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THE IMPACT ON ECONOMIC ACTIVITY AND HOUSING MARKET OF THE 2023 EMILIA-ROMAGNA FLOODS

by Elena Gentili*

Abstract

In May 2023, two floods hit the Italian region of Emilia-Romagna, causing 17 deaths and €10 billion in damages. This paper investigates the impact of such floods on economic activity and household wealth. Using nightlight data to measure economic activity and considering a triple difference-in-differences empirical framework, we find a decline in nightlight activity in flooded municipalities in the three weeks surrounding the two floods, a rebound effect in the following three weeks, but no effect thereafter. In the most pessimistic scenario, the total reduction in regional GDP growth in 2023 is between 0.1 and 0.2 per cent, i.e. between €3 and 5 million, excluding the agricultural sector. The duration of the impact of the floods is broadly confirmed by the other two proxies for economic activity available at the daily frequence and municipal level, i.e. hiring and road traffic data. We also find temporary effects on the housing market demand, but no effects on the house prices asked by the sellers nor on the number of posted advertisements for house sales, suggesting that the housing market in flooded municipalities already discounts the risk of such natural events.

JEL Classification: C18, O18, O44, Q54, R11, R12, R21, R31.

Keywords: flood, nightlight, housing market, triple difference-in-differences, Emilia-Romagna.

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1 Introduction[1]

With climate change, extreme events such as droughts, floods and cyclones are becoming more and more frequent (see for instance OECD, 2016). Although preliminary estimates of the damage caused by these events are readily available through emergency satellite imagery, official statistics to measure the impact on economic activity take time to be released. Moreover, even when it is possible to calculate the value added at risk from a natural disaster, for example by adding up the value added by firms in the affected areas, it is still very difficult to provide an estimate of the timing of recovery, which is also an important information for assessing the true magnitude of the disaster. Overall, a timely understanding of the impact of natural disasters on economic activity is essential in order to correctly assess the costs of these events. This is particularly true for countries such as Italy, where 94% of municipalities have at least part of their territory at hydrogeological risk (Trigila et al., 2021) and almost 30% of manufacturing firms are potentially at risk of flooding (Loberto and Russo, 2024).

This paper uses big data to examine the economic consequences of the two floods that hit the Italian region of Emilia-Romagna (ER, hereafter) in May 2023. Using these data sources, the paper derives a methodology that can be replicated after similar events to provide insights into their magnitude before official statistics are released.

In particular, in the first part of the paper we proxy economic activity with nightlight luminosity data, as has been done extensively in the literature since the seminal work of Elvidge et al. (1997), Doll et al. (2006) and Henderson et al. (2012). Nightlight data can capture some of the consumption and production that takes place at night, thus providing an indicator of GDP. The main advantages of these data are that they are available with a lag of few days, at a daily time frequency and at very granular geographical level. These features make them particularly suitable for estimating the impact of geographically localised events for which official statistics are not available (as in the case of GDP) or are available with a considerable time lag and annual frequency (as in the case of population). Moreover, recent technological improvements in satellite sensors have increased the quality of such data (see for instance Elvidge et al., 2017, Levin et al., 2020, Gibson, 2021), improving their ability to proxy for GDP at a fine geographical level and for lower density areas (Gibson et al., 2021, Chen and Nordhaus, 2019, Bruederle and Hodler, 2018). For all these reasons, they have been widely used in the literature on natural disasters (see for example Elliott et al.,

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2015, Heger and Neumayer, 2019, Nguyen and Noy, 2020, Kocornik-Mina et al., 2020, Gandhi et al., 2022).

In designing the empirical methodology, we define as treated the ER municipalities that show some flooded areas in the images taken by the Copernicus satellite after the two floods and as control the municipalities in the furthest provinces of the ER region with respect to the flooded areas. By removing the municipalities in between, we avoid spillovers of the treatment to the control units. Given the high volatility of the daily nightlight data and the timing of the floods, which occurred twenty days apart, we pool the data every three weeks and show the differential impact of the floods in treated and control municipalities in the 3-week periods before and after the 3-week period of the two floods. Moreover, since treated and control municipalities have different economic structures, the regressions are weighted with a propensity score that takes into account the geographical and economic characteristics of the municipalities. Finally, as will be discussed in detail in Section 4, we apply a triple difference-in-differences design to disentangle the effects of the two floods from short-term fluctuations in economic activity and compare the differences in nightlight intensity between treated and control municipalities before and after the floods in 2023 and 2022. This allows us to control for municipality-specific time effects and for year-specific short-term seasonality in the estimates, captured by the combination of municipality, year and 3-week period fixed effects.

We find a 16% decrease in nightlight activity in the three weeks of the floods (27% of the standard deviation of the dependent variable), a rebound effect in the following three weeks, and no effect thereafter. The rebound in nightlight intensity after the floods is consistent with other evidence in the literature (Zhao et al., 2018), and is likely related to relief and rescue efforts. The timing of the rebound is also consistent with other studies showing that declines in economic activity after floods tend to be short-lived (Kocornik-Mina et al., 2020; Gandhi et al., 2022). Given a benchmark correlation between changes in nightlight data and GDP growth of between 0.18 and 0.42 (see Gibson et al., 2024 for a recent review), our estimated coefficient suggests a negative impact of the two floods on the GDP growth of flooded municipalities between 2.9% and 6.7% in the 3-week period of the floods. Even if we extend the estimate we found for the 3-week period of the floods to the subsequent 3-week period (assuming that the increase in nightlight activity in the 3-week period after the floods is evidence of a persistent negative economic impact), we would find an overall reduction in economic activity of between 5.8% and 13.4% over a 6-week horizon, which translates into a decline ranging between 0.3% and 0.8% over an annual horizon. Scaling up the impact on the flooded municipalities to the whole ER region, this implies a reduction in regional GDP growth of between 0.1% and 0.2%, i.e. between 3 and 5 million euros. The loss of GDP due to the two floods thus appears to be rather limited if compared to the estimated direct damage of 10 billion euros. It should be noted that these figures may slightly underestimate the total impact on GDP, since nightlight data are not suitable for capturing economic activity in the agricultural sector, which nevertheless accounts for only 2% of the regional value added.

To provide robustness on this evidence, we replicate our empirical strategy using two other data sources available for the ER region at the daily and municipal level: mandatory notifications to the Ministry of Labour about the start and the end of employment contracts and road traffic data measured by road sensors. Both of these variables show a negative effect in the 3-week period of the two floods and in the 3-week period after the floods. The negative effect disappears from the second 3-week period after the floods, confirming the timing we find using nightlight data. In particular, hiring data show a statistically significant and large decline in agriculture, which disappears in the second 3-week period after the floods. This suggests that the agricultural sector was indeed affected, although we cannot quantify this effect in terms of GDP. However, the timing of this effect is similar to that of the other variables examined, so that the fall in agricultural value added may have lasted only up to three weeks after the floods.

In the last part of the paper, we provide evidence on the impact of the two floods on the housing market. Indeed, the damage experienced by some households and the increased perception of flood risk may have affected the wealth of residents through changes in house values. As Kocornik-Mina et al. (2020) point out, Bayesian updating after a natural disaster may induce the resident population to migrate elsewhere. However, since building in plane and flood-prone areas tends to be less expensive than elsewhere, house prices may already discount the risk of adverse natural events, so that a new flood conveys little new information. Using weekly data from *Immobiliare.it*, the main Italian website for buying and selling houses, we find that the average municipal price of housing units asked by sellers and the number of posted advertisements do not change after the two floods. Looking at two indicators of housing demand, i.e. the number of online visits per advertisement and the number of requests that potential buyers send to the sellers through the platform, we find a large drop in the week of the second flood and in the following one, but then they return to pre-event levels in approximately 8 weeks. Since temporary changes in housing demand should not permanently alter the supply of housing units and thus the equilibrium outcomes in the housing market, these results suggest that there is little Bayesian updating after the two floods and that current prices already discount the risk of flooding. Nevertheless, it cannot be excluded that the increased awareness of the possibility of such adverse meteorological events may structurally change individuals' perceptions in the longer run, as shown by Bellaver et al. (2025). If this is the case, permanent adaptation measures aimed at counteracting the negative impact of floods in high-risk areas may offset the fall in house value associated with an increased perception of risk (see for instance Benetton et al., 2023 on Venice).

This paper contributes to two strands of the existing literature. First, it adds to the literature on assessing the impact of natural disasters using nightlight data. The two most closely related papers are Kocornik-Mina et al. (2020) and Gandhi et al. (2022), which provide cross-country evidence on the negative economic impact of floods. Using annual data, the first paper finds a reduction in nightlights between 2% and 8% in the year of the flood and a full recovery from the following year. This paper also discusses a model to rationalise the small population displacement found after the floods. The latter paper uses monthly data and finds that on average nightlights decrease by 1.4% in high-income countries in the month of the flood, but then recover within a month. With respect to these papers, we focus on a single flooded area and are thus able to: (i) provide evidence on the overall economic magnitude and duration of the consequences of a natural disaster even for a very localised geographical area; (ii) discuss a tailor-made empirical strategy to extract signal from the data; (iii) test the results on nightlight data with additional data sources; (iv) directly test the impact of the floods on the housing market. For all these reasons, this paper also provides empirical guidance to researchers and policy makers who wish to evaluate a natural disaster only a few weeks after the event.

Second, it adds to the literature on the impact of floods on the housing market. In this literature, there is evidence that house prices are lower in areas where the risk of flooding is higher (Bosker et al., 2019; Giglio et al., 2021; Bellaver et al., 2025) and that the housing markets respond to new information about the actual risk of flooding (Bin and Landry, 2013; Ortega and Taṣpınar, 2018; Yi and Choi, 2020; Addoum et al., 2024). In particular, using mortgage data from a large Italian bank, Bellaver et al. (2025) show that flood-prone Italian regions have approximately 1% lower house prices than less risky areas, but that the second flood occurred in ER in May 2023 had no impact on the housing market. Our results confirm the latter finding using a different data source that takes into account all potential housing market transactions.

The remainder of this paper is structured as follows. The next section briefly describes the economic structure of ER and the floods that hit the region in May 2023. Section 3 presents the data used and some descriptive statistics, as well as the main empirical choices. Section 4 presents the methodology and the results on economic activity, while Section 5 discusses the methodology and the results on the housing market. Finally, Section 6 concludes.

2 Background

The ER region.– The upper left panel of Figure 1 shows the physical geography of the ER region. ER is characterised by the presence of the Appennine mountain range in the south and the fertile plane of the Po Valley in the central and north-eastern parts of the region. The main cities are almost all located in the central part of the region, right in between the mountains and the plane, with the exception of Ravenna and Ferrara, which are located in the flat area to the north-east. The cities at the foot of the mountains are all connected by major motorways connecting the east and west coasts of Italy to the industrial north.

The ER region has strategic infrastructure for the Italian economy and is one of the most developed areas in northen Italy. Its economic structure is based on manufacturing, particularly in the mechanical, automotive, food processing and ceramics sectors. Nevertheless, because of its fertile planes, it is also one the Italian regions with the highest agricultural value added (3.7 billion euros in 2022), together with the other two main regions of the Po Valley (Veneto and Lombardy) and Sicily. In summer, the eastern municipalities bordering the Adriatic Sea are characterised by mass tourism. The upper right and lower left panels of Figure 1 show the distribution of value added in the private non-agricultural sector and of cultivated land. Private sector activity is mainly concentrated in the central part of the region, along with the main cities. Cultivated land, on the other hand, is more widely distributed in the north-east, reflecting the availability of flat land.

The physical geography of the region also makes it vulnerable to adverse natural events. Due to its proximity to the Adriatic Sea and the lack of natural barriers to cold winds from northen and eastern Europe, it is characterised by dump weather in both summer and winter. This makes the summers particularly hot and the winters particularly cold compared to the average mild Italian climate. The eastern part of the plane is also characterised by a very low elevation, which makes this area prone to river flooding. As shown in the lower right panel of Figure 1, one third of the municipalities in ER have their entire territory at hydrogeological risk.

The two floods of May 2023.– In May 2023, two floods hit the ER region. The first episode took place on May, $2^{nd} - 3^{nd}$, the second one on May, $15 - 17^{th}$. The heavy rains caused more than 280 landslides and 21 rivers in the area overflowed their banks. 17 people lost their lives and the damage to buildings and infrastructure amounted to 10 billion euros. To support the recovery efforts, the Italian national authorities activated the Copernicus Rapid Mapping Emergency Management Service. This service supports emergency management after a natural disaster and consists of a set of aerial images provided by Copernicus, a satellite launched and managed by the European

Space Agency, showing the extent of the flooded areas and an estimate of the number of buildings and people affected by the flooding. The left panel of Figure 2 shows an example of such imagery, taken immediately after the second flood.

The right panel of Figure 2, instead, shows in red the flooded municipalities within the ER area. The flooded area represents 2% of the Italian population (about 1.2 million inhabitants), 2.1% of the national cultivated land and 2.3% of the Italian value added in the private non-agricultural sector.

3 Data

In this section, we provide a description of the data sources used to analyze the impact of the floods, as well as the empirical choices made to conduct the empirical analysis. Summary statistics are provided in Table 1.

3.1 Data sources

Nightlight data.– The nightlight data series used in this paper are the Visible Infrared Imaging Radiometer Suite (VIIRS) Day-Night Band (DNB), made available for download by the Colorado School of Mines. The VIIRS data come from a joint programme of the National Oceanic and Atmospheric Administration (NOAA) and the National Areonautic and Space Administration (NASA) and are provided at daily (Nightly DNB Mosaic), monthly (Monthly Cloud-free DNB Composite) and annual (Annual VNL V1 and Annual VNL V2) frequencies. The daily data are raw, while the monthly and annual data are partially processed to account for some of the data limitations. The resolution of the imagery is of 15 arc seconds, i.e. approximately 500 square meters at the Equator.

We download daily data from February, 27^{th} to July, 23^{rd}, both in 2022 and in 2023 and restrict our attention to the municipalities of the ER region. Brightness is measured in radiance units, which is a positive number ranging from 0 to very high values in the case of peculiar phenomena, such as thunder lightning, biomass burning, gas flares or high-energy particles. However, due to the automatic adjustment of satellite equipment to clouds and other weather conditions, some pixels may have negative values. Also, because light travels through space, it is possible to detect low but positive radiance values in empty areas, where no light should be detected. To avoid problems related to such facts, we trim the pixels below the first and above the 99^{th} percentile of the radiance distribution in our sample. This removes negative values and pixels likely to be associated with empty areas, as well as large values associated with extremely bright events unrelated to electric lighting. While in the original sample the radiance values ranged from -999 to 5.809, in the trimmed sample they range from 0.4 to 44.4. The radiance values at the 25^{th}, 50^{th} and 75^{th} percentiles of the distribution are virtually the same before and after the trimming, suggesting that we are indeed removing extreme observations.[2] The distribution of such data across the ER region is shown in the top panels of Figure 3.

Weather conditions, lunar phases and the timing of the sunset can also affect the quality of the data. Restricting our attention to the ER region for a short period of time should limit the impact of natural phenomena such as lunar phases or the timing of sunset, as they should affect all the municipalities considered in the same way. Furthermore, in our empirical design we explicitly control for lunar phases and seasonality in the data, as will be discussed in the next section. To control for weather conditions, we merge the VIIRS-DNB nightlight data with two other data sources. First, we add data from the VIIRS-DNB Cloud imagery, which is still provided by the Colorado School of Mines. In particular, they consist of a discrete variable for each pixel that is equal to 0 if there are no clouds, 2 if it was probably cloudy, 4 for cloudy weather.[3] We then collect data on temperature, visibility, humidity and wind for each municipality and day from the website `www.meteo.it`, as any of these weather conditions may be relevant in determining the brightness detection by the satellite.

Other high-frequency data sources.– In order to cross-check the results with the nightlight data, we also use two other high-frequency data sources available at the daily and municipal level, namely mandatory notifications to the Ministry of Labour on the start and the end of employment contracts and road traffic. The employment data come from the Italian Ministry of Labour and consist of the number of contracts activated and terminated each day by municipality. We replicate the empirical exercise on nighlight data using the number of activations (hereafter called "hiring"). The centre-left panel of Figure 3 shows their distribution across the ER region. Because of the relevance of short-term contracts and dismissals, we also repeat the same exercise using the difference between activations and terminations ("net hiring"). However, as net hiring can take negative values and its logarithm is not always defined, we present these results in the Appendix.

Data on road traffic are collected by the Monitoring System of the ER Region, which is based on 278 monitoring stations.[4] However, most of the monitoring stations were not consistently active throughout the period of interest. Therefore, in the analysis we restrict the sample to the data from consistently active monitoring stations, which correspond to 74 municipalities out of the 328 municipalities in ER. The centre right panel of Figure 3 shows their distribution. The results using data from all the monitoring stations are consistent with those from this restricted sample, but are

[2]These values are 1.2, 2.5 and 5.4 in the full sample, 1.2, 2.5 and 5.3 in the trimmed sample.

[3]In our sample, more than 50% of the observations are in the absence of clouds and less than 5% when it was probably cloudy.

[4]Data available at `https://servizissiir.regione.emilia-romagna.it/FlussiMTS/`.

less precise and not reported.

Housing data.– Finally, the housing data come from the digital platform *Immobiliare.it*, the main online site for buying and selling housing units in Italy. These data do not track actual transactions, but they contain detailed information about each advertisement posted. For each ad, we have all the information available on the website, such as the geographical coordinates, the main characteristics of the housing unit, the price asked by the seller and the number of online visits by users. As the platform allows users to get in contact with the potential seller of the housing unit, we also have information on the requests for contact that each ad receives. Online visits and contact requests are particularly interesting because they can be regarded as a measure of the potential demand on the market, with the latter being even more informative than the former. The data are updated on a weekly basis, so that we can not only geolocate the housing units, but also track prices, the number of online visits and the number of contact requests to the seller over time.[5]

We restrict our attention to housing units for sale and exclude from the sample garages, buildings, hotels, land, housing units at auction, those larger than 10,000 square metres and those with an unknown municipality. In order to better visualise the evolution of the variables of interest over time, we work with a longer time period with respect to the analysis on economic activity and extend the time series of interest until September, 24^{th}. The advertisements in the dataset between February, 27^{th} and September, 24^{th} 2023 in the ER region are almost 87,000, 3.4% of the ER housing unit stock.[6] The lower panels of Figure 3 show the distribution of average prices and the number of advertisements in the ER municipalities.

3.2 Nightlights, hiring and road traffic data as proxies for economic activity

Cross-sectional correlations.– To check whether the data discussed in the previous subsection are convincing proxies for economic activity, we now examine some useful correlations. We average the data on nightlights, hiring and road traffic at the municipal level over the period of interest and check their corss-sectional pairwise correlations with the two proxies for sectoral GDP available at

[5]In the dataset, the number of online visits and the number of contact requests include the cumulative value of clicks received by each ad from the time it was first added until the week of interest. However, it is not straightforward to impute the number of clicks received in each week, because the website allows users to hide or unhide ads. If an ad is hidden we do not observe the date on which this happened, but only the date on which the ad starts to receive online visits again (and thus presumably became visible again). Obviously, this problem is a more severe issue for the contact requests, as they are not as numerous as the number of online visits. Nevertheless, since we have the dates on which the number of clicks is updated we calculate the daily clicks as the difference between the cumulative number of clicks at each update and at the previous update and divide by the number of days between the two updates. This procedure may introduce some measurement error in these variables, but since we consider them as outcome variables in the empirical analysis, such measurement error does not bias our estimates.

[6]The ER housing stock comes from the 2021 housing census.

municipal level: value added in the private non-agricultural sector and the area of cultivated land.

Table 2 shows the results. Nightlight values, hiring and road traffic data are all strongly and positively correlated with private non-agricultural value added, with correlations ranging from 70% for nightlights and road traffic to almost 90% for hiring. These measures of economic activity are also highly correlated with each other: road traffic and hiring have a 60% correlation with each other and a 70% correlation with nightlight data. Interestingly, the correlations with cultivated land are much lower. Nightlights and road traffic are only 3% correlated. Instead, hiring data is the only proxy for economic activity that seems to capture some activity in the agricultural sector, with a correlation of around 50%. Thus, nightlights and road traffic seem to be better proxies for GDP in the private non-agricultural sector and poor proxies for agricultural GDP, while hiring data should be an adequate proxy for GDP in both sectors.[7]

Elasticity of GDP to nightlight data.– However, since in the empirical analysis we want to evaluate changes in economic activity before and after the floods, ideally we would like to test whether the previous cross-sectional correlations hold in a time series setting, i.e. we would like to test whether *changes* in nightlights, hiring and road traffic are actually informative about *changes* in GDP. This is an important point because while the previous results on the cross-sectional correlations between nightlights and GDP are widely accepted in the literature (Chen and Nordhaus, 2019), there is an ongoing and extensive debate on the ability of changes in nightlights to predict changes in GDP (Gibson et al., 2024).

Indeed, there are a number of issues in the estimation of the elasticity of GDP to nightlights. First, nightlight data are more sensitive to changes in the extensive margin of artificial lighting than in the intensive margin, which means that they are more likely to capture the creation of a new neighbourhood of a city rather than an increase in lighting in existing neighbourhoods. Thus, there is a non-linear relationship between nightlight data and GDP at different levels of GDP (Bluhm and McCord, 2022; Gibson et al., 2024). A second issue concerns the size of the geographical unit considered. On the one hand, some papers show that the elasticity of GDP with respect to nightlights becomes smaller for finer geographies because the places where value added is produced may not correspond to the places where nightlight sources are observed (for instance, people may live in different areas with respect to industrial sites) and the correlation between the two dissipates the smaller the geographical unit considered (Khachiyan et al., 2022). On the other hand, other papers find an aggregation bias, so that elasticities for larger geographies may be inflated or deflated depending on the country considered (Chen and Nordhaus, 2019; Gibson et al., 2024).

[7]These findings are also confirmed by graphical inspection, comparing the maps in Figures 1 and 3.

As we focus on one of the most developed regions of Italy, the first caveat suggests that the observed change in nightlights may indeed be smaller than the actual change in GDP. However, the direction of the bias associated with the second caveat is unclear. Italian municipalities are much smaller geographical units than US counties or districts, which are the finest geographical levels for which elasticities of GDP to nightlights are available. Thus, on the one hand, the actual correlation between nightlights and GDP in our context could be smaller than those estimated in the reference papers. On the other hand, estimates of the elasticities of GDP to nightlights should suffer less from aggregation bias. The overall direction of the bias in the estimation of such an elasticity is therefore not clear ex-ante.

There are many estimates of the elasticity of GDP to nightlights available in the literature (see the Appendix A of Gibson et al., 2024 for a thorough review of such estimates), calculated using different data sources, years and geographical units. If we restrict our attention to elasticities estimated using multiple years of VIIRS data, these estimates range from 0.18, as estimated by Gibson et al. (2024), to 0.42, as estimated by Kim et al. (2023). In addition, most studies (see for instance Michalopoulos and Papaioannou, 2018 and Kocornik-Mina et al., 2020) use the benchmark value of 0.3, as first estimated by Henderson et al. (2012),[8] a value in between these two extremes.

In Italy, the most granular proxy for GDP available at the municipal level is the annual value added in the private non-agricultural sector between 2015 and 2022. Using this variable as a proxy for total GDP and averaging daily nightlights between February 27^{th} and July 23^{rd} each year from 2015 to 2022, we also provide an estimate of the elasticity of GDP to nightlights in our context. In the most demanding specification, the estimating equation is:

$$Ln(ValueAdded)_{m,y} = \beta_0 + \beta_1 ln(Nightlights)_{m,y} + \lambda_m + \lambda_y + u_{m,y} \quad (1)$$

where the dependent variable is the logarithm of value added in the private non-agricultural sector, m and y are the subscripts for municipality and year, λ_m and λ_y are municipality and year fixed effects, u_i is the stochastic term. β_0 is a constant and β_1 is the coefficient of interest, i.e. the elasticity of value added to nightlights.

Table 3 shows the results. The unconditional correlation in Column (1) is very large and does not change much after adding year fixed effects (Column 2) and local labour market fixed effects (Column 3). Instead, including municipality fixed effects reduces the coefficient to 0.15 with a standard error of 0.04 (Column 4), indicating a positive and statistically significant correlation between value added in the private non-agricultural sector and nightlights. As value added in the private non-agricultural sector is only a proxy for total GDP, this estimated coefficient should

[8] This estimate is based on nightlight data from the U.S. Air Force Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS), which was the only source of nightlight data available in the 2000s.

be downward biased because of measurement error. Nevertheless, this figure is very similar in magnitude to the value of 0.18 estimated by Gibson et al. (2024) using US county data.

As a last note before moving to the empirical analysis, it is important to bear in mind that the estimates of the elasticity of GDP to nightlights are computed in "normal" times, i.e. using years that were not affected by shocks or natural disasters. However, several factors may further bias this correlation during a flood. For instance, power outages in private residences could lead to an overestimation of the true impact of the floods on GDP. Conversely, the presence of emergency lighting could lead to an underestimation of the effect on economic activity. Given that the direction of the overall bias in the true nightlight-GDP correlation is unclear, in Section 4.4 we provide some back-of-the-envelope calculations of the impact of the two floods on regional GDP using the upper and lower bounds of the elasticity suggested by the literature, i.e. 0.18 and 0.42.

3.3 Selection of the relevant dimensions

Since most of the variables in this analysis are measured at the municipal level, we average the nightlight, road traffic and housing market data at the municipal level. As shown in the right panel of Figure 2, the floods affected a geographically well-defined part of the ER territory. To avoid spillovers of the treatment to untreated units, we remove from the sample the municipalities close to the flooded area.[9] We use the remaining municipalities, shown in blue in Figure 2, as controls. However, these control municipalities have a different geography and economic structure compared to the flooded municipalities.[10] To account for these differences, we compute a propensity score regressing the dummy for flooded municipalities on a vector of municipality characteristics, including altitude, degree of urbanisation, area, share of workers in manufacturing, trade, hotels and restaurants, share of land at hydrogeological and landslide risk and population at the beginning of 2023 and weight the regressions in the empirical analysis accordingly.[11]

The temporal dimension also requires some discussion. Figure 4 plots the logarithm of the daily nightlight values in 2022 and 2023. The two vertical dashed lines represent the first days of the

[9] In particular, we remove unaffected municipalities in the same administrative provinces as the flooded municipalities (i.e. in the provinces of Bologna, Ferrara, Ravenna, Forlí-Cesena and Rimini) and the municipalities in the nearby province of Modena, which is still very close to the affected area.

[10] For instance, there is more activity in the food processing industry in the control area than in the treated area, while the flooded municipalities have more manufacturing activity in leather products and furniture.

[11] Formally, the propensity score is calculated using a logistic regression of the form

$$log\left(\frac{P(T_m = 1|X_{1,m}, ..., X_{n,m})}{1 - P(T_m = 1|X_{1,m}, ..., X_{n,m})}\right) = \beta_0 + \beta_1 X_{1,m} + ... + \beta_n X_{n,m}$$

where m is the subscript for municipalities, T_m is a dummy variable equal to 1 for flooded municipalities and 0 for control municipalities and X_1 ... X_n are the control variables listed in the main text. The predicted values from this regression are the propensity scores used to weight the observations in the regressions.

two floods. There is high volatility in the daily observations in both 2022 and 2023, especially after the second flood. This is in line with the existing literature, which suggests that there is more light consumption at night during weekends, public holidays and with the start of the tourist season (Román and Stokes, 2015). To overcome this problem, we aggregate the data over longer time intervals. However, as weeks shift over calendar days each year and nightlight data can be influenced by sunset timing, we regard each week as starting on Sunday in 2022 and on Monday in 2023. This ensures that the same calendar days are included in each week across years, enabling a more accurate comparison of nightlight data under similar sunlight conditions. As the floods occurred between 2^{nd} and 17^{th} May, the weeks between these two dates are also affected by the events. To normalize with respect to a pre-event period not affected from floods and to further decrease the volatility in the data, we consider the two floods as a single event and pool the data every three weeks. Nevertheless, we also provide robustness checks by pooling the data over different time horizons. For consistency, we make the same timing choice for the other variables tracking economic activity, i.e. hiring and road traffic data.

In the second part of the analysis, we use housing market data and retain the definition of treated and control municipalities from the first part. However, we use weekly variation, since the dynamics of the housing market are less volatile than those of underlying economic activity, enabling us to explore the information contained in these data in more detail. Thus, we average the price, the number of daily visits and the number of daily contact requests from potential buyers at municipality-week level. We also count the number of advertisiment on the platform for each municipality-week combination.

4 The impact of ER floods on economic activity

4.1 Empirical strategy: why triple differences?

To assess the impact of the two floods that hit the ER region in May 2023, we first compare treated and control municipalities in the 3-week periods before and after the floods. The event study design is formulated as follows:

$$\begin{aligned} Ln(Nightlight)_{m,w,2023} = &\sum_{w=-3}^{-2} \beta_w T_m \times W_w + \sum_{w=0}^{3} \beta_w T_m \times W_w + \\ &+ \gamma X_{m,w,2023} + \lambda_m + \lambda_w + \varepsilon_{m,w,2023} \end{aligned} \tag{2}$$

where m and w index the municipalities and the 3-week periods, T_m is a dummy variable equal to 1 for flooded municipalities, W_w is a dummy variable equal to 1 for each 3-week period in the sample. $X_{m,w,2023}$ are time-varying control variables, i.e. weather conditions. We also include the square of temperature to account for non-linear trends in heat that may affect the start of the tourist season. λ_m are municipality fixed effects, λ_w are 3-week period fixed effects and $\varepsilon_{m,w,2023}$ is a stochastic term.[12] The event study is normalised with respect to the 3-week period before the floods and the observations are weighted according to the the propensity score described in the previous section.[13] Standard errors are robust and clustered at the municipality level.

The left panel of Figure 5 shows the results. The vertical line indicates the 3-week period of the two floods. The negative impact of the floods seems to persist for several periods after the event. However, the pre-trends are not null and the treated municipalities were already on a lower economic activity path than the control municipalities before the floods. As a falsification test, the right panel of Figure 5 reports the same event study using data in 2022. Interestingly, treated municipalities still show lower economic activity with respect to control municipalities also in 2022, suggesting that this event study design may not adequately control for the different structure in economic activity between treated and control municipalities.

Another possible control group for flooded municipalities are flooded municipalities one year before. In this way, we compare the same municipalities in two different years and take into account different trends over time in the economic structure of the municipalities. The formulation of the event study is:

$$\begin{aligned} Ln(Nightlight)_{m,w,y} = & \sum_{w=-3}^{-2} \beta_w Y_y \times W_w + \sum_{w=0}^{3} \beta_w Y_y \times W_w + \gamma X_{m,w,y} + \\ & + \lambda_m + \lambda_w + \lambda_y + \lambda_{m,w} + \lambda_{m,y} + \epsilon_{m,w,y} \end{aligned} \tag{3}$$

where the notation is the same as before, but now the subscript y indexes the year, Y_y is a dummy variable equal to 1 for observations in 2023, λ_y are year fixed effects and $\epsilon_{m,y,w}$ is the stochastic term. Note that this formulation still retains the municipality subscript m and the municipality fixed effects λ_m, which allow to account for time-invariant differences in treated municipalities. In this context, we also have sufficient degrees of freedom to control for municipality-year fixed effects and municipality-3-week period fixed effects. The former should account for year-specific trends in municipal economic activity common to all the 3-week periods in the sample, while the latter should account for 3-week period effects in municipal economic activity common to all years, such as different seasonality in municipal economic activity related to different industrial specialisations at the municipal level.

[12] Municipality fixed effects allow to control for time-invariant characteristics of the municipalities, while 3-week period fixed effects account for specific events common to all the municipalities in a given period of time, such as the Italian public holidays celebrated on April 25^{th}, May 1^{st} and June, 2^{nd}.

[13] In particular, each observation is weighted by the inverse of the probability of receiving the treatment.

The left panel of Figure 6 shows the resulting event study. The treated municipalities performed better in 2023 than in 2022 after the floods, but this trend was already present before the floods. The right panel of Figure 6 shows the same event study on control municipalities as a falsification test. Again, there is no clear pattern in economic activity in 2023 compared to 2022. This evidence suggests that the economic activity may be characterised by short-term seasonality that is specific to each year, which cannot be adequately controlled for in this empirical framework.

To control for all the possible sources of variation in economic activity and identify the impact of the floods, we now turn to an event study that exploits all the three dimensions we have in a triple difference setting: year, 3-week period and dummy for treated/control municipalities (see Muralidharan and Prakash, 2017 for a similar empirical design[14]). In this way, we are able to compare the difference in nightlight activity between treated and control municipalities in 2023 with the difference between treated and control municipalities in 2022, thus accounting for the structural differences in economic activity between treated and control municipalities as well as year-specific seasonality. The estimated equation is as follows:

$$\begin{aligned} Ln(Nightlight)_{m,w,y} = \sum_{w=-3}^{-2} \beta_w T_m \times Y_y \times W_w + \sum_{w=0}^{3} \beta_w T_m \times Y_y \times W_w + \\ + \gamma X_{m,w,y} + \lambda_{m,w} + \lambda_{m,y} + \lambda_{w,y} + \varphi_{m,w,y} \end{aligned} \tag{4}$$

where the notation is as before and $\varphi_{m,y,w}$ is the new stochastic term. We are now able to control for year and 3-week period fixed effects $\lambda_{y,w}$, i.e. short-term year-specific seasonality common to all municipalities.[15] The results are presented in the following subsection.

4.2 Main results and robustness using nightlight data

Figure 7 shows the results of the triple difference event study described above. Comparing the treated and control municipalities in 2022 and 2023 before and after the floods, we now have null pre-trends and a 16% negative effect on nightlight activity in the treated municipalities in the 3-week period of the floods. This effect is not negligible since it accounts for 27% of the standard deviation of the dependent variable. Nevertheless, the economic activity recovered soon after. The effect in the 3-week period immediately after the floods is even positive (14%) and statistically

[14] They evaluate a programme to reduce the gender gap in access to secondary school in the Indian state of Bihar comparing female enrolment in Bihar with male enrolment in the same state before and after the introduction of the policy. However, as male and female secondary school enrolment trends are fundamentally different, they further compare these differences with the difference between female and male secondary school enrolment in the neighbouring state of Jharkhand.

[15] Among the other sources of short-term year-specific seasonality, these effects should account for differences between years in lunar phases, which may affect the detected brightness from the satellite, and public holidays falling in different periods of the year, such as Easter.

significant at 5%, suggesting that the decline in economic activity in the weeks of the floods may have been partly compensated in the following weeks. This finding is consistent with the literature documenting an increase in nightlight activity related to relief and recovery efforts in the aftermath of natural disasters (as in Zhao et al., 2018) and will be better discussed in the Subsection 4.4.

Table 4 shows how these effects materialise when adding each set of control variables. Column (1) only includes municipality and 3-week period fixed effects. The results are a bit odd in this specification, as almost all the treatment effects are significant with alternating signs. Column (2) adds weather variables. The treatment variable in the 3-week period of the floods (indexed with 0) is quite stable between the two specifications, although the treatment coefficients after the floods become negative and the first treatment coefficient before the floods remains positive and statistically significant. Cloudiness is negatively related to recorded brightness, while visibility and windiness are positively related. The coefficient for temperature is also statistically significant, although with an unexpected negative sign. Column(3) adds the interaction between year and municipality fixed effects and 3-week period and municipality fixed effects. These effects control for municipality-specific trends both over annual and short-term horizons. Again, the coefficient for the 3-week period of the floods is quite stable, while there are some changes in the other treatment effects, all of which become positive and significant. The coefficients for cloudiness, visibility and windiness retain their sign and magnitude, while temperature is now positive but not statistically significant and the coefficient for the square of temperature becomes negative and significant, suggesting that nightlights increase with temperature but at a decreasing rate. The last column, Column (4), shows the most demanding specification also reported in Figure 7. Adding year and 3-week period fixed effects, all the coefficients for treatment variables before the floods and from the second period after the floods become smaller in magnitude and not significant. Instead, the treatment coefficients for the 3-week period of the floods and the 3-week period after, as well as the weather variables, retain their magnitude and statistical significance. Thus, all the batteries of time-varying controls and fixed effects are needed to obtain nil pre-trends.

Before moving to the next subsections, we also test our empirical choice of pooling the data over three weeks. The left panel of Figure 8 replicates the triple difference empirical strategy over 2-week periods, while the right panel of Figure 8 shows the results over 4-week periods. While our results are basically confirmed, it is important to note that the choice of the time horizon is highly relevant in highlighting the effect of interest. By pooling the data over 2-week periods we still find nil pre-trends before the first flood and a negative impact in the 2-weeks of the first flood. However, the coefficient for the second flood is only slightly negative and not statistically different from zero, as it partly absorbs the rebound effect observed from the first week after the second flood. To the same extent, pooling the data over 4-week periods still produces a null pre-trend, but adding the first week after the second flood to the 3-week period of the floods dilutes the overall negative effect on the 4-week period of the floods.

4.3 Other data sources tracking economic activity

We now check the robustness of our results using other high-frequency data sources tracking economic activity at the municipal level. Column (1) of Table 5 and the top panel of Figure 9 show the coefficients of the triple difference strategy outlined above using hiring data as the dependent variable without controlling for weather variables. We find a decrease in hiring of 25% in the 3-week period of the floods and a decline of a similar magnitude in the 3-week period after (about 16% of the standard deviation of the dependent variable). In the second 3-week period after the floods the coefficient goes back to 0. Adding weather variables decreases the precision of the estimates (Column 2), even though the magnitude of the coefficients in the 3-week period of the floods and in the 3-week period after decreases only slightly.

In the following four columns of Table 5, results are reported separately for the agricultural sector (Columns 3 and 4 and the bottom left panel of Figure 9) and the private non-agricultural sector (Columns 5 and 6 and the bottom right panel of Figure 9). Focusing on agriculture, the negative effects in the 3-week period of the floods and in the 3-week period after the floods are larger than those estimated for the whole economy and survive to the introduction of weather variables (at least in the 3-week period of the floods). Thus, the two floods led to a 48% reduction in hiring in the 3-week period of the floods and a 40% reduction in the subsequent period (37% and 31% of the standard deviation of the dependent variable, respectively). These effects are not detectable in the private non-agricultural sector.[16] These findings are broadly confirmed by replicating the analysis on net hiring data (Table A.1 and Figure A.1 in the Appendix).

Overall, nightlight data are less suitable for tracking economic activity in agriculture than in industry and private services (Chen and Nordhaus, 2019; Gibson and Boe-Gibson, 2021), so looking at nightlight data alone may underestimate the overall impact of the two floods on the economy. Nevertheless, in the present context the negative effect on hiring in agriculture disappears in the second 3-week period after the floods, suggesting that the negative effect in this sector was also short-lived.

The top panel of Figure 10 and Column (1) of Table 6 shows the impact of the two floods on road traffic, measured as the number of vehicles passing through each municipality per day. The

[16] In fact, anecdotal evidence suggests that some of the people hired in the private non-agricultural sector during the days of the floods were employed in cleaning and restoring damaged buildings and machinery before returning to business.

treated municipalities experienced a statistically significant 13% decrease in daily traffic in the 3-week period of the floods, a non-statistically significant 10% decrease in the 3-week period after the floods, and no differential effect from the second period after the floods. Again, including weather variables in Column (2) does not alter the overall result. The road traffic data provided by the ER region also allow to distinguish between light and heavy vehicles, i.e. cars and trucks. Indeed, car traffic is mainly related to people travelling for work or leisure, while truck movements are more related to the transport of goods and manufacturing activity.[17] Columns (3) and (4) of Table 6 and the bottom left panel of Figure 10 report the results of the triple difference design for heavy vehicles, while Columns (5) and (6) and the bottom right panel of Figure 10 report the results for light vehicles. Interestingly, the effect is fairly evenly distributed between the two, although the number of heavy vehicles recovered earlier than the number of light vehicles.[18]

All in all, these results are consistent with the soft information we collected from firms and employers' associations, which suggests that the two floods had a severe impact on some private individuals and firms in the short term, but that the recovery was quite rapid, with most of economic activity being restored within a month.

4.4 The impact of the two floods on economic activity

The final step of this analysis consists in back-of-the-envelope calculations to determine the impact of the two floods on GDP. As discussed in Section 3, since the direction of the bias in the true elasticity of GDP to nightlights is unclear, we rely on a range of elasticities between 0.18 and 0.42. This range is derived from direct evidence related to our context, as well as from estimates available in the literature.

Given these bounds, a 16% loss in nightlights translates into a loss in GDP growth in flooded municipalities of between 2.9% and 6.7% over the three weeks of flooding. We do not know whether the increase in lighting in the 3-week period after the floods can be attributed to the actual economic activity needed to clean up the buildings and to rebuild damaged infrastructure, so that it can be regarded as actual economic growth, or whether it is due to private, unpaid recovery efforts. While the truth probably lies somewhere in the middle, we consider a worst-case scenario in which the estimated decline in nightlights in the 3-week period of the floods continues into the 3-week period after the floods. We exclude a longer duration of the impact of the floods on economic activity,

[17] As explained in Section 2, the flooded areas are located on a major traffic hub connecting the central and south-eastern coast with the industrial north. Unfortunately, it is not possible to distinguish between the number of vehicles merely passing through the area without direct connection with local economic activity.

[18] Nevertheless, the early readjustment of heavy vehicles may also be due to the relief and recovery efforts following the two floods.

as the results for hiring and road traffic data broadly confirm what we observe for nightlights, i.e. that the bulk of the economic activity recovered from the second 3-week period after the floods.

In this pessimistic scenario, the loss of GDP growth in the flooded municipalities is between 5.8% and 13.4% over a 6-week period, i.e. between 0.3% and 0.8% over an annual horizon. Considering that in 2023 flooded municipalities accounted for 22% of the regional value added in the private non-agricultural sector, this implies a reduction in regional GDP growth in 2023 of between 0.1% and 0.2%, i.e. between 3 and 5 million euros.[19] Thus, the overall impact on economic activity was rather limited compared to the 10 billion of direct damage inflicted to buildings and infrastructure. The impact could have been even smaller if we partly take into account the rebound effect we observe in the 3-week period after the floods. On the other hand, as shown in Section 3.2, nightlight data are a poor proxy for agricultural value added, so that these results may not take into account the loss of GDP in this sector. Nevertheless, agriculture accounts for only about 2% of GDP in ER. As hiring in agriculture recovered in the second 3-week period after the floods, the underestimation of the loss in regional annual GDP is likely to be quite limited.

5 The impact of ER floods on the housing market

We now turn to the impact of the floods on the housing market. Although economic activity can influence housing market dynamics, the underlying fundamentals are basically different. There is considerable evidence in the literature suggesting that house values are also influenced by permanent neighbourhood characteristics such as amenities, infrastructure, fast connections to the city centres (see for instance Ahlfeldt et al., 2015), which are unlikely to change in the short term. For this reason, in this part of the analysis we simply apply a difference-in-differences design similar to that in Equation 2 and provide evidence from a triple difference setting as a robustness in the Appendix.

5.1 Main results

As discussed in Section 3, we exploit the weekly time frequency of the data and collapse the ad characteristics to the municipality level. The following equation is estimated using data for 2023:

$$\begin{aligned} Ln(HM)_{m,w} = &\sum_{w=-10}^{-2} \beta_w T_m \times W_w + \sum_{w=0}^{20} \beta_w T_m \times W_w + \\ &+ \lambda_m + \lambda_w + \phi_{m,w} \end{aligned} \tag{5}$$

where HM are four different outcome variables of interest: average price asked by sellers, number of ads, daily online visits per ad, daily contact requests from potential buyers per ad. As before,

[19] These values are calculated from real regional GDP growth. The current values of GDP are deflated by the regional consumer price index (Nic), using 2022 as the reference year for prices.

m indexes the municipalities, w indexes the week of interest, T_m is a dummy variable equal to 1 for flooded municipalities and W_w are weekly time dummies. We also control for municipality and week fixed effects, λ_m and λ_w, while $\phi_{m,w}$ is the error term. The event study is normalised with respect to the first week before the first flood and the estimates are weighted according to a propensity score based on municipality characteristics, as in the previous section. Standard errors are robust and clustered at the municipality level.

Figure 11 and Table 7 show the results. There is basically no effect on the prices asked by the sellers and on the number of ads.[20] Then, we also test whether, compared to control municipalities, treated municipalities show a differential number of advertisements added to or removed from the platform every week before and after the floods.[21] A decrease in the number of advertisements added or an increase in the number of those removed in treated municipalities with respect to controls may indicate a reduction in the willingness to sell following the floods. Instead, a decrease in the number of advertisements removed may suggest that it takes longer to sell properties. Results are reported in Figure A.3 in the Appendix. There are no differential effects in either dimension. However, we find a strong decrease in the number of daily online visits in the week of the second flood and in the week immediately after (up to 20%, 67% of the standard deviation of the dependent variable), which gradually recovers within 8 weeks after the second flood. The same is true for contact requests from potential buyers (we find a reduction of up to 26%, 43% of the standard deviation of the dependent variable).

Figures 12 and 13 show the heterogeneity of such effects across housing units on the ground floor and on upper floors. Particularly, we define the former category as including not only flats at or below the ground level, but also independent villas and terraced houses. Housing units on upper floors are defined as the residual category with respect to those on ground floor and represent almost 50% of the sample. While there are no price effects in either category, ground floor housing units experience a temporary decline in the number of advertisements. In an unreported check, we find that this result is mainly related to a small and statistically not signicant decrease in the number of advertisements added to the platform in the weeks immediately following the floods,

[20] As shown in Figure A.2 in the Appendix, the decrease in relative prices from the week of the first flood to the third week after the second flood is mainly related to price dynamics in the control municipalities and cannot be attributed to the floods.

[21] We consider an advertisement to have been added in a given week if it was not present on the platform the previous week. Similarly, we consider an advertisement to have been removed if it is not present on the platform the following week. It is important to note that this analysis is likely to be affected by significant measurement error, given that, as emphasised in footnote 5, we cannot see whether ads are visible or hidden on the platform. Therefore, it is possible that an ad is removed after it has already been hidden for several weeks. Furthermore, this analysis is carried out in units rather than in logarithms due to the large number of observations equalling 0. A proper analysis of the duration that advertisements remain on the platform would require different empirical techniques (see for instance Cox, 1972).

as well as to a slight increase in the number of advertisements removed from the platform. These effects suggest a temporary reduction in the propensity to sell housing units at the ground floor. However, the difference in the number of advertisements between treated and control municipalities returns to pre-event levels within approximately two months. Also, the decline in the number of daily online visits and contact requests from potential buyers is stronger for ground floor housing units than for flats on upper floors.

Overall, the impact of the two floods on the housing market was only temporary. Nevertheless, some caution is needed in interpreting these results. First, we only observe posted prices, not actual transaction prices. Indeed, sellers may be willing to accept a lower price after bargaining with buyers. This may be particularly true after a flood. Second, these floods may contribute to long run changes in perceptions about the riskiness of the area, thus affecting the housing market in the long run, as the results by Bellaver et al. (2025) suggest. Our analysis is only limited to the short run. Finally, we do not observe private and public investments in mitigation measures. Indeed, the lack of a short-term effect of the floods on the housing market may be also related to the implementation of flood prevention measures, such as the construction of artificial barriers.

5.2 Robustness checks

It is also important to stress that our results are not driven by the aggregation of observations at the municipality level. In order to check whether the flooded municipalities show relevant within-municipality variation in the prices asked by sellers, we use the latitude and longitude of housing units to calculate their distance from the flooded areas as reported by the satellite imagery. Since satellite imagery is less effective in detecting flooding in built-up areas rather than in rural areas, we make different assumptions about the actual distance of housing units from flooded areas. In the first scenario, we consider all the housing units within a neighbourhood of 500 meters from the flooded areas as treated and those located further than 1 kilometer as controls. In the second scenario, we regard all the housing units within a neighbourhood of 1 kilometer from the flooded areas as treated and those located further than 2 kilometers as controls. We remove housing units between 500 meters and 1 kilometer in the first scenario and those between 1 and 2 kilometers in the second scenario to avoid possible spillovers of treatement to control units. We then estimate the following event study regression:

$$Ln(Price)_{h,w} = \sum_{w=-10}^{-2} \beta_w T_h \times W_w + \sum_{w=0}^{20} \beta_w T_h \times W_w + \lambda_h + \lambda_w + e_{h,w} \tag{6}$$

where the notation is the same as in the previous equation, but now the dependent variable of interest is the price asked by the seller as reported in the online ad, h is the housing unit subscript,

λ_h are housing unit fixed effects and $e_{h,w}$ is an error term. Housing unit fixed effects control for all the time invariant housing unit characteristics reported in the ad, such as floor number, size, number of rooms, etc. The event study is normalised with respect to the week before the first flood. Standard errors are robust to heteroskedasticity and autocorrelation. Figure 14 shows the results. Indeed, in both scenarios there is little variation in asked prices and no trends before and after the floods. Thus, we can exclude substantial within-municipality variation in asked prices after the two floods.

Finally, Figure A.4 in the Appendix shows the main results exploiting the variation in housing market dynamics in treated and control municipalities in 2022 and in 2023 and replicating the analysis in the previous subsection in a triple difference-in-differences setting. The results are basically the same, although in this context controlling for the interaction between week and year fixed effects absorbs much of the variation in housing demand, confirming the short-term impact of the two floods.

6 Conclusive remarks

This paper investigates the impact of the two floods that hit the Emilia-Romagna region in May 2023. We proxy economic activity with nightlight data and develop an empirical framework to adequately control for trends and seasonality in the data. The negative effect in the three weeks of the two floods is likely to have been partially offset in the following three weeks and we find no effect thereafter. The dynamics of these results are broadly confirmed by the data on hiring and road traffic. We cannot rule out a significant impact on agriculture, although the hiring data suggest that this effect lasted at most 6 weeks, as did the overall impact on GDP growth. In the worst-case scenario, our results suggest a reduction in regional GDP growth in 2023 of between 0.1% and 0.2%, i.e. between 3 and 5 million euros. Finally, we find no lasting impact on the housing market. The prices asked by the sellers and the number of advertisements were not affected, while the decline in housing demand, measured by the number of online visits and the number of contact requests from potential buyers, recovered within approximately two months after the second flood.

This analysis highlights the data and the empirical methods that can be used to rapidly assess the impact of geographically localised floods on overall economic activity and housing market dynamics. The value of foregone GDP growth can be added to the direct quantification of the flood damage to buildings and infrastructure to provide a more comprehensive assessment of the impact of a natural disaster. Nightlight data have proved useful in assessing the overall impact of the two floods on economic growth, because of their high temporal and geographical granularity and their ability to improve the causal identification of the effects, as a simple pre-post comparison between treatment and control groups would not be sufficient to disentangle the impact of the two floods from municipal and year-specific short-term seasonality in economic activity. Further research is needed to show whether these data can provide interesting insights into more destructive events whose effects may last for longer. The lack of long-lasting effects on the housing market suggests that house prices in flooded areas already discount the costs of such natural events.

References

Addoum, J. M., Eichholtz, P., Steiner, E., and Yönder, E. (2024). Climate change and commercial real estate: Evidence from Hurricane Sandy. *Real Estate Economics*, 52(3):687–713.

Ahlfeldt, G. M., Redding, S. J., Sturm, D. M., and Wolf, N. (2015). The economics of density: Evidence from the Berlin Wall. *Econometrica*, 83(6):2127–2189.

Bellaver, A., Costantini, L., Fosch, A., Monticelli, A., Scala, D., and Pangallo, M. (2025). Floods do not sink prices, historical memory does: How flood risk impacts the Italian housing market. *Mimeo.*

Benetton, M., Emiliozzi, S., Guglielminetti, E., Loberto, M., and Mistretta, A. (2023). Does climate change adaptation matter? Evidence from the city on the water. *Mimeo.*

Bin, O. and Landry, C. E. (2013). Changes in implicit flood risk premiums: Empirical evidence from the housing market. *Journal of Environmental Economics and Management*, 65(3):361–376.

Bluhm, R. and McCord, G. C. (2022). What can we learn from nighttime lights for small geographies? Measurement errors and heterogeneous elasticities. *Remote Sensing*, 14(5):1190.

Bosker, M., Garretsen, H., Marlet, G., and van Woerkens, C. (2019). Nether lands: Evidence on the price and perception of rare natural disasters. *Journal of the European Economic Association*, 17(2):413–453.

Bruederle, A. and Hodler, R. (2018). Nighttime lights as a proxy for human development at the local level. *PloS one*, 13(9):e0202231.

Chen, X. and Nordhaus, W. D. (2019). VIIRS nighttime lights in the estimation of cross-sectional and time-series GDP. *Remote Sensing*, 11(9):1057.

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society: Series B (Methodological)*, 34(2):187–202.

Doll, C. N., Muller, J.-P., and Morley, J. G. (2006). Mapping regional economic activity from night-time light satellite imagery. *Ecological Economics*, 57(1):75–92.

Elliott, R. J., Strobl, E., and Sun, P. (2015). The local impact of typhoons on economic activity in China: A view from outer space. *Journal of Urban Economics*, 88:50–66.

Elvidge, C. D., Baugh, K., Zhizhin, M., Hsu, F. C., and Ghosh, T. (2017). VIIRS night-time lights. *International Journal of Remote Sensing*, 38(21):5860–5879.

Elvidge, C. D., Baugh, K. E., Kihn, E. A., Kroehl, H. W., Davis, E. R., and Davis, C. W. (1997). Relation between satellite observed visible-near infrared emissions, population, economic activity and electric power consumption. *International Journal of Remote Sensing*, 18(6):1373–1379.

Gandhi, S., Kahn, M. E., Kochhar, R., Lall, S., and Tandel, V. (2022). Adapting to flood risk: Evidence from a panel of global cities. *NBER Working Paper*, 30137.

Gibson, J. (2021). Better night lights data, for longer. *Oxford Bulletin of Economics and Statistics*, 83(3):770–791.

Gibson, J. and Boe-Gibson, G. (2021). Nighttime lights and county-level economic activity in the United States: 2001 to 2019. *Remote Sensing*, 13(14):2741.

Gibson, J., Kim, B., and Li, C. (2024). Luminosity and local economic growth. *University of Waikato Working Paper*, 8.

Gibson, J., Olivia, S., Boe-Gibson, G., and Li, C. (2021). Which night lights data should we use in economics, and where? *Journal of Development Economics*, 149:102602.

Giglio, S., Maggiori, M., Rao, K., Stroebel, J., and Weber, A. (2021). Climate change and long-run discount rates: Evidence from real estate. *The Review of Financial Studies*, 34(8):3527–3571.

Heger, M. P. and Neumayer, E. (2019). The impact of the Indian Ocean tsunami on Aceh's long-term economic growth. *Journal of Development Economics*, 141:102365.

Henderson, J. V., Storeygard, A., and Weil, D. N. (2012). Measuring economic growth from outer space. *American Economic Review*, 102(2):994–1028.

Khachiyan, A., Thomas, A., Zhou, H., Hanson, G., Cloninger, A., Rosing, T., and Khandelwal, A. K. (2022). Using neural networks to predict microspatial economic growth. *American Economic Review: Insights*, 4(4):491–506.

Kim, J., Kim, K., Park, S., and Sun, C. (2023). The economic costs of trade sanctions: Evidence from North Korea. *Journal of International Economics*, 145:103813.

Kocornik-Mina, A., McDermott, T. K., Michaels, G., and Rauch, F. (2020). Flooded cities. *American Economic Journal: Applied Economics*, 12(2):35–66.

Levin, N., Kyba, C. C., Zhang, Q., de Miguel, A. S., Román, M. O., Li, X., Portnov, B. A., Molthan, A. L., Jechow, A., Miller, S. D., et al. (2020). Remote sensing of night lights: A review and an outlook for the future. *Remote Sensing of Environment*, 237:111443.

Loberto, M. and Russo, R. (2024). The exposure of italian manufacturing firms to hydrogeological risk. *Bank of Italy Occasional papers*, 899.

Michalopoulos, S. and Papaioannou, E. (2018). Spatial patterns of development: A meso approach. *Annual Review of Economics*, 10(1):383–410.

Muralidharan, K. and Prakash, N. (2017). Cycling to school: Increasing secondary school enrollment for girls in India. *American Economic Journal: Applied Economics*, 9(3):321–350.

Nguyen, C. N. and Noy, I. (2020). Measuring the impact of insurance on urban earthquake recovery using nightlights. *Journal of Economic Geography*, 20(3):857–877.

OECD (2016). Financial management of flood risk. OECD Publishing, Paris.

Ortega, F. and Taşpınar, S. (2018). Rising sea levels and sinking property values: Hurricane Sandy and New York's housing market. *Journal of Urban Economics*, 106:81–100.

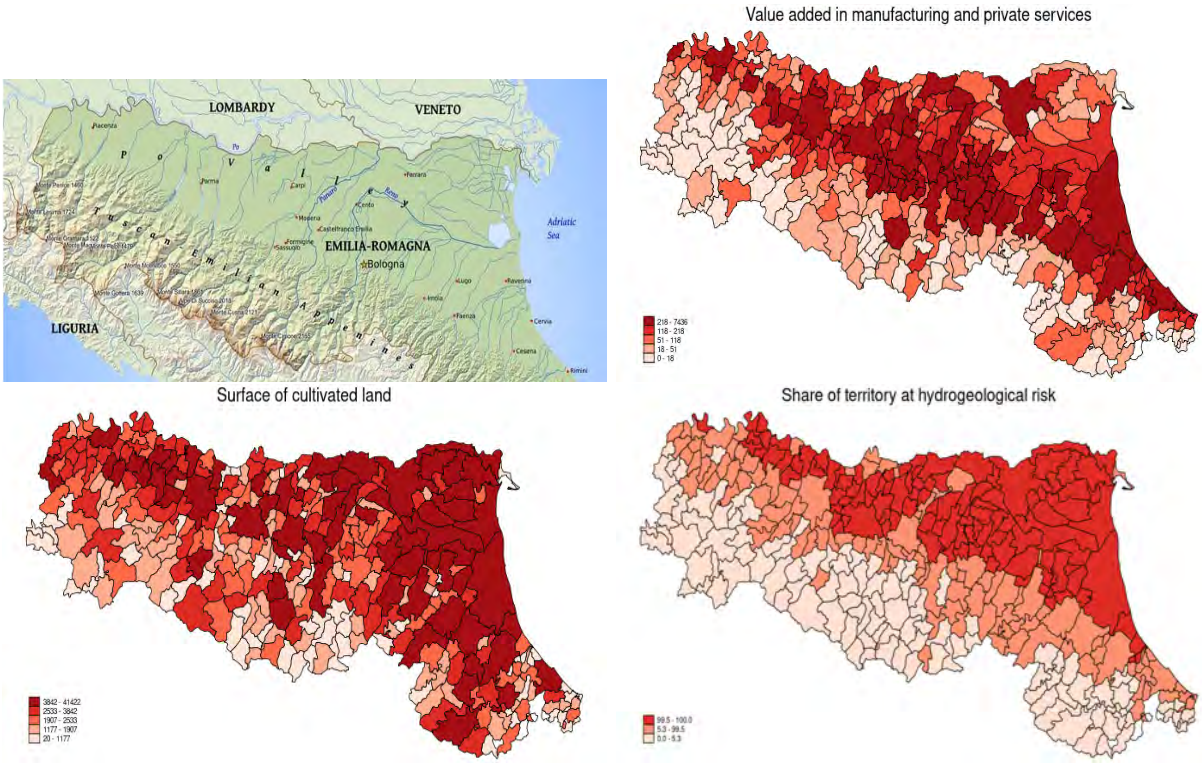
Román, M. O. and Stokes, E. C. (2015). Holidays in lights: Tracking cultural patterns in demand for energy services. *Earth's Future*, 3(6):182–205.

Trigila, A., Iadanza, C., Lastoria, B., Bussettini, M., and Barbano, A. (2021). Dissesto idrogeologico in Italia: pericolositá e indicatori di rischio - Edizione 2021. *ISPRA, Rapporti*, 356.

Yi, D. and Choi, H. (2020). Housing market response to new flood risk information and the impact on poor tenant. *The Journal of Real Estate Finance and Economics*, 61(1):55–79.

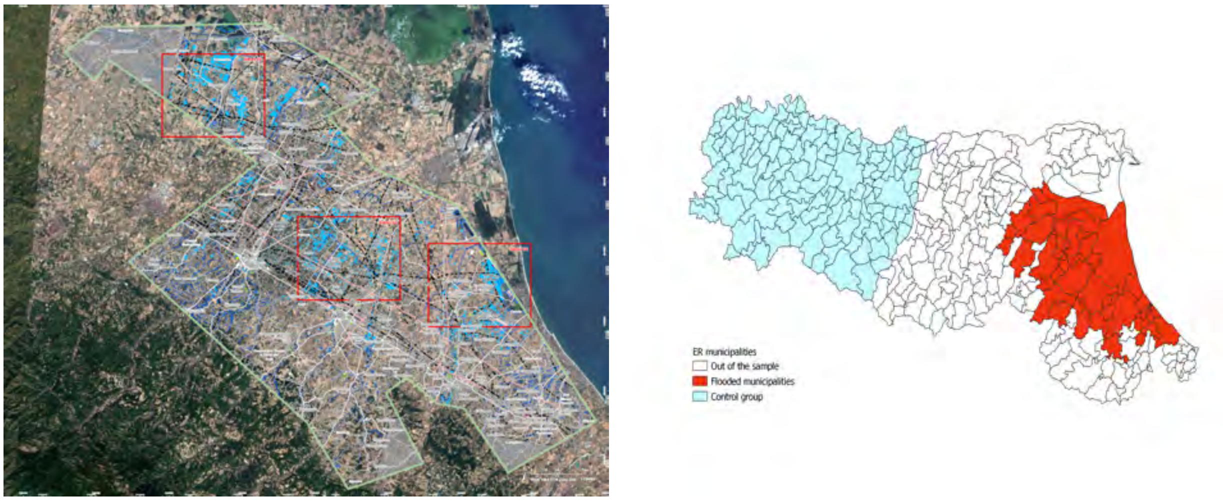
Zhao, X., Yu, B., Liu, Y., Yao, S., Lian, T., Chen, L., Yang, C., Chen, Z., and Wu, J. (2018). NPP-VIIRS DNB daily data in natural disaster assessment: Evidence from selected case studies. *Remote Sensing*, 10(10):1526.

Figure 1: Physical and economic geography of the ER region



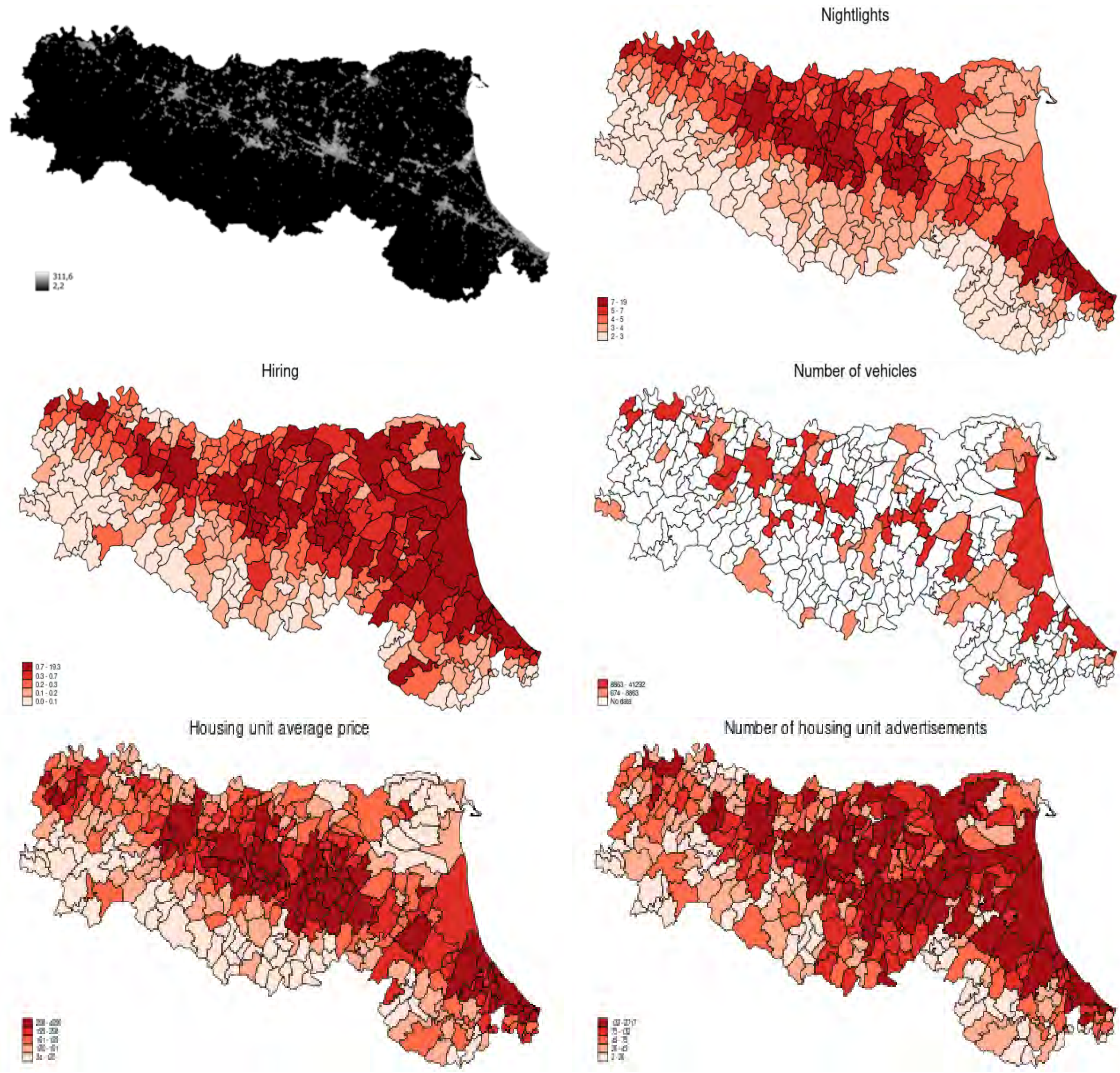
Notes - The map on the top left shows the physical geography of ER. The map on the top right shows the distribution of value added in the private non-agricultural sector in million euro. The data refer to 2020 and are provided by the Italian National Statistics Institute (Istat). The map on the bottom left shows the distribution of hectares of cultivated land. The data come from the 2010 Istat agricultural census. The map on the bottom right shows the share of the municipal territory at medium-high hydrogeological risk according to Trigila et al. (2021).

Figure 2: Maps of flooded municipalities



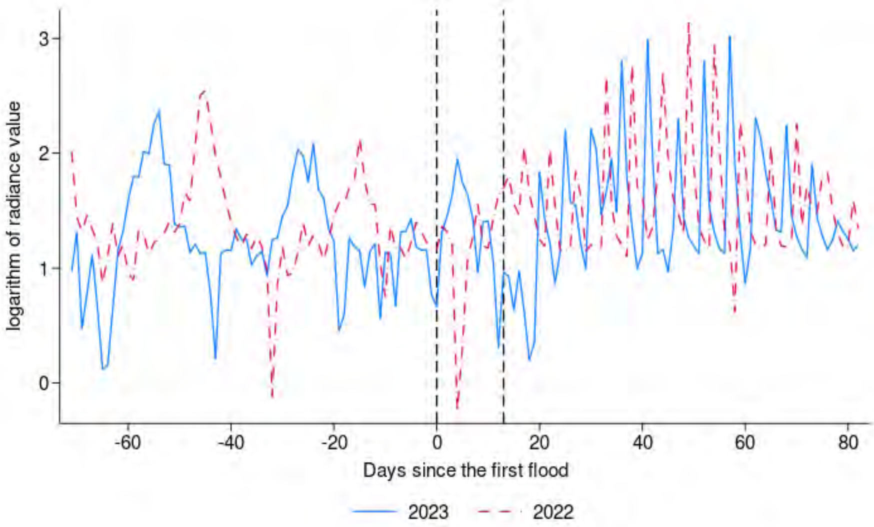
Notes - The left panel shows an example of the Rapid Mapping provided by the Copernicus Emergency Management Service. The reported imagery refers to the first delination of the flood made on May 17^{th}. The right panel shows a map of the ER municipalities in the treated and control groups of the empirical analysis. In red are depicted the flooded municipalities, defined according to the satellite imagery released by the Rapid Mapping on May 19^{th}, 21^{st} and 22^{nd}, in blue are the municipalities chosen as control group, since they belong to the furthest provinces of the ER region with respect to the affected municipalities.

Figure 3: Maps of the outcome variables of interest



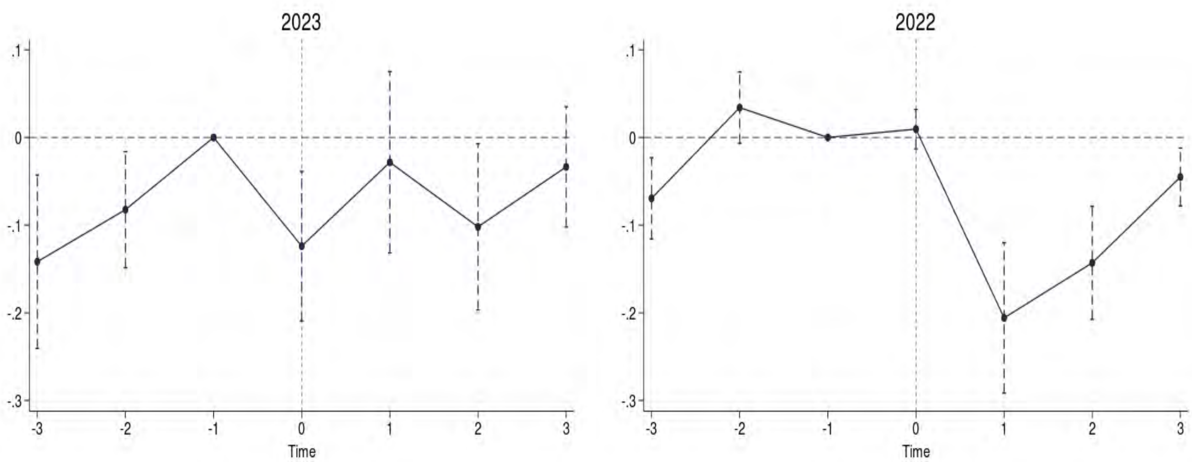
Notes - The map on the top left shows the distribution of nightlight data in radiance units on July 2023, 9^{th}. The map on the top right shows the distribution of nightlight data averaged over all the observations in the period of interest at the municipal level. The map in the centre left shows the average number of daily employment contracts activated at the municipal level over the period of interest. The contract types considered for hiring data are permanent contracts, fixed-term contracts and apprenticeships. Contracts in the public sector and domestic work are excluded from the sample. The map on the centre right shows the average daily number of vehicles passing through each municipality during the period of interest. Data from monitoring stations that are not consistently active throughout the period of interest are excluded from the sample. The maps at the bottom show the average housing unit prices and number of ads over the period of interest.

Figure 4: Logarithm of nightlight values per day in the ER region



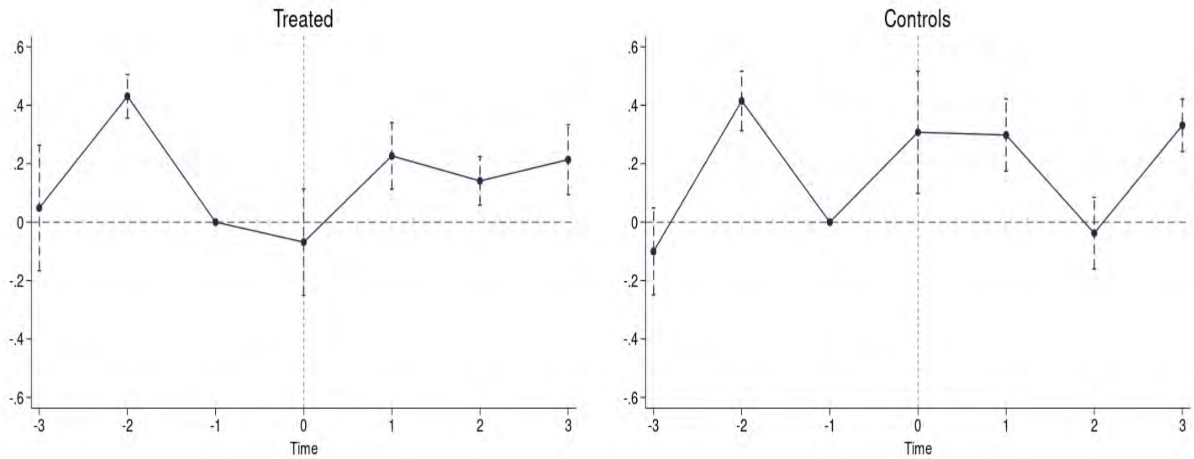
Notes - Logarithm of nightlight values at daily frequency in 2022 and in 2023 for the whole ER region. Nightlight values in the sample are trimmed at the first and the last percentile of their distribution. The two vertical lines refer to May, 2^{nd} and May, 15^{th}, the first days of the two floods.

Figure 5: Impact of 2023 ER floods on nightlight data: treated vs. control municipalities



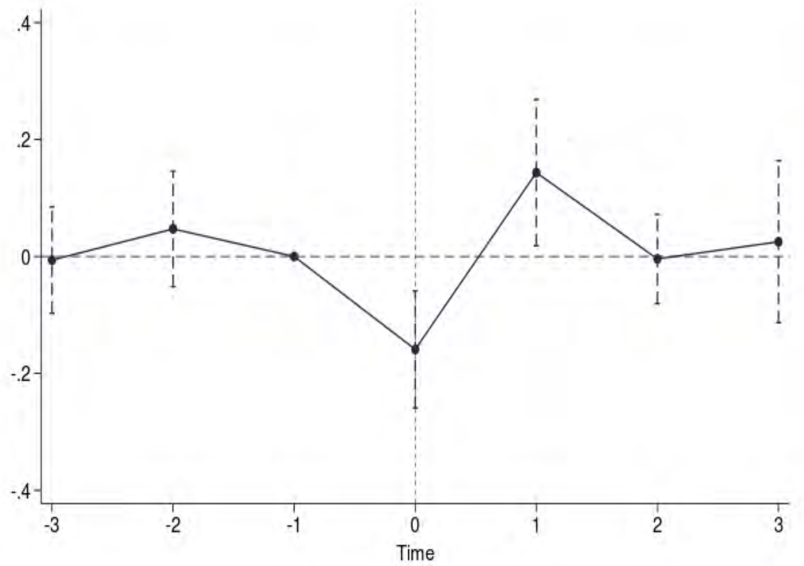
Notes - The two event studies are carried out separately for 2022 and 2023. Each event study is normalised with respect to the first 3-week period before the floods. The reported coefficients refer to the interactions between a dummy equal to 1 for flooded municipalities and a dummy equal to 1 for each 3-week period in the sample. The dependent variable is the logarithm of the nightlight values, while the time-varying control variables are cloudiness, temperature, temperature squared, visibility, humidity and windiness. The regressions include municipality fixed effects and 3-week period fixed effects. The regressions are weighted according to a propensity score obtained by regressing the treatment dummy on a vector of municipality characteristics including altitude, degree of urbanisation, area, share of workers in manufacturing, share of workers in trade, share of workers in hotels and restaurants, share of land at medium-high hydrogeological risk, share of land at medium-high landslide risk and population at the beginning of 2023. Point estimates are reported with 95% confidence intervals. Standard errors are robust and clustered at the municipality level.

Figure 6: Impact of 2023 ER floods on nightlight data: year 2022 vs. 2023



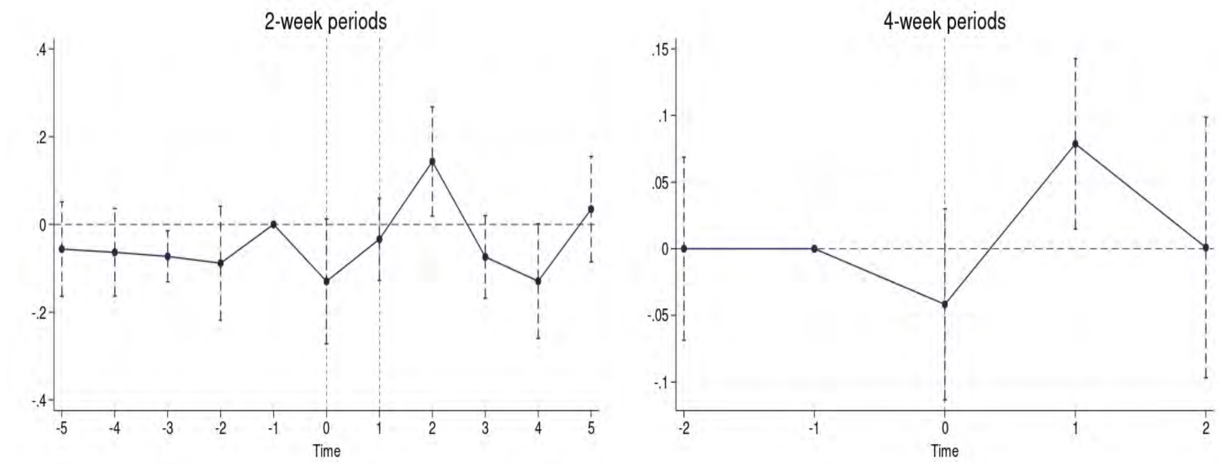
Notes - The two event studies are carried out separately for treated and control municipalities. Each event study is normalised with respect to the first 3-week period before the floods. The reported coefficients refer to the interactions between a dummy equal to 1 for 2023 and a dummy equal to 1 for each 3-week period in the sample. The dependent variable is the logarithm of the nightlight values, while the time-varying control variables are cloudiness, temperature, temperature squared, visibility, humidity and windiness. The regressions include municipality fixed effects, 3-week period fixed effects, year fixed effects, the interaction between municipality and year fixed effects and the interaction between municipality and 3-week period fixed effects. Point estimates are reported with 95% confidence intervals. Standard errors are robust and clustered at the municipality level.

Figure 7: Impact of 2023 ER floods on nightlight data: triple differences



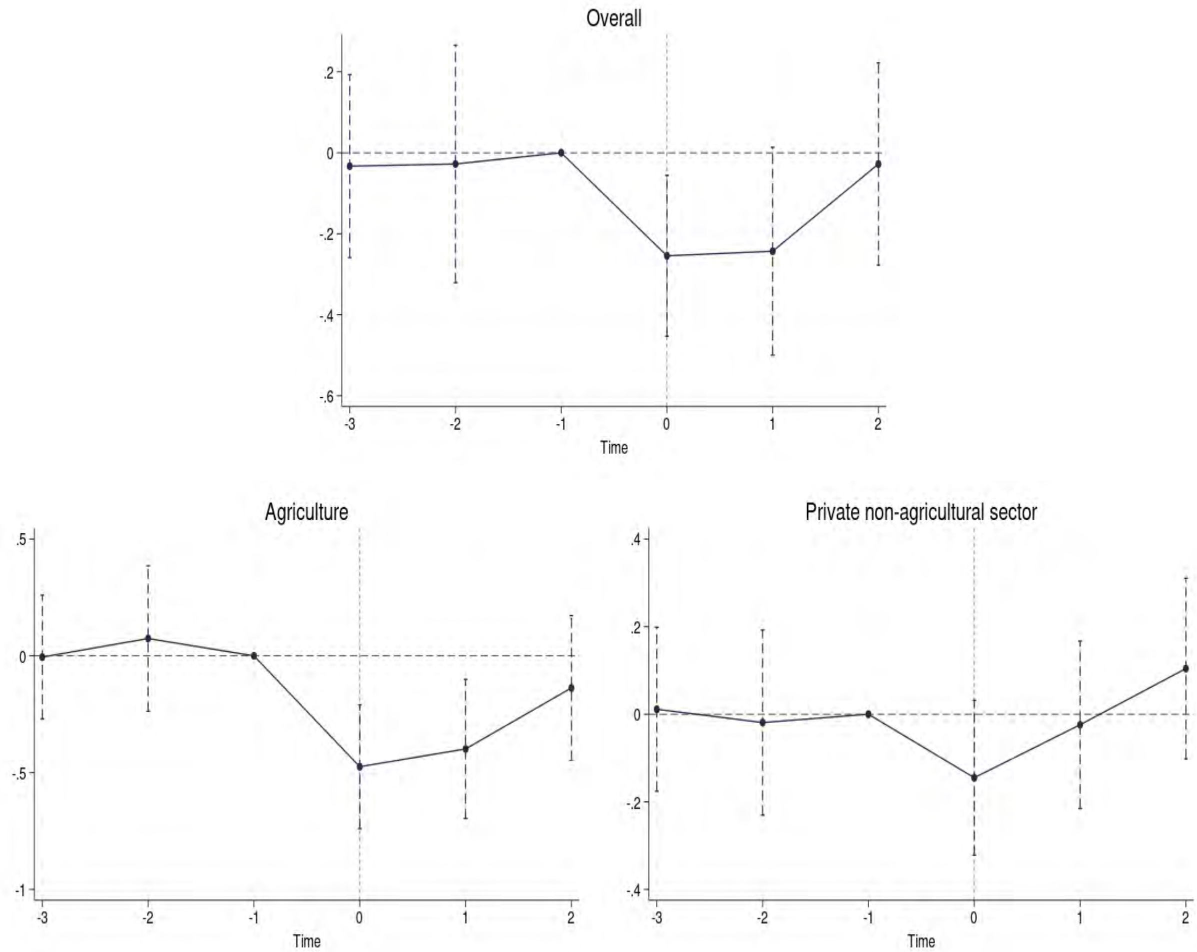
Notes - The event study is normalised with respect to the first 3-week period before the floods. The reported coefficients refer to the interactions between a dummy equal to 1 for flooded municipalities, a dummy equal to 1 for 2023 and a dummy equal to 1 for each 3-week period in the sample. The dependent variable is the logarithm of the nightlight values, while the time-varying control variables are cloudiness, temperature, temperature squared, visibility, humidity and windiness. The regressions include municipality fixed effects, 3-week period fixed effects, year fixed effects, the interaction between municipality and year fixed effects, the interaction between municipality and 3-week period fixed effects and the interaction between year and 3-week period fixed effects. The regressions are weighted according to a propensity score obtained by regressing the treatment dummy on a vector of municipality characteristics including altitude, degree of urbanisation, area, share of workers in manufacturing, share of workers in trade, share of workers in hotels and restaurants, share of land at medium-high hydrogeological risk, share of land at medium-high landslide risk and population at the beginning of 2023. Point estimates are reported with 95% confidence intervals. Standard errors are robust and clustered at the municipality level.

Figure 8: Impact of 2023 ER floods on nightlight data: triple differences for different time periods



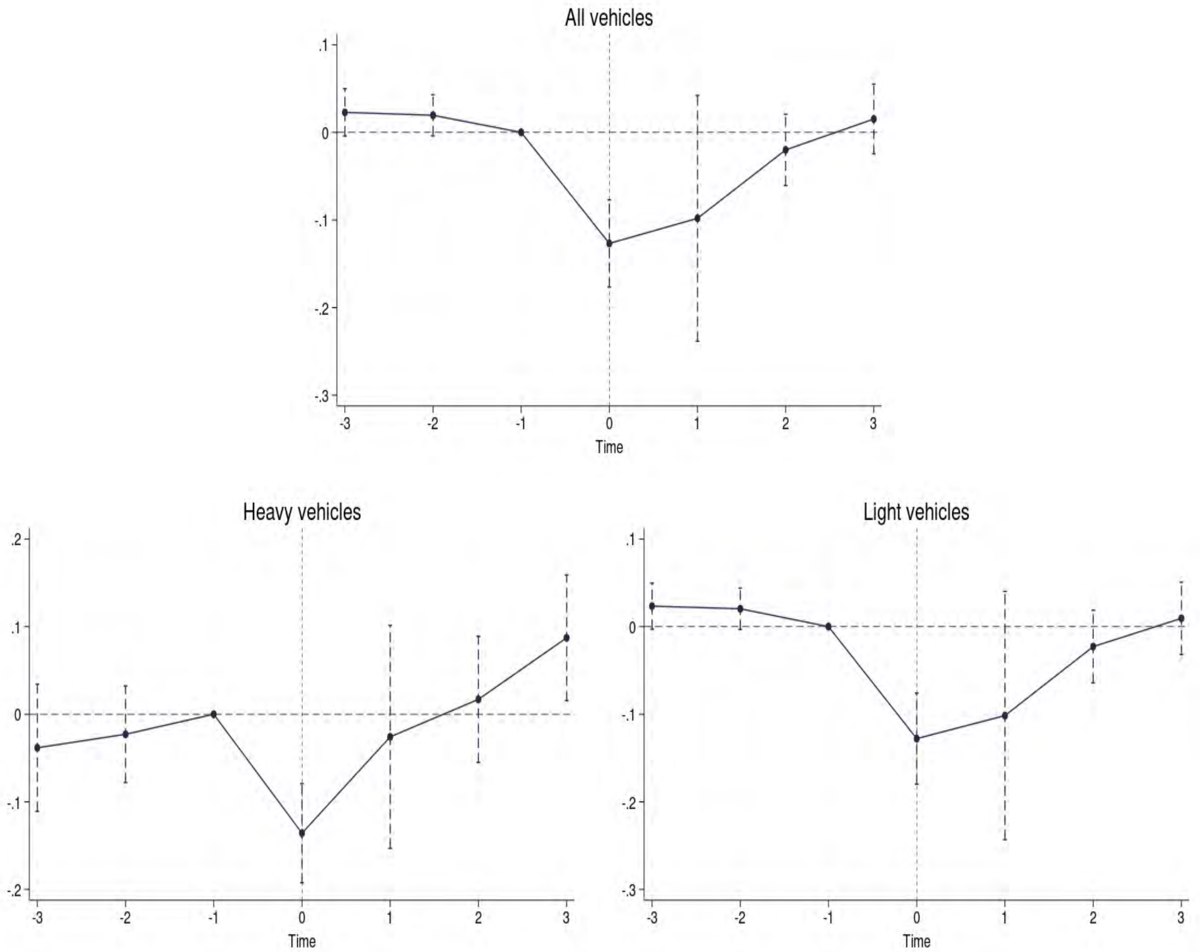
Notes - The event study is normalised with respect to the first period before the floods. The reported coefficients refer to the interactions between a dummy equal to 1 for flooded municipalities, a dummy equal to 1 for 2023 and a dummy equal to 1 for each period in the sample. The dependent variable is the logarithm of the nightlight values averaged over 2-week periods in the left panel, averaged over 4-week periods in the right panel. The time-varying control variables are cloudiness, temperature, temperature squared, visibility, humidity and windiness. The regressions include municipality fixed effects, period fixed effects, year fixed effects, the interaction between municipality and year fixed effects, the interaction between municipality and period fixed effects and the interaction between year and period fixed effects. The regressions are weighted according to a propensity score obtained by regressing the treatment dummy on a vector of municipality characteristics including altitude, degree of urbanisation, area, share of workers in manufacturing, share of workers in trade, share of workers in hotels and restaurants, share of land at medium-high hydrogeological risk, share of land at medium-high landslide risk and population at the beginning of 2023. Point estimates are reported with 95% confidence intervals. Standard errors are robust and clustered at the municipality level.

Figure 9: Impact of 2023 ER floods on hiring



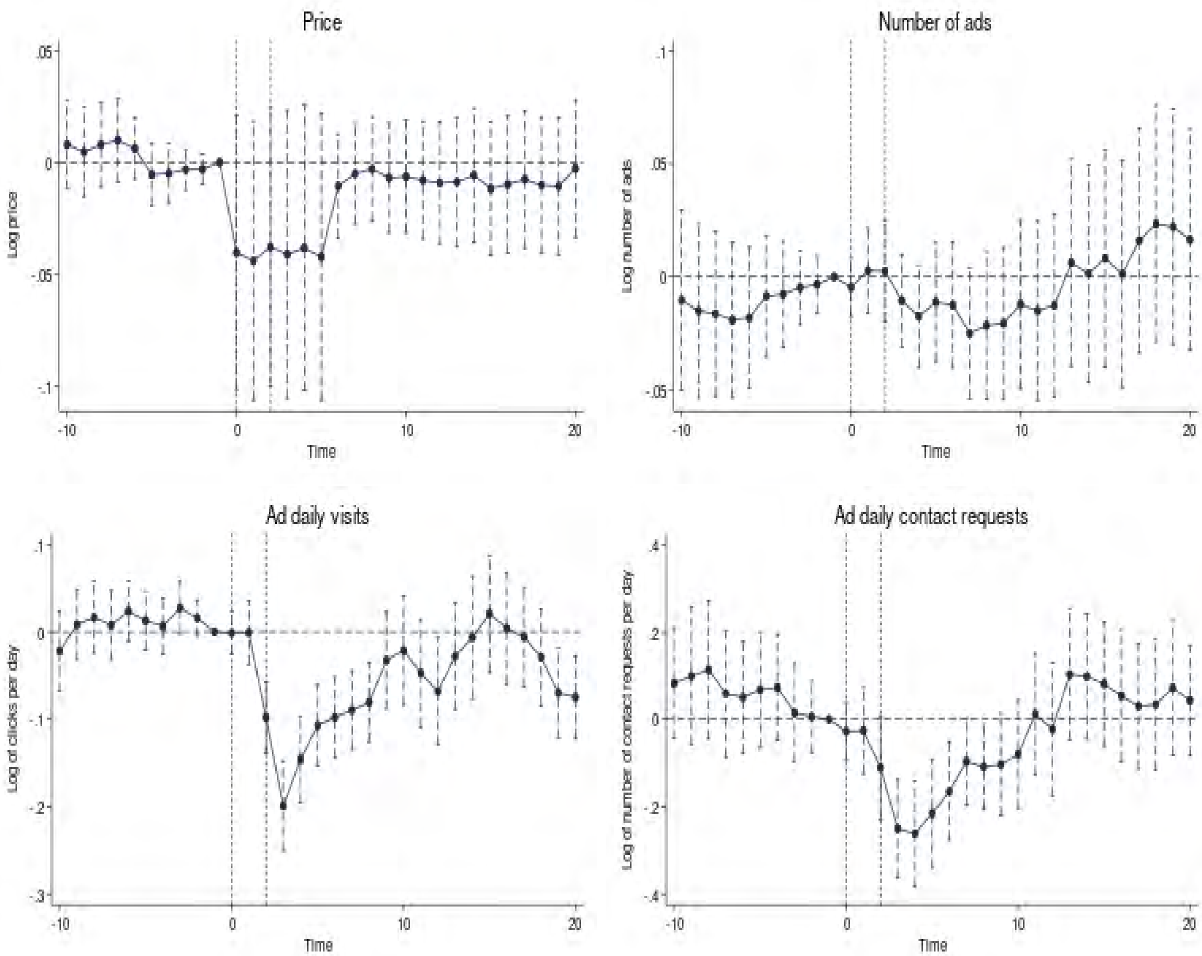
Notes - The event study is normalised with respect to the first 3-week period before the floods. The reported coefficients refer to the interactions between a dummy equal to 1 for flooded municipalities, a dummy equal to 1 for 2023 and a dummy equal to 1 for each 3-week period in the sample. The dependent variable is the logarithm of the average number of daily employment contracts activated at municipal and 3-week period level. Hiring data are only available until June 2023, 30^{th}. The contract types considered for hiring data are permanent contracts, fixed-term contracts and apprenticeships. Contracts in the public sector and domestic work are excluded from the sample. The top left panel reports the results for overall hiring, the top right panel for hiring in agriculture, and the bottom panel for hiring in the private non-agricultural sector. The regressions include municipality fixed effects, 3-week period fixed effects, year fixed effects, the interaction between municipality and year fixed effects, the interaction between municipality and 3-week period fixed effects and the interaction between year and 3-week period fixed effects. The regressions are weighted according to a propensity score obtained by regressing the treatment dummy on a vector of municipality characteristics including altitude, degree of urbanisation, area, share of workers in manufacturing, share of workers in trade, share of workers in hotels and restaurants, share of land at medium-high hydrogeological risk, share of land at medium-high landslide risk and population at the beginning of 2023. Point estimates are reported with 95% confidence intervals. Standard errors are robust and clustered at the municipality level.

Figure 10: Impact of 2023 ER floods on road traffic data



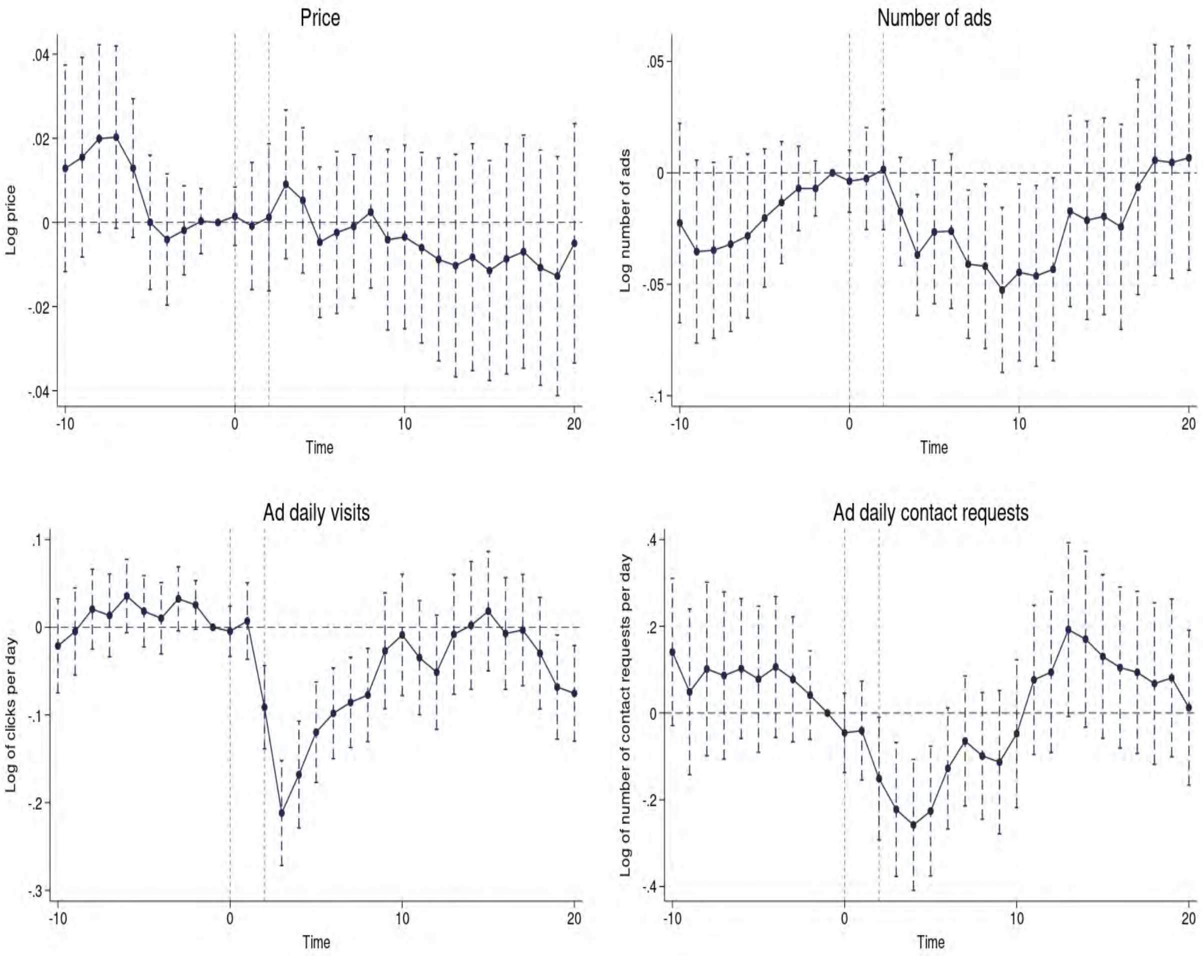
Notes - The event study is normalised with respect to the first 3-week period before the floods. The reported coefficients refer to the interactions between a dummy equal to 1 for flooded municipalities, a dummy equal to 1 for 2023 and a dummy equal to 1 for each 3-week period in the sample. The dependent variable is the logarithm of the average number of vehicles per municipality over the 3-week period in the top left panel, the logarithm of the average number of heavy vehicles per municipality over the 3-week period in the top right panel, and the logarithm of the average number of light vehicles per municipality over the 3-week period in the bottom panel. The regressions include municipality fixed effects, 3-week period fixed effects, year fixed effects, the interaction between municipality and year fixed effects, the interaction between municipality and 3-week period fixed effects and the interaction between year and 3-week period fixed effects. The regressions are weighted according to a propensity score obtained by regressing the treatment dummy on a vector of municipality characteristics including altitude, degree of urbanisation, area, share of workers in manufacturing, share of workers in trade, share of workers in hotels and restaurants, share of land at medium-high hydrogeological risk, share of land at medium-high landslide risk and population at the beginning of 2023. Point estimates are reported with 95% confidence intervals. Standard errors are robust and clustered at the municipality level.

Figure 11: Impact of 2023 ER floods on the housing market



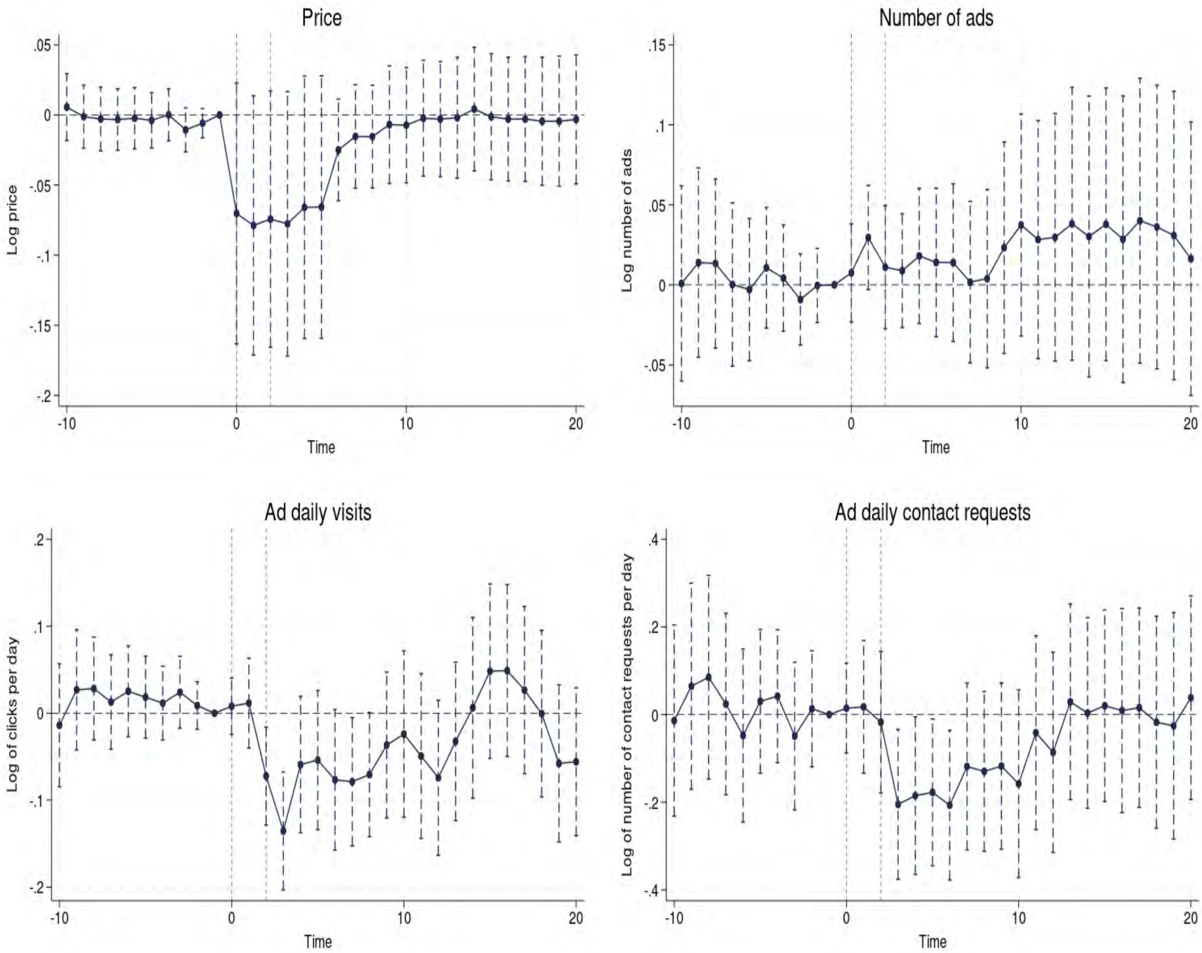
Notes - The event study is normalised with respect to the week before the first flood. The reported coefficients refer to the interactions between a dummy equal to 1 for flooded municipalities and a dummy equal to 1 for each week in the sample. The dependent variable is the logarithm of the average housing unit prices per municipality in the top left panel, the logarithm of the average number of advertisements per municipality in the top right panel, the logarithm of the average number of clicks per day on each advertisement at the municipality level in the bottom right panel, the logarithm of the average number of contact requests per day on each advertisement at the municipality level in the bottom left panel. The regressions include municipality and week fixed effects. The regressions are weighted according to a propensity score obtained by regressing the treatment dummy on a vector of municipality characteristics including altitude, degree of urbanisation, area, share of workers in manufacturing, share of workers in trade, share of workers in hotels and restaurants, share of land at medium-high hydrogeological risk, share of land at medium-high landslide risk and population at the beginning of 2023. Point estimates are reported with 95% confidence intervals. Standard errors are robust and clustered at the municipality level.

Figure 12: Impact of 2023 ER floods on the housing market - ground floor



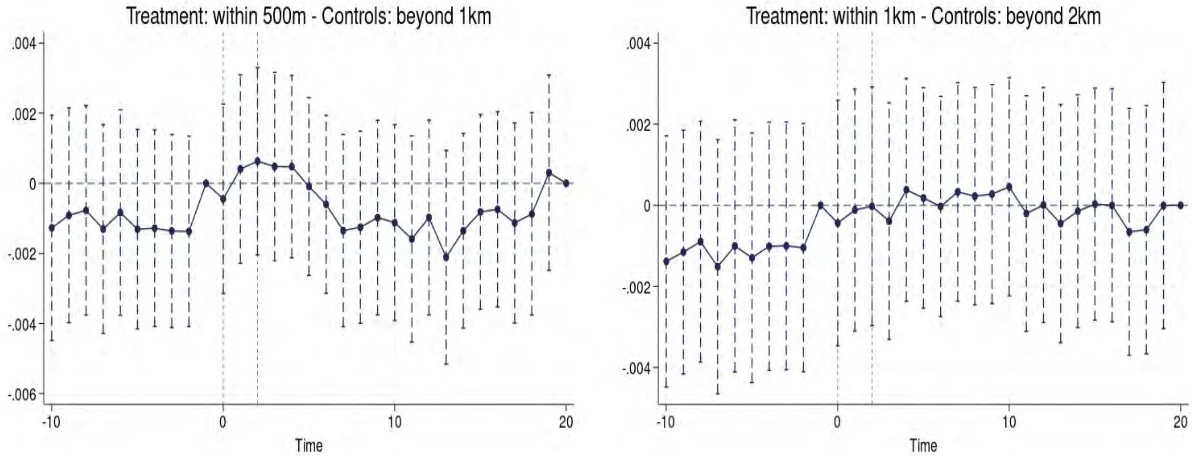
Notes - Ground floor housing units are defined as flats at or below ground level, as well as independent villas and terraced houses. Housing units at upper floors are defined as a residual category with respect to ground floor housing units. The event study is normalised with respect to the week before the first flood. The reported coefficients refer to the interactions between a dummy equal to 1 for flooded municipalities and a dummy equal to 1 for each week in the sample. The dependent variable is the logarithm of the average housing unit prices per municipality in the top left panel, the logarithm of the average number of advertisements per municipality in the top right panel, the logarithm of the average number of clicks per day on each advertisement at the municipality level in the bottom right panel, the logarithm of the average number of contact requests per day on each advertisement at the municipality level in the bottom left panel. The regressions include municipality and week fixed effects. The regressions are weighted according to a propensity score obtained by regressing the treatment dummy on a vector of municipality characteristics including altitude, degree of urbanisation, area, share of workers in manufacturing, share of workers in trade, share of workers in hotels and restaurants, share of land at medium-high hydrogeological risk, share of land at medium-high landslide risk and population at the beginning of 2023. Point estimates are reported with 95% confidence intervals. Standard errors are robust and clustered at the municipality level.

Figure 13: Impact of 2023 ER floods on the housing market - upper floors



Notes - Ground floor housing units are defined as flats at or below ground level, as well as independent villas and terraced houses. Housing units at upper floors are defined as a residual category with respect to ground floor housing units. The event study is normalised with respect to the week before the first flood. The reported coefficients refer to the interactions between a dummy equal to 1 for flooded municipalities and a dummy equal to 1 for each week in the sample. The dependent variable is the logarithm of the average housing unit prices per municipality in the top left panel, the logarithm of the average number of advertisements per municipality in the top right panel, the logarithm of the average number of clicks per day on each advertisement at the municipality level in the bottom right panel, the logarithm of the average number of contact requests per day on each advertisement at the municipality level in the bottom left panel. The regressions include municipality and week fixed effects. The regressions are weighted according to a propensity score obtained by regressing the treatment dummy on a vector of municipality characteristics including altitude, degree of urbanisation, area, share of workers in manufacturing, share of workers in trade, share of workers in hotels and restaurants, share of land at medium-high hydrogeological risk, share of land at medium-high landslide risk and population at the beginning of 2023. Point estimates are reported with 95% confidence intervals. Standard errors are robust and clustered at the municipality level.

Figure 14: Within-municipality variation in housing unit prices



Notes - The event study is normalised with respect to the week before the first flood. The dependent variable is the logarithm of housing unit prices. In the left panel housing units in the treated group are those within 500 meters from the flooded areas reported by CEMS satellite imagery, while housing units in the control group are those beyond 1 kilometer from the flooded areas. The housing units between 500 meters and 1 kilometer are removed from the sample to avoid spillovers of the treatment to untreated units. In the right panel housing units in the treated group are those within 1 kilometer from the flooded areas, while housing units in the control group are those beyond 2 kilometer from the flooded areas. The housing units between 1 and 2 kilometers are removed from the sample to avoid spillovers of the treatment to untreated units. The reported coefficients refer to the interactions between a dummy equal to 1 for treated municipalities and a dummy equal to 1 for each week in the sample. The regressions include advertisement fixed effects and week fixed effects. Point estimates are reported with 95% confidence intervals. Standard errors are robust to heteroskedasticity and autocorrelation.

Table 1: Summary statistics

	Mean (1)	Std. deviation (2)	Observations (3)	Measurement unit (4)	Source (5)
Nightlights	1.5	0.6	2,470	Logarithm	NOAA/NASA
Cloudiness	1.7	0.8	2,470	Categorical 0; 2; 4	NOAA/NASA
Temperature	19.4	7.0	2,470	Celsius	Meteo.it
Temperature squared/100	4.3	2.8	2,470	Celsius	Meteo.it
Humidity	62.6	10.5	2,470	Percentage	Meteo.it
Visibility	17.9	1.7	2,470	Kilometers	Meteo.it
Windiness	9.5	1.3	2,470	Kilometers per hour	Meteo.it
Altitude	3.7	1.5	2,470	Categorical 1-5	Istat
Urbanization	2.6	0.6	2,470	Categorical 1-3	Istat
Municipal surface	71.3	69.5	2,470	Squared-km	Istat
Workers in manufacturing	45.1	14.5	2,470	Share	Istat
Workers in trade	16.2	6.5	2,470	Share	Istat
Workers in hotels and restaurants	9.8	8.4	2,470	Share	Istat
Medium-high hydrogeological risk	48.2	43.6	2,470	Share	Ispra
Medium-high landslide risk	11.5	14.7	2,470	Share	Ispra
Population in 2023	13.5	27.9	2,470	Thousands	Istat
Hiring	-0.6	1.5	2,034	Logarithm	Ministry of Labor
Hiring - agriculture	-1.0	1.3	1,740	Logarithm	Ministry of Labor
Hiring - no agriculture	-1.5	1.6	1,964	Logarithm	Ministry of Labor
Net hiring	-1.3	1.6	1,170	Logarithm	Ministry of Labor
Net hiring - agriculture	-1.2	1.3	842	Logarithm	Ministry of Labor
Net hiring - no agriculture	-2.2	1.6	982	Logarithm	Ministry of Labor
Road traffic	9.1	0.8	542	Logarithm	ER Region
Road traffic - heavy vehicles	6.2	1.0	542	Logarithm	ER Region
Road traffic - light vehicles	9.0	0.8	542	Logarithm	ER Region
Housing unit price	12.1	0.5	5,487	Logarithm	Immobiliare.it
Number of ads	4.1	1.1	5,487	Logarithm	Immobiliare.it
Ad visits per day	2.2	0.3	5,487	Logarithm	Immobiliare.it
Ad contact requests per day	-4.0	0.6	5,374	Logarithm	Immobiliare.it
Number of added ads	4.2	10.9	5,310	Units	Immobiliare.it
Number of removed ads	3.8	9.8	5,310	Units	Immobiliare.it
House price - Ground floor (GF)	12.3	0.5	5,462	Logarithm	Immobiliare.it
Number of ads - GF	3.6	1.0	5,462	Logarithm	Immobiliare.it
Ad visits per day - GF	2.2	0.3	5,462	Logarithm	Immobiliare.it
Ad contact requests per day - GF	-4.1	0.6	5,339	Logarithm	Immobiliare.it
House price - Upper floors (UF)	11.7	0.5	5,383	Logarithm	Immobiliare.it
Number of ads - UF	3.0	1.4	5,383	Logarithm	Immobiliare.it
Ad visits per day - UF	2.1	0.5	5,383	Logarithm	Immobiliare.it
Ad contact requests per day - UF	-4.1	0.9	4,901	Logarithm	Immobiliare.it

Notes - All the variables are averaged at the municipality and 3-week period level in 2022 and 2023, except for data on the housing market which are averaged at the municipality and week level and only refer to 2023. The nightlight values in the sample are trimmed at the first and the last percentile of their distribution before being collapsed at the municipality and 3-week period level. Data on municipal characteristics come from the Italian National Statistics Institute (Istat), data on the share of land at hydrogeological and landslide risk at municipal level come from the National Institute for Environmental Protection and Research (Ispra). Hiring and net hiring data are only available until June 2023, 30^{th}. The contract types considered for hiring data are permanent contracts, fixed-term contracts and apprenticeships. Contracts in the public sector and domestic work are excluded from the sample. The logarithm of hiring is missing for municipalities and 3-week periods with 0 hired workers. Net hiring is defined as the difference between the number of activations and the number of terminations of employment contracts. The logarithm of net hiring is missing for municipalities and 3-week periods with 0 or negative net hiring values. Data on road traffic refer to the monitoring stations consistently active during the whole period. As not all the housing unit advertisements show contact requests, there are missing values for this variable. Added advertisements are defined as the number of ads in a given week that were not present in the dataset the previous week, while removed advertisements are defined as the number of ads in a given week that are not present in the dataset the following week. Ground floor housing units are defined as flats at or below ground level, as well as independent villas and terraced houses, while housing units at upper floors are defined as a residual category with respect to ground floor housing units.

Table 2: Cross-sectional correlation across variables tracking economic activity

	Log value added in private sector	Log cultivated land	Log nightlights	Log hiring	Log road traffic
Log value added in private sector	1.000				
Log cultivated land	0.432	1.000			
Log nightlights	0.767	0.027	1.000		
Log hiring	0.883	0.502	0.720	1.000	
Log road traffic	0.690	0.034	0.686	0.600	1.000

Notes - Data on nightlights, hiring and road traffic are averaged at municipal level over the period of interest. Municipal data on value added refer to the year 2022 and come from the Italian National Statistics Institute (Istat). The private sector does not include agriculture. Municipal data on cultivated land come from the 2010 Istat agricultural census.

Table 3: Elasticity of value added in the non-agricultural private sector to nightlights

	Log value added in private sector	Log value added in private sector	Log value added in private sector	Log value added in private sector
Log nightlights	2.417***	2.451***	2.627***	0.154***
	(0.048)	(0.049)	(0.057)	(0.040)
Observations	2,608	2,608	2,608	2,608
Year fixed effects	No	Yes	Yes	Yes
Local labour market fixed effects	No	No	Yes	No
Municipality fixed effects	No	No	No	Yes

Notes - Data on value added and nightlights refer to the years from 2015 to 2022. In each year, daily nightlights data between February, 27^{th} and July, 23^{rd} are averaged at municipality and year level. Municipal data on value added come from the Italian National Statistics Institute (Istat). Value added data refer to the private sector excluding agriculture and are deflated according to the regional consumer price index (Nic) for the ER region.

Table 4: Event study coefficients in a triple difference setting - nightlight data

Variable	Log nightlights (1)	Log nightlights (2)	Log nightlights (3)	Log nightlights (4)
Treated*2023*3-week period=-3	0.006	-0.047	0.144***	-0.006
	(0.026)	(0.031)	(0.041)	(0.046)
Treated*2023*3-week period=-2	0.160***	0.112***	0.262***	0.047
	(0.022)	(0.019)	(0.041)	(0.050)
Treated*2023*3-week period=0	-0.133***	-0.131***	-0.101**	-0.159***
	(0.020)	(0.020)	(0.045)	(0.051)
Treated*2023*3-week period=1	0.148***	-0.069**	0.125*	0.143**
	(0.025)	(0.028)	(0.071)	(0.064)
Treated*2023*3-week period=2	-0.090***	-0.046*	0.072***	-0.004
	(0.023)	(0.028)	(0.027)	(0.039)
Treated*2023*3-week period=3	0.055***	0.002	0.151***	0.025
	(0.015)	(0.016)	(0.036)	(0.071)
Cloudiness		-0.136***	-0.125***	-0.047**
		(0.008)	(0.018)	(0.019)
Temperature		-0.031***	0.003	0.013
		(0.011)	(0.012)	(0.015)
Temperature squared		0.051	-0.106***	-0.135**
		(0.031)	(0.038)	(0.055)
Humidity		-0.002	0.004**	-0.004
		(0.001)	(0.002)	(0.004)
Visibility		0.015***	0.064***	0.010
		(0.006)	(0.015)	(0.012)
Windiness		0.041***	0.048***	0.022***
		(0.007)	(0.006)	(0.008)
Constant	1.725***	1.812***	0.435	1.960***
	(0.004)	(0.239)	(0.379)	(0.601)
Observations	2,470	2,470	2,470	2,470
Year fixed effects	Yes	Yes	Yes	Yes
3-week period fixed effects	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes
Municipality*Year fixed effects	No	No	Yes	Yes
Municipality*3-week period fixed effects	No	No	Yes	Yes
Year*3-week period fixed effects	No	No	No	Yes

Notes - Nightlight values are trimmed at the first and the last percentile of their distribution and then collapsed at the municipality and 3-week period level. The dependent variable is the logarithm of these values. The treatment coefficients are the interaction between a dummy equal to 1 for flooded municipalities, a dummy equal to 1 for 2023 and a dummy equal to 1 for each 3-week period in the sample. The regressions are weighted according to a propensity score obtained by regressing the treatment dummy on a vector of municipality characteristics including altitude, degree of urbanisation, area, share of workers in manufacturing, share of workers in trade, share of workers in hotels and restaurants, share of land at medium-high hydrogeological risk, share of land at medium-high landslide risk and population at the beginning of 2023. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at the municipality level.

Table 5: Event study coefficients in a triple difference setting - hiring data

Variable	Log hiring	Log hiring	Log hiring agriculture	Log hiring agriculture	Log hiring withouth agric.	Log hiring withouth agric.
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*2023*3-week period=-3	-0.008	0.063	0.011	0.103	0.025	0.144
	(0.118)	(0.147)	(0.136)	(0.188)	(0.099)	(0.126)
Treated*2023*3-week period=-2	-0.028	0.026	0.074	0.105	-0.019	0.038
	(0.150)	(0.149)	(0.159)	(0.177)	(0.108)	(0.119)
Treated*2023*3-week period=0	-0.254**	-0.190	-0.475***	-0.326**	-0.145	-0.115
	(0.101)	(0.117)	(0.135)	(0.145)	(0.090)	(0.110)
Treated*2023*3-week period=1	-0.243*	-0.182	-0.399***	-0.225	-0.024	-0.005
	(0.131)	(0.183)	(0.152)	(0.205)	(0.097)	(0.150)
Treated*2023*3-week period=2	-0.028	0.003	-0.137	0.001	0.104	0.117
	(0.127)	(0.152)	(0.158)	(0.185)	(0.105)	(0.128)
Cloudiness		0.032		0.031		0.007
		(0.058)		(0.081)		(0.060)
Temperature		-0.144***		-0.140		0.011
		(0.039)		(0.102)		(0.027)
Temperature squared		0.278**		0.333		-0.027
		(0.115)		(0.220)		(0.112)
Humidity		-0.026**		-0.003		-0.010
		(0.013)		(0.020)		(0.009)
Visibility		0.021		0.036		0.033
		(0.029)		(0.045)		(0.033)
Windiness		0.001		-0.022		-0.005
		(0.019)		(0.036)		(0.024)
Constant	0.469***	3.199**	-0.214***	0.759	-0.438***	-0.498
	(0.025)	(1.284)	(0.027)	(2.474)	(0.019)	(1.104)
Observations	2,034	2,034	1,740	1,740	1,964	1,964
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
3-week period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Municipality*Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Municipality*3-week period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year*3-week period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes - The dependent variable is the logarithm of the average number of daily employment contracts activated at municipal and 3-week period level. Data on hiring are only available until June 2023, 30^{th}. The contract types considered for hiring data are permanent contracts, fixed-term contracts and apprenticeships. Contracts in the public sector and domestic work are excluded from the sample. The logarithm of hiring is missing for municipalities and 3-week periods with 0 hired workers. The treatment coefficients are the interaction between a dummy equal to 1 for flooded municipalities, a dummy equal to 1 for 2023 and a dummy equal to 1 for each 3-week period in the sample. The regressions are weighted according to a propensity score obtained by regressing the treatment dummy on a vector of municipality characteristics including altitude, degree of urbanisation, area, share of workers in manufacturing, share of workers in trade, share of workers in hotels and restaurants, share of land at medium-high hydrogeological risk, share of land at medium-high landslide risk and population at the beginning of 2023. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at the municipality level.

Table 6: Event study coefficients in a triple difference setting - road traffic data

Variable	Log number vehicles (1)	Log number vehicles (2)	Log number heavy vehicles (3)	Log number heavy vehicles (4)	Log number light vehicles (5)	Log number light vehicles (6)
Treated*2023*3-week period=-3	0.028*	0.047	-0.034	-0.003	0.028*	0.047
	(0.016)	(0.051)	(0.039)	(0.078)	(0.016)	(0.052)
Treated*2023*3-week period=-2	0.020	0.033	-0.023	0.007	0.020*	0.032
	(0.012)	(0.025)	(0.028)	(0.038)	(0.012)	(0.025)
Treated*2023*3-week period=0	-0.127***	-0.119***	-0.136***	-0.115*	-0.128***	-0.121***
	(0.025)	(0.027)	(0.029)	(0.058)	(0.026)	(0.027)
Treated*2023*3-week period=1	-0.098	-0.066	-0.026	0.046	-0.102	-0.071
	(0.072)	(0.066)	(0.065)	(0.094)	(0.072)	(0.067)
Treated*2023*3-week period=2	-0.020	0.002	0.017	0.026	-0.023	-0.000
	(0.021)	(0.039)	(0.037)	(0.076)	(0.021)	(0.040)
Treated*2023*3-week period=3	0.015	0.015	0.087**	0.009	0.009	0.013
	(0.020)	(0.070)	(0.037)	(0.095)	(0.021)	(0.071)
Cloudiness		-0.006		0.025		-0.007
		(0.022)		(0.025)		(0.023)
Temperature		-0.001		-0.002		0.002
		(0.028)		(0.023)		(0.029)
Temperature squared		0.027		0.126**		0.018
		(0.058)		(0.049)		(0.061)
Humidity		0.009**		0.007*		0.009*
		(0.004)		(0.004)		(0.004)
Visibility		0.019		0.038		0.018
		(0.015)		(0.027)		(0.016)
Windiness		0.003		0.001		0.003
		(0.006)		(0.013)		(0.005)
Constant	9.320***	8.322***	6.377***	4.717***	9.261***	8.270***
	(0.005)	(0.554)	(0.006)	(0.421)	(0.005)	(0.579)
Observations	542	542	542	542	542	542
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
3-week period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Municipality*Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Municipality*3-week period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year*3-week period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes - In Columns (1)-(2), the dependent variable is the logarithm of the average number of vehicles per municipality over the 3-week period. In Columns (3)-(4), the dependent variable is the logarithm of the average number of heavy vehicles per municipality over the 3-week period. In Columns (5)-(6), the dependent variable is the logarithm of the average number of light vehicles per municipality over the 3-week period. Data on road traffic refer to the monitoring stations that are consistently active throughout the period. The treatment coefficients are the interaction between a dummy equal to 1 for flooded municipalities, a dummy equal to 1 for 2023 and a dummy equal to 1 for each 3-week period in the sample. The regressions are weighted according to a propensity score obtained by regressing the treatment dummy on a vector of municipality characteristics including altitude, degree of urbanisation, area, share of workers in manufacturing, share of workers in trade, share of workers in hotels and restaurants, share of land at medium-high hydrogeological risk, share of land at medium-high landslide risk and population at the beginning of 2023. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at the municipality level.

Table 7: Event study coefficients - housing market data (continues on the next page)

Variable	Log housing unit price (1)	Log number ads (2)	Log number daily visits (3)	Log number contact requests (4)
Treated*Week=-10	0.008	-0.010	-0.022	0.082
	(0.010)	(0.020)	(0.023)	(0.065)
Treated*Week=-9	0.005	-0.015	0.008	0.099
	(0.010)	(0.020)	(0.020)	(0.080)
Treated*Week=-8	0.008	-0.016	0.016	0.113
	(0.010)	(0.019)	(0.021)	(0.081)
Treated*Week=-7	0.010	-0.019	0.008	0.059
	(0.009)	(0.018)	(0.020)	(0.074)
Treated*Week=-6	0.006	-0.018	0.024	0.050
	(0.007)	(0.016)	(0.017)	(0.066)
Treated*Week=-5	-0.005	-0.009	0.013	0.067
	(0.007)	(0.014)	(0.017)	(0.067)
Treated*Week=-4	-0.005	-0.008	0.006	0.073
	(0.007)	(0.012)	(0.016)	(0.062)
Treated*Week=-3	-0.003	-0.005	0.027*	0.015
	(0.005)	(0.008)	(0.015)	(0.057)
Treated*Week=-2	-0.003	-0.003	0.016	0.006
	(0.003)	(0.006)	(0.011)	(0.042)
Treated*Week=0	-0.040	-0.005	-0.001	-0.028
	(0.031)	(0.007)	(0.013)	(0.034)
Treated*Week=1	-0.044	0.003	-0.001	-0.026
	(0.032)	(0.010)	(0.019)	(0.051)
Treated*Week=2	-0.038	0.003	-0.098***	-0.111*
	(0.032)	(0.011)	(0.021)	(0.060)
Treated*Week=3	-0.041	-0.011	-0.199***	-0.250***
	(0.033)	(0.010)	(0.026)	(0.057)
Treated*Week=4	-0.038	-0.018	-0.146***	-0.261***
	(0.033)	(0.012)	(0.025)	(0.061)
Treated*Week=5	-0.042	-0.011	-0.107***	-0.215***
	(0.033)	(0.013)	(0.024)	(0.064)
Treated*Week=6	-0.011	-0.012	-0.098***	-0.165***
	(0.012)	(0.014)	(0.024)	(0.057)
Treated*Week=7	-0.005	-0.025*	-0.090***	-0.097*
	(0.012)	(0.015)	(0.023)	(0.051)
Treated*Week=8	-0.003	-0.022	-0.081***	-0.109**
	(0.012)	(0.017)	(0.023)	(0.050)
Treated*Week=9	-0.007	-0.021	-0.033	-0.103*
	(0.013)	(0.017)	(0.028)	(0.060)
Observations	5,487	5,487	5,487	5,374
Week fixed effects	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes

Notes - In Column (1), the dependent variable is the logarithm of the average housing unit price per municipality. In Column (2), the dependent variable is the logarithm of the average number of advertisements per municipality. In Column (3), the dependent variable is the logarithm of the average number of clicks per day on each advertisement at the municipality level. In Column (4), the dependent variable is the logarithm of the average number of contact requests per day of each advertisement at the municipality level. As not all advertisements show contact requests, there are missing values for this variable. The reported coefficients refer to the interactions between a dummy equal to 1 for flooded municipalities and a dummy equal to 1 for each week in the sample. The regressions are weighted according to a propensity score obtained by regressing the treatment dummy on a vector of municipality characteristics including altitude, degree of urbanisation, area, share of workers in manufacturing, share of workers in trade, share of workers in hotels and restaurants, share of land at medium-high hydrogeological risk, share of land at medium-high landslide risk and population at the beginning of 2023. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at the municipality level.

Table 7: Event study coefficients - housing market data (continued from the previous page)

Variable	Log housing unit price (1)	Log number ads (2)	Log number daily visits (3)	Log number contact requests (4)
Treated*Week=10	-0.006	-0.012	-0.021	-0.080
	(0.013)	(0.019)	(0.032)	(0.063)
Treated*Week=11	-0.008	-0.015	-0.047	0.012
	(0.013)	(0.020)	(0.031)	(0.071)
Treated*Week=12	-0.009	-0.013	-0.068**	-0.023
	(0.014)	(0.021)	(0.031)	(0.078)
Treated*Week=13	-0.009	0.006	-0.028	0.103
	(0.015)	(0.023)	(0.031)	(0.077)
Treated*Week=14	-0.006	0.001	-0.006	0.098
	(0.015)	(0.025)	(0.036)	(0.073)
Treated*Week=15	-0.012	0.008	0.021	0.081
	(0.015)	(0.024)	(0.034)	(0.072)
Treated*Week=16	-0.010	0.001	0.004	0.054
	(0.016)	(0.026)	(0.032)	(0.077)
Treated*Week=17	-0.008	0.016	-0.006	0.030
	(0.016)	(0.025)	(0.029)	(0.073)
Treated*Week=18	-0.010	0.023	-0.029	0.034
	(0.016)	(0.027)	(0.028)	(0.077)
Treated*Week=19	-0.011	0.022	-0.070***	0.072
	(0.016)	(0.027)	(0.026)	(0.078)
Treated*Week=20	-0.003	0.016	-0.075***	0.043
	(0.016)	(0.025)	(0.024)	(0.064)
Constant	12.322***	4.854***	2.239***	-3.797***
	(0.006)	(0.006)	(0.009)	(0.024)
Observations	5,487	5,487	5,487	5,374
Week fixed effects	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes

Notes - In Column (1), the dependent variable is the logarithm of the average housing unit price per municipality. In Column (2), the dependent variable is the logarithm of the average number of advertisements per municipality. In Column (3), the dependent variable is the logarithm of the average number of clicks per day on each advertisement at the municipality level. In Column (4), the dependent variable is the logarithm of the average number of contact requests per day of each advertisement at the municipality level. As not all advertisements show contact requests, there are missing values for this variable. The reported coefficients refer to the interactions between a dummy equal to 1 for flooded municipalities and a dummy equal to 1 for each week in the sample. The regressions are weighted according to a propensity score obtained by regressing the treatment dummy on a vector of municipality characteristics including altitude, degree of urbanisation, area, share of workers in manufacturing, share of workers in trade, share of workers in hotels and restaurants, share of land at medium-high hydrogeological risk, share of land at medium-high landslide risk and population at the beginning of 2023. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at the municipality level.

APPENDIX

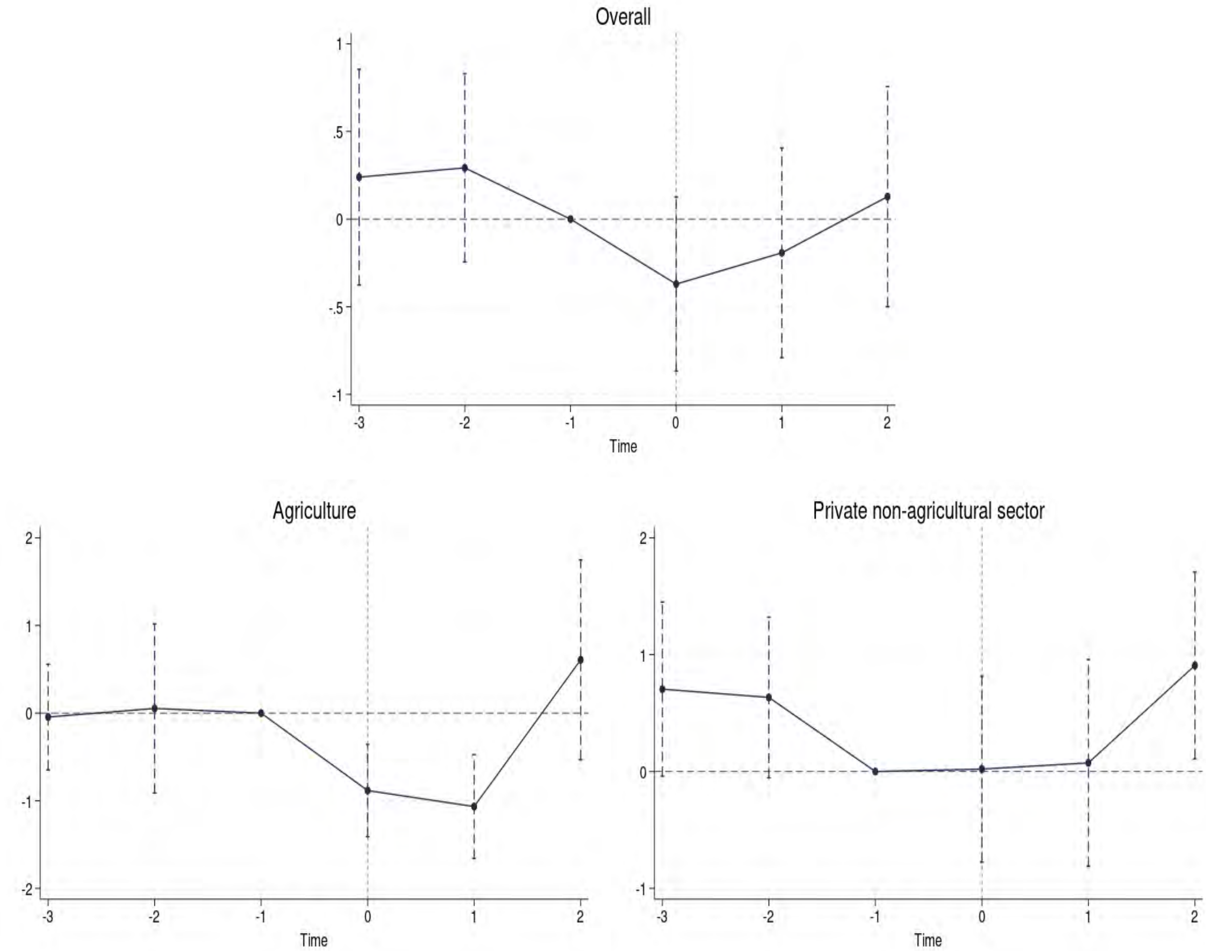
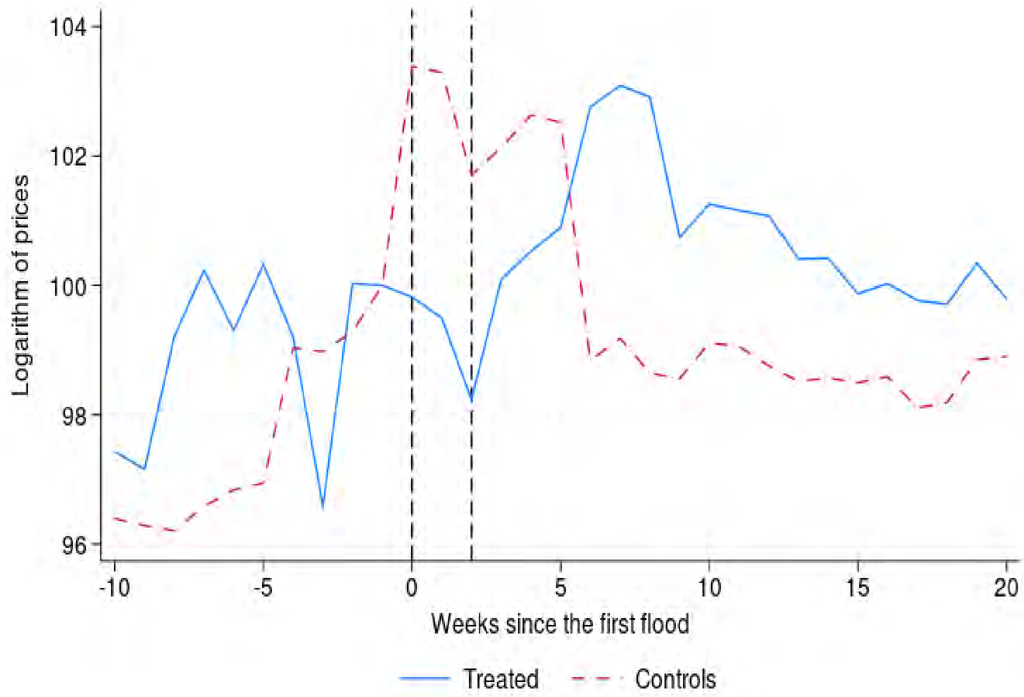


Figure A.1: Impact of 2023 ER floods on net hiring

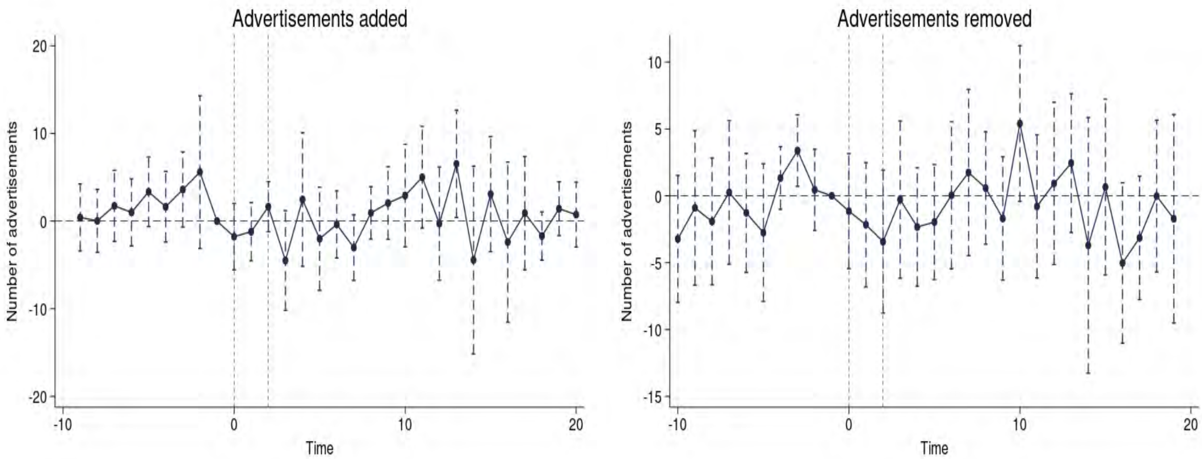
Notes - The event study is normalised with respect to the first 3-week period before the floods. The reported coefficients refer to the interactions between a dummy equal to 1 for flooded municipalities, a dummy equal to 1 for 2023 and a dummy equal to 1 for each 3-week period in the sample. The dependent variable is the logarithm of net hiring at the municipality and 3-week period level, defined as the difference between the average daily number of employment contracts activated and terminated in the period. Data on net hiring are only available until June 2023, 30^{th}. Contract types considered are permanent contracts, fixed-term contracts and apprenticeships. Contracts in the public sector and domestic work are excluded from the sample. The top left panel reports the results for total net hiring, the top right panel for net hiring in agriculture, and the bottom panel for net hiring in the private non-agricultural sector. The regressions include municipality fixed effects, 3-week period fixed effects, year fixed effects, the interaction between municipality and year fixed effects, the interaction between municipality and 3-week period fixed effects and the interaction between year and 3-week period fixed effects. The regressions are weighted according to a propensity score obtained by regressing the treatment dummy on a vector of municipality characteristics including altitude, degree of urbanisation, area, share of workers in manufacturing, share of workers in trade, share of workers in hotels and restaurants, share of land at medium-high hydrogeological risk, share of land at medium-high landslide risk and population at the beginning of 2023. Point estimates are reported with 95% confidence intervals. Standard errors are robust and clustered at the municipality level.

Figure A.2: Municipal prices by treatment group



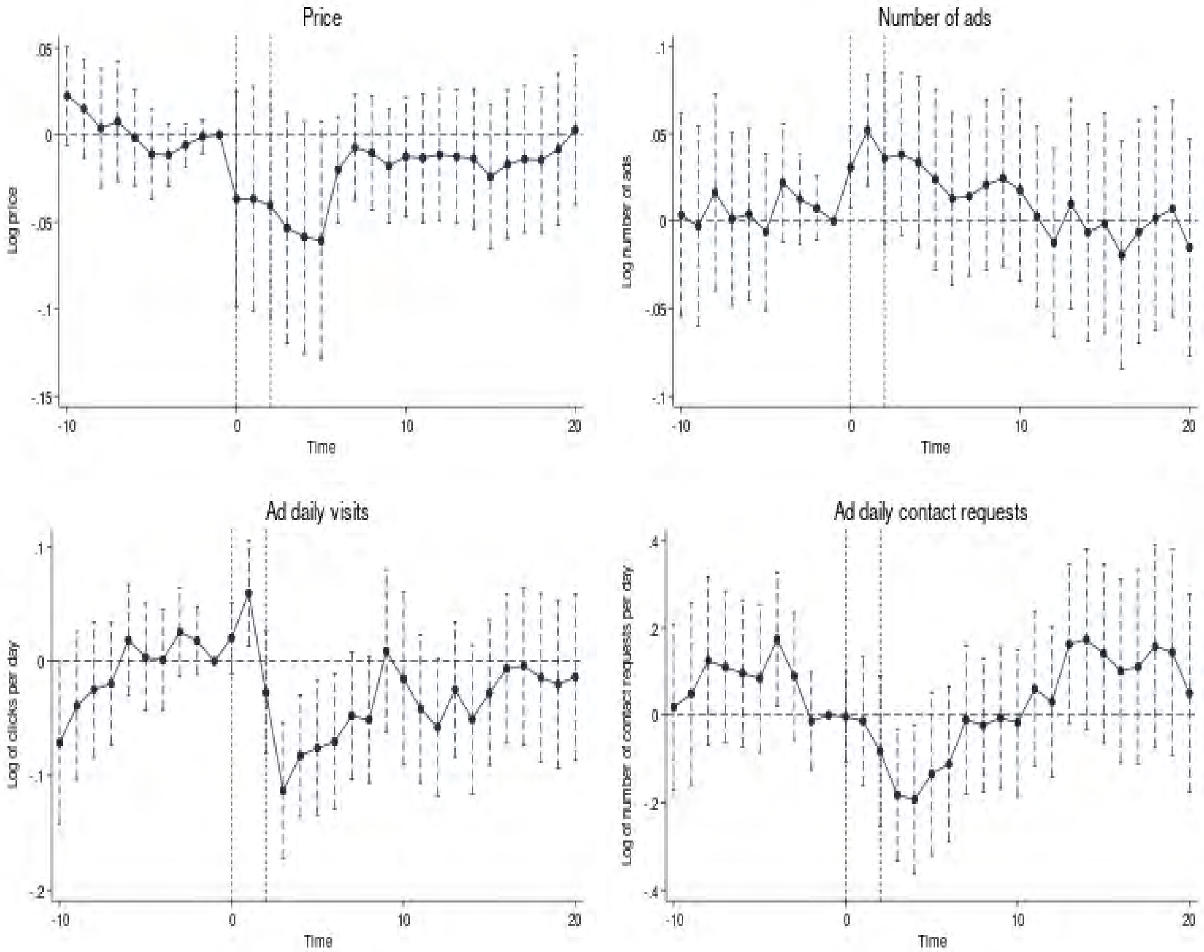
Notes - Prices are normalised to 100 in the week before the first flood.

Figure A.3: Number of advertisements added to and removed from the platform



Notes - The event study is normalised with respect to the week before the first flood. The reported coefficients refer to the interactions between a dummy equal to 1 for flooded municipalities and a dummy equal to 1 for each week in the sample. The dependent variable is the number of advertisements added to the platform in the left panel and the number of advertisements removed from the platform in the right panel. Added advertisements are defined as the number of ads in a given week that were not present in the dataset the previous week. Removed advertisements are defined as the number of ads in a given week that are not present in the dataset the following week. The regressions include municipality and week fixed effects. The regressions are weighted according to a propensity score obtained by regressing the treatment dummy on a vector of municipality characteristics including altitude, degree of urbanisation, area, share of workers in manufacturing, share of workers in trade, share of workers in hotels and restaurants, share of land at medium-high hydrogeological risk, share of land at medium-high landslide risk and population at the beginning of 2023. Point estimates are reported with 95% confidence intervals. Standard errors are robust and clustered at the municipality level.

Figure A.4: Impact of 2023 ER floods on the housing market - triple difference setting



Notes - The event study is normalised with respect to the week before the first flood. The reported coefficients refer to the interactions between a dummy equal to 1 for flooded municipalities, a dummy equal to 1 for 2023 and a dummy equal to 1 for each week in the sample. The dependent variable is the logarithm of the average housing unit price per municipality in the top left panel, the logarithm of the average number of advertisements per municipality in the top right panel, the logarithm of the average number of clicks per day on each advertisement at municipal level in the bottom right panel, and the logarithm of the average number of contact requests per day of each advertisement at the municipality level in the bottom left panel. The regressions include municipality fixed effects, week fixed effects, year fixed effects, the interaction between municipality and year fixed effects, the interaction between municipality and week fixed effects and the interaction between year and week fixed effects. The regressions are weighted according to a propensity score obtained by regressing the treatment dummy on a vector of municipality characteristics including altitude, degree of urbanisation, area, share of workers in manufacturing, share of workers in trade, share of workers in hotels and restaurants, share of land at medium-high hydrogeological risk, share of land at medium-high landslide risk and population at the beginning of 2023. Point estimates are reported with 95% confidence intervals. Standard errors are robust and clustered at the municipality level.

Table A.1: Event study coefficients in a triple difference setting - net hiring data

Variable	Log net hiring	Log net hiring	Log net hiring agriculture	Log net hiring agriculture	Log net hiring without agric.	Log net hiring without agric.
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*2023*3-week period=-3	0.282	0.238	-0.070	-0.549	0.671*	0.614
	(0.349)	(0.431)	(0.343)	(0.682)	(0.390)	(0.491)
Treated*2023*3-week period=-2	0.287	0.270	0.055	-0.045	0.634*	0.670*
	(0.274)	(0.343)	(0.498)	(0.584)	(0.351)	(0.379)
Treated*2023*3-week period=0	-0.372	-0.026	-0.878***	-0.680**	0.021	0.084
	(0.253)	(0.303)	(0.268)	(0.328)	(0.406)	(0.478)
Treated*2023*3-week period=1	-0.192	0.352	-1.066***	-0.956	0.076	0.513
	(0.305)	(0.444)	(0.300)	(0.650)	(0.451)	(0.590)
Treated*2023*3-week period=2	0.126	0.316	0.609	0.570	0.908**	0.844*
	(0.321)	(0.373)	(0.582)	(0.605)	(0.408)	(0.481)
Cloudiness		0.297		-0.047		0.261*
		(0.190)		(0.318)		(0.151)
Temperature		-0.125		-0.191		0.003
		(0.144)		(0.563)		(0.111)
Temperature squared		0.858**		1.497		0.137
		(0.409)		(1.103)		(0.321)
Humidity		0.012		0.107***		0.002
		(0.031)		(0.035)		(0.032)
Visibility		0.020		0.112		0.024
		(0.106)		(0.164)		(0.094)
Windiness		-0.100*		0.001		0.012
		(0.057)		(0.095)		(0.093)
Constant	-0.220***	-1.716	-0.518***	-10.905	-1.291***	-3.028
	(0.047)	(2.390)	(0.048)	(8.495)	(0.091)	(3.256)
Observations	1,170	1,170	842	842	982	982
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
3-week period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Municipality*Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Municipality*3-week period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year*3-week period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes - The dependent variable is the logarithm of net hiring at municipal and 3-week period level, defined as the difference between the average daily number of employment contracts activated and terminated in the period. Net hiring data are available only up to June 2023, 30^{th}. The contract types considered for hiring data are permanent contracts, fixed-term contracts and apprenticeships. Contracts in the public sector and domestic work are excluded from the sample. The logarithm of net hiring is missing in municipalities and 3-week periods with 0 or negative net hiring values. Treatment coefficients are the interaction between a dummy equal to 1 for flooded municipalities, a dummy equal to 1 for 2023 and a dummy equal to 1 for each 3-week period in the sample. The regressions are weighted according to a propensity score obtained by regressing the treatment dummy on a vector of municipality characteristics including altitude, degree of urbanisation, area, share of workers in manufacturing, share of workers in trade, share of workers in hotels and restaurants, share of land at medium-high hydrogeological risk, share of land at medium-high landslide risk and population at the beginning of 2023. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at the municipality level.