# Do investment grants have an effect on the quality of employment? –

# Evidence from a staggered treatment adoption approach

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**Abstract (200-400 words)**
The aim of the intended study is the estimation of establishment-level employment effects of investment grants in Germany in terms of quantity and quality. As a starting point I estimate the average treatment effect for the treated establishment on the quantity of employed persons over the periods of one to seven years after the treatment is finished. Subsequently, I analyze potential changes in the quality of employment with the help of different proxies. The shares of high-skilled employees and at least medium-skilled employees are proxies for high quality employment in terms of employee qualification; the share of low-skilled employees represents the counterpart. The share of so-called 'normal contracts' (full-time employment subject to social insurance contributions) is regarded as high-quality employment in terms of security and duration. Additionally, the median wage of full-time employees serves as a rough approximation of the labor productivity. For the estimation I apply a modification of Heckman's matching and difference-in-differences approach suitable for a staggered adoption design. So I am able to consider the flexibility of investment grants in terms of treatment timing and duration.

I base the analysis on a rich data set that combines treatment-related, establishment-specific and regional information from different sources. The sample consists of establishments working in sectors eligible for investment grants in Germany, thereof are 10,215 treated establishments located in eligible regions. Non-treated establishments regarded as potential controls are found exclusively in non-eligible regions. This decision is made to circumvent potential selection problems due to unobservable characteristics, since in general all establishments in eligible regions (in the eligible sectors) have access to the GRW program. And I cannot observe why some establishments apply for investment grants and others do not. Resulting from the definition of the eligibility of regions with the help of a composite structural weakness score, the regions eligible for GRW investment grants and the non-eligible regions are remarkably different in terms of e. g. infrastructure, tax revenues, unemployment rate and other factors that describe the economic environment and influence the success/development of establishments and thus, the employment effect of investment grants. This fact rises a methodological question I would like to discuss at the conference: Is it possible to control for such regional differences between the region types? Is there a (non-parametric) equivalent to the tripple DID model that is compatible to the staggered treatment adoption framework?

*Keywords*:

staggered adoption design, variation in treatment timing, employment quality, causal inference, place-based policy

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**Extended Abstract (1200-2000 words)**

Although the 'Joint Task for Improving Regional Economic Structures' (GRW).* is the oldest German placed based policy program, providing investment grants for establishments and communities in economically disadvantaged regions within the framework of this program is still the most important and most expensive instrument of this kind of policy in Germany. Comparable programs one can find in many other countries not only in Europe. The best analyzed examples are the Italian Law 488/1992 and the British Regional Selective Assistance (RSA), but also for other European countries we find empirical evaluation studies of investment grants. Summing up, the results available so far suggest that subsidies have positive effects on overall firm-level employment, investments, turnover, output and firm survival. Effects on productivity and location choice are rather negative or negligible. From the results of previous studies of GRW investment grants we know that they have positive short and mid-term effects on the number of employees. Besides – or alternatively to – the quantitative effects, investment grants are issued with the intention to influence the employment quality in the treated establishments and the regions as a whole.

The results of a (not yet published) companion study that analyzes the heterogeneity of employment effects suggest a negative influence of human capital on the strength of the quantitative employment effect. At the same time, we observe a variation of the costs of the employment effect, i.e. the amount of subsidy per additionally provided job, dependent on the employee structure of the treated establishments. One possible explanation for the results is that treated establishments with better qualified employees provide higher qualified (and thus, more expensive) jobs. In order to verify this presumption, the focus of the intended study is on the quality of the employment. The aim is to estimate establishment-level employment effects of investment grants in Germany for the funding period 2007 to 2013 in terms of quantity and quality. As a starting point I estimate the average treatment effect for the treated establishment on the quantity of employed persons over the periods of one to seven years after the treatment is finished. Subsequently, I analyze potential changes in the quality of employment with the help of different proxies. The shares of high-skilled employees and at least medium-skilled employees are proxies for high quality employment in terms of employee qualification; the share of low-skilled employees represents the counterpart. The share of so-called 'normal contracts' (full-time employment subject to social insurance contributions) is regarded as high-quality employment in terms of security and duration. Additionally, the median wage of full-time employees serves as a rough approximation of the labor productivity.

The first main challenge for the study results from the requirements associated with the estimation approach. Following the development of new estimation approaches for empirical research in the 1990s and controversial discussions mainly at the beginning of the new millennium,

*The abbreviation GRW refers to the German title of the program, 'Gemeinschaftsaufgabe Verbesserung der Regionalen Wirtschaftsstruktur'.

the idea of a combined control for selection bias resulting from observable and unobservable heterogeneity within the framework of difference-in-differences models became quite common in the treatment evaluation literature. However, a comparably new issue raised in current econometric literature is the impact of variations in the treatment timing and the influence of a dynamic economic environment on the treatment effect in the context of panel data. Various studies prove that in case of time-dependent treatment effects, the assumptions of the two-way fixed effects DID models usually applied for causal analysis, particularly the implicit presumption of effect homogeneity, are not fullfilled (see e. g. de Chaisemartin and D'Haultfœuille 2020, Goodman-Bacon 2021, Sun and Abraham 2020). More recent estimation approaches therefore include the treatment timing in the estimation process. In so called 'staggered adoption designs', the treated units are categorized by groups (or cohorts) based on when they first receive treatment (see e. g. Athey and Imbens 2021, Callaway and Sant'Anna 2021).

For the intended estimations I will apply a modification of Heckman's matching and difference-in-differences approach that is able to consider panel data with more than two periods and belongs to the group of estimators within the framework of staggered adoption design. The most important modification lies in the definition of the observation period. Instead of an a priory definition of fixed observation times before and after treatment, the period of observation is defined individually for each treated observation. The 'flexible conditional DID estimator' consists of a preprocessing to define individual selection groups, a matching process that refines the selection groups by selecting the best possible control(s), and a non-parametric DID to estimate the average treatment effect for the treated (see Dettmann et al. (2020) for more details). In the preprocessing, the observation time of the matching variables and the outcomes are related to the individual treatment start. Furthermore, the preprocessing process works like a filter. For the defined matching time and the defined matching variables, the algorithm finds all non-treated units that have no missings in the variables and saves them in an individual selection group for every treated. The same is true for the outcome development. The next step is the matching algorithm that selects one or more statistical twins for every treated unit among the pre-selected units in it's individual selection group. As a novelty, the matching is based on a combined statistical distance function instead of the standard distance measures like the Propensity score. This statistical distance function gives a 'pure' description of the similarities and disparities regarding the individual covariates in that each included covariate is equally weighted, and the overall indicator reflects the comparability of the observations without covariate weights in favour of 'important' or particularly similar/dissimilar covariates. Based on this matching process, the average treatment effect for the treated is estimated. The 'flexible conditional DID' estimates the effect as the mean of individual comparisons. The approach compares differences in outcome development between a treated unit and its control(s) for individually defined outcome observation periods. Due to heterogeneous treatment durations, the observed periods may be heterogeneous among the treated individuals. The described approach is able to consider the flexibility of investment grants in terms of treatment timing and duration in an appropriate way.

The second challenge is related to the data base and the construction of the sample of analyzed establishments. I base the analysis on a rich data base that combines treatment-related, establishment-specific and regional information from different sources. The treatment data of the responsible Federal governments contains information at the project level for every project in the funding period, e. g. the start and end of the subsidized projects, but also monetary information on the project. Unfortunately, I find no information on rejected projects in the data, and very limited information on the subsidized establishments. I use Employment History data of the Federal Employment Agency (Bundesagentur fuer Arbeit) to characterize the treated establishments and also non-treated establishments. In additin, I use the establishment's location to enrich the data with regional information from the INKAR data-base of the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR). From this combined data, I draw a sample that consists of establishments working in sectors eligible for investment grants in Germany, thereof are 10,215 treated establishments located in eligible regions. When selecting non-treated establishments as potential controls, I face a trade-off between two sources of distortion of the estimation results. The first one is the selection bias due to unobserved characteristics of the non-treated establishments in eligible regions: Since the GRW is a demand driven program, all establishments in eligible regions (in the eligible sectors) have access to the GRW program, and I cannot observe why some establishments apply for grants and others do not. The second one applies to the non-treated establishments located in non-eligible regions: They benefit from an economically more favourable environment in economically stronger regions. Since the economic environment has an influence on the estimated effect, a comparison between the treated establishments located in economically weak regions and non-eligible establishments in economically stronger regions will probably underestimate the true effect. To avoid selection problems due to unobservable characteristics, I exclude non-treated establishments in eligible regions from the sample and only consider establishments that do not have access to GRW funding as potential controls. In the the interpretation of the estimation results, the resulting potential underestimation of the employment effect will be taken into account. This fact also rises a methodological question that I would like to discuss at the conference: Is it possible to control for such regional differences between the region types? Is there a (non-parametric) equivalent to the tripple DID model that is compatible to the staggered treatment adoption framework?

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