The Role of Location-based Accessibility for the Effectiveness of Startup Subsidies

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Abstract

Startup companies and their innovative products and services contribute to technological progress. Startups, however, face a multitude of challenges related to the liability of newness. Therefore, public policies aim at providing support, for example, through startup subsidies to overcome early-stage financing constraints which may hamper investments and hence firm development. In this study, we investigate how a startup's location influences the effectiveness of such public support. We build on detailed data from a country-wide agent-based transport model used to derive local accessibilities for different modes of transport while accounting for road congestion. Theoretically, the link between local accessibility and the effectiveness of startup subsidies is ambiguous. Providing support to firms in less accessible regions may be more effective if they help to compensate for the disadvantages of the location. However, targeting support to better accessible places could be more effective if subsidy and accessibility are complements, i.e. startups can make better use of additional resources in better accessible places. Results based on detailed information on founder and startup characteristics show that better accessibility, especially better accessibility of the R&D workforce, indeed increases the effectiveness of subsidies. In particular, we find subsidies trigger more additional own-financed R&D when startups have better access to potential (R&D) employees. For non-R&D-related outcomes, local accessibility does not seem to matter.

Key words: Accessibility, Human Capital, Innovation, Startup Subsidies, Transport Model.

JEL-Classification: G32, H25, O32, O33, O38

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1 Introduction

Newly founded firms are increasingly in the focus of economic research because of their crucial role in enhancing innovation and technological progress (Acs and Audretsch, 1988; Haltiwanger et al., 2013). Moreover, the creation of new employment is disproportionately driven by startups (Haltiwanger et al., 2016; Stuetzer et al., 2018) and they contribute to the development of radically new products (Schneider and Veugelers, 2010a; Pellegrino et al., 2012). Startup entrepreneurs also increase the competitive pressure on incumbents in their respective technology field (Changoluisa and Fritsch, 2020) and enhance a region's economic growth (Audretsch and Keilbach, 2004). However, for startups, financial resources make or break a new firm's success. Thus, most young firms need external financial resources to develop their business idea and grow (Cassar, 2004). Initially, startups need to invest in machinery, components, research and development (R&D), employees, and office space without drawing from previous cashflows. Technological and market uncertainties are additional hurdles. Therefore, limited financing, in the beginning, can result in slower growth and underperformance of a startup. To avoid this trap, public subsidy programs have been created to support young firms with high innovation potential (Lerner, 2020). While the evidence is still rather scarce, most existing studies show that public funding seems to positively impact firm growth (Cantner and Kösters, 2015; Howell, 2017a; Hottenrott and Richstein, 2020). However, it remains unclear under which conditions such programs are most effective. Founder and firm characteristics may certainly matter, but also the program design as such likely plays a role.

One other important dimension is the location of the startup. For example, some programs favor urban areas with more universities, banks, and innovation hubs (Cumming et al., 2006; Rephann, 2020), and some programs are limited to certain locations, such as the city or county that provides the grant. Some programs also target their support to specific types of founders who tend to locate in certain locations. For example, the EXIST program (Kulicke and Kripp, 2013) is a public subsidy scheme that exclusively supports academic founders who collaborate with universities in Germany. Although many programs have a regional dimension, it is largely unexplored how the location of a company to which the support is provided matters for the policy's effectiveness.

Empirically it has been clearly shown that location matters for innovation (Feldman, 2004; Black and Henderson, 1999; Glaeser and Gottlieb, 2009; Bandelow et al., 2023). Studies found that location characteristics, especially access to human capital, impact the innovation performance of firms (Czarnitzki and Hottenrott, 2009) and that local knowledge spillovers through interactions play an important role (Fudickar and Hottenrott, 2019). While location factors have been studied extensively with regard to established companies, their impact on startups is not as clear yet (Hottenrott and Lopes-Bento, 2014; Nilsen et al., 2018). Moreover, simple location characteristics such as the distinction between urban and rural areas may not be sufficient to really capture relevant aspects of a new firm's location. For instance, Fritsch and Wyrwich (2020) find that in most

OECD countries innovative activity does not only happen in larger cities but also outside of metropolitan areas. This is also in line with Berkes and Gaetani (2021) who document that there is more unconventional innovation in urban areas of the United States, but also a significant amount of patenting in rather remote locations. Therefore, measuring the transport accessibility of a location rather than relying on a simple urban-rural dichotomy may help to capture innovation-relevant aspects of a certain place.

While it is ex-ante unclear whether the effectiveness of startup support depends on the location, one may theorize that the effectiveness is higher in places where the constraints and hence the need for support is higher. This may apply to less accessible places. Moreover, the more accessible a location, the more prone it may be to high competition for resources, congestion, a general over-use of infrastructure, and rising prices in terms of renting and wages (Gertler et al., 2022). On the other hand, startups may be able to make more effective use of additional resources in locations that are better accessible and hence provide complementary infrastructure and resources. Finally, while the location may matter for innovation in general, it may not make a difference in the effectiveness of support. Crass et al. (2019) investigate how the geographical clustering of beneficiaries affects the effectiveness of public innovation support programs for established companies and conclude that there are no effects of geographical clustering on the program's effectiveness. Yet geographical clustering and accessibility are different concepts. Therefore, it remains unclear which of these two arguments prevails, whether they outweigh each other, and which role potential congestion plays.

This study contributes to closing this gap in our understanding of the effectiveness of public startup support. For our empirical study, we employ a fine-grained measure for accessibility that captures car transport, public transport, and trains for 11,717 municipalities in Germany. We derive different measures of a location's potential accessibility depending on whether we intend to capture how accessible a location is to the general population, to the workforce (employees), or to R&D employees (employees with research-related jobs). Since one may argue that potential accessibility might overestimate the accessibility of zones with more opportunities (i.e. have a higher attractiveness) because there is more competition for these opportunities. Therefore, we construct *competitive accessibilities* that discount places with high competition between seekers of these opportunities. We combine these indicators with data from newly founded companies surveyed via the IAB/ZEW Startup Panel. This data provides information on the financing of the startups including information on public sources. It also requires various characteristics of the startups, such as team/one-person founding, gender distribution in a team, age, number of employees, revenue, profit, and others. We first estimate the average treatment effects from receiving startup support using econometrics matching techniques that take into account that the subsidy award is highly selective. In particular, we replicate the analysis by Hottenrott and Richstein (2020) for an updated and larger sample of German startups. Subsequently, we perform a treatment effect heterogeneity analysis (Hottenrott and Lopes-Bento, 2014). In this dissection, we test whether the magnitude of the individual treatment effect depends on the accessibility of a startup's location. The results show that there is indeed a positive average treatment effect of public subsidies on various outcomes: R&D spending, investment, revenues, innovation, and survival. Yet, we find little impact of accessibility on most of these outcomes. However, startups in locations with better accessibility to R&D employees and higher competitive accessibility show more additional R&D efforts (expenditures and R&D employees) in response to public support. We find subsidies trigger more additional own-financed R&D additionality when startups have better access to potential (R&D) employees. This suggests that better accessibility, especially better accessibility of R&D workforce, indeed increases the effectiveness of startup subsidies. For non-R&D-related outcomes, local accessibility does not seem to matter for the magnitude of the treatment effect.

In the following, we discuss how subsidies, such as grants and loans may help startup a company in the form of financing of the founder's salary and investments into research and development of their product or service. We subsequently discuss relevant outcome indicators such as future product innovations, revenue, and probability of bankruptcy. Next, we describe the main measures used in the empirical analysis, the calculation of accessibilities based on an integrated land-use transport model (Geurs and Van Wee, 2004), and how the startup support is defined. We derive a set of hypotheses to be tested empirically and set out the method of analysis. Finally, the results are presented and discussed.

2 Theoretical Framework and Hypotheses

New firms have the potential to generate and diffuse transformative innovations that require organizational flexibility and break with existing technology paths (Huergo and Jaumandreu, 2004; Plehn-Dujowich, 2009; Lebdi, 2015; Bouncken et al., 2021). Successful innovation in young firms is, however, not guaranteed. While the societal returns to entrepreneurial activities are potentially large, so are the risk and barriers for founders. Firms entering markets with novel complex products and services are particularly prone to suffer from the liability of newness (Hottenrott et al., 2018).

Unlike mature firms, which have a track record of past activities, new firms are more likely to fail due to uncertainty related to the technological viability and the market success of their products, uncertainty about their management capacity as well as their ability to compete with established and new competitors (Ostgaard and Birley, 1994). In light of declining startup numbers in several European countries and the United States and highly skewed distributions in new firms' growth rates (Decker et al., 2016; EFI, 2017), governments increasingly aim to support founders in overcoming initial hurdles (Lerner, 2020). The fact that entry and growth barriers appear to persist despite a multitude of policy programs in place, calls for research evaluating the effectiveness of the support instruments used. It seems therefore crucial to better understand the conditions under which support programs are most effective.

While the generally positive effects of public support for startups have been studied in a number of recent studies (Almus, 2004; Colombo et al., 2012; Howell, 2017b; Hottenrott and Richstein, 2020; Grilli, 2020), important dimensions that facilitate possible higher effectiveness per Euro spent on these programs remain unexplored. In particular, since the location of a new company matters for its performance, it may also matter for how much use founders can derive from additional support. To investigate the mechanisms through which public subsidies affect activities in young companies, Hottenrott and Richstein (2020) matched newly founded firms that are either recipients or non-recipients of subsidized loans and grants and performed an analysis on various firm and founder characteristics. They find that both subsidized loans and - even more impactful - combined with grants increased the growth of revenue and employment, as well as R&D investments. This suggests that overcoming initial financing constraints can have an enormous impact on firm development. Recent research focuses on whether startup subsidies also facilitate follow-on financing by (non-public) investors. Berger and Hottenrott (2021), for instance, study how different types of venture capitalists invest in startups based on whether they received public subsidies or not. They find a positive relationship between subsidies and follow-on venture capital (VC) funding. VC investors, however, typically cluster in more accessible locations (near airports, for instance) to have better access to potential investment targets (Lutz et al., 2013; Woo, 2020). Previous research also stressed the role of knowledge spillovers in hubs (Bikard and Marx, 2020) and R&D alliances leading to a higher innovation performance depending on whether such activities are feasible (Hottenrott and Lopes-Bento, 2015). For instance, Agrawal et al. (2017) focus on the role of knowledge flows between and within regions through more mobility and goods flow. Looking at historic highway plans, they find that the building of roads caused an increase in the number of patents and more patent citations. Besides closeness to investors and networks, the location of a startup may also affect its access to non-financial resources such as human capital. Studies by Asher and Novosad (2020) and Gertler et al. (2022) highlight the important role of transport infrastructure in achieving accessibility and eventual economic development of regions. Moreover, Zheng et al. (2022) stress the importance of going beyond the analysis of roads by showing the significant impacts of high-speed rail infrastructure on entrepreneurial activity.

Based on these insights, this study aims to extend research on agglomeration economies or the flow of human capital in cities (Black and Henderson, 1999; Glaeser and Gottlieb, 2009) by explicitly measuring accessibility using a portfolio of transport modes (including roads as well as public transport) and by focusing on new firms. The need for going beyond the urban/rural dichotomy is also stressed in the findings by Fritsch and Wyrwich (2021). In their study, they find that patenting activity in selected OECD countries does not decrease with a less urbanized environment. This only happened in more centrally structured countries, like South Korea and the United States, whereas the effect disappeared in countries like Germany. They conclude that the role of big cities as innovation hubs might be overemphasized. The question that is of interest in this study, therefore is how public subsidies are best placed in order to support startups most efficiently.

To study the effects of subsidized loans and grants on knowledge-intensive startups' growth and R&D expenditures, we replicate the study of Hottenrott and Richstein (2020) using data including more recent years. As mentioned before, the initial paper showed that - on average - financial startup support is indeed effective in facilitating additional innovation activities and investments. We expand the analysis in this paper by further differentiating between the locations of the subsidy recipients and by testing whether the extent to which subsidies result in higher investments and performance (i.e. the treatment effect) depends on the transport accessibility of the location.

Based on insights from previous research, we set up two opposing hypotheses. The first is based on the idea, that startups in less accessible places have a higher need for support *(Need-Hypothesis)* because their location provides for less infrastructure and fewer spillovers. Public support may therefore be more effective since the constraint is more binding and hence there is more potential to be uncovered. Moreover, better accessibility may come at the cost of higher competition for resources and therefore higher costs including for renting and wages (Gertler et al., 2022) which may make expansion of business activities in response to subsidies less costly and more feasible in less accessible locations. This implies that:

Hypothesis 1: *(Need): Treatment effects of startup subsidies are larger in less accessible locations.*

On the other hand, startups may be able to make more effective use of subsidies in better accessible locations because they provide complementary infrastructure and resources. Moreover, there may be better opportunities in more accessible places with regard to collaboration and exchange with other organizations. Perhaps most importantly, better accessibility as we define it in this study means better access to people *(Opportunity-Hypothesis)*. People are important as customers, i.e. they may reflect local demand, as well as constitute potential employees. While not everyone is of the same relevance to new firms, access to individuals with matching skills may matter a lot. Since young firms find it particularly difficult to hire their first employees as they compete with established firms and have limited financial resources (Römer and Hottenrott, 2023), they may need to locate in places where there is a sufficiently large pool of potential hires or where wages are lower. Especially, R&D intensive startups have high human capital requirements and access to potential employees with the necessary R&D skills may be crucial for their business to succeed. Therefore being in a better accessible location could increase the returns to (R&D) investment and hence lead to a better cost-effectiveness of public startup support. We, therefore, hypothesize that:

Hypothesis 2: *(Opportunity): Treatment effects of startup subsidies are higher in better accessible locations.*

To answer the research question of whether local accessibility matters for the effectiveness of startup subsidies, it seems crucial to differentiate between the population attraction factor that defines accessibility. Using the general population as attraction is plausible following the market-access argument (Chen and Wang, 2022; Donaldson and Hornbeck, 2016). However, following the human capital idea, we may need to differentiate between more and less relevant populations with more relevant being people who may help the performance of the startup, for instance in knowledge-intensive tasks and areas that matter for the development and market introduction of new products and services.

3 Estimation Methods and Data

In order to calculate whether accessibility impacts the effectiveness of subsidies for startups, we first estimate whether public financial support generally makes a difference for young companies. We create two groups of startups, one that received some form of subsidy and one that did not. By doing this, we replicate Hottenrott and Richstein (2020) with five more years of data and conduct a nearest neighbor propensity score matching with a caliper. Then we combine it with elements of exact matching, e.g. Huber et al. (2013). After having estimated the average treatment effects on different outcomes, we can analyze whether the individual firm's treatment effect depends on the accessibility of its location.

3.1 Method

In a first step, we estimate the treatment effect of subsidies on a set of outcome variables for subsidized versus non-subsidized new firms. We use a probit model to predict whether a startup will be subsidized by any kind of funding instrument given the predictor (control) variables during the observation period. We collect the following variables that predict the treatment: Founder(s)' academic background, age, industry experience, entrepreneurial experience, prior negative entrepreneurial experience, founding motive, team (composition, e.g. gender), current number of employees, revenue, profit, other financing sources, patents, market penetration (e.g. export), R&D activity, capacity utilization. We conduct t-tests to detect differences between the variable means before (see Table 1) and after (see Table 2) the matching process. Before the matching, we expect subsidized and non-subsidized startups to differ in both control and outcome variables. After the matching, given that the matching is successful, we would not expect differences in those firm and founder characteristics on which the matching was based. The remaining differences in the outcome variables could then be attributed to the treatment. Our main outcome variables are R&D expenditure, R&D personnel, tangible investments, product innovation, number of employees, revenue, and bankruptcy. The average treatment effect can be described with:

$$\alpha^{TT} = \frac{1}{N^T} \sum_{i=1}^{N} (Y_i^T - \widehat{Y}_i^C) \tag{1}$$

where Y_i^T is the outcome of a firm in the treatment group and vice versa, $\widehat{Y}_i^C$ is the outcome when the treatment group would not have been treated. The $\widehat{Y}_i^C$ needs to be estimated, since the counterfactual situation is not directly observable. It is therefore crucial to model the selection stage carefully. Public funders select startups based on specific observable criteria. They could either favor underperforming companies (backing losers) that need the support to enhance their business or overperforming firms (picking winners) that are more likely to prevail (Cantner and Kösters, 2012). The firms also self-select into funding programs when applying for a subsidy. Both mechanisms lead to a selection bias in the subsidized versus unsubsidized groups and without making both groups comparable through matching, we may incorrectly attribute differences in firm performance to the treatment (Imbens and Wooldridge, 2009).[1] To come close to an experimental setup, we employ a great number of control variables (Set X), which according to Lechner and Wunsch (2013) reduces selection bias. The survey data that we use provides extensive firm and founder characteristics making the matching quite comprehensive. Building on the conditional independence assumption (CIA) of Rubin (1977), we use the counterfactual group with the same criteria of X to estimate any outcome Y. $S = 1$ being the subsidized startups and $S = 0$ being the unsubsidized ones as $S \in \{0, 1\}$. If the CIA hold, we can claim that *E(Y | S = 1, X) = E(Y | S = 0, X)* and hence any observable differences in Y must be explained by the treatment.

We estimate the propensity score used in the matching approach from a probit regression for the probability of a subsidy receipt conditional on the criteria X. This leaves us with one propensity score that contains all the information about the criteria. Following Hottenrott and Richstein (2020), we then use a nearest-neighbor matching method to ensure that we match firms with the most similar characteristics and a very similar probability of receiving a subsidy. Additionally, a caliper is used to avoid matching firms which exceed a maximum distance between propensity scores. Moreover, we combine this with exact matching within the same technology sector and within the geographical location in former East or West Germany. That is, we only select within these strict bins. Following the matching, we compute the average treatment effect on each Y outcome:

$$\alpha^{TT} = E(Y^T|S = 1, X = x) - E(Y^C|S = 0, X = x) \tag{2}$$

After the propensity score matching, we can estimate whether the accessibility impacts the treatment effect on subsidized companies in terms of their outcomes in the following period: R&D expenditure and employees, tangible investment, product innovation, employees, revenue, and the probability of bankruptcy (outcomes O). To reduce the impact of skewed distributions in some of the variables on the mean values, we use the logged version and ratios of R&D expenditures, employment, revenue, and tangible assets and

[1]Besides matching, there are other methods of estimating a counterfactual situation and hence treatment effects such as difference-in-differences estimation. However, due to missing pre-treatment data for most of the startups, this is not a suitable option in our case since most startups receive public funding in their first or second year of operations.

investment. In this analysis, we distinguish between different attraction factors in the accessibility calculation such as the general population, potential employees, potential *research* employees, and how competitive the labor market is. We use the predicted factor scores as an index rather than the individual accessibility transport modes. A detailed description of the utilized data follows in the next section. In particular, we estimate linear models such that:

$$\alpha_i^{TT}(O) = Y_i^T - Y_i^C \tag{3}$$

Higher values in the respective outcome $\alpha_i^{TT}(O)$ indicate that a firm benefited from a larger individual treatment effect as measured in the distance of the firm's achieved outcomes as compared to its matched twin firm. Since we match based on many firm and founder characteristics, industry dummies or other controls turn out insignificant in these models.

3.2 Data

Our data set stems from two main sources of information: the IAB/ZEW Startup Panel from which we obtain founder and firm information as well as the subsidy status of a company and the company locations' accessibility.

3.2.1 Startup Panel

The main data set is retrieved from the representative IAB/ZEW Startup Panel, which contains economic characteristics of young companies and their founders in Germany. It draws its data from annual computer-assisted telephone interviews conducted annually with around 5000-6000 startups, that build a subset of the Mannheim Enterprise Panel. The firms in the panel are at maximum seven years old and for the first interview, the age limit is three years. Spin-offs (or demergers) and subsidiaries of other companies are excluded since they do not constitute new independent ventures. A detailed description of the Panel can be found in Fryges et al. (2009). We categorize firms into 11 sectors: cutting technology manufacturing (8.3%), high-technology manufacturing (6.5%), or technology-intensive services (18.4%), software (6.8%), low-technology manufacturing (13.4%), scientific services (5.9%), other company services (5.9%), creative services (3.7%), other customer services (7.7%), construction (11.8%), and retail (11.6%). The average founder age is 45 years and 13.3% have at least one female founder. About 86% of startups are located in western Germany. Teams make up 38.7% of founders, thus the majority of startups are founded by one person. The final data set consists of 10,435 firms that were founded between 2005 and 2018.

3.2.2 Treatment Variable

We consider a startup to be subsidized if it received either a grant (e.g. cash payment to founders or wage substitute) or a preferential, publicly-backed loan. This includes programs like the *EXIST* program or startup bank loans from the KfW Banking Group. Regional banks also offer support through loans that do not require collateral or have other favorable conditions such as low interest rates or repayment-free years.[2]

3.2.3 Outcome Variables

We focus on relevant outcome variables that describe or determine a startup's success. With regard to innovation efforts, these are *R&D expenditures*, the number of *employees*, the ratio of R&D expenditures per employee as well as the share of R&D employment among the total employees. These variables can be termed input oriented. These measures are also used in other studies on the effect of startup subsidies (Colombo et al., 2013; Czarnitzki and Lopes-Bento, 2013). Following Hottenrott and Richstein (2020), we also consider investments in tangible assets (*tangible investment*) and to capture the innovation output of a company, we use the binary variable *product innovation*, which covers products that are new to the market and were introduced in the years after the subsidy (up to three years). We also analyze the revenue of a startup, as well as whether it filed for bankruptcy in the years following the subsidy receipt. We obtain this indicator is captured from Creditreform, Germany's largest credit rating agency.

To account for the skewness of the distribution in the monetary variables, we apply the logarithm and one unit in the case of zero values.

3.2.4 Matching Variables

To replicate previous studies using the same data as closely as possible, we primarily rely on the same variables and method as Hottenrott and Richstein (2020) to match the firms. As shown in literature (Chandler and Hanks, 1994; Mitchelmore and Rowley, 2010), it is important for public funders to selectively distribute startup subsidies in order to achieve the best value for taxpayers' money. Consequently, the allocation of subsidies to startups is not random, i.e. founder and firm characteristics significantly explain whether or not a firm received public financial support. Startups by older founders, for instance, are less likely to be financially supported while those founded by a team are more likely. The higher the innovation orientation, as measured by R&D expenditures, the more likely it is that a firm received a subsidy. To reduce omitted variable bias and selection bias, we employ a set of control variables that are firm-related and founder-related on which the allocation is likely based on. More precisely, the variables include indicators that may explain a startup's subsidy receipt as well as firm performance. These are the founders'

[2] See Hottenrott and Richstein (2020) for a more detailed dissection of differences between grants and loans.

human capital measured by formal education of the founder(s) (*university degree*), *vocational training*, or *Master craftsperson* title, the highest non-academic rank in Germany). Moreover, industry experience is captured as the number of years of the most experienced founder. As some research shows, having founded a company before might be preferred by subsidy providers to those that are novice founders, due to their potential lack of managing knowledge or a business network (Wright et al., 1997). Therefore, it counts as entrepreneurial experience if at least one founder has founded before. To capture life experience more generally, the oldest founders' age is included and startups are also distributed into team founders and solopreneurs. Although gender should not influence the success probability of a startup, recent research shows, that the amount of funding given to a young firm is influenced by founder gender (Lins and Lutz, 2016). Therefore, we include an indicator for whether the start has at least one female founder. For the startup characteristics, we employ the age of the firm, as younger firms empirically are more prone to financial constraints and rely more on funding than more established startups. Young firms are also seen as more interested in pursuing innovation (Czarnitzki and Lopes-Bento, 2013). Additionally, the number of patents that the firm already produced is included. Since there are still some structural differences between former East and West Germany, we also only match firms strictly only within these broad regions. We examine whether there are any significant differences between the groups in these characteristics using *t*-tests before and after matching. Table 1 shows t-tests of differences in variable means before matching. As expected subsidized and non-subsidized firms differ quite substantially in most characteristics. Table 2 shows the t-tests after matching with sample means no longer showing significant differences.

Figures 1a and 1b graphically illustrate the distribution of the propensity score by groups before and after matching. While the curves differ before matching, they almost perfectly overlap after matching. Figure 2 further illustrates that after matching, we obtain quite a comparable regional distribution of recipients and non-recipients across Germany.

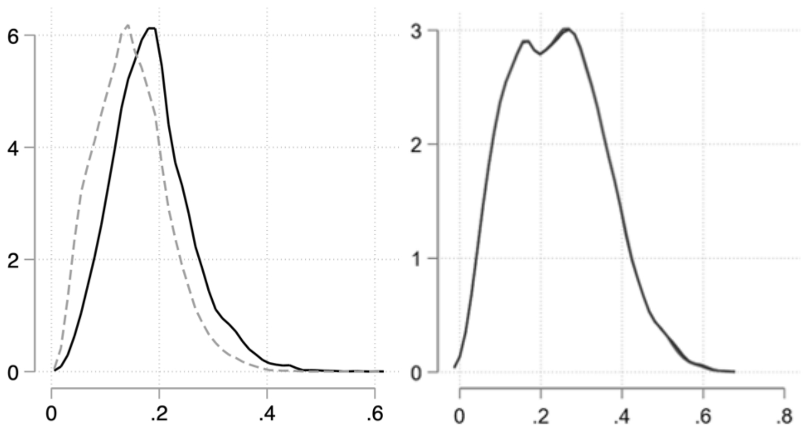
3.2.5 Accessibility

The accessibility of a region is a value between 0 and 1 indicating how accessible a region is for a specific group of people. Thus, how many people of the general population, employees (i.e. individuals of working age), research employees can travel from one zone to another zone using different transport modes? Our short and long-distance model follows an approach that consists of trip generation, destination choice, mode choice, time of day choice, and trip assignment. Figure 3 illustrates the model in more detail.

To calculate the accessibility of a region an agent-based transport model is employed. For the purpose of this model, Germany is divided into 11,717 zones that match all German municipalities, with the 14 largest cities additionally divided into smaller units at the borough level. Cross-border accessibility is also accounted for as all neighboring country

Table 1: Comparison of control variables before matching

	Non-recipients N = 43891		**Recipients** N = 8017		
	Mean	SD	Mean	SD	*t-test*
Founder characteristics					
University education	.281	.002	.270	.005	.049
Vocational training	.287	.002	.275	.005	.030
Master craftsperson	.229	.002	.276	.005	.000
Founder age	44.855	.051	43.329	.109	.000
Industry experience	16.748	.049	15.795	.104	.000
Entre. experience	.416	.002	.355	.005	.000
Failure experience	.065	.001	.065	.003	.925
Opportunity driven	.751	.002	0.755	.004	.001
Female founder	.181	.002	.187	.004	.211
Startup characteristics					
Team	.307	.002	.336	.005	.000
Startup age$_{t-1}$	2.986	.009	2.453	.018	.000
Limited liability	.480	.002	.479	.006	.782
ln(Tangible assets)	5.558	.021	5.315	.051	.000
Patent stock	.099	.011	.073	.010	.350
Export activity$_{t-1}$	.157	.002	.180	.004	.000
Capacity utilization$_{t+1}$	82.831	.120	84.992	.269	.000
East Germany	.125	.002	.188	.004	.000
ln(R&D-Expenditure)$_{t-1}$	1.346	.017	1.821	.045	.000
ln(Employees)$_{t-1}$	.880	.004	.824	.011	.000
ln(Revenue)$_{t-1}$	7.471	.028	6.254	.068	.000
ln(Tangible Investment)$_{t-1}$	4.957	.023	4.995	.057	.518
Profit$_{t-1}$	.065	.001	.065	.003	.925



(a) Before matching: Treatment group and potential control group (dotted line).

(b) After matching: Treatment group and selected control group.

Figure 1: Estimated propensity score of the treatment group and selected control group before and after matching.

Table 2: Comparison of control variables after matching

	Non-recipients		Recipients		
	Mean	SD	Mean	SD	*t-test*
Founder characteristics					
University education	.273	.005	.269	.005	.593
Vocational training	.271	.005	.276	.005	.445
Master craftsperson	.273	.005	.276	.005	.619
Founder age	43.301	.119	43.343	.109	.795
Industry experience	15.709	.112	15.809	.105	.515
Entre. experience	.364	.005	.355	.005	.255
Failure experience	.071	.08	.065	.003	.186
Opportunity driven	.766	.005	0.767	.005	.970
Female founder	.183	.004	.187	.004	.528
Startup characteristics					
Team	.336	.005	.334	.005	.814
Startup age$_{t+1}$	2.483	.017	2.453	.018	.240
Limited liability	.489	.006	.477	.006	.154
ln(Tangible assets)	5.237	.051	5,326	.051	.220
Patent stock	.058	.007	.072	.010	.213
Export activity$_{t+1}$	.178	.004	.178	.004	.901
Capacity utilization$_{t+1}$	85.340	.301	84.875	.269	.249
East Germany	.185	.004	.185	.004	1.0
ln(R&D-Expenditure)$_{t+1}$	1.796	.044	1.784	.045	.857
ln(Employees)$_{t+1}$	.829	.009	.819	.011	.475
ln(Revenue)$_{t+1}$	6.303	.067	6.254	.068	.611
ln(Tangible Investment)$_{t+1}$	4.916	.056	4.98	.058	.420
Profit$_{t+1}$	7.439	.065	7.315	.066	.185

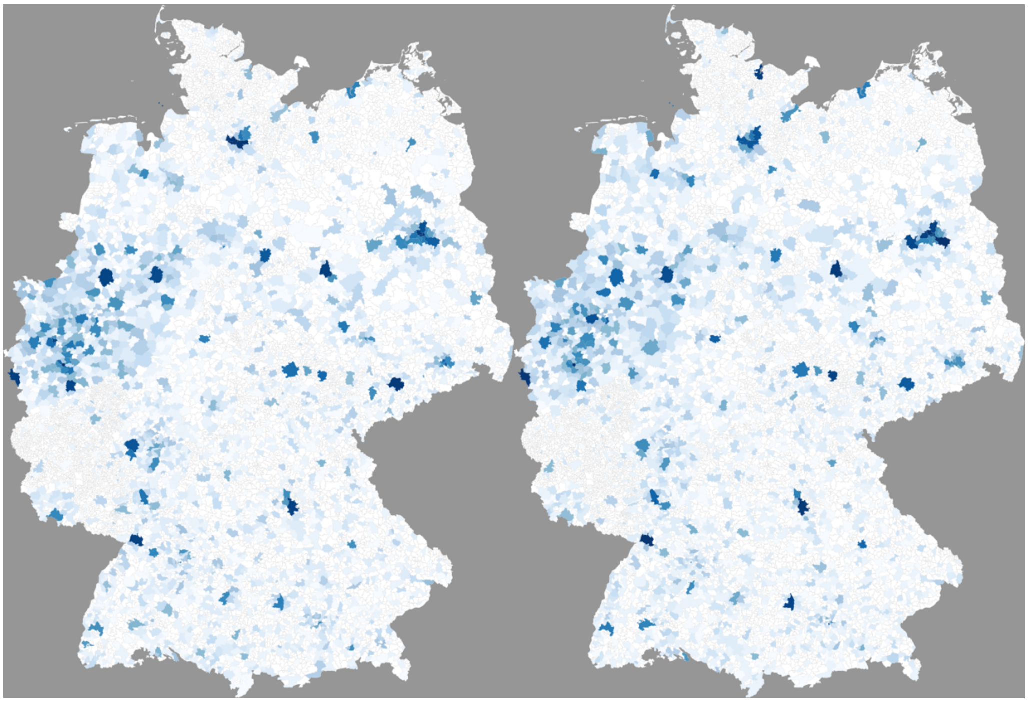
Observations: 7977 each group, except for variable *Profit*: non-recipients $n = 5189$; recipients: $n = 5073$.

Table 3: Outcome variables after matching

	Non-recipients			Recipients			
Variables	N	Mean	SD	N	Mean	SD	*t*-test
ln(R&D-Expenditure)$_{t+1}$	6748	1,738	.047	6714	1,983	.051	.001
ln(R&D-Personnel)$_{t+1}$	6853	.248	.011	6812	.379	.016	.000
ln(Tangible Investment)$_{t+1}$	7530	3,772	.055	7491	4,370	.057	.000
Product innovation$_{t+n}$	7977	.286	.005	7977	.318	.005	.000
ln(Employees)$_{t+1}$	6797	.926	.011	6774	1,096	.012	.000
ln(Revenue)$_{t+1}$	6834	6,928	.074	6838	7,735	.074	.000
Bankruptcy$_{t+n}$	7977	.278	.005	7977	.253	.005	.001

zones are included in the calculation. A transport network consisting of roads, railroads, and local public transport ways, such as sub-urban rails, is used to estimate travel times[3]. Short distances are under 40km long, as long-distance trips are over 40km. Note that local public transport modes are used to access long-distance modes, such as taking the

[3]Information on the road and rail network and public transport schedules and is retrieved from the following sources: OpenStreetMaps (https://www.openstreetmap.org) and GTFS (https://gtfs.de). Retrieved on 13.03.23.



(a) Subsidy non-recipients (b) Subsidy recipients

Figure 2: Spacial distribution across German regions of the treatment group and selected control group after matching.

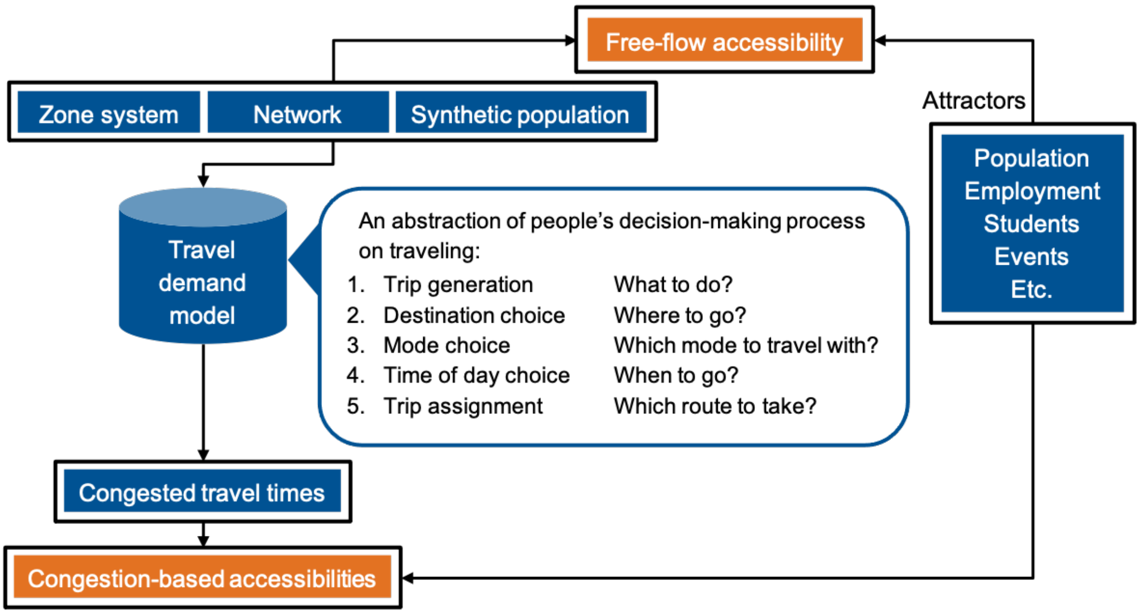


Figure 3: Accessibility modeling approach by Huang (2023).

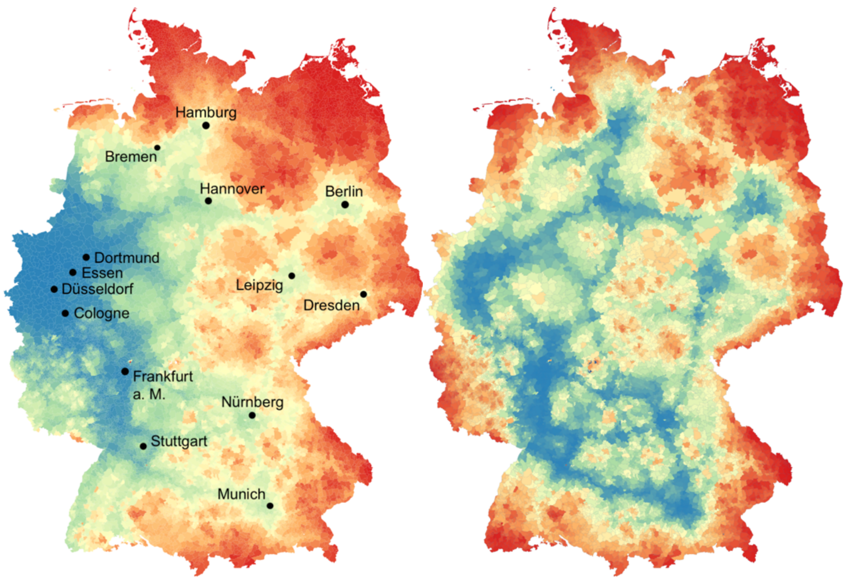
bus to the closest train station. For our model, an agent chooses a route and a mode of transport to get from zone A to a chosen zone B. The calculation is based on real travel behavior captured by the Mobility in Germany survey, a nationwide travel survey by the Ministry of Transport and Digital Infrastructure (Federal Ministry of Transport and Digital Infrastructure, 2017). This survey is conducted every five to nine years since 1970, we use the 2017 survey data. The survey includes socio-demographic information about the interviewees within different groups and regions, as well as information on the trips a person took. This information is then used to simulate a synthetic population. A matrix system between every zone in Germany is employed to calculate the accessibility for every zone using the gathered information from the mobility survey and the synthetic population as well as information on the transport network (Pukhova et al., 2021). This provides us the information about the freeflow travel times between all zones. To include congested traffic in the analysis, the Multi-Agent Transport Simulation (MATSim) by Horni et al. (2016) is used. In this study, we call the different groups of population attractors. This leaves us with an accessibility score for access to the general population, potential employees, potential research employees, or employees when taking into account the competitiveness of the location. The competitive accessibility is lower when there is a high number of potential employees which might increase the competition between local firms for employees. All accessibilities are considered to be relatively stable over time, which might be a plausible assumption in the German context with long building times. In Figure 4, the congested-car accessibility for the general population is mapped in comparison to the competitive employment accessibility distribution across Germany. For informational purposes, the ten biggest cities of Germany are marked in Map 4a. Compared to the accessibility for the general population, which is higher in mid-west Germany, the competitive employment accessibility is higher is more balanced among the cities. In Figure 5, the four different transport modes are mapped for the competitive employment accessibility. For the car accessibility, highway routes across Germany are distinguishable with higher accessibility, the public transport modes also correspond to smaller cities in between larger cities.

4 Estimation Results

In this section, we will describe the results of the first analysis of how subsidies are distributed to startups to build up our matching sample. Then we will discuss whether the accessibility makes a difference for our subsidy recipients and non-recipients. Table 6 shows the results of the probit estimation for obtaining the propensity score which we use in the sample balancing with some elements of exact matching. The model predicts about 89% of the observations correctly indicating a good model fit. After the matching, we estimated whether the accessibility has an impact on the size of the estimated treatment effect on subsidized companies. We consider the same outcome variables as in the estimation of the average treatment effects, i.e. R&D expenditure and employees, tangible investment, product innovation, employees, revenue, and the probability of bankruptcy. In terms of different accessibilities, we distinguish between the general population, potential employees, potential research employees, and competitive employment as the attraction factor in the accessibility calculation. The main results are presented in Table 7.

Table 4: Factor analysis for different types of accessibilities

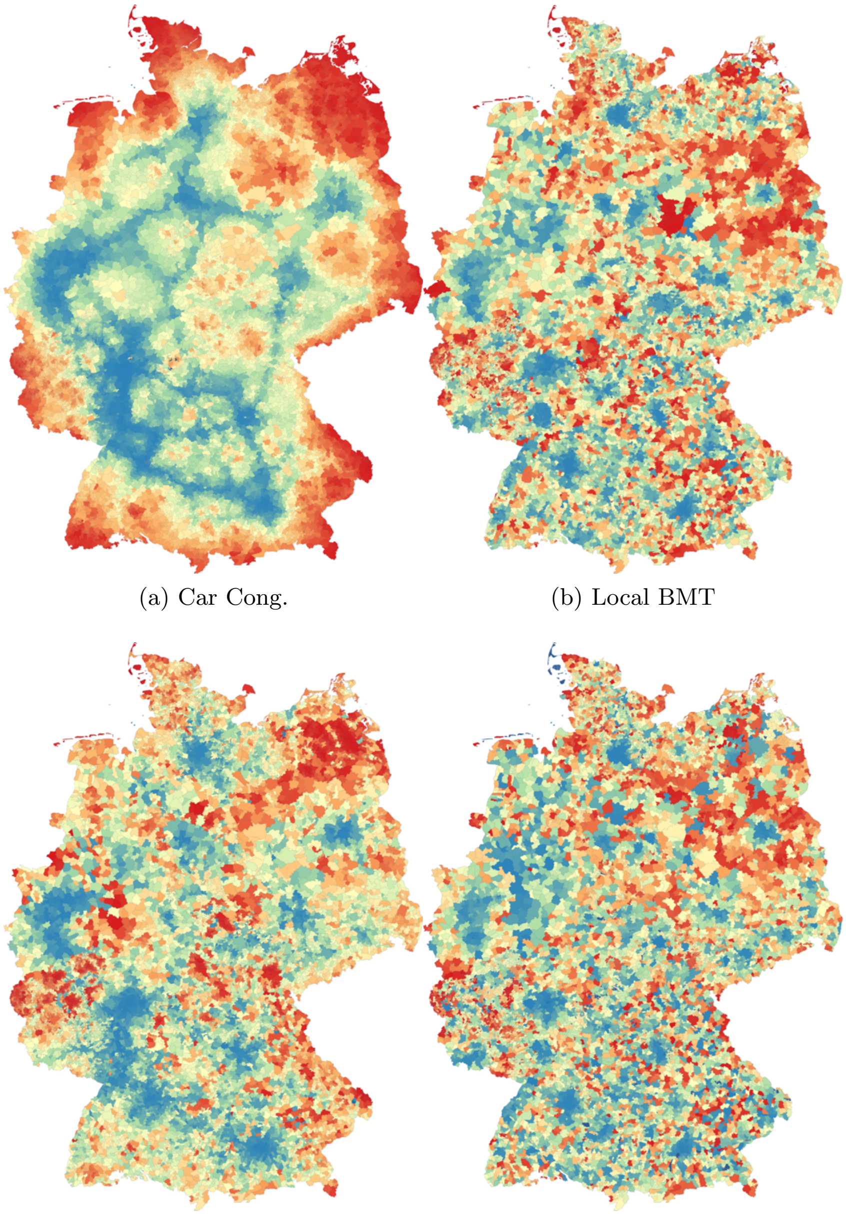
Accessibility Attractor	**Mobility Mode** at $\alpha = 1.0$ and β=1.0	**Factor loadings** (Factor 1)
Population	Car (congested)	0.629
	Bus, metro, tram	0.914
	Long distance rail	0.865
	Long distance bus	0.862
Employees	Car (congested)	0.611
	Bus, metro, tram	0.920
	Long distance rail	0.868
	Long distance bus	0.879
Research employees	Car (congested)	0.650
	Bus, metro, tram	0.903
	Long distance rail	0.878
	Long distance bus	0.897
Competitive employees	Car (congested)	0.722
	Bus, metro, tram	0.779
	Long distance rail	0.799
	Long distance bus	0.734



(a) Potential population (b) Competitive employment

Figure 4: Congested car accessibility with the potential population (left) and competitive employment (right) as the attraction factor ($\alpha = 1.0$, $\beta = 1.0$). Scaling color gradient: Blue = high accessibility (1); yellow = medium accessibility; red = low accessibility (0).

The results indicate that there are significant positive effects of the general population accessibility on the treatment effect on the logged number of R&D employees ($\beta = 0.032$). This is also the case for the accessibility to employees ($\beta = 0.045$) and particularly to



(a) Car Cong. (b) Local BMT

(c) LD Rail (d) LD Bus

Figure 5: Accessibility within Germany with competitive employment as the attraction factor ($\alpha = 1.0$, $\beta = 1.0$). Scaling color gradient: Blue = high accessibility (1); yellow = medium accessibility; red = low accessibility (0).

research employees ($\beta = 0.080$) in a region. The effect is thus most pronounced when we consider potential R&D workers. This shows that subsidies are most effective in terms of hiring additional R&D employees in startups when such human capital is actually available and accessible. When taking competition for employees into account, the effect is even stronger ($\beta = 0.128$), stressing the importance of access to potential hires. On R&D expenditure, the accessibility for research employees has a positive and significant effect ($\beta = 0.122$), as well as the accessibility for competition on employment ($\beta = 0.213$). One

Table 5: Descriptive statistics of accessibilities

Accessibility: BMT	**Mean**	**Std. Dev.**	**Min**	**Max**
Population (n = 11717)				
Potential population	0.081	0.089	0	1
Potential employees	0.080	0.097	0	1
Potent. Research employees	0.047	0.078	0	1
Competitive employment	0.309	0.129	0	1
Sample: subsidized (n = 7974)				
Potential population	0.218	0.211	0	0.914
Potential employees	0.220	0.218	0	1
Potent. Research employees	0.152	0.183	0	1
Competitive employment	0.426	0.153	0	1
Sample: unsubsidized (n = 7974)				
Potential population	0.223	0.213	0	1
Potential employees	0.228	0.224	0	1
Potent. Research employees	0.154	0.185	0	1
Competitive employment	0.430	0.159	0	1

Notes: Raw accessibility values normalized between zero and one.
Bus, metro, tram accessibility with $\alpha = 1.0$ and $\beta = 1.0$.

can see a slightly positive trend for competitive accessibility on product innovation ($\beta = 0.013$). When looking at R&D expenditures, we find that while access to the general population does not have any impact, access to researchers explains the magnitude of the treatment effect, supporting our previous conclusions that the availability of adequate human capital increases the effectiveness of public startup subsidies.
Thus, being located in a better accessible location in terms of research employees leads to higher additional spending on R&D through the subsidy. This supports our first hypothesis (opportunity) stating that the treatment effect of startup subsidies is higher in better accessible locations for R&D externalities due to human capital suited to the needs of young companies. We find no evidence for the treatment effects in terms of tangible investments to be larger for firms in better accessible places. Similarly, we cannot conclude that revenue or bankruptcy effects of subsidies vary depending on the accessibility of the location. In terms of innovation and overall employee growth, we find some (weak) indication that the better accessible the location in terms of competitive accessibility the larger the subsidy's effect on the total number of employees and the likelihood of innovating. The latter results may be due to the short-term perspective of our outcome variables. In other words, the presented results show that local accessibilities matter particularly for the magnitude of input additionality and provide support for the *Opportunity Hypothesis*.

5 Discussion and Conclusion

In this study, we investigated whether the location of a startup impacts the effectiveness of startup subsidies. We hypothesized that the local accessibility of a startup's location

Table 6: Probit estimations before matching

Variables	Coefficient	$P > \|z\|$
Founder characteristics		
University	0.001	0.962
Vocational training	-0.052	0.024
Master craftsperson	0.003	0.903
Founder age	-0.003	0.020
Industry experience	-0.002	0.068
Entrepreneurial experience	-0.178	0.000
Bankruptcy experience	0.110	0.005
Opportunity driven	-0.042	0.049
Gender diversity	-0.009	0.728
Startup characteristics		
Team	0.079	0.000
Startup age	-0.124	0.000
Limited liability	0.013	0.557
ln(Tangible assets)	0.001	0.955
Patent stock	-0.004	0.522
Export activity$_{t-1}$	0.153	0.000
Capacity utilization$_{t-1}$	0.003	0.000
East/west	0.451	0.000
ln(R&D-Expenditure)$_{t-1}$	0.038	0.000
ln(Employees)$_{t-1}$	0.170	0.000
ln(Revenue)$_{t-1}$	-0.024	0.000
ln(Tangible Investment)$_{t-1}$	0.003	0.144
Profit$_{t-1}$	0.000	0.002
Observations	10262	

Notes: Chi^2(3) = 85.94, $Prob > chi2$ = 0.001; Correctly classified = 88.65%, p-values of two-sided t-tests for mean difference between subsidized and non-subsidized startups. Period t-1 refers to the year before the subsidy receipt in year t. SD = standard deviation. No time subscript indicates that the information is time-invariant or based on the founding year. The model contains industry and year-fixed effects.

could affect the use that it can make from the provision of financial support. On the one hand, startup subsidies given to new firms in better accessible regions could make more of a difference because of the opportunities that the firms have in such locations. Thus, the money falls on more fruitful grounds. On the other hand, it could be argued that firms in less accessible locations have a need for additional resources to help them compensate for the weaknesses of the location in terms of accessibility. Based on very detailed, regionally fine-grained information on local accessibility, we constructed scores capturing a location's access to potential employees taking into account various modes of transportation. The calculation of the accessibilities was based on an agent-based model taking into account congestion and actual travel times between more than 11,000 zones within Germany. We further made use of detailed data on newly founded companies which allowed us to re-

Table 7: Results: Impact of Accessibility on the Effectiveness of Subsidies

	Accessibility			
Outcome variables	Population	Employees	Research employees	Comp. employ.
$\ln(\text{R\&D Expend.})_{t+1}$	0.028 (0.033)	0.048 (0.035)	0.122** (0.037)	0.213*** (0.055)
$\ln(\text{R\&D Employ.})_{t+1}$	0.032*** (0.010)	0.045*** (0.011)	0.080*** (0.016)	0.128*** (0.022)
$\ln(\text{Tang. Invest.})_{t+1}$	-0.001 (0.042)	0.005 (0.044)	0.023 (0.043)	0.041 (0.069)
Innovation_{t+n}	0.003 (0.004)	0.004 0.004	0.005 (0.004)	0.013* (0.007)
$\ln(\text{Employees})_{t+1}$	0.008 (0.008)	0.011 (0.009)	0.014 (0.009)	0.028* (0.014)
$\ln(\text{Revenue})_{t+1}$	0.033 (0.054)	0.053 (0.056)	0.061 (0.055)	0.103 (0.087)
Bankruptcy_{t+n}	-0.001 (0.004)	-0.002 (0.004)	-0.007 (0.004)	-0.003 (0.007)

Notes: N = 5692, * p<0.05, ** p<0.01, *** p<0.001. OLS regressions are used to calculate results.

estimate the treatment effect models of Hottenrott and Richstein (2020). We thereby build on previous research that documented positive *average* treatment effects for startup subsidy programs (Almus, 2004; Colombo et al., 2012; Howell, 2017b; Hottenrott and Richstein, 2020; Grilli, 2020).

Going beyond the estimation of the average treatment effects, we estimate individual treatment impacts showing that they vary substantially around the mean. In our main results, we show that local accessibility, especially for research employees, positively and significantly affects the magnitude of the individual treatment effects. Thus the subsidy is more effective when there are more research institutions in the area providing highly skilled knowledge workers to research and develop new products. Conclusively, the accessibility to research employees seems to make the most impact in this department.

This finding might be explained by the role that access to human capital plays in firms' ability to actually expand their R&D activities in response to additional financial resources. For treatment effects on tangible investment, however, local accessibilities do not seem to matter. This indicates that depending on the objective of the subsidy program, location matters or not. If it is the goal of the funding agency to promote R&D and innovation, selecting firms in locations that have better access to qualified employees may be advisable. For other goals, the accessibility of the location does not impact the magnitude of the individual treatment effect.

We also find weak evidence for the role of better access to employees for new product development. However, longer-term effects are not considered and hence, we are careful regarding conclusions related to innovation performance or startup growth.

The findings of this study contribute to research on the role of startup subsidies as an innovation policy tool. Our findings suggest that accessibility matters especially in terms of input additionality, but there are no differences depending on the location for non-R&D inputs. This finding is in line with previous results by Rammer et al. (2020) who also found no strong evidence of regional effects on the effectiveness of government subsidies. Our results contribute to previous work because of the particular focus on young firms. Due to the important role that these firms play for innovation and regional development (Haltiwanger et al., 2016; Schneider and Veugelers, 2010b), our findings have direct policy implications. Funding new firms in locations that have better access to high-skilled human capital may increase the *bang for the buck* in terms of additional R&D in the region.

In future research, however, it seems crucial to account for potential non-stability in regional accessibility. Greater startup rates and a higher inflow of established firms in some locations may have a longer-lasting impact on local transport infrastructure. Especially in the long term, accessibility could be endogenous to firm and regional performance. It would be interesting to further study whether the accessibility actually changes over time in regions where there is a lot of firm entry. For example, specific new railroad lines such as the one between Munich and the German capital Berlin implemented in 2017 could lead to a different accessibility evaluation and a higher number of long-distance commuters. Accounting for sector-specific subsidy programs could also lead to more insights on the topic. Finally, differences in the level of digitization in companies could make a difference in our findings. While unobserved in our data, startups that rely less on in-site work and do not have fixed production sites may respond differently to the availability of local human capital. Recent trends in remote work could potentially lower the impact of local accessibility.

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