The Effect of Public Sector Relocations on Regional Development in Germany

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March 20, 2025

Regional economic disparities within countries have become increasingly large, often surpassing the disparities observed between countries. To address regional inequality, governments have been turning away from standard subsidies and are experimenting with public employment reallocation as a place-based policy. This paper estimates the causal effect of public employment reallocation on local labor markets. I study the 'Heimatstrategie,' which relocates around 3,000 public sector jobs from Munich to economically lagging regions in Bavaria, Germany. Using novel data on 60 agency relocations between 2015 and 2025, I exploit the government's quantitative selection criteria for receiving municipalities and implement a long-differences design comparing treated Bavarian municipalities to Mahalanobis-matched control municipalities in other German states. My estimates show that relocations increased private sector employment shares by up to 2.3%, reduced unemployment rates by up to 11.9%, and increased local population by up to 1.6% without harming sending locations. These results provide new causal evidence on public employment multipliers from non-capital city relocations, addressing external validity concerns in the existing literature.

JEL Classifications: J21, J45, J68, R23
Keywords: Regional Inequality, Public Employment Reallocation, Place-Based Policy, Local Labour Markets

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Acknowledgements: I thank Jordi Jofre-Monseny, Alexander Kemnitz, Cailin Slattery, Katja Bergonzoli, Nils Grashof, Simon Syga, and participants of the AQR Research Seminar University of Barcelona, 13th European UEA Meeting, 2024 RSA Annual Conference, Aix-Marseille Research Seminar, and NBER Conference on Place-Based Policies for their helpful comments.

1 Introduction

Within-country inequality is currently growing faster than between-country inequality. Recent research indicates that while between-country inequality has decreased due to economic growth in countries like China and India, within-country inequality has been on the rise, particularly since the mid-1980s (Goda and Torres García 2017; Kanbur 2019). Even in high-income countries, the gains of economic growth have not been distributed uniformly across regions. In the United States, a country performing in the top decile of OECD countries, the average real GDP per person is about 90 percent higher than in Slovakia. At the same time, within the United States, per capita GDP in New York is 100 percent higher than in Mississippi (Bluedorn et al. 2019). One might assume this phenomenon is unique to the United States, as its income inequality has been consistently higher than in Europe (Burkhauser and Poupore 1997; Piketty and Saez 2014; Filauro and Parolin 2019; Hoffmann et al. 2020). However, Germany exhibits similar tendencies. In 2023, Germany's GDP per capita was 1.7 times higher than that of the Czech Republic, but within Germany, Hamburg's GDP per capita was 2.2 times higher than that of the state of Thuringia (International Monetary Fund 2024; German Regional Database 2024).

Yet, in the German federal constitution, Article 72, paragraph 2, anchors the objective of equal living conditions across regions as a state goal. Germany has historically implemented various policies to achieve more equal living conditions, including federal grants, municipal tenders, and subsidies. Recently, Germany has been trying to incentivize chip manufacturers like Intel and TSMC to open new locations in the country's East, which has had challenges in converging economically to the rest of the country since reunification in 1991. However, attracting such firms means taking part in a fierce international competition for high-tech jobs and making the subsidies offered in the process costly in terms of the amount of taxpayer money paid per job created. Slattery (2024) investigates the effect of subsidy competition on welfare at the national level. She finds that within the US, states compete away most of the surplus, transferring welfare gains to firms, and posits that the US would be better off with a subsidy ban. In Germany, Intel just announced that it will postpone the construction of the promised chip manufacturing plant that was supposed to create 3,000 in Saxony-Anhalt. The German government had offered the company nearly 3.3 million euros in subsidies per job, a total of 9.9 billion euros in subsidies for the whole project (Richtmann 2024). Because of such cases, governments are increasingly looking for alternative policies to help lagging areas. Since its capital relocation from Berlin to Bonn after WWII, Germany had gained experience with public employment reallocation. When the country relocated the capital back to Berlin in 1999, several ministries were distributed between the new Eastern states (German Bundestag 1992). More recently, Germany joined South Korea, the United Kingdom, Denmark, and Sweden, among other nations, in implementing public employment reallocation strategies as an alternative to subsidies to revive labor markets in lagging behind areas (Freitas forthcoming). Currently, Germany has two public employment reallocation policies in place. The first was launched at the regional level by the state government of Bavaria. In 2015, the state government initiated the 'Heimatstrategie' (Homeland Strategy), which aims to transfer over 3,000 jobs and study

places and more than 50 agencies (roughly 1% of all public sector jobs) from Munich to lagging regions by 2025. The initiative was further expanded in 2018, with a second phase to continue until 2030. The main objective of the policy is to establish equal living conditions between urban areas like the state capital, Munich, and lagging regions, mainly in the north of the state and near the border regions with the Czech Republic and Austria. Despite being one of the most economically thriving states in Germany, Bavaria exhibits significant intraregional economic disparities. It encompasses municipalities that rank among both the highest and lowest in terms of wealth within the national German context. In certain jurisdictions, such as Gruenwald located immediately south of Munich, the mean income per taxpayer was recorded at over 136,000 euros in the year 2014. This figure is in stark contrast to other regions such as Simbach, located on the Austrian border, where the average income per taxpayer was 19,637 euros in the same year (German Regional Database 2024).

The second public employment reallocation policy is being implemented at the federal level as a compensation mechanism for regions losing coal plants due to the energy transition. The federal government's 'Strukturstaerkungsgesetz Kohleregionen' also aims to relocate 5,000 federal government jobs by 2028 alongside providing a 40 million Euro fund for affected regions (Press and Information Office of the Federal Government 2023).

The recent, widespread implementation of public employment reallocation policies has raised questions regarding their impact on employment in the private sector of the economy. Specifically, there is uncertainty about whether an increase in public sector jobs leads to a corresponding rise in private employment, known as "crowding in," or results in a decline in private sector jobs, referred to as "crowding out." Research by Faggio and Overman (2014) and Jofre-Monseny et al. (2020) examines the effects of changes in public employment within the United Kingdom and Spain, respectively. Their findings suggest that an increase in public employment leads to a rise in private sector employment. However, Faggio and Overman (2014) also identify a negative long-term impact on the traded sector, particularly manufacturing industries.

Conversely, Senftleben-König (2014) and Auricchio et al. (2020) analyze the repercussions of reducing public employment in Germany and Italy. Their studies indicate that a decrease in public sector jobs leads to an increase in private sector employment. Further investigation by Faggio (2019) and Lee et al. (2024) focusing on specific relocation policies for public employment in the United Kingdom and South Korea, respectively, also report a crowding-in effect on private employment. For a detailed review on the impact of public employment reallocation as a place-based policy, see Freitas (forthcoming).

Moreover, Becker et al. (2021) and Faggio, Schluter, et al. (2022) assess the implications of relocating Germany's capital from Berlin to Bonn post-World War II and back to Berlin following reunification in 1991. Both studies note a crowding-in effect concerning private employment. However, Becker et al. (2021) observe that while there is a positive impact on non-traded private sector employment, it has to offset a negative effect on the traded private sector. In contrast, Faggio, Schluter, et al. (2022) do not find evidence of adverse effects on the traded sector.

In a briefing by the What Works Centre for Local Economic Growth (2023), a benchmark for the local employment multiplier effect of public sector relocation is established at

0.37 for tradable private sector occupations. Nevertheless, empirical research presents significant variability in multiplier estimates. Faggio and Overman (2014) identify that 10 additional public sector jobs result in the creation of only 0.8 private sector jobs when considering the entirety of the United Kingdom's economy. Contrarily, in an analysis of a specific relocation initiative targeting designated regions within the UK, known as Lyon's review, Faggio (2019) reports that each increase of 10 public sector positions generates approximately 15 additional positions within the private sector.

Apart from the fact that different studies lead to different conclusions about the effect of public employment reallocation on the remainder of the economy, the literature also presents other major limitations. A primary concern is the lack of external validity in many studies. For instance, Becker et al. (2021) and Faggio, Schluter, et al. (2022) focus on capital relocations, while Jofre-Monseny et al. (2020) examines provincial capitals. The unique characteristics of capital cities, which are generally more affluent than other regions, drive these results to hardly be applicable to smaller economically disadvantaged localities.

Additionally, studies that assess expansions or contractions in a country's public sector, such as those by Faggio and Overman (2014), Senftleben-König (2014), and Auricchio et al. (2020), obscure spatial asymmetries. For example, a reduction in the local public sector size in a prosperous city might alleviate congestion and allocate resources to the private sector. Conversely, in a small city characterized by high unemployment and a rudimentary private sector, an increase in the local public sector size could stimulate private economic activity.

Moreover, even investigations addressing these issues through analyses of specific relocation policies targeting smaller areas, such as those conducted by Faggio (2019) and Lee et al. (2024), have limitations. An issue is that these policies typically do not involve a random selection of target areas biasing conclusions from study outcomes.

This study addresses these shortcomings in different ways. First, it focuses on the German 'Homeland Strategy 2015,' program implemented in the state of Bavaria mentioned above, which redistributes public sector employment from Munich, the state capital, to over 50 smaller municipalities, providing a distinct opportunity to address external validity issues.

Second, the analysis encompasses both the impact on the sending location Munich, and the economic effects experienced by economically lagging recipient regions. This approach addresses spatial asymmetries and general equilibrium effects that are often overlooked in the literature.

Finally, I can use the policy's unique allocation mechanism to address selection bias concerns. The Bavarian government is among the first regional governments to employ a quantitative approach to pinpoint distressed areas. It developed a structural index to determine which districts are eligible for relocation initiatives. The index is calculated using a weighted average of five economic and demographic metrics: the population forecast, the unemployment rate, employment density, disposable income, and net migration of individuals aged 18 to 30.

I analyze the policy by employing a long differences approach combined with Mahalanobis matching. The control group in the difference-in-differences analysis is determined

by comparing municipalities within Bavaria that received an agency with municipalities located in other German states outside Bavaria, which by design, were not eligible for the state program. The selection of comparable municipalities was executed through a Mahalanobis matching procedure that utilized the structural index indicators mentioned above. The identifying assumption is that had these control municipalities been located in Bavaria, they would have been eligible for treatment.

Since the program is being rolled out within a time frame of ten years between 2015 and 2025, I apply the Callaway and Sant'Anna (2021) estimator to account for treatment time heterogeneity. The year 2014 serves as the baseline year for comparisons across different event-years within the staggered treatment framework. The program will be concluded in 2025. So far, this study includes all relocations that were completed until 2023. I use manually collected relocation data from government documents, parliamentary inquiries, and newspaper articles on the relocation program, and administrative data on economic and demographic measures at the municipal level from the German Regional Database.

I find that the public employment reallocation program has led to an increase in employment levels, total population, and working-age population, alongside a reduction in unemployment rates within the treated localities. After subtracting the mechanical effect of the job relocations, I find an increase in private sector employment shares by 1.1% following the start of relocations in 2015, rising to as much as 2.3% by 2021. These findings are statistically significant for the period spanning from 2019 to 2023. The relocation initiative resulted in a decrease in unemployment rates across all subsequent years after the program started, with the exception of 2016. The empirical findings show statistically significant reductions in unemployment for the years 2017 and 2018. Specifically, the unemployment rate declined by 5.6% in 2017 and by 11.9% in 2018 compared to 2014. Treated municipalities experienced an increase in the local population, amounting to 1.2% in the year 2017, followed by a further rise of 1.6% in 2018. The effect on the working age population was even more pronounced, reaching up to a 2.1% increase in 2018. This upward trajectory in population growth was notably disrupted during and after the pandemic period. Preliminary results show that the relocation did not harm but benefit the sending locations. Overall, this study addresses external validity, spatial heterogeneity, and selection bias concerns, while using a novel, manually collected dataset of the German public employment reallocation policy.

The following sections are organized as follows. First, I describe the specifics of the policy program under analysis and introduce both the novel data collected and the administrative data used. Next, I explain the matching procedure and methodology used prior to discussing the empirical results and concluding the study.

2 Institutional Setting

In 2014, the Bavarian government introduced the Homeland Strategy to strengthen economically weak areas in Bavaria. Running from 2015 to 2025, the program is designed to decentralize around 60 agencies and redistribute 2,063 public jobs along with 930 study places for public sector training across 56 municipalities.

The program's scope includes expansions within existing agencies, relocations predominantly from the state capital, Munich, to smaller regions, and the formation of new regional branches of state agencies. Relocations are responsible for most job creation, accounting for 1,554 positions and 600 study places. In contrast, new branch establishments contribute an additional 380 jobs, while workforce expansions are responsible for generating 129 jobs and providing 330 study places.

These two categories represent a lesser share of overall job growth than relocations. In December 2021, the program the Bavarian government extended the program and announced a second phase, 'Heimatstrategie Stufe 2', running until 2032. The program extension reallocates fewer agencies but more jobs, with 15 agencies and 2,720 jobs slated for redistribution to 13 municipalities in 11 districts.

In addition to these measures, supplementary relocations were initiated in 2016 to support the regions of Middle Franconia and Lower Bavaria specifically. Given that these relocations were focused on these specific areas rather than being based on the structural index that designates areas with particular need for action, they were excluded from this analysis. Hence, I only analyze receiving locations that are in line with a quasi-experimental set-up created through the index-based selection. Table 1 illustrates all relocation programs running in Bavaria, including the mechanism for selecting receiving locations.

Phase	**Program Name**	**Allocation Rule**
I	Homeland Strategy. Regionalisation of the Administration	Areas with particular need for action as of RDP 2013/14*
II	Homeland Strategy. Concept Administration Relocation Bavaria 2030	Areas with particular need for action as of RDP 2018**
Other	Structural Concept "Opportunities in the Whole State"	Regionally Bound to Middle Franconia and Lower Bavaria
Other	Additional single regionalization measures	None

Table 1. Policy Background on Public Sector Relocations in Bavaria.
*Based on the Bavarian Regional Development Plans 2014 and 2018. I only include relocations from the first phase of the Homeland Strategy program in the analysis.

The selection criteria for agencies destined for relocation encompass several specific requirements: Agencies must engage in non-local activities with a supra-regional scope of responsibilities. The relocation pertains specifically to state authorities or affiliated entities under the jurisdiction of the Free State of Bavaria. Furthermore, it involves the transfer of lower, middle, and upper-tier authorities whose headquarters are currently situated in densely populated Bavarian areas, mainly Munich. Consequently, entities such as police stations and educational institutions are excluded from this process due to

their inherently local operational focus. The criteria for selecting a relocation site include several specific considerations. A significant majority, 88 %, of relocation projects are directed towards areas with particular need, identified through a structural index. Among the remaining projects not situated in this selected area, six are within municipalities that have experienced base closures, known as conversion municipalities.

Receiving sites have to be medium-sized regional centers in a district called "Mittelzentren," designated in the Bavarian regional development plan. Notably, receiving locations should also not already receive funding under other policies, like the Bavarian University initiatives. Fig. 1 shows the spatial scope of the relocation by treatment status. Table 2 shows the different costs for the relocation program up until 2022. The table delineates the financial expenditures incurred over several fiscal periods. Personnel costs, encompassing the period from 2016 to 2022, amount to 16 million euros. They mainly consist of several different incentive payments the Bavarian state government offers employees willing to relocate. These include mobility premia, a one-time lump sum incentive of 3,000 euros for permanent relocation, additional variable moving costs, expense reimbursement for employees commuting between locations or staying near the new workplace during the week and being at home during the weekends, and a separation allowance to cover supplementary costs when an employee is temporarily separated from their main residence due to work relocation.

Construction expenditures total almost 75 million euros. Renovation expenses for various locations aggregate to 3 million euros. Moving costs are calculated from 2015 to 2021 and total 450,000 euros. Rental costs span from 2015 through 2022 and total 18 million euros. The cumulative financial outlay across all categories is quantified at roughly 114 million euros (Kaltenhauser 2023).

Summarizing the costs so far, I estimate that the Bavarian government has paid roughly 38,000 euros per job relocated. However, these expenses are subject to change, and some fixed costs, like construction and renovation costs, were already paid, but they will also support future jobs to be relocated in the upcoming years.

Cost Category	**Total Cost (€)**
Personnel Costs (2016-2022)	16,623,849.00
Construction Costs	74,923,320.64
Renovation Costs	3,708,003.37
Moving Costs (2015-2021)	450,713.00
Rental Costs (2015-2022)	18,188,015.00
Total	113,893,901.01

Note: This table summarizes costs across multiple years: personnel costs from 2016 to 2022, construction costs for four sites, moving costs from 2015 to 2021, and rental costs from 2015 to 2022.

Table 2. Cost Overview

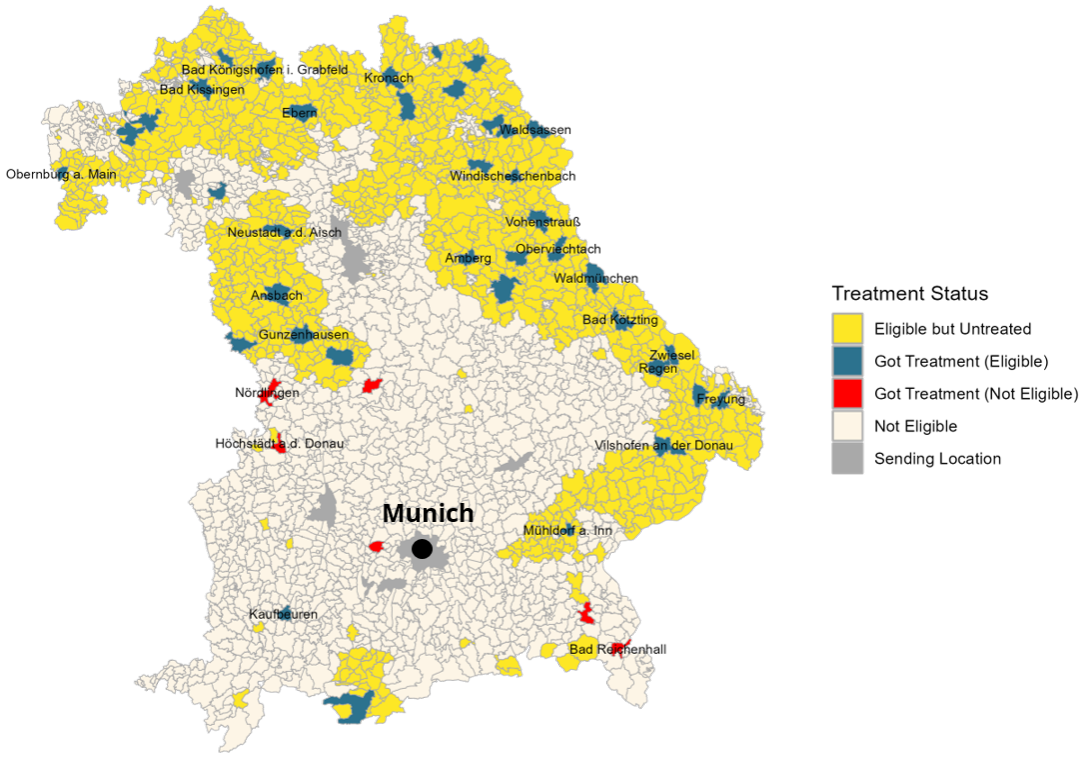


Figure 1. Spatial scope of the Bavarian relocation program by treatment status determined through the quantitative structural index. Districts and municipalities performing at 90% or less than the Bvarian average are included in the area with particular need for action. Municipalities that lost defense employment in 2011 were also eligible regardless of the index (in red).

3 Data

The analysis encompasses 7559 German municipalities, 2027 of which are located in Bavaria. The Bavarian relocation dataset is manually extracted from the BayernAtlas, a digital atlas of the state of Bavaria that is available free of charge to the general public (State Office for Digitization, Broadband and Geodetic Measurement 2024). I observe the program name, managing state ministry, agency address, job relocation figures, and relocation status. Completion dates for relocations were extracted from annual government reports on the Homeland Strategy program. I conducted manual searches in local newspapers to find the exact relocation date for agencies not documented in these reports. On average, the relocations amounted to 1.3% of total employment in receiving municipalities. Appendix Fig. 8 depicts the distribution of distances from origin sites, predominantly ranging from 150 to 250 km. This translates to an average of 126 minutes when taking the road distance.

The Bavarian structural index, designed to allocate agencies based on municipal economic and demographic profiles, guides the matched sample creation for the difference-in-differences analysis. The index aggregates five metrics: population projections, unemployment rates, employment, income levels, and net migration of young adults (aged 18-30). Table Table 3 catalogs these indicators alongside their respective data sources. Contrary to the original structural index, I utilizes log differences spanning 2009 to 2014[1]—preceding the policy announcement—to ensure that matched municipalities are comparable in trends rather than in isolated annual levels.

I use unemployment and employment measures to calculate pre-treatment employment density statistics included in the structural index and as post-treatment outcome measures. In Germany, there are two different administrative measures for employment, one following the European employment accounting framework ('Erwerbstaetigenrechnung') and one developed by the German Federal Employment Agency based on employees subject to social security contributions in Germany ('Sozialversicherungspflichtig Beschaeftigte'). For the former employment measure following the EU framework, data is collected by the

[1] I use the 2010-14 log differences for the income per taxpayer variable.

Weight	Indicator	Statistic	Source
30%	Population Predictions	Change betw. 2009–2021	GRD, BSO
30%	Unemployed Persons	2012	GRD
10%	Employment Density per 1,000 inh.	2012	GRD, FEA
20%	Inc. per taxpayer	2007	BSO
10%	Net migration of 18-to-30-yr-olds per 1,000 inh.	2011	GRD, BSO

Table 3. Weights and composition for each indicator of the structural index on the municipal level. The German Regional Database (GRD), the Federal Employment Agency database (FEA), and the Bavarian Statistical Office (BSO) are data sources.

state statistical offices. This data encompasses the whole labor force, including public servants, and self-employment down to the district level but not the municipal level. On the other hand, the employment measure by the Federal Employment Agency is available down to the municipal level, but since public servants and self-employed persons do not pay into the German social security system, they are excluded from this dataset. Hence, I have to trade off data availability and completeness for the analysis. I decide to use the disaggregated data at the municipal level for different reasons. First, the average number of jobs relocated is quite low, at around 67 jobs per relocation. Therefore, I assume that such a relatively low treatment intensity probably has an effect at the most local level and might not be identifiable at the aggregate district level. Second, using this data, I still account for around 80% of the workforce, meaning that I still believe that I can draw significant conclusions for local labor markets. Third, I can analyze commuters and local employees, aka. people who live and work in the same municipality. This is an important question when analyzing public sector relocations since it is unclear how many people move to the new location from the sending locality and how many people are hired locally.

Mandatory employer reporting provides insured employees demographic, employment data to the social security system at the end of June each year. Information on an employees place of residence is based on the location the employee reports to the employer (German Regional Database 2024).

4 Empirical Methodology

4.1 Long Differences

In terms of method, I combine difference-in-differences (DiD) estimation and Mahalanobis distance matching. The focal equation for the long-difference analysis is articulated as follows:

$$\Delta Y_{ik} = \delta_p + \beta T_i + \gamma X_i' + \epsilon_i$$

Where ΔY_{ik} represents the log differences in local labor market outcomes k (for example, the employment share, the working population share, and the unemployment share) for municipality i between 2022[2] and 2014. In this formulation, δ_p signifies pair fixed effects for each closest neighbor matched via the Mahalanobis distance. The term T_i denotes the treatment indicator, while X_i' comprises a vector of municipality characteristics, informed by the structural index employed by policymakers to ascertain treatment eligibility. To establish causality in this framework, I need to ascertain that both the parallel trends assumption and the no antecipation assumption hold. The parallel trends assumption predicates that, absent the public sector relocation, Bavarian municipalities would have mirrored the trajectory of control municipalities in terms of local labor market and population outcomes. Concurrently, the no-anticipation assumption posits that outcomes were unaffected by the impending treatment in pre-treatment periods. The announcement in 2015, and the staggered implementation of relocations from 2015 to

[2]2023 for population outcomes

2025 might introduce potential anticipation effects. To address this potential violation, I include event studies in the empirical analysis, which do not reveal significant anticipation effects. This absence of anticipation effects could be attributed to private sector entities' reluctance to expand employment or establish new operations prior to observing tangible increases in local demand or the fact that employees only relocate when new agencies open.

The Mahalanobis distance, defined as

$$D^2 = (X - Y)' S^{-1} (X - Y)$$

X and Y represent the vectors of observable covariates for treated and control municipalities, respectively. The multiplication by the inverse covariance matrix, S^{-1}, weights the distance calculation, significantly emphasizing dimensions with lower variance. This adjustment is intuitive, as smaller differences in these low-variance dimensions could indicate more substantial disparities.

I identify the nearest control unit for each treated municipality. However, exact matching is often impractical due to the curse of dimensionality[3]. I match 38 treated municipalities to 38 control counterparts from outside Bavaria. I employ the MatchIt package in R to facilitate the Mahalanobis distance matching, which aims to emulate the conditions of a fully blocked experiment[4].

I examine municipalities within and outside Bavaria to select an appropriate control group. Boxplots in Fig. 2 demonstrate that both sets form viable control groups based on the distribution of covariates used for matching. Yet, balance plots in Fig. 3 and in Fig. 9 in appendix C reveal superior matching quality with municipalities outside Bavaria, particularly in terms of the variance ratio between treated and control groups, which approaches unity more closely. Importantly, selecting controls from outside Bavaria mitigates potential spatial spillover effects, a risk underscored by the proximity of treated municipalities within Bavaria, as depicted in the map in Fig. 4. Additionally, I reduce the risk of including a municipality in the control group that received a relocation through other programs mentioned in Table 1.

Post-matching improvements in these metrics were particularly notable for employment and the young population (ages 18-30), as detailed in Tables 3 and 4, highlighting the

[3]The 'curse of dimensionality' refers to the phenomenon where, as the number of dimensions (i.e., variables or features) in a dataset increases, the volume of the space increases so rapidly that the available data become sparse. This sparsity is problematic because it makes it difficult to identify meaningful patterns, increases the noise-to-signal ratio, and requires exponentially more data to achieve statistical significance. In the context of matching treated and control units based on multiple covariates, the curse of dimensionality can hinder the ability to find closely matched pairs, as the dimensional space becomes increasingly populated with dissimilar, rather than similar, units.

[4]A 'fully blocked experiment' is an experimental design where the experimental units are grouped into blocks based on certain characteristics, and within each block, units are randomly assigned to treatment or control groups. This design aims to control for the blocking variables, reducing the impact of confounding variables and increasing the precision of the estimated treatment effects. In observational studies, techniques like Mahalanobis distance matching attempt to approximate the conditions of a fully blocked experiment by ensuring that matched treated and control units are as similar as possible across a range of observed covariates, thereby mimicking the blocking process to control for confounding factors.

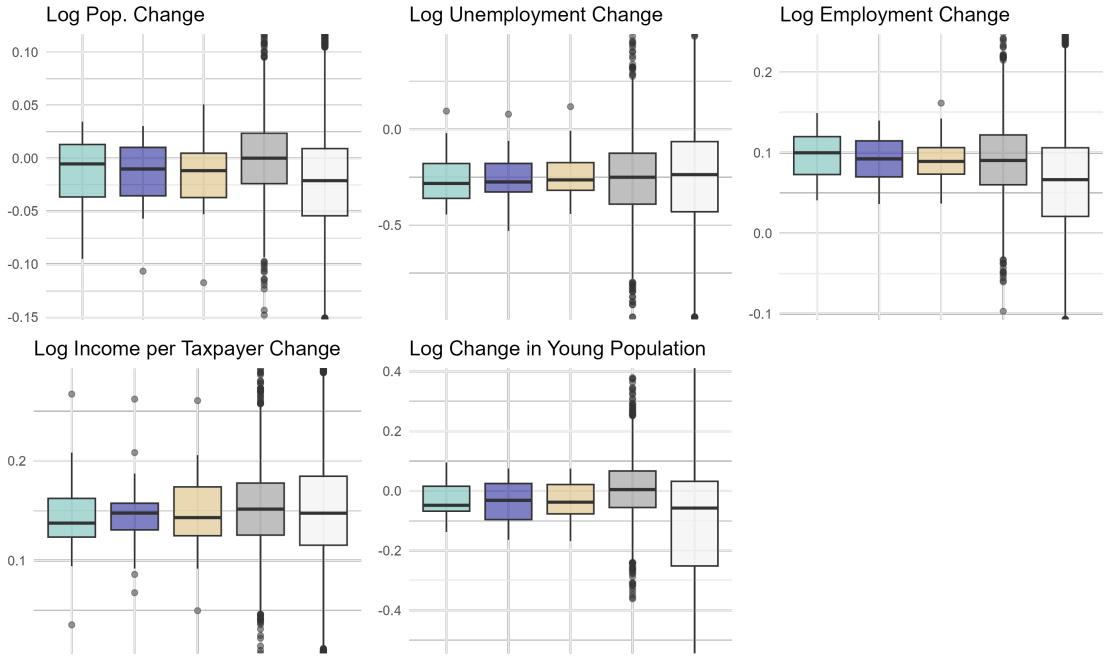


Figure 2. Boxplots showing the distribution of covariates used for matching comparing treated and possible control groups. Teal: Treated Municipalities, Dark Blue: Control group municipalities in Bavaria, Orange: Control group municipalities outside of Bavaria, Grey: Other Bavarian Municipalities, White: Other German Municipalities.

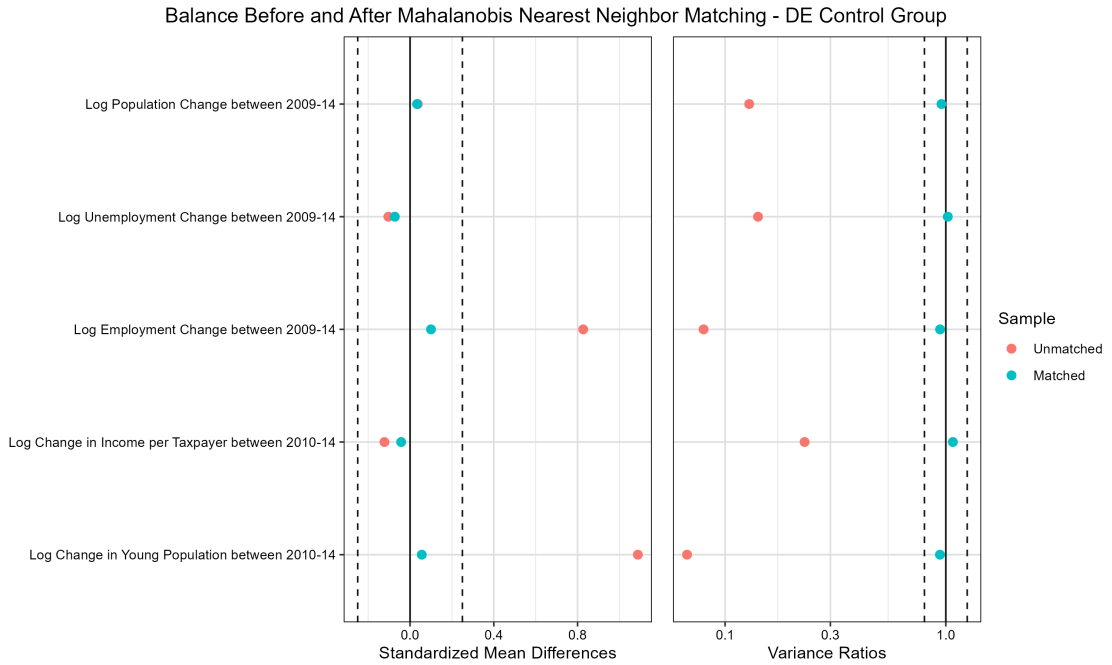


Figure 3. Balance Plot illustrating Standardized Mean Differences, and variance ratios between treatment and control group of municipalities outside of Bavaria before and after Mahalanobis nearest neighbor matching.

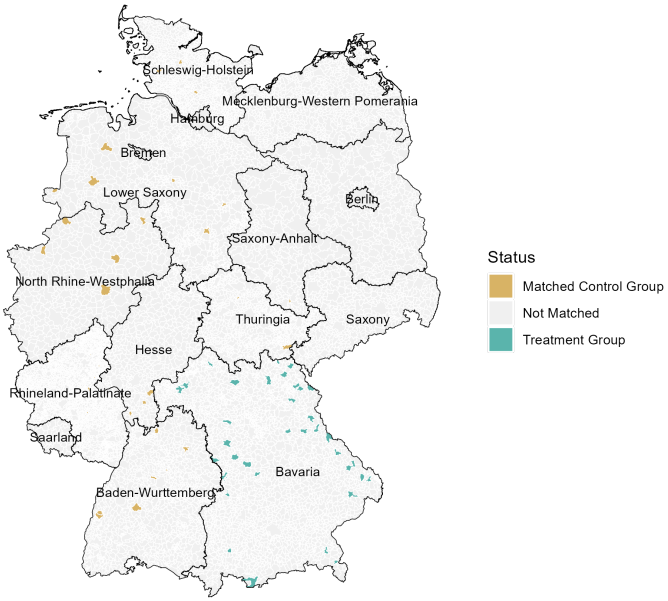


Figure 4. Map of Germany showing the treated municipalities in Bavaria (teal) and their control group counterparts (ocher) outside of Bavaria.

effectiveness of our matching procedure in aligning the covariate distributions of the treatment and control groups.

Variable	Means Treated	Means Control	Std Mean Diff	Var Ratio
Population	-0,01	-0,02	0,04	0,13
Unemployment	-0,25	-0,24	-0,1	0,14
Employment	0,1	0,07	0,83	0,08
Income per Taxpayer	0,14	0,15	-0,12	0,23
Population 18-30 yrs	-0,03	-0,1	1,09	0,07

Table 4. Balance pre-matching between treated municipalities in Bavaria and other municipalities outside of Bavaria.

Variable	Means Treated	Means Control	Std Mean Diff	Var Ratio
Population	-0,01	-0,02	0,03	0,96
Unemployment	-0,25	-0,24	-0,07	1,02
Employment	0,1	0,09	0,1	0,94
Income per Taxpayer	0,14	0,15	-0,04	1,08
Population 18-30 yrs	-0,03	-0,03	0,06	0,94

Table 5. Balance post-matching between treated municipalities in Bavaria and matched municipalities outside Bavaria.

4.2 Staggered Difference-in-Differences

I implement an event study to explore the time-varying effects of the policy. The staggered timing of the policy roll-out introduces challenges, especially regarding treatment time heterogeneity, which has been well-debated in the difference-in-differences literature. A common issue is that units treated early in the policy implementation can receive negative weights when they control later-treated units. To address this, I adopt the methodology proposed by Callaway and Sant'Anna (2021) and Sun and Abraham (2021), using clean control groups of units that are never treated.

Both estimators allow us to break down the treatment effect by each cohort, defined by their year of treatment. Then, I aggregate them to create different standard measures of the treatment effect. These aggregated measures can be averages over time or related to the duration since treatment. For the Callaway & Sant'Anna estimator, the cohort-specific average treatment effect (ATT) is defined as:

$$ATT(g,t) = E\left[Y_{it}(g) - Y_{it}(\infty) \mid \mathcal{G}_i = g\right] \tag{1}$$

The effect is identified by comparing the expected change in outcomes for a given cohort g between periods $g-1$ and t with those for units that are either yet-to-be-treated or

never-treated:

$$ATT(g,t) = E\left[Y_{it} - Y_{i,g-1}(\infty) \mid \mathcal{G}_i = g\right] - E\left[Y_{it} - Y_{i,g-1}(\infty) \mid \mathcal{G}_i \in \mathcal{G}_{comp}\right], \quad (2)$$

where $\mathcal{G}_{comp} = \{g' : g' > t\}$. To aggregate these cohort-specific effects into a single event-study parameter, I use:

$$ATT_l^w = \sum_g w_g \times ATT(g, g+l), \quad (3)$$

Here, l represents the number of periods after the policy was implemented. For statistical inference, bootstrap methods are employed. The Sun & Abraham estimator works similarly, modifying TWFE by estimating the underlying weights on cohort-specific average treatment effects using auxiliary regressions. The major difference is that in Callaway & Sant'Anna's specification, the parallel trend assumption only needs to hold for one pre-treatment period per cohort, meaning that all coefficients are calculated as long differences to the first pre-treatment period for each cohort. However, in the following graph, I translate the results to a universal base period, making these coefficients more comparable to the previous long difference results.

5 Long Difference Results

Table 6 presents the results of a long differences estimation comparing log changes in unemployment and employment shares between 2014 and 2022, and total population and working age population between 2014 and 2023 for municipalities in Bavaria that received relocated public sector jobs (the treatment group) and matched municipalities outside Bavaria (the control group). Column 1 shows the estimated treatment effect on the log change in unemployment share between 2014 and 2022. The relocation program reduced the unemployment share in treated municipalities by approximately 7.9% relative to matched controls over this period. However, the effect is not statistically significant at conventional levels. Column 2 shows that the employment share grew significantly by roughly 2% in the same period. Column 3 reports the estimated treatment effect on the log change in population between 2014 and 2023. The program did not increase total population substantially in that year, though the working age population grew by 2.2%. Both effects are not statistically significant in 2023.

5.1 Labor Market Outcomes

Table 7 presents the results of long differences estimations for years between 2015 and 2023 compared to 2014. The treatment effect in the first row represents the log differences in employment shares between treated municipalities in Bavaria that received relocated public sector jobs and matched untreated municipalities outside Bavaria compared to 2014 as the base year. The estimated treatment effects are positive, indicating that the program consistently increased employment shares in treated municipalities relative to matched controls. The magnitude of the effect is strongest at the beginning of the

	(1)	(2)	(3)	(4)
Treatment (Bin)	-0.0785	0.0201**	0.0067	0.0229
	(0.0564)	(0.0080)	(0.0111)	(0.0136)
Controls:	✓	✓	✓	✓
Observations	76	76	76	76
R^2	0.73549	0.70676	0.72743	0.70365
Within R^2	0.19972	0.42486	0.15903	0.17938
Mahalanobis Pair Fixed Effect	✓	✓	✓	✓

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1
Notes: The table reports the the simple differences in the employment and unemployment shares between 2014 and 2022, and the log differences in population and working age population between 2014, and 2023. The control group consists of municipalities outside of the state of Bavaria matched with treated municipalities in Bavaria through a Mahalanobis distance. I compare the treated municipality to its Mahalanobis nearest neighbor.

Table 6. Main results for log differences in unemployment (column 1), employment shares (column 2), total (column 3) and working age population (column 4) between treated and untreated municipalities compared to 2014.

program in 2015 (column 1) and 2016 (column 2) and in its seventh year (column 7). The effect becomes significant in 2019 (column 5).

Table 8 presents the same results for log changes in unemployment shares across the same years. In 2015, unemployment shares decreased by 4.8%. However, the effect is not statistically significant at conventional levels. In 2017 and 2018, the effect is significant, with a reduction in unemployment shares by 5.5 and 11.8%, respectively. Surprisingly, the effect on unemployment shares was positive and significant in 2016. This result could be due to an initial influx of job-seekers into treated municipalities following the announcement of the relocation program. A second explanation would be that if a whole household relocates, other household members might have to look for a new job locally. If they are temporarily unemployed, this would explain the small positive impact on unemployment shares.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment (Bin)	0.0114	0.0109	0.0015	0.0069	0.0164*	0.0199**	0.0225**	0.0201**
	(0.0073)	(0.0096)	(0.0065)	(0.0067)	(0.0088)	(0.0076)	(0.0084)	(0.0080)
Controls:	✓	✓	✓	✓	✓	✓	✓	✓
Observations	76	75	76	76	76	76	76	76
R^2	0.64451	0.50807	0.42891	0.49072	0.50961	0.72563	0.71682	0.70676
Within R^2	0.18655	0.09062	0.12520	0.19133	0.24101	0.45450	0.50749	0.42486
Mahalanobis Pair Fixed Effect	✓	✓	✓	✓	✓	✓	✓	✓

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: The table reports the log differences in employment shares for all years from 2015 to 2022. Column 1 shows the 2014-15 log differences in employment share. Column 2 shows the 2014-16 log differences in employment share and so on. The control group consists of municipalities outside of the state of Bavaria matched with treated municipalities in Bavaria through a Mahalanobis distance. I compare the treated municipality to its Mahalanobis nearest neighbor.

Table 7. Log differences in employment shares between treated and untreated municipalities compared to 2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment (Bin)	-0.0483	0.0771***	-0.0556*	-0.1184**	-0.0682	-0.0672	-0.0906	-0.0785
	(0.0303)	(0.0259)	(0.0328)	(0.0437)	(0.0479)	(0.0485)	(0.0592)	(0.0564)
Controls:	✓	✓	✓	✓	✓	✓	✓	✓
Observations	76	75	76	76	76	76	76	76
R^2	0.59636	0.76802	0.65349	0.62658	0.65531	0.71969	0.70465	0.73549
Within R^2	0.17518	0.49257	0.13976	0.27633	0.27036	0.35671	0.34809	0.19972
Mahalanobis Pair Fixed Effect	✓	✓	✓	✓	✓	✓	✓	✓

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: The table reports the log differences in unemployment shares for all years from 2015 to 2022. Column 1 shows the 2014-15 log differences in unemployment share. Column 2 shows the 2014-16 log differences in unemployment share and so on. The control group consists of municipalities outside of the state of Bavaria matched with treated municipalities in Bavaria through a Mahalanobis distance. I compare the treated municipality to its Mahalanobis nearest neighbor.

Table 8. Log differences in unemployment shares between treated and untreated municipalities compared to 2014.

5.2 Population Outcomes

I repeat the long difference analysis of both the total population and the working age population at the municipal level. As displayed in table Table 9, I find that the population started increasing slightly after the treatment and reached a 1.3% increase in 2019. In 2017 and 2018, the total population increased by 1.2 and 1.6 in treated municipalities. The results are statistically significant for these years. When only considering the working age population in Table 10, I find that it increased by 1.6% in 2017, 2.1% in 2018, and then slightly less by 1.8% in 2019. This result shows that the treated municipalities attracted new citizens after the relocations started, especially those with the potential to participate in the workfoce. These could be the movers from sending locations as well as other people attracted by the new jobs available in the treated municipal labor markets. However, after 2019 the population stops increasing likely due to lockdown during the pandemic that likely made relocations increasingly difficult. Another aspect might be that with pandemic, the possibility of working from home became widely available making relocations obsolete.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment (Bin)	0.0012	0.0047	0.0119*	0.0156**	0.0127	0.0056	-0.0026	-0.0025	0.0067
	(0.0028)	(0.0048)	(0.0059)	(0.0075)	(0.0080)	(0.0079)	(0.0088)	(0.0101)	(0.0111)
Controls:	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	76	76	76	76	76	76	76	76	76
R^2	0.61324	0.59471	0.65472	0.70977	0.68598	0.71950	0.72862	0.72492	0.72743
Within R^2	0.08832	0.08919	0.18766	0.23909	0.23355	0.18877	0.23241	0.19828	0.15903
Mahalanobis Pair Fixed Effect	✓	✓	✓	✓	✓	✓	✓	✓	✓

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: The table reports the log differences in total population between 2014 and 2023. Column 1 shows the 2014-15 log differences in total population. Column 2 shows the 2014-16 log differences in total population. The control group consists of municipalities outside of the state of Bavaria matched with treated municipalities in Bavaria through a Mahalanobis distance. I compare the treated locations to matched Mahalanobis nearest neighbors..

Table 9. Log differences in population between treated and untreated municipalities compared to 2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment (Bin)	0.0026	0.0078	0.0160*	0.0214**	0.0175*	0.0144	0.0045	0.0104	0.0229
	(0.0037)	(0.0064)	(0.0080)	(0.0088)	(0.0098)	(0.0087)	(0.0088)	(0.0118)	(0.0136)
Controls:	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	76	75	76	76	76	76	76	76	76
R^2	0.59974	0.57962	0.62544	0.68325	0.67397	0.72029	0.73993	0.71406	0.70365
Within R^2	0.08166	0.10689	0.17604	0.26848	0.25232	0.23957	0.24922	0.21094	0.17938
Mahalanobis Pair Fixed Effect	✓	✓	✓	✓	✓	✓	✓	✓	✓

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: The table reports the log differences in working age population between 2014 and 2022. Column 1 shows the 2014-15 log differences in working age population. Column 2 shows the 2014-16 log differences in working age population. The control group consists of municipalities outside of the state of Bavaria matched with treated municipalities in Bavaria through a Mahalanobis distance. I compare the treated locations to matched Mahalanobis nearest neighbors.

Table 10. Log differences in working age population between treated and untreated municipalities compared to 2014.

5.3 Sending Locations

Munich is the main sending location for the program alongside with seven other localities. In the following, I analyze the impact of the relocation program on its sending locations. Here, the treatment is the withdrawal of public sector jobs at the municipal level. Hence, I do not consider new jobs created or topped up at existing receiving locations. Due to the low number of treated units, I use a simple two-period, static difference-in-differences estimation to gauge the effect of public employment reallocation on sending locations. Like in the main analysis, the control group units are matched through a Mahalanobis distance.

The employment share increases by 0.77 percentage points in sending locations as displayed in Table 11, while the unemployment share decreases by -0.59 percentage points after public sector employees relocate (Table 12). In terms of population outcomes, Table 13 shows that the working age population share increases by 1.1 percentage points in sending locations. The results should be interpreted with caution since the municipalities vary in size. For example, Munich, the third biggest city in Germany, is considered a single municipality alongside much smaller locations like Herrsching, Bavaria.

Overall, preliminary results show that the relocation did not harm but benefit the sending locations.

	Employment Share (Residence)		
	(1)	(2)	(3)
Post (Binary) × Treatment (Binary) = 1	5.947***	0.7748**	0.7748**
	(0.7572)	(0.3800)	(0.3860)
Controls:	✓		
Observations	192	192	192
R^2	0.19394	0.90383	0.90383
Within R^2		0.01321	0.01321
Municipality Fixed Effect		✓	✓
Year Fixed Effect		✓	✓
Mahalanobis Pair Fixed Effect			✓

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1
Notes: The table reports simple DiD estimates of the employment and unemployment shares for sending locations. The control group consists of municipalities outside of the state of Bavaria matched with sending municipalities in Bavaria through a Mahalanobis distance.

Table 11. Two-period difference-in-difference results for the effect of public employment reallocation on employment in sending locations.

	Unemployment Share		
	(1)	(2)	(3)
Post (Binary) × Treatment (Binary) = 1	-0.4625***	-0.5907***	-0.5907***
	(0.1369)	(0.1287)	(0.1307)
Controls:	✓		
Observations	192	192	192
R^2	0.75983	0.92236	0.92236
Within R^2		0.12749	0.12749
Municipality Fixed Effect		✓	✓
Year Fixed Effect		✓	✓
Mahalanobis Pair Fixed Effect			✓

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1
Notes: The table reports simple DiD estimates of the employment and unemployment shares for sending locations. The control group consists of municipalities outside of the state of Bavaria matched with sending municipalities in Bavaria through a Mahalanobis distance.

Table 12. Two-period difference-in-difference results for the effect of public employment reallocation on unemployment in sending locations.

	Working Age Population Share		
	(1)	(2)	(3)
Post (Binary) × Treatment (Binary) = 1	-1.068**	1.111***	1.111***
	(0.4422)	(0.3210)	(0.3260)
Controls:	✓		
Observations	192	192	192
R^2	0.67548	0.92396	0.92396
Within R^2		0.07336	0.07336
Municipality Fixed Effect		✓	✓
Year Fixed Effect		✓	✓
Mahalanobis Pair Fixed Effect			✓

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1
Notes: The table reports simple DiD estimates of the working age population share for sending locations. The control group consists of municipalities outside of the state of Bavaria matched with sending municipalities in Bavaria through a Mahalanobis distance.

Table 13. Two-period difference-in-difference results for the effect of public employment reallocation on working age population shares in sending locations.

6 Event Study Results

As a robustness check, I also estimate the Callaway and Sant'Anna (2021) estimator[5]. Using this estimator, I check if treatment time heterogeneity affects the treatment effects. However, these results should be interpreted with caution. The Callaway and Sant'Anna (ibid.) estimator requires numerous observations (at least 20 as a rule of thumb) per treatment year to disaggregate the treatment effects in group-time cohorts. However, in my case, since I disregard municipalities that received relocations due to other programs and reduce those treated multiple times to the first treatment year, my sample consists of 38 treated municipalities. Consequently, the cohorts could be too small for the estimator.

Fig. 5 shows the event study plots for two different measures of employment shares. Employment shares continue to decrease in the first two years after the treatment and start to slowly increase after. Results show the highest increase seven years after the treatment, indicating that early treated cohorts might be driving the effect. Yet, the results are not statistically significant. However, in panel B, I create a subset of the employment shares and consider only employees who not only live but also work at the treated localities. There I find that right after the treatment, the local employment share increased for this particular group. The effect is statistically significant from three years into treatment onward. The same event study for the unemployment shares in Fig. 6 shows that unemployment started to decrease right after the relocations started in 2015.

Fig. 7 shows the event study results for population outcomes. Total population starts to increase after the treatment and peaks eight years after the policy started. The increase in working age population share is more pronounced and becomes statistically significant six years after the policy starts.

Since the policy is ongoing and will be completed in 2025, these results are only preliminary. However, in the first five years after its implementation, the policy increased employment shares, population, and working age population shares and decreased unemployment shares. The event study results show that the employment effects are sizable and pronounced for the section of the local workforce that works and lives in the treated municipalities. Together with the population increases, this could be suggestive evidence that employees either moved from the sending location or that more locals are being employed by the initiative.

[5]Alongside with the Callaway and Sant'Anna (2021) estimator; I also show the results for canonical TWFE estimations and the Sun and Abraham (2021) estimator.

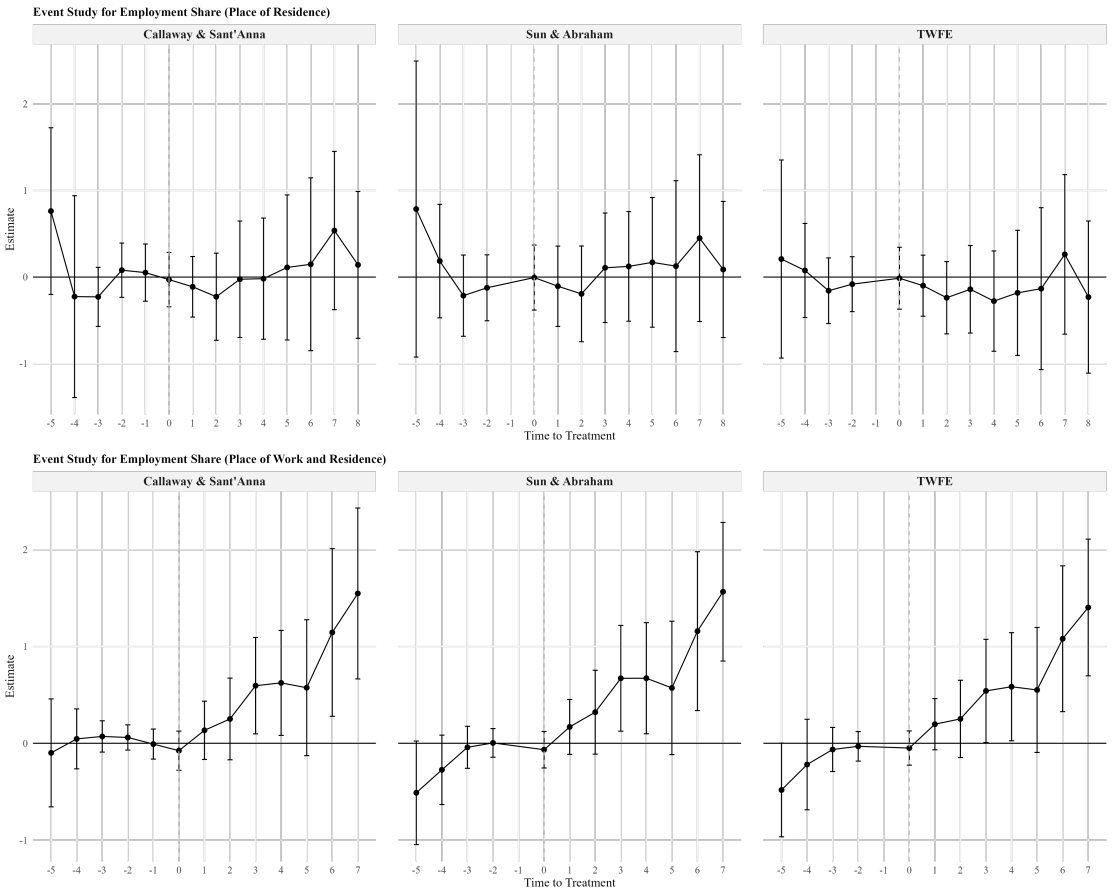


Figure 5. Callaway and Sant'Anna (2021) and Sun and Abraham (2021), and TWFE estimators for employment shares. In the first panel, I count the number of employees who live in a municipality and divide it by the working age population to determine employment shares. In the second panel, I only count employees who live and work at the same location and divide them by the working age population to determine the employment shares. Treatment starts in 2015. The base year is for all event-time comparisons is 2014.

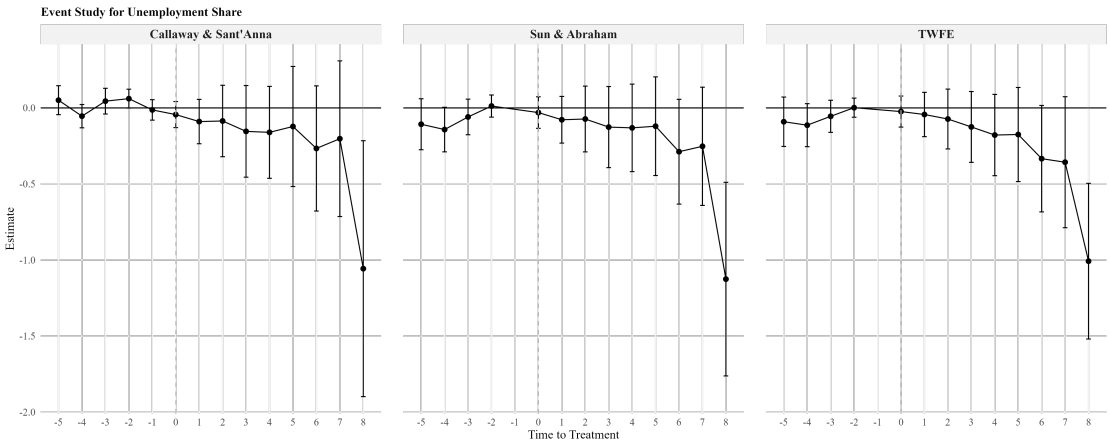


Figure 6. Callaway and Sant'Anna (2021) and Sun and Abraham (2021), and TWFE estimators for unemployment shares. To create unemployment shares at the municipal level, I count the number of unemployed in a municipality and divide it by the working age population. Treatment starts in 2015. The base year is for all event-time comparisons is 2014.

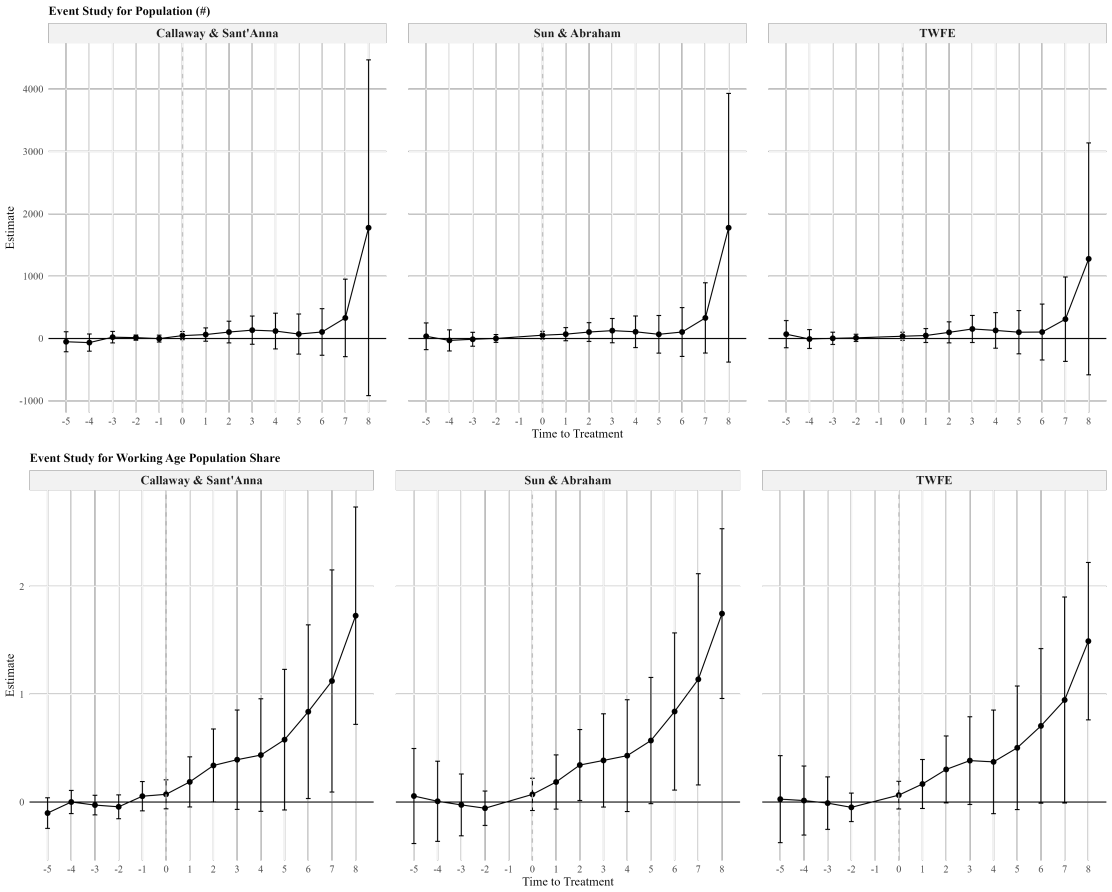


Figure 7. Callaway and Sant'Anna (2021) and Sun and Abraham (2021), and TWFE estimators estimator for population and working age population shares. The base year for all event-time comparisons is 2014.

7 Multiplier Analysis

To be added.

8 Conclusion

This study investigates the effectiveness of public sector employment relocation as a place-based policy tool to mitigate regional economic disparities in Germany. By exploiting Bavaria's quantitative approach to selecting receiving municipalities for its 'Heimatstrategie' (Homeland Strategy) initiated in 2015, I implement a difference-in-differences design comparing treated Bavarian municipalities to matched control municipalities in other German states.

The results indicate that the relocation of 3,000 public sector jobs from Munich to economically lagging regions led to statistically significant positive impacts on local labor markets in the treated municipalities. Private sector employment shares increased by 1.1% following the start of relocations in 2015, rising to 2.3% by 2021. Unemployment rates declined by 5.6% in 2017 and by 11.9% in 2018 compared to 2014. Local population grew by 1.2% in 2017 and by 1.6% in 2018, with the working age population increasing by up to 2.1% in 2018. These effects were achieved without any evidence of negative impacts on the sending location of Munich.

This study addresses external validity concerns in the existing literature by providing causal evidence on the impacts of public employment relocation in non-capital city contexts. It utilizes novel, manually-collected data on agency relocations across Bavaria between 2015-2025. Moreover, it is the first study to exploit the quasi-random nature of the government's quantitative selection criteria, based on a structural index of economic and demographic indicators, for receiving municipalities to achieve credible identification.

While these findings suggest public sector employment relocation can be an effective place-based policy, further research is needed to understand the conditions under which crowding-out of private sector employment may occur, and to assess longer-term impacts on a broader set of economic and social outcomes. Combining these quantitative results with qualitative case studies of specific municipalities could provide a more comprehensive understanding of the mechanisms and experiences underlying the aggregate impacts identified in this analysis.

Nonetheless, this study offers important new empirical evidence on the potential for public sector employment relocation to serve as a policy tool for governments aiming to address regional inequality and promote economic development in lagging regions.

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Appendix

Appendix A: Introduction

Structured News Search

To better understand to which extent and how German legislators resort to relocations of public sector jobs to boost the economy in lagging areas, I conducted a structured news search via the Nexis Uni news search of the platform Nexis Lexis in May 2022. I conducted the search in German using the search string **"Behoerdenverlagerung OR Behoerdenumzug OR "Umzug von Behoerden" OR "Umzug vom Amt" OR "Amtsumzug"** restricting the time period from 1991 onward. I limited the search to only news articles, excluding publications by private companies and persons to juridical texts.

The query yielded 1531 different results. I found news articles on 22 federal and 87 state agencies from 2005 to 2032. In total, 13,395 jobs will be relocated in this period, with the majority occurring in 2019 (5843 jobs), followed by 2030 (2300 jobs) and 2021 (1070 jobs). Table 14 shows how many jobs were relocated by state and Table 15 lists all sending and destination cities. In total, I found 82 agency relocations and 26 cases where new branches of agencies were established in new localities. I find both single agency relocations as well as three programs involving several relocations: a program by the German federal government to help former coal mining regions to bridge structural change called 'Foerderprogramm der Bundesregierung für Kohleanbaugebiete', the Bavarian Homeland Strategy 'Heimatstrategie: Foerderung gleichwertiger Lebens- und Arbeitsbedingungen,' and a program to boost the Lausitz region in Saxony called 'Lausitzprogramm 2038'.

State	N of Relocated Jobs	N of Relocated Study Places
Bavaria	9681	1730
Brandenburg	510	
Hesse	100	
Saxony	2214	
Saxony-Anhalt	850	
Thuringia	40	

Table 14. Number of public sector jobs and study places relocated to each state according to Nexis Uni news search.

Sending Cities	Destination Cities
Ammersee	Amberg, Ansbach, Augsburg
Berlin, Bonn	Bad Kissingen, Bad Koenigshofen im Grabfeld,
Bad Kissingen	Bad Koetzting, Bad Neustadt an der Saale, Bad Reichenhall,
	Bad Steben, Bautzen, Berlin, Bischofswerda, Borna
	Cottbus
Dresden	Dessau, Dinkelsbühl, Dresden
Erlangen, Eschborn, Essen	Ebern, Eichstaett
	Freital, Freyung, Fürstenfeldbruck, Fürth
Grossenhain	Garmisch-Partenkirchen, Gemünden am Main, Gera,
	Goerlitz, Grafenau, Gunzenhausen
Herrsching a. Ammersee	Halle (Saale), Hoechstaedt a.d.Donau, Hof
	Ingolstadt
	Kaufbeuren, Kemnath, Kitzingen, Kronach, Kulmbach
	Lauterbach, Leipzig, Lohr am Main
München	Marktredwitz, Meissen, Merseburg, Mittenwald
	Mühldorf a. Inn, Münchberg
Nürnberg	Nabburg, Neustadt an der Aisch, Noerdlingen, Nürnberg
	Obernburg am Main, Oberviechtach
	Pegnitz
Regensburg	Regen, Rosenheim
Starnberg	Schwandorf, Schweinfurt
	Tirschenreuth, Traunstein
	Vilshofen an der Donau, Vohenstrauss
Würzburg	Waldkirchen, Waldmünchen, Waldsassen, Weiden in der Oberpfalz
	Weissenburg i. Bay., Weisswasser, Windischeschenbach, Wunsiedel
	Zittau, Zwiesel

Table 15. List with all sending and destination cities found in the Nexis Uni news search in alphabetical order. Some cities like Berlin or Dresden are both sending and destination cities.

Appendix B: Data

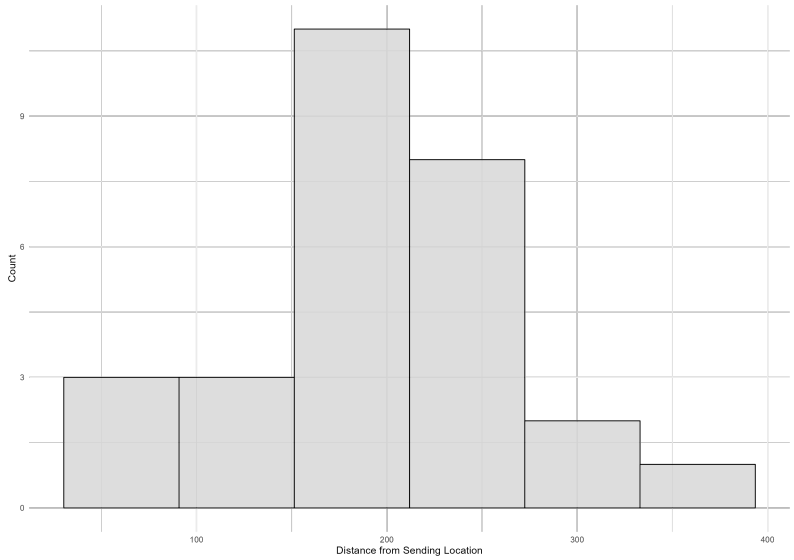


Figure 8. Distance between municipalities receiving and municipalities sending agencies. Own illustration based on own distance calculations using the statistical software R.

Appendix C: Empirical Methodology

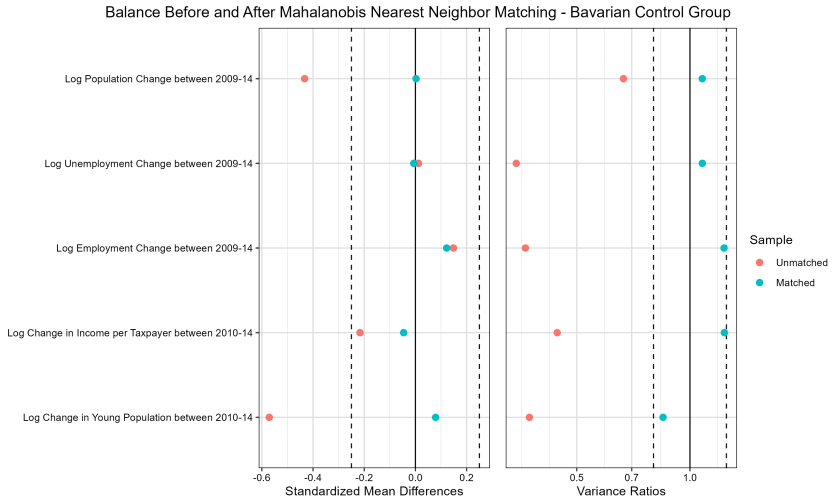


Figure 9. Balance Plot illustrating Standardized Mean Differences and variance ratios between treatment and control group of municipalities inside of Bavaria before and after Mahalanobis nearest neighbor matching.

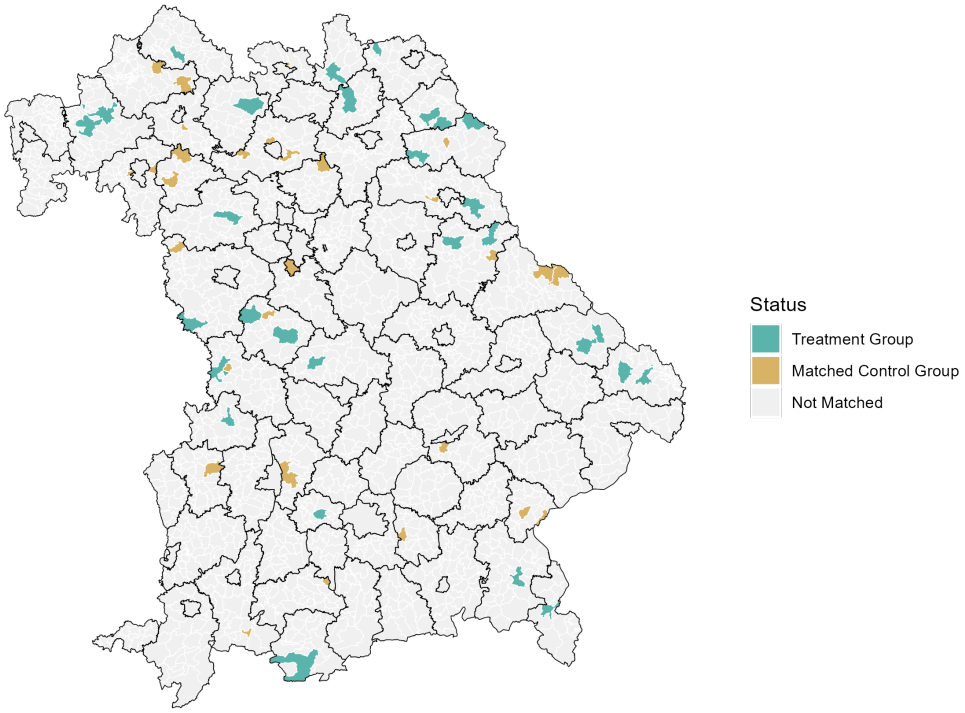


Figure 10. Map of Bavaria showing the treated municipalities in Bavaria (teal) and their control group counterparts (ocher) in Bavaria.

Variable	Means Treated	Means Control	Std Mean Diff	Var Ratio
Population	-0,01	0	-0,43	0,67
Unemployment	-0,25	-0,26	0,01	0,35
Employment	0,1	0,09	0,15	0,37
Income per Taxpayer*	0,14	0,15	-0,22	0,44
Population 18-30 yrs*	-0,03	0,01	-0,57	0,37

Table 16. Balance pre-matching between treated municipalities in Bavaria and other municipalities in Bavaria.

Variable	Means Treated	Means Control	Std Mean Diff	Var Ratio
Population	-0,01	-0,01	0	1,08
Unemployment	-0,25	-0,25	-0,01	1,08
Employment	0,1	0,09	0,12	1,23
Income per Taxpayer*	0,14	0,15	-0,05	1,23
Population 18-30 yrs*	-0,03	-0,04	0,08	0,85

Table 17. Balance post-matching between treated municipalities in Bavaria and other municipalities in Bavaria.

Appendix D: Long Difference Results with Bavarian Control Group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment (Bin)	0.0067	0.0080	0.0056	0.0066	0.0032	0.0053	0.0051	0.0055
	(0.0046)	(0.0058)	(0.0072)	(0.0066)	(0.0076)	(0.0091)	(0.0093)	(0.0091)
Controls:	✓	✓	✓	✓	✓	✓	✓	✓
Observations	76	76	76	76	76	76	76	76
R^2	0.54864	0.55713	0.44794	0.53607	0.52680	0.51694	0.50185	0.53778
Within R^2	0.08746	0.16938	0.10287	0.12975	0.09933	0.22052	0.15279	0.17164
Mahalanobis Pair Fixed Effect	✓	✓	✓	✓	✓	✓	✓	✓

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: The table reports the log differences in employment shares for all years from 2015 to 2022. Column 1 shows the 2014-15 log differences in employment share. Column 2 shows the 2014-16 log differences in employment share and so on. The control group consists of municipalities inside of the state of Bavaria matched with treated municipalities in Bavaria through a Mahalanobis distance. I compare the treated municipality to its Mahalanobis nearest neighbor.

Table 18. Long Difference Results for Employment Share from 2015 to 2022

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment (Bin)	-0.0102	-0.0215	-0.0244	-0.0393	-0.0297	0.0438	0.0009	-0.0145
	(0.0331)	(0.0371)	(0.0355)	(0.0360)	(0.0335)	(0.0396)	(0.0351)	(0.0454)
Controls:	✓	✓	✓	✓	✓	✓	✓	✓
Observations	76	76	76	76	76	76	76	76
R^2	0.52555	0.58116	0.65309	0.63236	0.60578	0.73557	0.69041	0.68891
Within R^2	0.06125	0.11097	0.25980	0.21547	0.12309	0.27213	0.29037	0.19130
Mahalanobis Pair Fixed Effect	✓	✓	✓	✓	✓	✓	✓	✓

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: The table reports the log differences in unemployment shares for all years from 2015 to 2022. Column 1 shows the 2014-15 log differences in unemployment share. Column 2 shows the 2014-16 log differences in unemployment share and so on. The control group consists of municipalities inside of the state of Bavaria matched with treated municipalities in Bavaria through a Mahalanobis distance. I compare the treated municipality to its Mahalanobis nearest neighbor.

Table 19. Long Difference Results for Unemployment Share from 2015 to 2022

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment (Bin)	0.0027	0.0075*	0.0105	0.0111	0.0149	0.0125	0.0133	0.0224	0.0310*
	(0.0031)	(0.0041)	(0.0064)	(0.0083)	(0.0091)	(0.0101)	(0.0112)	(0.0135)	(0.0168)
Controls:	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	76	76	76	76	76	76	76	76	76
R^2	0.63082	0.69660	0.68915	0.69285	0.74585	0.73832	0.71614	0.68532	0.64910
Within R^2	0.07998	0.19086	0.19880	0.19749	0.20461	0.17238	0.17179	0.20876	0.21334
Mahalanobis Pair Fixed Effect	✓	✓	✓	✓	✓	✓	✓	✓	✓

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: The table reports the log differences in working age population between 2014 and 2023. Column 1 shows the 2014-15 log differences in working age population. Column 2 shows the 2014-16 log differences in working age population. The control group consists of municipalities within the state of Bavaria matched with treated municipalities through a Mahalanobis distance. I compare the treated locations to matched Mahalanobis nearest neighbors.

Table 20. Long Difference Results for Working Age Population from 2015 to 2023

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment (Bin)	0.0033	0.0076**	0.0103*	0.0097	0.0095	0.0050	0.0003	0.0056
	(0.0026)	(0.0034)	(0.0054)	(0.0069)	(0.0078)	(0.0083)	(0.0080)	(0.0095)
Controls:	✓	✓	✓	✓	✓	✓	✓	✓
Observations	76	76	76	76	76	76	76	76
R^2	0.64695	0.66852	0.66129	0.67484	0.70966	0.69278	0.69274	0.63442
Within R^2	0.07340	0.21783	0.23168	0.24875	0.22126	0.16491	0.18066	0.15370
Mahalanobis Pair Fixed Effect	✓	✓	✓	✓	✓	✓	✓	✓

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: The table reports the log differences in total population between 2014 and 2022. Column 1 shows the 2014-15 log differences in total population. Column 2 shows the 2014-16 log differences in total population. The control group consists of municipalities within the state of Bavaria matched with treated municipalities through a Mahalanobis distance. I compare the treated locations to matched Mahalanobis nearest neighbors.

Table 21. Long Difference Results for Total Population from 2015 to 2022

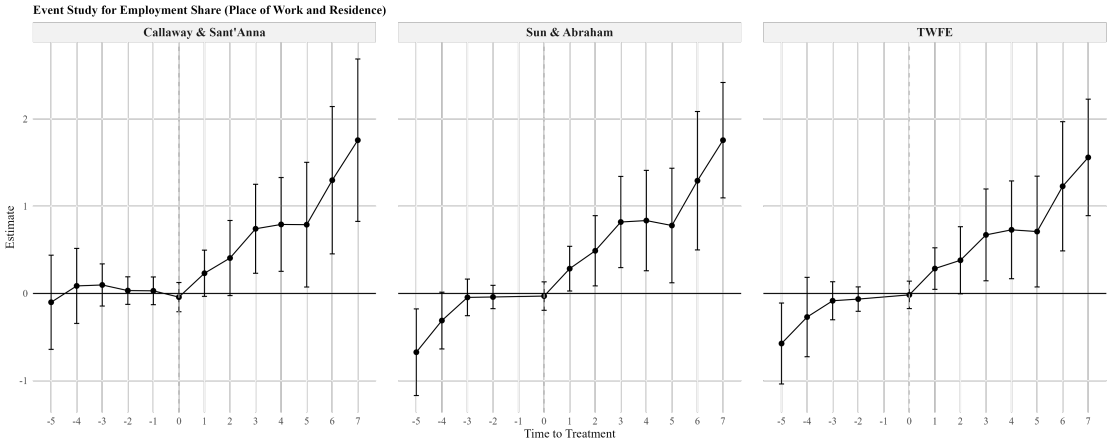


Figure 11. Callaway and Sant'Anna (2021) and Sun and Abraham (2021), and TWFE estimators for employment shares, where I compared treated municipalities to control municipalities in Bavaria. Employment is measured for individuals who live and work in the same municipality.

Appendix E: Event Study Results with Bavarian Control Group

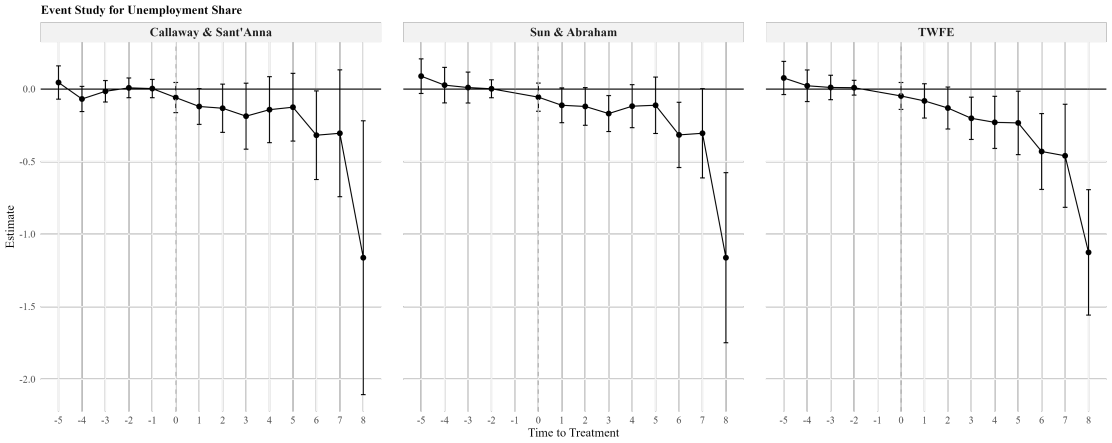


Figure 12. Callaway and Sant'Anna (2021) and Sun and Abraham (2021), and TWFE estimators for unemployment shares where I compared treated municipalities to control municipalities in Bavaria.

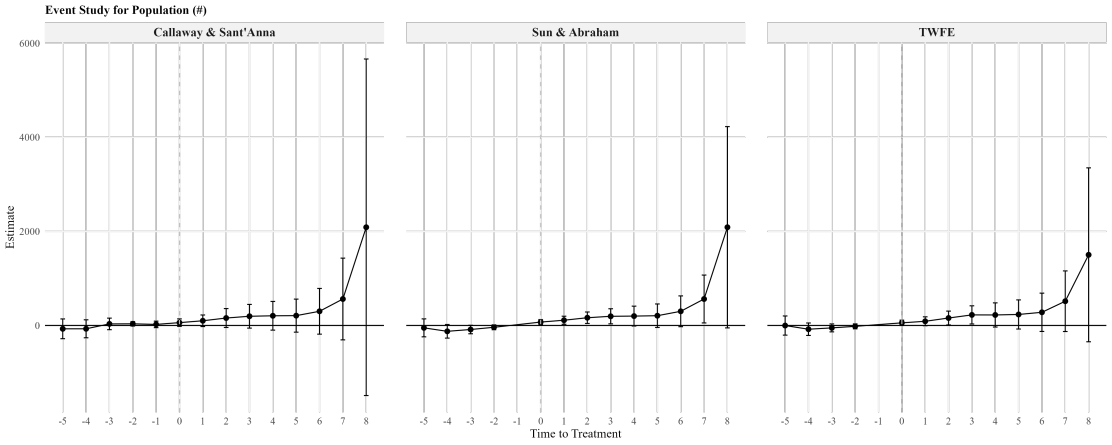


Figure 13. Callaway and Sant'Anna (2021) and Sun and Abraham (2021), and TWFE estimators for total population where I compared treated municipalities to control municipalities in Bavaria.

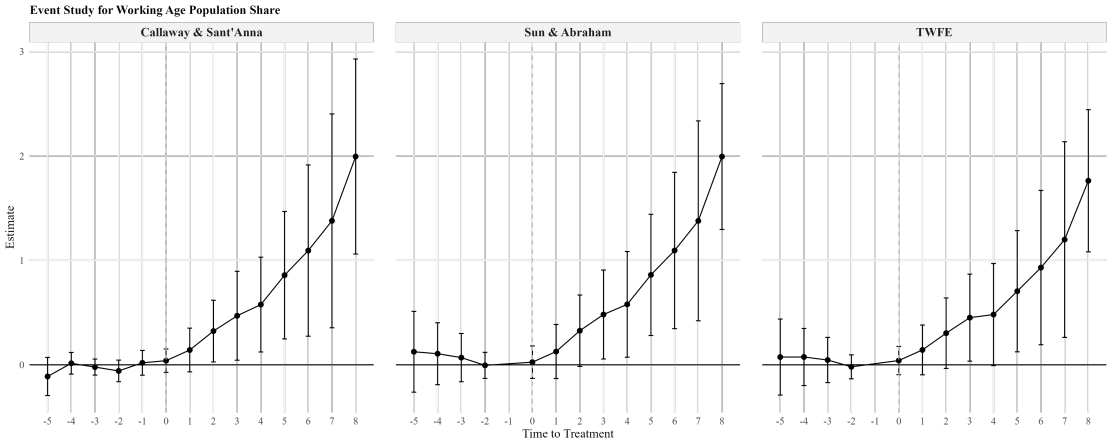


Figure 14. Callaway and Sant'Anna (2021) and Sun and Abraham (2021), and TWFE estimators for the working age population share where I compared treated municipalities to control municipalities in Bavaria.