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Subsidizing Start-Ups:
Policy Targeting and Policy Effectiveness

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Abstract

Start-up subsidies are a frequently employed policy instrument, the use of which is justified by alleged market failure resulting from positive external effects and capital market imperfections. This article investigates whether the allocation of subsidies reflects a policy focus on addressing these market failure occurrences. However, using survey data from the East German state of Thuringia, logistic regressions reveal a rather random subsidization of start-ups. Furthermore, propensity score matching suggests that subsidized start-ups would have survived and thrived in any case, an indication of deadweight losses of start-up subsidies. The analysis points to serious information problems arising when subsidies should be allocated to remedy market failure. Making the situation even more problematic is that failure to precisely target start-up subsidies is likely to result in market distortions and ineffectiveness.

Key words: Start-ups; Subsidies; Subsidy allocation; Policy evaluation

JEL classification: L53; O38; H59

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1. Introduction

Entrepreneurship plays an increasingly prominent role in both academic and policy circles. It is regarded as the driving force behind structural change that links investments in knowledge with economic growth (Audretsch and Thurik, 2001). The increased role of new and small enterprises has led to an increase in entrepreneurship policies aimed at encouraging more people to consider entrepreneurship as an option and act on a business idea (Lundström and Stevenson, 2005). Especially in East Germany, which still lags behind West Germany in all economic performance indicators, policymakers pin their hopes on various policy instruments (Bundesregierung, 2007). Although entrepreneurship policies focus on soft policy instruments like consulting services, the overall subsidy environment is dominated by soft loans, loan guarantees, and grants—offering start-ups an extensive choice of support (Thüringer Aufbaubank, 2008). The policy focus on hard policy instruments is also reflected in the allocation of public funds. For example, although 5.3 million Euro were allocated to public initiatives offering consulting services to Thuringian business founders in 2005 and 2006, direct financial subsidies for business set-ups in Thuringia amounted to more than 104 million Euro during that same period (TMWTA, 2007).[1]

Traditionally, policy intervention in favor of nascent and young entrepreneurs and their start-ups is justified by presumed market failure. First, positive externalities accruing from entrepreneurship create a disparity in the valuation of (potential) entrepreneurs by investors and policymakers (Audretsch et al., 2007). Whereas individual entrepreneurs and investors are only interested in single firm performance, policymakers should be more interested to allow for positive external effects. Second, policy intervention aims at remedying asymmetric information, which has been argued to restrict young and small firms' access to capital and thus hinder entrepreneurial performance (van Praag et al., 2005). Start-ups differ in both their ex-ante characteristics, such as economic and environmental features, and by the individual characteristics of their founders and, therefore, capital constraints will also vary (Blumberg and Letterie, 2008). Similarly, positive external effects do not accrue from every entrepreneurial project (Santarelli and Vivarelli, 2007; Fritsch and Schroeter, 2009).

The identification of market failures that hamper the start-up and growth of otherwise efficient ventures is thus a necessary but not sufficient condition for effective and efficient

[1] The latter figure comprises only those funds from the *Gemeinschaftsaufgabe „Verbesserung der regionalen Wirtschaftsstruktur" (GA)* (TMWTA, 2007), which are allocated for genuine business start-ups and for setting up new branches of existing businesses. Although the *GA* is the most important scheme of German regional policy, there are other programs that offer soft loans, loan guarantees, and grants to Thuringian start-ups (TMWTA, 2007; Thüringer Aufbaubank, 2008).

policy intervention. When deciding on policy intervention, policymakers should be aware of the market distortions that can result from subsidization. Market distortions arise because policymakers and program officials do not have complete information which would allow to fund marginal projects. In the absence of complete information, public support schemes give subsidized start-ups an artificial competitive edge that could lead to their substitution for other start-ups or incumbents that are ex-ante more efficient but nonsubsidized. In general, the distortions arising from substitution effects are larger than those resulting from deadweight losses: not only is public money spent ineffectively, but the subsidy enables the subsidized start-up to crowd out a potentially more efficient firm (Santarelli and Vivarelli, 2007).

The start-up subsidy environment is diverse. Various subsidization policies coexist, leading to a broad range of support schemes administered by a similarly broad range of agencies (TMWTA, 2007). In this study, I do not examine a specific scheme but take an aggregate view of the receipt of any kind of financial subsidy within the first three business years of a start-up. I use data from 162 start-ups in innovative industries in the East German state of Thuringia.[2] More than 45% of these start-ups make use of financial subsidies which are primarily given as soft loans, loan guarantees, or grants. A broad set of ex-ante characteristics allows me to analyze the allocation of subsidies. Does the allocation of subsidies provide evidence of policy geared toward positive external effects? Or is the policy instead focused on remedying capital market imperfections? The answer to both questions turns out to be “no”. Logistic regressions reveal that the allocation of subsidies is neither based on the rationale of positive external effects nor on subsidies’ potential to cure capital market imperfections. Instead, the rather random subsidization reveals likely substitution effects. Moreover, I apply propensity score matching to identify the causal effect of subsidization and find neither a significant effect of subsidies on business survival nor on employment growth. The matching results suggest that subsidized start-ups would have survived and thrived in any case and thus indicate deadweight losses. These findings highlight the relevance of information and incentive problems when designing and allocating start-up subsidies, since policy targeting affects potential market distortions and policy effectiveness.

The remainder of the article is structured as follows. The next section contains a review of the literature that examines the market failure argument to justify start-up subsidies. Ex-ante characteristics of start-ups that are most likely to be affected by market failure are

[2] This subset of a larger survey does not contain start-ups that engage in R&D within the first three business years, since they are eligible for R&D subsidies whose effectiveness has been examined in a previous study (Cantner and Kösters, 2009a, b). R&D subsidies have been found to be highly effective, leading to an increase in employment growth of about 66% and a rise in patent output of 184%. However, start-ups that do not engage in R&D are also widely subsidized and therefore justify a separate analysis.

derived and the market distortions resulting from policy intervention are discussed. In the empirical analysis (Section 3), a logistic regression first investigates the characteristics of subsidized start-ups. Second, I employ propensity score matching to examine the effectiveness of financial subsidies in the survival and growth of start-ups. Section 4 concludes.

2. Rationale for (no) policy intervention

Incidences of market failure constitute a necessary but not sufficient condition for policy intervention. Market failure arises from a lacking appropriability of returns from entrepreneurial activity (Section 2.1) as well as from asymmetric information leading to capital market imperfections (Section 2.2). In these two sections, the ex-ante characteristics of start-ups that will likely lead to market failure, and that thus should guide subsidy allocation, are derived. Section 2.3 then summarizes these conjectures for subsidy allocation and discusses the implications of policy targeting for market distortions and policy effectiveness.

2.1 Positive external effects

Audretsch and Thurik (2004) identify three channels through which entrepreneurial activity has an impact on economic growth. First, entrepreneurship spurs knowledge spillovers, since it is a mechanism by which knowledge—captured in founders and their business ideas—is commercialized. Second, entrepreneurship is accompanied by firm entry, exit, and turnover, which implies increased competition. Increased competition will be more conducive to knowledge externalities (Jacobs, 1969; Porter, 1990) because it increases the pressure to innovate. Third, a start-up contributes to diversity since it is an attempt to commercialize knowledge that otherwise would have remained uncommercialized (Audretsch and Keilbach, 2004). Increased diversity among firms and a higher variety of enterprises are argued to enhance regional growth since knowledge spillovers external to an industry are believed to be the most valuable kind (Jacobs, 1969; Glaeser et al., 1992). However, industry characteristics can create a tradeoff between the benefits of diversity resulting from a high number of small firms and large firms' advantage of appropriating the returns from innovative activity (Cohen and Klepper, 1992). For instance, an industry structure dominated by many small firms will be socially beneficial if the respective technology is characterized by a number of different approaches to innovation and if appropriability can be ensured by rapid growth, licensing, and other mechanisms.

The above mechanisms make clear that entrepreneurship does not always contribute to economic growth. Santarelli and Vivarelli (2007) point out that new firm formation leads not only to Schumpeterian "creative destruction", but also to "market churning", which occurs when ill-equipped firms continuously enter and exit the market. Market churning is reflected in the positive correlation between entry and exit rates that is found in many empirical studies (Bartelsman et al., 2005; Geroski, 1995). High-quality start-ups are argued to contribute most to economic performance (Fritsch, 2008). The characteristics and impact of these high-quality start-ups include the following. First, *innovative* start-ups commercialize knowledge and thus give rise to knowledge spillovers. Their innovations imply greater variety for customers and better matching customer preferences and will, ultimately, result in higher utility for customers (Fritsch, 2008). Innovative start-ups are additionally characterized by a *high endowment of human capital* because a rich knowledge base enables the recognition and exploitation of high-quality entrepreneurial opportunities (Ucbasaran et al., 2009; Baron, 2006). Entrepreneurs' human capital positively affects the post-entry performances of their start-ups and will thus contribute to static and dynamic efficiency (Colombo and Grilli, 2005; Fritsch, 2008). The empirical evidence supports the view that innovative start-ups and/or start-ups with a high endowment of human capital make a strong contribution to structural change (Acs and Mueller, 2008; Baptista and Preto, 2006).

Second, start-ups with superior *financial resources* have higher survival chances and better performance (Cooper et al., 1994; Holtz-Eakin et al., 1994; Brüderl et al., 1992). Cooper et al. (1994) argue that initial capital has both direct and indirect impacts on performance. As a direct effect, financial resources allow start-ups to pursue more capital-intensive strategies (which might be more efficient and better protected from imitation) and to realize venture growth. Furthermore, financial resources constitute a buffer against random shocks. Indirectly, superior financial resources might reflect higher endowments of human capital and more extensive planning that has attracted outside lenders and investors. Start-ups with high endowments of financial capital are thus able to mount a greater challenge to incumbents and, in this way, will ensure efficiency and stimulate productivity (Fritsch, 2008).

Third, the rare phenomenon of *high-growth entrepreneurship* accounts disproportionately for innovative change and economic growth (Autio, 2005; Henrekson and Johansson, 2008; Wong et al., 2005; Stam et al., 2009). There are various definitions of and terms used to describe high-growth entrepreneurship (Buss, 2002), ranging from "gazelles"

(Birch, 1979) to "high-expectation" (Autio, 2005) and "ambitious" start-ups (Stam et al., 2009).[3] All these definitions, though, have in common that they combine the above characteristics (innovativeness, rich endowment with human capital, and financial capital) with an ambition to grow.

To sum up, the impact of heterogeneous start-up activity on economic performance is ambiguous. Nevertheless, there is some evidence that *innovative, well-equipped (in terms of a rich knowledge base* and *financial strength),* and *growth-oriented* start-ups yield positive external effects in the long run.[4] This is especially true if they are started in a supportive regional environment (Fritsch, 2008). For instance, Fritsch and Mueller (2004) find that new business formation has a particularly strong impact on employment change in agglomerations and high-productivity regions, whereas even a negative impact can be observed in regions with low productivity. Entrepreneurial activity varies not only within but across countries. Cross-country studies find that the impact of entrepreneurial activity on a country's innovative capacity (Wennekers et al., 2005), as well as on its macro-economic performance, increases with per capita income (Thurik et al., 2008; van Stel et al., 2005; Stam et al., 2009). This work thus suggests that entrepreneurship plays different roles in different countries, depending on their stage of economic development. It is important to note, also, that positive external effects only become apparent in the long run: the estimated time lag between entrepreneurial activity and subsequent economic performance can be as much as 10 years (Fritsch and Mueller, 2004; Thurik et al., 2008; van Stel and Suddle, 2007).

More generally, Auerswald (2007) questions whether potential social returns from innovative entrepreneurial activity are a suitable rationale for policy intervention. He argues that innovative start-ups can give rise to knowledge spillovers but, at the same time, can reap considerable private returns from their innovation due to legal protection in the product market or because of high entry costs for potential imitators. Furthermore, the social benefits accruing from innovative entrepreneurship are uncertain and will generally lie far in the future. They are thus unlikely to much of a motivating factor in the entrepreneur's decision-making process. Therefore, Auerswald argues that information asymmetries affect

[3] For instance, high-potential innovative start-ups are defined by the Global Entrepreneurship Monitor as ventures that fulfill the following criteria: (1) start-up aims to employ at least 20 employees in five years; (2) the start-up indicates at least some market creation impact; (3) the start-up targets international markets to the extent that at least one-fourth of its customer base is abroad; and (4) the applied technologies had not been widely available more than a year ago (Wong et al., 2005).

[4] Even failed start-ups may give rise to positive externalities since they may have challenged incumbents and given rise to knowledge externalities, e.g., when the ideas and experiences of their former employees become an integral part of products made by successful firms (Audretsch et al., 2007; Fritsch, 2008).

(technology) entrepreneurship far more than positive external effects do. I thus turn next to capital constraints, which result from information asymmetries.

2.2 Capital constraints

Information imperfections leading to credit market failure are accused of creating a barrier to the acquisition of loan capital by nascent and young entrepreneurs. If this is indeed the case, such imperfections thus impede the actual start-up of a venture as well as jeopardize both its survival and growth. Stiglitz and Weiss (1981) argue that credit rationing characterizes the equilibrium state if banks cannot observe borrowers' risks. In the presence of imperfect information, the price (i.e., the interest rate) affects the nature of the transaction since increasing interest rates or collateral requirements attract riskier entrepreneurs (adverse selection) and induce borrowers to invest in riskier projects (moral hazard). Therefore, it may not be profitable for a bank to raise interest rates to clear the market, but it will rather limit the number of loans. In other words, credit rationing implies that banks grant credit only to a fraction of observationally identical projects. A project could still be denied credit even if it offered to pay a higher interest rate (Parker, 2002). The likelihood of credit rationing is, ceteris paribus, higher for start-ups and small firms because the fixed costs of granting and servicing loans lower the profit margin on lending to smaller businesses. Furthermore, according to Blumberg and Letterie (2008), the fewer the number of repeat transactions, the less the incentive for business analysts to collect information and the fewer the instruments with which start-ups can signal their credibility. Asymmetric information can be resolved by commitments such as collateral, the investment of own resources, and the provision of costly information that increase the credibility of the credit application. Additionally, founders can signal good prospects for later business success since banks are interested in long-term relationships with successful start-ups (Storey, 1993; Blumberg and Letterie, 2008). However, the theoretical case for credit rationing is ambiguous. De Meza and Webb (1987) diagnose the problem as overlending rather than credit rationing when just slightly modifying the assumptions of the Stiglitz and Weiss model.[5] This theoretical debate has spawned a huge body of empirical literature analyzing the impact of capital constraints on the decision to start a venture as well as on the performance of newborn firms (Cressy, 2002; van Praag et al., 2005).

[5] De Meza and Webb (1987) allow the expected return to vary across firms, whereas Stiglitz and Weiss (1981) assume that all firms have the same expected return but that the dispersion of returns is different.

The extent of credit constraint will vary across heterogeneous start-ups, depending on individual characteristics of the founders and their start-ups (Blumberg and Letterie, 2008). First, *innovative start-ups* are argued to be particularly affected by asymmetric information in capital markets (Colombo and Grilli, 2007; Carpenter and Petersen, 2002; Guiso, 1998) since the returns from innovative activity are uncertain, highly skewed, and difficult for outsiders to evaluate. Additionally, investment in innovative activity mainly encompasses salaries and the acquisition of highly specialized assets, neither of which provide much collateral value in the event of failure (Carpenter and Petersen, 2002). Parker and van Praag (2006) find that entrepreneurs in capital-intensive industries are significantly more likely to be affected by credit constraints. Since this effect is in addition to the scale effect from higher capital needs, they argue that banks' screening errors are systematically greater in industries in which production techniques are more complicated and involve intangible capital. Still, innovative start-ups might self-select into other forms of lending (Åstebro and Bernhardt, 2003; Carpenter and Petersen, 2002), therefore easing potential capital constraints. Carpenter and Petersen (2002) argue that equity financing has a number of advantages over debt for highly innovative firms since equity financing allows unbounded upside returns for investors. Furthermore, it neither increases a start-up's probability of financial distress nor does it induce managers to engage in excessively risky projects. However, Lerner (2002) points to the limited scope of the venture capital industry, which backs only a tiny fraction of technology-oriented start-ups.

Ventures started by founders with limited *financial resources* might be a second group that suffers from capital constraints. Poor people's restricted access to credit markets can be explained by their inability to commit themselves by investing own resources. The commitment of personal wealth is another important mechanism for mitigating asymmetric information (Blumberg and Letterie, 2008). This implies that collateral-based lending tends to discriminate against the poor, regardless of the quality of the project itself (Cowling and Mitchell, 2003). Van Praag et al. (2005) summarize studies that relate personal wealth to various performance measures of entrepreneurial ventures, all of which finds either a positive or no impact of assets on performance. This literature can be traced back to Evans and Jovanovic (1989), who estimate that the capital stock that entrepreneurs can invest is restricted to 1.5-fold of their initial assets. In this way, liquidity constraints prevent people with few assets from either engaging in entrepreneurship altogether, or force them to start a business with less than the optimal amount of capital. On the other hand, however, a lack of personal assets may suggest a lack of human capital, implying, in turn, deficient economic viability of the venture (Parker and van Praag, 2006). This endogeneity problem is solved when the relationship between windfall gains (e.g., inheritances or lottery prizes) and performance is analyzed. Nevertheless, such studies still point to the presence of liquidity constraints, since the receipt of windfall gains increases the probability of becoming self-employed and enhances start-up performance (Lindh and Ohlsson, 1996; Taylor, 2001, Holtz-Eakin et al., 1994).

Finally, capital constraints might particularly affect start-ups endowed with *low human capital*, since they are deprived of an important signaling mechanism that helps overcome asymmetric information. Low human capital implies both a limited chance of success of the start-up and low post-failure earning capacity. However, a positive assessment of the potential for success and the consequently increased probability that the founder will be able to repay the debt is crucial in overcoming a bank's reluctance to lend (Blumberg and Letterie, 2008). Empirically, Åstebro and Bernhardt (2005), as well as Parker and van Praag (2006), show that higher endowments of human capital lower initial capital constraints. Åstebro and Bernhardt (2005) find this effect to be nonlinear, that is, a high-school diploma offsets the credit constraint, but higher levels of education have only limited impact on reducing capital constraints. In contrast to the studies discussed above, Cressy (1996) finds that the positive relation between financial capital and survival disappears once human capital is controlled for. This finding throws doubt on the case for credit rationing since financing decisions made on the basis of observable characteristics such as human capital merely reflect the bank's desire to allocate funds wisely.

In summary, although credit rationing cannot be rejected on theoretical grounds, the empirical evidence for it appears to be rather limited at best, no doubt in part due to the difficulty of identifying credit rationing. On the one hand, there are at least two reasons why a positive effect of financial variables on performance does not necessarily imply credit rationing (Parker, 2002; van Praag et al., 2005). First, these studies make the initial assumption that there is no direct way of obtaining external finance (van Praag et al., 2005). Second, the problem of endogeneity is often neglected. Endogeneity arises because assets could have been accumulated by superior entrepreneurial ability (human capital), which is in turn responsible for above-average entrepreneurial performance. On the other hand, survey studies measure the extent of credit constraints more directly. Levenson and Willard (2002) analyze survey data from the United States in the late 1980s and find that 6.36% firms are credit-rationed, which is stated to be an outside estimate because this figure includes discouraged borrowers and unsuccessful applicants who might not be creditworthy. Using Dutch survey data from the mid-1990s, Parker and Van Praag (2006) find that 19% of new founders obtained less finance than they required. However, self-reports of credit constraints bear the risk of bias, since entrepreneurs might see the lack of external finance as the main cause of their problems, whereas it might be just a symptom of other deficiencies of the start-up (Santarelli and Vivarelli, 2007; Parker, 2002). Additionally, empirical studies differ in their definitions of credit rationing.[6] Parker (2002) thus questions whether credit rationing is a suitable rationale for policy intervention and points to positive external effects of entrepreneurship, thereby contradicting Auerswald (2007). Having in mind data and measurement limitations, the literature summarized above nevertheless suggests that *innovative* start-ups as well as start-ups with *few financial resources* and *low endowments of human capital* are more likely to be affected by capital constraints.

2.3 Targeting of policy intervention

The previous subsections have shown that the extent of positive external effects and capital market imperfections is disputed (Auerswald, 2007; Parker, 2002). Nevertheless, regardless of the degree to which they exist, they may still hamper start-up and growth of efficient ventures and thus constitute a necessary condition for policy intervention. However, the information requirements for identifying incidences of market failure are extremely demanding. Not only do policymakers and funding agencies need to know social and private returns ex-ante in order to discern external effects, they also have to identify the information asymmetries that lead to capital market imperfections. Incidences of market failure have to be identified ex-ante for every single project that applies for subsidization. If exact policy targeting of the individual marginal entrepreneur is not possible, it is questionable whether policy intervention will do any good at all. Subsidies give their recipients an artificial competitive edge and might thus lower the intrinsic difference between ex-ante less efficient and more efficient start-ups. In this way, subsidization distorts market selection as well as the learning processes inherent in a new business. Market selection remains the crucial mechanism for singling out innovative entrepreneurship from less viable start-ups and ridding the market of less efficient incumbent firms (Fritsch, 2008; Santarelli and Vivarelli, 2007). Moreover, actual subsidy allocation has

[6] For instance, Parker (2002) defines credit rationing as a situation where some entrepreneurs are denied credit although they are willing to pay a higher interest rate and even though they are observationally identical to entrepreneurs who receive credit. In contrast, Evans and Jovanovich (1989) estimate the multiple of the founder's assets that can be devoted to the business. This multiple is then used as a measure of the degree of liquidity constraints. For an overview of definitions of credit rationing, see Jaffee and Stiglitz (1990).

implications for policy effectiveness. If policy does succeed in targeting the marginal entrepreneur, subsidies will be granted where most needed and thus will produce the best results, leading to high effectiveness. Additionally, a specific policy focus will increase efficiency because it allows realizing the most economic impact with the least amount of funds (Stam et al., 2009; Bridge et al., 2003).

Given the implications of policy targeting, the actual allocation of start-up subsidies is of crucial importance in assessing likely market distortions and evaluating policy effectiveness and efficiency. Assuming that the primary policy aim is addressing positive external effects (cf. Section 2.1), policy should primarily support innovative founders and founders with high endowments of human and financial capital. Potential high-growth entrepreneurship should be especially targeted. If, on the other hand, the primary policy aim is addressing capital market imperfections (cf. Section 2.2), policy should be designed chiefly to support, again, innovative founders, but this time also those founders with low human capital and a lack of financial resources. Table 1 summarizes the expected patterns of correlation between start-up characteristics and the receipt of subsidies depending on whether the policy goal is creation of positive external effects or, alternatively, addressing capital market imperfections. It is unclear whether high-growth entrepreneurship is affected by capital market imperfections, since relationship banking and private venture capital firms can be expected to circumvent this problem (Binks and Ennew, 1996; Carpenter and Petersen, 2002). Therefore, this relation is denoted with a question mark. Apart from innovative entrepreneurship, potential sources of market failure thus point to diverging target groups of policy initiatives.

	Policy targeting: Expected signs according to policy goal	
	Positive external effects	**Capital market imperfections**
Innovativeness	+	+
High-growth entrepreneurship	+	**?**
Human capital	+	**-**
Financial resources	+	**-**

Table 1: Start-up characteristics and expected policy support according to policy goal

Policy targeting that aims to realize positive external effects has the positive side-effect of minimizing the risk of substitution effects because it implies a policy focus on the ex-ante most promising start-ups—in terms of both social and private returns (Santarelli and Vivarelli, 2007; Shane, 2009). If policy intervention is successful in "picking winners", subsidies will not protect inefficient start-ups from market competition. Therefore, this policy strategy is least likely to interfere with market selection, which forces inefficient start-ups out of business. However, if policymakers cannot sufficiently distinguish between social returns and private returns ex-ante, a policy focus on innovative high-growth start-ups that are endowed with superior human and financial capital runs the risk of enormous deadweight losses because these firms might survive and thrive regardless of whether they receive a subsidy (Santarelli and Vivarelli, 2007).

In the next section, I investigate empirically whether policy allocation follows the rationale of positive external effects or is based on addressing capital market imperfections. Alternatively, the difficulties in quantifying social and private returns and identifying information imperfections ex-ante might blur the actual targeting of policies (Stiglitz and Wallsten, 2000). Therefore, it could turn out that the diverse subsidy environment, with its myriad programs, engages in no coherent targeting strategy whatsoever. However, if overall policy allocation is not targeted towards alleged market failure, the rationale for policy intervention disappears. Furthermore, seemingly random subsidization of start-ups distorts market selection and is likely to be ineffective and inefficient.

3. Empirical analysis

In the empirical analysis, I first examine the allocation of subsidies to start-ups within their first three business years. The logistic regressions will determine whether policy targeting either addresses positive external effects potentially accruing from entrepreneurship or focuses on alleged capital market imperfections resulting from asymmetric information. Additionally, insights about actual policy targeting shed light on the likelihood of market distortions arising from substitution effects. In a second step, I analyze the effectiveness of subsidization with respect to employment growth and survival. To detect potential deadweight losses, I employ propensity score matching.

3.1 The data

Data for this study were collected by the Thuringian Founder Study (*Thüringer Gründer Studie*), an interdisciplinary project on the success and failure of innovative start-ups in the East German state of Thuringia. The survey population consists of 4,215 founders (first-registered owner-managers) who registered 2,971 start-ups in innovative industries in the Thuringian *Handelsregister* between 1994 and 2006. Innovative industries, according to ZEW classification (Grupp and Legler, 2000), encompass "advanced technology" and "technology-oriented services". This design made it possible to interview not only founders of active companies but also founders of ventures that had failed. From the survey population, we selected a random sample of 3,671 start-up founders. Due to team start-ups, this corresponds to 2,604 start-ups in innovative industries. Between January and October 2008, we conducted 639 face-to-face interviews with solo entrepreneurs or with one member of a start-up team (a response rate of about 25%).

The structured interviews were conducted by the members of the research project. We were supported by student research assistants who were trained in various sessions in December 2007. On average, an interview took one and a half hours. The interviews covered a broad set of questions regarding sociodemographic and psychological data of the founder. Moreover, we inquired into the founder's activities along the founding process. Economic data focused on the time before the first business year and the first three business years. Retrospective data relating to events in the founder's life and to the business history were collected using a modified version of the Life-History Calendar (Belli et al., 2004), which increases the validity of retrospective data.[7]

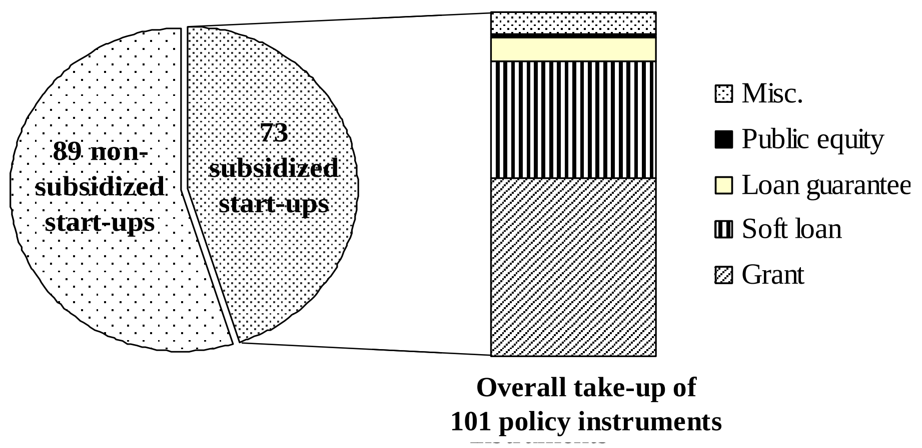
I analyze 162 genuinely new start-ups that were all founded later than 1993[8] and that did not engage in R&D within their first three business years. Financial subsidies were given to 73 of these firms (45.1%) at sometime during the first three business years. The mere receipt of any subsidy within the first three business years is denoted with the dummy variable *Subsidy*. Since start-ups can make use of several policy instruments simultaneously, policy take-up is further specified by five policy instruments: soft loans, loan guarantees, grants, public equity financing, and other support. Soft loans and grants are the most widespread instruments (see Fig. 1). Loan guarantees are only used in combination with soft loans.

[7] This method is based on the principles of autobiographic memory. In a first step, we asked interviewees about the timing of well-known events (e.g., marriage). In a second step, these events served as anchors for less well represented events (e.g., first interest in entrepreneurship).

[8] This is done to exclude any effects of German Reunification in 1990. Additionally, 88 start-ups were removed because they were not genuinely new (e.g., they were a new branch or new business area of an existing company) or because they suffered from poor interview quality.

Therefore, these two instruments are closely related and thus are pooled in the following analysis.

Three observations are dropped from further analysis: the only observation that received public equity funding and two observations that received "other" policy support. All remaining subsidized start-ups receive either soft loans (possibly combined with loan guarantees) and/or grants. Founders were asked which instrument was the most important. These answers are captured by the variable *Subsidy_type*, which distinguishes between "no subsidies", "soft loan/loan guarantee", and "grant": 17.0% of founders received soft loans (potentially combined with loan guarantees) and consider these as the most important policy support. Grants constitute the most important policy support for 27.0% of the start-ups investigated.



Note: N = 162; start-ups can make use of more than one policy instrument

Fig. 1: Take-up of policy instruments within the first three business years

3.2 Targeting of policy support

Does actual policy allocation follow the rationale of positive external effects or do policymakers focus on remedying capital market imperfections? In the following, the targeting of policy support is analyzed with a logistic regression.

Variables

The variables below specify ex-ante characteristics that describe whether policy targeting is oriented toward innovativeness, high-growth entrepreneurship and endowments of human capital, and/or financial resources. Variable definitions and descriptive statistics are given in Table 2; Table 3 sets out the intercorrelations.

	Variables	**Variable description**	**Mean**	**Sd**
Innovativeness	Novelty	The novelty of the business idea refers to the degree of its newness. Five categories were given: novelty (0), regional or local (1), supra-regional but national (2), European (3), and global novelty (4).	0.62	1.01
High-growth entrepreneur-ship	Growth goals	Interviewees had to classify their goals at the beginning of the first business year given the following contradictory pair with a 5-level scale in-between: to generate constant revenues vs. to generate constantly rising revenues. If founder's growth goals are above the mean, the dummy variable is coded 1.	0.60	0.49
Human capital	University degree	The dummy variable indicates if the interviewed founder had (at least) a university degree at the beginning of the first business year.	0.70	0.46
	Previous self-employment	The dummy variable indicates if the interviewed founder was self-employed at any time before the first steps in the founding process.	0.39	0.49
	Team start-up	Team start-ups are defined as venture set-ups where more than one person was actively involved in the founding process and was intended to become an owner of the company. This dummy variable is coded 0 in the case of a single founder, and 1 in the case of a team start-up.	0.65	0.48
Financial resources	Initial capital	The amount of starting capital at the beginning of the first business year was asked for with the help of the following categories: 1,000 EUR or less (1), more than 1,000 to 10,000 EUR (2), more than 10,000 to 50,000 EUR (3), more than 50,000 to 100,000 EUR (4), more than 100,000 to 250,000 EUR (5), more than 250,000 to 500,000 EUR (6), more than 500,000 EUR (7).	3.14	1.10
Control variables				
Year dummies	Year 1994–1997	Dummy variables that capture the time of business start, i.e., the first business year of the company when accounting started either because of obligations from the commercial register or because of first revenues.	0.44	0.50
	Year 1998–2001		0.36	0.48
	Year 2002–2006		0.19	0.40
Nace industry dummies (NACE, 1 digit)	Nace 2	Chemical industry, metalworking industry, engineering	0.16	0.37
	Nace 3	Electrical engineering, fine mechanics, and optics	0.19	0.40
	Nace 7	Information and communication technology, R&D, services	0.33	0.47
	Nace x	Miscellaneous industries	0.31	0.47
N = 159				

Table 2: Variable definition and descriptive statistics

Founders' ambitions have been found to be positively related to subsequent firm growth (Wiklund and Shepherd, 2003), thus justifying *Growth goals* as an ex-ante characteristic of high-growth entrepreneurship. Three variables describe the start-up's endowment with human capital. The variable *University degree* captures general human capital, whereas *Previous self-*

employment is regarded as an important indicator for specific human capital (Brüderl et al., 1992). For instance, experienced entrepreneurs have been found to identify more opportunities and exploit more innovative opportunities with greater wealth creation potential (Ucbasaran et al., 2009). A *team start-up* accumulates the human capital of its members; therefore, it is controlled for multiple founders.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	**Employment growth**	-															
(2)	**Credit rating**	-0.15 *	-														
(3)	**Subsidies**	0.19 **	0.04	-													
(4)	**Novelty**	-0.14 *	-0.03	-0.04	-												
(5)	**Growth goals**	0.07	0.10	-0.05	-0.08	-											
(6)	**University degree**	-0.13 *	-0.11	0.06	0.04	-0.09	-										
(7)	**Previous self-employment**	-0.18 **	0.18 **	-0.14 *	0.35 ***	-0.03	-0.04	-									
(8)	**Team start-up**	-0.09	0.12	0.06	-0.06	-0.08	0.01	0.04	-								
(9)	**Initial capital**	-0.04	-0.07	0.23 ***	-0.07	0.14 *	-0.02	-0.12	0.10	-							
(10)	**Year 1994–1997**	0.04	-0.02	-0.12	-0.10	-0.10	-0.02	-0.14 *	0.01	0.12	-						
(11)	**Year 1998–2001**	0.01	-0.00	0.04	0.08	0.20 **	0.10	0.20 **	-0.03	-0.11	-0.67 ***	-					
(12)	**Year 2002–2006**	-0.06	0.03	0.11	0.03	-0.11	-0.09	-0.07	0.02	-0.03	-0.44 ***	-0.37 ***	-				
(13)	**Nace 2**	0.24 ***	-0.11	0.26 ***	0.21 **	0.05	-0.12	-0.04	-0.11	0.15 *	-0.05	0.05	-0.00	-			
(14)	**Nace 3**	-0.04	-0.02	-0.02	-0.01	0.08	-0.13	-0.07	0.09	0.19 **	0.08	-0.08	-0.00	-0.22 ***	-		
(15)	**Nace 7**	-0.07	0.02	0.06	0.01	-0.06	0.20 **	0.02	0.03	-0.13	-0.05	0.03	0.03	-0.31 ***	-0.34 ***	-	
(16)	**Nace x**	-0.09	0.09	-0.25 ***	-0.17 **	-0.05	0.00	0.07	-0.02	-0.15 *	0.03	-0.01	-0.03	-0.30 ***	-0.33 ***	-0.47 ***	-

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
N = 159; however, due to missing values for the credit rating, the intercorrelations with the survival indicator comprise only 125 observations.

Table 3: Correlation matrix

Logistic regressions

The following regressions reveal the determinants of subsidization. In a first step, the logistic regression analyzes whether innovativeness, high-growth entrepreneurship, human capital, and/or financial resources determine subsidization. Therefore, the variables described in Table 2 are employed as independent variables. The estimates of the logistic regression are given in the first column of Table 4. The novelty of the business idea *(Novelty)*, founder's *Growth goals* as well as the human capital variables have no impact on the probability of receiving subsidies. The amount of *Initial capital* exerts a positive and highly significant impact on the probability of receiving subsidies. Having been founded more recently increases the probability of subsidization (significant at the 10% level). Subsidies are more likely to be given to start-ups operating in the chemical industry, metalworking industry, and engineering (*Nace 2*) (r: 1.912; p = 0.002). Furthermore, the coefficient of *Nace 7* (information and communication technology, R&D, services) indicates a positive relationship to subsidization at the 5% significance level.

	Logistic regression	Multinomial logistic regression (base outcome: no subsidization)	
Dependent variable	*Subsidy*	*Subsidy_type*	
	Take-up of subsidies yes/no	Soft loans (and loan guarantees)	Grants
Novelty	-0.067	-0.084	-0.098
Growth goals	-0.553	-0.455	-0.650
University degree	0.348	-0.168	0.684
Previous self-employment	-0.557	-1.285**	-0.187
Team start-up	0.370	0.626	0.234
Initial capital	0.569***	0.586**	0.553**
Year 1998–2001	0.757*	0.156	1.160**
Year 2002–2006	0.923*	-0.115	1.507***
Nace 2	1.912***	2.204***	1.714**
Nace 3	0.529	0.435	0.563
Nace 7	0.922**	1.138	0.824
Constant	-3.130***	-3.582***	-4.039***
Number of observations	159	27	43
		159	
Log likelihood	-91.888	-131.934	
Pseudo-R^2	0.1575	0.1529	
Note: * p < 0.1; ** p < 0.05; *** p < 0.01 89 non-subsidized start-ups form the base outcome in the multinomial logistic regression.			

Table 4: Logistic regressions

In a second step, a multinomial analysis is conducted to distinguish between the two major policy instruments—soft loans (combined with loan guarantees) and grants. The results of the multinomial logistic regression are shown in Columns 2 and 3 of Table 4. A history of previous self-employment reduces the chances of receiving a soft loan/loan guarantee (r: -1.285; p=0.035), but has no effect of the receipt of a grant. Grants are given significantly more often to start-ups founded more recently (time dummies significant at 1% and 5% levels). Otherwise, the separate analysis of grants and soft loans/loan guarantees in the multinomial logit regression does not reveal different determinants of subsidization compared to the aggregate measure *Subsidies*.[9]

Results

The logistic regressions fail to reveal that subsidy allocation is based on start-ups' ex-ante characteristics as hypothesized in Table 1. Hence, the analysis sheds no light on whether policy is focused on remedying capital market imperfections or on the creation of positive external effects. Apart from a positive impact of the amount of financial resources (*Initial capital)* on subsidization, which indicates policy targeting of start-ups likely to yield positive external effects, all other indicators of the rationale for policy targeting are insignificant (*Novelty, Growth goals, University degree*, *Team start-up*). Hence, the allocation achieved by policy schemes does not suggest that the schemes are working to address market failure. Furthermore, the multinomial logistic regression reveals no distinct differences between subsidies in the form of soft loans/loan guarantees and grants, thus raising doubts as to the necessity of different instruments.

However, it is not only policymakers and program officials that play a role in the selection of subsidy beneficiaries; founders and their start-ups might self-select into the programs (Storey, 2000). Figure 2 shows the self-reported reasons for nonsubsidization. The first two categories, which represent 74.2% of nonsubsidized founders, can be viewed as founder self-selection. Self-selection is thus the primary driver of selective policy support. The other categories can be more or less regarded as committee selection. The founders of 7.9% of nonsubsidized ventures reported that is was the too-complicated application procedures that prevented them from applying. This category probably blurs with the fourth category ("not eligible, therefore not applied"), as both are simply different forms of dropping out of the information and application process. The applications of 5.6% of nonsubsidized founders were rejected, indicating clear-cut committee selection.

[9] Given the relatively low number of observations in each category of the variable *Subsidy_type* and the descriptive character of the logistic regressions, the multinomial logistic regression was run with a reduced set of independent variables, resulting in only minor changes of the coefficients.

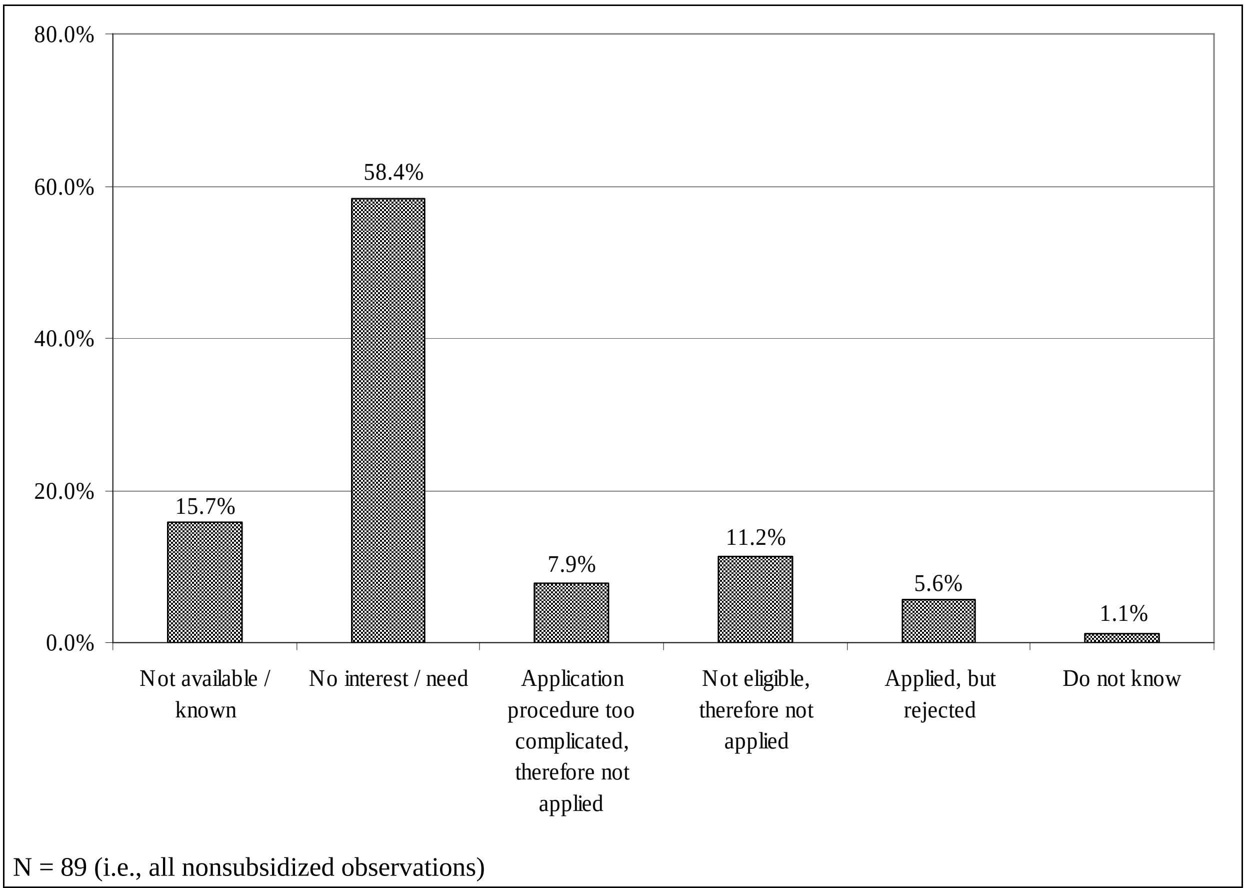


Fig. 2: Reasons for nonsubsidization

Hence, the allocation of start-up subsidies could be driven by both demand and supply and might thus reflect changes in the availability and the design of policy schemes, as well as changing policy take-up over time. For instance, the increased subsidization via grants over time matches the introduction and the increased popularity of start-up subsidies for the unemployed starting in 2002, all of which are grant-based (Caliendo et al., 2008).

3.3 Effectiveness of policy support

The previous section demonstrates that subsidies are given neither based on the rationale of positive external effects nor on the rationale of capital market imperfections. Therefore, the necessary condition for policy intervention does not appear to be met. Furthermore, random subsidization is argued to be ineffective. Hence, I additionally assess the effectiveness of subsidization with respect to employment growth and survival. First, employment growth is a prominent indicator of firm growth and prosperity; moreover, employment growth is an important policy goal. Second, the long-run survival of a start-up indicates a sustainable policy intervention.

(Outcome) Variables

A start-up's employment growth and survival probability are captured by the following variables:

Employment growth within the first three business years is defined as

$$Employment\ growth = (Employment_{3rd\ year} - Employment_{1st\ year}) / Employment_{1st\ year}\ .$$

Here *Employment* includes work by founders, active partners, conventional employees, hired labor, and trainees. The measure is normalized on full-time positions, thereby considering part-time jobs.

Long-term survival is proxied by the start-up's credit rating five years after founding, which we obtained for each start-up from Creditreform, the leading rating agency in Germany. The variable *Credit rating* thus contains Creditreform's rating index, which ranges from 100 (best) to 600 (worst). Creditreform uses several sources of information in making its ratings, for example, financial and structural risks such as industry, firm size, and productivity, as well as payment history, quantity of orders, firm development, and management quality.[10] The credit rating aims to proxy the start-up's default risk and, indeed, credit rating and survival are highly correlated in the present sample (r: -0.462, p = 0.000). The credit rating thus serves as a continuous variable for the highly skewed dichotomous variable survival.[11]

Matching approach

To identify the causal effect of subsidization, the performance of subsidized and nonsubsidized start-ups cannot be compared directly. Although the findings set out in Section 3.2 did not reveal distinct policy targeting, the first two columns of Table C1 (see the Appendix) show differences in previous self-employment, initial capital, and industry between subsidized and nonsubsidized start-ups. These differences, i.e., the selection bias, might lead to different outcomes even in absence of subsidies. Therefore, the counterfactual outcome must be discovered, that is, the outcome of a nonsubsidized start-up if it were subsidized.

Matching procedures based on the potential outcome approach of Roy (1951) and Rubin (1974) have been developed to address the selection bias in observational data. To

[10] For more information on the Creditreform's credit rating system, see Czarnitzki and Kraft (2007).
[11] Creditreform does not routinely generate credit ratings for each new start-up, but only if there is an external request from other firms. Because of missing credit ratings, I exclude 34 observations when analyzing the outcome variable *Credit rating*. These nonrated start-ups turn out to have significantly less initial capital than rated start-ups. Hence, it should be borne in mind that the credit rating might imply a systematic bias in favor of the larger start-ups.

approach the counterfactual outcome, these authors assume that the selection of firms into subsidization is completely based on observable characteristics. The conditional independence assumption (CIA) states that, given a set of observable exogenous (not affected by the treatment) characteristics, potential outcomes are independent of the treatment assignment (Smith and Todd, 2005). In other words, if one wants to attribute the differential performance to the receipt of subsidies, subsidized and nonsubsidized start-ups should not differ in any other characteristics that impact on the outcome variable. Implicit in this matching approach is the stable unit treatment value assumption (SUTVA), which states that subsidization does not impact on any start-ups other than those that are explicitly treated (Rubin, 1991). In the present context, this implies that subsidies do not impact on nonsubsidized start-ups via market effects or knowledge spillovers. Thus, SUTVA rules out general equilibrium effects of subsidies.

It can be difficult, however, to find a nonsubsidized control unit if there is a great number of characteristics on which matching takes place. To solve this "curse of dimensionality", Rosenbaum and Rubin (1983) propose the use of propensity score matching. The basic idea is not to match on covariates directly, but to match on a function of the covariates that describes the propensity to receive subsidies. This predicted probability of group membership is usually obtained from logistic regression. There are various matching algorithms, all of which contrast the outcome of a subsidized start-up with a weighted average of the outcome of (some) nonsubsidized observations. Asymptotically, all matching algorithms should yield the same results (Smith, 2000).

I apply kernel matching, which uses all nonsubsidized start-ups to construct a match for each subsidized start-up. This method is the best choice for my data, since the sample is small and there are almost as many subsidized as nonsubsidized start-ups. Basically, kernel matching juxtaposes the outcome of each subsidized start-up to the weighted sum of all nonsubsidized start-ups. The weights assigned by the weighting function to the nonsubsidized start-ups are higher the closer the nonsubsidized start-ups match the subsidized start-up with respect to the observed characteristics that are captured by the propensity score. The total weight of all controls adds up to 1 for each subsidized start-up. The implementation of kernel matching involves two choices: the choice of a kernel function and the choice of the bandwidth parameter. DiNardo and Tobias (2001) note that the kernel employed is relatively unimportant in practice, but that choice of the bandwidth parameter matters. The bandwidth parameter determines a tradeoff between "few but good matches" (yielding higher variance) and "many but potentially bad matches" (leading to biased estimates). Here, Silverman's

(1986) rule of thumb is used to determine the bandwidth parameter and thus to balance bias and variance. The exact matching protocol is set out in Table 5. Estimations are made with the psmatch2 Stata ado package by Leuven and Sianesi (2003).

Step 1. A logit model for both outcome variables (employment growth and credit rating) is specified and estimated. In this way, the propensity scores for each observation are obtained. The choice of variables and the estimation of the propensity score are explained in Appendix A.

Step 2. The sample is restricted to the region of common support. The common support condition ensures that any set of characteristics of subsidized start-ups (as captured by the propensity score) can also be observed for nonsubsidized ones. The region of common support is determined by a minimum-maximum comparison of the distribution of the propensity score. The imposition of the common support requires dropping 9 (4) observations from the analysis of employment growth (credit rating). The distributions of the propensity score that determine the region of common support can be found in Appendix B.

Step 3. The average treatment effect on the treated (ATT) (Table 5) is the difference between the mean outcome of subsidized start-ups and matched nonsubsidized start-ups. Following the notation of Caliendo (2006), the average treatment effect for the treated (ATT) can be stated as $ATT = \frac{1}{N_1}\sum_{i \in I_1}[Y_i^1 - \sum_{j \in I_0} W_{N_0}(i, j)\, Y_j^0]$ with Y_i^1 denoting the outcome of the subsidized start-up i and Y_j^0 the outcome of nonsubsidized start-ups j. N_1 (N_0) is the number of observations in the subsidized group I_1 (control group I_0). The outcome of i is thus contrasted with the average weighted outcome of the control group, where the weights are given by $W_{N_0}(i, j) = \frac{G_{ij}}{\sum_{k \in I_0} G_{ik}}$. Thereby, G_{ik} denotes a Gaussian kernel $G[(P_i - P_k)/h]$ with P_i (P_k) standing for the propensity score of subsidized (nonsubsidized) start-ups. The bandwidth parameter h is determined with the following formula, $h = 0.9 \cdot A \cdot n^{-0.2}$ (Silverman, 1986), in which n denotes the number of observations and the term $A = \min(\textit{standard deviation}, \frac{\textit{interquartile range}}{1.34})$ accounts for the distribution of the propensity score.[12]

Step 4. The standard error of the matching estimators is calculated using bootstrapping (200 replications).[13] The estimates for the average treatment effect (ATT) as well as their bootstrapped standard errors and p-values are set out in Table 6.

Step 5. The matching quality is assessed by analyzing the mean differences between nonsubsidized and subsidized matched start-ups. After matching, there should be no significant differences regarding any characteristics that are assumed to have an impact on both the receipt of subsidies and the respective outcome variable. A comparison of mean differences between subsidized and nonsubsidized start-ups is given in Appendix C.

Step 6. To check the robustness of the results, Steps 3, 4, and 5 are repeated for different bandwidth parameters h, which are employed in the kernel matching algorithm in Step 3.

Table 5: Matching protocol

[12] The calculation is as follows. For the analysis of employment growth, $A = \min(0.2037, \frac{0.2937}{1.34}) = 0.2037$ is inserted in $h = 0.9 \cdot A \cdot 148^{-1/5}$. Hence, the optimal bandwidth is $h = 0.0675$. Analogous to the previous calculation, the optimal bandwidth for the analysis of our survival indicator is derived by estimating $A = \min(0.1752, \frac{0.2220}{1.34}) = 0.1657$ and $h = 0.9 \cdot A \cdot 121^{-1/5} = 0.0571$.

[13] Although a distribution theory for the cross-sectional and difference-in-difference kernel and local linear matching is derived in Heckman et al. (1998), standard errors for matching estimators are in practice generated using bootstrap resampling methods. The use of bootstrapping is backed by Abadie and Imbens (2008), who suggest that the standard bootstrap can be applied to assess the variability of kernel matching estimators.

Results

The employment growth of subsidized start-ups exhibits an ATT of 0.3650, i.e., the difference between the mean employment growth of subsidized start-ups (0.9831) and matched nonsubsidized start-ups (0.6180). However, the higher employment growth of subsidized start-ups is not significant. Looking at the indicator for survival, subsidized start-ups have a mean credit rating of 302.63 compared to the mean rating of 291.45 of their nonsubsidized matched counterparts. Again, the worse credit rating of subsidized start-ups fails to reach significance. Table 6 shows that other bandwidth parameters also result in insignificant estimates.[14]

The matching procedure thus does not reveal any impact of subsidies on employment growth or credit rating and thus indicates deadweight losses. Interviewees' self-report of windfall gains is in line with these mixed results. Each founder of a subsidized start-up was asked: "Would you have continued your start-up [or, alternatively, important business projects] without the subsidies?" About one-third (32.9%) answered "yes, readily"; 37.0% said "yes, perhaps or on a reduced scale"; only 26.0% said "no".[15]

	Matching algorithm	Mean outcome of		ATT	S.E.	p-value	# Observations	
		subsidized start-ups	non-subsidized start-ups				Sub-sidized	Non-subsidized
Employment growth	**Kernel**							
	Optimal bandwidth (0.0675)	0.9544	0.6087	0.3456	0.2809	0.218	64	84
	Bandwidth 0.02	0.9544	0.5751	0.3793	0.2806	0.177	64	84
	Bandwidth 0.04	0.9544	0.6075	0.3469	0.2714	0.201	64	84
	Bandwidth 0.06	0.9544	0.6130	0.3414	0.2686	0.204	64	84
	Bandwidth 0.08	0.9544	0.5991	0.3553	0.2349	0.130	64	84
	Bandwidth 0.10	0.9544	0.5838	0.3706	0.2780	0.183	64	84
Credit rating – Survival	**Kernel**							
	Optimal bandwidth (0.0571)	302.63	291.45	11.18	19.12	0.559	67	54
	Bandwidth 0.02	302.63	306.23	-3.60	29.23	0.902	67	54
	Bandwidth 0.04	302.63	296.55	6.08	21.74	0.780	67	54
	Bandwidth 0.06	302.63	290.86	11.77	19.28	0.542	67	54
	Bandwidth 0.08	302.63	288.25	14.37	18.14	0.428	67	54
	Bandwidth 0.10	302.63	287.23	15.40	20.21	0.446	67	54
Note: No estimate reaches the 0.1 significance level.								

Table 6: Overview of results obtained from kernel matching employing various bandwidth parameters

Matching relies on strong untestable assumptions, particularly the conditional independence assumption. The validity of the conditional independence assumption relies crucially on the possibility of comparing subsidized and nonsubsidized start-ups on the basis

[14] The use of other matching algorithms, such as radius matching, does not yield significant results either. These results are not shown here, but can be obtained from the author.
[15] Due to three refusals, the percentages do not add up to 100.

of pretreatment characteristics. Given the rich dataset, which includes personal data for the founder and the founding team as well as characteristics of the start-up and the business idea, it is plausible to assume that the outcomes and the allocation of subsidies are independent, conditional on observed attributes. Heckman et al. (1997) point out that matching methods substantially reduce biases when, first, all information is collected with the same questionnaire for both the subsidized and nonsubsidized start-ups and, second, these are drawn from the same random sample (which is supported by the experimental evidence of Michalopoulos et al. (2004)). Both requisites are met by my dataset. Moreover, the sample is considerably homogenous, since I only consider genuinely new start-ups in innovative industries in the East German state of Thuringia that were not engaged in R&D.

4. Discussion and conclusions

In general the results of this paper indicate policy failure. The logistic regressions suggest that alleged market failure is not targeted and, furthermore, the matching analysis shows no impact of subsidization in terms of higher employment growth or higher chances of firm survival. Ineffective subsidies do not imply that subsidies have no effects at all, however, since subsidies might provide inefficient start-ups with an artificial competitive edge and thus distort market selection. However, I can only speculate about substitution effects because the matching approach explicitly ignores the market effects of subsidies.[16] The present study has several limitations. To begin with, the likelihood and the extent of substitution effects depend on the amount of subsidies, information I do not have. This also implies that I cannot analyze a potential targeting that bases the amount of subsidy on start-up characteristics. Furthermore, small sample sizes and high standard deviations provide good reasons to interpret the present results with some caution.

Still, the analysis has significant implications for future evaluations. Although I cannot distinguish between individual programs and funding agencies, my study does point out the limited potential of policy targeting. Since no distinct differences between grant-based intervention and loan-based intervention are found, it is worth asking whether the myriad programs and the diverse structure of funding agencies mitigate intricate information problems in allocating subsidies. If the wide range of different schemes and funding agencies do not, in practice, improve policy targeting, they very well may be quite successful at increasing administrative costs and enhancing the difficulty of policy evaluation, the latter

[16] This is due to the stable unit treatment value assumption (SUTVA).

problem arising because each program serves so few beneficiaries that analysis of effectiveness is hampered by low sample sizes (a problem this study ran up against itself).

Moreover, the present findings question fundamentally the general subsidization of start-ups as an instrument to tackle market failure. First, the existence of market failure is far from clear and cannot be claimed to universally hamper entrepreneurship. This is true both for positive external effects (Auerswald, 2007) and capital market imperfections (Parker, 2002). Moreover, some authors state excessive participation in entrepreneurship resulting from overlending and overoptimism and thus argue for discouraging entrepreneurship (de Meza, 2002; Parker, 2007; Shane, 2009).

Second, if policy intervention is agreed upon, incidences of market failure have to be identified individually ex-ante to guide subsidy allocation. Precise policy targeting, however, is unlikely due to fundamental information problems (Holtz-Eakin, 2000). Presumably, banks use the best screening technology available to minimize information asymmetries that cause capital market imperfections, and Parker and van Praag (2006) doubt that government can do a better or even equal job at this, an ability that would be necessary for successful policy intervention. Similarly, Stiglitz and Wallsten (2000, p. 47) describe the "monumental task" of identifying marginal projects that have the potential to yield social returns but that will not be realized in the absence of subsidies because the private returns are too low. Moreover, the extent of self-selection into subsidization (remember that 58.4% of founders indicated no interest and/or need for policy support) limits policymakers' potential of selective policy targeting.

Third, public-choice considerations suggest that policymakers and funding authorities may have incentives that actually conflict with a policy targeting market failure. On the one hand, policymakers and funding authorities are keen on portraying themselves as the engineers of success and are thus motivated to fund projects that would have succeeded even without their help (Lerner, 1999). This situation is further aggravated by a different culture of risk-taking in the public sector. Stiglitz and Wallsten (2000) point out that program officials may have a tendency to focus on choosing projects that have a high probability of success instead of funding projects for which even higher returns can be expected but that are riskier. On the other hand, start-up subsidies also serve as a labor market instrument and thus are given to the potentially less promising ventures (Caliendo et al., 2008; Santarelli and Vivarelli, 2007). Additionally, applicants can apply for subsidies using language and descriptions that enhance the probability of receiving the subsidy—a kind of "playing the system".

The difficulties in identifying incidences of market failure as well as the interplay of policymakers, program officials, and potential awardees blur the actual targeting of policies. However, arbitrary policy allocation has severe implications for policy effectiveness and market distortions. On the one hand, if market failure does not exist, recipients probably do not need subsidization and taxpayers' money spent on such is wasted (Stam et al., 2009). Conversely, a previous evaluation of R&D subsidies finds a distinct policy focus on innovative start-ups and academic spin-offs as well as a high effectiveness of R&D subsidies regarding patent output and employment growth (Cantner and Kösters, 2009a, b). The findings for the present subset of non-R&D start-ups put the highly positive effects of subsidies earmarked for R&D into perspective and show how important the analysis of subsets of heterogeneous start-ups is. On the other hand, market distortions arise if subsidies cannot be limited to selectively remedy market failure. Therefore, some authors suggest a policy strategy of "picking the winner" because then subsidies are least likely to interfere with market selection (Santarelli and Vivarelli, 2007; Shane, 2009). Yet, those start-ups that exhibit the most promising characteristics are probably the ones that need government support the least.

The information needs for policymaking can be alleviated by choice of policy instrument. Human-capital-based policy instruments are favored by most economists (e.g., Fritsch, 2008; Audretsch and Thurik, 2001), since start-ups with high endowments of human capital are less likely to face capital constraints and, at the same time, are more likely to yield social returns. Moreover, Schmitt-Rodermund and Vondracek (2002) emphasize that career interests are formed early in adolescence. They thus suggest policy action that helps adolescents discover their interests and abilities and makes them aware of entrepreneurship as a career option. This kind of entrepreneurship education should be offered to all adolescents, i.e., all potential future entrepreneurs. Thereafter, special training should be provided for those who have the right combination of personality and entrepreneurial orientation. In this way, the targeting problem is more clear-cut and, additionally, such a policy initiative will not distort market selection, since it targets the individual before the actual start-up of the venture. However, such a policy focus would require a major shift in actual policymaking—away from targeting start-ups and established firms and toward empowering the individual (potential) entrepreneur.

Appendix

A—Variable choice and estimation of the propensity score

A propensity score model must be estimated for each outcome variable, including those variables that influence both the receipt of subsidies as well as the respective outcome variable. To identify these variables, I look for variables that correlate with the receipt of subsidies and simultaneously with the respective success measure (employment growth and survival) (Table 3). Moreover, I conduct multivariate analyses to identify other distinguishing characteristics between subsidized and nonsubsidized start-ups that have an impact at the same time on employment growth and survival, respectively. In the following, the variable choice for each propensity score model is explained.

Employment growth. Table 3 shows that the variables *Previous self-employment* and *Nace 2* are correlated with both the take-up of subsidies as well as employment growth. Initial capital varies greatly between subsidized and nonsubsidized start-ups. Although not in line with the present data, previous studies suggest that initial capital impacts on employment growth (e.g., Cooper et al., 1994). I thus include *Initial capital* as a balancing variable. Initial matching procedures show that the matched samples differed in founders' *Growth goals*. Since ambitions have also been found to impact on realized employment growth (Wiklund and Shepherd, 2003), this variable is also included.[17] Ordinary least squares regressions cannot identify other joint determinants of subsidization and employment growth, so that the propensity score is finally estimated with the variables *Initial capital*, *Previous self-employment*, *Growth goals*, and the industry dummies.

Credit rating. Only the variable *Previous self-employment* is correlated with both the receipt of subsidies as well as with survival as proxied by the credit rating (Table 3). Additionally, I balance subsidized and nonsubsidized start-ups on the basis of *Initial capital* and industry because financial endowment and industry characteristics strongly differentiate between subsidized and nonsubsidized start-ups and have been shown to impact on the survival probability of start-ups (e.g., Cooper et al., 1994). Since ordinary least squares regression models cannot reveal any further determinants of credit rating that distinguish between subsidized and nonsubsidized start-ups, the propensity score model is estimated with the variables *Previous self-employment, Initial capital*, and the industry dummies.

The propensity to receive subsidies is estimated with a logit model (Table A1). In accordance with the discussion above, the selected variables for each of the two models are regressed on the binary dependent variable *Subsidy* (i.e., take-up of financial subsidies within the first three business years). Since we are primarily interested in prediction and data reduction, redundancy and collinearity are of little account (Smith, 1997). However, this limits the interpretation of the coefficients, which are not further discussed here.

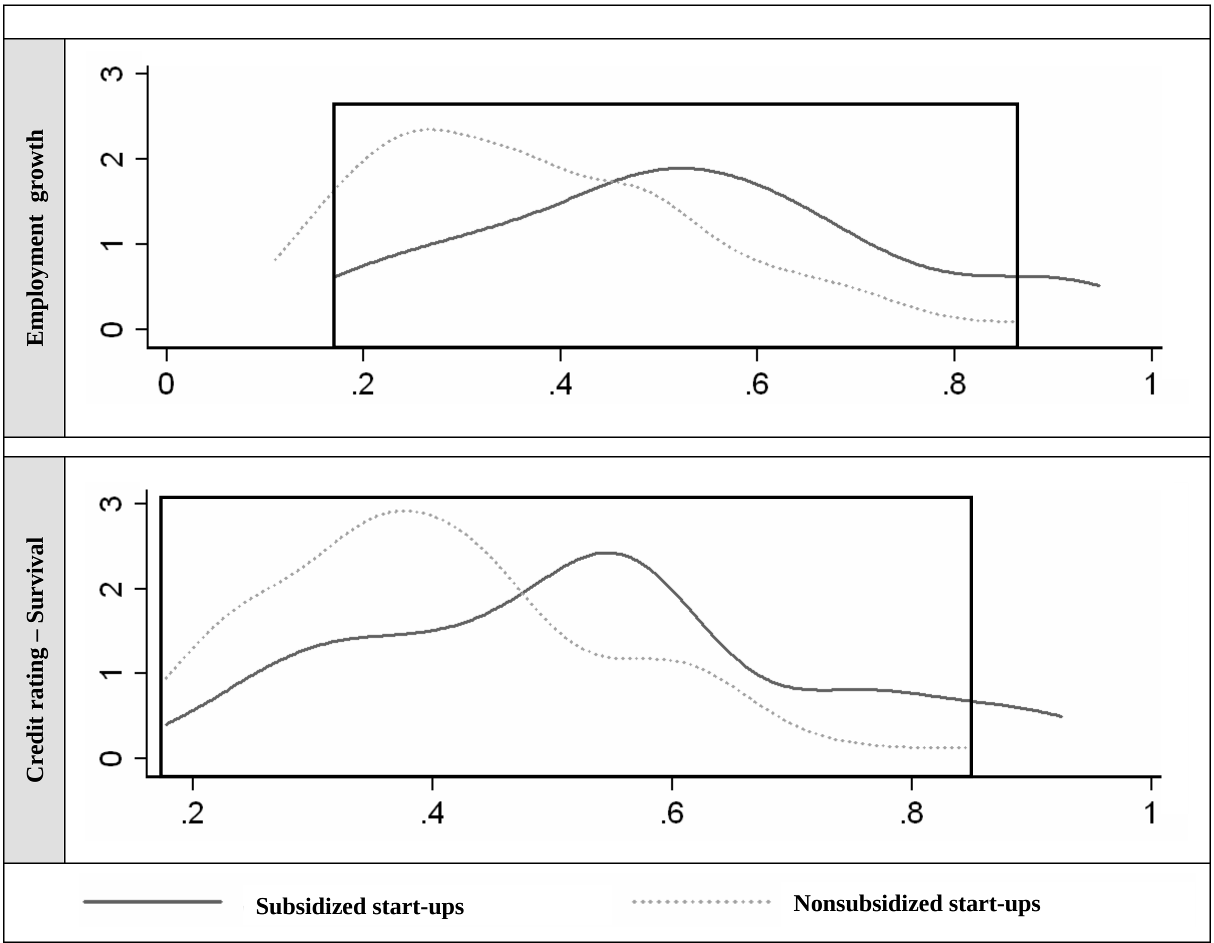
	Employment growth		Credit rating—Survival
Dependent variable: *Subsidy*			
Growth goals	-0.450		
Previous self-employment	-0.492		-0.479
Initial capital	0.515	***	0.397**
Nace 2	1.827	***	1.586**
Nace 3	0.469		0.248
Nace 7	0.975	**	0.912*
Constant	-2.113	***	-1.851**
N	159		125
LR chi2 (k)	(6) 27.54		(5) 16.28
Prob > LR	0.0001		0.0061
McFadden's R2	0.1263		0.0943
Note: * p < 0.1; ** p < 0.05; *** p < 0.01			

Table A1: Estimation of the propensity score

[17] This approach follows Rubin and Thomas (1996, p. 253), who recommend including a variable in doubt "unless […] it can be excluded because there is a consensus that it is unrelated to the outcome variables or not a proper covariate".

B—Imposition of the common support

The common support condition ensures that any set of characteristics of subsidized start-ups (captured by the propensity score) can also be observed for nonsubsidized ones. The kernel density functions (Figure B1) illustrate the distribution of the propensity score for subsidized and nonsubsidized start-ups.[18] The region of common support is found in the overlap and requires discarding 11 (4) observations from the analysis of employment growth (credit rating).



Please note: Observations inside the region of common support lie within the black box. All observations outside the box are excluded from matching.

Figure B1: Distribution of the propensity score: employment growth (top), credit rating (bottom)

[18] The kernel density estimate is calculated using a Gaussian kernel function. The bandwidth is specified by Stata, using the kdensity function.

C—Matching quality

T-tests for equality of means in the subsidized and nonsubsidized start-ups indicate the balancing of the variables before and after matching (Table C1).

	Before matching		Employment growth After matching		Credit rating After matching	
	Mean of…		Mean of matched…		Mean of matched…	
	… subsidized start-ups **N = 70**	… nonsubsidized start-ups (potential controls) **N = 89**	… subsidized start-ups **N = 66**	… nonsubsidized start-ups (actual controls) **N = 84**	… subsidized start-ups **N = 54**	… nonsubsidized start-ups (actual controls) **N = 67**
Novelty	0.61	0.62	0.52	0.58	0.56	0.57
Growth goals	0.57	0.62	0.55	0.59	0.52	0.66
University degree	0.73	0.67	0.73	0.63	0.74	0.69
Previous self-employment	**0.31**	**0.45**	0.34	0.37	0.35	0.39
Team start-up	0.69	0.63	0.70	0.61	0.67	0.61
Initial capital	**3.47**	**2.89**	3.20	3.21	3.28	3.35
Year 1994–1997	0.37	0.49	**0.34**	**0.50**	0.37	0.48
Year 1998–2001	0.39	0.35	0.41	0.34	0.43	0.35
Year 2002–2006	0.24	0.16	0.25	0.16	0.20	0.17
Nace 2	**0.27**	**0.08**	0.20	0.19	0.20	0.18
Nace 3	0.19	0.20	0.20	0.21	0.20	0.21
Nace 7	0.36	0.30	0.39	0.39	0.39	0.38
Nace x	**0.19**	**0.42**	0.20	0.21	0.20	0.23
Employment growth	0.96	0.83	0.95	0.61	0.97	0.60
Rating	298.16	292.15	303.97	283.41	302.63	291.45
Propensity score (Employment growth)	**0.53**	**0.37**	0.49	0.48	-	-
Propensity score (Rating)	**0.53**	**0.41**	-	-	0.50	0.49

Please note: The balancing of the variables is shown after kernel matching with the optimal bandwidth. Bold numbers indicate significant different means between observation from subsidized start-ups and nonsubsidized start-ups before and after matching in a two-sided t-test (10% significance level). Because of the imposition of the common support (see Appendix B), the matched samples have fewer observations.

Table C1: Group differences between subsidized and nonsubsidized start-ups before and after matching

After matching, subsidized and nonsubsidized start-ups differ only with respect to *Year 1994–1997* in the analysis of employment growth. This should not be of concern since there is no evidence that this variable impacts on employment growth.

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