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The Effect of Public Sector Relocations on Regional Development in Germany

Dimitria Freitas*

September 13, 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 correspond to a public-to-private jobs multiplier of 1.08. To assess general equilibrium effects the relocation program, I implement a quantitative spatial model with a two-sector (public and private) framework showing modest increases in amenities through the relocation counterfactual and negligible welfare effects.

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1 Introduction

This paper studies how relocating public-sector jobs to lagging regions affects local private-sector jobs and population in Germany.

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). For example, residents of the state of Mississippi in the US share more similarities in living standard with the people of Slovakia than with New Yorkers (Bluedorn et al. 2019). Given that income inequality has been consistently higher in the US than in Europe (Burkhauser and Poupore 1997; Piketty and Saez 2014; Filastro and Parolin 2019; Hoffmann et al. 2020), one might be tempted to classify it as an American issue. However, a German living in the state of Thuringia might unknowingly relate more to the economic situation of someone in the Czech Republic than to that of someone in Hamburg (International Monetary Fund 2024; German Regional Database 2024).

Yet, the German federal constitution anchors the objective of equivalent living conditions across regions as a state goal (*GG Art. 72(2)* 1949). In order to meet it, policymakers resort to place-based policies¹ like infrastructure development, tax credits, or subsidies for firms that locate in a certain area. However, business incentives for subsidies have been hard to configure in a way that achieves policy goals, prompting governments to increasingly look for different policies. One alternative gaining traction is the strategic spatial reallocation of public employment. Recently, Germany joined South Korea, the United Kingdom, Denmark, and Sweden, among other nations, in implementing public employment reallocation as an alternative to subsidies to revive labor markets in lagging behind areas (Freitas 2025). In 2015, the state government of Bavaria in Southern Germany launched 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.

My paper evaluates this policy and answers the question 'Do relocations of public-sector jobs to lagging regions improve targeted areas' local labor-market and demographic outcomes, and what are the economy-wide general-equilibrium consequences in Germany?'

My research connects to the literature on the effect of place-based policies (Moretti 2012; Kline and Moretti 2014; Ehrlich and Seidel 2018; G. Duranton and A. Venables 2018; Ehrlich and Overman 2020), and to the more specific field of public employment reallocation. The latter examines if public jobs create (crowding in) or destroy (crowding out) jobs in the private sector, and distinguishes between studies assessing an *expansion or contraction* of the public sector from studies examining a spatial *redistribution* of public jobs.

Expansion or contraction studies like Faggio and Overman (2014) and Senftleben-König (2014), and Auricchio et al. (2020) find a crowding out of private employment through

¹Place-based policies address the spatial concentration of deprived people by targeting job opportunities and higher wages in a specific area (Neumark and Simpson 2015). See Gaubert et al. (2025) for an updated discussion of place-based policies.

public employment. If the assumption holds that national labor supply is fixed, expanding the public sector without expanding the labor supply results in a compression of the private sector (Freitas 2025).

Studies focusing on redistributing the public sector from capital cities to other areas like Faggio (2019) in the United Kingdom, and Lee et al. (2024) in South Korea, report a crowding-in of private employment. 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. 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.

The size of the public-to-private sector employment multiplier varies. In a briefing by the What Works Centre for Local Economic Growth (2023), a benchmark is established at 0.37 for *tradable* private sector occupations. In another study, I review the public employment literature and find an average multiplier effect of 0.7 summarizing over the tradable and non-tradable sector (Freitas 2025).

I make three contributions using a new hand-collected dataset on Bavaria’s public-sector relocation program².

First, I address external validity. With the exceptions of Faggio (2019) and Lee et al. (2024), prior studies center on capital cities shaped by capital primacy³ unlike the distressed regions typically analyzed in the place-based policy literature. Bavaria’s program shifts public jobs from Munich, the state capital, to more than 50 smaller municipalities, letting me study settings closer to usual place-based policy targets.

Second, I mitigate selection bias by exploiting the program’s transparent allocation rule. The Bavarian government built a structural index to identify distressed districts⁴. Districts with an index score at most 90% of the Bavarian average qualified for relocation, generating quasi-random variation in receiving locations.

Third, I move beyond partial-equilibrium outcomes. I estimate effects on both receiving and sending places and develop a quantitative spatial model of Bavaria to assess general-equilibrium impacts for the entire state, not only municipalities directly touched by the policy.

I estimate reduced-form effects using long differences combined with Mahalanobis matching. Treated Bavarian municipalities that received an agency are matched to comparable municipalities outside Bavaria, which by design were ineligible for the state program. Matching uses the structural-index components. The identification assumption is that if these control municipalities had been located in Bavaria, they would have met

²I compile relocation records from government documents, parliamentary inquiries, and newspaper reports and merge them with municipal economic and demographic data from the German Regional Database.

³Capital primacy occurs when a nation’s largest city is also the political-administrative hub, concentrating power and employment (Galiani and Kim 2008; Dascher 2000).

⁴A weighted average of five indicators: population forecast, unemployment rate, employment density, disposable income, and net migration of 18–30-year-olds.

the eligibility threshold and been treated.

Because relocations phase-in between 2015 and 2025, I implement the Callaway and Sant’Anna (2021) estimator to accommodate treatment-time heterogeneity. The analysis currently covers relocations completed through 2023. The program concludes in 2025.

To interpret spillovers and economy-wide adjustments, I embed the policy in a quantitative spatial model. Following Ahlfeldt, Redding, et al. (2015), I adapt their framework into a two-sector structure that distinguishes between public and private employment. The model allows public employment relocations to affect both productivity and residential amenities through sector-specific spillovers, and it captures the resulting equilibrium adjustments in wages, housing prices, and employment distributions.

The program increased private employment, population, and the working-age population in treated municipalities, and reduced unemployment. After netting out the mechanical addition of relocated public jobs, 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.

The preliminary counterfactual quantification shows that relocations redistribute private jobs from Munich to smaller municipalities, with modest increases in amenities, slight decreases in productivity, and essentially no effects on wages, housing prices, or overall welfare.

Sending locations were not harmed by the policy, instead, their employment share rises by 0.77 percentage points, unemployment falls by 0.59 points, and the working-age population increases by 1.11 points. The preliminary quantitative spatial model results point in the same direction. Counterfactuals shift some private jobs from Munich to recipient towns while wages and housing barely move, leaving origin-side welfare essentially unchanged.

The following sections are organized as follows. First, I describe the policy program and the data sources, including both the novel relocation dataset and administrative statistics. Next, I outline the matching procedure and empirical methodology before presenting the reduced-form results on labor markets, population, and sending locations. I then introduce the quantitative spatial model, describe its setup and calibration, and present the counterfactual simulations. The final section concludes.

2 Institutional Setting

Germany has relocated public jobs for decades. After World War II it moved the capital from Berlin to Bonn, and in 1999, it moved the capital back to Berlin and shifted several ministries to the new eastern states (German Bundestag 1992).⁵ Germany currently runs two relocation policies.⁶

Federal Program (Energy Transition). To compensate coal-producing regions for the energy transition, the federal government enacted the *Strukturstärkungsgesetz Kohleregionen*. It will relocate about 5,000 federal jobs by 2028 and deploy a €40 million subsidy fund for affected areas (Press and Information Office of the Federal Government 2023). The rollout is pending, and most funds remain undisbursed.

Bavarian Program (Heimatstrategie). In 2014 Bavaria launched the *Heimatstrategie*. From 2015 to 2025 the state is decentralizing roughly 60 agencies, redistributes 2,063 public jobs (about 1% of state public employment), and creates 930 study places across 56 municipalities. Relocations from Munich supply 1,554 jobs and 600 study places. New regional branches add 380 jobs. Expansions of existing agencies contribute 129 jobs and 330 study places. On average, a relocation shifts 67 jobs.

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 the German wealth distribution. 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 at the Austrian border, where the average income per taxpayer was 19,637 euros in the same year (German Regional Database 2024).

In December 2021, the program the Bavarian government extended the program to *Heimatstrategie Stufe 2*, through 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. Table 1 illustrates all relocation programs running in Bavaria, including the mechanism for selecting receiving locations. My analysis focuses on *Heimatstrategie Stufe 1*.

The site selection criteria entail both quantitative and qualitative elements. A structural

⁵See Becker et al. (2021) on the move from Berlin to Bonn and Faggio, Schluter, et al. (2022) on the return to Berlin.

⁶To document the scope of current public employment policies in Germany, I conducted a structured search on Nexis Uni (LexisNexis), identifying press reports on 22 federal and 87 state agencies from 2005 to 2032. Appendix A details sources and coding.

Phase	Program Name	Allocation Rule
I	<i>Heimatstrategie</i> . Regionalisation of the Administration	Distressed Areas as of RDP 2013/14*
II	<i>Heimatstrategie</i> . Concept Administration Relocation Bavaria 2030	Distressed Areas 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.

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 2. 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.

index flags distressed districts using administrative data on five indicators: (i) population projections, (ii) unemployment, (iii) employment density, (iv) income per taxpayer, and (v) net migration of 18–30-year-olds. Table 2 catalogs the indicators alongside their respective administrative data sources and weighting for the index. The Bavarian government normalizes the weighted sum of the index to 100 at the Bavarian mean and sets 90 as the eligibility cutoff. Districts reaching 90 or less in index value are eligible for the public employment reallocation program. Municipalities below the cutoff qualify even if their district lies above it⁷.

Beyond the index, receiving sites must appear as *Mittelzentren* in the Regional Development Plan and must not already receive major place-based funds (e.g., from concurring

⁷A significant majority, 88 %, of relocation projects are directed towards areas identified through a structural index. The program directs about 88% of projects to index-selected areas. The remainder includes six conversion municipalities hit by defense base closures in 2011, when Germany paused national conscription.

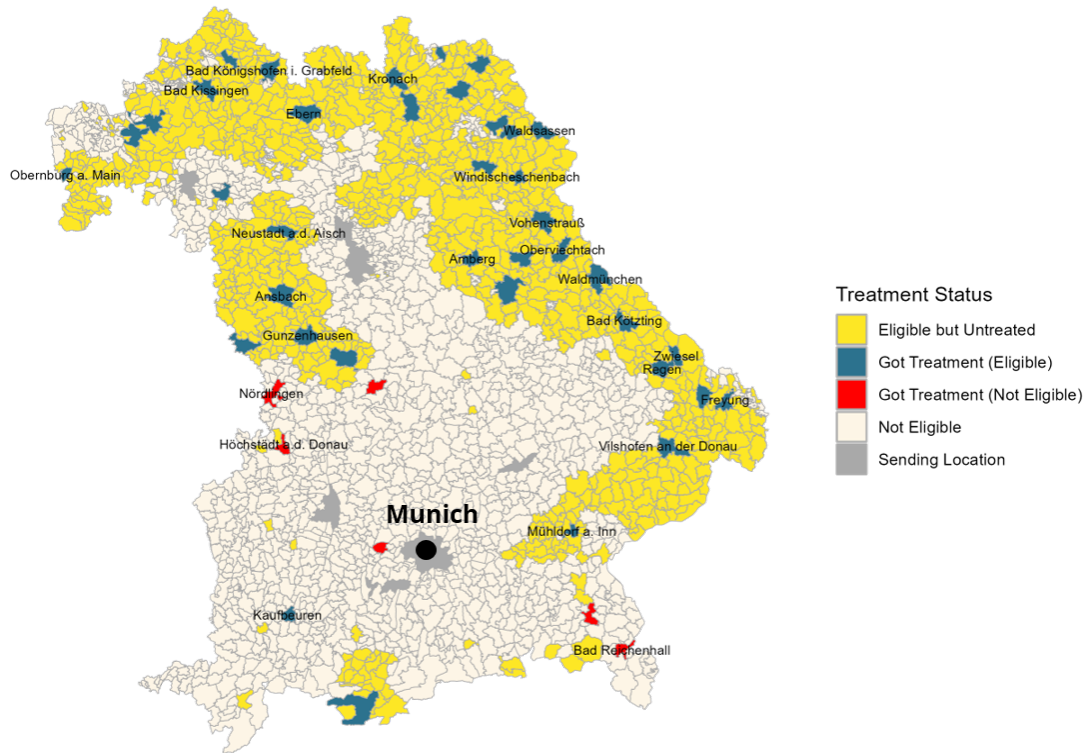


Figure 1. Spatial scope of the Bavarian relocation program by treatment status determined through the quantitative structural index. Districts and municipalities performing at 90% or less than the Bavarian average are included in the area with particular need for action. Municipalities that lost defense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

place-based university initiatives). Figure 1 maps treatment status.

The state government agencies to be relocated were selected based on the spatial scope of their activities. The state selects agencies with supra-regional mandates under the jurisdiction of the Free State of Bavaria and excludes inherently local providers such as police stations and schools. Furthermore, their office location should be situated in densely populated areas in Bavaria before the relocation.

Relocation costs are usually opaque, but Bavaria published an itemized cost report after a parliamentary inquiry (Kaltenhauser 2023). Table 3 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 €16.6 million. They mainly consist of several different incentive payments that the Bavarian state government offers employees willing to relocate. These include mobility premia, a one-time lump sum incentive of €3,000 for permanent relocation, excluding 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 a relocation.

Construction expenditures total €74.9 million. Renovation expenses for various locations aggregate to €3.7 million. Moving costs are calculated from 2015 to 2021 and total €0.45 million. Rental costs span from 2015 through 2022 and total €18.2. The cumulative financial outlay across all categories is quantified at roughly €113.9 million (Kaltenhauser 2023).

A back-of-the-envelope division yields roughly €38,000 per job relocated so far. Because fixed costs front-load spending and support future placements, the average cost per job should fall as additional moves occur.

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 3. Relocation program costs in Bavaria, 2015–2022.

3 Data

3.1 Data on the Relocation Program

I assemble data on Bavaria’s relocation program from the BayernAtlas open-data portal (State Office for Digitization, Broadband and Geodetic Measurement 2024). For each relocation case, I record the program name, lead ministry, agency address, the number of jobs relocated, and the relocation’s status. I complete missing completion dates from the annual *Heimatstrategie* reports and, when needed, from searches in local newspapers. On average, a relocation corresponds to 1.3% of total employment in the receiving municipality. Fig. 22 in Appendix B shows origin–destination distances clustered between 150 and 250 km, implying a mean road travel time of about 126 minutes. The full dataset is available on request.

3.2 Employment Data

I use annual municipal employment for 2008–2024 from the German Regional Database (GRD), compiled from the Federal Employment Agency (FEA) (German Regional Database 2024) to estimate long-differences and event-studies in the empirical section. The data includes employee headcounts by place of residence, by workplace, and for residents who also work in their home municipality. Table 6 reports descriptive statistics

for the outcomes by control group used in the empirical analysis. A yearly private–public sector split is unavailable at the municipal level in Germany.

To construct employment in the public and private sectors for the QSM model calibration, I rely on commuting data from the 2011 German Census. I use the in-commuting tables by sector (code 2000X.2041) and the out-commuting tables by sector (code 2000X.2045) from the Census database. Both tables are available at the municipal level as a sample. The reference date of the Census is May 9, 2011, which predates the introduction of the *Heimatstrategie* by four years.

Workplace employment is constructed from the in-commuting table by filtering for the category “*Einpendelnde in Arbeitsortgemeinde*” (in-commuters to the workplace community). Residence employment is constructed from the out-commuting table by filtering for the category “*Arbeitsort in Hauptwohnsitzgemeinde*” (place of work in main municipality of residence). This category includes workers who are “*Binnenpendler innerhalb der Hauptwohnsitzgemeinde*” (commuters within their main municipality of residence), workers who are “*überwiegend zuhause*” (working predominantly at home), and “*Auspendler aus der Hauptwohnsitzgemeinde*” (out-commuters from the main place of residence).

To define public sector employment, I filter the sectoral classification for the category “*öffentliche Verwaltung, Verteidigung, Sozialversicherung*” (public administration, defense, social security). All other categories in the Census count towards private employment. Applying this taxonomy results in the spatial distribution of private employment illustrated in Fig. 2. Fig. 3 depicts the distribution of public employment in Germany.

The German sample and the Bavarian subsample show similar average magnitudes of workplace employment, with mean values of roughly 59,000 jobs in both cases, as decomposed in Table 4 and Table 5. The composition of workplace employment is also stable across the two samples: public employment accounts for around 10 percent, and private employment for around 90 percent. The more pronounced differences appear on the residence side. Average residence employment is substantially lower in Bavaria (25,600) compared to the German sample (34,000), reflecting the greater role of commuting into Bavarian municipalities. Correspondingly, the maximum number of residents employed in a single municipality is much smaller in Bavaria (1.8 million) than in the German sample (4.3 million). The shares of public and private residence employment are comparable, with public employment representing about 11 percent in the German sample and 10.5 percent in Bavaria. Variability, as measured by the standard deviation, is consistently lower in the Bavarian subsample, which reflects both the smaller number of municipalities and the reduced heterogeneity relative to the national distribution.

3.3 Unemployment Data

I use annual municipal unemployment for 2008–2024 from the German Regional Database (GRD), which compiles Federal Employment Agency (FEA) records, to estimate long-differences and event-study models (German Regional Database 2024).

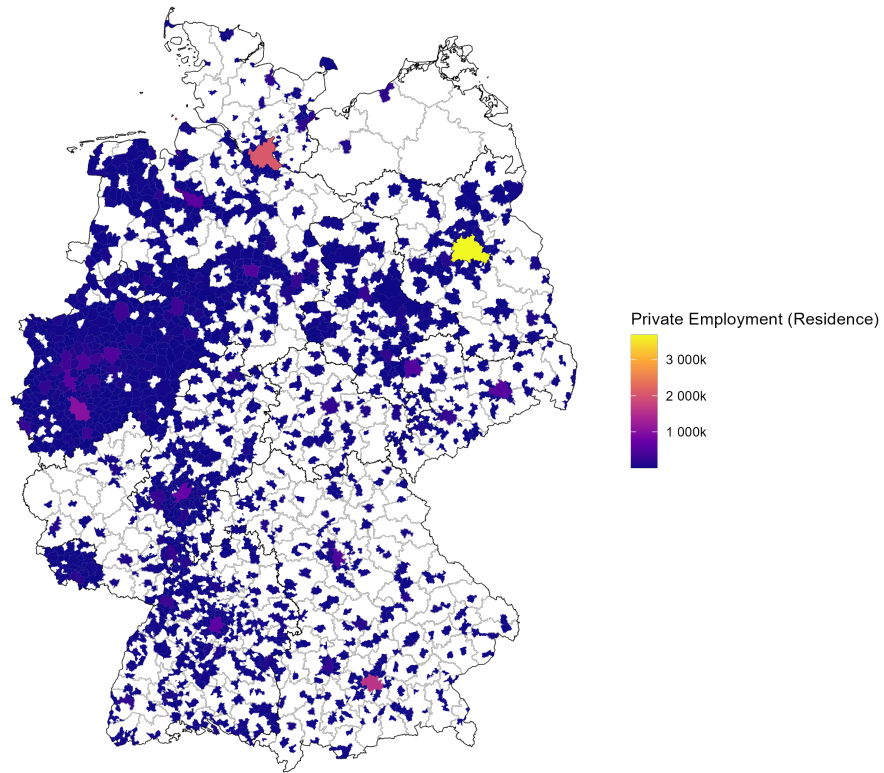
Variable	Mean	SD	Min	P25	P75	Max
Total Workplace Employment (1,000s)	58.48	149.66	1.12	14.22	49.80	2135.30
Public Workplace Employment (1,000s)	6.38	16.03	0.00	1.22	5.62	228.94
Private Workplace Employment (1,000s)	52.10	134.08	1.12	12.79	44.50	1919.60
Total Residence Employment (1,000s)	33.99	158.19	1.65	6.37	20.59	4297.12
Public Residence Employment (1,000s)	4.17	20.78	0.17	0.61	2.40	612.53
Private Residence Employment (1,000s)	29.82	137.54	1.39	5.77	18.16	3684.59
Public Workplace Employment Share	10.08	4.80	0.00	7.04	13.29	28.37
Private Workplace Employment Share	89.92	4.80	71.63	86.71	92.96	100.00
Public Residence Employment Share	10.87	2.60	4.26	9.00	12.64	21.48
Private Residence Employment Share	89.13	2.60	78.52	87.36	91.00	95.74

Table 4. Summary Statistics of Workplace and Residence Employment Variables for the Germany Sample (N = 1600).

Variable	Mean	SD	Min	P25	P75	Max
Total Workplace Employment (1,000s)	59.81	151.93	2.54	18.17	51.47	2135.30
Public Workplace Employment (1,000s)	6.24	15.82	0.00	1.53	5.48	215.70
Private Workplace Employment (1,000s)	53.57	136.35	2.54	16.59	44.65	1919.60
Total Residence Employment (1,000s)	25.59	117.23	2.16	6.30	16.14	1816.58
Public Residence Employment (1,000s)	2.96	13.86	0.20	0.63	1.76	213.91
Private Residence Employment (1,000s)	22.63	103.39	1.90	5.67	14.46	1602.67
Public Workplace Employment Share	10.07	4.46	0.00	7.00	13.02	26.69
Private Workplace Employment Share	89.93	4.46	73.31	86.98	93.00	100.00
Public Residence Employment Share	10.53	2.55	5.56	8.64	12.14	21.48
Private Residence Employment Share	89.47	2.55	78.52	87.86	91.35	94.44

Table 5. Summary statistics of Workplace and Residence Employment Variables for the Bavarian Sample (N = 270).

Private Residence Employment



Private Workplace Employment

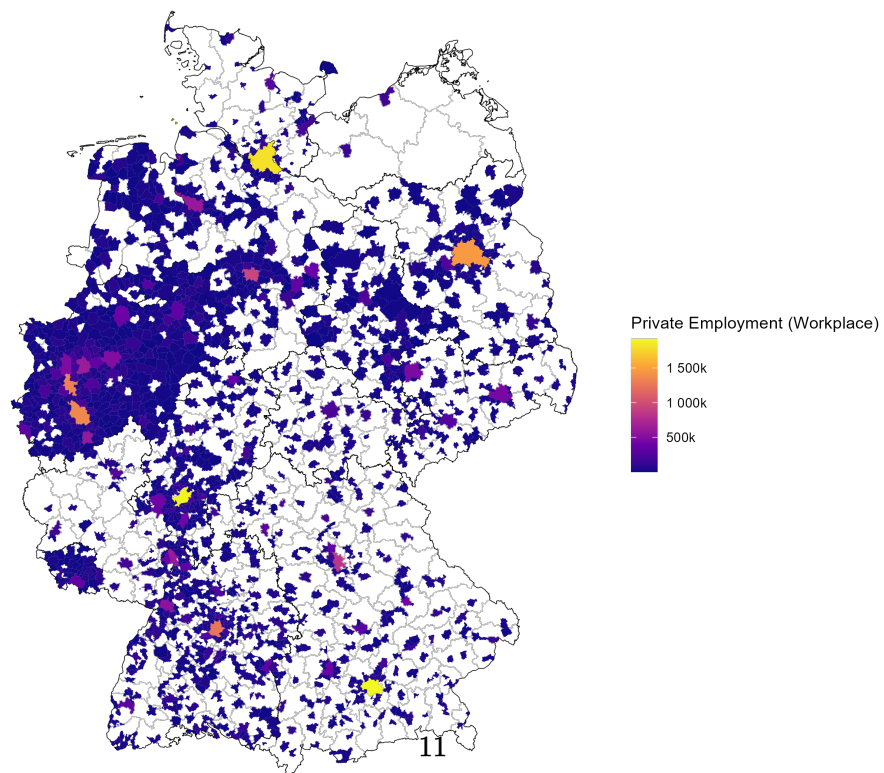
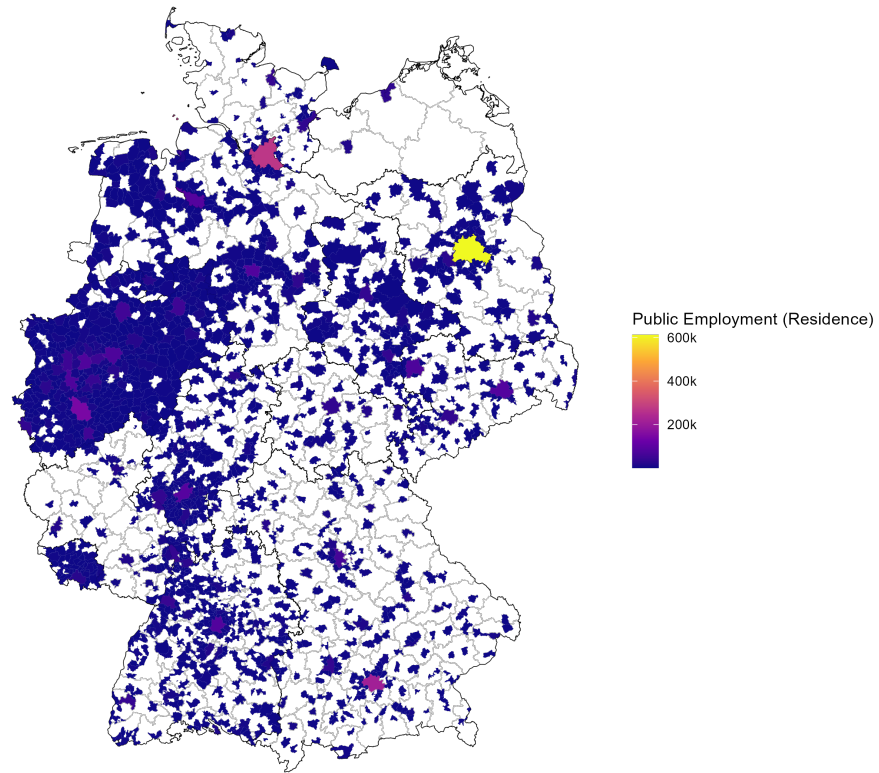


Figure 2. Spatial Distribution of Residence and Workplace Private Employment in Germany. Source: Census 2011.

Public Residence Employment



Public Workplace Employment

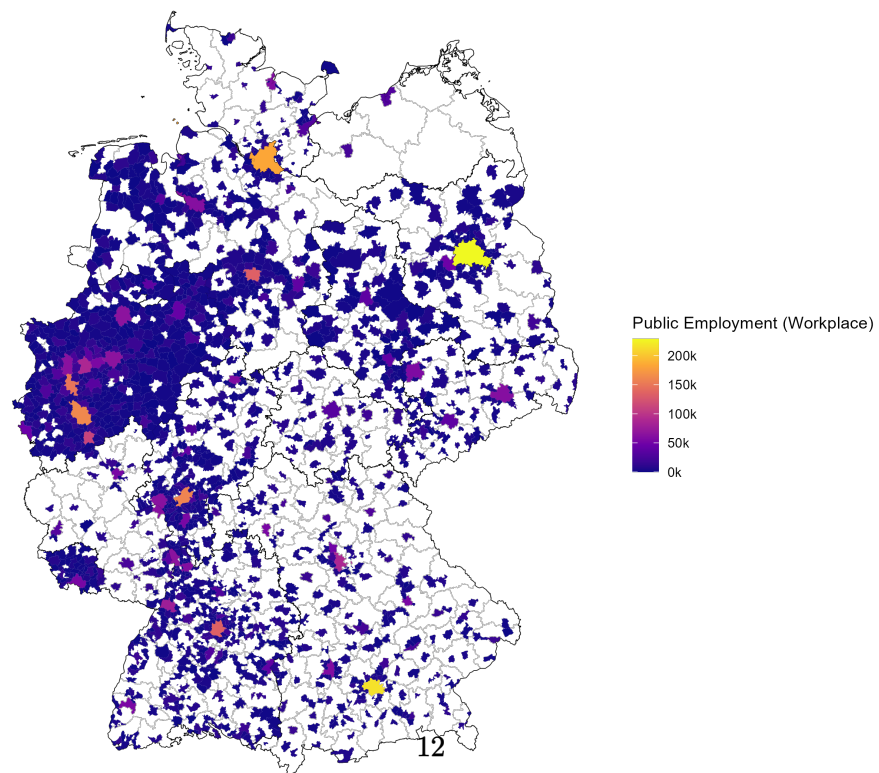


Figure 3. Spatial Distribution of Residence and Workplace Public Employment in Germany. Source: Census 2011.

3.4 Controls Used in Mahalanobis Matching

I draw the matching controls (total population, working-age population, disposable income, and net migration) from the German Regional Database. Population outcomes are observed for the years 2008 to 2023. More current data is not available yet.

Treated Variable	BY Control			DE Control			Treated		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
<i>Outcomes</i>									
Log Residence Employment	38	7.2	0.98	38	7.4	1.5	38	8.4	0.67
Residence Employment Share	38	60	3.5	38	59	4.2	38	58	3.4
Log Workplace Employment	38	6.6	1.5	38	6.4	2.8	38	8.6	0.83
Workplace Employment Share	38	39	28	38	38	26	38	77	25
Log Employment (Res. = Workp.)	38	5.2	1.4	35	5.8	2.1	38	7.6	0.89
Employment (Res. = Workp.) Share	38	9.4	5.8	35	13	8.9	38	26	7.5
Log Unemployment	38	4	1.1	38	4.5	1.7	38	5.6	0.81
Unemployment Share	38	2.5	0.78	38	3.4	1.5	38	3.7	0.98
Log Total Population	38	8.2	0.99	38	8.4	1.5	38	9.4	0.66
Total Population (1000s)	38	6	8.1	38	10	12	38	15	11
Log Working Age Pop.	38	7.8	0.98	38	7.9	1.5	38	9	0.66
Working Age Pop. Share	38	67	2.1	38	66	2	38	64	2.6

Table 6. Descriptive statistics: Outcomes by Control Group. All Outcome variables correspond to the year 2014. DE Control corresponds to the control group of municipalities outside the State of Bavaria. BY Control corresponds to the control group of municipalities inside the state of Bavaria. Res. = Residence, Workp. = Workplace., Pop. = Population., Unemp. = Unemployment, Inc. = Income.

3.5 Travel Costs

I obtain commuting flows at the municipal level from the Bundesagentur für Arbeit. Pairwise travel times between Bavarian municipalities are computed in R using the `osrm` package, which interfaces with OpenStreetMap routing data. The procedure requests car-routing durations along the road network for every ordered municipality pair (i, j) and returns a matrix of shortest-path times in minutes, denoted τ_{ij} . The routing profile follows the package defaults for private vehicles, so τ_{ij} captures network connectivity and congestion-related penalties implicit in the underlying OSRM engine. Diagonal elements are set to zero, $\tau_{ii} = 0$, and though τ_{ij} need not equal τ_{ji} because one-way streets and network asymmetries can induce directional differences, only the former enters the travel costs in the model.

Municipality-level summaries used for descriptive maps are obtained by averaging τ_{ij} across all destinations j for each origin i . The resulting mean travel times provide a compact measure of network centrality within Bavaria and are visualized in Fig. 4. The full $\{\tau_{ij}\}$ matrix enters the model via commuting costs $d_{ij} = \exp(\kappa \tau_{ij})$.

Average Travel Times for Municipalities in Bavaria
(Diverging at Mean)

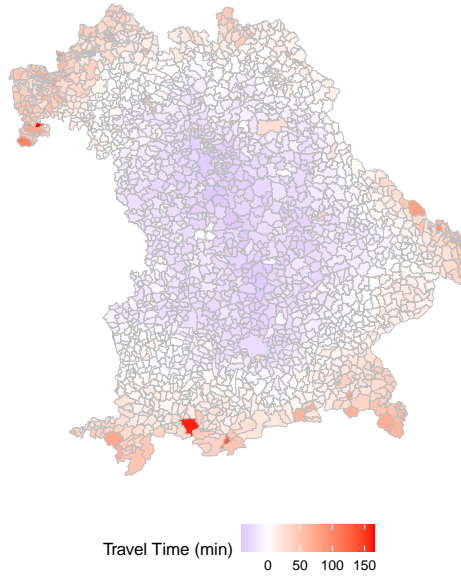


Figure 4. Travel Times in Bavaria Compared to the Mean Travel Time of 142 minutes. Source: Own calculation based on the travel times extracted from the OSRM package in R.

3.6 Rents and Housing Prices

I use a rent price index as a proxy for floor space prices available via the GitHub toolkit⁸ for Ahlfeldt, Heblich, et al. (2023). The R code is available at <https://github.com/dndfreitas/ps.emp.qsm> and can be accessed upon request.

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 2022⁹ 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,

⁸<https://github.com/Ahlfeldt/AHS2023-toolkit>

⁹2023 for population outcomes

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 anticipation 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 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 dimensionality¹⁰. 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 experiment¹¹.

I examine municipalities within and outside Bavaria to select an appropriate control group. Boxplots in Fig. 5 demonstrate that both sets form viable control groups based on the distribution of covariates used for matching. Yet, balance plots in Fig. 6 and in Fig. 23 in Appendix C reveal superior matching quality with municipalities outside

¹⁰The '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.

¹¹A '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 5. 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.

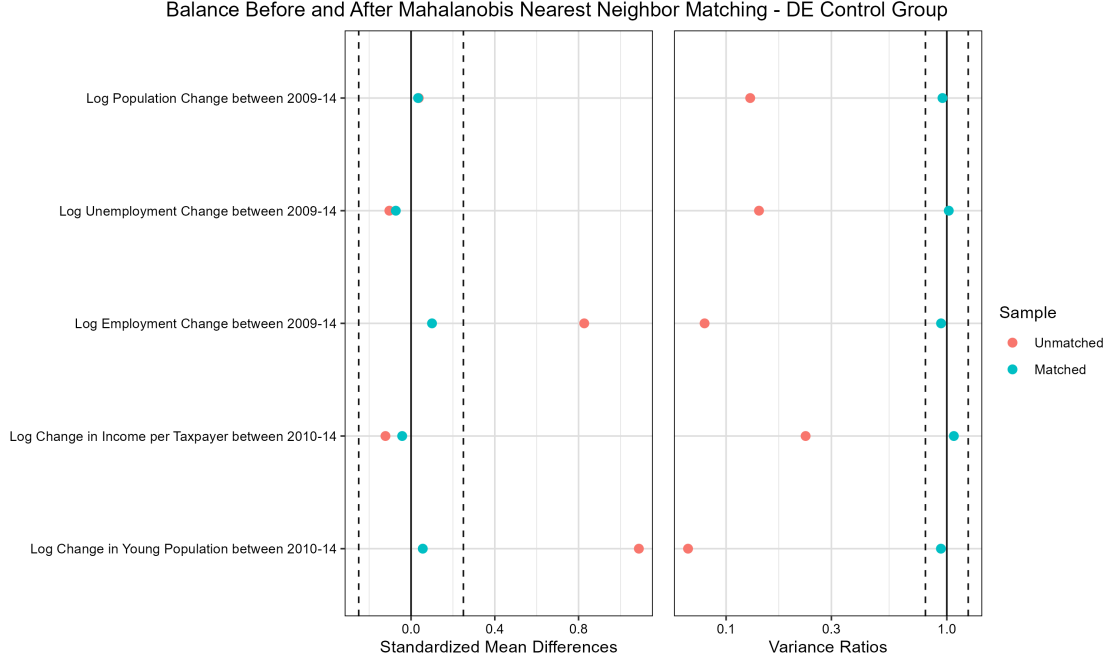


Figure 6. Balance Plot illustrating Standardized Mean Differences, and variance ratios between treatment and control group of municipalities outside of Bavaria before and after Mahalanobis nearest neighbor matching.

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

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



Figure 7. Map of Germany showing the treated municipalities in Bavaria (teal) and their control group counterparts (ocher) outside of Bavaria.

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

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:

$$ATT(g, t) = E[Y_{it}(g) - Y_{it}(\infty) | \mathcal{G}_i = g] \quad (1)$$

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:

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

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

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 9 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.

	(1)	(2)	(3)	(4)
Treatment (Bin)	-0.0785 (0.0564)	0.0201** (0.0080)	0.0067 (0.0111)	0.0229 (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 9. 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.

5.1 Labor Market Outcomes

Table 10 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 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 11 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 (0.0073)	0.0109 (0.0096)	0.0015 (0.0065)	0.0069 (0.0067)	0.0164* (0.0088)	0.0199** (0.0076)	0.0225** (0.0084)	0.0201** (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 10. 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 (0.0303)	0.0771*** (0.0259)	-0.0556* (0.0328)	-0.1184** (0.0437)	-0.0682 (0.0479)	-0.0672 (0.0485)	-0.0906 (0.0592)	-0.0785 (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 11. 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 12, 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 13, 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 workforce. 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 (0.0028)	0.0047 (0.0048)	0.0119* (0.0059)	0.0156** (0.0075)	0.0127 (0.0080)	0.0056 (0.0079)	-0.0026 (0.0088)	-0.0025 (0.0101)	0.0067 (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 12. 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 (0.0037)	0.0078 (0.0064)	0.0160* (0.0080)	0.0214** (0.0088)	0.0175* (0.0098)	0.0144 (0.0087)	0.0045 (0.0088)	0.0104 (0.0118)	0.0229 (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 13. 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 14, while the unemployment share decreases by -0.59 percentage points after public sector employees relocate (Table 15). In terms of population outcomes, Table 16 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, results show that the relocation did not harm but benefit the sending locations.

	Employment Share (Residence)		
	(1)	(2)	(3)
Post (Binary) \times Treatment (Binary) = 1	5.947*** (0.7572)	0.7748** (0.3800)	0.7748** (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 14. 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) \times Treatment (Binary) = 1	-0.4625*** (0.1369)	-0.5907*** (0.1287)	-0.5907*** (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 15. 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) \times Treatment (Binary) = 1	-1.068** (0.4422)	1.111*** (0.3210)	1.111*** (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 16. 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. Using this estimator, I check if treatment time heterogeneity affects the treatment effects.

6.1 Receiving Locations

Fig. 8b 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.

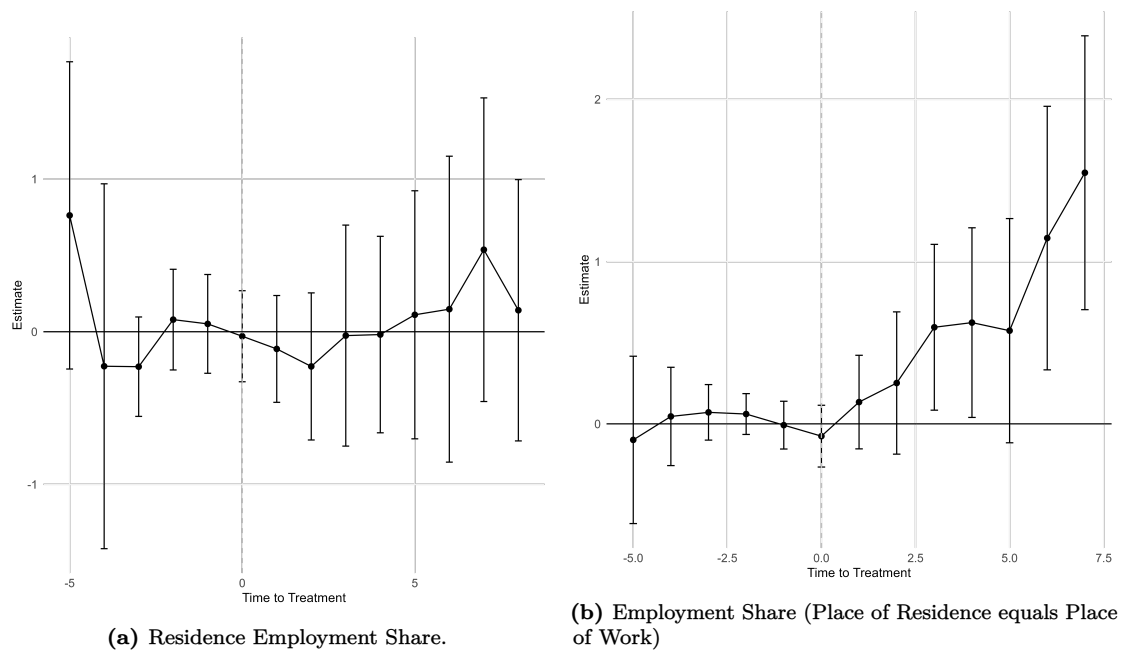


Figure 8. Callaway and Sant'Anna (2021) estimator for disaggregated employment shares. Treatment starts in 2015.

The same event study for the unemployment shares in Fig. 9 shows that unemployment started to decrease right after the relocations started in 2015.

Fig. 10b 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.

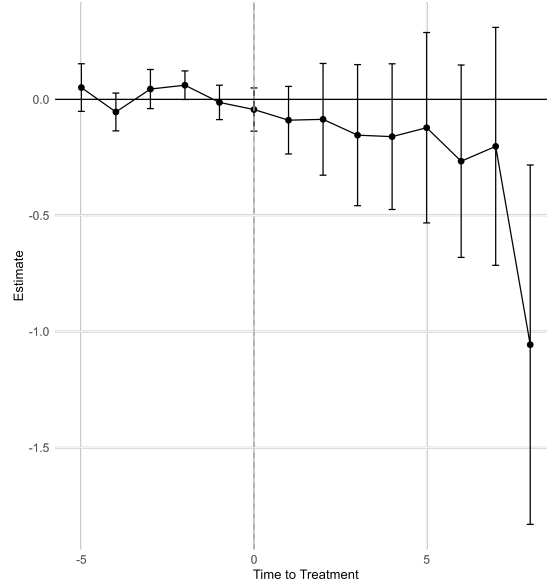


Figure 9. Callaway and Sant’Anna (2021) estimator for unemployment shares. To create unemployment shares at the municipal level, I count the number of unemployed in a municipality and divide it by the working age population. Treatment starts in 2015.

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 in receiving locations. 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.

6.2 Sending Locations

I define a sending municipality as treated in the first year it loses public jobs and estimate dynamic effects using the Callaway–Sant’Anna estimator with never-treated municipalities outside of Bavaria as the comparison group. Event time is normalized so that $\tau = 0$ is the last pre-exposure year for each municipality, and I aggregate cohort-specific effects to event time.

In the employment figures, the two panels of Figure 11b display residence-based employment shares (panel a) and the subset where residence equals workplace (panel b). In both panels, the post-exposure paths increase with treatment time up to seven years after the relocation, indicating gains in employment shares at sending locations.

The unemployment event study in Figure 12 shows no pre-trend and a decrease in unemployment share after exposure, consistent with reductions in unemployment in sending municipalities. The effect is biggest (but also most unprecise) five years after the

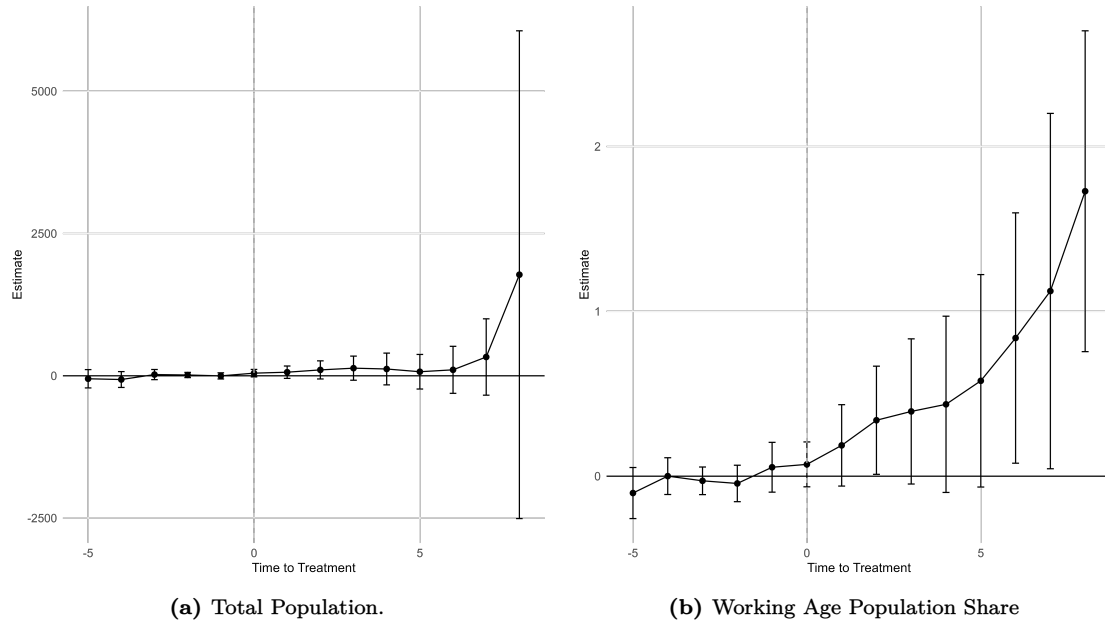


Figure 10. Callaway and Sant’Anna (2021) estimator estimator for population and working age population shares.

relocation program starts.

For total population, Figure 13b (panel a) shows an increase, which is significant for first years after the relocation program starts. Panel B also shows a clear upward trajectory in the working-age population share after the program starts.

Surprisingly, the sending-location outcome paths mirror the receiving-location event studies reported earlier (compare, for example, with Figure 8b). Seeing the same qualitative response at both ends of the relocation which employment share increases, unemployment share decreases, and a higher working-age population share is puzzling and counterintuitive if we think only in terms of subtracting public labor demand at origin and adding it at destination. The origin does not contract. Instead, it appears to backfill and even improve after a party of the public sector is reallocated somewhere else.

I interpret this symmetry as indicative of spillovers that might act both within and between sectors and that are not modeled in the existing public employment reallocation literature yet. To rationalize positive multipliers at destinations and non-negative dynamics at origins, I develop a quantitative spatial model developed in Section ?? by allowing for within- and between-sector productivity, and amenity spillovers, and spatial sorting.

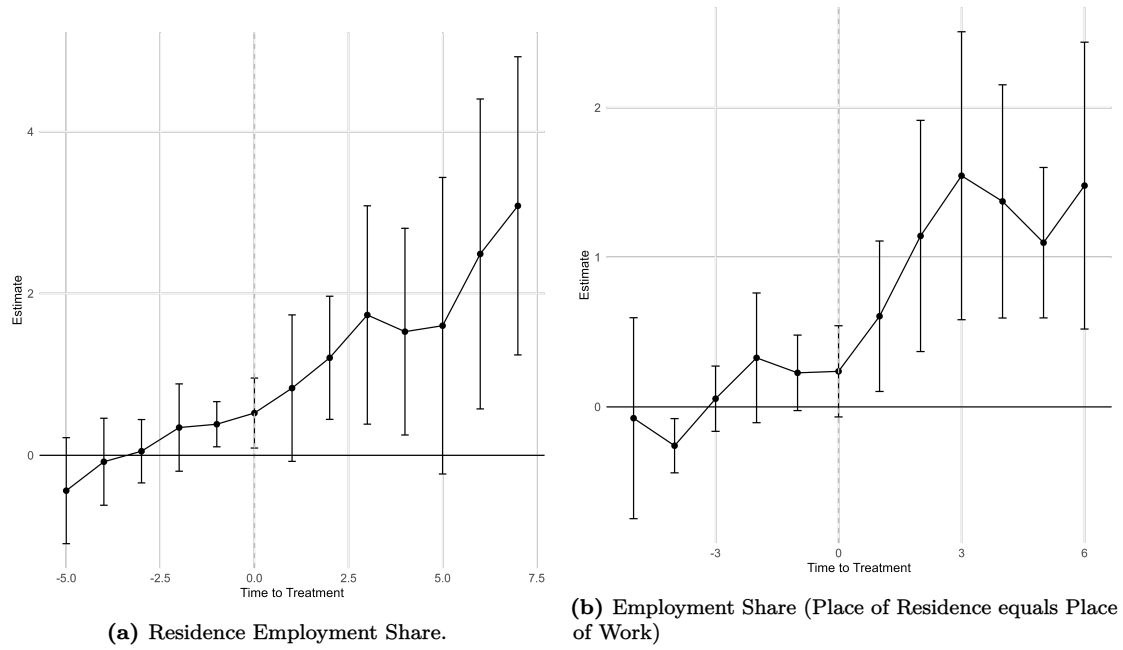


Figure 11. Callaway and Sant'Anna (2021) estimator for disaggregated employment shares for sending locations. Treatment starts in 2015.

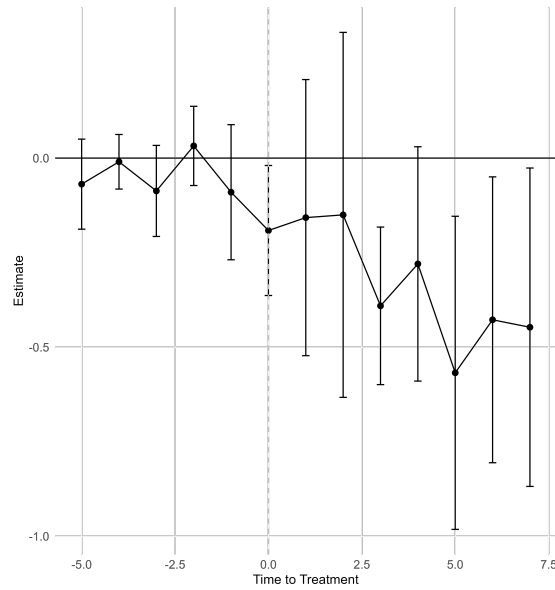


Figure 12. Callaway and Sant'Anna (2021) estimator for unemployment shares for sending locations. To create unemployment shares at the municipal level, I count the number of unemployed in a municipality and divide it by the working age population. Treatment starts in 2015.

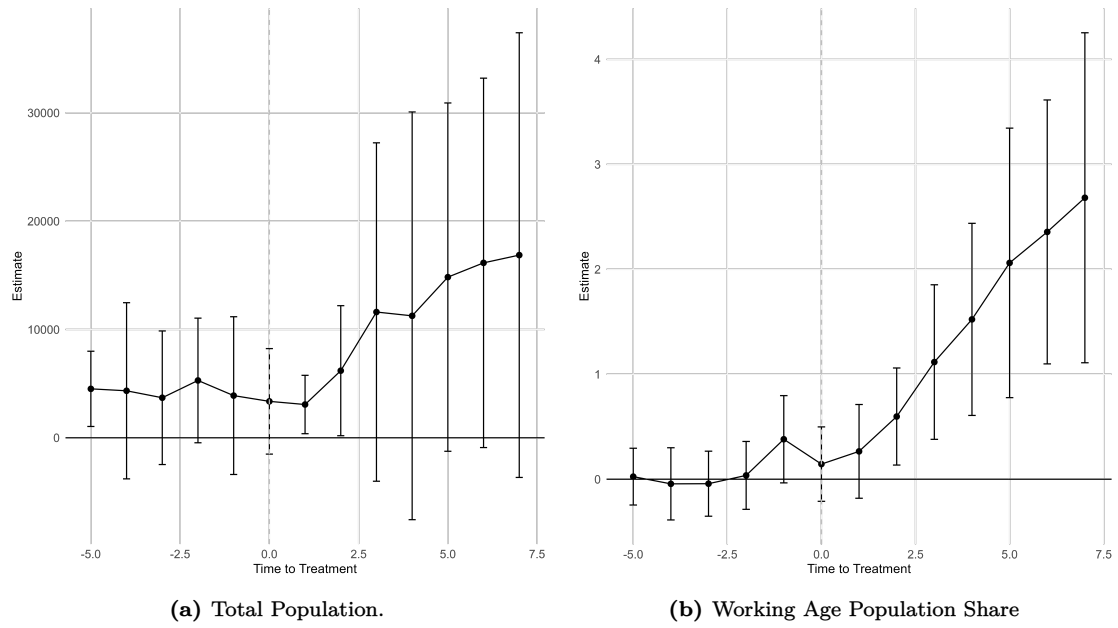


Figure 13. Callaway and Sant'Anna (2021) estimator estimator for population and working age population shares for sending locations.

7 Multiplier Analysis

I estimate a long-difference model at the municipality level. Let municipalities be indexed by m and different employment outcome measures by d . I denote private employment by $E_{m,d,t}$ in year $t \in \{2014, 2022\}$.

$$\Delta E_{m,d} \equiv E_{m,d,2022} - E_{m,d,2014}. \quad (4)$$

I measure relocation intensity with two counts: (i) R_m^{all} , the total number of relocated public jobs *and* study places that m receives between 2015 - 2022; and (ii) R_m^{jobs} , the total number of relocated public jobs only. I net out the direct mechanical addition of relocated positions from the private employment outcome:

$$\Delta E_{m,d}^{\text{net,all}} \equiv \Delta E_{m,d} - R_m^{\text{all}}, \quad (5)$$

$$\Delta E_{m,d}^{\text{net,jobs}} \equiv \Delta E_{m,d} - R_m^{\text{jobs}}. \quad (6)$$

I control for pre-treatment characteristics X_m (log changes in population, unemployment, tax income per capita, young population, and employment over 2009-2014/2010-2014) . I cluster standard errors at the district level.

$$\Delta E_{m,d}^{\text{net,all}} = \alpha_d + \beta_d^{\text{all}} R_m^{\text{all}} + X_m' \gamma_d + \varepsilon_{m,d}, \quad (7)$$

$$\Delta E_{m,d}^{\text{net,jobs}} = \alpha_d^{(J)} + \beta_d^{\text{jobs}} R_m^{\text{jobs}} + X_m' \gamma_d^{(J)} + u_{m,d}. \quad (8)$$

I read β_d^{all} as the *public-to-private jobs multiplier* in measure d : net additional private jobs per relocated public job or study place. I read β_d^{jobs} as the same multiplier when I restrict R to relocated jobs only. Fig. 14 relates R_m^{all} on the x -axis to $E_{m,d}^{\text{net,all}}$ on the y -axis. The upward fitted line slopes shows that larger relocations go together with larger net gains, consistent with a positive multiplier. The median public-to-private employment multiplier for employment where place of resident equals place of work is 1.08, meaning that relocating 10 public jobs create 10.8 additional jobs in the private sector.

To study heterogeneity, I form municipality-level multipliers using matched subclasses from my Mahalanobis matching. Let $\hat{Y}_{m,d}^{\text{all}}$ and $\hat{Y}_{m,d}^{\text{jobs}}$ be the fitted values from the previous long differences model. I compare each treated municipality to the average predicted outcome of its control partners c within the same Mahalanobis subclass:

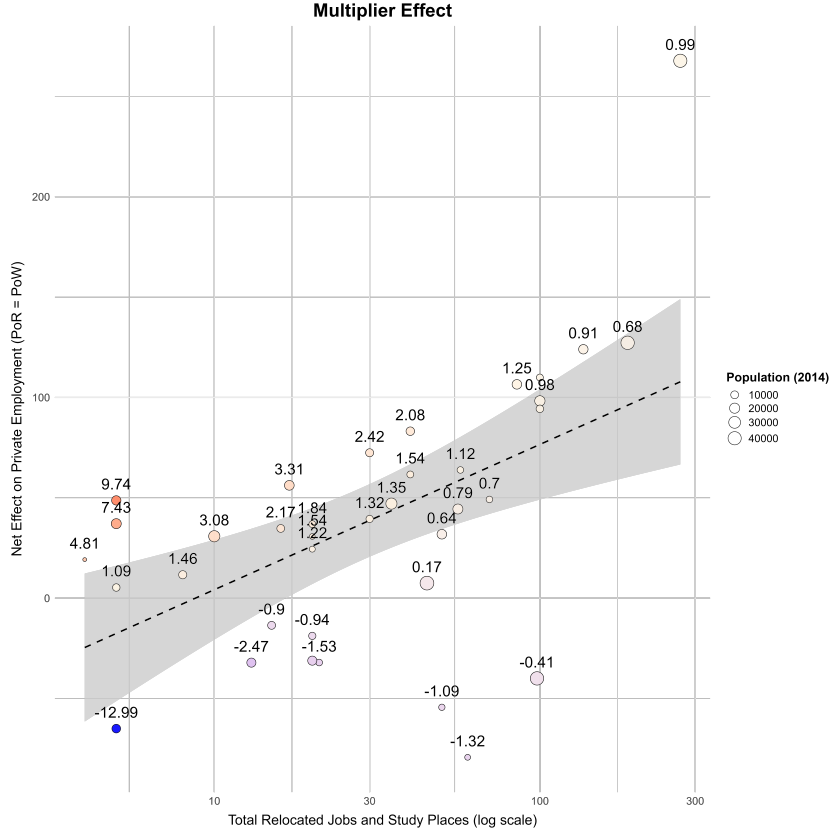


Figure 14. Relocation dose and net employment gains (PoR = PoW).

$$\widehat{\text{effect}}_{m,d}^{\text{all}} \equiv \hat{Y}_{m,d}^{\text{all}} - \hat{Y}_{c,d}^{\text{all}}, \quad (9)$$

$$\hat{\mu}_{m,d}^{\text{all}} \equiv \frac{\widehat{\text{effect}}_{m,d}^{\text{all}}}{R_m^{\text{all}}}, \quad (10)$$

$$\widehat{\text{effect}}_{m,d}^{\text{jobs}} \equiv \hat{Y}_{m,d}^{\text{jobs}} - \hat{Y}_{c,d}^{\text{jobs}}, \quad (11)$$

$$\hat{\mu}_{m,d}^{\text{jobs}} \equiv \frac{\widehat{\text{effect}}_{m,d}^{\text{jobs}}}{R_m^{\text{jobs}}}. \quad (12)$$

Fig. 15 plots $\hat{\mu}_{m,d}^{\text{all}}$ as net private jobs per relocated unit (jobs + study places) showing where employment gains concentrate.

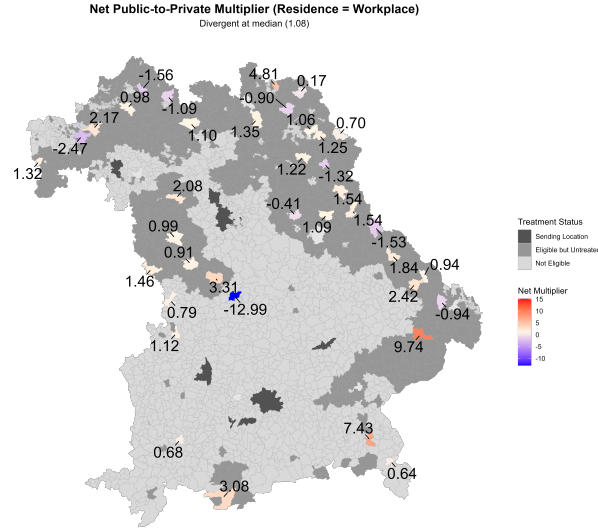


Figure 15. Municipality-level multipliers, above/below the state median

8 Two-Sector Quantitative Spatial Model

The empirical approach employed in this study allows for an analysis of how the *Heimatstrategie* policy affects employment and population outcomes in both sending and receiving locations. However, a shift in the spatial distribution of public sector workers has the potential to influence the Bavarian economy more broadly. Such shifts could lead to relative changes in wages and house prices, affecting general equilibrium conditions.

To incorporate these general equilibrium effects into the analysis of public employment reallocation policy, I adapt the Ahlfeldt, Redding, et al. (2015) quantitative spatial model. The model is extended into a two-sector framework that includes both public and private sectors. Public sector activity can generate spillovers that impact private sector productivity. These spillovers may alter workplace employment across all municipalities in Bavaria, extending beyond those directly impacted by job relocations. Additionally, changes in public sector job distribution could affect local amenity externalities as suggested by Becker et al. (2021). This adjustment might alter where people choose to live and work, influencing residential employment patterns across regions.

8.1 Model Setup

I follow Ahlfeldt, Redding, et al. (2015) for the general setup of workers, firms, and the construction sector. The model considers Bavaria as a regional economy embedded in the wider German economy. The economy is closed at the state level, which implies that migration between Bavaria and the rest of Germany is ruled out in the current version of the model, while Bavaria itself remains open internally. The analysis runs at the municipal level.

Calibration at the municipal level addresses two considerations. First, Faggio (2019)

and Freitas (2025) show that public employment reallocations generate highly localized effects that dissipate rapidly with distance. Second, the empirical analysis in the previous chapter was conducted at the municipal level. To ensure consistency between the empirical estimates and the quantitative model, I conduct counterfactuals at the municipal level. The quantification of the two-sector model requires data on both residence and workplace employment, disaggregated by public and private sectors. For Germany, such data is only available from the German census. However, the census provides only a ready-to-use sample at the municipal level. While I have successfully requested access to the full municipal data, delivery is still pending. Until then, I rely on the publicly available sample at the municipal level.

The key innovation in this study is a two-sector structure that distinguishes between public and private employment. Let $m \in \{P, G\}$ denote the private and public sector. Workers are exogenously assigned to a sector but otherwise perfectly mobile across locations within Bavaria. Employment in sector m at workplace j is denoted H_{jm}^M , and employment in sector m at residence j is denoted H_{jm}^R . Spatial employment density is given by H_{sm}^M/K_j , where K_j is geographic land area.

8.1.1 Productivity Spillovers

Endogenous productivity at workplace j reflects both within- and cross-sector spillovers. Define sector-specific spillover terms as

$$\Upsilon_{jP} \equiv \sum_s e^{-\delta\tau_{js}} \frac{H_{Ps}^M}{K_j}, \quad \Upsilon_{jG} \equiv \sum_s e^{-\delta\tau_{js}} \frac{H_{Gs}^M}{K_j}, \quad (13)$$

where τ_{js} denotes travel time between j and s , and δ governs the rate of spatial decay. Let $\lambda > 0$ denote the elasticity of productivity with respect to employment density. Let $\rho \in [0, 1]$ be the ratio of cross- to within-sector spillovers. Productivity in the private sector at j is then

$$A_{jP} = \alpha_j [\Upsilon_{jP} + \rho\Upsilon_{jG}]^\lambda, \quad (14)$$

and productivity in the public sector is

$$A_{jG} = \alpha_j [\Upsilon_{jG} + \rho\Upsilon_{jP}]^\lambda. \quad (15)$$

If $\rho = 0$, only within-sector spillovers matter. If $\rho = 1$, within- and cross-sector spillovers are identical and the model collapses to the one-sector case in Ahlfeldt, Redding, et al. (2015). The general form is

$$A_{jm} = \alpha_j [\Upsilon_{jm} + \rho\Upsilon_{jm'}]^\lambda. \quad (16)$$

8.1.2 Amenity Spillovers

Residential amenities follow the same logic. Define

$$\Omega_{jP} \equiv \sum_s e^{-\delta\tau_{js}} \frac{H_{Ps}^R}{K_j}, \quad \Omega_{jG} \equiv \sum_s e^{-\delta\tau_{js}} \frac{H_{Gs}^R}{K_j}. \quad (17)$$

Amenities in location j are given by

$$B_{jm} = b_j [\Omega_{jm} + \rho\Omega_{jm'}]^\eta, \quad (18)$$

where η measures the strength of amenity spillovers. The specification allows public employment relocations to affect local amenities directly through residential employment density and indirectly through cross-sector effects.

8.2 Baseline and Counterfactual Results

This section quantifies the spatial model at the municipal level, inverts it to recover location fundamentals, and then uses these fundamentals to simulate counterfactual public employment relocations. The calibration follows the approach of Ahlfeldt, Redding, et al. (2015), but is adapted to the municipal level to reflect the localized effects of public sector relocations documented in the empirical analysis.

8.2.1 Quantification

I recode the ARSW quantitative spatial model from MATLAB¹² into R (see Appendix F for replication details).

The first step is to estimate the commuting decay parameter $\kappa\epsilon$ using bilateral commuter flows between municipalities from the Bundesagentur für Arbeit. The regression

$$\log(\text{commuters}_{ij}) = \alpha_i + \gamma_j - \kappa\epsilon\tau_{ij} + \varepsilon_{ij}$$

yields $\kappa\epsilon = 0.0466$.

Next, I calibrate the Fréchet shape parameter ϵ by matching the variance of adjusted log wages in the model to the observed variance across municipalities in 2011 (rather than at the district level as in ARSW). This delivers $\hat{\epsilon} = 5.68$, which implies an iceberg commuting cost parameter of $\kappa = \kappa\epsilon/\epsilon = 0.0082$.

All other parameters of the model (e.g., the production and housing expenditure shares (α, β) , the density elasticities (λ, δ) , and the decay parameters for spillovers (η, ρ)) are set to the benchmark values reported in Ahlfeldt, Redding, et al. (ibid.) in the current version of the model.

Figure 16 shows the resulting adjusted wages, $\log \tilde{w}_j$, normalized by the geometric mean across municipalities. Values peak in Munich and other metropolitan centers such as Ingolstadt, Regensburg, Augsburg, and Nuremberg–Fürth–Erlangen, while declining smoothly toward peripheral areas like the Bavarian Forest and the Alpine fringe.¹³

¹²The toolkit version of the model that serves as the baseline for the code replication is available here: <https://github.com/Ahlfeldt/ARSW2015-toolkit>.

¹³Outside Bavaria, the map is gray-shaded because the quantification is restricted to Bavarian municipalities.

Adjusted Wages ($\log w$) by Municipality

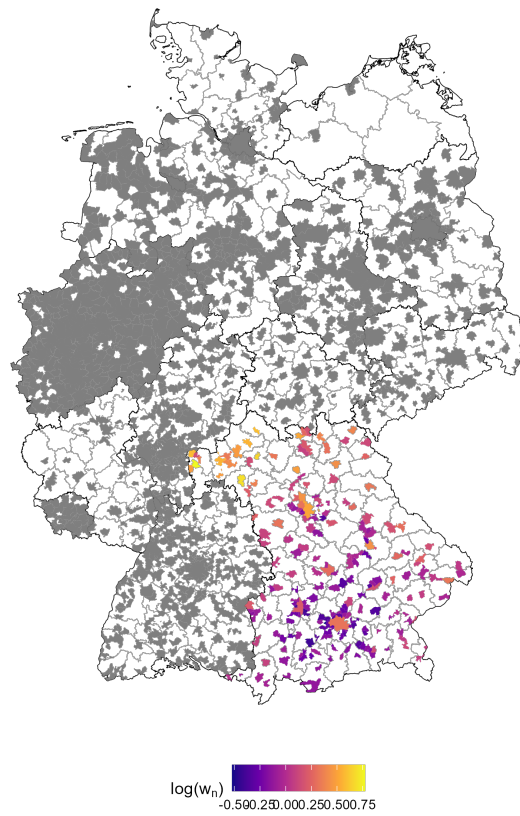


Figure 16. Commuter Market-Clearing Adjusted Wages

8.2.2 Inversion

With the calibrated parameters, I invert the model to recover location fundamentals. Following the ARSW structure, adjusted productivities and amenities at location j combine exogenous fundamentals with endogenous spillovers:

$$A_j^{\text{adj}} = \tilde{a}_j (\Upsilon_j^{\text{mix}})^\lambda, \quad B_j^{\text{adj}} = \tilde{b}_j (\Omega_j^{\text{mix}})^\eta,$$

where λ and η are the density elasticities for production and amenities, respectively.

Spillovers aggregate sectoral employment densities through spatial-decay kernels. For productivity,

$$\Upsilon_j^{\text{mix}} \equiv \Upsilon_j^G + \rho_A \Upsilon_j^P, \quad \Upsilon_j^m = \sum_s e^{-\delta_A \tau_{js}} \frac{H_{Ms}^m}{K_s},$$

and for amenities,

$$\Omega_j^{\text{mix}} \equiv \Omega_j^G + \rho_B \Omega_j^P, \quad \Omega_j^m = \sum_s e^{-\delta_B \tau_{js}} \frac{H_{Rs}^m}{K_s}.$$

Here $m \in \{P, G\}$ indexes private/public sectors, H_{Ms}^m and H_{Rs}^m denote workplace and residence employment in sector m at municipality s , K_s is geographic land, τ_{js} is bilateral travel time (in hours), and (δ_A, δ_B) are the decay parameters. The mixing weights (ρ_A, ρ_B) allow private-sector spillovers to enter the public aggregator (and vice versa), with $\rho_A = \rho_B = 1$ corresponding to the pooled ARSW case.

Given the observed adjusted objects $(A_j^{\text{adj}}, B_j^{\text{adj}})$, I back out the exogenous fundamentals by netting out the endogenous components:

$$\tilde{a}_j = \frac{A_j^{\text{adj}}}{(\Upsilon_j^{\text{mix}})^\lambda}, \quad \tilde{b}_j = \frac{B_j^{\text{adj}}}{(\Omega_j^{\text{mix}})^\eta}.$$

These fundamentals remain fixed in the counterfactual simulations, while public-sector spillovers are reallocated according to the policy experiment.

8.2.3 Counterfactual Relocations

Using the recovered fundamentals $(\tilde{a}_j, \tilde{b}_j)$, I simulate a closed-city reallocation of public employment under the *Heimatstrategie*. The counterfactual input is a list of municipality pairs (r, s) with job counts n_{rs} indicating moves from sender s to receiver r .

Let K_j denote geographic land and τ_{js} travel time (in hours). With decay parameters (δ_A, δ_B) , the production and amenity kernels for the *public* component become

$$\Upsilon_j^{G, \text{cf}} = \sum_s e^{-\delta_A \tau_{js}} \frac{H_{Ms}^{G, \text{cf}}}{K_s}, \quad \Omega_j^{G, \text{cf}} = \sum_s e^{-\delta_B \tau_{js}} \frac{H_{Rs}^{G, \text{cf}}}{K_s}.$$

I keep the private component at baseline and combine sectors via the mixing weights (ρ_A, ρ_B) ,

$$\Upsilon_j^{\text{mix, cf}} = \Upsilon_j^{G, \text{cf}} + \rho_A \Upsilon_j^P, \quad \Omega_j^{\text{mix, cf}} = \Omega_j^{G, \text{cf}} + \rho_B \Omega_j^P,$$

with $\rho_A = \rho_B = 1$ in the pooled ARSW benchmark.

Municipality-by-municipality anchors for total workplace and residence employment update with the public moves,

$$H_{Mj}^{\text{tot,cf}} = H_{Mj}^{\text{tot}} + \Delta H_{Mj}^G, \quad H_{Rj}^{\text{tot,cf}} = H_{Rj}^{\text{tot}} + \Delta H_{Rj}^G,$$

and the equilibrium solver then finds $(w_j^{\text{cf}}, Q_j^{\text{cf}}, \theta_j^{\text{cf}}, H_{Mj}^{\text{cf}}, H_{Rj}^{\text{cf}})$ consistent with: (i) labor-market clearing at workplaces, (ii) residence allocation, (iii) housing market clearing (with expenditure share β), and (iv) the mixed externalities $(\Upsilon_j^{\text{mix,cf}}, \Omega_j^{\text{mix,cf}})$ while holding fundamentals fixed at $(\tilde{a}_j, \tilde{b}_j)$:

$$A_j^{\text{adj,cf}} = \tilde{a}_j (\Upsilon_j^{\text{mix,cf}})^\lambda, \quad B_j^{\text{adj,cf}} = \tilde{b}_j (\Omega_j^{\text{mix,cf}})^\eta.$$

Expected utility uses the standard ARSW closed-city aggregator with $M_\epsilon = \exp(-\epsilon\kappa\tau)$, Frechét shape ϵ , and housing share β :

$$\mathcal{U} = \Gamma\left(\frac{\epsilon-1}{\epsilon}\right) \left(\sum_j (w_j^\epsilon) \sum_i M_{\epsilon,ji} \left(\frac{B_i}{Q_i^{1-\beta}} \right)^\epsilon \right)^{1/\epsilon}.$$

I report $\Delta\mathcal{U}/\mathcal{U}$ alongside the geographic distributions of outcomes.

The relocation induces a negligible welfare effect, with aggregate expected utility declining by only -0.000027% . Table 17 shows summary statistics of the counterfactual scenario. Under the policy, private workplace employment (HP) falls in Munich and rises in recipients: the largest loss is 394 jobs in Munich; the largest gain is $\sim 1,900$ jobs in a target municipality. Median effects are near zero, but several small places see sizable proportional gains. Housing price responses are modest (mean $+0.04\%$, 95th percentile $+0.29\%$, max $+1.66\%$; down to -2.5%), wages are essentially unchanged (no municipality exceeds $\pm 0.01\%$), amenities B tick up slightly (mean $+0.004\%$) and productivity A edges down marginally (mean -0.002%). Overall, the policy redistributes jobs from Munich to smaller municipalities without adverse general equilibrium effects on housing, wages, amenities, or productivity.

Table 17. Summary of Counterfactual Changes

Variable	Mean	95th Percentile	Maximum
Private Workplace Employment (HP, jobs)	≈ 0	+27	+1,899
Housing Prices (Q, %)	+0.04	+0.29	+1.66
Wages (w, %)	0.00	0.00	0.00
Amenities (B, %)	+0.004	+0.008	+0.013
Productivity (A, %)	-0.002	-0.0003	-0.0001

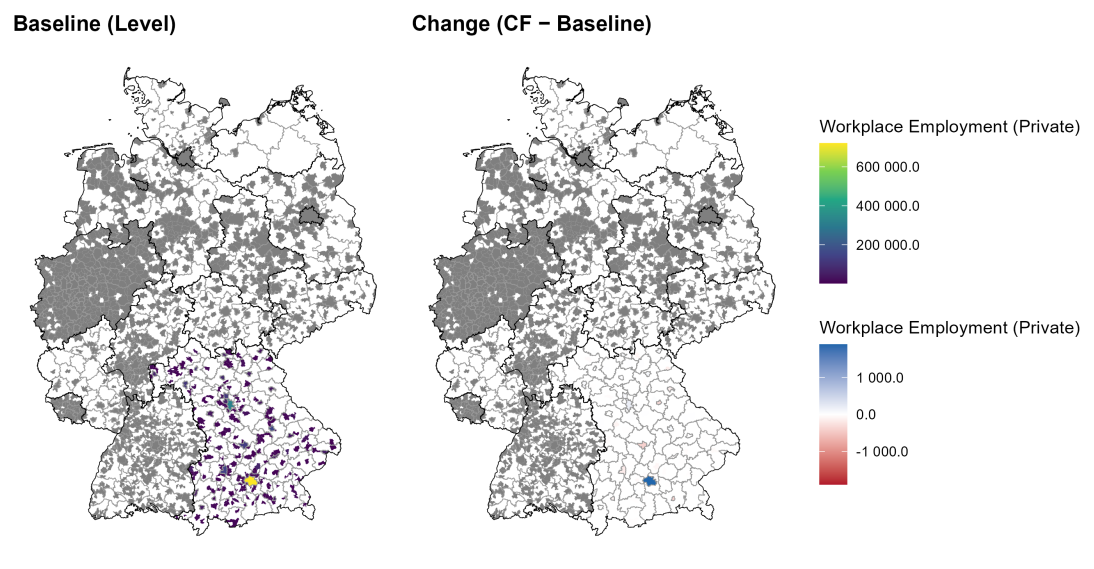


Figure 17. Private Workplace Employment (HP): Baseline and Counterfactual Change

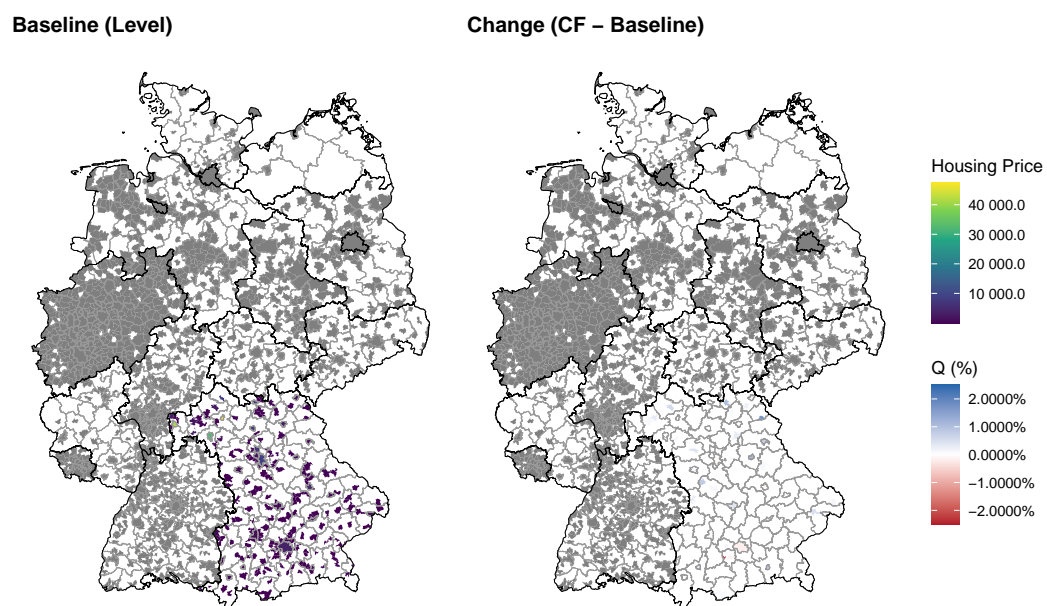


Figure 18. Housing Prices (Q): Baseline and Counterfactual Change

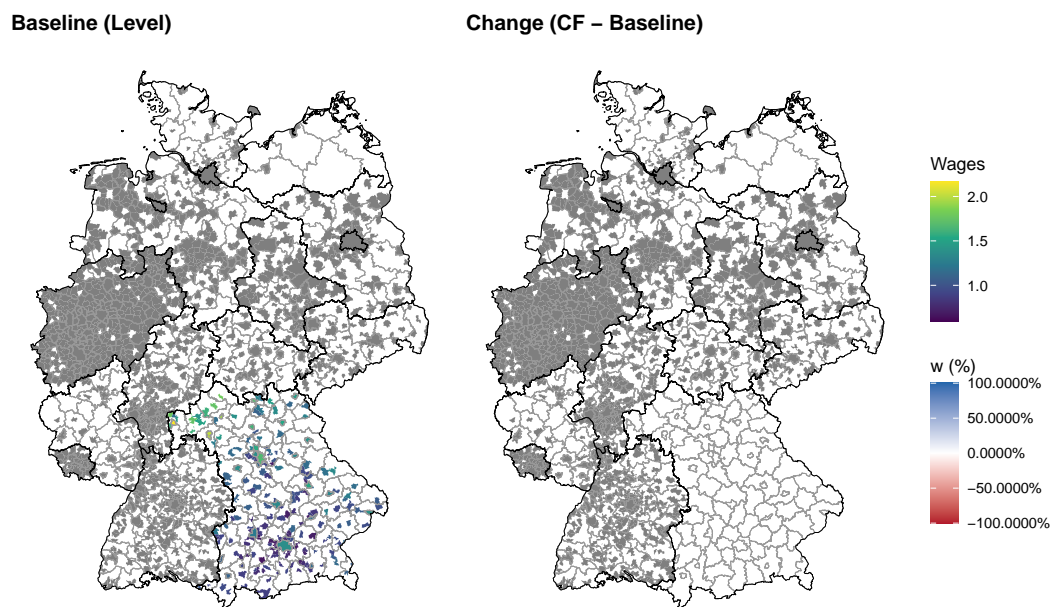


Figure 19. Wages (w): Baseline and Counterfactual Change

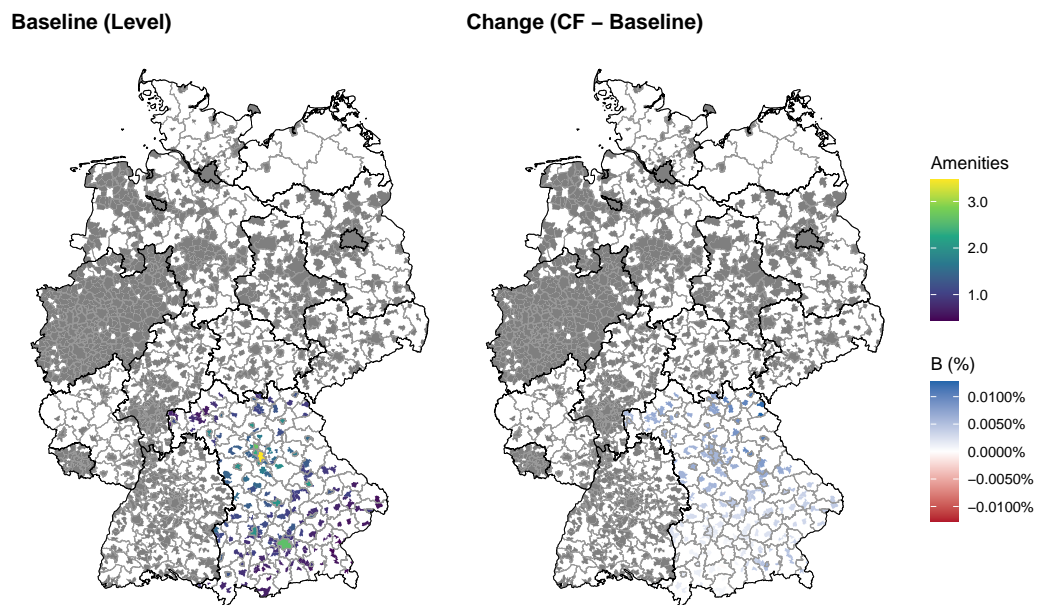


Figure 20. Amenities (B): Baseline and Counterfactual Change

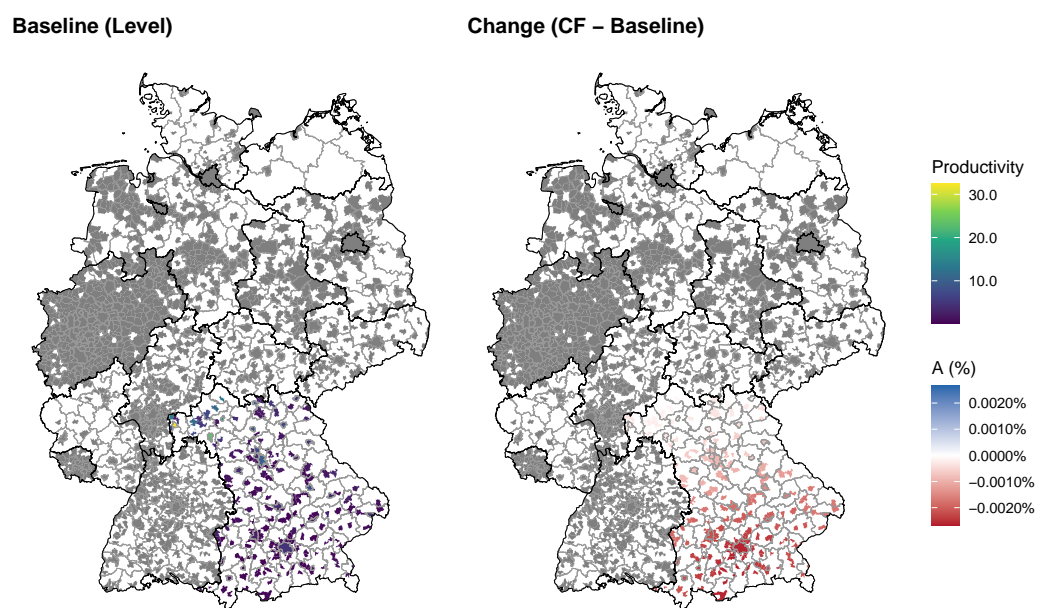


Figure 21. Productivity (A): Baseline and Counterfactual Change

9 Conclusion

In this study, I investigate 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 long 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.

Complementing these empirical results, the quantitative spatial model provides a first step toward assessing the general equilibrium effects of public employment reallocation. Preliminary simulations suggest that relocations primarily shift private employment from Munich to smaller municipalities while leaving wages and housing markets largely unaffected. The estimated amenity gains and slight productivity declines are quantitatively small, and the overall welfare effect is essentially zero.

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.

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Appendix

Appendix A: Institutional Setting

Structured News Search

I conducted the search in German using the search string **"Behördenverlagerung OR Behördenumzug OR "Umzug von Behörden" 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 18 shows how many jobs were relocated by state and Table 19 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 18. 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 Koetzing, 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), Hoechst a.d. Donau, Hof
	Ingolstadt
	Kaufbeuren, Kemnath, Kitzingen, Kronach, Kulmbach
	Lauterbach, Leipzig, Lohr am Main
München	Marktredwitz, Meissen, Merseburg, Mittenwald
	Mühlendorf 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 19. 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

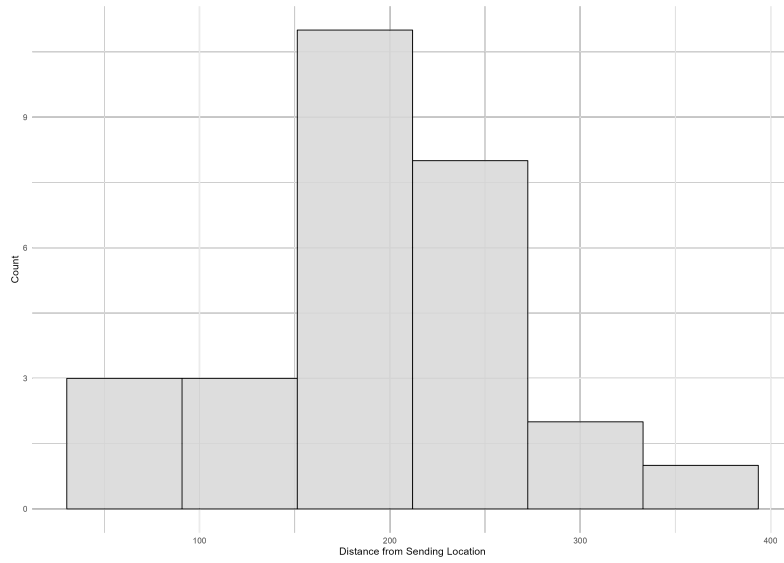


Figure 22. Distance between municipalities receiving and municipalities sending agencies. Own illustration based on own distance calculations using the statistical software R.

Appendix C: Empirical Methodology

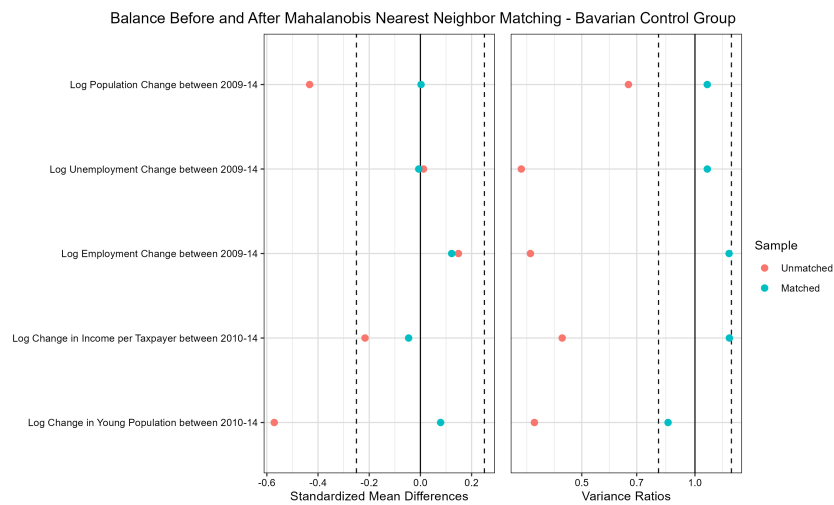


Figure 23. Balance Plot illustrating Standardized Mean Differences and variance ratios between treatment and control group of municipalities inside of Bavaria before and after Mahalanobis nearest neighbor matching.

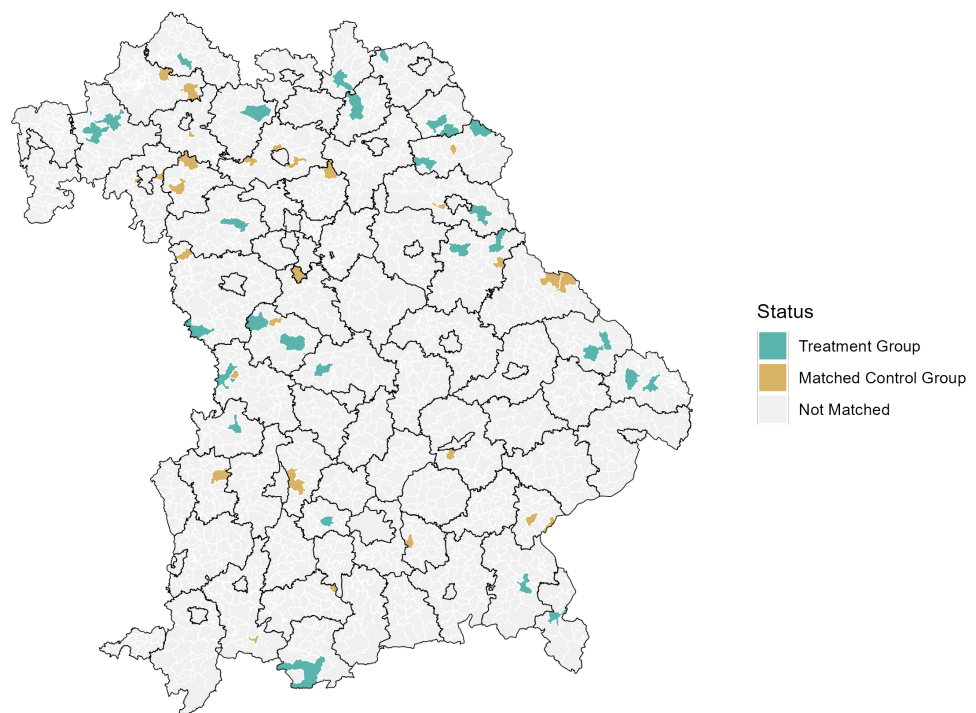


Figure 24. Map of Bavaria showing the treated municipalities in Bavaria (teal) and their control group counterparts (ocher) in Bavaria.

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 20. 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 21. 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 (0.0046)	0.0080 (0.0058)	0.0056 (0.0072)	0.0066 (0.0066)	0.0032 (0.0076)	0.0053 (0.0091)	0.0051 (0.0093)	0.0055 (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 22. Long Difference Results for Employment Share from 2015 to 2022

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment (Bin)	-0.0102 (0.0331)	-0.0215 (0.0371)	-0.0244 (0.0355)	-0.0393 (0.0360)	-0.0297 (0.0335)	0.0438 (0.0396)	0.0009 (0.0351)	-0.0145 (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 23. Long Difference Results for Unemployment Share from 2015 to 2022

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment (Bin)	0.0027 (0.0031)	0.0075* (0.0041)	0.0105 (0.0064)	0.0111 (0.0083)	0.0149 (0.0091)	0.0125 (0.0101)	0.0133 (0.0112)	0.0224 (0.0135)	0.0310* (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 24. Long Difference Results for Working Age Population from 2015 to 2023

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment (Bin)	0.0033 (0.0026)	0.0076** (0.0034)	0.0103* (0.0054)	0.0097 (0.0069)	0.0095 (0.0078)	0.0050 (0.0083)	0.0003 (0.0080)	0.0056 (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 25. Long Difference Results for Total Population from 2015 to 2022

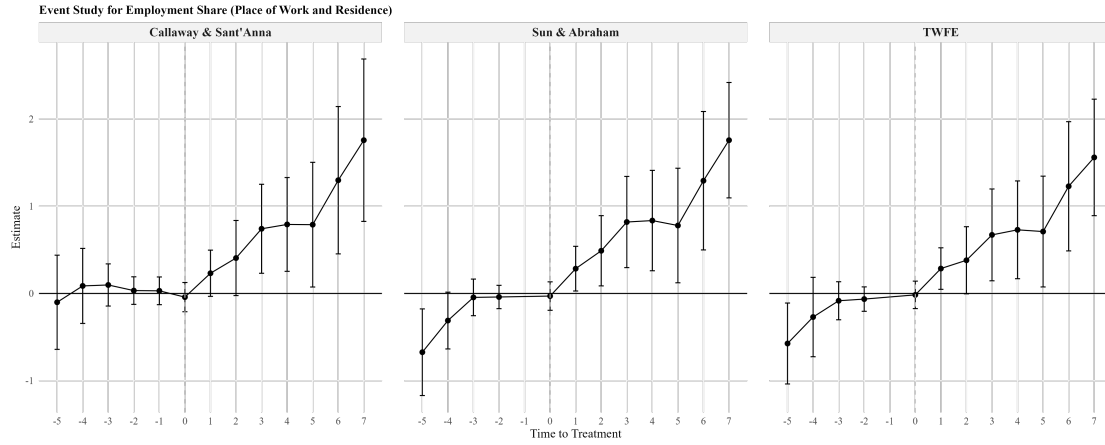


Figure 25. Callaway and Sant'Anna (2021) and Sun and Abraham (2021), and TWFE estimators for employment shares, where I compared treated municipalities to control municipalities in Bavaria. Employment is measured for individuals who live and work in the same municipality.

Appendix E: Event Study Results with Bavarian Control Group

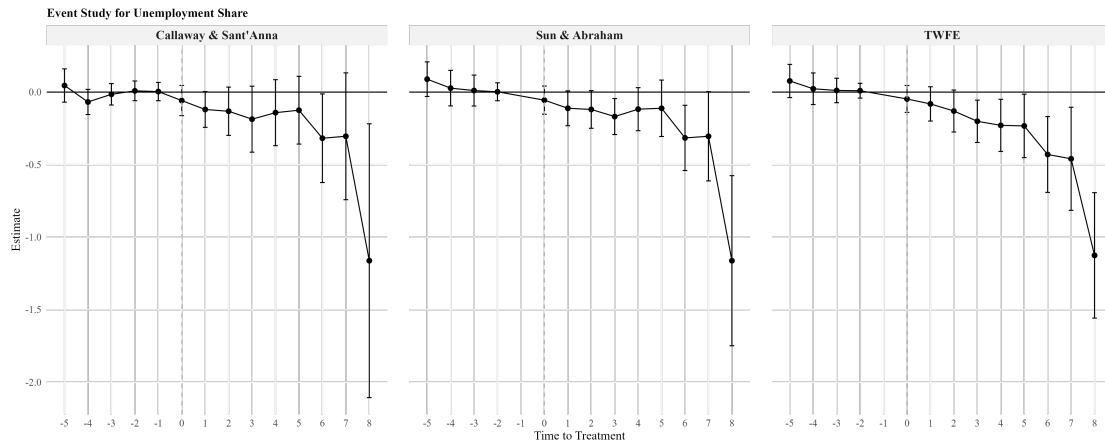


Figure 26. Callaway and Sant'Anna (2021) and Sun and Abraham (2021), and TWFE estimators for unemployment shares where I compared treated municipalities to control municipalities in Bavaria.

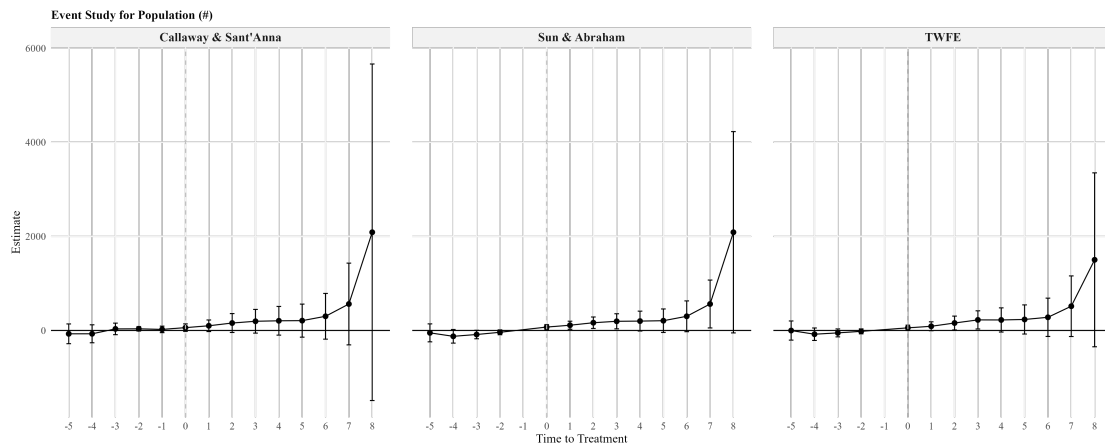


Figure 27. Callaway and Sant'Anna (2021) and Sun and Abraham (2021), and TWFE estimators for total population where I compared treated municipalities to control municipalities in Bavaria.

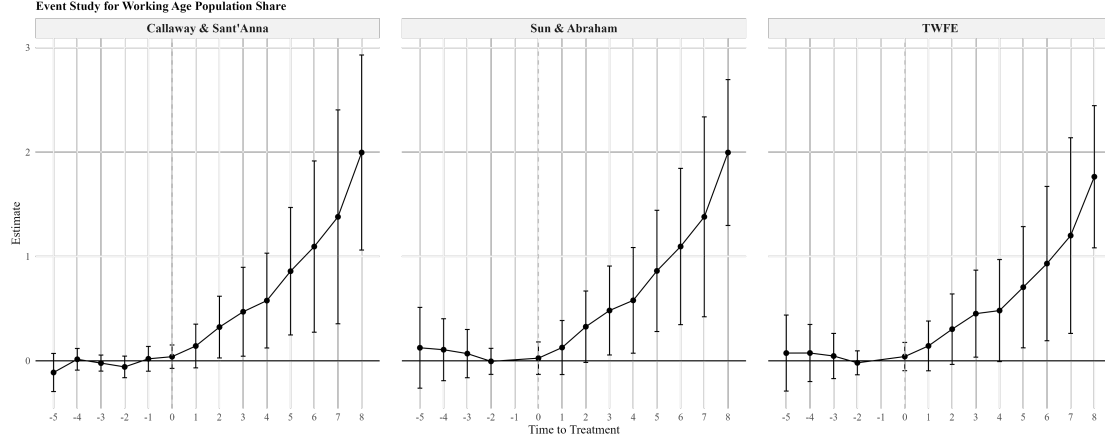


Figure 28. Callaway and Sant’Anna (2021) and Sun and Abraham (2021), and TWFE estimators for the working age population share where I compared treated municipalities to control municipalities in Bavaria.

Appendix F: Recode of ARSW Toolkit into R

The quantitative spatial model of Ahlfeldt, Redding, et al. (2015) was originally implemented in MATLAB. I recoded the entire toolkit in R, retaining the modular structure of the original code while adapting it to tidyverse-style workflows. This section documents the recode in detail to facilitate reproducibility and to provide a crosswalk between the MATLAB scripts and the new R implementation.

Data Preparation (clean_data.R). The input data are the 2011 German Census commuting tables (2000X_2041 for in-commuters and 2000X_2045 for out-commuters), supplemented with municipality shapefiles (VG250_GEM) and socio-economic variables. The R scripts parse the flat Census CSV files, filter the relevant categories, and collapse sectors into public and private aggregates. Employment variables are produced for both workplace (H_j^W) and residence (H_i^R) definitions. Unique municipal identifiers (AGS codes) are extracted from Census keys, harmonized across datasets, and merged with geospatial data. The procedure replicates the ARSW concept of “blocks,” but the unit of observation is the municipality.

Travel Times (compute_tt.R). The ARSW toolkit relies on historical Berlin travel times. In my recode, bilateral car travel times between all Bavarian municipalities are computed from OpenStreetMap using the `osrm` package. The script loops over centroid pairs in chunks of 100 origin–destination points to avoid server overload. The resulting duration matrix τ_{ij} is stored in CSV and RDS formats. This replaces the Berlin-specific transport matrices in the MATLAB toolkit.

Estimation of $\kappa\epsilon$ (estimate_kappaepsilon.R). The commuting decay parameter is estimated from bilateral commuter flows obtained from the Bundesagentur für Arbeit.

The regression

$$\log(\text{commuters}_{ij}) = \alpha_i + \gamma_j - \kappa\epsilon \tau_{ij} + \varepsilon_{ij}$$

is estimated with the `fixest` package, absorbing origin and destination fixed effects. The coefficient on travel time delivers an estimate of $\kappa\epsilon$, which is stored for later calibration.

Calibration of ϵ (`optimepsilon_TD86.R`). The script recodes `optimepsilon_TD86.m`. It sets up helper functions (`gm()` for geometric means, `scale_workplace_to_res_total()` to rescale jobs, and `group_logvar()` for variance calculations). Municipalities are assembled into a `blocks` tibble containing employment, floor-space rents (AHS index), and land area. The OSRM-based travel-time matrix is aligned to this ID set.

The fixed-point solver for transformed wages, $\omega_j = w_j^\epsilon$, iterates on labor market clearing conditions:

$$\hat{H}_j^W(\omega) = \sum_i \pi_{ji}(\omega) H_i^R, \quad \pi_{ji}(\omega) = \frac{\omega_j / c_{ji}}{\sum_s \omega_s / c_{si}}, \quad c_{ji} = e^{\kappa\tau_{ji}}.$$

Updates follow

$$\omega_j^{\text{new}} = \frac{H_j^W}{\hat{H}_j^W(\omega)} \cdot \omega_j,$$

dampened by a mixing weight and normalized by the geometric mean. Convergence is declared when the absolute gap between predicted and observed jobs falls below tolerance.

The calibrated ϵ is obtained by minimizing the squared difference between model and data variances of demeaned log wages at the municipal level. This matches ARSW's method-of-moments procedure but integrates directly with gross wage data from the GENESIS database at the municipal level.

Recovery of Fundamentals (`calcal_TD.R`). The script recodes `calcal_TD.m`, `cmodexog.m`, `camen.m`, and related routines. Given adjusted wages and rents, it inverts the production function

$$A_j = \left(\frac{Q_j}{1 - \alpha} \right)^{1 - \alpha} \left(\frac{w_j}{\alpha} \right)^\alpha$$

for productivity and uses the commuting market access term to back out amenities:

$$B_i = \frac{H_{R_i}^{1/\epsilon} Q_i^{1-\beta}}{\left(\sum_j e^{-\kappa\epsilon\tau_{ij}} \omega_j \right)^{1/\epsilon}}.$$

Development density is then computed as $V_j = LD_j / K_j^\mu$, where LD_j is the sum of commercial and residential floor space. Outputs include adjusted productivities, amenities, commuter market access, and floor-space density.

Back-Out of κ (`backout_kappa.R`). The calibrated ϵ and the regression-based estimate of $\kappa\epsilon$ are combined to yield $\kappa = (\kappa\epsilon)/\epsilon$.

Counterfactuals with Public Sector (`final_endog_model_ge_and_cf.R`). Building on the ARSW equilibrium solver, I extend the model to two sectors. Public and private employment are separated, with sector-specific productivity spillovers defined as

$$A_{jP} = \alpha_j (\Upsilon_{jP} + \rho \Upsilon_{jG})^\lambda, \quad A_{jG} = \alpha_j (\Upsilon_{jG} + \rho \Upsilon_{jP})^\lambda,$$

and analogous definitions for amenities. Here ρ governs the strength of cross-sector spillovers relative to within-sector spillovers. Counterfactual reallocations of public employment are read from Excel files of sending and receiving municipalities and re-imposed in both workplace and residence anchors. The general equilibrium solver iterates on wages, rents, and spillovers to obtain the new allocation. Welfare is computed from the expected indirect utility

$$\bar{U} = \gamma \left(\frac{\epsilon - 1}{\epsilon} \right) \cdot \Phi^{1/\epsilon},$$

where Φ is the inclusive value across all residence–workplace pairs.

Visualization (`plot_data.R`). The plotting module uses `ggplot2` and `sf` to map baseline employment, transformed wages, adjusted wages, and counterfactual changes in productivity, amenities, wages, and house prices. This replaces the MATLAB mapping routines (`MAPIT.m`). The output includes municipality-level maps and bar plots of travel times.

Validation. The recode was validated in two steps. First, the solver reproduced the benchmark calibration of ϵ (around 6.8) and the resulting distribution of adjusted wages. Second, sequential inversion of fundamentals yielded the expected core–periphery patterns in productivity and amenities, matching the ARSW results.