in the average outcome variables are no longer due to differences in these characteristics and may be attributed to the treatment.

When we distinguish among immediate effects that occur in the same year as the subsidy was received, a short-term effect that occurs the following year, and medium-term effects, we find that grants have an immediate effect on R&D expenditures (R&D), employees, and investment (Table 3a). However, the amount of R&D per employee remains constant, suggesting that the increase in R&D expenditures reflects the employment of an additional person rather than an increase in wages. Small but positive effects on revenue materialize in *t+1*. When allowing a longer time between receiving the grant and the outcome, we find a higher likelihood of innovation (53% vs. 48% in the control group) and a slightly higher likelihood of bankruptcy (13.8% vs. 10.5% in the control group). This last difference may suggest that the funding agencies support start-ups that are riskier in terms of unobserved characteristics.

The results for subsidized loans differ from those for grants (Table 3b), as the average values of the R&D-related and innovation-related variables for loan recipients are not significantly different from those of their non-subsidized counterparts. However, we still observe higher investment levels, higher (non-R&D) employment, and higher future revenues (in *t+1*) in the treatment group. The likelihood that a start-up will obtain venture capital in the years after it receives a subsidized grant is also higher (9% vs. 5%).

These results confirm the idea that grants are used to finance R&D activities, while loans are used to finance investments in tangible assets, but both types of support stimulate employment and revenues.

For start-ups that receive both types of support, we find higher R&D spending, higher R&D employment, and higher investments than we do in the control group (Table 3c). Moreover, those start-ups show a significantly higher likelihood of innovation (62% versus 47%). Interestingly, there is a virtually zero likelihood of acquisition in the treatment group, suggesting that start-ups that apply for both types of support plan to remain independent, while at least some of the matched controls are open to being acquired.

To test whether the receipt of subsidized loans in addition to grants increases the likelihood of innovation, we compare firms that received both grants and loans with those that received only the former. For this comparison, we repeat the matching procedure as described above but draw the control units from the sample of start-ups that received only grants and consider the recipients of both subsidies and grants as treated. Thus, this test focuses exclusively on firms that received some form of public support, which results in a more homogenous sample. The new matching accounts for differences between firms that apply to only one program and those that apply to both types. After matching, we find no significant differences in the control variables between these groups (Table A2d). The results for the outcome variables, shown in Table 3d, indicate that firms that receive both grants and loans are more likely to innovate than those that receive only grants (64% versus 50%), despite similar levels of R&D. Employment and future revenues are also higher in the group with both grants and loans than in the group with grants only, perhaps because of the larger investments in the group of firms that received both. Finally, recipients of both types of support are more than twice as likely to receive venture capital later than are recipients of grants alone (14% versus 6%) and are less likely to be acquired or to go bankrupt (3.6% versus 9%).

– Tables 3a, 3b, 3c, 3d about here –

6.3. Robustness tests

To test the sensitivity of these results to the onset of the financial crisis that occurred during the period of our data, we examine whether the results depend on the period investigated. More generally, previous research suggests behavioral changes and changes in business practices depending on the business cycle (Alcalde and Guerrero, 2016). While the three years from 2008 to 2010 can be described as a period of economic downturn and financial crisis, affecting both internal and external business financing, the years after 2010 were characterized by low interest rates, which reduced lending costs.

If there was an impact on the treatment, we should see higher or lower treatment effects over time, so we follow Hottenrott et al. (2017) in calculating the individual start-up's treatment effect as the difference in the outcome variable Y_i between the treatment firm and its matched control firm:

$$\alpha_i^{TT} = Y_i - \hat{Y}_i^c \,. \tag{11}$$

Thus, the individual treatment effect is measured as the deviation of the treated firms' outcome from that of its matched firm. We then regress the treatment effects ${\alpha_i}^{TT} = \Delta Y$ on an indicator variable that takes the value of one for the years up to (and including) 2010. As Table 4 shows, the time indicator (*before 2011*) is insignificant for all outcome variables (except for revenues in the case of loans), which suggests that the average treatment effect does not vary between the years during and after the financial crisis. The results that the difference in revenues is larger between treated and control firms during the crisis may suggest that this tool was slightly more effective during the crisis.

Next, we test the sensitivity of the average results to the firm's geographic location, differentiating in particular between western Germany and eastern Germany, where structural economic differences persist thirty years after the country's reunification. Regarding regional differences (*East)*, we observe no differences for the "both" treatment or the "both versus grant-only" treatment. Some significant differences appear with regard to R&D expenditures in the "grant-only" treatment (and some that are weakly significant also in the loan-only treatment), suggesting that the difference between the treated firms and their matched controls is slightly larger when both firms are located in eastern Germany.

Finally, we test the robustness of the key findings to making an alternative assumption about the initial values of the time-varying control variables. Instead of assuming zero values for the pre-founding period, we assume that start-ups would have had the same values in *t-1* as they show in *t*. That is, we do not include lags in the estimation of the propensity score, but contemporaneous variables if not otherwise measurable. Note that a large share of firms receives a subsidy in their first year of business activity (see Figure A.3). Without making assumptions about their pre-treatment values, our analysis would be limited to start-ups receiving support in their second year or later which constitutes a minority of the sample. Tables 5a and 5b show the results (after matching) for the case of assuming $x_{t-1} = x_t$ for the x representing R&D expenditures, investments, turnover, profits, the number of employees and the variables referring to the financing mix. The conclusions regarding the higher levels of investment in firms receiving both a grant and subsidized loan compared to unsubsidized firms or grant-only receivers as well as the higher innovation performance remain unchanged.

Likewise, the results for employment and turnover growth as well as for venture capital hold also for this specification (see Tables A3a and A3b for the balancing tests of the covariates).

7. Conclusion

This study focuses on the role of subsidies in start-ups' performance. Public support is usually motivated by the social returns that new firms generate directly through radical innovation and employment creation and indirectly by increasing pressure on incumbents to innovate. Our research contributes to previous studies that investigated the effectiveness of start-up support programs in the US, Italy, Israel, Spain and Sweden. In addition, the study provides new insights on the role of the policy instrument design for its effects on firm performance. We consider a variety of performance indicators to capture the various dimensions in which start-up subsidies may impact a newly founded firm including R&D and tangible investments as inputs, along with successful innovation, employment and turnover growth as output measures. In addition, particularly in the context of new firms, policy tools should be evaluated with regard to outcomes like the likelihood of equity investment, mergers, acquisitions, and bankruptcy.

Based on a large sample of start-ups in high-tech manufacturing and in knowledge-intensive service sectors that were founded between 2005 and 2012 in Germany, our results show that start-ups that received grants outperformed non-subsidized matched firms in terms of R&D investments, employment numbers, tangible investments, innovation likelihood and revenues. Recipients of subsidized loans do not appear to invest the additional money in R&D projects but rather in tangible assets, so their innovation probability does not differ from that of similar non-recipients, although their revenues and employment numbers are higher. This result is in line with the findings by Bertoni et al. (2019) for young companies in Spain.

These findings may be attributed to two central channels. The first, the liquidity channel, suggests that government support in the form of both grants and loans increases the volume of project funding available in the firm thereby enabling additional investment. As loan volumes tend to be larger than grants, the former may appear particularly suitable to finance larger scale fixed investments that require large up-front payments. The result that loans are not used for R&D, but rather for other investments, points to a second channel, the policy instrument channel. Because of the repayment obligation attached to loans, the actual subsidy rate (and amount) may be larger for grants than for loans. Grants may therefore be more suitable for financing risky activities like R&D.

Moreover, in line with findings for older, established Spanish companies (Huergo and Moreno, 2017), we find that grants and subsidized loans have a larger impact when combined. Compared to recipients of grants only, beneficiaries of both types of support perform better in terms of tangible investments, are 14 percentage points more likely to bring new products and services to the market, have higher employment and revenue numbers and are more than twice as likely to receive venture capital later.

While we conclude that government-backed loans may not be used to finance risky R&D investments directly and that grants seem better suited to increasing R&D spending, we also see that the combined receipt of loans and grants facilitates innovation most effectively. This finding may materialize via the liquidity channel as grants combined with loans substantially increase the investment volume available to the start-up. That loans are used to finance tangible investments and to scale up production, rather than to finance R&D, appears central to firms' ability to introduce new products and services to the market that trigger sales and lower the risk of bankruptcy.

Furthermore, we find no support for the hypothesis that subsidy programs prevent firms from seeking financing from private investors. We further cannot conclude that public support has per-se beneficial effects on business survival, as the slightly larger bankruptcy rate in the group of grant recipients suggests that funding programs target riskier start-ups whose projects are enabled through the public support but eventually fail.

These results have several implications for policy, founders, and for future research. First, they show that facilitating early-stage R&D activities may require financial support without repayment obligation. Second, they suggest that, since the amount of funding raised from grants is typically limited, access to loans can help new ventures to finance final product development that leads to introducing new products and services to the market. Therefore, funding agencies may consider grants and loans not as alternative policy tools but as two elements of a successful start-up support policy. Grants and loans could, for instance, be administered jointly as this would reduce the administrative burden on founders and managers in young firms of dealing with multiple institutions. It could also speed up the processes that lead to the provision of growth capital.

Third, our study does not confirm the idea that public support crowds out private sector investors; funding through public support programs may precede investments and facilitate access to venture capital. Implications for the financial sector arise from the finding that frictions prevent start-ups from raising growth financing through standard business loans. Threatened by the high failure rates of start-ups and non-participation in the upside potential, commercial loans are not profitable from a bank's point of view. However, if banks would focus their expertise and use start-up-specific risk-evaluation tools, they may find that lending to new grant-receiving founders is worthwhile when engaging them in a longer-term bank relationship.

The results are also relevant to founders of start-ups as they may encourage them to seek support from public support programs that can help developing their products until the firm can attract other investors.

Our study contributes to insights from previous research that are based on data from other countries by providing new evidence that start-up support is also effective in the German context. The results may also be of interest for policy makers in countries that are planning to implement loan-based start-up support programs. Nevertheless, it requires additional research to test whether the result regarding the differential impact and complementarity of grants and loans are specific to the context in which our study is based and to the specific design of subsidized loans and grants in Germany. Future research could also focus on the long-term effects of receiving public support by following start-ups for several decades. Even for the most mature firms in our sample it may be too early to derive conclusions regarding the sustainability of start-ups' growth or the long-term effects of early public support. Moreover, studying the differential impact of different policy tools in different types of technologies or sectors could help to explain which policy tools best support which kind of entrepreneur. Future research may also take into account the amount of money received, which would allow a much more fine-grained analysis regarding the roles played by the liquidity channel and the policy instrument channel. Such a study could also shed light on the question concerning whether the complementarity found between grants and loans is due to the resulting higher amount of support or the complementary design of the two policy tools. Moreover, from a policy perspective, it would be useful to know the minimum effective grant size.

Limited data availability means we did not investigate the effects of agglomeration economies in detail, although studying the multiplier effects generated by regional characteristics and network effects would be useful. Previous research suggests that new technology-based firms benefit from spatial proximity to universities, suppliers, and customers (Audretsch et al., 2012; Guerrero et al., 2015; Fudickar and Hottenrott, 2018) and that modes of technology transfer should be integral elements of start-up support public policies (Kochenkova et al., 2016). Future work could determine whether start-up support is more effective in regions where regional spillovers are weak or whether prospering regions amplify the effects of start-up support.

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Table 1a: Differences in founder and start-up characteristics before matching

	Unsubsidized N= 4,057		Grant N= 822			Subsidized loan N= 235			Grant & Subsidized Loan N= 153		
Variables	Mean	SD	Mean	SD	t-test	Mean	SD	t-test*	Mean	SD	t-test
Founder characteristics											
University	0.332	0.471	0.341	0.474	0.623	0.302	0.460	0.348	0.294	0.457	0.331
Vocational training	0.190	0.392	0.178	0.382	0.415	0.187	0.391	0.922	0.209	0.408	0.550
Master craftsman	0.221	0.415	0.210	0.408	0.502	0.315	0.465	0.001	0.248	0.433	0.426
Founder age	44.746	10.079	44.797	9.211	0.893	43.936	8.557	0.228	44.608	9.071	0.868
Industry experience	17.239	9.660	16.591	9.021	0.076	16.515	7.991	0.260	16.895	9.346	0.665
Entrepreneurial experience	0.458	0.498	0.416	0.493	0.029	0.366	0.483	0.006	0.379	0.487	0.055
Bankruptcy experience	0.072	0.258	0.071	0.256	0.886	0.068	0.252	0.822	0.098	0.298	0.224
Opportunity driven	0.779	0.415	0.755	0.430	0.138	0.774	0.419	0.867	0.856	0.352	0.023
Female	0.128	0.334	0.108	0.311	0.120	0.140	0.348	0.578	0.131	0.338	0.919
Start-up characteristics											
Team	0.374	0.484	0.384	0.487	0.589	0.413	0.493	0.238	0.503	0.502	0.001
Start-up age$_{t-1}$	2.796	1.655	2.331	1.524	0.000	2.128	1.213	0.000	1.987	1.272	0.000
Limited liability	0.520	0.500	0.557	0.497	0.051	0.566	0.497	0.169	0.582	0.495	0.133
ln(Tangible assets)	5.814	4.468	5.733	4.551	0.634	4.571	4.746	0.000	5.439	4.695	0.309
Patent stock	0.183	3.672	0.130	1.586	0.688	0.106	0.661	0.751	0.170	1.317	0.966
Export activity$_{t-1}$	0.151	0.358	0.212	0.409	0.000	0.183	0.387	0.191	0.183	0.388	0.285
Capacity utilization$_{t-1}$	84.988	29.852	88.104	28.668	0.006	90.943	28.495	0.003	85.963	31.365	0.692
Bankruptcy index$_{t-1}$	0.374	0.171	0.379	0.176	0.416	0.379	0.187	0.642	0.355	0.154	0.181
GDP per capita$_{t-1}$	34.096	14.837	33.274	14.041	0.144	31.495	11.003	0.008	32.295	14.634	0.140
East	0.131	0.338	0.210	0.408	0.000	0.111	0.314	0.364	0.333	0.473	0.000
ln(R&D-Expenditure)$_{t-1}$	1.832	3.946	2.714	4.676	0.000	1.534	3.707	0.260	2.271	4.483	0.179
ln(Employees)$_{t-1}$	0.865	0.753	0.833	0.934	0.284	0.664	0.877	0.000	0.623	0.920	0.000
ln(Revenue)$_{t-1}$	7.695	5.620	6.451	5.973	0.000	6.500	6.107	0.002	5.279	5.833	0.000
ln(Tangible Investment)$_{t-1}$	5.471	4.817	5.017	5.052	0.015	5.580	5.340	0.737	5.046	5.405	0.287
Profit$_{t-1}$	17.724	105.303	6.123	94.865	0.003	14.843	83.856	0.681	-0.355	51.589	0.035
Debt financing$_{t-1}$	19.969	19.920	21.472	22.451	0.054	22.667	20.255	0.044	22.817	19.515	0.083
Equity financing$_{t-1}$	2.836	7.167	3.437	11.032	0.048	2.489	6.243	0.468	3.058	8.131	0.709

Notes: p-values of two-sided t-tests for mean difference between subsidized and non-subsidized start-ups. Period *t-1* refers to the year before the subsidy receipt in year *t*. SD stands for standard deviation. No time subscript indicates that the information is time invariant or based on the founding year.

Table 1b: Differences in outcome variables before matching

	Unsubsidized N= 4,057		Grant N= 822			Subsidized Loan N= 235			Grant & Subsidized Loan N= 153		
Variables	Mean	SD	Mean	SD	t-test	Mean	SD	t-test	Mean	SD	t-test
Immediate											
(R&D-Exp/ Employees)$_t$	592.428	1,940.668	821.434	2,890.395	0.005	550.356	1,773.102	0.746	768.863	1,657.242	0.267
(R&D-Emp/ Employees)$_t$	14.545	33.752	18.157	34.773	0.005	10.521	24.951	0.072	18.112	34.984	0.200
ln(R&D-Expenditure)$_t$	3.192	4.784	4.178	5.222	0.000	3.604	4.941	0.201	4.499	5.405	0.001
ln(R&D-Employees)$_t$	0.230	0.479	0.353	0.585	0.000	0.216	0.436	0.660	0.402	0.679	0.000
ln(Employees)$_t$	1.281	0.593	1.429	0.714	0.000	1.558	0.664	0.000	1.628	0.721	0.000
ln(Revenue)$_t$	10.347	4.043	10.573	3.876	0.142	10.728	4.288	0.162	11.200	3.220	0.010
ln(Tangible Investment)$_t$	7.071	4.262	7.884	3.961	0.000	8.677	4.313	0.000	9.417	3.605	0.000
Short-term											
(R&D-Exp/ Employees)$_{t+1}$	402.437	1,029.974	494.084	1,173.777	0.023	322.840	764.348	0.244	405.549	853.378	0.971
(R&D-Emp/ Employees)$_{t+1}$	11.200	26.318	15.003	28.326	0.000	8.363	21.407	0.105	12.660	25.963	0.500
ln(R&D-Expenditure)$_{t+1}$	3.208	4.835	4.178	5.277	0.000	3.424	4.972	0.507	4.412	5.458	0.003
ln(R&D-Employees)$_{t+1}$	0.220	0.482	0.347	0.596	0.000	0.215	0.449	0.869	0.376	0.719	0.000
ln(Employees)$_{t+1}$	1.340	0.637	1.504	0.746	0.000	1.687	0.686	0.000	1.746	0.720	0.000
ln(Revenue)$_{t+1}$	11.035	3.559	11.260	3.534	0.098	12.047	3.135	0.000	12.001	2.761	0.001
ln(Tangible Investment)$_{t+1}$	6.254	4.606	7.001	4.441	0.000	6.692	4.823	0.158	7.345	4.607	0.004
Medium-term											
Innovation$_{t+j}$	0.471	0.499	0.549	0.498	0.000	0.562	0.497	0.007	0.641	0.481	0.000
Venture Capital$_{t+k}$	0.061	0.240	0.086	0.281	0.008	0.085	0.280	0.145	0.144	0.352	0.000
Merger$_{t+k}$	0.022	0.146	0.026	0.158	0.525	0.004	0.065	0.066	0.013	0.114	0.459
Acquisition$_{t+k}$	0.020	0.139	0.027	0.161	0.198	0.026	0.158	0,537	0.000	0.000	0.080
Bankruptcy$_{t+k}$	0.143	0.350	0.133	0.339	0.426	0.119	0.325	0.304	0.078	0.270	0.024

Notes: p-value of two-sided t-tests for mean difference between subsidized and non-subsidized ventures, j indicates innovation was introduced in either one of the three years following the subsidy receipt, k indicates event happened in any year after t as long as the firm is observed in the sample. SD = standard deviation.

Table 2: Probit estimations for obtaining the propensity scores

Variables	Grant			Subsidized loan			Grant & Subsidized Loan		
	Coefficient	S.E.	p-value	Coefficient	S.E.	p-value	Coefficient	S.E.	p-value
University	-0.060	0.056	0.286	-0.015	0.085	0.859	-0.278	0.102	0.006
Vocational training	-0.014	0.064	0.829	-0.014	0.095	0.885	0.015	0.110	0.893
Master craftsman	-0.111	0.065	0.087	0.093	0.090	0.301	-0.174	0.115	0.130
Founder age	0.005	0.003	0.095	<0.001	0.005	0.939	0.003	0.006	0.637
Industry experience	-0.009	0.003	0.008	-0.010	0.005	0.040	-0.002	0.006	0.667
Entrepreneurial experience	-0.194	0.053	0.000	-0.216	0.079	0.006	-0.343	0.096	0.000
Bankruptcy experience	0.048	0.097	0.622	-0.024	0.144	0.869	0.239	0.156	0.126
Opportunity driven	-0.148	0.056	0.008	-0.076	0.084	0.367	0.210	0.115	0.068
Team	0.013	0.056	0.818	0.153	0.083	0.066	0.376	0.097	0.000
Female	-0.216	0.074	0.003	-0.065	0.104	0.534	-0.138	0.123	0.260
Start-up age$_{t-1}$	-0.205	0.023	0.000	-0.200	0.038	0.000	-0.210	0.048	0.000
Limited liability	-0.052	0.058	0.372	0.027	0.086	0.754	-0.031	0.103	0.761
ln(Tangible assets)	0.006	0.005	0.263	-0.023	0.008	0.002	-0.002	0.009	0.796
Patent stock	-0.006	0.013	0.665	-0.061	0.058	0.292	-0.003	0.017	0.875
Export activity$_{t-1}$	0.227	0.065	0.000	0.160	0.099	0.105	0.053	0.120	0.660
Capacity utilization$_{t-1}$	0.002	0.001	0.010	0.004	0.001	0.002	0.001	0.001	0.347
Bankruptcy index$_{t-1}$	0.107	0.135	0.428	-0.017	0.200	0.931	-0.046	0.254	0.858
GDP per capita$_{t-1}$	<0.001	0.002	0.891	-0.007	0.003	0.018	0.002	0.003	0.510
East	0.417	0.064	0.000	-0.162	0.111	0.144	0.670	0.104	0.000
ln(R&D-Expenditure)$_{t-1}$	0.042	0.006	0.000	0.008	0.011	0.464	0.047	0.012	0.000
ln(Employees)$_{t-1}$	0.208	0.047	0.000	-0.143	0.070	0.043	-0.115	0.088	0.193
ln(Revenue)$_{t-1}$	-0.021	0.007	0.004	0.007	0.010	0.475	-0.021	0.013	0.100
ln(Tangible Investment)$_{t-1}$	-0.005	0.006	0.390	0.023	0.010	0.016	0.026	0.012	0.033
Profit$_{t-1}$	<0.001	<0.001	0.996	<0.001	<0.001	0.309	<0.001	<0.001	0.886
Debt financing$_{t-1}$	0.003	0.001	0.022	0.002	0.002	0.323	0.004	0.002	0.075
Equity financing$_{t-1}$	0.003	0.003	0.279	-0.001	0.006	0.859	<0.001	0.005	0.948
Joint sign. of industry dummies [$chi^2(3)$]	32.32***			38.21***			28.41***		
Joint sign. of year dummies [$chi^2(4)$]	155.00***			31.60***			29.80***		
Pseudo R^2	0.106			0.111			0.165		
Correctly specified (in %)	83.19			94.52			96.37		
# observations	4879			4292			4210		
# treated	822			235			153		
# not treated	4057			4057			4057		

Notes: S.E. stands for standard error. *** (**, *) indicate a significance level of 1% (5%, 10%). No time subscript indicates that the information is time invariant or based on the founding year.

Table 3a- Differences in outcome variables after matching (grants)

Outcome variables	Selected Control Group N= 732 Mean	SD	Grant N= 732 Mean	SD	t-test
Immediate					
(R&D-Exp/ Employees)$_t$	586.601	1,844.362	708.327	2,709.259	0.315
(R&D-Emp/ Employees)$_t$	15.054	32.779	17.039	33.765	0.254
ln(R&D-Expenditure)$_t$	3.298	4.852	3.820	5.071	0.044
ln(R&D-Employees)$_t$	0.244	0.459	0.308	0.541	0.014
ln(Employees)$_t$	1.277	0.603	1.354	0.669	0.020
ln(Revenue)$_t$	10.092	4.302	10.396	3.890	0.156
ln(Tangible Investment)$_t$	7.072	4.237	7.850	3.883	0.000
Short-term					
(R&D-Exp/ Employees)$_{t+1}$	465.111	1,070.221	464.538	1,118.555	0.992
(R&D-Emp/ Employees)$_{t+1}$	11.738	26.208	14.028	27.890	0.106
ln(R&D-Expenditure)$_{t+1}$	3.624	4.979	3.800	5.124	0.506
ln(R&D-Employees) $_{t+1}$	0.236	0.511	0.299	0.543	0.024
ln(Employees)$_{t+1}$	1.349	0.640	1.428	0.700	0.026
ln(Revenue)$_{t+1}$	10.791	4.019	11.132	3.546	0.085
ln(Tangible Investment)$_{t+1}$	5.995	4.672	6.916	4.403	0.000
Venture Capital$_{t+1}$	0.029	0.167	0.027	0.163	0.874
Merger$_{t+1}$	0.014	0.116	0.014	0.116	1.000
Acquisition$_{t+1}$	0.001	0.037	0.012	0.110	0.011
Bankruptcy$_{t+1}$	0.059	0.235	0.066	0.248	0.589
Medium-term					
Innovation$_{t+j}$	0.480	0.500	0.534	0.499	0.037
Venture Capital$_{t+k}$	0.066	0.248	0.074	0.262	0.538
Merger$_{t+k}$	0.020	0.142	0.025	0.155	0.598
Acquisition$_{t+k}$	0.016	0.127	0.026	0.159	0.204
Bankruptcy$_{t+k}$	0.105	0.307	0.138	0.345	0.055

Notes: p-value of two-sided t-tests for mean difference between subsidized and non-subsidized start-ups. SD stands for standard deviation, j indicates innovation was introduced in either one of the three years following the subsidy receipt, k indicates event happened in any year after t as long as the firm is observed in the sample. Three treated observation is lost due to lack of common support and 87 are dropped because of the caliper.

Table 3b- Differences in outcome variables after matching (subsidized loans)

Outcome variables	Selected control group N= 205 Mean	SD	Subsidized loan N=205 Mean	SD	t-test of mean difference
Immediate					
(R&D-Exp/ Employees)$_t$	577.086	1,423.696	581.165	1,866.692	0.980
(R&D-Emp/ Employees)$_t$	13.534	34.667	11.425	26.255	0.488
ln(R&D-Expenditure)$_t$	3.326	4.798	3.649	4.974	0.505
ln(R&D-Employees)$_t$	0.201	0.456	0.229	0.451	0.534
ln(Employees)$_t$	1.280	0.554	1.545	0.667	0.000
ln(Revenue)$_t$	9.966	4.471	10.593	4.396	0.153
ln(Tangible Investment)$_t$	7.225	4.256	8.651	4.274	0.001
Short-term					
(R&D-Exp/ Employees)$_{t+1}$	551.471	1,227.852	335.861	757.089	0.033
(R&D-Emp/ Employees)$_{t+1}$	14.407	29.344	9.393	22.680	0.054
ln(R&D-Expenditure)$_{t+1}$	3.873	5.029	3.434	4.995	0.375
ln(R&D-Employees)$_{t+1}$	0.255	0.501	0.234	0.467	0.652
ln(Employees)$_{t+1}$	1.375	0.608	1.674	0.685	0.000
ln(Revenue)$_{t+1}$	11.142	3.521	12.050	3.093	0.006
ln(Tangible Investment)$_{t+1}$	6.166	4.681	6.695	4.821	0.261
Venture Capital$_{t+1}$	0.020	0.139	0.044	0.205	0.160

Merger$_{t+1}$	0.010	0.099	0.000	0.000	0.157
Acquisition$_{t+1}$	0.010	0.099	0.005	0.070	0.563
Bankruptcy$_{t+1}$	0.068	0.253	0.073	0.261	0.848
Medium-term					
Innovation$_{t+j}$	0.532	0.500	0.571	0.496	0.428
Venture Capital$_{t+k}$	0.049	0.216	0.093	0.291	0.083
Merger$_{t+k}$	0.020	0.139	0.005	0.070	0.178
Acquisition$_{t+k}$	0.015	0.120	0.024	0.155	0.476
Bankruptcy$_{t+k}$	0.132	0.339	0.112	0.316	0.547

Notes: p-value of two-sided t-tests for mean difference between subsidized and non-subsidized start-ups. SD stands for standard deviation, j indicates innovation was introduced in either one of the three years following the subsidy receipt, k indicates event happened in any year after t as long as the firm is observed in the sample. Twenty treated observations are dropped because of the caliper.

Table 3c: Differences in outcome variables after matching (grants & subsidized loans)

	Selected Control Group N= 135		Grant & Subsidized Loan N= 135		
Outcome variables	Mean	SD	Mean	SD	t-test
Immediate					
(R&D-Exp/ Employees)$_t$	562.384	2,401.510	643.949	1,516.419	0.739
(R&D-Emp/ Employees)$_t$	12.915	28.773	14.735	31.266	0.619
ln(R&D-Expenditure)$_t$	2.926	4.734	4.215	5.255	0.035
ln(R&D-Employees)$_t$	0.215	0.437	0.333	0.595	0.064
ln(Employees)$_t$	1.363	0.579	1.604	0.724	0.003
ln(Revenue)$_t$	10.311	4.189	11.166	3.225	0.061
ln(Tangible Investment)$_t$	6.782	4.668	9.187	3.757	0.000
Short-term					
(R&D-Exp/ Employees)$_{t+1}$	488.206	1,094.944	359.885	789.352	0.270
(R&D-Emp/ Employees)$_{t+1}$	11.071	24.123	10.288	23.005	0.785
ln(R&D-Expenditure)$_{t+1}$	3.635	5.078	4.108	5.298	0.455
ln(R&D-Employees)$_{t+1}$	0.249	0.517	0.312	0.643	0.378
ln(Employees)$_{t+1}$	1.458	0.653	1.717	0.729	0.002
ln(Revenue)$_{t+1}$	11.622	3.219	11.963	2.705	0.347
ln(Tangible Investment)$_{t+1}$	6.146	4.876	7.158	4.630	0.082
Venture Capital$_{t+1}$	0.030	0.170	0.037	0.190	0.736
Merger$_{t+1}$	0.007	0.086	0.007	0.086	1.000
Acquisition$_{t+1}$	0.007	0.086	0.000	0.000	0.318
Bankruptcy$_{t+1}$	0.037	0.190	0.037	0.190	1.000
Medium-term					
Innovation$_{t+j}$	0.474	0.501	0.622	0.487	0.014
Venture Capital$_{t+k}$	0.081	0.275	0.133	0.341	0.170
Merger$_{t+k}$	0.030	0.170	0.015	0.121	0.411
Acquisition$_{t+k}$	0.022	0.148	0.000	0.000	0.082
Bankruptcy$_{t+k}$	0.089	0.286	0.089	0.286	1.000

Notes: p-value of two-sided t-tests for mean difference between subsidized and non-subsidized start-ups. SD stands for standard deviation, j indicates innovation was introduced in either one of the three years following the subsidy receipt, k indicates event happened in any year after t as long as the firm is observed in the sample. One treated observation is lost due to lack of common support and 17 are dropped because of the caliper.

Table 3d: Differences in outcome variables after matching (grants versus grants & subsidized loans)

	Grant (selected control group) N= 110		Grant & Subsidized Loan N= 110		
Outcome variables	Mean	SD	Mean	SD	t-test
Immediate					
(R&D-Exp/ Employees)$_t$	468.352	1,585.451	577.904	1,468.551	0.596
(R&D-Emp/ Employees)$_t$	11.411	24.322	15.536	34.552	0.307
ln(R&D-Expenditure)$_t$	3.223	4.906	3.787	5.083	0.403
ln(R&D-Employees)$_t$	0.261	0.527	0.290	0.541	0.690
ln(Employees)$_t$	1.294	0.615	1.510	0.664	0.013
ln(Revenue)$_t$	10.166	3.819	10.909	3.251	0.122
ln(Tangible Investment)$_t$	8.052	3.824	9.495	3.316	0.003
Short-term					
(R&D-Exp/ Employees)$_{t+1}$	417.746	1,138.216	425.204	965.334	0.958
(R&D-Emp/ Employees)$_{t+1}$	11.199	23.047	10.649	24.531	0.864
ln(R&D-Expenditure)$_{t+1}$	3.881	5.151	3.697	5.178	0.791
ln(R&D-Employees)$_{t+1}$	0.269	0.568	0.282	0.602	0.875
ln(Employees)$_{t+1}$	1.355	0.620	1.618	0.666	0.003
ln(Revenue)$_{t+1}$	10.808	3.822	11.972	2.368	0.007
ln(Tangible Investment)$_{t+1}$	7.182	4.161	7.126	4.599	0.924
Venture Capital$_{t+1}$	0.036	0.188	0.045	0.209	0.735
Merger$_{t+1}$	0.009	0.095	0.009	0.095	1.000
Acquisition$_{t+1}$	0.018	0.134	0.000	0.000	0.157
Bankruptcy$_{t+1}$	0.091	0.289	0.036	0.188	0.098
Medium-term					
Innovation$_{t+j}$	0.500	0.502	0.636	0.483	0.041
Venture Capital$_{t+k}$	0.064	0.245	0.136	0.345	0.073
Merger$_{t+k}$	0.009	0.095	0.018	0.134	0.563
Acquisition$_{t+k}$	0.055	0.022	0.000	0.000	0.013
Bankruptcy$_{t+k}$	0.164	0.372	0.100	0.301	0.165

Notes: p-value of two-sided t-tests for mean difference between subsidized and non-subsidized start-ups. SD stands for standard deviation, j indicates innovation was introduced in either one of the three years following the subsidy receipt, k indicates event happened in any year after t as long as the firm is observed in the sample. One treated observation is lost due to lack of common support and 42 are dropped because of the caliper.

Table 4: Robustness tests for variation in treatment effects (α_i) over time and regions

	ΔEmployees	ΔRevenue	ΔTangible Investment	ΔR&D expenditures	ΔInnovation
Grant only					
before 2011	0.925	0.818	0.922	0.709	1.068
	(0.058)	(0.330)	(0.433)	(0.343)	(0.054)
East	1.069	0.939	1.818	6.743***	1.131
	(0.088)	(0.478)	(1.180)	(3.797)	(0.076)
# observations	732	732	732	732	732
R^2	0.003	0.000	0.001	0.014	0.007
Loan only					
before 2011	1.281	6.237**	0.451	0.395	0.950
	(0.166)	(3.721)	(0.403)	(0.391)	(0.094)
East	1.348	0.883	0.550	16.771*	1.086
	(0.337)	(0.692)	(0.747)	(20.065)	(0.165)
# observations	205	205	205	205	205
R^2	0.027	0.042	0.004	0.019	0.003
Both					
before 2011	0.790	0.913	0.200	0.465	0.925
	(0.114)	(0.671)	(0.244)	(0.616)	(0.112)
East	1.281	0.291	1.188	6.259	0.907
	(0.201)	(0.254)	(1.754)	(9.493)	(0.140)
# observations	135	135	135	135	135
R^2	0.041	0.016	0.014	0.015	0.006
Both versus grants					
before 2011	0.811	0.221	0.108	0.967	0.920
	(0.130)	(0.181)	(0.128)	(1.294)	(0.113)
East	0.989	0.351	0.483	2.778	0.854
	(0.205)	(0.384)	(0.692)	(4.299)	(0.119)
# observations	110	110	110	110	110
R^2	0.015	0.039	0.033	0.004	0.014

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%). Results obtained from OLS regressions. Robust standard errors in parentheses below coefficients. All models contain a constant (not presented).

Table 5a: Differences in outcome variables after matching, alternative specification for grants & subsidized loans

	Selected control group, N= 135		Grant & Subsidized Loan N= 135		
Outcome variables	Mean	SD	Mean	SD	t-test
Short-term					
(R&D-Exp/ Employees)$_{t+1}$	551.755	1,290.063	386.055	794.952	0.205
(R&D-Emp/ Employees)$_{t+1}$	15.388	27.733	12.610	25.718	0.394
ln(R&D-Expenditure)$_{t+1}$	4.070	5.133	4.444	5.480	0.563
ln(R&D-Employees)$_{t+1}$	0.325	0.512	0.384	0.724	0.434
ln(Employees)$_{t+1}$	1.422	0.628	1.764	0.751	0.001
ln(Revenue)$_{t+1}$	11.075	3.806	12.038	2.735	0.018
ln(Tangible Investment)$_{t+1}$	5.715	4.772	7.537	4.559	0.002
Venture Capital$_{t+1}$	0.037	0.190	0.052	0.223	0.556
Merger$_{t+1}$	0.015	0.121	0.007	0.086	0.563
Acquisition$_{t+1}$	0.007	0.086	0.000	0.000	0.318
Bankruptcy$_{t+1}$	0.037	0.190	0.030	0.170	0.736
Medium-term					
Innovation$_{t+j}$	0.422	0.496	0.652	0.478	0.001
Venture Capital$_{t+k}$	0.052	0.223	0.148	0.357	0.008
Merger$_{t+k}$	0.030	0.170	0.015	0.121	0.411
Acquisition$_{t+k}$	0.015	0.121	0.000	0.000	0.157
Bankruptcy$_{t+k}$	0.052	0.223	0.081	0.275	0.331

Notes: p-value of two-sided t-tests for mean difference between subsidized and non-subsidized start-ups. SD stands for standard deviation, j indicates innovation was introduced in either one of the three years following the subsidy receipt, k indicates event happened in any year after t as long as the firm is observed in the sample.

Table 5b: Differences in outcome variables after matching (alternative specification, grants versus grants & subsidized loans)

	Grant N= 110		Grant & subsidized loans N= 110		
Outcome variables	Mean	SD	Mean	SD	t-test
Short-term					
(R&D-Exp/ Employees)$_{t+1}$	524.488	1,456.105	401.432	865,180	0.447
(R&D-Emp/ Employees)$_{t+1}$	12.482	26.375	12.083	26.104	0.910
ln(R&D-Expenditure)$_{t+1}$	3.124	4.936	3.868	5.203	0.278
ln(R&D-Employees)$_{t+1}$	0.232	0.457	0.316	0.627	0.260
ln(Employees)$_{t+1}$	1.273	0.580	1.649	0.687	0.000
ln(Revenue)$_{t+1}$	10.969	3.290	12.102	2.088	0.003
ln(Tangible Investment)$_{t+1}$	7.086	4.328	7.366	4.451	0.637
Venture Capital$_{t+1}$	0.027	0.164	0.045	0.209	0.474
Merger$_{t+1}$	0.036	0.188	0.009	0.095	0.176
Acquisition$_{t+1}$	0.000	0.000	0.000	0.000	1.000
Bankruptcy$_{t+1}$	0.100	0.301	0.036	0.188	0.062
Medium-term					
Innovation$_{t+j}$	0.500	0.502	0.645	0.481	0.029
Venture Capital$_{t+k}$	0.055	0.228	0.118	0.324	0.094
Merger$_{t+k}$	0.036	0.188	0.018	0.134	0.410
Acquisition$_{t+k}$	0.018	0.134	0.000	0.000	0.157
Bankruptcy$_{t+k}$	0.155	0.363	0.082	0.275	0.096

Notes: p-value of two-sided t-tests for mean difference between subsidized and non-subsidized start-ups. SD stands for standard deviation, j indicates innovation was introduced in either one of the three years following the subsidy receipt, k indicates event happened in any year after t as long as the firm is observed in the sample.

Figures:

Figure 1: Investment without subsidy

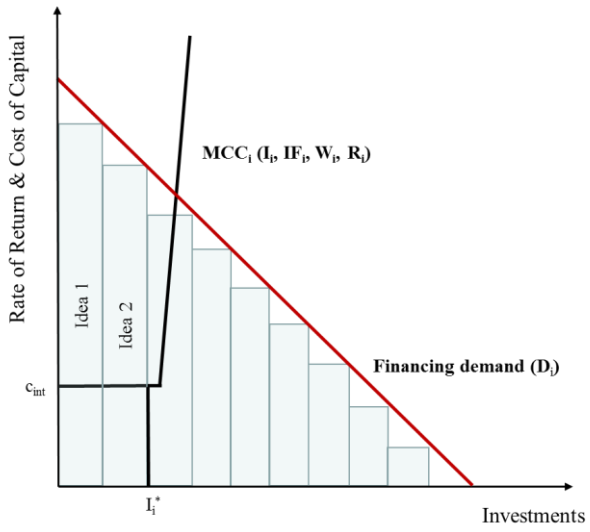


Figure 2: Investment with grants

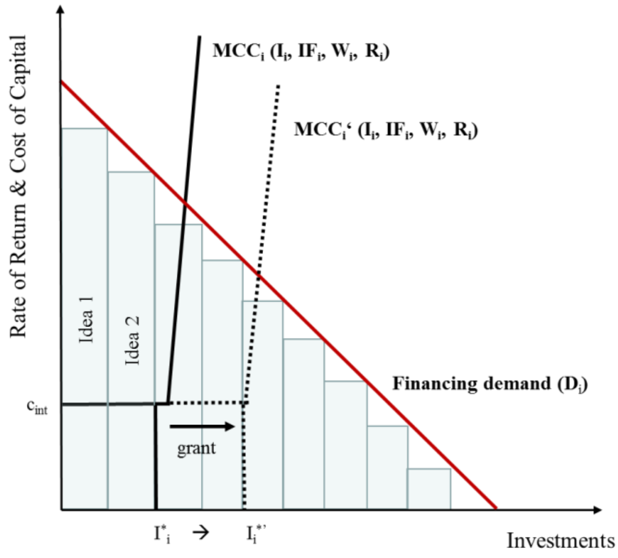


Figure 3: Investment with subsidized loans

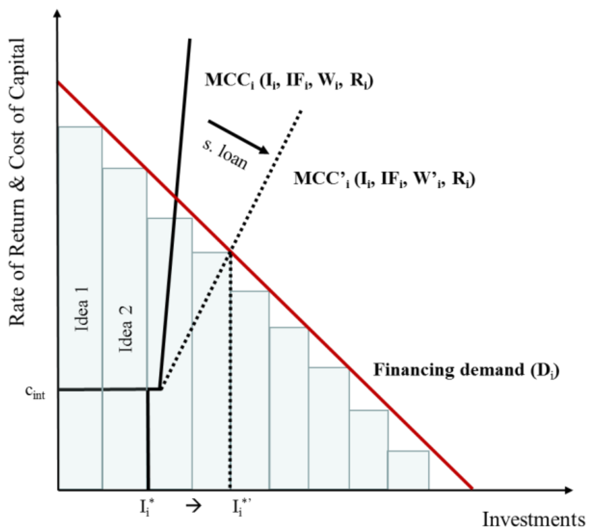
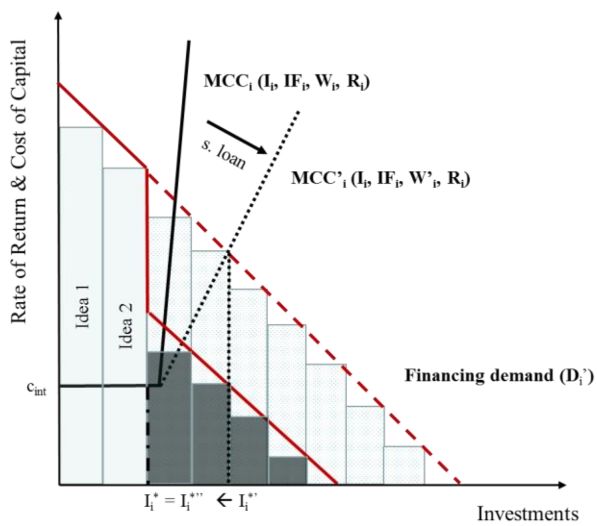


Figure 4: Investment with subsidized loans and failure risk



Appendix

Table A1: Sector definition and distribution

	NACE Rev. 1	%	with grant	with subsidized loan	with both
Cutting-edge technology manufacturing (N = 776)	23.30, 24.20, 24.41, 24.61, 29.11, 29.60, 30.02, 31.62, 32.10, 32.20, 33.20, 33.30, 35.30	14.73	0.179	0.079	0.054
High-technology manufacturing (N = 535)	22.33, 24.11, 24.12-4, 24.17, 24.30, 24.42, 24.62-4, 24.66, 29.12-4, 29.31-2, 29.40, 29.52-6, 20.01, 31.10, 31.40, 31.50, 23.30, 33.10, 33.40, 34.10, 34.30, 35.20	10.16	0.204	0.073	0.049
Technology-intensive services (N = 3,059)	64.2, 72 (w/o 72.2), 73.1, 74.2, 74.3	58.08	0.152	0.037	0.024
Software (N = 897)	72.2	17.03	0.122	0.026	0.014

Source: IAB/ZEW-Start-up Panel. N refers to the number of firm-year observations (Total N = 5,267).

Table A2a: Differences in control variables after matching (grants)

	Selected Control Group N= 732		**Grant N= 732**		
Control variables	Mean	SD	Mean	SD	t-test
University	0.340	0.474	0.329	0.470	0.658
Vocational training	0.190	0.392	0.186	0.389	0.841
Master craftsman	0.178	0.382	0.213	0.410	0.087
Founder age	44.440	10.989	44.456	8.978	0.975
Industry experience	16.389	10.036	16.469	8.982	0.874
Entrepreneurial experience	0.439	0.497	0.413	0.493	0.316
Bankruptcy experience	0.077	0.266	0.077	0.266	1.000
Opportunity driven	0.766	0.423	0.746	0.436	0.362
Team	0.361	0.481	0.363	0.481	0.914
Female	0.094	0.292	0.104	0.305	0.541
Start-up age$_{t-1}$	2.270	1.526	2.270	1.526	1.000
Limited liability	0.571	0.495	0.529	0.500	0.104
ln(Tangible assets)	5.895	4.450	5.849	4.484	0.843
Patent stock	0.108	0.676	0.089	1.064	0.682
Export activity$_{t-1}$	0.178	0.382	0.178	0.382	1.000
Capacity utilization$_{t-1}$	86.199	33.350	87.742	28.995	0.345
Bankruptcy index$_{t-1}$	0.397	0.182	0.378	0.174	0.044
GDP per capita$_{t-1}$	34.089	14.760	33.135	14.032	0.205
East	0.178	0.382	0.178	0.382	1.000
ln(R&D-Expenditure)$_{t-1}$	2.211	4.245	2.251	4.344	0.856
ln(Employees)$_{t-1}$	0.702	0.804	0.753	0.887	0.248
ln(Revenue)$_{t-1}$	5.813	5.976	6.170	5.941	0.252
ln(Tangible Investment)$_{t-1}$	4.647	4.954	4.779	4.972	0.611
Profit$_{t-1}$	15.443	73.702	10.881	72.358	0.232
Debt financing$_{t-1}$	20.603	19.303	20.961	20.927	0.734
Equity financing$_{t-1}$	2.486	5.404	2.756	8.077	0.453
Propensity score	0.231	0.110	0.234	0.111	0.562
Balancing test	*chi*^{2}(33) = 22.36 (p-value: 0.919)				

Notes: p-value of two-sided t-tests for mean difference between subsidized and non-subsidized start-ups. SD stands for standard deviation. The balancing test is based on overall model significance after matching. An insignificant test statistics indicates that the set of control variables in the prediction model no longer has any predictive power in the matched sample. No time subscript indicates that the information is time invariant or based on the founding year.

Table A2b: Differences in control variables after matching (subsidized loans)

	Selected Control Group N= 205		Subsidized Loan N=205		
Control variables	Mean	SD	Mean	SD	t-test
University	0.307	0.463	0.307	0.463	1.000
Vocational training	0.200	0.401	0.195	0.397	0.902
Master craftsman	0.263	0.442	0.278	0.449	0.740
Founder age	44.034	9.746	44.000	8.800	0.970
Industry experience	16.088	9.589	16.488	8.067	0.648
Entrepreneurial experience	0.405	0.492	0.395	0.490	0.841
Bankruptcy experience	0.102	0.304	0.073	0.261	0.296
Opportunity driven	0.795	0.405	0.790	0.408	0.903
Team	0.439	0.497	0.410	0.493	0.550
Female	0.146	0.354	0.122	0.328	0.470
Start-up age$_{t-1}$	2.210	1.260	2.210	1.260	1.000
Limited liability	0.615	0.488	0.561	0.497	0.271
ln(Tangible assets)	4.823	4.618	4.944	4.720	0.793
Patent stock	0.068	0.321	0.098	0.664	0.570
Export activity$_{t-1}$	0.166	0.373	0.166	0.373	1.000
Capacity utilization$_{t-1}$	88.936	26.740	89.821	28.378	0.745
Bankruptcy index$_{t-1}$	0.373	0.167	0.377	0.191	0.815
GDP per capita$_{t-1}$	33.668	13.518	32.348	11.338	0.285
East	0.083	0.276	0.083	0.276	1.000
ln(R&D-Expenditure)$_{t-1}$	2.011	4.022	1.672	3.859	0.385
ln(Employees)$_{t-1}$	0.685	0.745	0.713	0.898	0.734
ln(Revenue)$_{t-1}$	6.565	5.903	6.732	6.118	0.779
ln(Tangible Investment)$_{t-1}$	5.043	4.937	5.551	5.266	0.314
Profit$_{t-1}$	14.877	39.834	15.577	83.249	0.914
Debt financing$_{t-1}$	20.091	17.155	21.758	19.818	0.363
Equity financing$_{t-1}$	2.302	2.277	2.532	6.661	0.641
Propensity score	0.093	0.065	0.095	0.065	0.794
Balancing test	*chi*^{2}(33) = 9.87 (p-value: 1.000)				

Notes: p-value of two-sided t-tests for mean difference between subsidized and non-subsidized start-ups. SD stands for standard deviation. The balancing test is based on overall model significance after matching. An insignificant test statistics indicates that the set of control variables in the prediction model no longer has any predictive power in the matched sample. No time subscript indicates that the information is time invariant or based on the founding year.

Table A2c: Differences in control variables after matching (grants & subsidized loans)

Control variables	Selected Control Group N= 135		Grant & Subsidized Loan N= 135		
	Mean	SD	Mean	SD	t-test
University	0.252	0.436	0.289	0.455	0.495
Vocational training	0.222	0.417	0.215	0.412	0.884
Master craftsman	0.185	0.390	0.237	0.427	0.298
Founder age	45.615	9.042	44.422	9.202	0.284
Industry experience	17.548	9.643	16.778	9.185	0.502
Entrepreneurial experience	0.407	0.493	0.407	0.493	1.000
Bankruptcy experience	0.044	0.207	0.111	0.315	0.041
Opportunity driven	0.926	0.263	0.844	0.364	0.036
Team	0.496	0.502	0.467	0.501	0.628
Female	0.111	0.315	0.111	0.315	1.000
Start-up age	1.963	1.278	1.963	1.278	1.000
Limited liability	0.600	0.492	0.563	0.498	0.539
ln(Tangible assets)	5.494	4.766	5.562	4.694	0.905
Patent stock	0.096	0.771	0.193	1.401	0.485
Export activity	0.163	0.371	0.163	0.371	1.000
Capacity utilization	87.943	31.596	85.351	31.197	0.498
Bankruptcy index	0.375	0.169	0.360	0.160	0.473
GDP per capita	34.903	17.983	33.210	15.075	0.403
East	0.267	0.444	0.267	0.444	1.000
ln(R&D-Expenditure)$_{t-1}$	1.772	3.957	1.832	4.107	0.904
ln(Employees)$_{t-1}$	0.647	0.832	0.587	0.913	0.572
ln(Revenue)$_{t-1}$	5.455	5.862	5.181	5.833	0.701
ln(Tangible Investment)$_{t-1}$	4.618	5.236	4.807	5.329	0.769
Profit$_{t-1}$	3.088	56.766	2.867	43.584	0.971
Debt financing$_{t-1}$	22.645	20.087	22.596	19.755	0.984
Equity financing$_{t-1}$	2.725	8.596	3.158	8.579	0.679
Propensity score	0.092	0.079	0.094	0.081	0.851
Balancing test	*chi*^{2}(33) = 19.61 (p-value: 0.969)				

Notes: p-value of two-sided t-tests for mean difference between subsidized and non-subsidized start-ups. SD stands for standard deviation. The balancing test is based on overall model significance after matching. An insignificant test statistics indicates that the set of control variables in the prediction model no longer has any predictive power in the matched sample. No time subscript indicates that the information is time invariant or based on the founding year.

Table A2d: Differences in control variables after matching (grants versus grants & subsidized loans)

Control variables	Grant (Selected Control Group) N= 110		Grant & Subsidized Loan N= 110		
	Mean	SD	Mean	SD	t-test
University	0.264	0.443	0.282	0.452	0.763
Vocational training	0.236	0.427	0.209	0.409	0.629
Master craftsman	0.227	0.421	0.227	0.421	1.000
Founder age	43.018	9.222	43.173	8.865	0.899
Industry experience	15.318	8.730	15.936	8.799	0.602
Entrepreneurial experience	0.355	0.481	0.364	0.483	0.889
Bankruptcy experience	0.100	0.301	0.100	0.301	1.000
Opportunity driven	0.809	0.395	0.827	0.380	0.728
Team	0.427	0.497	0.436	0.498	0.892
Female	0.091	0.289	0.100	0.301	0.820
Start-up age$_{t-1}$	1.718	1.042	1.718	1.042	1.000
Limited liability	0.482	0.502	0.536	0.501	0.421
ln(Tangible assets)	5.742	4.395	5.870	4.597	0.834
Patent stock	0.100	0.867	0.218	1.541	0.484

Export activity$_{t-1}$	0.118	0.324	0.145	0.354	0.552
Capacity utilization$_{t-1}$	82.773	27.626	86.476	33.306	0.370
Bankruptcy index$_{t-1}$	0.392	0.171	0.362	0.163	0.179
GDP per capita$_{t-1}$	33.998	16.494	33.679	14.952	0.881
East	0.255	0.438	0.273	0.447	0.761
ln(R&D-Expenditure)$_{t-1}$	1.980	4.275	1.164	3.377	0.118
ln(Employees)$_{t-1}$	0.441	0.694	0.394	0.720	0.619
ln(Revenue)$_{t-1}$	3.954	5.465	4.025	5.526	0.924
ln(Tangible Investment)$_{t-1}$	3.502	4.716	3.620	4.995	0.857
Profit$_{t-1}$	-7.500	153.810	2.782	27.656	0.491
Debt financing$_{t-1}$	18.270	11.849	18.270	11.849	1.000
Equity financing$_{t-1}$	3.779	10.691	2.542	3.638	0.252
Propensity score	0.196	0.104	0.199	0.099	0.801
Balancing test	*chi*^{2}(33) = 14.09 (p-value: 0.998)				

Notes: p-value of two-sided t-tests for mean difference between subsidized and non-subsidized start-ups. SD stands for standard deviation. The balancing test is based on overall model significance after matching. An insignificant test statistics indicates that the set of control variables in the prediction model has any predictive power in the matched sample. No time subscript indicates that the information is time invariant or based on the founding year.

Table A3a: Differences in control variables after matching (alternative specification grants & subsidized loans)

	Selected control group N= 135		**Grant & Subsidized Loan N= 135**		
Control variables	Mean	SD	Mean	SD	t-test
University	0.244	0.431	0.311	0.465	0.223
Vocational training	0.237	0.427	0.207	0.407	0.560
Master craftsman	0.200	0.401	0.222	0.417	0.656
Founder age	45.837	10.468	44.644	9.266	0.323
Industry experience	17.755	9.883	17.015	9.418	0.529
Entrepreneurial experience	0.444	0.499	0.400	0.492	0.462
Bankruptcy experience	0.163	0.371	0.116	0.324	0.296
Opportunity driven	0.800	0.401	0.844	0.364	0.341
Team	0.489	0.502	0.504	0.502	0.809
Female	0.207	0.407	0.148	0.356	0.204
Start-up age$_{t-1}$	2.000	1.333	2.000	1.333	1.000
Limited liability	0.652	0.478	0.578	0.496	0.213
ln(Tangible assets)	5.459	4.586	5.471	4.677	0.982
Patent stock	0.089	0.465	0.200	1.403	0.383
Export activity$_{t-1}$	0.178	0.384	0.178	0.384	1.000
Capacity utilization$_{t-1}$	86.147	26.603	85.647	30.152	0.885
Bankruptcy index$_{t-1}$	0.347	0.165	0.363	0.159	0.416
GDP per capita$_{t-1}$	31.319	13.228	33.550	15.355	0.202
East	0.252	0.436	0.252	0.436	1.000
ln(R&D-Expenditure)$_{t-1}$	1.959	4.170	1.765	4.179	0.703
ln(Employees)$_{t-1}$	0.554	0.727	0.575	0.923	0.835
ln(Revenue)$_{t-1}$	4.933	5.849	5.040	5.838	0.881
ln(Tangible Investment)$_{t-1}$	4.448	5.011	4.880	5.411	0.497
Profit$_{t-1}$	10.889	36.997	-1.325	55.121	0.033
Debt financing$_{t-1}$	19.435	14.023	22.167	17.860	0.163
Equity financing$_{t-1}$	2.388	2.023	3.409	7.590	0.132
Propensity score	0.086	0.073	0.090	0.076	0.678
Balancing test	*chi*^{2}(33) = 28.41 (p-value: 0.695)				

Notes: p-value of two-sided t-tests for mean difference between subsidized and non-subsidized start-ups. SD stands for standard deviation. The balancing test is based on overall model significance after matching. An insignificant test statistics indicates that the set of control variables in the prediction model has any predictive power in the matched sample. No time subscript indicates that the information is time invariant or based on the founding year.

Table A3b: Differences in control variables after matching (alternative specification, grants versus grants & subsidized loans)

	Grant (Selected Control Group) N= 110		Grant & Subsidized Loan N= 110		
Control variables	Mean	SD	Mean	SD	t-test
University	0.318	0.468	0.273	0.447	0.462
Vocational training	0.182	0.387	0.191	0.395	0.863
Master craftsman	0.236	0.427	0.236	0.427	1.000
Founder age	43.582	8.132	43.318	8.748	0.817
Industry experience	15.545	8.830	15.955	8.926	0.733
Entrepreneurial experience	0.427	0.497	0.345	0.478	0.215
Bankruptcy experience	0.136	0.345	0.100	0.301	0.406
Opportunity driven	0.818	0.387	0.827	0.380	0.861
Team	0.400	0.492	0.418	0.496	0.785
Female	0.073	0.261	0.118	0.324	0.253
Start-up age$_{t-1}$	1.727	1.040	1.727	1.040	1.000
Limited liability	0.509	0.502	0.527	0.502	0.788
ln(Tangible assets)	6.715	4.188	5.602	4.627	0.063
Patent stock	0.073	0.351	0.227	1.542	0.307
Export activity$_{t-1}$	0.109	0.313	0.154	0.363	0.321
Capacity utilization$_{t-1}$	78.506	29.784	86.340	32.662	0.064
Bankruptcy index$_{t-1}$	0.371	0.160	0.369	0.165	0.940
GDP per capita$_{t-1}$	31.999	12.348	33.848	14.738	0.314
East	0.255	0.438	0.273	0.447	0.761
ln(R&D-Expenditure)$_{t-1}$	1.182	3.417	1.080	3.284	0.821
ln(Employees)$_{t-1}$	0.344	0.602	0.367	0.720	0.794
ln(Revenue)$_{t-1}$	4.117	5.381	4.218	5.569	0.891
ln(Tangible Investment)$_{t-1}$	3.864	4.924	3.893	5.058	0.966
Profit$_{t-1}$	7.572	56.441	0.318	37.469	0.263
Debt financing$_{t-1}$	18.512	11.659	18.512	11.659	1.000
Equity financing$_{t-1}$	2.603	4.066	3.294	7.986	0.420
Propensity score	0.203	0.105	0.207	0.105	0.790
Balancing test	$chi^2(33) = 22.50$ (p-value: 0.916)				

Notes: p-value of two-sided t-tests for mean difference between subsidized and non-subsidized start-ups. SD stands for standard deviation. The balancing test is based on overall model significance after matching. An insignificant test statistics indicates that the set of control variables in the prediction model has any predictive power in the matched sample. No time subscript indicates that the information is time invariant or based on the founding year.

Figure A.1: Investment with grants (left) or subsidized loans (right) in absence of financing constraints

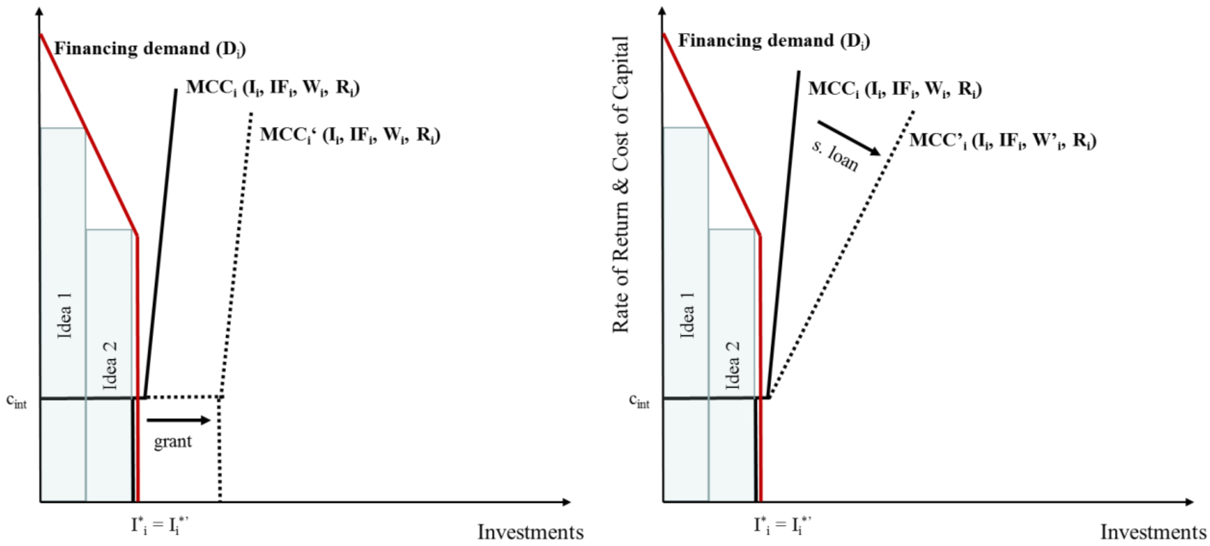


Figure A.2: Subsidies for high-tech start-ups by type (sample shares)

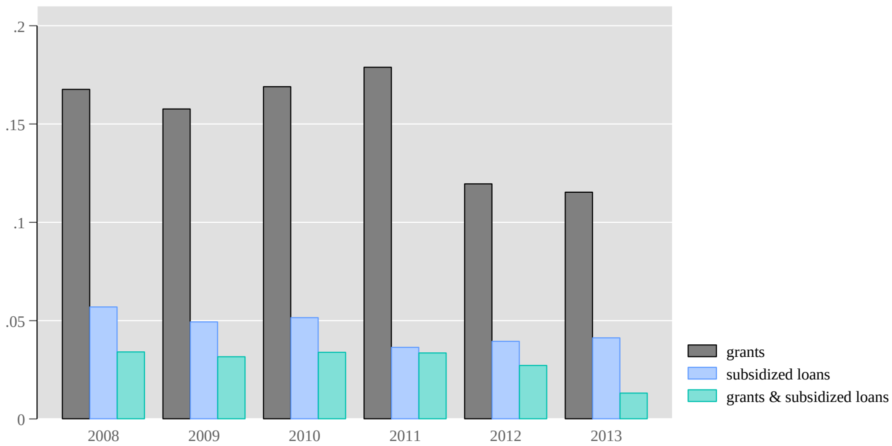
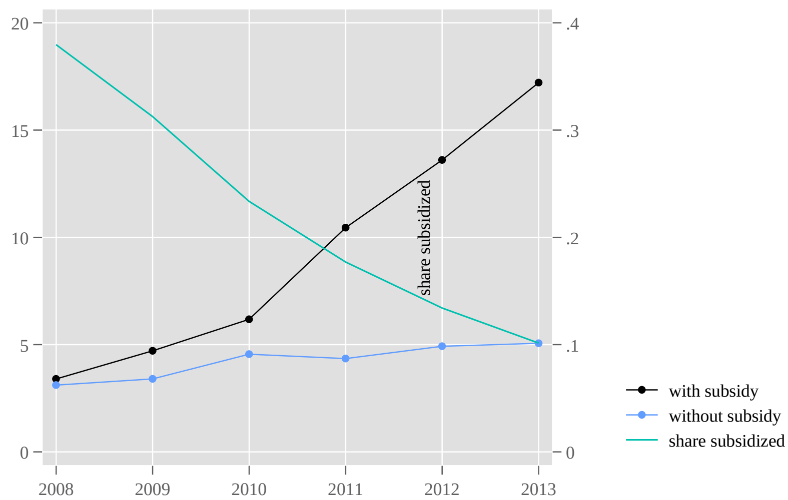


Figure A.3: Employment growth for subsidized and unsubsidized start-ups (2008 cohort)



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