

The Labor Market Effects of Flood Events

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Abstract

As climate change increases the frequency and geographic reach of natural disasters, understanding their economic consequences in previously unaffected regions becomes increasingly important. We study the medium-run labor market and mobility effects of two major floods in Germany using administrative data and a dynamic difference-in-differences design. While disasters often imply economic disruption, we find that affected individuals—especially those whose home and workplace were both flooded—experienced sustained gains in employment and earnings. These effects appear to be driven by reconstruction efforts and local demand shocks. In contrast, individuals whose home alone was affected saw delayed reductions in labor supply. We also document limited residential mobility and signs of structural change in local economies. Future work will incorporate the 2021 flood and refined geospatial measures.

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1 Introduction

Natural disasters can cause severe and lasting disruptions to individual lives and regional economies. Affected individuals may lose their homes, jobs, or accumulated wealth, while entire regions may suffer from damaged infrastructure, displaced workers, and persistent labor market disruptions. These concerns are becoming more urgent as climate change increases the frequency and intensity of extreme weather events worldwide. Importantly, the geography of exposure is shifting with disasters beginning to strike previously unaffected regions. This includes parts of Central and Southern Europe which have experienced an increase in catastrophic floods and droughts in recent years. While much of the existing evidence comes from disaster-prone regions, populations and institutions in previously unaffected areas may respond very differently—both in terms of vulnerability and in how public policy mediates the economic impact. Understanding these dynamics is essential for designing effective disaster responses as climate risk continues to expand.

In this study, we examine the economic effects of natural disasters in a context where such events have historically been rare. Specifically, we analyze three major flood events in Germany, which occurred in 2002, 2013, and most recently in 2021. Using rich administrative data, we focus on the short- and medium-run consequences for individual labor market trajectories and regional adjustment. We ask how exposure to a flood affects employment, wages, and the mobility decisions of affected workers. Do individuals leave the affected labor markets, or do they remain despite potential disruptions? More broadly, we aim to assess how resilient local labor markets are when confronted with unexpected environmental shocks.

To estimate the causal effects of flood exposure, we employ a dynamic difference-in-differences framework at the individual level. We exploit variation in the timing and location of the three flood events and compare outcomes before and after the flood between affected and matched control individuals. We implement two matching strategies: a two-step approach that first matches treated counties to similar control counties based on observable characteristics, and then matches treated individuals within these county pairs; and a within-county approach that matches treated individuals to controls in unaffected municipalities of the same county. We analyze two distinct treatment definitions—living in a flooded area and working in a flooded area—and conduct all analyses separately for each. The empirical design allows us to trace labor market and mobility outcomes over a ten-year

window, covering five years before and after the flood.

We find that, on average, workers benefited from living or working in a flooded area.¹ Those who experienced flood events increased both their employment and benefited from increased wages, leading to substantial earnings increases. In year one after flood exposure, affected individuals earned an additional 120 EUR per year; this increased to 300 EUR four years out. In line with the existing literature ([Nakamura et al., 2022a](#)), affected individuals were more geographically mobile, increasing both their probability to change workplace and home.

We also find that treatment type matters. To investigate this, we divide workers in our sample into three groups. Those whose workplace and home were located in a flooded area, those whose workplace only was affected, and those whose home only was affected. We find that individuals in the *double treatment* group benefited most in terms of earnings increases, and they were most likely to expand employment. In contrast, individuals whose homes were flooded experienced the greatest losses, primarily due to reduced employment. This suggests that their engagement in rebuilding efforts led to a negative labor supply effect.

Finally, we provide evidence for structural change. Firms exited or relocated from flooded municipalities in the long term, leading to a 4ppt decrease in the share of firms by year five. This average effect masks important heterogeneity. Firms in sectors that provide important infrastructure, such as energy and health, were more likely to disappear. In contrast, we document a strong increase in the share of firms in public administration, amounting to 12ppt five years out. This suggests that rebuilding efforts required a substantial amount of bureaucracy.

Our work contributes to the growing literature on the economic effects of natural disasters. A first branch of this research examines aggregate outcomes at the regional or local level, with a particular focus on population mobility. [Hornbeck and Naidu \(2014\)](#) document large outflows of the Black population from the Mississippi Delta following the 1927 flood. [Long and Siu \(2018\)](#) and [Hornbeck \(2023\)](#) analyze out-migration from the U.S. Plains during the Dust Bowl of the 1930s. [Spitzer et al. \(2020\)](#), by contrast, find no long-term emigration response to the 1908 Messina-Reggio Calabria earthquake. [Ager et al. \(2020\)](#) show that cities more severely

¹We focus on individuals who were employed at the time of the flood event.

affected by the 1906 San Francisco earthquake experienced slower population growth. For Hurricane Katrina, studies such as [Sastry and Gregory \(2014\)](#) and [Deryugina et al. \(2018\)](#) find that many displaced individuals remained in the vicinity of New Orleans, though population shifts were substantial and persistent.

A second strand of the literature studies the individual-level labor market consequences of displacement. Several papers on Hurricane Katrina find that displaced individuals experienced improved labor market outcomes in the long run (e.g. ([Deryugina et al., 2018](#); [Groen et al., 2020](#))). [Sacerdote \(2012\)](#) additionally shows that displaced students performed better in school a few years after the event. However, these findings are not universal. Even for Katrina, [Bleemer and van der Klaauw \(2019\)](#) documents a persistently lower homeownership rate among displaced individuals. In other contexts, such as the 1906 San Francisco fire, [Schwank \(2024\)](#) finds no evidence of long-term labor market benefits. Similarly, [Nakamura et al. \(2022b\)](#) show that a volcanic eruption in Iceland had heterogeneous effects: individuals who were older than 25 at the time experienced small negative impacts, while those who were younger benefited in the long run.

A growing body of research has also examined the long-run and intergenerational effects of natural disasters in developing countries. [Caruso and Miller \(2015\)](#) show that individuals exposed to the 1970 Ancash earthquake in utero experienced significant educational and labor market disadvantages in Peru, with intergenerational effects concentrated on maternal exposure. Similarly, [Paudel and Ryu \(2018\)](#) find long-term educational losses and increased caste-based inequality following the 1988 Nepal earthquake, particularly among female infants. Other studies highlight how disaster impacts depend on state capacity and external aid. [Carlin et al. \(2014\)](#) document that the erosion of interpersonal trust in post-disaster settings—such as Haiti or El Salvador—was mitigated in countries with stronger public institutions. [Andrabi and Das \(2017\)](#) show that the active involvement of Western relief organizations after the 2005 Pakistan earthquake significantly improved local perceptions of Western actors. These findings underscore the importance of institutional and contextual factors in shaping disaster responses and outcomes.

The remainder of the paper is structured as follows: Section 2 provides background information on the three flood events in our study. Section 3 outlines the data, and section 4 describes the empirical strategy. Results are presented and discussed in section 5. Section 6 concludes. Figures and Tables are included in Sections 7 and 8 respectively.

2 Background

We will study three major flood events in Germany: the 2002, 2013, and 2021 European floods. All three were triggered by several days of heavy rainfall and caused severe damage across different regions.

The 2002 flood primarily affected the Elbe River basin in Saxony and Saxony-Anhalt. Around 370,000 people were directly or indirectly affected, and damages were estimated at EUR 11.6 billion. Notably, the city of Dresden experienced widespread flooding. The government responded with immediate aid, longer-term reconstruction funds totaling EUR 7.1 billion, and investments in flood protection infrastructure.

The 2013 flood again impacted the Elbe, as well as the Danube, with major flooding in Bavaria, Saxony, and Saxony-Anhalt. While the overall flooded area exceeded that of 2002, population centers were less severely hit. Damages were estimated at EUR 6.7 billion, and another large-scale reconstruction program was launched, supported by EUR 8 billion in public funds.

The 2021 flood was the most destructive in recent German history. The Ahr Valley and Eifel region in Rhineland-Palatinate and parts of North Rhine-Westphalia were hardest hit. 186 people lost their lives, and damages exceeded EUR 33 billion. Unlike earlier floods, the 2021 event primarily struck rural and small-town areas. A EUR 30 billion reconstruction fund was established, alongside immediate aid for affected households and firms.

Across all three floods, disaster relief efforts included immediate assistance and substantial public reconstruction funding. These programs typically covered a large share of private and business losses and were jointly financed by the federal and state governments.

3 Data

3.1 Spatial Flood Data

We obtain spatial flood data for the three flood events of 2002, 2013, and 2021. These data indicate which areas were flooded during each event and serve as the basis for constructing treatment variables at the county and municipality levels. The data are sourced from a range of public institutions, including state environmental offices, federal agencies, and, for 2021, the Copernicus Emergency Management Service. A detailed list of sources and data process-

ing steps is provided in Appendix A, along with graphical illustrations of the areas reported flooded. While comprehensive nationwide data are not available for every event, we were able to obtain high-quality spatial flood maps for the most severely affected federal states, which together cover the vast majority of flood-related damages and include all key areas.

Table 1 provides a summary of the geographic extent of flooding across the three events. It reports the number of affected counties and municipalities, along with the average, minimum, and maximum share of flooded area at each level. Each flood affected substantial portions of the municipalities within the impacted regions. On average, 6.3% of the area of an affected municipality was flooded in 2002, compared to 9.2% in 2013 and 2.0% in 2021. In the most severely affected municipalities, up to 41.7% of the area was flooded in 2002, 99.0% in 2013, and 15.4% in 2021.

3.2 Employment Data

For our empirical analysis, we use social security data provided by the IAB (Institut für Arbeitsmarkt- und Berufsforschung). The *Integrated Employment Biographies* (IEB) comprise a complete record of employment spells subject to social security contribution (i.e., excluding civil servants and self-employment) as well as (registered) unemployment spells on a daily basis. This data contains a rich set of labor market characteristics (e.g., employment status, wages, industry, occupation, a firm identifier), as well as sociodemographic characteristics (such as age, gender, education). A key advantage of the IEB data for our empirical approach is the availability of both residence and workplace information at the municipality or county level. Our sample comprises the spells of all individuals who lived or worked in the treated or control counties at the time of the flood event,² covering a period from five years before to five years after the event.

We process the IEB data into a yearly panel as of the dates before the flood events, closely following the approach of Dauth and Eppelsheimer (2020). To construct a balanced panel, we assign zero earnings, zero days worked, the status *not employed*, and missing wages to individuals who are missing in the data in either year. We further conduct imputation procedures to improve the validity of our data: To correct implausible information on education, we follow Fitzenberger et al. (2008);

²As cutoff date, we use the day before the onset of the flood event, i.e., August 5, 2002, June 1, 2013, and July 13, 2021, respectively.

To study the effects of flood events on firms, we use the establishment panel (*Betriebs-Historik-Panel*, BHP) provided by the IAB, which contains detailed annual information³ on each establishment's industry, numbers of employees in total and by various subgroups, as well as exits and entries.

3.3 Aggregate Data at the Municipal and County Level

Furthermore, we draw on various sources for aggregate municipal and county level data. From INKAR (Indicators and Maps for Spatial and Urban Development), published by the German Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR), we collected county classification (*siedlungsstruktureller Kreistyp*), population flows at the county level, and data on overall population as well as population by age groups at the municipality level.⁴

Yearly unemployment rates by county are provided by the Federal Statistical Office (Destatis), while yearly median wages per county are derived from a 2% sample of employment histories maintained by the IAB.⁵ Yearly industry composition by county is obtained from the BHP.⁶

To be able to take into account momentary local recessions, we use county-level GDP data from the Statistical Offices of the Federation and the Federal States (Statistische Ämter des Bundes und der Länder). To identify periods of local economic downturns, we compute relative GDP trends using the Hodrick-Prescott (HP) filter. Specifically, we apply the HP filter to the difference between local GDP and national average GDP, allowing us to isolate region-specific deviations from the broader national economic cycle. Local downturns are defined as periods after a local peak but before the subsequent trough in the trend component of this relative GDP series. The resulting dummy variable equals 1 if a county is in a local downturn in a given year, and 0 otherwise.

Finally, we obtain spatial data from the Federal Agency for Cartography and Geodesy that allows us to calculate the ratio of the accumulated lengths of all rivers in each municipality,

³All information is taken as of June 30th each year.

⁴All INKAR data reflects the territorial status as of December 31, 2022. We have harmonized it to match the IEB data, which is based on the territorial status as of December 31, 2023.

⁵The employment histories (BeH) contain the subset of all employment spells from the IEB. For the processing into a yearly panel, we follow [Dauth and Eppelsheimer \(2020\)](#).

⁶We aggregate the detailed information from the BHP into 21 industry sectors according to the classification of industries (2008) by the Federal Statistical Office (Destatis).

to its area.

4 Empirical Strategy

We estimate the causal effect of exposure to the three floods using a dynamic difference-in-differences framework. This design exploits variation in the timing and location of flood events, comparing outcomes before and after the flood between affected individuals and matched controls. As outlined in the previous section, we use yearly data at the individual level. Our key outcome variables for the analysis of labor market effects include yearly earnings, average daily wages, employment status, and the number of days worked per year (full-time or part-time). To gain further insights, we conduct analyses separately by gender and industry. For the mobility analysis, we examine effects on changes in the workplace municipality, municipality of residence, establishment of employment, occupation, and industry.

In our data, we distinguish between two types of treatment: (i) living in a flooded municipality (*residence treatment*) and (ii) working in a flooded municipality (*workplace treatment*).⁷ We conduct all analyses separately for each treatment and additionally explore potential interaction effects between them.

We implement two distinct matching strategies. The first, *Control County Matching*, involves a two-step procedure. In the first step, for each treated county, we identify a comparable control county using observable aggregate characteristics. In the second step, we match treated individuals to control individuals within each matched county pair. The second strategy, *Within County Matching*, matches treated individuals to control individuals from unaffected municipalities within the same county.

Finding Control Counties. For the *Control County Matching* approach, we conduct the matching procedure separately for each flood, using county characteristics measured in year $t-1$. To identify suitable control counties, we combine exact matching, coarse exact matching, and propensity score matching. Matching is performed separately for East and West Germany. We exactly match on county type (four categories), a relative downturn indicator,

⁷At this stage, treatment is assigned based on municipality boundaries. We plan to incorporate precise address-level geolocation once data access is complete.

and an indicator for net positive population inflow over the past five years.⁸ We also coarsen county unemployment rates and median wages to binary indicators (above/below median) and match on these. Among counties that match on all these criteria, we select the final match based on the closest propensity score. The propensity score is estimated using the number of employees per county, 21 industry-share dummies, the age structure in 10 bins, county population size, the size of the largest municipality, average in- and out-migration over the past five years, and the ratio of river length to municipality area. Using this procedure, we find matches for 20 of 25 counties in 2002, 43 of 45 in 2013, and 31 of 32 in 2021. Tables 2 and 3 show that treated and matched control counties are well balanced across key labor market, demographic, and structural characteristics.

Individual Matching. The second step in both matching strategies is the matching at the individual level. Each treated individual—defined as living or working in a flooded area, respectively—is matched to a control individual, either from a matched control county (*Control County Matching*) or from an unaffected municipality in the same county (*Within County Matching*). This matching also combines exact matching and propensity score matching. For both treatments, we restrict the sample to individuals who were employed (either full-time or part-time) in the year before the flood and had at least three years of tenure. Exact matching variables include one-digit industry and gender, as well as employment status (for the residence treatment). The propensity score is estimated based on tenure (in the establishment and in the occupation), education, age, full-time employment indicators (in years t , $t-1$, and $t-2$),⁹ and log wages (in years $t-1$ and $t-2$). Tables 4 and 5 show summary tables for matched individuals in the *Control County Matching* approach for the 2002 and 2013 floods, respectively. Tables A1 and A2 show summary tables for matched individuals in the *Within County Matching* approach.

To estimate the impact of flood exposure, we run dynamic difference-in-differences regressions of the following form:

$$y_{it} = \alpha_i + \sum_{k=-3, k \neq -1}^5 \beta_k \mathbb{I}(t = k) \cdot \text{Treated}_i + \delta_t + \varepsilon_{it} \quad (1)$$

⁸The county type categories are independent large cities, urban districts, semi-urban districts with urbanization tendencies, and rural districts.

⁹All other characteristics, unless otherwise noted, are measured in the year $t-1$.

where y_{it} denotes the outcome variable for individual i in year t . Treated_i is an indicator for whether individual i belongs to the treated group (either residence or workplace treatment, or both). The event time k is defined relative to the year of the flood ($k = 0$), with $k = -1$ omitted as the baseline category. We include observations from up to three years before to up to five years after the flood event.¹⁰ The coefficients β_k capture the dynamic treatment effects in event time. Individual fixed effects α_i control for time-invariant heterogeneity, and year fixed effects δ_t absorb common shocks. Our baseline estimation pools all floods.¹¹ Standard errors are clustered at the individual level throughout.

5 The Labor Market Effects of Flood Events

Ex ante, it is unclear which labor market effects we may expect as the result of a flood event. On the one hand, the short-term disruption of employment and damage or even destruction of firms may lead to lay-offs or wage decreases for affected workers. On the other hand, the emergency aid and subsequent reconstruction efforts may have favorable spillover effects. Some industries, like the construction sector, may benefit in particular.

Similarly, the effects on workers' geographic and workplace mobility are unclear ex-ante: While the loss of homes and jobs may incentivize affected individuals to move, reconstruction subsidies often strongly incentivize rebuilding in the same place, and jobs may be created due to reconstruction efforts.

Note that for our baseline analysis, we compare individuals in treated municipalities with matched control individuals in matched control counties. Treated municipalities are municipalities with an above zero share of area flooded.

5.1 Labor Market

We start by pooling all flood events and treatment types, and estimating the joint effect of experiencing a flood event on earnings. Figure 2 presents the results. As Panel (a) shows, total earnings per year (in EUR) increased in the year immediately following the flood event, with

¹⁰Some outcomes, e.g. residential mobility can only be observed from 1999 onward, therefore shortening the number of pre-event observations for the first flood. Similarly, we only have data until 2023, reducing the number of post-event observations for the 2021 flood.

¹¹We currently analyze the 2002 and 2013 floods. Data access for the 2021 flood is underway, and we plan to include it in a future version of this paper.

an additional 120 EUR per year for treated individuals. The earnings increase then continues building up and peaks in year four after the flood event at an additional 300 EUR earned per year. As Panel (b) shows, part of this is driven by an increase in full-time earnings.

Next, we separately examine employment and wages to determine which is driving the positive effect on earnings. We find that both employment and wages increased. As Panel (c) of Figure 2 shows, the probability to be employed increased for treated individuals, starting in year one (.2ppt) and reaching .6ppt in year four. Wages increased modestly in the short run (.2% in year one) and more substantially in the long run (.6% by year five).

Note that employment increased both on the extensive and intensive margin. Treated individuals worked about one day more per year in the five years following the flood event (Panel e). Most of this was due to an increase in full-time employment (Panel f).

As Appendix Figure A4 shows, labor market effects are positive even when comparing individuals in affected municipalities to matched controls in the same county, but in unaffected municipalities. This specification is more likely to provide lower bounds of the true treatment effect, since the control group was very likely subject to spillover effects. Going forward, we will estimate the labor market effects of workplace and home destruction more precisely by defining treatment based on geo-coded flood data.

Overall, our results suggest that affected individuals benefited from rebuilding efforts in terms of improved labor market outcomes. This implies that the positive effects of reconstruction aid outweighed the negative impacts of damage or destruction to infrastructure, workplaces, or homes. Alternatively, the positive effects could be driven by a relocation to areas with stronger labor markets.

5.2 Mobility

In a next step, we examine whether being affected by a flood event impacted geographic and workplace mobility. In line with the existing literature (e.g., Nakamura et al. (2022a)), we find that treated individuals became more mobile. As Figure 3 shows, they were both more likely to move workplace and home (Panels a and b).¹²

Panel (a) shows that in the year after a flood event, individuals were .5ppt more likely to work in a workplace county that differed from their pre-flood workplace. The effect on resi-

¹²We define mobility by examining whether workplace county or home county differ from the county recorded in $t=-1$, the year before the flood event. There are 400 counties in Germany.

dence mobility was substantially weaker: By year five after a flood event, treated individuals were .15ppt more likely to have changed their home county. Note, however, that the presence of pre-trends in this figure implies that this effect should be interpreted with caution.

Figure 3, Panel (c), complements the picture by investigating establishment switches: Treated individuals were substantially more likely to work at a different establishment in the year immediately after a flood event (.5ppt), but they were more likely to return to their original establishment in the following years.¹³ As Panel (d) reveals, they were moreover substantially less likely to switch 1-digit industry (-.6ppt to -.8ppt) in the years following a flood event.

These results indicate mixed effects on mobility: While geographic mobility moderately increased, workplace mobility decreased, at least in the long run. The absence of a strong increase in residential mobility may be due to the fact that insurance payouts are typically contingent on rebuilding at the same location. In addition, the strong positive labor market effects may have incentivized some individuals to stay in their region of origin.

5.3 The Importance of Treatment Type

We have documented the average effects of being affected by a flood event.¹⁴ In a next step, we will more closely examine the role of treatment type. We distinguish between three treatment types: (i) workplace and home in a flooded municipality, (ii) workplace only in flooded municipality, and (iii) home only in flooded municipality.

It is important to distinguish between these treatment types because they imply differences in how individuals experience a flood event. Individuals whose workplace and home are affected may suffer the strongest income losses, and given higher loss of wealth, they may be less likely to move. In turn, individuals whose workplace was affected may be laid off, but find it easier to change their job. Individuals whose home was located in the flooded area may be preoccupied with rebuilding efforts and have less time available to spend at work.

Tables 4 and 5 provide summary statistics for our sample of matched treated and control workers. They show that the vast majority of workers lived *and* worked in a flooded municipality. Individuals' demographic characteristics slightly differ across treatment types. For example, individuals exposed to both treatments exhibit higher tenure, lower wages, and

¹³ Establishment switches might involve employer switches, but may also happen within the same firm.

¹⁴ In Sections 5.1 and 5.2

fewer days worked under a full-time contract, based on characteristics measured the day before the flood event. Consequently, any post-flood differences in labor market outcomes that we observe may be driven, at least in part, by pre-existing differences in these demographic characteristics.

Labor Market Figure 4 shows how labor market effects differ by treatment type. A clear pattern emerges: Individuals whose workplace and home was located in a flooded municipality benefited the most in terms of earnings increases. They were moreover most likely to expand employment, both on the intensive and extensive margin.

In contrast, individuals whose home was flooded lost the most. They suffered earnings losses of 500 EUR per year by year five, their employment probability decreased by around .5ppt, and their wages decreased (though not statistically significant). Most importantly, they substantially reduced days worked by 2 to 3 days starting in year two. Interestingly, these differences only started opening up in year two after the flood event. Overall, our results suggest a delayed negative labor supply effect, possibly due to a delayed pay-out of reconstruction aid funds.

Finally, our findings for individuals who were affected only through their workplace are mostly zero. We report a small, though statistically insignificant increase in earnings in the short run, and a stronger and more persistent increase in daily wages (potentially due to compositional changes). Days worked for this sample slightly decreased in the short run, suggesting that affected firms' labor demand may have decreased.

Mobility While our evidence on labor market effects by treatment group provides a mixed picture, Figure 5 reveals a clear pattern for geographic and workplace mobility. Individuals where both workplace and home were located in a flooded municipality were somewhat less likely to move or switch employer and industry, relative to matched controls. In contrast, individuals who faced either workplace or home treatment were substantially more likely to move geographically, and to switch employer.

Perhaps not surprisingly, mobility increased in particular for individuals who lost their home. By year five after the flood event, they were a staggering 20ppt more likely to have moved workplace relative to their matched control worker. They were also 5ppt more likely to have moved their home to a different county. Similarly, individuals whose workplace was

affected were more likely to move workplace (15ppt by year five) and home (4ppt by year five).

The fact that mobility increased for individuals who faced one treatment type only, but decreased for individuals whose workplace and home were affected simultaneously, points to a strong wealth effect. Workers who lived and worked in the flooded area potentially lacked the resources to move geographically. At the same time, as Figure 4 shows, they were most likely to benefit from rebuilding efforts in terms of improved labor market outcomes. Going forward, further analysis using the geo-coded flood data will be necessary to shed more light on the underlying mechanisms.

5.4 Labor Market Effects by Industry

In addition to heterogeneity by treatment type, we also observe heterogeneity by industry. We categorize industries into five broad groups: (i) manufacturing, (ii) services, (iii) agriculture, mining, energy, and water, (iv) construction, and (v) public administration and education. We classify workers based on their industry in $t = -1$. Ex ante, we may expect the construction sector to benefit in particular from rebuilding efforts and reconstruction aid. There may also be spillover effects to other sectors, such as manufacturing. For this analysis, we consider only workers whose workplace was located in a flooded area (both single or double treatment).

Figure 6 shows that workers in all industries benefited. Employment and wages increased for workers in all industries. Panel (a) shows that the strongest employment increase (extensive margin) occurred in public administration and education.

Turning to the intensive margin of employment, we find that days worked per year increased for workers in all industries, in particular in the construction sector and in agriculture, mining, energy and water (Panel c). Panel (d) shows that while workers in most industries increase days worked in full-time employment, this does not hold for workers in public admin: while employment in this sector increases most strongly, full-time employment decreases by up to 9 days per year five years out. This suggests that the employment opportunities that were created in this sector were concentrated in part-time contracts.

Finally, Panels (e) and (f) of Figure 6 reveal heterogeneity with respect to mobility. Workers in public administration and education are most likely to switch establishment, while workers in manufacturing are least likely to change their employer. Workers in manufacturing and

agriculture, mining, energy and water are moreover more likely to change workplace county but not employer, suggesting that their firms relocated.

5.5 Establishment Composition

Finally, we examine whether the establishment composition of affected regions changed systematically, potentially pointing to structural change. In this analysis, our treatment group consists of municipalities with an above zero share of flooded area, and the control group consists of all municipalities in the respective matched control counties. We re-write our baseline regression equation to focus on municipalities instead of workers:

$$y_{mt} = \alpha_m + \sum_{k=-3, k \neq -1}^5 \beta_k \mathbb{I}(t = k) \cdot \text{Treated}_m + \delta_t + \varepsilon_{m,t} \quad (2)$$

where y_{mt} denotes the outcome variable for municipality m in year t . Treated_m is an indicator for whether municipality m experienced an above zero share of flooded area. As in the baseline equation, event time k is defined relative to the year of the flood ($k = 0$), with $k = -1$ omitted as the baseline category. Municipality fixed effects α_m control for time-invariant heterogeneity, and year fixed effects δ_t absorb common shocks. Our baseline estimation pools all three floods. Standard errors are clustered at the municipality level.

Figure 7 presents the results. Panel (a) shows how the number of firms, relative to the number of firms in the year before the flood, developed pre and post flood. It points to a delayed exit of firms, with the number of firms relative to $t = -1$ decreasing by 2 to 4ppt in years 3 to 5 after the flood event. This average effect masks substantial heterogeneity across industries.

As Panel (b) shows, the number of manufacturing firms in treated municipalities was increasing starting in year one, though not statistically significant. Similarly, Panel (d) reveals a small short-term, insignificant increase in the share of construction firms. Simultaneously, the share of firms in energy supply and health decreased (Panels c and e). Panel (f) shows a striking increase in firms in public administration. By year five, the share of public administration firms had increased by 12ppt.

This evidence points to structural change in flooded municipalities. Service providers,

such as energy supply and health, either closed down or relocated to more "flood-proof" areas. The strong increase in public administration firms points to long-term firm creation, directly linked to the bureaucratic effort around paying out reconstruction funds.

6 Conclusion

This paper examines the medium-run labor market and mobility effects of major flood events in Germany. Using administrative data and a dynamic difference-in-differences framework, we analyze the 2002 and 2013 floods and show that, on average, affected individuals experience positive labor market outcomes in the years following a flood. Earnings, employment probabilities, and days worked increase steadily for up to five years after the event. These gains are concentrated among individuals whose residence and workplace are both located in flooded areas, suggesting that they disproportionately benefited from reconstruction efforts and public support programs.

Our results indicate that emergency aid and rebuilding policies can more than offset the negative economic impact of a natural disaster, at least in the short to medium run. However, the effects vary by exposure type. Individuals whose home was affected but not their workplace experience losses in earnings and employment over time, suggesting a delayed negative labor supply response, possibly due to disruptions in daily life or delays in insurance payouts. Workers exposed only through their workplace see no meaningful changes in earnings or employment, but display higher mobility.

We also find substantial heterogeneity in labor market effects across industries. While most sectors see employment gains, the public administration sector expands most strongly, though predominantly through part-time employment. At the regional level, we observe evidence of structural change, with declines in service-oriented firms and increases in public sector activity.

Mobility responses are nuanced. Geographic mobility increases modestly for those with partial exposure, while individuals affected at both home and work are less likely to relocate, likely due to resource constraints or stronger place attachment.

Future work will extend the analysis to the 2021 flood and refine treatment definitions using geocoded address data. These extensions will allow for a more precise understanding of individual exposure and its consequences.

References

- Ager, P., Eriksson, K., Hansen, C. W., and Lønstrup, L. (2020). How the 1906 san francisco earthquake shaped economic activity in the american west. *Explorations in Economic History*, 77:101342.
- Andrabi, T. and Das, J. (2017). In aid we trust: Hearts and minds and the pakistan earthquake of 2005. *The Review of Economics and Statistics*, 99(3):371–386.
- Bleemer, Z. and van der Klaauw, W. (2019). Long-run net distributionary effects of federal disaster insurance: the case of hurricane katrina. *Journal of urban economics*, 110:70–88.
- Carlin, R. E., Love, G. J., and Zechmeister, E. J. (2014). Trust shaken: Earthquake damage, state capacity, and interpersonal trust in comparative perspective. *Comparative Politics*, 46(4):419–437.
- Caruso, G. and Miller, S. (2015). Long run effects and intergenerational transmission of natural disasters: A case study on the 1970 ancash earthquake. *Journal of Development Economics*, 117:134–150.
- Dauth, W. and Eppelsheimer, J. (2020). Preparing the sample of integrated labour market biographies (SIAB) for scientific analysis: a guide. *Journal for Labour Market Research*, 54(1):1–14.
- Deryugina, T., Kawano, L., and Levitt, S. (2018). The economic impact of hurricane katrina on its victims: Evidence from individual tax returns. *American Economic Journal: Applied Economics*, 10(2):202–33.
- Fitzenberger, B., Osikominu, A., and Voelter, R. (2008). Get training or wait? long-run employment effects of training programs for the unemployed in west germany. *Annales d'Economie et de Statistique*, (91/92):321–355.
- Groen, J., Kutzbach, M., and Polivka, A. (2020). Storms and jobs: The effect of hurricanes on individuals' employment and earnings over the long term. *Journal of Labor Economics*, 38:653–685.
- Hornbeck, R. (2023). Dust bowl migrants: Environmental refugees and economic adaptation. *The Journal of Economic History*, 83(3):645–675.
- Hornbeck, R. and Naidu, S. (2014). When the levee breaks: black migration and economic development in the american south. *American Economic Review*, 104(3):963–990.
- Long, J. and Siu, H. (2018). Refugees from dust and shrinking land: Tracking the dust bowl migrants. *The Journal of Economic History*, 78(4):1001–1033.
- Nakamura, E., Sigurdsson, J., and Steinsson, J. (2022a). The gift of moving: Intergenerational consequences of a mobility shock. *The Review of Economic Studies*, 89(3):1557–1592.

- Nakamura, E., Sigurdsson, J., and Steinsson, J. (2022b). The Gift of Moving: Intergenerational Consequences of a Mobility Shock. *The Review of Economic Studies*, 89(3):1557–1592.
- Paudel, J. and Ryu, H. (2018). Natural disasters and human capital: The case of nepal’s earthquake. *World Development*, 111:1–12.
- Sacerdote, B. (2012). When the saints go marching out: Long-term outcomes for student evacuees from hurricanes katrina and rita. *American Economic Journal: Applied Economics*, 4(1):109–135.
- Sastry, N. and Gregory, J. (2014). The location of displaced new orleans residents in the year after hurricane katrina. *Demography*, 51(3):753–775.
- Schwank, H. M. (2024). Disruptive effects of natural disasters: The 1906 san francisco fire. Technical report, ECONtribute Discussion Paper.
- Spitzer, Y., Tortorici, G., and Zimran, A. (2020). International migration responses to modern europe’s most destructive earthquake: Messina and reggio calabria, 1908. Technical report, National Bureau of Economic Research.

Tables

Table 1: Summary Statistics on Flooded Area

(1) Number affected		(2) Average share of area flooded		(3) Min share of area flooded		(4) Max share of area flooded	
Counties	Municipalities	County	Municipality	County	Municipality	County	Municipality
Panel A: 2002							
20	251	0.049	0.063	0.001	0.000	0.187	0.417
Panel B: 2013							
43	255	0.031	0.092	0.000	0.000	0.146	0.990
Panel C: 2021							
31	264	0.007	0.020	0.000	0.000	0.020	0.154

Notes: This table provides summary statistics on the area flooded for all counties and municipalities in the flood data, by flood event. We consider all counties and municipalities with above zero share of area flooded. Column (1) shows the number of counties and municipalities affected, Column (2) shows the average share of area flooded, Column (3) shows the minimum share of area flooded, and Column (4) shows the maximum share of area flooded.

Table 2: County Summary Statistics: Flood Event in 2002

	(1) All Regions		(2) Matched Controls		(3) Flooded Region		(4) (3)-(2)	
	Mean	SD	Mean	SD	Mean	SD	Difference	p-Value
Panel A: Labor Market								
Size of biggest municipality	93436.9	[222790.8]	52387.5	[47469.2]	70504.2	[106880.9]	18116.7	0.49
Unemployment rate	7.460	[2.962]	5.629	[1.976]	6.187	[4.315]	0.56	0.60
Median wage	69.66	[11.01]	59.26	[3.476]	57.76	[3.532]	-1.50	0.18
Panel B: Age Structure								
< 19 years old	0.190	[0.0220]	0.172	[0.0143]	0.168	[0.0126]	-0.0037	0.38
19-29 years old	0.137	[0.0143]	0.143	[0.0109]	0.138	[0.0106]	-0.0046	0.18
30-64 years old	0.501	[0.0161]	0.514	[0.0124]	0.510	[0.0128]	-0.0034	0.39
> 64 years old	0.173	[0.0180]	0.172	[0.0144]	0.184	[0.0159]	0.012	0.018
Panel C: Industry Structure								
Agriculture	0.0251	[0.0219]	0.0334	[0.0224]	0.0398	[0.0287]	0.0064	0.44
Manufacturing	0.0803	[0.0279]	0.0696	[0.0207]	0.0759	[0.0166]	0.0062	0.30
Services	0.240	[0.0327]	0.235	[0.0386]	0.237	[0.0365]	0.0013	0.91
Construction	0.0994	[0.0256]	0.128	[0.0253]	0.130	[0.0197]	0.0014	0.85
Hospitality	0.0735	[0.0180]	0.0751	[0.0168]	0.0665	[0.00843]	-0.0087	0.046
Panel D: Type of Region								
City	0.168	[0.374]	0.100	[0.308]	0.100	[0.308]	0	1
Town	0.343	[0.475]	0.100	[0.308]	0.100	[0.308]	0	1
Rural Area	0.490	[0.501]	0.800	[0.410]	0.800	[0.410]	0	1
Observations	400		20		20			

Notes: This table provides summary statistics on the counties in our baseline sample. Column (1) pools all counties, Column (2) shows matched control counties, and Column (3) shows treatment counties. Column (4) provides the results of a t-test of equal means. A treatment county is defined as having an above zero flooded area. Differences in bold signal statistical significance at the 5%-level. Outcomes measured in 2001.

Table 3: County Summary Statistics: Flood Event in 2013

	(1) All Regions		(2) Matched Controls		(3) Flooded Region		(4) (3)-(2)	
	Mean	SD	Mean	SD	Mean	SD	Difference	p-Value
Panel A: Labor Market								
Size of biggest municipality	92666.5	[225773.3]	42606.7	[45383.9]	53316.4	[87891.5]	10709.7	0.48
Unemployment rate	5.475	[2.963]	3.990	[2.309]	3.237	[2.285]	-0.75	0.13
Median wage	63.30	[10.23]	59.35	[7.581]	60.83	[8.252]	1.48	0.39
Panel B: Age Structure								
< 19 years old	0.162	[0.0178]	0.155	[0.0233]	0.153	[0.0215]	-0.0026	0.59
19-29 years old	0.137	[0.0247]	0.129	[0.0232]	0.131	[0.0293]	0.0019	0.74
30-64 years old	0.489	[0.0170]	0.497	[0.0182]	0.496	[0.0230]	-0.00036	0.94
> 64 years old	0.212	[0.0238]	0.219	[0.0269]	0.220	[0.0301]	0.0011	0.85
Panel C: Industry Structure								
Agriculture	0.0298	[0.0248]	0.0408	[0.0300]	0.0378	[0.0241]	-0.0031	0.60
Manufacturing	0.0754	[0.0254]	0.0831	[0.0280]	0.0775	[0.0183]	-0.0056	0.27
Services	0.204	[0.0316]	0.196	[0.0373]	0.201	[0.0331]	0.0050	0.51
Construction	0.0913	[0.0252]	0.109	[0.0280]	0.111	[0.0298]	0.0020	0.74
Hospitality	0.0685	[0.0175]	0.0705	[0.0182]	0.0654	[0.0104]	-0.0051	0.11
Panel D: Type of Region								
City	0.168	[0.374]	0.116	[0.324]	0.116	[0.324]	0	1
Town	0.343	[0.475]	0.0930	[0.294]	0.0930	[0.294]	0	1
Rural Area	0.490	[0.501]	0.791	[0.412]	0.791	[0.412]	0	1
Observations	400		43		43			

Notes: This table provides summary statistics on the counties in our baseline sample. Column (1) pools all counties, Column (2) shows matched control counties, and Column (3) shows treatment counties. Column (4) provides the results of a t-test of equal means. A treatment county is defined as having an above zero flooded area. Differences in bold signal statistical significance at the 5%-level. Outcomes measured in 2012.

Table 4: Summary Statistics of Workers by Treatment Type, Flood Event in 2002

	(1)	(2)	(3)	(4)
	Control	Treatment		
		Workplace & Home	Workplace	Home
Panel A: Individual Characteristics				
Education (years)	12.4	12.3	12.5	12.3
	[1.8]	[1.8]	[1.9]	[1.7]
Experience (years)	10.4	10.4	10.5	10.4
	[2.3]	[2.0]	[2.1]	[2.1]
Tenure (years)	7.3	7.3	6.3	6.1
	[2.9]	[2.9]	[2.7]	[2.5]
Daily wage (EUR)	81.0	78.5	88.3	87.4
	[28.0]	[27.7]	[28.4]	[29.8]
Days worked	362.9	363.1	363.1	363.0
	[13.4]	[12.8]	[12.4]	[12.9]
Days worked fulltime	308.3	306.9	330.3	319.6
	[129.1]	[130.5]	[103.8]	[117.6]
Panel B: 1-Digit Industries				
Agriculture, Mining, Energy, Water	0.05	0.05	0.04	0.04
	[0.2]	[0.2]	[0.2]	[0.2]
Manufacturing	0.2	0.2	0.2	0.1
	[0.4]	[0.4]	[0.4]	[0.4]
Construction	0.09	0.09	0.1	0.09
	[0.3]	[0.3]	[0.3]	[0.3]
Services	0.5	0.5	0.5	0.5
	[0.5]	[0.5]	[0.5]	[0.5]
Public Admin., Education	0.2	0.2	0.2	0.3
	[0.4]	[0.4]	[0.4]	[0.4]
Number of Observations	252880	246598	8489	10137

Notes: Characteristics of treated and control workers on day before flood event. Control group: individuals in matched counties. Standard deviations in brackets.

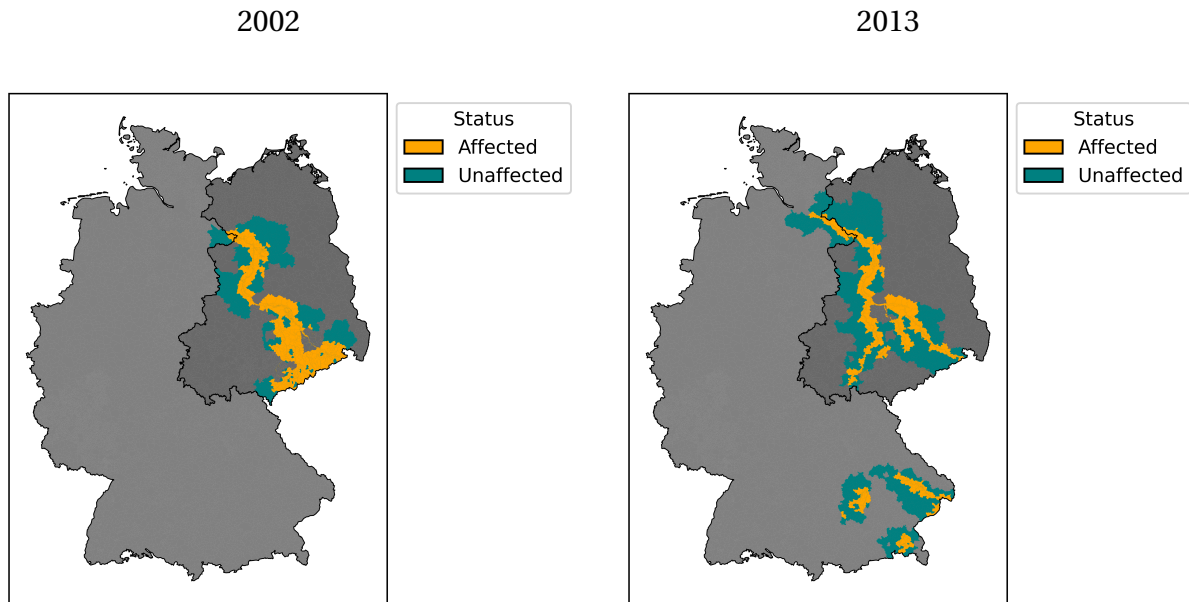
Table 5: Summary Statistics of Workers by Treatment Type, Flood Event in 2013

	(1)	(2)	(3)	(4)
	Control	Treatment		
		Workplace & Home	Workplace	Home
Panel A: Individual Characteristics				
Education (years)	12.3	12.3	12.5	12.5
	[1.8]	[1.9]	[2.0]	[2.0]
Experience (years)	19.7	19.4	19.1	18.5
	[7.5]	[7.4]	[6.7]	[6.4]
Tenure (years)	10.0	10.1	8.7	8.3
	[6.3]	[6.4]	[5.3]	[4.9]
Daily wage (EUR)	87.1	88.2	98.2	92.5
	[41.6]	[41.8]	[43.8]	[42.4]
Days worked	361.9	362.0	361.9	361.6
	[18.7]	[18.4]	[18.8]	[19.6]
Days worked fulltime	274.0	272.1	301.4	308.7
	[155.3]	[156.5]	[135.5]	[128.5]
Panel B: 1-Digit Industries				
Agriculture, Mining, Energy, Water	0.03	0.03	0.04	0.05
	[0.2]	[0.2]	[0.2]	[0.2]
Manufacturing	0.3	0.3	0.3	0.3
	[0.4]	[0.4]	[0.4]	[0.4]
Construction	0.07	0.06	0.09	0.10
	[0.2]	[0.2]	[0.3]	[0.3]
Services	0.5	0.5	0.5	0.5
	[0.5]	[0.5]	[0.5]	[0.5]
Public Admin., Education	0.1	0.1	0.09	0.09
	[0.3]	[0.3]	[0.3]	[0.3]
Number of Observations	553368	528189	20574	24539

Notes: Characteristics of treated and control workers on day before flood event. Control group: Individuals in matched counties. Standard deviations in brackets.

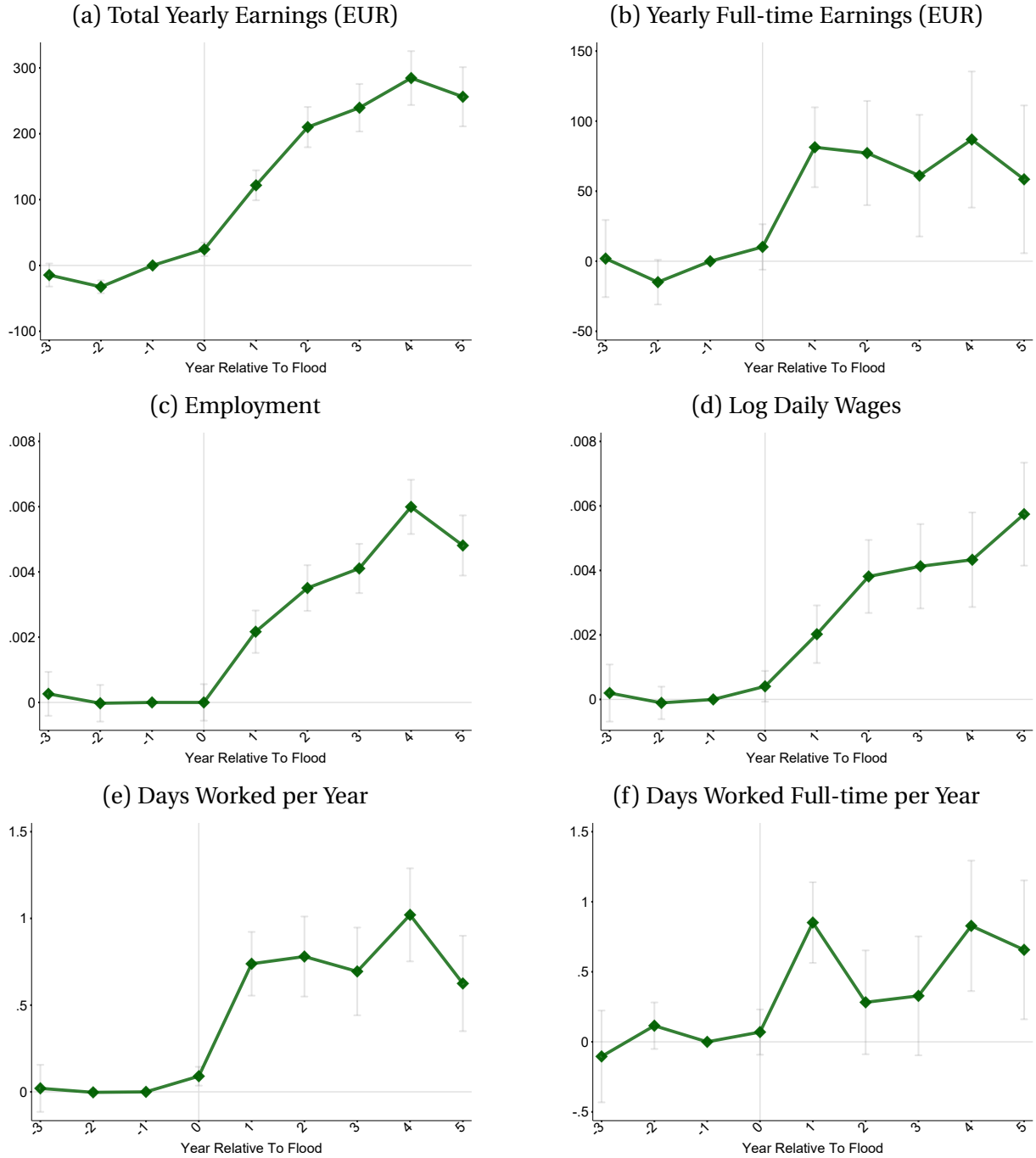
Figures

Figure 1: Affected Counties



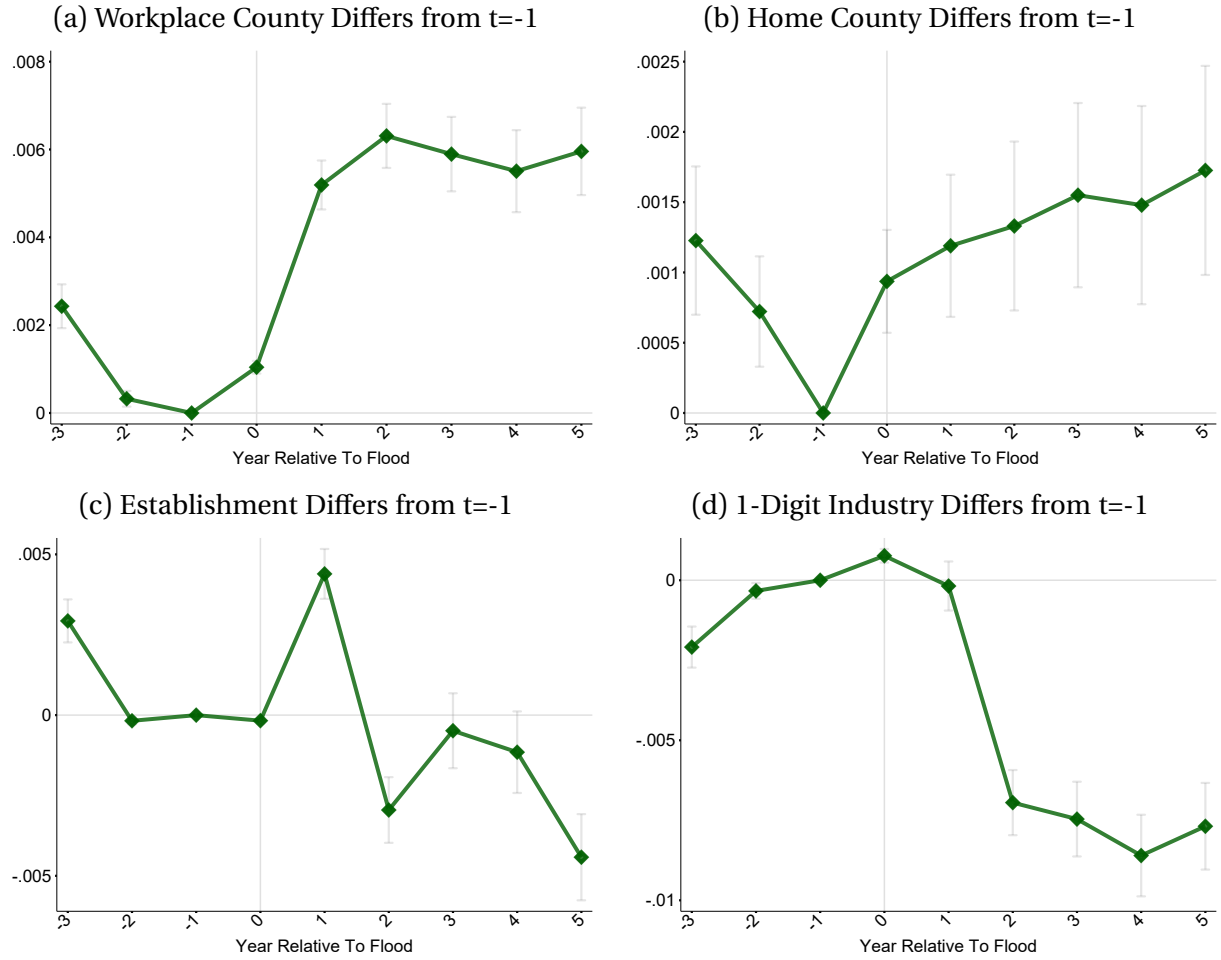
Notes: Affected counties during the floods of 2002 (left) and 2013 (right). Affected municipalities within these counties are shown in orange, unaffected municipalities are shown in green. East- and West Germany are shown in grey.

Figure 2: The Labor Market Effects of Big Flood Events



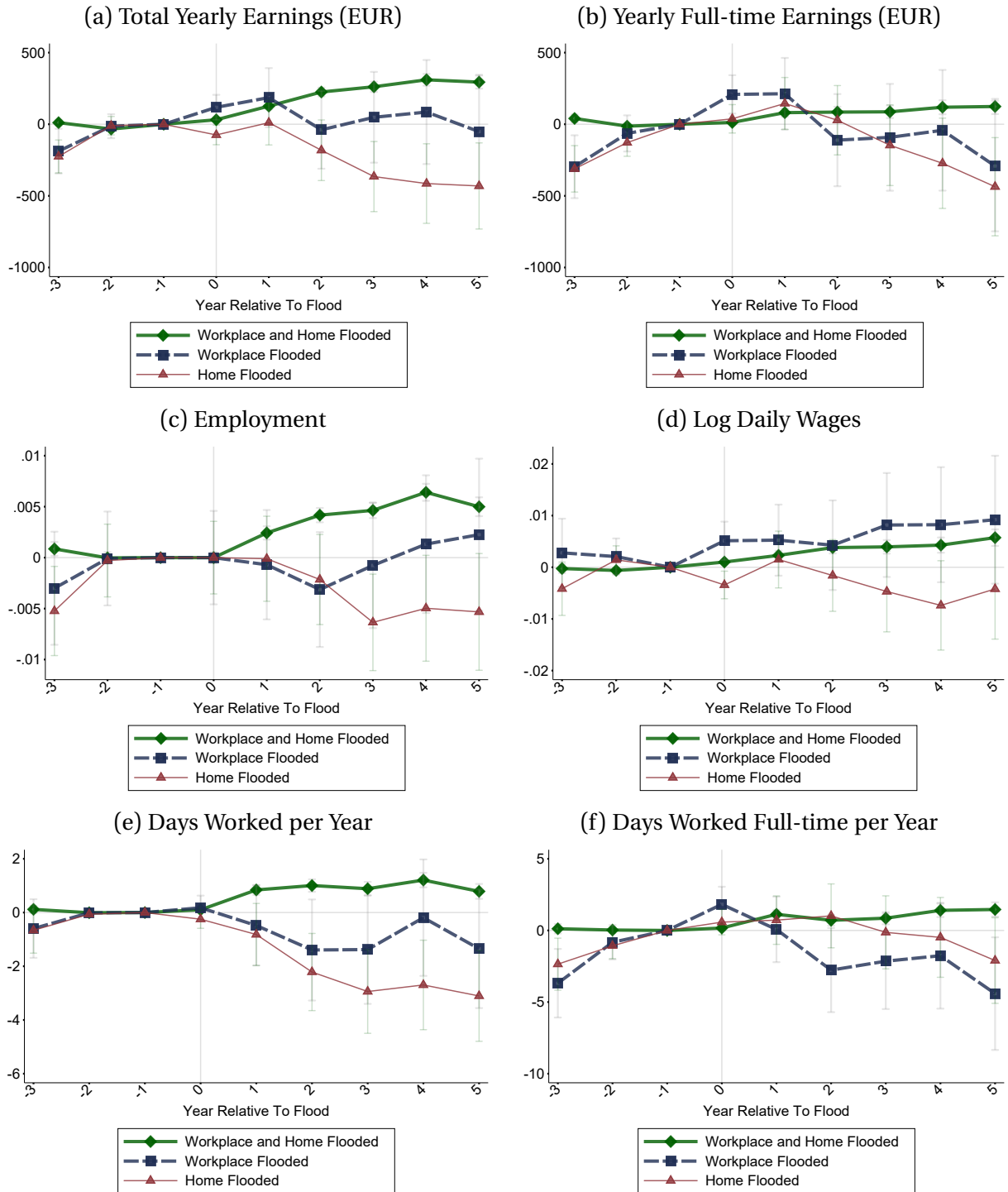
Notes: This figure plots event study regression coefficients for different labor market outcomes. Pooling all treatment types and all flood events. Green diamonds plot β_k coefficients estimated using Equation 1. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Control group: Matched individuals in matched county pair.

Figure 3: The Mobility Effects of Big Flood Events



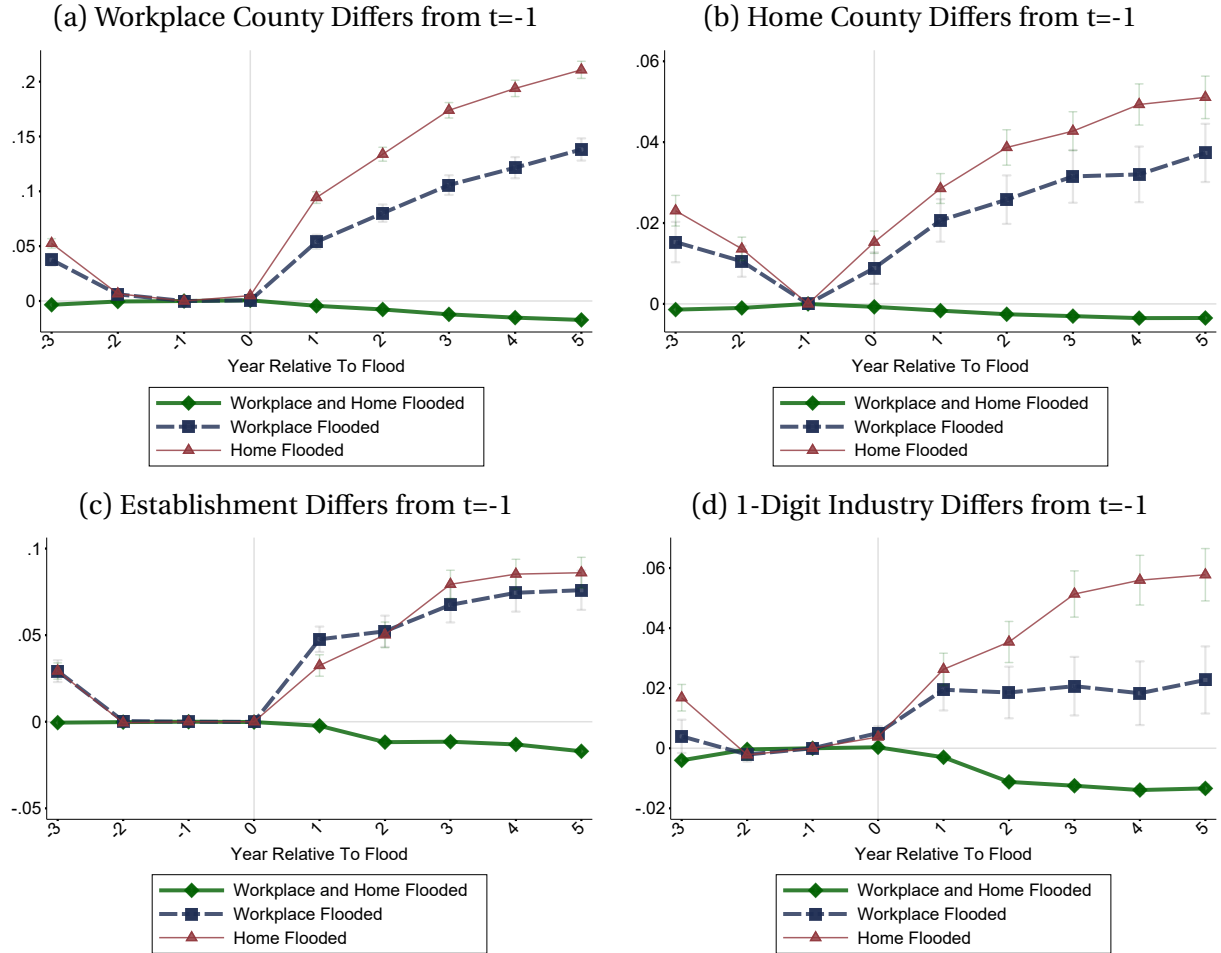
Notes: This figure plots event study regression coefficients for different mobility outcomes. Pooling all treatment types and all flood events. Green diamonds plot β_k coefficients estimated using Equation 1. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Control group: Matched individuals in matched county pair.

Figure 4: The Labor Market Effects by Treatment Type



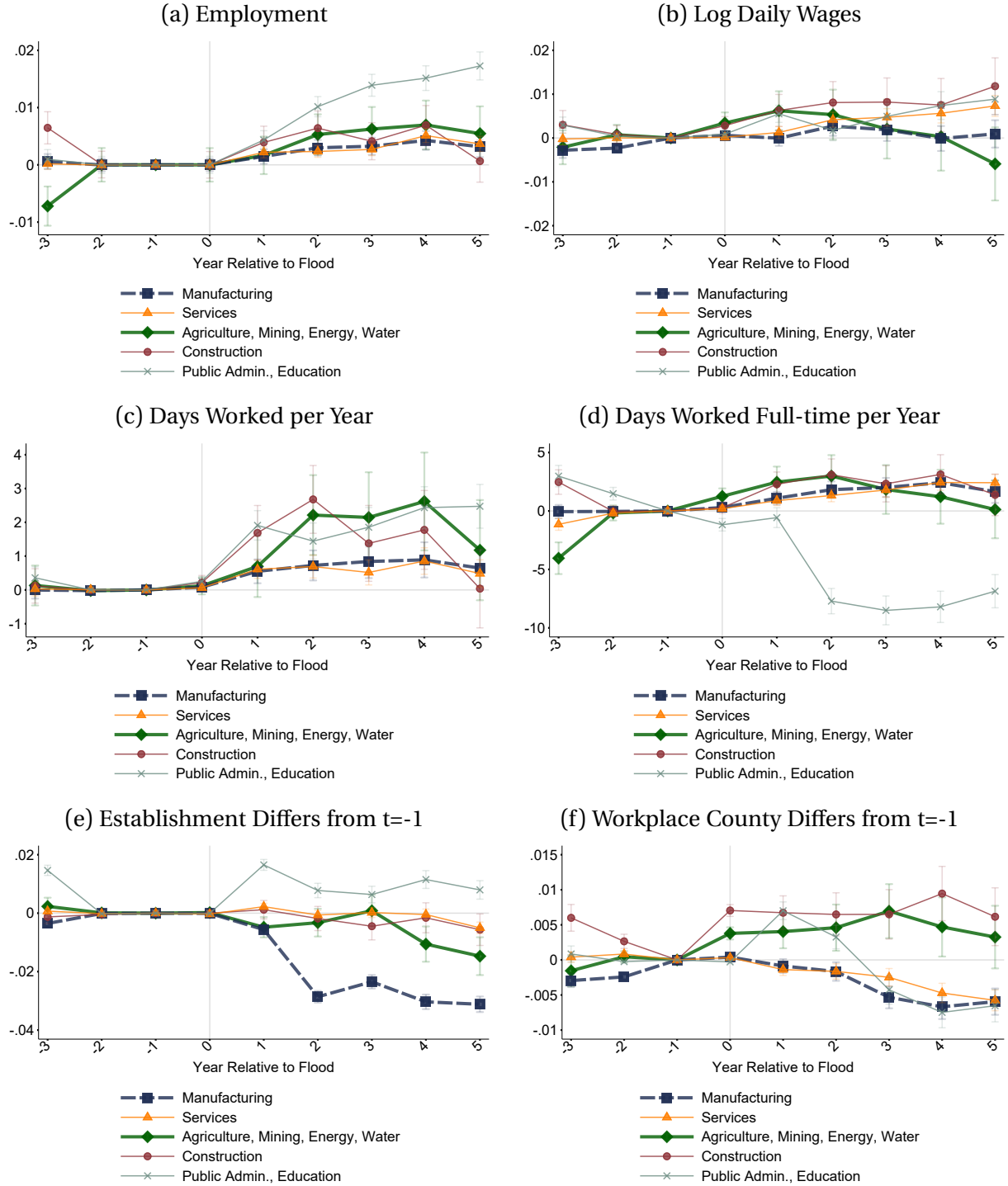
Notes: This figure plots event study regression coefficients for different labor market outcomes. Pooling all flood events. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Control group: Matched individuals in matched county pair.

Figure 5: Mobility by Treatment Type



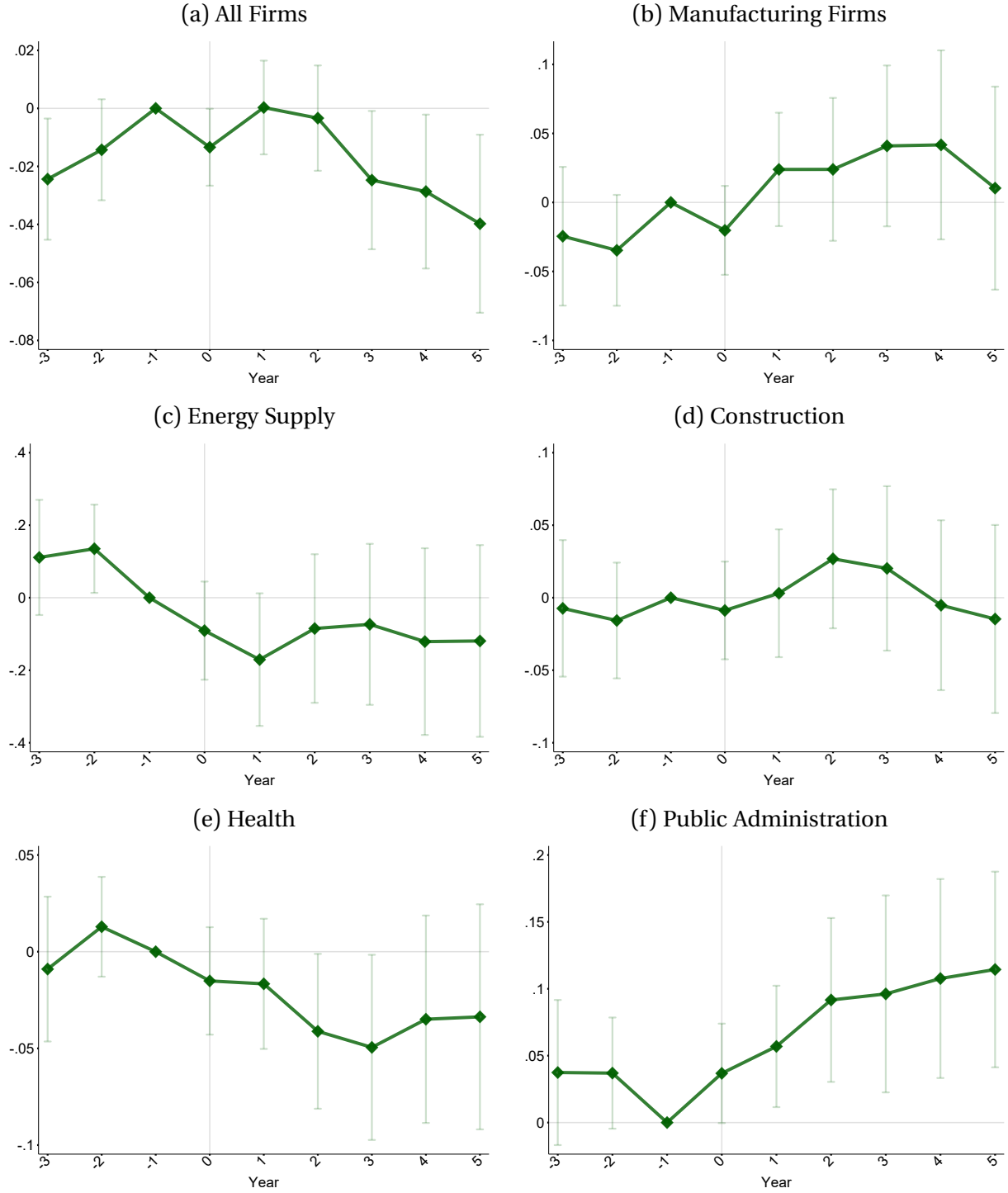
Notes: This figure plots event study regression coefficients for different mobility outcomes. Pooling all flood events. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Control group: Matched individuals in matched county pair.

Figure 6: The Labor Market Effects by Industry



Notes: This figure plots event study regression coefficients for different labor market and mobility outcomes by five broad industry categories. We classify workers based on their industry in $t = -1$. Pooling all flood events, excluding individuals whose home was flooded, only. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Control group: Matched individuals in matched county pair.

Figure 7: Firm Survival: Share of Firms Relative to t=-1



Notes: This figure plots event study regression coefficients for firm survival on the municipality level. Pooling all treatment types and all flood events. Green diamonds plot β_k coefficients estimated using Equation 2. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Control group: Municipalities in matched counties.

A Flood Data Sources and Processing

2002 Flood

For the 2002 flood, we collect flood extent data for the two most affected states: Saxony and Saxony-Anhalt. Institutions from other states were unable to provide spatial data of the flood extent.

- **Saxony:** Flood extent data were obtained from the Saxon State Office for Environment, Agriculture and Geology (LfULG).
- **Saxony-Anhalt:** Data were obtained from the Federal Agency for Cartography and Geodesy (BKG).

The two datasets are combined and create a unified spatial representation of flooded areas. We then overlay these data with municipality and county boundaries to compute the share of each administrative unit that was flooded.

2013 Flood

For the 2013 flood, we gather data from the three most affected states: Saxony, Saxony-Anhalt, and Bavaria. Again, institutions from other states were unable to provide spatial data of the flood extent.

- **Saxony:** Flood data were again provided by the Saxon State Office for Environment, Agriculture and Geology (LfULG).
- **Saxony-Anhalt:** We use two datasets from the Federal Institute of Hydrology (BfG), each based on a separate aerial reconnaissance mission, as well as data from the State Office for Flood Protection and Water Management (LHW). We take the union of these datasets to account for differences in geographic coverage.
- **Bavaria:** Flood extent data were obtained from the Office for Water Management in Deggendorf, which documented flooding along the Danube, particularly in the area around Passau.

For 2013, since the flood boundaries are geometrically more complex, more coordinate points are needed for its representation. To reduce resulting computational complexity, we simplify all flood polygons using the Douglas-Peucker algorithm with a 10-meter tolerance, smoothing out the points that contain the least information. This substantially reduces the number of coordinates without materially affecting the spatial accuracy of the flooded areas.

As with the 2002 data, we merge individual datasets, and calculate the flooded area share for each municipality and county.

2021 Flood

For the 2021 flood, all flood extent data come from the Copernicus Emergency Management Service (EMS), an EU satellite-based rapid mapping system activated during natural disasters.

- **Copernicus EMS:** We use post-event delineation maps derived from Sentinel-3 satellite imagery. These maps were made available shortly after the event and provide high-resolution coverage of affected areas in North Rhine-Westphalia and Rhineland-Palatinate.

Since Copernicus was not operational prior to 2014, it is only used for the 2021 event. The processed satellite-derived flood masks are overlaid with administrative boundaries to compute the flooded area shares.

Appendix Tables

Table A1: Summary Statistics of Workers by Treatment Type, Flood Event in 2002

	(1) Control	(2) Treatment Workplace & Home	(3) Treatment Workplace	(4) Treatment Home
Panel A: Individual Characteristics				
Education (years)	12.3 [1.8]	12.3 [1.7]	12.4 [1.9]	12.4 [1.9]
Experience (years)	10.4 [2.3]	10.4 [2.0]	10.4 [2.2]	10.4 [2.3]
Tenure (years)	7.0 [2.9]	7.4 [2.9]	6.8 [2.8]	6.6 [2.8]
Daily wage (EUR)	82.8 [29.4]	76.8 [28.1]	83.3 [28.2]	86.3 [29.6]
Days worked	362.9 [13.3]	363.0 [13.0]	363.2 [12.3]	362.9 [13.4]
Days worked fulltime	316.4 [120.2]	304.7 [132.4]	314.9 [122.5]	323.6 [111.7]
Panel B: 1-Digit Industries				
Agriculture, Mining, Energy, Water	0.05 [0.2]	0.06 [0.2]	0.04 [0.2]	0.05 [0.2]
Manufacturing	0.2 [0.4]	0.2 [0.4]	0.2 [0.4]	0.2 [0.4]
Construction	0.09 [0.3]	0.09 [0.3]	0.08 [0.3]	0.10 [0.3]
Services	0.5 [0.5]	0.5 [0.5]	0.5 [0.5]	0.5 [0.5]
Public Admin., Education	0.2 [0.4]	0.2 [0.4]	0.2 [0.4]	0.1 [0.4]
Number of Observations	275974	106815	50105	88791

Notes: Characteristics of treated and control workers on day before flood event. Control group: individuals in same county, living or working in unaffected municipalities. Standard deviations in brackets.

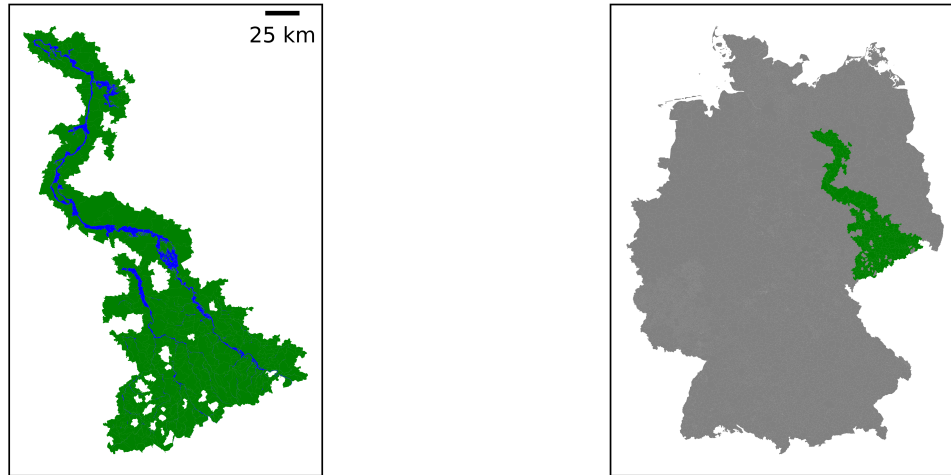
Table A2: Summary Statistics of Workers by Treatment Type, Flood Event in 2013

	(1) Control	(2) Treatment Workplace & Home	(3) Treatment Workplace	(4) Treatment Home
Panel A: Individual Characteristics				
Education (years)	12.3 [1.9]	12.2 [1.7]	12.3 [1.8]	12.4 [2.0]
Experience (years)	20.0 [7.6]	19.6 [7.3]	20.1 [7.7]	19.7 [7.5]
Tenure (years)	9.6 [6.2]	10.5 [6.6]	10.1 [6.7]	9.1 [5.9]
Daily wage (EUR)	96.3 [45.8]	87.8 [43.1]	97.0 [44.6]	100.7 [45.9]
Days worked	362.1 [18.2]	362.1 [18.2]	362.1 [17.9]	362.0 [18.2]
Days worked fulltime	290.1 [144.7]	274.2 [155.3]	285.9 [147.8]	299.1 [137.4]
Panel B: 1-Digit Industries				
Agriculture, Mining, Energy, Water	0.03 [0.2]	0.04 [0.2]	0.03 [0.2]	0.03 [0.2]
Manufacturing	0.3 [0.5]	0.3 [0.5]	0.3 [0.5]	0.3 [0.4]
Construction	0.08 [0.3]	0.07 [0.3]	0.06 [0.2]	0.08 [0.3]
Services	0.5 [0.5]	0.5 [0.5]	0.5 [0.5]	0.5 [0.5]
Public Admin., Education	0.09 [0.3]	0.1 [0.3]	0.1 [0.3]	0.08 [0.3]
Number of Observations	826336	231750	165906	289710

Notes: Characteristics of treated and control workers on day before flood event. Control group: individuals in same county, living or working in unaffected municipalities. Standard deviations in brackets.

Appendix Figures

Figure A1: Flood Data 2002



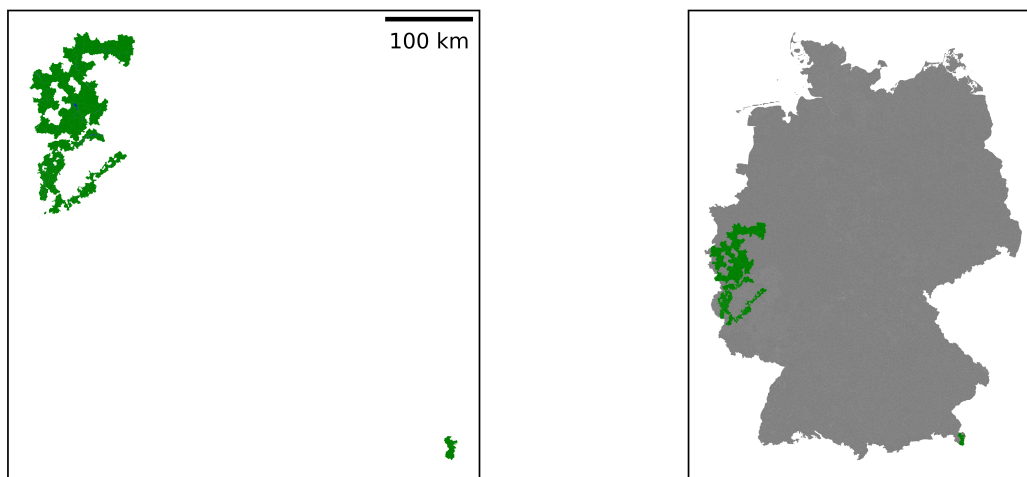
Notes: The plot on the left shows the extent of the flooded area in blue for the 2002 flood. The green area is the set of affected municipalities. The plot on the right shows the same affected municipalities in green, with Germany in grey.

Figure A2: Flood Data 2013



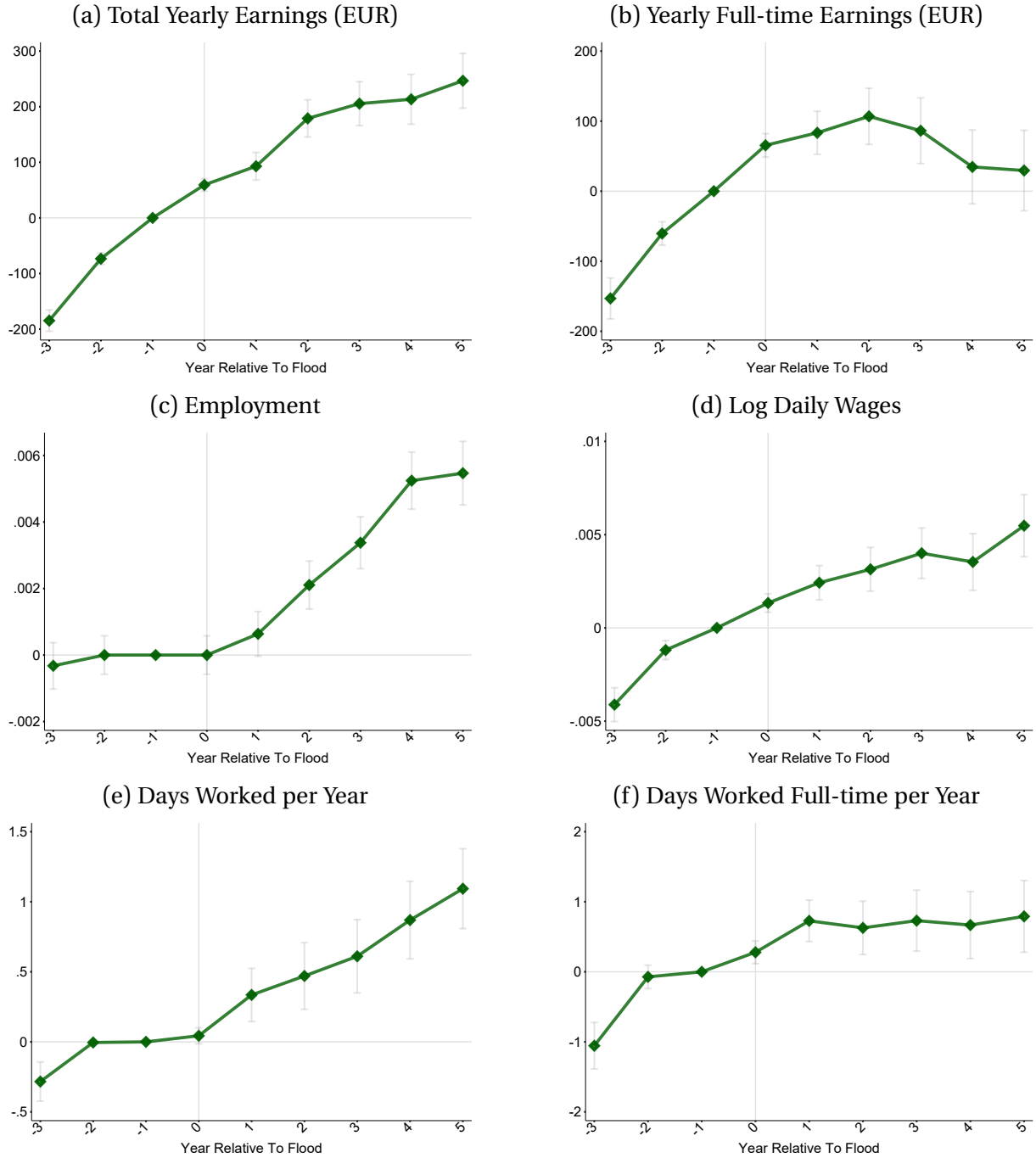
Notes: The plot on the left shows the extent of the flooded area in blue for the 2013 flood. The green area is the set of affected municipalities. The plot on the right shows the same affected municipalities in green, with Germany in grey.

Figure A3: Flood Data 2021



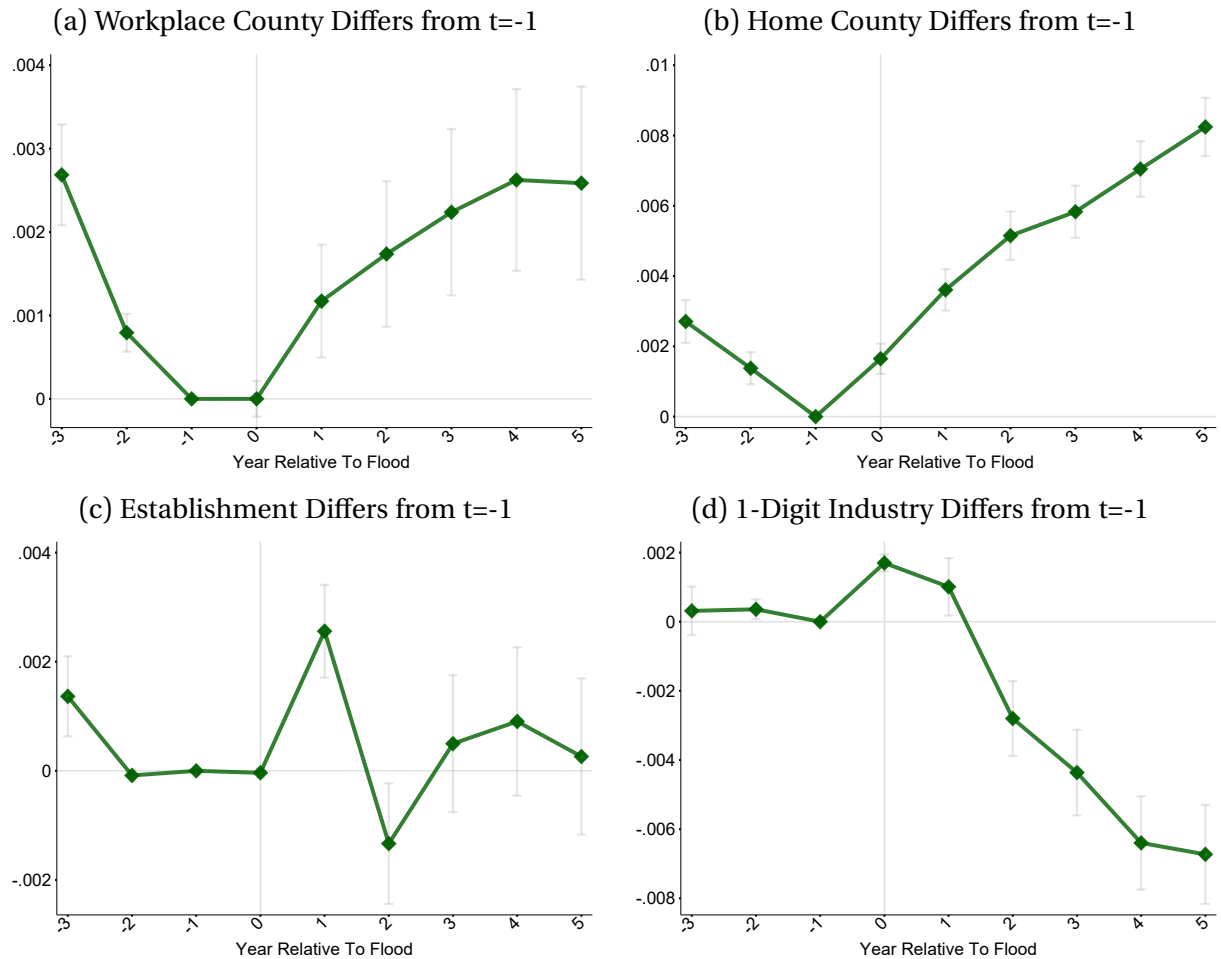
Notes: The plot on the left shows the extent of the flooded area in blue for the 2021 flood. The green area is the set of affected municipalities. The plot on the right shows the same affected municipalities in green, with Germany in grey.

Figure A4: The Labor Market Effects of Big Flood Events - Same County Control Group



Notes: This figure plots event study regression coefficients for different labor market outcomes. Pooling all treatment types and all flood events. Green diamonds plot β_k coefficients estimated using Equation 1. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Control group: Matched individuals in same county.

Figure A5: The Mobility Effects of Big Flood Events - Same County Control Group



Notes: This figure plots event study regression coefficients for different mobility outcomes. Pooling all treatment types and all flood events. Vertical bars indicate the estimated 95% confidence interval based on standard errors clustered at the individual level. Control group: Matched individuals in same county.