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Weathering the storm: sectoral economic and inflationary effects of floods and the role of adaptation

Matteo Ficarra[1] and Rebecca Mari[2]

Abstract

This paper investigates the impact of floods on economic output and prices at the sectoral level for local authorities in England using highly granular climate and economic data. We use precipitation z-scores as an instrument for floods to deal with endogeneity stemming from adaptation capital and we obtain dynamic impulse responses to the shock on GDP and inflation with a local projection approach (LP-IV). We find significant heterogeneities across sectors in terms of size, timing and sign, with sectoral output (prices) declining (increasing) up to 20% (250 basis points) following an increase in the number of floods. This evidence explains well the response of aggregate GDP and inflation found in the literature. Our estimates suggest that reduced investment can only partially explain the decline in output, and only in manufacturing. The response of the number and value of real estate market transactions is instead consistent with a wealth effect that is line with the demand side behaviour in wholesale and retail trade. To shed more light on the interaction among sectors, we use input-output tables and show that flood shocks propagate through the production network. Finally, using local authority expenditure on flood defences and a proxy for adaptation capital, we find that investments in adaptation strongly reduce the likelihood of flooding, but are less effective at mitigating economic damages once a flood hits. Our analysis highlights the importance of disentangling the economic impact of climate change at the sectoral level and the need for adaptation investments.

Key words: Climate change, natural disasters, flooding, inflation.

JEL classification: Q54, R11, R53.

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1 Introduction

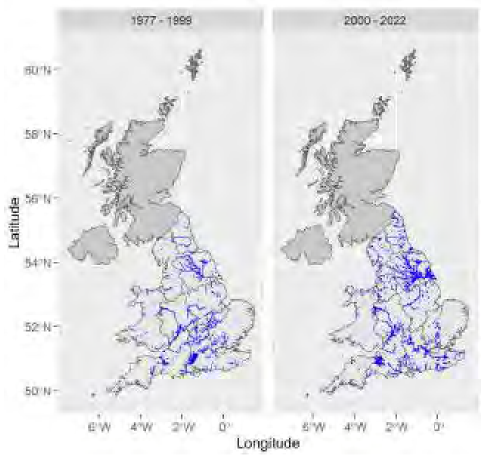
Floods are the most costly natural disaster in Europe, causing more than EUR 12 billion in damages each year (European Environment Agency, 2020; Fatica et al., 2024). For instance, the estimated cost of the 2021 floods in Germany, Belgium and the Netherlands is EUR 44 billion, and the 2023 floods in Slovenia caused direct damages for around 16% of GDP. Increased flooding stems from more frequent and intense heavy precipitation events, which hydrological models only project to intensify in the upcoming decades (IPCC, 2021). While floods directly damage properties and businesses through repair costs, loss of inventory and suspension of business activities (Crampton et al., 2024), the macroeconomic implications are not obvious. In the long run, flood events increase uncertainty and relocation of economic and human activity, harming local economic growth (Fried, 2022). However, available evidence on the short run impact is ambiguous, and the simultaneous demand and supply pressures of floods can have opposite consequences on prices. Against this backdrop, this paper studies the impact of floods on output and prices at the aggregate and sector level in counties in England, and investigates whether and how investing in adaptation can mitigate economic losses.

Our contribution is twofold. First, available evidence on the macroeconomic impact of floods focuses on aggregate GDP and inflation. Studying the response of different sectors to the same shock, however, allows us to pin down the underlying drivers of aggregate variations in output and prices following a weather shock, which are often delayed in time in a way that is hard to make sense of (Cevik and Jalles, 2023; Bilal and Känzig, 2024). It also reveals significant heterogeneities, showing that impacts vary by sector in a non trivial fashion which is hard determine *a priori*. Secondly, by studying how expenditure in flood defences can reduce the likelihood of flooding and the economic losses it causes, we provide the first empirical assessment of adaptation policies. While Fried (2022) shows that adaptation capital can reduce the economic impact of floods in a heterogeneous agent model, she does not test this assumption empirically. On the other hand, Canova and Pappa (2022) focus on transfers from the federal government to flood affected areas in the aftermath of severe flooding events, which is an *ex-post* rather than *ex-ante* intervention.

We expand the existing literature along two further dimensions. The majority of the available evidence pools together countries from different climate zones and with different economic systems (Kabundi et al., 2022; Cevik and Jalles, 2023), with the only exceptions focusing on emerging economies where flooding is not yet the most relevant natural hazard (Panwar and Sen, 2020; Crofils et al., 2023). This makes it hard to draw significant conclusions for any particular country or group of similar countries, especially advanced economies. Our setting thus provides a useful benchmark. Secondly, we use a more comprehensive measure of flooding. Most studies rely on proxies such as fatalities caused by flood events, the number of people affected or economic damages (Parker, 2018; Heinen et al., 2019). However, these approaches are not ideal to study the macroeconomic impact of flood events, as they do not account for floods that do not cause deaths but might still affect economic activity, and are more indicative of where the flood happened rather than how severe it was. Using these estimates risks overestimating the true impact of floods. In this paper, we make use of a detailed dataset containing verified records of all flood events in England from 1998 to 2021, which allows to take into account small and large floods alike, providing more accurate estimates.

The UK represent a good setting, as floods account for around GBP 1.4 billions (equivalent to EUR 1.7 billions) in annual damages (HMGovernment, 2023), and their frequency has intensified significantly over the last 50 years (Figure 1). The July-December 2023 semester was the wettest on record since 1890[1] and the government estimates that there are more than 3 million properties at risk from surface water flooding and close to another 3 million at risk of flooding from rivers and sea (HMGovernment, 2022; Environment Agency, 2023). England's exposure to flooding, in particular, is far from new, with a third of the country that has been flooded at least once before (Figure A1 in the Appendix shows a map of all floods recorded since the XVIIIth century). On top of the economic losses, flooding represents a significant expenditure item on the UK government's budget in terms of adaptation. Flood and coastal risk erosion management expenditure in 2021 reached more than GPB 1 billion (roughly EUR 1.2 billions), twice as much as in 2006.[2]

Figure 1: Flooding in the UK: 1977-1999 vs. 2000-2022



Source: EA and NRW Recorded Flood Outline.
Note: Historical records for England and Wales.

While natural disasters are often considered exogenous events, the geographical granularity of our analysis poses two main empirical challenges that we address with an instrumental variable approach. First, the risk of flooding is not random and it is heterogeneously distributed

[1]The Guardian, January 6th, 2024, see https://www.theguardian.com/environment/2024/jan/06/warmer-winters-and-more-flooding-will-be-the-norm-in-the-uk-scientists-warn.

[2]ONS, see https://www.ons.gov.uk/economy/economicoutputandproductivity/output/articles/investmentinflooddefen

across local authorities. Structural endowments like coasts and watercourses are determinants of historical growth trajectories such as trade specialisation, but their presence also increases the probability of flooding (Andrew et al., 2000; Environment Agency, 2009). Restricting the analysis to the impact of floods on regional economic outcomes could be biased by the fact that regions more exposed to flooding respond differently because of structural economic differences. Structural characteristics can be accounted for through fixed effects if they are time invariant, but there is increasing anecdotal evidence of economic activity altering river flows and worsening flooding.[3] In addition, investments in adaptation capital pose further endogeneity concerns. On the one hand, an increase in adaptation capital can reduce the frequency of flood events while increasing output through a multiplying effect and a reduction in economic damages (Fried, 2022). On the other, richer areas might have more policy space or political will to build up adaptation capital, that in turn can reduce flooding. The approach usually adopted in the literature rests on the identification of plausibly exogenous climate anomalies in the form of deviations from long-term means or unanticipated climate events (Kabundi et al., 2022; Crofils et al., 2023; Natoli, 2023). However, using weather anomalies shifts the focus on out of the ordinary weather events. While increasingly frequent, at present these are not yet the most relevant economic shocks in developed economies.

Instead, we adopt a local projection approach *à la* Jordà (2005) augmented with an instrumental variable (LP-IV *à la* Jordà et al., 2015), and use rainfall as an instrument for floods. What causes flood events is an unusually large and unsustainable amount of rain, which can occur in the form of either or both heavy, short-lived rainstorms or prolonged precipitation (Environment Agency, 2009; IPCC, 2021). We construct rainfall z-scores as deviations from each local authority's average precipitation and use them as our instrument. Our empirical identification rests on the assumption that precipitation can only impact economic growth and prices through increased flood risk. While rain can have a direct impact on the economy through the agriculture and energy sectors, evidence of this is limited only to developing countries subject to severe droughts (Miguel et al., 2004; Barrios et al., 2010). Moreover, with only 0.7% of UK's GDP coming from agricultural activity and 2.2% of its total generating capacity coming from hydroelectric power stations, this would most likely be a second order issue. Other direct channels, such as livestock death, farmers' changes in behaviour, and land ownership appear to be also relevant only for developing countries (Di Falco et al., 2019; Bezabih et al., 2021; Röckert and Kraehnert, 2022; Murken et al., 2024).

Our results show that following a one standard deviation shock in the number of floods (corresponding to around 17 floods), aggregate GDP drops by more than 1 percent after two years and after five years it is still 2 percent lower than its initial level. Prices fluctuate significantly,

[3]The Guardian, January 5th, 2024, see https://www.theguardian.com/uk-news/2024/jan/05/uk-floods-and-deaths-will-keep-rising-without-proper-defences-and-conservation.

but the repeated positive and negative deviations make it hard to determine whether, at the aggregate, floods are more akin to a demand or a supply shock. Our first contribution is to show that aggregate results hide significant sector heterogeneities not just in size, but also in timing and sign. While in some sectors (manufacturing and trade in particular) output dampens immediately, in others (such as construction and food and beverage services) it takes longer to see an impact. Output in accommodation services and civil engineering increases on impact. In all affected sectors, the variation in economic activity is three to six times higher than what we observe at the aggregate level. Similarly, inflation shows significant heterogeneities across sectors. Except for manufacturing of textiles, floods generally cause a reduction in inflation. Prices react immediately and temporarily in most sectors, with the exception of wholesale and retail trade that shows a delayed and more persistent response. Our analysis contributes to the debate on whether and how central banks should react to climate change and weather shocks, showing that core inflation, and not just headline, is impacted by floods. Taken together, our sector level evidence accounts well for the aggregate results.

We investigate the mechanisms behind our results by studying the impact of floods on investments and on the real estate market. The former is usually considered to be a driver of declining economic activity following weather shocks, while the latter can generate a wealth effect that would be consistent with the more demand-like type of response that we find in some sectors. Our findings only show a contraction of investments in manufacturing, while in all other sectors the investment channel does not seem to be at play. On the other hand, floods significantly reduce the number of real estate market transactions and their value for the postcodes affected, which is consistent with the reduction of both output and prices that we observe in wholesale and retail trade, but it is harder to reconcile with the more ambiguous response in other sectors. Next, we investigate how flood shocks propagate through sectors. Because sectors are highly connected, it is possible that small, localised shocks amplify through the production network. We find that input-output linkages play a role in the propagation of flooding shocks, especially in sectors at the top and at the bottom of the production network. While we are not able to provide a definitive answer as to whether floods are a purely supply or demand type of shock, this exercise shows they are not an isolated shock and highlights the importance of focusing at the sector level.

The second important contribution of this paper is our assessment of adaptation policy. We show that investing in adaptation does mitigate the impact of flooding, especially at the extensive margin. What matters is building up adaptation capital over time, more than one-off expenditure increases. We find that local authorities increasing their flood defences capital strongly reduce the likelihood of being hit by a flood. At the intensive margin, however, adaptation is less efficient and can only limit the economic consequences of floods in certain sectors when defences are overtopped.

Related Literature. Our paper contributes to the growing body of literature studying the empirical effects on economic activity of climate change related natural disasters, and in particular floods.

While it is reasonable to assume a dampening of GDP following extreme weather events, the response of inflation is *a priori* ambiguous and depends on the predominance of demand or supply side effects. Heinen et al. (2019) examine the impact of extreme weather on consumer prices by constructing a monthly dataset of potential hurricane and flood destruction indices for 15 Caribbean islands. They proxy flooding with a weighted measure of the three-day moving sum of daily rainfall, and find a large inflationary effect of hurricanes, while the increase in inflation from floods is smaller and rarely significant.

An important dimension is that of geographical and sectoral heterogeneities. Parker (2018) finds that natural disasters persistently increase inflation in developing economies, while their impact in advanced countries is negligible. Compared to other natural events, floods have a more temporary effect on prices and are only relevant for headline inflation, while food, housing and energy inflation are not affected. Our contribution is to show that floods can affect prices in advanced economies as well, and to expand the analysis on a wide range on industries.

Kabundi et al. (2022) use a large sample of 183 countries over the period 1970 to 2018 and find that floods tend to have a dampening impact on inflation, pointing to the predominance of demand shocks. They proxy flooding with a moving-average precipitation z-score. Instead, we construct our z-scores as deviations from the whole panel average, and use them as the instrument for our measures of floods. Our results are also in line with Cevik and Jalles (2023), who report higher prices following droughts and storms, although this effect varies nonlinearly depending on the state of the economy and the level of fiscal space.

To the best of our knowledge, there are only two papers that study the impact of floods on output at a more disaggregated level. Panwar and Sen (2020) examine sector-specific impacts on growth dynamics in 24 Indian states over the period 1990-2015. Results indicate that floods dampen growth in the short-term, except for the agricultural sector, where the effects are observed to be positive. The authors focus on the number of people affected by floods, including casualties. Their industry analysis distinguishes between agricultural, manufacturing, and services sector. We build on these results by bringing evidence for an advanced economy using a wider set of sectors. From a more microeconomic point of view, Crofils et al. (2023) investigate the dynamic effect of weather shocks in Peru measured as excess heat or rain. They find a monthly decline of agricultural production by 5 percent up to four consecutive months. The response is time and space dependent, and varies based on the type of crop.

The remainder of this paper is structured as follows: the next section introduces our various sources of data and the construction of our instrument. Section 3 presents our empirical strategy and motivates the use of precipitation z-scores as our instrument. In Section 4 we discuss our aggregate and sectoral level results. We dedicate Section 5 to the analysis of our sectoral results. We focus on investments, real estate market transactions and production networks. In Section 6 we investigate whether and how adaptation can mitigate the impact of floods. Section 7 concludes.

2 Data and Stylized Facts

This section provides a summary of the data sources used for the analysis. We provide summary statistics for the most relevant variables in Table 1 and further data description in the Appenidx.

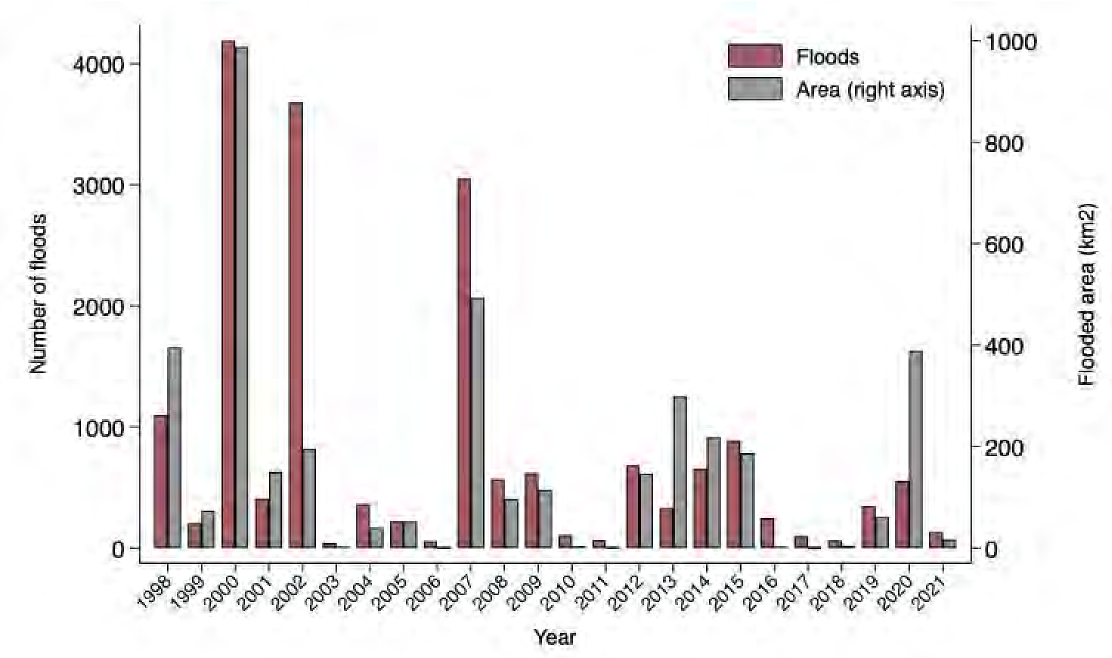
2.1 Flood Events

We retrieve flood events for England from the UK Environment Agency's (EA) Recorded Flood Outlines database. This dataset is a GIS layer with 50m×50m resolution, which shows all verified records of historic flooding extents from rivers, the sea, groundwater and surface water. Each individual Recorded Flood Outline contains a consistent list of information about the recorded flood, such as the start and end dates of flooding and the extension of the area flooded. Records began in 1946, although some flood events date back to the 18th century. We restrict our sample to the years 1998-2021 due to availability of macroeconomic variables. More than 80% of the floodings start and end in the same year. When this is not the case, we consider the starting year as the reference year.

When flood events data is available, the most common approach in the literature is to either use a binary variable that takes value 1 if at least one flood event occurred (Barbaglia et al., 2023), or a continuous variable that proxies intensity by the number of fatalities and the population affected (Parker, 2018; Panwar and Sen, 2020). The former strategy is not able to capture floods' severity and frequency, and is more of a proxy for flood risk rather than for floods themselves. It also risks misestimating the true impact of flooding, as one single flood has the same weight as, say, 150. One the other hand, severe flood events can occur in scarcely populated but economically relevant areas, such as agricultural lands or industrial hubs. Using casualties and affected population as measures of floods' intensity might underestimate their economic impact. At the same time, flooding causes deaths only in the most extreme cases, and focusing on these extremes overestimates the average damages of floods. We depart from the existing literature and use the number of floods in local authority i in year t.

We perform our analysis at the local level. There are 309 local authorities in England (ITL3 regions encompassing counties and groups of unitary authorities, broadly corresponding to NUTS3 in the EU). For each flood, we use its outline to assign it to a given local authority. If a flood intersects more than one area, we assign it to all interested authorities (affecting the value of the *number of floods* variable) and then compute each authority's flooded area separately. Our final sample is composed of 18,735 flood events. The average flood extends for 0.21 squared kilometers, which corresponds roughly to 30 football fields. The median is much lower (0.06 squared kilometers), denoting a highly right skewed sample. On average, each authority gets flooded 2.31 times per year although the median number of floods is 0. Table 1 reports relevant summary statistics. We plot the total number of floods and flooded area by year in Figure 2 below: more floods correspond to larger flooded areas. Floods are rather consistent throughout the years, with a few relevant spikes (2000, 2002, and 2007 in particular).

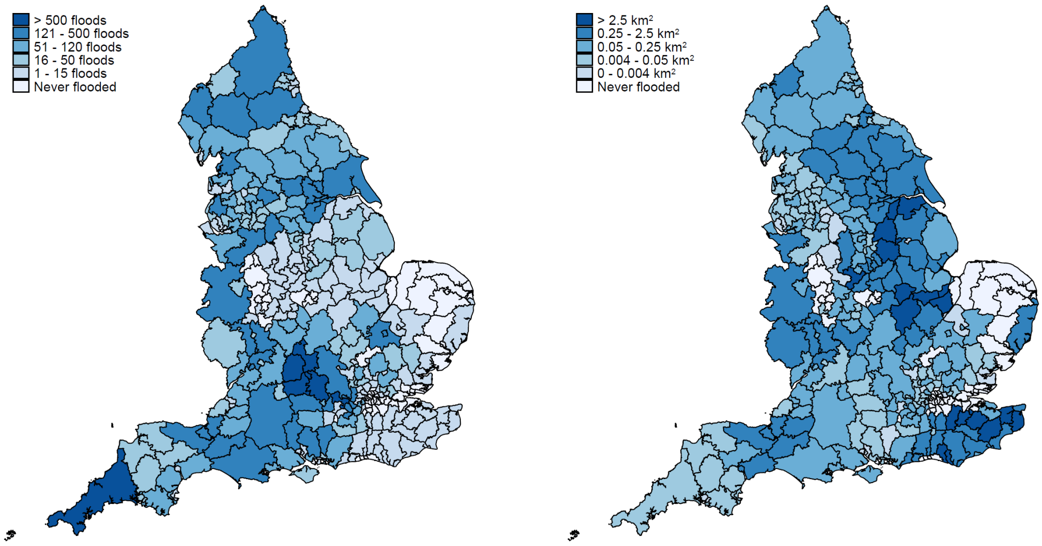
Figure 2: England's Annual Number of Floods and Total Flooded Area



Source: EA Recorded Flood Outlines and authors' calculations.
Note: We treat each flood event as a single flood, and assign it to every ITL3 area hit and compute the flooded area accordingly.

In Figure 3 we show the spatial distribution of floods across England's local authorities (see Figure A2 for a zoom-in on Greater London's authorities). We plot the total number of floods (left panel) and the average flood extent (right panel) throughout the period under scrutiny. The map shows that floods are heterogeneously distributed, with some areas on the eastern coast that were never flooded throughout the panel, and others, such as Cornwall, that have been hit by more than 500 floods. The right panel reveals that more floods does not necessarily mean more severe floods, as average flood extent is not perfectly correlated with the number of floods. While we abstain from drawing causal conclusions here, we report that the number of floods seems to be larger in areas with higher density of watercourse, while areas with a higher average extent seem to be protected by more flood defences (see Figure A3).

Figure 3: Overall Number of Floods and Average Flood Extent by ITL3



(a) Number of floods (b) Average flood extent

Source: EA Recorded Flood Outlines and authors' calculations.
Note: We treat each flood event as a single flood, and assign it to every ITL3 area hit and compute the flooded area accordingly. Average flood extent is computed as each ITL3 area's total area flooded over the panel divided by the total number of floods.

2.2 Rainfall Data

We obtain rainfall data from the ERA5 database of the European Centre for Medium-Range Forecasts (ECMWF). The dataset has global coverage at 30km×30km resolution since 1940. We retrieve hourly precipitation data in millimetres for England for the years 1985 to 2022, and build a measure of hourly precipitation at yearly frequency. The advantage of this data is that it is collected from satellite observations rather than weather stations. Rainfall records from weather stations are generally more precise, but only include observations around the weather stations themselves, failing to provide a comprehensive overview. We provide a detailed description of how we aggregate rainfall data from grid to local authority level in the Appendix.

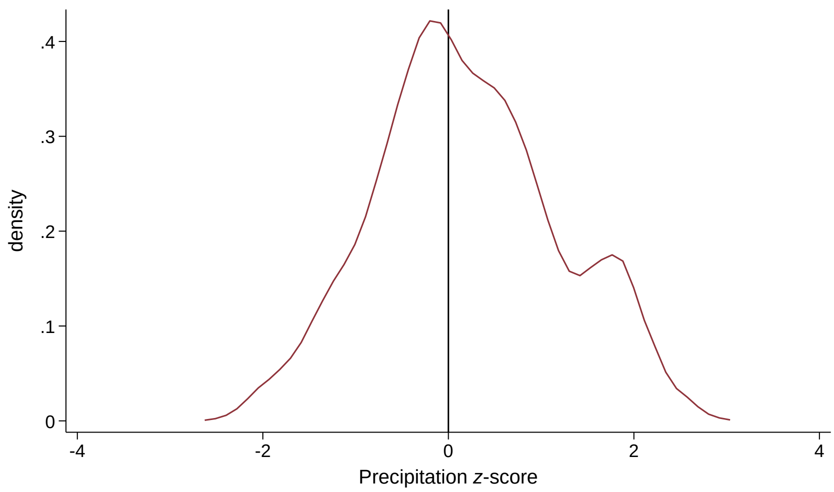
Rain is the main trigger of floods (Environment Agency, 2009; IPCC, 2021). If heavy rainfall overwhelms an area's local drainage capacity or an already waterlogged catchment, it can lead to groundwater and river flooding. Therefore, to instrument floods we are interested in unusually large and unsustainable amounts of rain. This can either occur in the form of short, heavy rainstorms or prolonged precipitation. To better predict flood events, we thus construct ITL3 area specific rainfall z-scores as deviations from the area's norm. Let $P_{i,t}$ be total precipitation for area i in year t; $\bar{P}_i$ the same area's average precipitation over the 1985-2022 panel; and σ_i^P its standard deviation. The z-score for ITL3 area i in year t is thus:

$$P_{i,t}^z = \frac{P_{i,t} - \bar{P}_i}{\sigma_i^P}. \tag{1}$$

Simply using total rainfall and fixed effects would give us the deviation in precipitation from the whole sample mean, which might not always be a good predictor for floods. For example, an area that is subject to more heavy rainfall than the country average could have better protection from flooding through better drainage systems or maintenance or flood defences. If area fixed effects can't absorb this feature, rainfall is a biased predictor for floods. On the other hand, z-scores are area specific, and thus account for any time varying, region specific unobservable factors. Moreover, Mendelsohn (2016) and Kahn et al. (2021) highlight how weather models are non linear. Hence, fixed effects models do not properly control for time-invariant variables and demeaning is necessary to estimate unbiased weather effects.

The mean z-score is positive and close to zero (0.21), implying that on average the amount of rainfall has slightly increased compared to its historical mean. Figure 4 shows that the z-score is skewed to the right, which suggests that heavy rainfall events are more severe than low precipitation events.

Figure 4: Precipitation z-score



Source: ERA5 and authors' calculations.
Note: z-score is defined as in equation (1).

2.3 Macroeconomic Data

GDP and inflation. Our dependent variables of interest are annual GDP and inflation at ITL3 level from the UK's Office of National Statistics (ONS). The ONS provides annual aggregate GDP at constant 2019 millions of pounds for the 1998-2021 period. At the sectoral level, we use GVA estimates at constant 2019 prices. GVA is a good proxy for GDP, and the use of time and region fixed-effects allows us to consider them as equivalent measures of economic activity.[4] Inflation data is not directly available at the ITL3 level. For both aggregate and

[4]GDP is equivalent to GVA plus Value Added Tax (VAT) plus other taxes on products less subsidies on products. Fixed effects thus absorb any year- and area-specific changes in taxation.

sectoral estimates, the ONS derives implied GVA deflators from whole economy current price and chained volume measure of GVA. We use them as proxies for CPI, and compute inflation as their yearly percentage change:

$$\pi_{i,t} = \frac{defl_{i,t} - defl_{i,t-1}}{defl_{i,t-1}} \times 100. \tag{2}$$

GDP and inflation data is available for 3 macro-sectors (production, construction, and services) and 18 sub-sectors. The ONS further decomposes them into 43 different sub-groups of activities. We provide a breakdown in Table A1. In our analysis, we focus on the 10 sectors arguably more subject to flood damages: *i)* agriculture, forestry, and fishing; mining and quarrying; *ii)* manufacture of food, beverages and tobacco; *iii)* manufacture of textiles, wearing apparel and leather; *iv)* other manufacturing, repair and installation; *v)* accommodation services; *vi)* food and beverage service activities; *vii)* civil engineering; *viii)* construction of buildings; *ix)* wholesale trade; and *x)* retail trade. For sector level data the ONS aggregates some local authorities that would not be relevant individually into larger economic areas. The final sample when studying GDP and inflation by sector is composed of 133 regions.

Investments. We use a proxy for annual investments from the ONS. The dataset presents regional estimates for gross fixed capital formation for the years 1997 to 2020, both at the aggregate and sectoral level. Sectors do not always match GDP and inflation data. In particular, ONS distinguishes investments in the agriculture, forestry and fishing industry from those in mining and quarrying. Moreover, it aggregates investments in wholesale and retail trade and in accommodation and food and beverage services.

Housing transactions. The HM Land Registry Price Paid Data tracks property sales in England at daily frequency from 1995 to 2024. These are sale prices and no information is provided concerning the square footage of each property sold. We thus retrieve median square footage by postcode in England using the Energy Performance of Buildings database of the Department for Levelling Up, Housing & Communities. We then assign to each property in the Land Registry Data the median square footage of the postcode it belongs to and compute the price per square metre. We remove the top and bottom 1% of the distribution from the sample.

Adaptation. To investigate the role of adaptation we make use of the data from the Ministry of Housing, Communities & Local Government, which provides a summary of local authority revenue expenditure and financing on cultural, environmental, regulatory and planning service for the fiscal years 2008-2009 to 2023-2024. We focus on revenue expenditure for flood defence, land drainage and coast protection at constant prices.[5] We construct a proxy of adaptation capital by cumulating expenditure over time. For coastal and fluvial protection we assume a depreciation rate of 0.02 (i.e., we assume flood defences to have an average life of 50 years), while for land drainage we set the depreciation rate to 0.067 (i.e., 15 years).

Other data. We study the role of production networks in propagating flood shocks using UK sector by sector input-output (IO) tables from the ONS. IO tables provide a highly disaggregated level of analysis. We thus aggregate sectors to match output and inflation data. Throughout our analysis we control for population size, which we also retrieve from the ONS.

Table 1: Descriptive statistics for the main variables

	Mean	**Median**	**Std. deviation**	**Min.**	**Max.**	**N. of obs.**
Weather variables						
N. of floods	2.31	0	17.49	0	723	8,101
Total precipitation	834.86	402.87	1,290.46	2.43	12,4399.13	7,725
Precipitation z-score	0.21	0.14	0.99	-2.48	2.89	7,725
Macroeconomic variables						
GDP	5,201.6	3,723	6,098.57	965	88,432	7,416
Inflation	1.97	1.96	2.24	-35.3	17.4	7,107
Investments	2,068	1,578.32	1,616.64	173.7	17,136.88	3,036
House prices	2,763.33	2,284.1	2,430.44	0.02	930,129	26,683,352
Adaptation expenditure	0.23	0.07	0.45	0	6.32	4,928

Note: Summary statistics of the main variables used in our analysis. Weather variables are summarized at the ITL3-year level for the years 1998 to 2023. Total precipitation is expressed in millimetres. z-scores are computed as defined in equation (1). GDP, investments and adaptation expenditure from the ONS are expressed in constant GBP 2019 million. Inflation is expressed as the percentage change in the GVA deflators. House prices are reported in 2019 GBP/square metre. We report the total number of property transactions from the HM Land Registry Data for the years 1995 - 2023.

3 Methodology

3.1 Empirical Strategy

Our empirical analysis builds upon the local projections (LP) approach of Jordà (2005), which allows us to identify the dynamic response of GDP and inflation to floods at the regional level. We use sector level GDP and inflation to explore heterogeneity across sectors.

[5]This data alone is not enough to solve the endogeneity issues. Firstly, the fact that expenditure refers to fiscal years instead of calendar years makes it hard to assess *when* money is actually spent. Secondly, defence spending data is only available starting in FY 2008-09, and including it in our estimates means losing almost half of the observations. Third, it is not trivial to distinguish between locally and centrally financed spending. Lastly, more than year-by-year investments, what matters for flood protection is the adaptation capital. How much a local authority spends on flood protection in a given year is not necessarily indicative of its overall adaptation capital.

We run a local projection model for $h = \{0; 5\}$ of the form:

$$y_{i,t+h} = \alpha_i + \beta^h f_{i,t} + \gamma X_{i,t} + \Theta y_{i,t-1} + \lambda_t + \varepsilon_{i,t+h}, \tag{3}$$

in which $f_{i,t}$ is the number of floods in local authority i in year t. In a robustness check, we weight the number of floods by each flood's extensions. In our baseline specifications, the dependent variable $y_{i,t+h}$ is in turn the natural logarithm of GDP and inflation as defined in (2). β^h is the impact of floods on annual GDP/inflation at horizon h. $X_{i,t}$ controls for population size, as more populated areas might be economically more dynamic, but also harder hit in case of floods. To control for persistence of the dependent variable, we include one lag of GDP/inflation on the left hand side. Unobserved characteristics specific to a local authority or year are absorbed, respectively, by fixed effects α_i and λ_t. Our sample includes 309 (133 when using sector level data) local authorities i and spans the years 1998 to 2021.

One concern with this specification is that flood events are not exogenous to economic activity. While it is possible that areas that are historically subject to more floods have a structural economic disadvantage, this gets absorbed by fixed effect α_i. However, adaptation capital poses more serious endogeneity concerns. As it might reduce the frequency of flood events, adaptation capital can increase output through a fiscal multiplying effect and by reducing the economic damages caused by floods (Fried, 2022). Moreover, richer areas could have more policy space or political will to build adaptation capital, that in turn can reduce flooding. As long as these concerns are area-year specific, fixed effects are not able to capture them and there is room for an omitted variable bias and reverse causality. We combine the standard LP approach with IV methods as in Jordà et al. (2015). We use the precipitation z-score defined in equation (1) as an instrument for floods and estimate the following first stage:

$$f_{i,t} = \alpha_i + \lambda_t + \delta P^z_{i,t} + \phi X_{i,t} + \Theta y_{i,t-1} + \xi_{i,t}. \tag{4}$$

We then plug the fitted values $\hat{f}_{i,t}$ into (3).

3.2 Rainfall as an Instrument for Floods

We now argue in favour of our instrument by discussing the two usual assumptions for instrumental variables, namely relevance and the exclusion restriction, and a third assumption specific to LP-IV, lead-lag exogeneity.

Relevance. The most common forms of floods in England are river, surface water, and groundwater flooding. These events occur for a combinations of factors, among which land conformation and wind, but are all triggered by heavy rainfall (Environment Agency, 2009). Surface water flooding, for example, happens when heavy rainfall overwhelms the drainage capacity of the local area. Since changes in extreme precipitation are the main proxy for inferring changes in fluvial and urban floods, multiple studies use rainfall as a proxy for floods (IPCC, 2021). Heinen et al. (2019), in the absence of a complete flood event database to run a hydrological model for the Caribbean, perform flood detection based solely on precipitation data. Akyapi et al. (2022) use the maximum amount of rainfall over different intervals in a year to capture short but intense precipitation that may cause a flood. Kabundi et al. (2022) use precipitation z-scores as their weather shock for flood events, and Crofils et al. (2023) proxy floodings with deviations of monthly rainfall with respect to their average.

Hence, we argue that our instrument is a relevant predictor of floods. Table A2 reports first-stage regressions results, in which we regress the number of floods on our instrument $P^z_{i,t}$. Following Jordà et al. (2015), we report both the F-statistics and the Kleibergen-Paap rank test statistics (Kleibergen and Paap, 2006). The results provide tangible intuition about the strength of the instrument.

Exclusion restriction. Although we have no formal way of confirming the exclusion restriction, we argue that floods are the only channel through which extreme rainfall can impact economic activity. Barrios et al. (2010) show that precipitation has a direct impact on the economy through the agriculture and energy sectors. However, they show that this result only holds for countries in sub-Saharan Africa, and not for advanced economies. Miguel et al. (2004) reach a similar conclusion, and find that rainfall affects economic growth in Africa through better agricultural production.

We believe these channels are not at play in England for various reasons. Firstly, the impact of rain on agricultural production is related to a decrease in droughts. Droughts can occur in England, but they do not yet represent as big of a threat to agricultural production as in dryer and less developed countries such as those considered by Miguel et al. (2004) and Barrios et al. (2010). Secondly, the agriculture sector is negligible in the UK's economy. According to World Bank data, it only accounted for 0.7 percent of UK's GDP in 2022, and never for more than 0.9 percent in our period of reference. Thus, we argue that the droughts channel, if present, is not relevant enough to undermine identification. Third, rainfall can impact the energy sector directly through increased hydroeletric energy production. Across the UK, however, hydroelectric power stations currently generate around 1.65GW of energy, which accounts for less than 2 percent of national capacity. Once again, we argue that the energy channel, if present, is negligible.

In a recent paper, Mellon (2023) argues that the use of rain as an instrument for several independent variables is by itself proof of the violation of the exclusion restriction. While we refrain from addressing each potential violation here, we believe that all the channels he identifies that might lead to an exclusion violation (namely crime, elections turnout, wages and health) are shut down in our environment. Other studies relate extreme rainfall events to economic growth, but the channels are only reasonable in developing economies, such as livestock death, farmers' behaviours, land ownership (Di Falco et al., 2019; Bezabih et al., 2021; Röckert and Kraehnert, 2022; Murken et al., 2024).

One potential threat is posed by spatial correlation. A local authority's z-score is correlated to that of its neighbours, as rain is a geographically consistent factor. This means that a high z-score in region i might indirectly be correlated with a positive number of floods in region i's neighbours. If floods in neighbouring regions impact output and prices in local authority i, the esxclusion restriction would be violated. We test this hypothesis by regressing the response of sectoral output and inflation in ITL3 area i to the number of floods in all of the ITL3 areas with which i shares at least a border. The specification is the same we have introduced earlier in this Section, but we control for $P^z_{i,t}$ to make sure neighbours floods are not a proxy of floods in i. Overall, results in Figures A4 - A5 in the Appendix confirm that the exclusion restriction holds.

Lead-lag exogeneity. Lastly, Stock and Watson (2018) identify a third condition for instruments' validity that only applies to LP-IV settings, namely "lead-lad exogeneity" (LLE). It requires the instrument to be uncorrelated with past and future error terms. The key idea is that $y_{i,t+h}$ generally depends on the entire history of shocks. If the instrument is to identify the effect of the shock at time t alone, it must be uncorrelated with all shocks at all leads and lags. We need $P^z_{i,t}$ to be uncorrelated to flooding measures in years $t+j$ for $j \neq 0$. Our z-scores should satisfy this condition. While precipitation partly depends on geographical factors (air pressure, altitude etc.) that are immutable and hence the amount of rainfall in a given area might not be orthogonal year by year, z-scores capture unusual precipitation occurrences, and should be uncorrelated over time by definition. Moreover, including fixed effects is usually enough to ensure LLE (Stock and Watson, 2018). It is possible, however, that a high z-score is driven by heavy rainfall concentrated in the last part of the year, which could cause flood events in the upcoming year. In this case, $P^z_{i,t}$ would be correlated to flooding in $t+1$. While we have no way of controlling for this, Stock and Watson (2018) argue that the requirement that the instrument be uncorrelated with future shocks is not restrictive.

4 Baseline Results

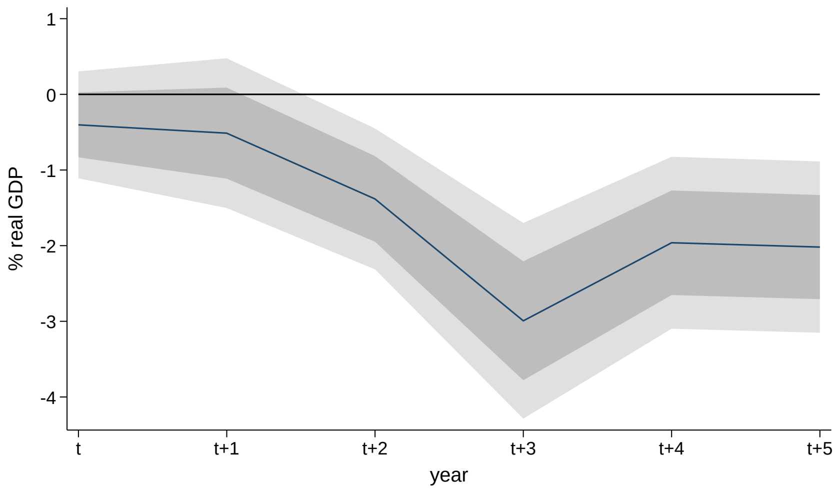
This section presents the main empirical results. We first provide evidence for aggregate GDP and inflation, showing that floods cause a delayed yet persistent decrease in economic activity and subsequent deviations in prices. We then show that a sector level analysis reveals significant heterogeneities and explains well the aggregate results.

4.1 Aggregate Analysis

We begin with the analysis on aggregate economic activity. Figure 5 and 6 plot, respectively, the impulse response functions for GDP and inflation to a one standard deviation shock in the number of floods. We report LP-OLS coefficients, for comparison, in the Appendix.

Floods have a delayed and persistent dampening effect on economic growth (Figure 5). In terms of size, the economic impact can be quantified as follows: a one standard deviation increase increase in the number of floods (around 17 floods) significantly reduces GDP by more than 1 percent after two years and 3 percent after three years. Five years after the shock, GDP is still 2 percent lower than in the absence of floods. Our results confirm the negative impact of adverse weather events on GDP (Akyapi et al., 2022; Natoli, 2023). In line with the temperature shock of Cevik and Jalles (2023), we find the impact of floods to be delayed and persistent.[6] Compared to other studies finding a dampening effect of flooding, our results are strongly significant, most likely due to the more precise measurement and identification of flood events (Kahn et al., 2021).

Figure 5: GDP Response to Floods



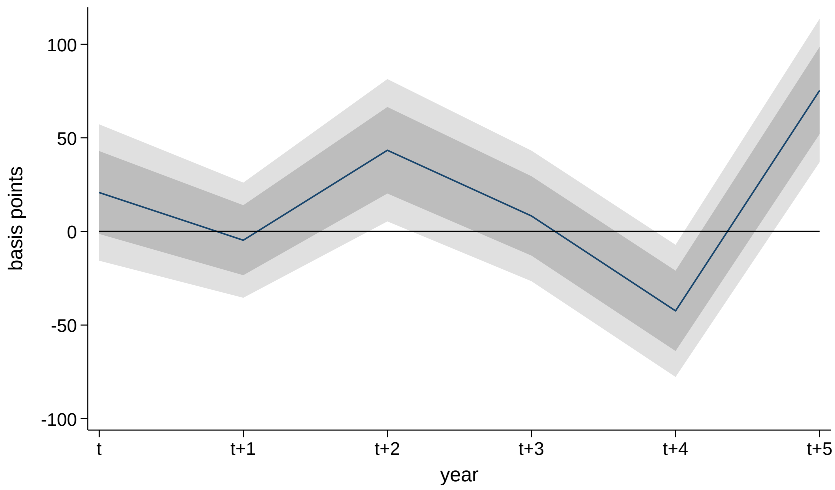
Note: Dynamic impulse response functions of GDP to a one standard deviation increase in the number of floods. All specifications include ITL3 and year fixed effects. Controls include population size and one lag of GDP. Standard errors are clustered at the ITL3 level. Shaded areas denote 68% and 90% confidence bands.

Similarly to what we find for GDP, prices react only two years after the shock (Figure 6). A one standard deviation increase in the number of floods causes an increase in inflation of around 50 basis points, followed by a deflationary shock of similar size two years later. Five years after the shock prices are again around 75 basis points above their initial level. The repeated positive and negative deviations in prices make it hard to determine whether floods are more akin to demand or supply shocks. The existing evidence on weather shocks is similarly inconclusive. For example, Cevik and Jalles (2023) find no significant impact of storm shocks

[6] Acevedo et al. (2020) find a similar pattern, but not for advanced economies.

on headline inflation in advanced economies, while in developing countries headline and core inflation respond in opposite directions. On the other hand, Kabundi et al. (2022) find an aggregate negative impact of floods on prices in the short-run, which in advanced economies turns positive for food prices.

Figure 6: Inflation Response to Floods



Note: Dynamic impulse response functions of inflation to a one standard deviation increase in the number of floods. All specifications include ITL3 and year fixed effects. Controls include population size and one lag of inflation. Standard errors are clustered at the ITL3 level. Shaded areas denote 68% and 90% confidence bands.

Our estimates reveal major economic effects capable of dampening potential output. While 17 floods represent a much larger shock compared to the average shock in the sample (on average a local authority is flooded 2.34 times every year), we are abstaining from potential non-linear effects. Throughout this paper, we effectively scale up the linear effect of smaller shocks: in presence of non-linearities, the impact might be larger than what we predict in our model.

Moreover, the delayed impact on GDP and inflation raises some questions. Flooding dampens economic activity by destroying physical and human capital and by damaging properties and business activities (Fried, 2022; Crampton et al., 2024). These impacts are immediate, and can cause second round effects in the longer run such as increased uncertainty and relocation of human activity (Panwar and Sen, 2020). However, it is not uncommon in the literature to find delayed reactions of economic activity to weather shocks. Because flooding is a rather localized shock which can affect different areas and industries in different ways, we argue that an aggregate analysis is not best suited to disentangle the economic impact of adverse weather events. Instead, the focus should be on sectors. As not all sectors are affected in the same way and our aggregate results effectively combine the different reactions of individual sectors, we now turn our attention to the sector level.

4.2 Exploring Sectoral Heterogeneity

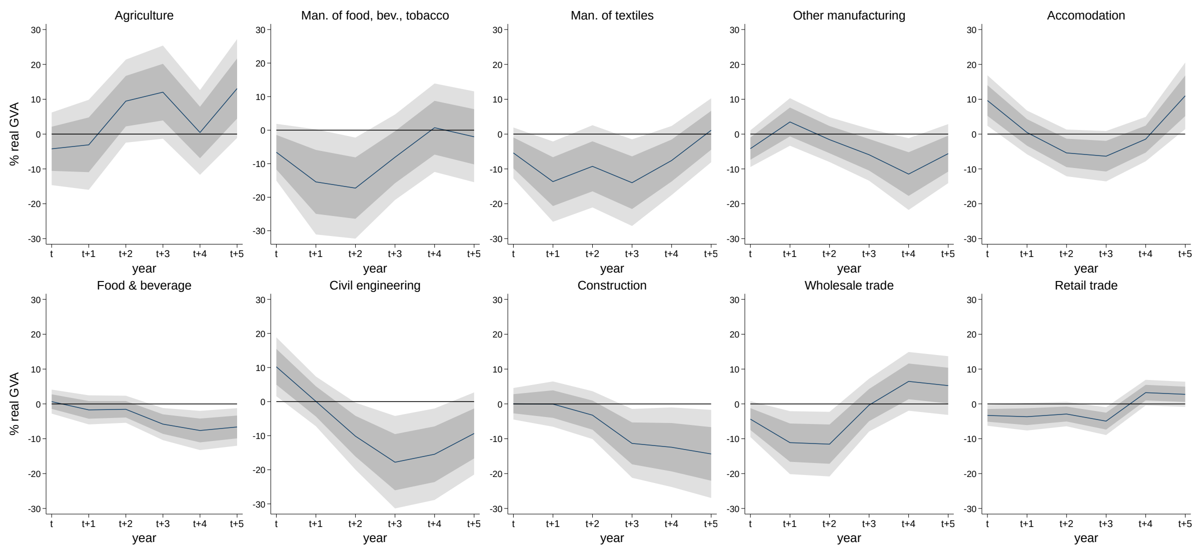
We have documented that floods dampen economic activity and cause fluctuations in prices. We now investigate the underlying responses at the sector level. Our goal is to explore how different sectors react to the same shock, which will help make sense of the delayed responses at the aggregate level. Figure 7 plots the IRFs of real GVA for *i)* agriculture, forestry and fishing; *ii)* manufacture of food, beverages and tobacco; *iii)* manufacture of textiles, wearing apparel and leather; *iv)* other manufacturing, repairs and installation; *v)* accommodation services; *vi)* food and beverage services; *vii)* civil engineering; *viii)* construction of buildings; *ix)* wholesale trade; and *x)* retail trade. We plot the corresponding IRFs for inflation in Figure 8. For representativeness reasons we aggregate inflation measures for wholesale trade and retail trade (wholesale and retail trade), accommodation services and food services (accommodation and food services) and civil engineering and construction of buildings (construction). In the Appendix (Figures A8-A9) we provide the responses of GVA and inflation for the main 18 sectors (i.e., the 18 sections within the UK SIC07 classification code).

Our estimates highlight significant heterogeneities among sectors not just in terms of magnitude, but also in terms of timing and sign. In manufacturing of textiles, wearing apparel and leather and in wholesale trade real GVA declines by more than 10% one year after a one standard deviation increase in the number of floods and the impact dies out by the fourth year. Similarly, retail trade's output immediately declines by around 3% and remains below its initial level for three years. On the other hand, real GVA of manufacturing of food, beverages and tobacco exhibits a one-off decline of about 17% two years after the shock, while other manufacturing, repairs and installation shows a temporary 10% decrease only in $t + 4$. The flood shock affects output of food and beverage services and construction of buildings negatively and persistently (-6% and -10% to -12% respectively), but the impact takes three years to emerge. Real GVA in the accommodation services and civil engineering sectors increase on impact by 10%. In the former case output exhibits a U-shaped response, while in the latter the impact turns negative after three years. The rise in output of accommodation activities is most likely due to the displacements caused by floods, which damage private properties forcing people to move out temporarily. This reaction leads to an increase in the demand for accommodation services. Similarly, the positive impact on civil engineering's GVA is driven by higher demand to sustain reconstruction and repair efforts. The civil engineering sector includes new work, repair, alteration and addition activities for civil engineering works such as motorways, streets, bridges, tunnels, railways, airfield, harbours, irrigation systems, sewerage systems, industrial facilities etc. When a flood shock hits, efforts to mitigate the damage to civil infrastructures lead to a temporary increase in output. This surge is cyclical rather than structural, and GVA quickly dampens alongside the rest of the construction sector. Lastly, unlike previous evidence seemed to suggest, floods do not significantly affect GVA in the agricultural sector (Panwar and

Sen, 2020; Crofils et al., 2023).

Taking together sector level estimates helps explain aggregate results. The response of GVA on impact is highly heterogeneous: while some sectors exhibit a decline, others are not affected until one or two years later, and some experience temporary growth. In the medium to long run, on the other hand, GVA declines in most sectors. This translates into the delayed impact we find at the aggregate level, and highlights the importance of disentangling sector level dynamics.

Figure 7: GVA Response to Floods by Sector



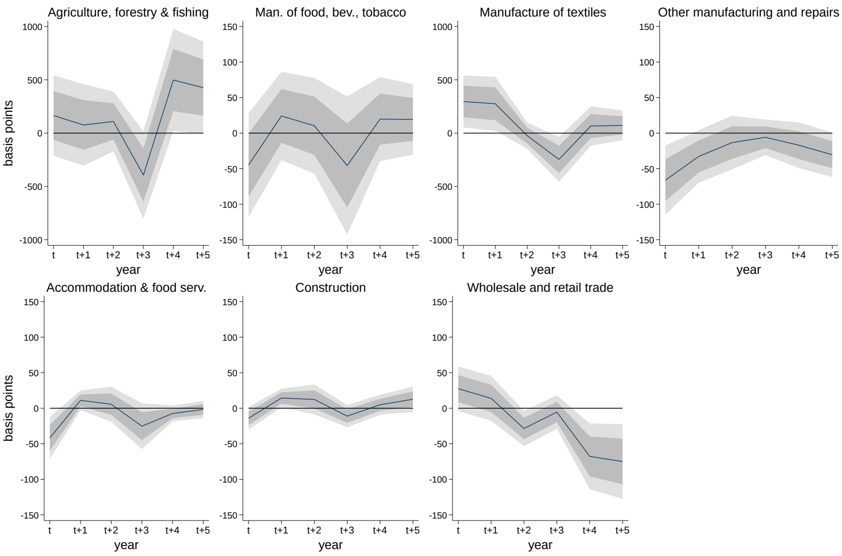
Note: Dynamic impulse response functions of GVA to a one standard deviation increase in the number of floods. Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population size and one lag of GVA. Standard errors are clustered at the ITL3 level. Shaded areas denote 68% and 90% confidence bands.

What happens to inflation? Our estimates show that deviations in output are not always accompanied by variations in prices. Floods do not not significantly impact inflation in the manufacturing of food, beverages and tobacco and in the construction sectors. On the other hand, a one standard deviation shock to the number of floods causes a one-off 70 basis point decline in inflation on impact in the other manufacturing, repairs and installation sector, and a 40bp decline in accommodation and food services activities. In both cases it is not trivial to draw conclusions with respect to supply and demand channels. While both GVA and prices drop in other manufacturing, repairs and installation, they do so at different time horizons. Similarly, prices *decline* on impact in the accommodation and food services sector along with an *increase* in GVA in accommodation and a non-significant reaction of output in food services. When output starts decreasing in the food services sector as well, however, prices have already gone back to their intial level.

In the wholesale and retail trade sector floods are akin to a demand shock. Prices drop alongside GVA by around 25bp after two years, and by a further 75bp five years after the shock. In the manufacturing of textiles, wearing apparel and leather sector the increase in GVA is preceded by a one-off 300bp rise in inflation, suggesting a supply side mechanism is at play.

These results challenge the idea that climate change affects only headline inflation through food and energy prices, while it has no impact on core prices. The literature usually distinguishes between food and non-food inflation, or core and food CPI and shows a generally higher sensibility of food-related prices (Parker, 2018; Faccia et al., 2021; Cevik and Jalles, 2023).[7] We do not find strong evidence that floods impact food manufacturing and electricity prices, while our estimates suggest prices fluctuations in services, in line with deviations in core inflation. This has important consequences for central banks.

Figure 8: Inflation Response to Floods by Sector



Note: Dynamic impulse response functions of inflation to a one standard deviation increase in the number of floods. Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population size and one lag of inflation. Standard errors are clustered at the ITL3 level. Shaded areas denote 68% and 90% confidence bands.

In sum, we have shown that aggregate GDP and inflation responses to flood events hide significant heterogeneity among sectors, which react differently not just in terms of size, but also in terms of timing and sign. Sector level heterogeneity explains well aggregate evidence, and highlights the importance of disentangling the economic impact of weather shocks. Intuitively, weather affects economic activity through a reduction in the capital stock, wealth, and income, which should have immediate impacts on both GDP and inflation. However, most of the available evidence finds delayed responses (Kabundi et al., 2022; Bilal and Känzig, 2024; Eickmeier et al., 2024). We argue that focusing on sectors solves this puzzle.

Our estimates reveal that whether floods are a supply or demand side type of shock is most

[7] While Faccia et al. (2021) and Cevik and Jalles (2023) show higher sensibility of food inflation, Parker (2018) is so far the only one to find significant results for headline inflation, and not for food prices.

likely sector-dependent. In the next Section we investigate two potential channels explaining our results, namely investments and real estate prices. While we do not attempt to provide a definitive answer, we show that a wealth effect is at play. Moreover, we find that the flood shock propagates through the production network. This is in line with the idea that a demand (supply) shock in one sector can turn into a supply (demand) shock in another.

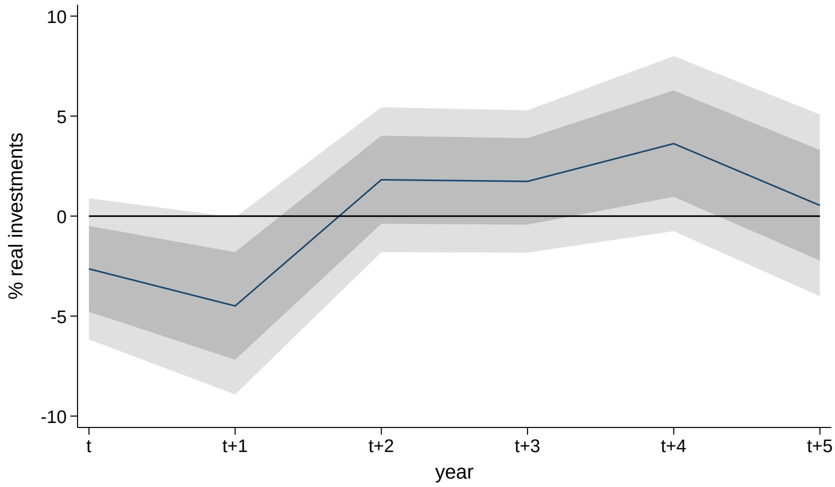
5 What Lies Behind the Sectoral Results?

5.1 Investments

One of the channels through which flooding can dampen output is investments. Following an extreme weather event, firms might suffer damages to their business premises, inventories and machines that warrant repair costs, loss of inventory and, at times, temporary suspension of business activities (Crampton et al., 2024). These damages can in turn hinder access to credit and more generally crowd out investments. For example, Natoli (2023) finds that investments react much more strongly to temperature shocks than consumption, driving the decline in GDP.

We estimate the response of investments using the empirical specification introduced in equations (3) and (4), where $y_{i,t+h}$ is now the log of (sectoral) investments in 2019 prices. We plot our estimates for aggregate and sector-level investments in Figure 9 and Figure 10, respectively. At the aggregate level, we find a borderline significant (p-value = 0.095) reduction in investments of 4.5% the year following a one standard deviation shock in the number of floods. This evidence might partly explain the decrease in aggregate GDP the following year, but cannot fully account for the persistently lower level of output in the following periods. A large enough one-off decline in investments, if spread throughout the whole economy, can negatively affect potential output. However, Figure 10 shows that aggregate results are driven solely by a decline in investments in the manufacturing sector, while investments in all other sectors are not significantly affected. Albeit critical, investments alone cannot explain the dampening impact of floods on aggregate economic activity.

Figure 9: Aggregate Investments Response to Floods



Note: Dynamic impulse response functions of investments to a one standard deviation increase in the number of floods. All specifications include ITL3 and year fixed effects. Controls include population size and one lag of investments. Standard errors are clustered at the ITL3 level. Shaded areas denote 68% and 90% confidence bands.

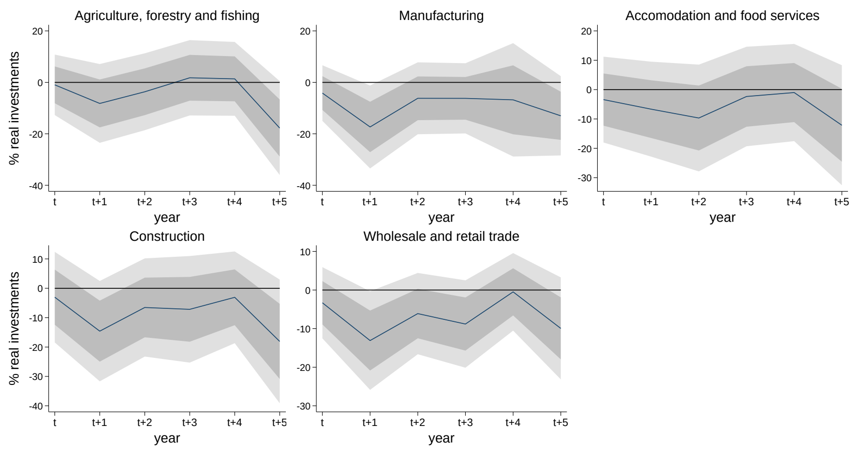
When measuring capital formation the ONS aggregates sectors at the SIC07 section level. We thus lose the categorization of the different manufacturing activities (now grouped into a unique manufacturing sector), accommodation services and food services (accommodation and food services), civil engineering and construction of buildings (construction) and wholesale trade and retail trade (wholesale and retail trade).[8] This limitation does not allow us to draw straightforward comparisons between sector level investments and GVA.

Our estimates show that investments contract only in manufacturing the year following the shock, which might explain at least partially the decline in GVA that we find in the various subcategories of manufacturing. This result suggests that manufacturing firms, either voluntarily or because they are credit constrained, choose to temporarely forego investments in the aftermath of an adverse climate shock. In all other sectors flooding does not significantly impact investments.

Among the many other factors that could explain the reduction in output in these sectors, in the next Sections we focus on two. First, we explore demand side channels by investigating the impact of floods on real estate market transactions. Second, we look at whether the flood shock propagates upstream and downstream along the production network.

[8]We report the IRFs for all the main sectors in the economy in the Appendix.

Figure 10: Investments Response to Floods by Sector



Note: Dynamic impulse response functions of investments to a one standard deviation increase in the number of floods. Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population size and one lag of investments. Standard errors are clustered at the ITL3 level. Shaded areas denote 68% and 90% confidence bands.

5.2 Real Estate Market Transactions

We now focus on real estate market transactions. Floods can cause temporary or permanent damages to private properties, causing a loss in the wealth of households which would be consistent with a demand side type of shock. If households have to incur unexpected expenses to repair or protect their properties or pay higher insurance premia, they will reduce or postpone consumption which in turn can generate a decline in economic activity and in prices. Moreover, as damaged properties decrease in value, households might temporarily lose access to credit and the possibility to smooth consumption.

We investigate this channel by looking at how a flood shock impacts the median transaction value and the number of transactions in the real estate market.[9] We estimate the following model:

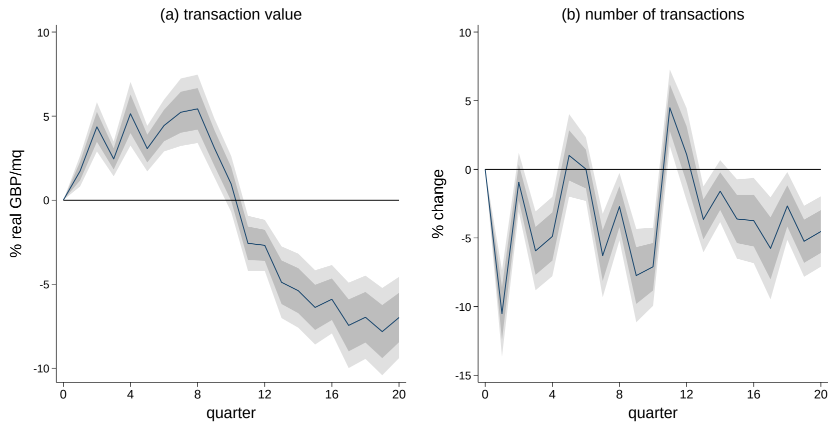
$$y_{i,t+h} = \alpha_i + \beta^h \hat{f}_{i,t} + \Theta y_{i,t-1} + \lambda_t + \varepsilon_{i,t+h}. \tag{5}$$

We perform our analysis at the quarterly frequency for the period 1996q1-2022q2, and set $h = 20$ to match the 5 year time horizon used so far. Because data for GDP, inflation and population is not available at the ITL3-quarter frequency, we limit our controls to 4 lags (i.e., 1 year) of the dependent variable. This approach, combined with local authority (α_i) and quarter (λ_t) fixed effects, should take care of underlying macroeconomic conditions. Our dependent variables are in turn the natural logarithm of the median transaction price expressed in real 2019 GBP/square metre and the natural logarithm of the number of transactions in local authority i and quarter

[9] We confirm our results also when looking at transaction values at the 10th, 25th and 75th percentiles of the distribution.

t. $\hat{f}_{i,t}$ is the fitted value of the number of floods from the first stage. We plot our estimates in Figure 11.

Figure 11: Real Estate Market Transactions Response to Floods



Note: Dynamic impulse response functions of median transaction value (panel (a)) and number of transactions (panel (b)) to a one standard deviation increase in the number of floods. Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include 4 lags (1 year) of the dependent variable. Standard errors are clustered at the ITL3 level. Shaded areas denote 68% and 90% confidence bands.

The impact of a one standard deviation shock on median transaction value (panel (a)) is strong and highly significant. Median price increases in the ten quarters immediately after the shock, with a peak of slightly more than 5%. Transaction prices start to decline entering the third year, and are still decreasing by around 7.5% five years after the shock. At the same time, the number of transactions (panel (b)) drops by 10% immediately after the shock. In the following quarters the impact fluctuates significantly, but still generates a 5% decline in transactions five years later. We complement these results with a postcode-level event study analysis included in the Appendix, where we find a negative impact of the flood event on the number of transactions and price per sqm (10th and 25th percentile) in the quarter of the event occurring in the postcodes flooded, relative to the ones not flooded.

The intuition is as follows. Floods cause damages to private properties. This reduces the valuation of the properties affected (see the results of the postcode-level analysis in the Appendix), but also reduces supply in the real estate market in the short run (the number of transactions declines both at ITL3 wide level and for the postocdes affected). At the same time, despite their high level of geographical granularity, ITL3 regions are vast areas that often encompass multiple towns while floods are often localized events that will only affect a portion of the stock of housing. Hence, in the short run households unaffected by floods will still be active in the real estate market, but supply will be reduced. Moreover, if the real estate market was homogeneous in terms of liquidity within each local authority, unaffected areas would be able to absorb demand and prices should not move significantly. However, floods are more likely to cause damages in densely populated areas, where the market is generally more liquid. As a consequence, we find that prices overall increase in the first two years in the ITL3 regions affected, akin to a supply side shock. In the medium and long run, more channels start to emerge. In particular, increased perceived flood risk can lead to relocation and economic uncertainty (Siders, 2019; Panwar and Sen, 2020; Seebauer and Winkler, 2020).

Concurrently, households affected by floods still face the consequences of unexpected expenses to repair the damages or pay the increased insurance premia, and their consumption remains low. Moreover, the intrinsic value of properties in flood-risk areas declines, reducing households ability to borrow (Harrison et al., 2001; Beltrán et al., 2019; Zhang and Leonard, 2019). The wealth effect is now predominant, and prices decline.

Our estimates thus confirm the presence of a wealth effect of flooding. While in the real estate market it seems to be dominating more in the longer run,[10] it is likely large enough to be consistent with the demand side type of shock we observe in some industries, e.g. wholesale and retail trade.

5.3 Production Networks

Our sectoral level analysis does not provide a definitive answer as to the nature of a flooding shock. In some sectors, such as wholesale and retail trade, floods hit economic activity and prices as a demand-side shock. In others, such as manufacturing of textiles, wearing apparel and leather, they are akin to a supply shock. On the other hand, for some sectors (such as accommodation and food services) we are not able to determine whether one effect dominates the other.

Recent studies have shown that demand shocks can originate from sectoral supply shocks that spillover to other sectors via a Keynesian supply mechanism, what Cesa-Bianchi and Ferrero (2021) and Guerrieri et al. (2022) define as "Keynesian supply shocks". The shutdown of a sector changes the set of goods available to consumers. If the intertemporal elasticity of substitution is larger than the elasticity of substitution across sectors, overall spending becomes less attractive and consumers are induced to postpone spending to the future. Moreover, the shutdown of a sector can cause income losses for the workers. In presence of incomplete markets and limited capacity to borrow, this translates into a depression of spending in the rest of the economy. Both these elements contribute to the rise of Keynesian supply shocks. However, this mechanism is best suited to explain how a supply shock in *one* sector causes *aggregate* demand deficiency. Our estimates point more towards simultaneous supply and demand effects in different sectors and an ambiguous response at the aggregate level.

At the same time, we cannot dismiss the fact that sectors are highly connected through the

[10]Figure A9 further proves that floods cause an inflationary surge in the real estate sector, followed by persistent deflation.

production network. The amplification and propagation of small, localized shocks through the economy via the network of input-output linkages has been widely studied both theoretically and empirically (Foerster, Andrew T. and Sarte, Pierre-Daniel G. and Watson, Mark W., 2011; Gabaix, 2011; Barrot and Sauvagnat, 2016; Acemoglu et al., 2016; Carvalho et al., 2021). In a setting somewhat similar to ours, Carvalho et al. (2021) find that the Great East Japan Earthquake of 2011 resulted in a decline in the growth rate of firms with disaster-hit suppliers and customers, which then propagated to their transactions partners, their transactions partners' partners and so on. While it is beyond the scope of this paper to fully disentangle the propagation of our flood shock through the production network, in this Section we investigate whether network effects exist and how they impact our sector level estimates.

We obtain an industry breakdown of input-output linkages from the ONS input-output analytical tables (IOATs), which we aggregate to match the sectors analysed thus far.[11] We first compute input-output weights as the proportion of total expenditure of firms in sector k on intermediate inputs that goes to intermediate inputs produced in sector j (upstream weights u_{kj}) and the proportion of total output produced by firms in sector k that is used as input from firms in sector j (downstream weight d_{kj}):[12]

$$u_{kj} = \frac{P_{kj} I_{kj}}{P_k I_k}, \quad \forall k, j; \qquad\qquad d_{kj} = \frac{P_{kj} Y_{kj}}{P_k Y_k}, \quad \forall k, j. \tag{6}$$

From here, we follow the empirical corollaries and specification derived by Ghassibe (2021) and adapt our IV-LP methodology to estimate both full and direct effects at all horizons. Hence, we first estimate the cumulated *full* effect of our flood shock:

$$y^k_{i,t+h} = \alpha_i + \beta^F_{k,h} \hat{f}_{i,t} + \gamma X_{i,t} + \Theta y^k_{i,t-1} + \lambda_t + \varepsilon^F_{i,t+h}, \tag{7}$$

where β^F_h is the usual coefficient of interest seen thus far. Secondly, we estimate an upper bound of the *direct effect* of floods, i.e. the impact of floods on sector k's output not considering its interactions with other sectors through the production network:

$$y^k_{i,t+h} = \alpha_i + \beta^D_{k,h} \hat{f}_{i,t} + \sum_{\tau=0}^{T} \psi^\tau_{k,J,N} \sum_{j=1}^{J} u_{kj} \sum_{r \in N} y^j_{r,t-\tau} + \sum_{\tau=0}^{T} \phi^\tau_{k,J,N} \sum_{j=1}^{J} d_{kj} \sum_{r \in N} y^j_{r,t} + \gamma X_{i,t} + \lambda_t + \varepsilon^D_{i,t+h}. \tag{8}$$

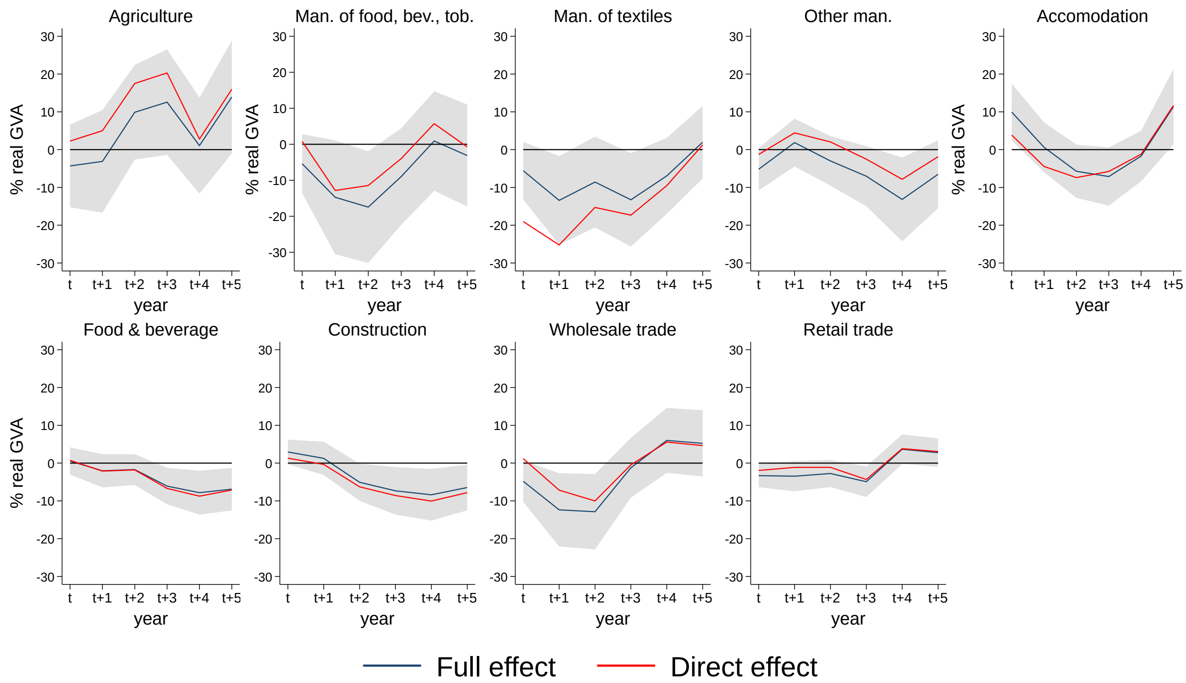
We multiply the upstream and downstream weights u_{kj} and d_{kj} introduced in equation (6) by

[11] IOATs contain a 105 industry breakdown, which we aggregate based on the classification provided by the ONS for GVA and prices data. For 17 out of the 18 UK SIC07 sections IOATs provide a more disaggregated level of analysis. The construction sector, however, is considered as a whole and we cannot distinguish between civil engineering and construction of buildings.

[12] One drawback of this approach is that the ONS does not provide a time series of IOATs, hence we assume our weights to be constant over time.

the sum of real GVA in sector j at time $t-\tau$ produced in local authority i and all its neighbouring regions - we define as N the set of regions neighbouring with i, which includes i itself. Because of the geographical granularity of our sample, we must assume that firms can easily switch suppliers and customers. For example, if a firm's supplier shuts down because of a flood event, the firm will be able to change supplier by going to the next nearest economic centre of activity. We therefore include GVA from all neighbouring regions in our analysis. $\psi^{\tau}_{k,J,N}$ measures the sensitivity of sector k's output to that of its suppliers at time $t-\tau$, whereas $\phi^{\tau}_{k,J,N}$ measures it with respect to its customers. $X_{i,t}$ controls for population size, and we maintain 1 lag of the upstream and downstream exposure throughout (i.e., $T = 1$). The coefficient β^D_h represents an upper bound of the *direct* effect of the flood shock. It follows that $(\beta^F_{k,h} - \beta^D_{k,h})$ gives a lower bound of the *production network* effect at horizon h. In other words, if $|\beta^F_{k,h}| > |\beta^D_{k,h}|$ the propagation of the shock through input-output linkages amplifies the initial direct effect of floods on sector j's output, and viceversa. We plot our estimates for $\beta^F_{k,h}$ and $\beta^D_{k,h}$ in Figure 12. In what follows, we limit our analysis to sectoral GVA.

Figure 12: Investments Response to Number of Floods by Sector (Main Sectors)



Note: Dynamic impulse response functions of GVA to a one standard deviation increase in the number of floods: full (blue line, $\beta^F_{k,h}$) and direct (red line, $\beta^D_{k,h}$) effects. The difference between the two gives a lower bound of the production network effect. Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population and one lag of GVA for the full effect; population, current and lagged upstream and downstream exposure to other sectors' GVA in i and all its neighbouring regions for the direct effect. Standard errors are clustered at the ITL3 level. Shaded areas denote 90% confidence bands around the full effect.

Our results suggest that input-output linkages play a role in the propagation of a flooding shock depending on the sector. In relatively upstream sectors, such as manufacturing, the point estimates for full and direct effects are considerably different. As we move downstream the production network, input-output linkages still cause direct and full effects to diverge, but by a smaller margin (i.e, $\beta^F_{k,h} - \beta^D_{k,h}$ is closer to 0).

In particular, the direct effect in manufacturing of food, beverages and tobacco and in other manufacturing, repairs and installation is smaller in absolute value compared to the full effect. In these sectors production networks amplify the initial direct impact of a flood shock. On the other hand, input-output linkages significantly dampen the direct effect of floods in manufacturing of textiles, wearing apparel and leather in the first three years.

In wholesale trade and retail trade the full effect is slightly larger in absolute terms compared to the direct effect, which likely relates to the flood shock hitting upstream industries and propagating downstream to the trade sector. Notably, production networks do not seem to strongly affect GVA response in food and beverage services and in construction, while they initially amplify the positive impact of floods in the accommodation services sector. Lastly, in the agriculture sector the full effect is smaller than the direct effect, but remains not significantly different from zero.

In the Appendix (Figure A11) we compare these results to the same analysis including upstream and downstream GVA within local authority i only. We show that the direct effect does not change significantly when we do not consider neighbouring regions. On the one hand, this result might partially depend on the large spatial correlation between industry GVAs: adding GVA of neighbours to the equation could simply not add much information. However, this evidence also suggests that a large part of the production network amplification of a flood shock comes from within-region input-output linkages. This conclusion has important implication with respect to the debate on adaptation policies. If the propagation of a shock through the production network is highly localized, adaptation investments might be even more effective.

Because we focus on a single, fairly small and well connected country, we should not expect production networks to impact sector level economic output majorly. There would need to be nation wide disruptions to cause severe interruptions in the production network. Nevertheless, our findings highlight the presence of propagation mechanisms through input-output linkages among sectors. Importantly, we see the largest difference between full and direct effect in sectors that are at the top (manufacturing) and at the bottom (wholesale and retail trade) of the production network. While our estimates do not allow us to determine with certainty whether or not flooding is akin to a (Keynesian) supply or demand shock, they underline once more the importance of focusing on sectors rather than aggregate figures.

6 The Role of Adaptation Policy

Having established that floods cause a reduction in sectoral output and fluctuations in prices, in this section we focus on adaptation policy. While investments in adaptation do not tackle the issue of flooding at its core, namely climate change, they represent the most readily available tool for central governments and local authorities to try and reduce the impact of floods. Despite their relevance, there is to date no empirical evidence assessing the effectiveness of adaptation policies. Fried (2022) uses a heterogeneous-agent model with adaptation capital that incorporates damages from storms as the realization of idiosyncratic shocks and finds that adaptation can significantly reduce the damage of climate change by approximately one-third. These conclusions, however, have not yet been tested empirically. Canova and Pappa (2022) analyse the role of fiscal policy and find that when U.S. states enjoy larger federal transfers on the onset of a climate disaster they display a more positive medium term output response. While essential, government intervention in the aftermath of a flood shock only mitigates the impact *ex-post* and is strongly dependent on countries' fiscal positions. Adaptation capital (i.e., flood defences), on the other hand, can potentially protect infrastructures and people from flooding itself, thus tackling the problem *ex-ante*.

This is not merely an academic exercise, but also a policy relevant experiment as governments are increasingly pressured to take action.[13] During the recent flooding season in the UK, in late fall and early winter of 2023, the poor state of flood defences has been deemed responsible for the rising number of people affected by flood events.[14] The National Audit Office has found that the number of properties to receive better protection from flooding by 2027 has been cut by 40%, and 500 of 2,000 new flood defence projects have been abandoned.[15]

We study the role of adaptation policy along both the extensive and the intensive margin. While we expect flood defences to be effective in reducing flood risk (the extensive margin), whether they can help once a flood hits (the intensive margin) is less obvious. Data on local authority expenditure on flood defences does not provide information on the adaptation capital built over time. Moreover, because it is only available starting in fiscal year 2008-09, our panel is not long enough to introduce a sufficient amount of lags of adaptation expenditure that can account for the building up of flood defences capital. These are crucial limitations, as large expenditure in one year does not necessarily reflect higher adaptation capital but might be a reaction to very low expenditure in the past, or more simply a one-off investment. As it is

[13] Financial Times, January 7th, 2024, see https://www.ft.com/content/78573e49-ee72-4140-807a-bc79a11aea8a.

[14] The Guardian, January 5th, 2024, see https://www.theguardian.com/uk-news/2024/jan/05/uk-floods-and-deaths-will-keep-rising-without-proper-defences-and-conservation.

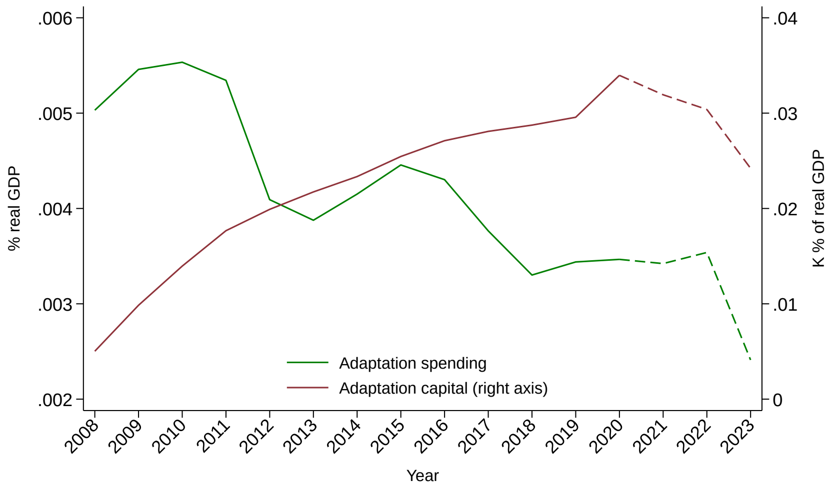
[15] The Guardian, see https://www.theguardian.com/environment/2023/oct/30/more-than-4000-english-flood-defences-almost-useless-analysis-finds (October 30th, 2023) and https://www.theguardian.com/environment/2023/nov/15/flooding-defence-protection-england-properties-cut-naore (November 15th, 2023).

adaptation *capital*, more than adaptation *expenditure*, that matters for protection against floods, we build a proxy by cumulating expenditure over time:

$$k_{i,t}^{adapt.} = exp_{i,t}^{adapt.} + \delta k_{i,t-1}^{adapt.}. \tag{9}$$

For coastal and fluvial protection we assume an average life of 50 years ($\delta = 0.02$), while for land drainage investments we set the depreciation rate to 15 years ($\delta = 0.067$).[16] We plot the time series for both adaptation expenditure and adaptation capital in Figure 13, which shows that adaptation expenditure by local authorities has been steadily declining since 2008, causing a flattening in the growth rate of adaptation capital.[17]

Figure 13: Adaptation Expenditure and Capital



Note: The figure plots the time series of adaptation expenditure (left axis) and adaptation capital (right axis) in England's local authorities as a percentage of their GDP for fiscal years 2009-09 to 2023-24 (real 2019 £). The dotted segments represent projected figures, as GDP values at the ITL3-level are not available after 2021. We proxy capital formation by cumulating adaptation expenditure over time using $\delta = 0.02$ for coastal and fluvial protection expenditure and $\delta = 0.067$ for land drainage protection expenditure.

6.1 Extensive Margin

We start our analysis by looking at whether adaptation policy is effective at reducing flood risk. We estimate the following model:

[16]Fried (2022) uses a depreciation rate of 0.03, which corresponds to an average life of 33 years. Various technical sources, however, suggest that 50 and 15 years are more appropriate life-spans for these types of investments. Floods potentially affect the rate of depreciation of adaptation capital, but we have no way of determining whether a given flood causes damages to flood defences (and to what extent). Hence, we abstain from any assumptions as to the depreciation of adaptation capital following a flood.

[17]The opposite is true for the central government as a big part of expenditure in the UK is sustained by the Environment Agency.

$$f_{i,t+h} = \alpha_i + \beta^h P^z_{i,t+h} + def_{i,t}(\gamma + \phi prone_i) + \Theta X_{i,t-1} + \lambda_t + \varepsilon_{i,t+h}, \tag{10}$$

in which $def_{i,t}$ is in turn adaptation expenditure ($exp^{adapt.}_{i,t}$) and our proxy for adaptation capital ($k^{adapt.}_{i,t}$) taken as percentages of GDP. We define the dummy $prone_i$ to be equal to 1 if local authority i is a flood prone area, i.e. if on average it has been subject to more floods than the national average over the panel ($prone_i = 1$ if $\overline{f}_i > \overline{f}$). Hence, γ measures how an increase in adaptation expenditure or capital as a percentage of GDP affects flooding in a non-flood prone local authority, and ϕ tells us how this relationship changes when a local authority is flood prone.[18] We control for population size, our precipitation z-score, 1 lag of GDP and 3 lags of the dependent variable, that is the number of floods $f_{i,t}$. We summarise results in Table 2.

Table 2: Adaptation Policy: Extensive Margin

Dep: n. of floods	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+4	(6) t+5
$exp_{i,t}$	-0.231	-0.791	-1.952	-3.879	-11.19**	-9.467
	(-0.14)	(-0.41)	(-0.79)	(-1.02)	(-2.50)	(-1.61)
$exp_{i,t} \times prone_i$	-8.187	-43.26	-74.51****	-1.762	-6.449	-12.14
	(-0.20)	(-1.30)	(-4.03)	(-0.04)	(-0.14)	(-0.39)
$k^{adapt.}_{i,t}$	-0.127	0.0195	-0.415	-0.877	0.0938	0.855
	(-0.26)	(0.04)	(-0.72)	(-1.15)	(0.09)	(0.93)
$k^{adapt.}_{i,t} \times prone_i$	-23.56*	-33.29**	-20.17***	-21.03**	-45.02**	-40.85***
	(-1.78)	(-2.48)	(-3.04)	(-2.31)	(-2.45)	(-2.94)
Obs.	4,326	4,326	4,017	3,708	3,399	3,090
ITL3 FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable is the number of floods in local authority i at time $t+h$. In the first two rows the independent variable of interest is adaptation expenditure $exp^{adapt.}_{i,t}$. In the third and fourth row the independent variable of interest is our proxy for adaptation capital $k^{adapt.}_{i,t}$ defined in equation (9). $prone_i$ is a dummy = 1 if local authority i is flood prone, i.e. if in an average year it is hit by more floods than the country average over the panel. We include three lags of the dependent variable, population size and 1 lag of GDP. All regressions include ITL3 and year fixed effects, and standard errors clustered at the ITL3 level. t-statistics in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Our estimates suggest that adaptation strongly reduces the likelihood of being hit by a flood in flood prone areas, especially if built up over time. In particular, a 1 percentage point increase in adaptation expenditure as percentage of GDP reduces the number of floods by 11.19 units after four years in non flood prone areas, and by 76,46 units after two years in flood prone ares. We should highlight three caveats. First, the delayed effect of adaptation expenditure is in line with the concept of "time-to-build", as expenditure in year t takes some time to turn into capital (Ramey, 2020). Second, the rarely significant coefficients are consistent with the

[18] The impact of adaptation policy in a flood prone area is instead given by $\gamma + \phi$.

fact that expenditure itself does not necessarily reduce flooding. What matters is adaptation capital, and capital is only built by consistently investing in flood defences. Lastly, a 1 percentage point increase in adaptation expenditure is far from what we observe in the data. The median expenditure is 0.002% of GDP, meaning that a flood prone local authority spending the median value in adaptation will reduce the number of floods by 0.15 units.[19]

The third and fourth row summarise the effect of adaptation capital. An increase in adaptation capital in flood prone areas is effective at reducing the risk of flooding at all horizons, while it does not significantly reduce the number of floods in non flood prone areas. Unlike for adaptation expenditure, the impact of capital does not take years to materialize. In particular, a 1 percentage point increase in the stock of adaptation capital as a percentage of GDP is associated to 23.7 fewer floods in year t, 33.3 in year $t+1$, 20.6 in $t+2$, 21.9 in $t+3$, 44.9 in $t+4$ and 40.8 in $t+5$. As median adaptation expenditure is 0.002 percent of GDP and capital depreciates at rate δ, we never observe a 1 pp increase in adaptation capital over GDP and should scale our coefficients by at least 500.[20] A local authority increasing its stock of adaptation capital by the median amount in year t will be flooded 0.4 fewer times by year $t+5$, which corresponds to a 3.5% reduction in the number of floods compared to the average local authority.[21] Our results strongly support the idea that investing in adaptation is an effective way to deal with flooding. Investments should be aimed at building up and maintaining a sufficient stock of adaptation capital.

6.2 Intensive Margin

We now turn to the intensive margin. The question is whether, once a flood happens, spending more on adaptation can reduce economic damages. While we find that investing in adaptation can prevent flooding, this could mean that in well protected areas only extremely severe conditions trigger a flood, potentially still causing significant damages. *A priori* this is not a straightforward question to answer.

We estimate a state-dependent IV-LP model along the lines of Auerbach and Gorodnichenko (2011) and Auerbach and Gorodnichenko (2012), in which instead of determining the state through a transition function F(.) we follow Ramey and Zubairy (2018) and use a regime-switching dummy:

[19] To get the decrease in the number of floods for a local authority spending the median amount on adaptation, we simply divide the coefficients in Table 2 by $\frac{1}{0.002}$.

[20] Net of depreciation, the median local authority has a stock of adaptation capital worth 0.019% of GDP in 2021, the last year in our sample.

[21] ITL3 regions are flooded on average 2.3 times every year, which means that over the five year horizon they register 11.5 flood. Notice however that the median number of floods is 0.

$$
\begin{aligned}
y_{i,t+h} = I_{i,t-1} & \left[\alpha_i + \beta_H^h \hat{f}_{i,t} + \gamma X_{i,t} + \Theta y_{i,t-1} + \lambda_t\right] \\
& + (1 - I_{i,t-1)} \left[\alpha_i + \beta_L^h \hat{f}_{i,t} + \gamma X_{i,t} + \Theta y_{i,t-1} + \lambda_t\right] + \varepsilon_{i,t+h}
\end{aligned} \tag{11}
$$

with

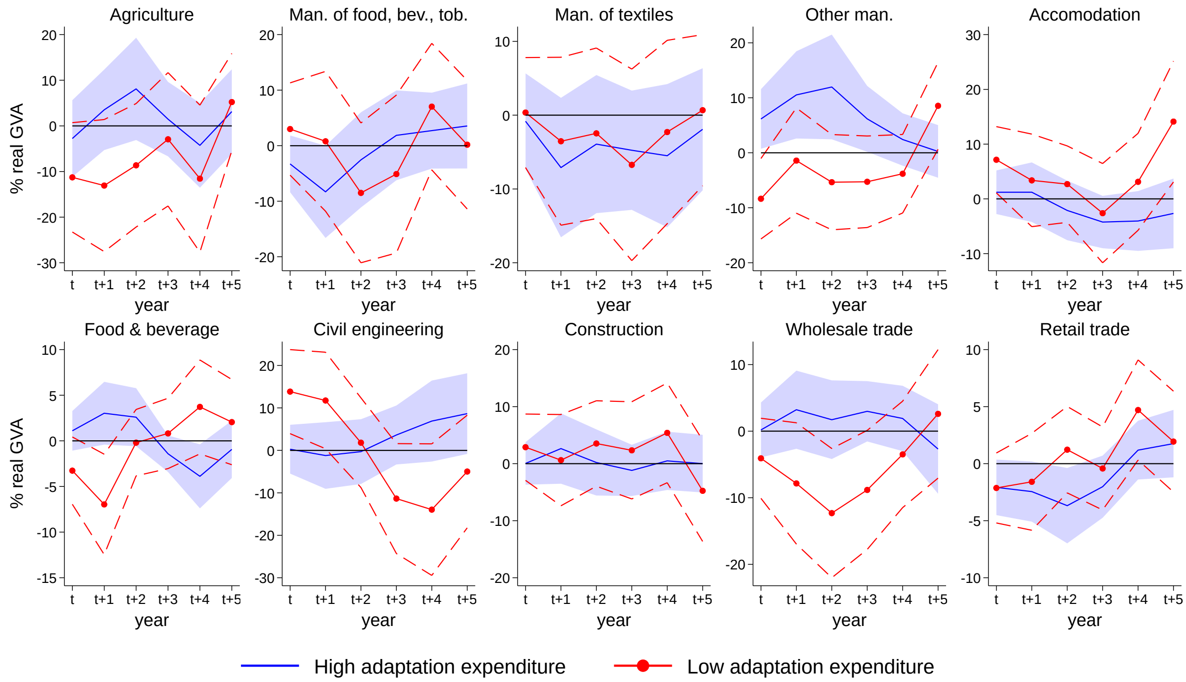
$$
I_{i,t-1} = \begin{cases} 1 & \text{if } exp_{i,t-1} > \overline{exp} \\ 0 & \text{otherwise} \end{cases} \tag{12}
$$

Our empirical strategy is the same introduced in equations (3) and (4), but we now allow the coefficients of the model to vary according to the state of the economy. β_H^h is the impact of floods on sectoral GVA or inflation in a high adaptation expenditure state, while β_L^h is the impact in a low adaptation expenditure state. We compute mean adaptation expenditure (as a percentage of GDP) over the whole sample, and let local authority i in year t be in a high adaptation expenditure state if it spent more than the average in year $t-1$. Following Ramey and Zubairy (2018), local authorities inherit their state from year $t-1$. As it builds up over time, we are unable to define the state based on the stock of adaptation capital. Doing so would be tantamount to comparing the impact of floods in the first and last years of our panel. We plot the IRFs for GVA in Figure 14. We leave the corresponding figures for sectoral inflation and aggregate measures of output and prices in the Appendix.

With the exception of the construction of buildings and manufacturing of textiles, wearing apparel and leather sectors, the difference in the point estimates is sizeable. However, the overlap of confidence bands suggest that this difference is rarely significant. Nevertheless, we point out that the positive impact on GVA we found in the accommodation sector and in civil engineering seems to be driven by local authorities in the low adaptation expenditure state. Similarly, the decrease in GVA observed in wholesale trade and in food and beverage services comes mostly from local authorities that do not invest enough in adaptation. The interpretation is simple: when a flood happens, these regions are less protected and sustain larger economic losses. Having invested more in flood defences likely reduces the destructive power of floods by limiting the overflow of water or simply delaying it, thus giving enough time to people and businesses to prepare.

In sum, we have shown that investing in adaptation does mitigate the impact of flooding primarily because flood defences reduce the likelihood of a flood happening, meaning they are effective at the *extensive* margin. On the other hand, we find evidence that in certain sectors high adaptation expenditure can limit the economic consequences of floods once a local authority is hit, meaning they might be able to reduce the effects of flooding at the *intensive* margin too. This evidence has important consequences for the policy debate, and indicates that adaptation is an effective way to protect the economy.

Figure 14: Investments Response to Number of Floods by Sector (Main Sectors)



Note: Dynamic impulse response functions of GVA to a one standard deviation increase in the number of floods: high (blue line, β_h^H) and low (red line, β_h^L) adaptation expenditure state. The state is defined in equation (12) using a regime-switch dummy as in Ramey and Zubairy (2018). The model we estimate is reported in equation (11). Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population size and one lag of GVA. Standard errors are clustered at the ITL3 level. Shaded areas denote 90% confidence bands.

7 Conclusions

In this paper, we study the impact of floods on output and inflation at the sector level for counties in England and we analyze whether and how investments in adaptation can limit economic losses. Our findings, drawing on very precise measurement of flood events and LP-IV techniques, highlight significant heterogeneities across sectors in terms of size, sign and timing of the response.

While output in manufacturing, wholesale and retail trade dampens in the short run, it only decreases in the longer run in food and beverage services and in construction. On the contrary, output shows an immediate and temporary increase in accommodation services and in civil engineering. Taken together, this evidence is sufficient to solve the aggregate puzzle encountered in the literature and confirmed by our analysis, whereby floods only impact GDP in the long run. Prices temporarily decline in most sectors, with the exception of manufacturing of textiles, wearing apparel and leather for which we find evidence of inflation and conclude that flooding represents a supply side type of shock. Pressure on the wholesale and retail sector, on the other hand, comes from demand factors. For all other sectors it is not trivial to determine whether floods are more akin to demand or supply side shocks.

We investigate two potential mechanisms behind our baseline results, namely investments and real estate transactions. We find that investments cannot explain the persistent decline in aggregate GDP, and are only partially responsible for the decrease in manufacturing output. Both the value and the number of real estate transaction drop in the postcodes affected, in line with a wealth effect that is consistent with a more demand side type of behavior. The price of real estate properties at regional level however increases on average as a response to a restriction in supply. We further analyze whether interactions among sectors can amplify or absorb the direct impact of floods, and find that the shock propagates through input-output linkages. Sectors at the top (manufacturing) and at the bottom (wholesale and retail trade) of the production network see their initial direct impact amplify the most.

Lastly, we focus on adaptation investments. We show that expenditure in adaptation can reduce the likelihood of floods, but only temporarily. On the other hand, building up adaptation capital over time strongly and consistently lowers the probability of being flooded for flood prone areas in the short, medium and long run. When floods do happen, adaptation is not as effective at reducing economic losses.

Our findings have important policy implications for both governments and central banks. Sector level heterogeneity suggests that a one-size-fit-all approach is not the most adequate response, and it should be kept into consideration if governments want to maximize the effectiveness of transfers to households and firms in the aftermath of flood events. Central banks, on the other hand, focus on the aggregate by design. While our results do not provide conclusive evidence as to the dynamics of aggregate inflation, they uncover significant price variations in sectors related to core inflation, and not just headline. What's more, the expected increases in the frequency and intensity of floods due to climate change might soon make our results obsolete. Central banks should keep an eye out for shifts in the distribution of flood events. Regardless of monetary policy responses, however, the most effective way to reduce the economic impact of floods seems to be flood defences. While not tackling the issue of flooding at its core, namely climate change, flood defences are the most readily available tool for central and local governments. Our results stress the importance of building up adaptation capital, rather than occasional one-off expenditures. A substantial stock of flood defences capital will not be able to significantly mitigate losses across all sectors if overtopped, but strongly reduces the probability of flooding occurring, which by itself is enough to avoid relevant economic losses.

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Appendix

Data

Aggregating grid data for rainfall. ERA5 provides each rainfall observation as the centroid of a 30km×30km grid. We construct around each centroid a buffer, i.e. a 15km-radius circle with the centroid as its focus. The total rainfall of a circle in year t is given by the annual sum of the hourly precipitation observations of its centroid. We then intersect each circle with the 309 local authorities in England. If a circle intersects more than one area, we assign to each area the share of rainfall corresponding to the share of the circle it intersects. For example, let a circle intersect local authority A with 75% of its area and local authority B with the remaining 25%. If, in year t, total precipitation amount in the circle is 1,000 millimetres, we assign 7,500mm to A and 2,500mm to B. One minor drawback of this approach is that we neglect to account for the space enclosed between the circumferences of the circles. One could avoid this issue by using squares instead of circles as buffers. However, given the level of geographical and time aggregation, our approach should be accurate enough for our scope.

Flood defences. The Environment Agency releases a range of flood asset information as open data. The AIMS Spatial Flood Defences data layer is the only comprehensive and up-to-date dataset in England that shows flood defences currently owned, managed or inspected by the EA. Flood defences are any assets that provide flood defence or coastal protection functions. They can be structures, buildings or parts of buildings. Typically, these are earth banks, stone and concrete walls, or sheet-piling that is used to prevent or control the extent of flooding.

For each flood defence, AIMS provides information concerning e.g. its state, its length, the year in which it was last refurbished and the date in which it started operating. This data, however, presents two major limitations. Firstly, most of the flood defences in the dataset (more than 70%) are natural high grounds, which speak more to the land structure of the area they protect rather than to the local authority's adaptation to flooding. Secondly, more than 90% of the flood defences in the data appear to have started operating between 2011 and 2013. This is most likely due to the administrative changes following the approval of the Flood and Water Management Act in 2010, which contained provisions to improve the management of local flood risk, and we thus cannot rely on the temporal information of this dataset.

Watercourse data. We obtain watercourse data from OS Open Rivers, a free dataset showing the high-level view of watercourses in Great Britain. OS Open Rivers GIS data contains over 144,000km of water bodies and watercourses map data. These include freshwater rivers, tidal estuaries and canals.

Postcode-level Real Estate Market Analysis

We complement the results of the real estate market analysis at ITL3 level presented in Section 5.2 through an event-study approach at postcode level. We estimate the following model:

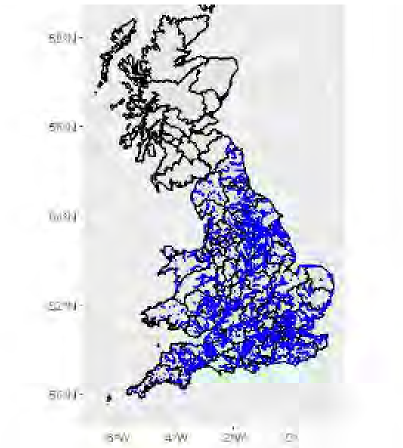
$$y_{i,t} = \alpha_i + \sum_{h=0}^{12} \beta^h T_{i,t-h} + \eta_i + \lambda_t + \varepsilon_{i,t+h}. \tag{13}$$

We perform our analysis at the quarterly frequency for the period 1995q1-2022q2. Each dummy ($T_{i,t-h}$) represents the interaction of a dummy identifying treated postcodes with a dummy controlling for the number of quarters after the flooding shock (h). We set max $h = 12$, equivalent to 3 years since the shock, This approach, combined with controls for the area code, proxying for the municipality, (η_i) and quarter (λ_t) fixed effects, aims to control for underlying macroeconomic conditions. Our dependent variables are in turn the natural logarithm of the median transaction price expressed in real 2019 GBP/square metre and the natural logarithm of the number of transactions in postcode i and quarter t. We present our estimates in Table A3.

We find a negative impact of the flood event on the number of transactions and price per sqm (10th and 25th percentile) in the quarter of the event occurring in the postcodes flooded, relative to the ones not flooded. The effect then appears to gradually unwinds over the following quarters. The negative effect of flooding on real estate valuation at postcode level is consistent both with the cost of damages inflicted to the properties affected - thus decreasing their valuation - and the distortion of risk perceptions following a natural disaster event. The perceived increase in flooding risk in the flooded postcodes supports the decrease in real estate transaction volumes we also detect. This is in line with existing literature on the topic (Lamond et al., 2010), which suggests that the effect is only temporary and attenuating over time (Lamond and Proverbs, 2006; Lamond et al., 2010; Atreya et al., 2013; Doupé et al., 2019) - unless the flood event is associated with a structural increase in the risk of flooding of that specific area (e.g., as a result of coastal erosion or damage to flood defenses).

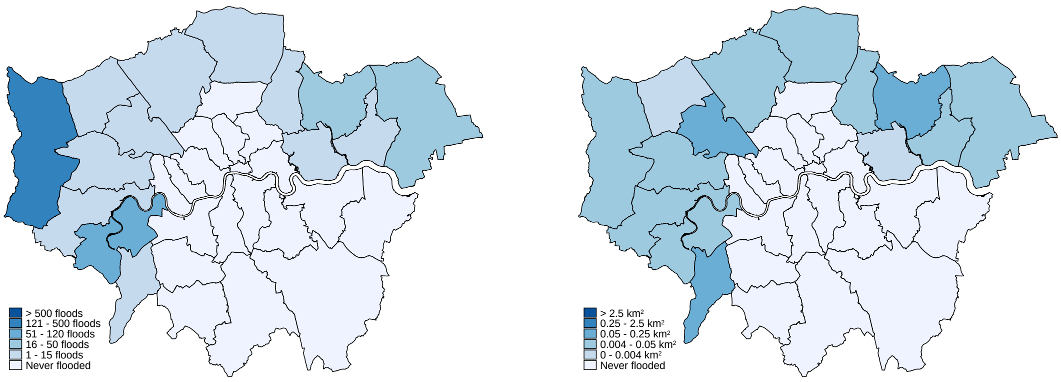
Figures and Tables

Figure A1: Historical Map of Flood Events



Source: EA and NRW Recorded Flood Outline.
Note: Historical records starting in the 1700s for England and Wales.

Figure A2: Overall Number of Floods and Average Flood Extent by ITL3 (London)

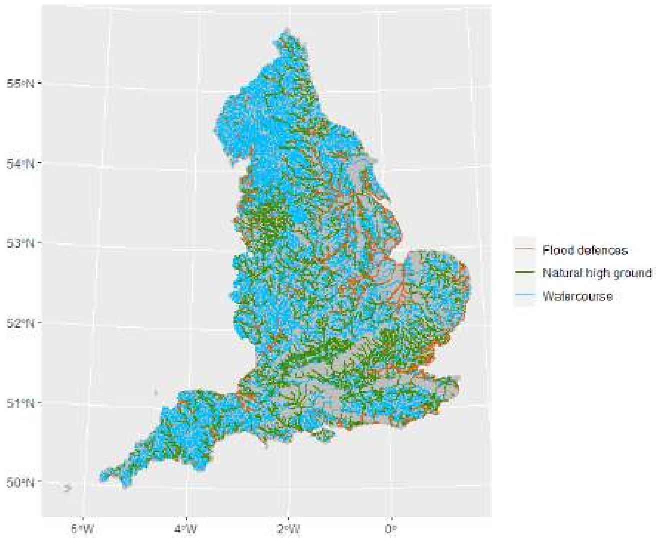


(a) Number of floods

(b) Average flood extent

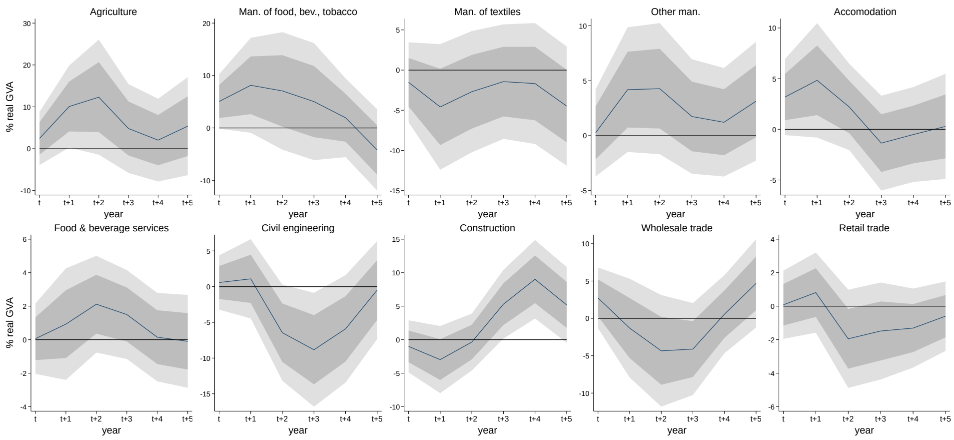
Source: EA Recorded Flood Outlines and authors' calculations.
Note: We treat each flood event as a single flood, and assign it to every ITL3 area hit and compute the flooded area accordingly. Average flood extent is computed as each ITL3 area's total area flooded over the panel divided by the total number of floods.

Figure A3: Map of Watercourse and Flood Defences



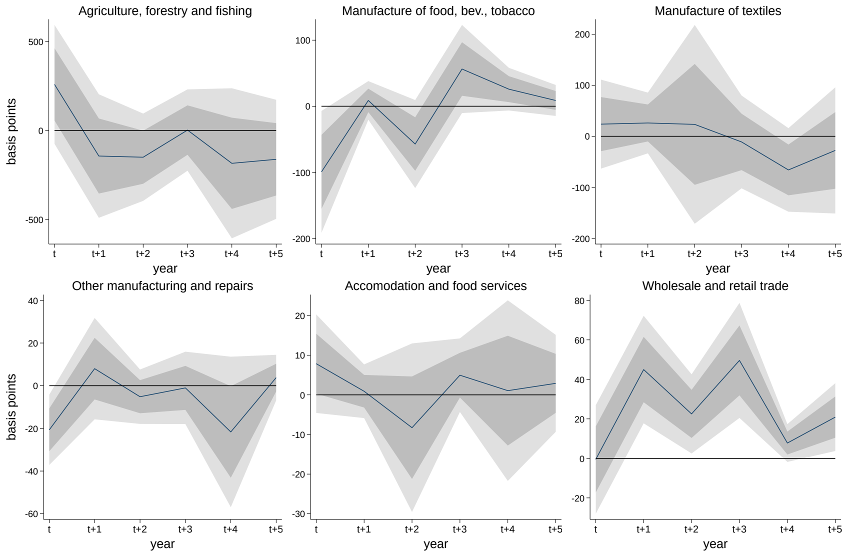
Source: OS Open Rivers, AIMS Spatial Flood Defences, and authors' calculations.
Note: We map watercourse and flood defences by matching the nodes and links in the data with shapefiles for England.

Figure A4: Confirming the Exclusion Restriction - GVA and Neighbouring Floods



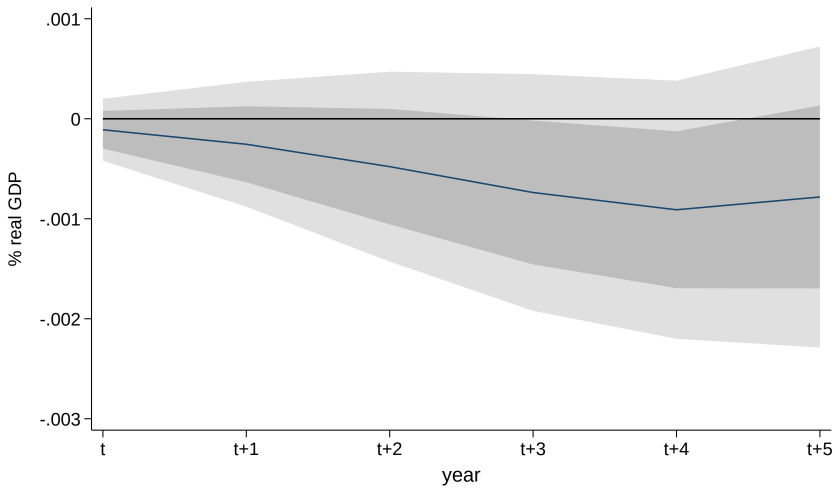
Note: Dynamic impulse response functions of GVA in region i to a one standard deviation increase in the number of floods in all of i's neighbouring regions. Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population size, $P^z_{i,t}$ and one lag of GDP. Standard errors are clustered at the ITL3 level. Shaded areas denote 68% and 90% confidence bands.

Figure A5: Confirming the Exclusion Restriction - Inflation and Neighbouring Floods



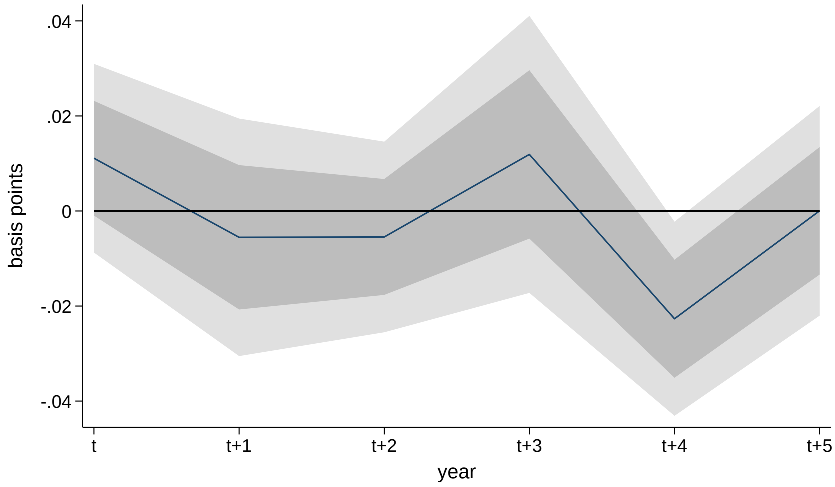
Note: Dynamic impulse response functions of inflation in region i to a one standard deviation increase in the number of floods in all of i's neighbouring regions. Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population size, $P^z_{i,t}$ and one lag of inflation. Standard errors are clustered at the ITL3 level. Shaded areas denote 68% and 90% confidence bands.

Figure A6: GDP Response to Floods - LP OLS



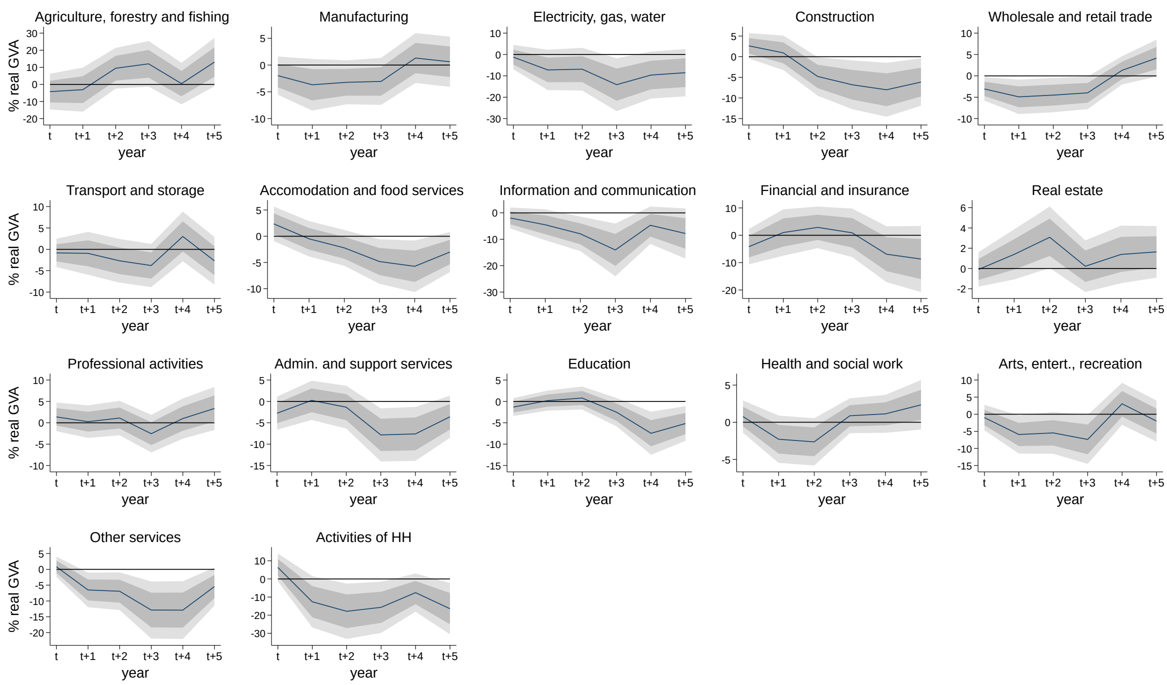
Note: Dynamic impulse response functions of GDP to a one standard deviation increase in the number of floods . All specifications include ITL3 and year fixed effects. Controls include population size and one lag of GDP. Standard errors are clustered at the ITL3 level. Shaded areas denote 68% and 90% confidence bands.

Figure A7: Inflation Response to Floods - LP OLS



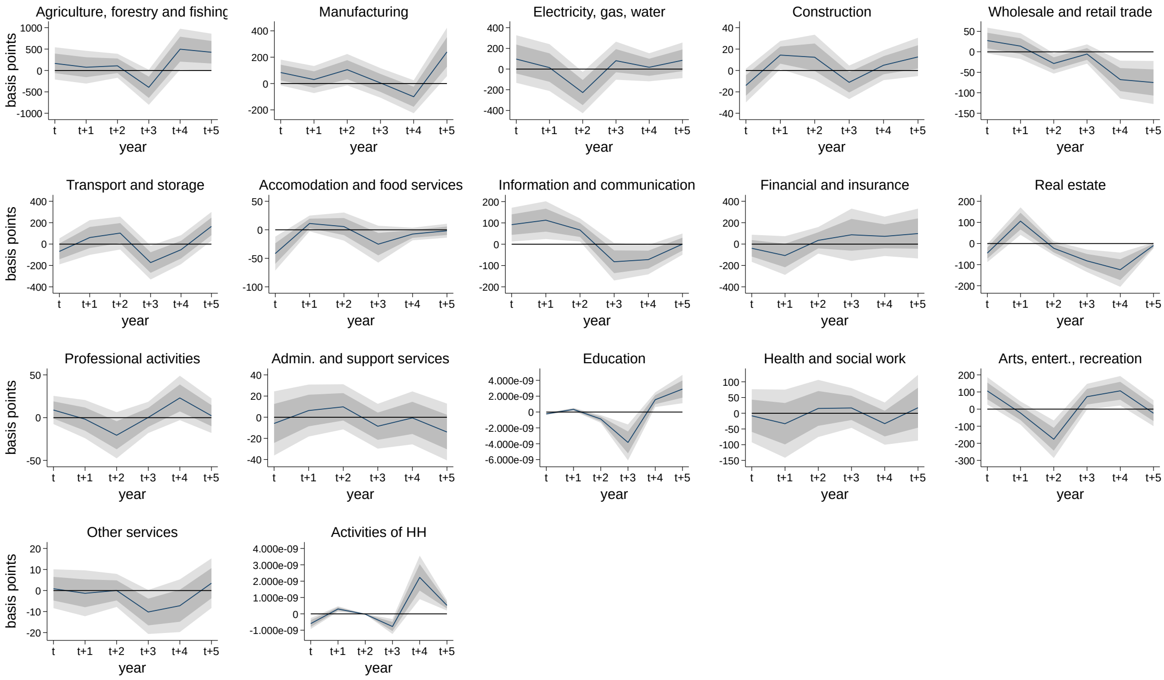
Note: Dynamic impulse response functions of inflation to a one standard deviation increase in the number of floods. All specifications include ITL3 and year fixed effects. Controls include population size and one lag of inflation. Standard errors are clustered at the ITL3 level. Shaded areas denote 68% and 90% confidence bands.

Figure A8: GVA Response to Number of Floods by Sector (Main Sectors)



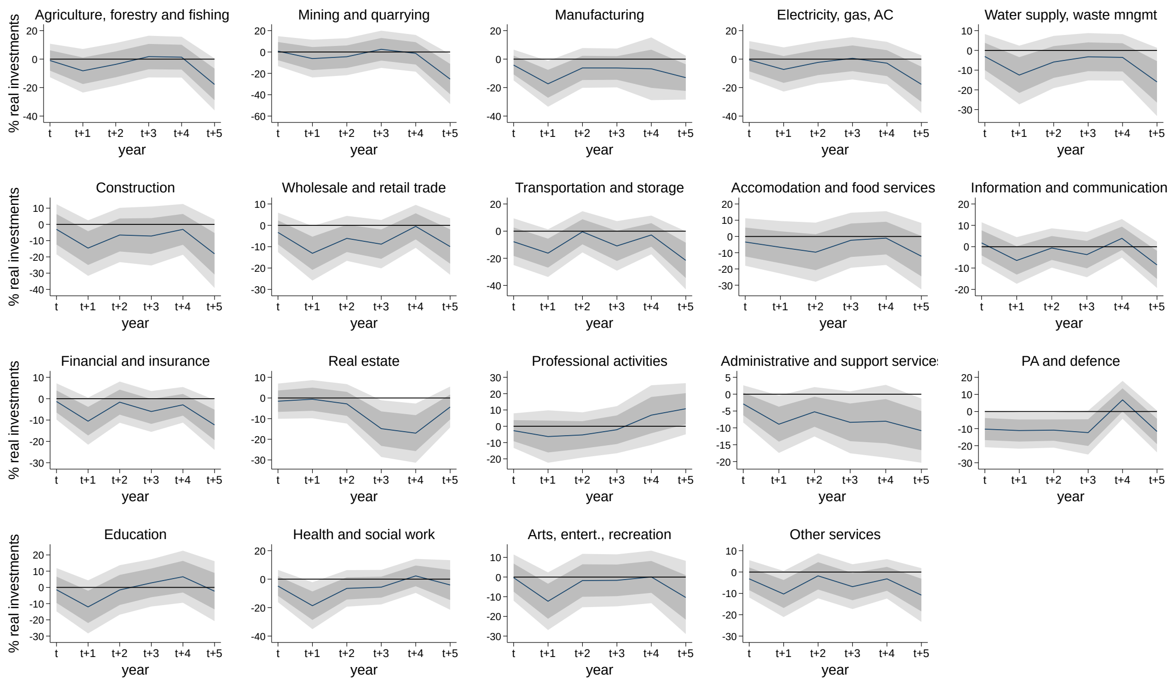
Note: Dynamic impulse response functions of GDP to a one standard deviation increase in the number of floods. Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population size and one lag of GDP. Standard errors are clustered at the ITL3 level. Shaded areas denote 68% and 90% confidence bands.

Figure A9: Inflation Response to Number of Floods by Sector (Main Sectors)



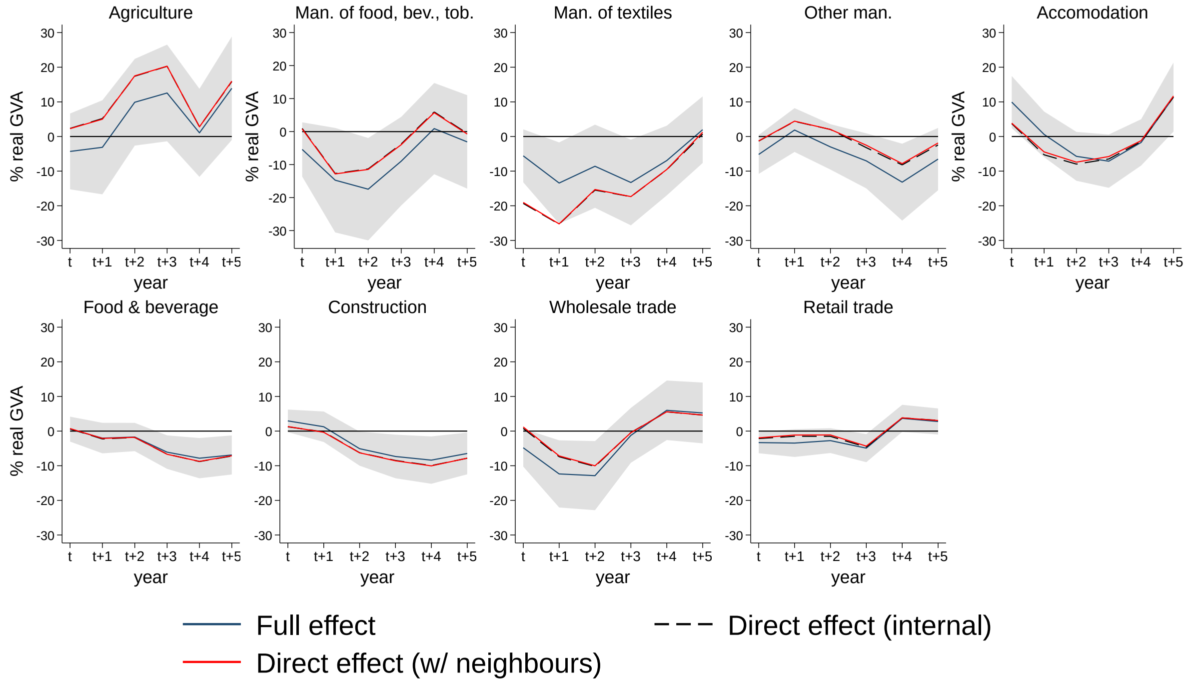
Note: Dynamic impulse response functions of inflation to a one standard deviation increase in the number of floods. Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population size and one lag of inflation. Standard errors are clustered at the ITL3 level. Shaded areas denote 68% and 90% confidence bands.

Figure A10: Investments Response to Number of Floods by Sector (Main Sectors)



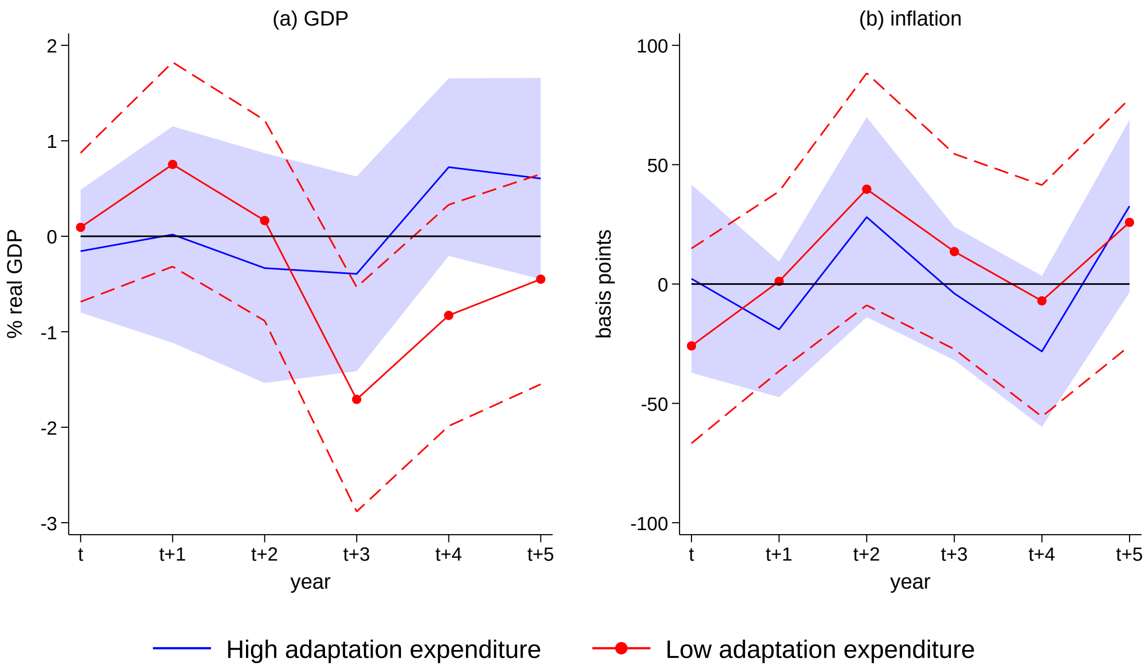
Note: Dynamic impulse response functions of investments to a one standard deviation increase in the number of floods. Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population size and one lag of investments. Standard errors are clustered at the ITL3 level. Shaded areas denote 68% and 90% confidence bands.

Figure A11: Investments Response to Number of Floods by Sector (Main Sectors)



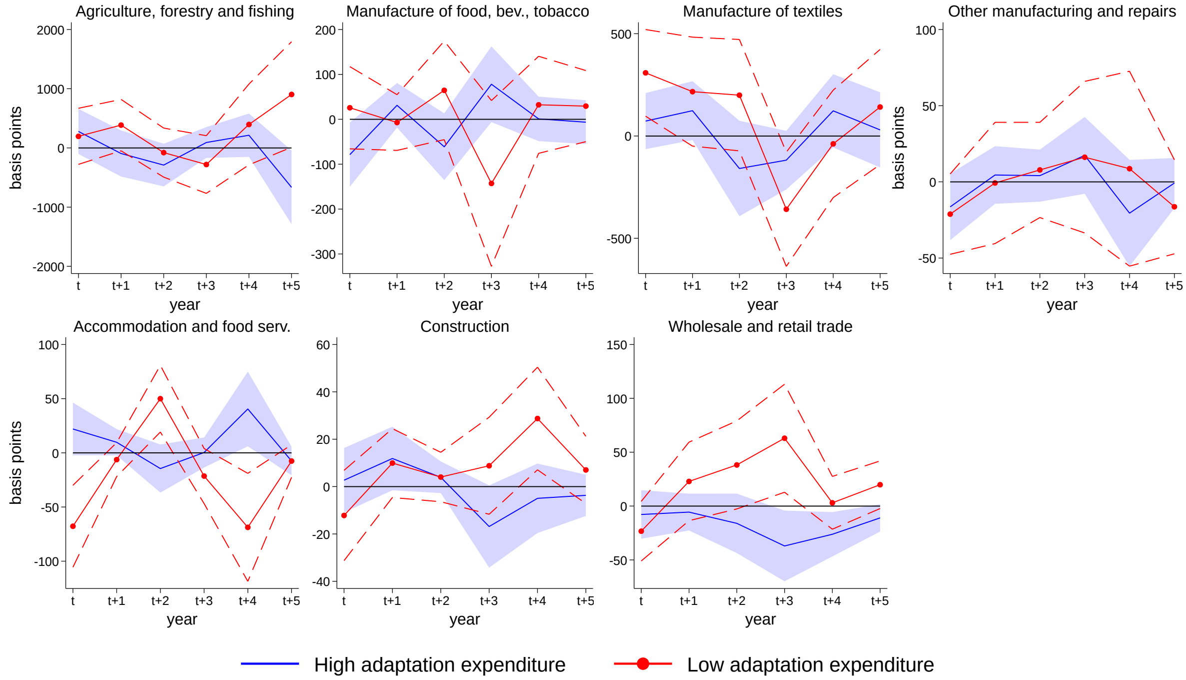
Note: Dynamic impulse response functions of GVA to a one standard deviation increase in the number of floods: full (blue line, $\beta^F_{k,h}$) and direct ($\beta^D_{k,h}$) effects. We compare the direct effect including both i and its neighbours' GVA (red solid line), and i's only (dashed black line). The difference between the full and the direct effects gives a lower bound of the production network effect. Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population and one lag of GVA for the full effect; population, current and lagged upstream and downstream exposure to other sectors' GVA in i and all its neighbouring regions (when applicable) for the direct effect. Standard errors are clustered at the ITL3 level. Shaded areas denote 90% confidence bands around the full effect.

Figure A12: State Dependent Response of GDP and Inflation to Floods



Note: Dynamic impulse response functions of GDP and inflation to a one standard deviation increase in the number of floods: high (blue line, β_h^H) and low (red line, β_h^L) adaptation expenditure state. The state is defined in equation (12) using a regime-switch dummy as in Ramey and Zubairy (2018). The model we estimate is reported in equation (11). Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population and one lag of the dependent variable. Standard errors are clustered at the ITL3 level. Shaded areas denote 90% confidence bands.

Figure A13: State Dependent Response of Inflation to Floods by Sector



Note: Dynamic impulse response functions of inflation to a one standard deviation increase in the number of floods: high (blue line, β_h^H) and low (red line, β_h^L) adaptation expenditure state. The state is defined in equation (12) using a regime-switch dummy as in Ramey and Zubairy (2018). The model we estimate is reported in equation (11). Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population and one lag of inflation. Standard errors are clustered at the ITL3 level. Shaded areas denote 90% confidence bands.

Table A1: Breakdown of Sectors

Macro sector	Sector code	Sector name	Macro sector	Sector code	Sector name
Production	**AB (1-9)**	**Agriculture, forestry and fishing; mining and quarrying**	Services	**L (68)**	**Real estate activities**
	C (10-33)	**Manufacturing**		68IMP	Owner-occupiers' imputed rental
	CA (10-12)	Manufacture of food, beverages and tobacco		68	Real estate activities, excluding imputed rental
	CB (13-15)	Manufacture of textiles, wearing apparel and leather		**M (69-75)**	**Professional, scientific and technical activities**
	CC (16-18)	Manufacture of wood and paper products and printing		69	Legal and accounting activities
	CD-CG (19-23)	Manufacture of petroleum, chemicals and other minerals		70	Head offices and management consultancy
	CH (24-25)	Manufacture of basic and fabricated metal products		71	Architectural and engineering activities
	CI-CJ (26-27)	Manufacture of electronic, optical and electrical products		72-73	Research and development; advertising and market research
	CK-CL (28-30)	Manufacture of machinery and transport equipment		74	Other professional, scientific and technical activities
	CM (31-33)	Other manufacturing, repair and installation		75	Veterinary activities
	DE (35-39)	**Electricity, gas, water; sewerage and waste management**		**N (77-82)**	**Administrative and support service activities**
Construction	41	Construction of buildings		77	Rental and leasing activities
	42	Civil engineering		78-80	Employment activities; tourism and security services
	43	Specialised construction activities		81	Services to buildings and landscape activities
Services	**G (45-47)**	**Wholesale and retail trade; repair of motor vehicles**		82	Office administration and business support activities
	45	Motor trades		**O (84)**	**Public administration and defence**
	46	Wholesale trade		**P (85)**	**Education**
	47	Retail trade		**Q (86-88)**	**Human health and social work activities**
	H (49-53)	**Transportation and storage**		86	Human health activities
	49-51	Land, water and air transport		87	Residential care activities
	52	Warehousing and transport support activities		88	Social work activities
	53	Postal and courier activities		**R (90-93)**	**Arts, entertainment and recreation**
	I (55-56)	**Accommodation and food service activities**		90-91	Creative, arts, entertainment and cultural activities
	55	Accommodation		92-93	Gambling and betting; sports and recreation activities
	56	Food and beverage service activities		**S (94-96)**	**Other service activities**
	J (58-63)	**Information and communication**		94	Activities of membership organisations
	58-60	Publishing; film and TV production and broadcasting		95	Repair of computers, personal and household goods
	61-63	Telecommunications; information technology		96	Other personal service activities
	K (64-66)	**Financial and insurance activities**		**T (97-98)**	**Activities of households**
	64	Financial service activities			
	65-66	Insurance, pension funding and auxiliary financial activities			

Source: Office for National Statistics (ONS).
Note: The three main sectors of activity are production, construction, and services. Each sector is composed of different sub-sectors, which are assigned a letter code. Each sub-sectors is further categorized into different activities, labeled with an alphanumeric code.

Table A2: LP-IV: First-Stage Regression of Floods Measures on the Instrument

	(1)
	N. of floods
IV coefficient	3.705****
	(0.603)
F-statistic	37.75
Kleibergen-Paap	34.12
Observations	7,107

Note: The Table reports the first stage regression of the aggregate LP-IV analysis - we use the natural logarithm of GDP as our y. The dependent variable is the number of floods. We report the F-statistics and the Kleibergen-Paap rank test statistics.W include ITL3 and year fixed effects. Controls include population size and one lag of the dependent variable. Standard errors clustered at the ITL3 level are reported in parentheses.
* $p < 0.1$, **$p < 0.05$,*** $p < 0.01$, **** $p < 0.001$

Table A3: Impact of Real Estate Market at Postcode-level

Dep: Real Estate Indicator	(1) Price (sqm)	(2) Price (sqm, 10th perc.)	(3) Price (sqm, 25th perc.)	(4) N. Transactions
$T_{i,0}$	-0.0666	-0.101**	-0.109***	-0.586*
	(0.0547)	(0.0392)	(0.0311)	(0.307)
$T_{i,1}$	0.00205	0.0154	0.0606	0.391
	(0.0882)	(0.102)	(0.0814)	(0.284)
$T_{i,2}$	0.121	0.0452	0.0574	-0.235
	(0.0719)	(0.0782)	(0.0726)	(0.256)
$T_{i,3}$	-0.114	0.00541	-0.0562	0.264
	(0.0673)	(0.0934)	(0.0954)	(0.317)
$T_{i,4}$	0.0829	0.0275	0.0209	0.0129
	(0.0882)	(0.103)	(0.104)	(0.234)
$T_{i,5}$	-0.138	-0.112	-0.0740	-0.156
	(0.103)	(0.0944)	(0.0895)	(0.214)
$T_{i,6}$	0.113	0.141	0.0813	-0.105
	(0.0923)	(0.0764)	(0.0680)	(0.403)
$T_{i,7}$	-0.117	-0.197**	-0.167***	0.535**
	(0.0719)	(0.0647)	(0.0461)	(0.162)
$T_{i,8}$	0.0463	0.0308	0.0717	-0.579
	(0.0997)	(0.111)	(0.100)	(0.375)
$T_{i,9}$	-0.00864	0.0135	0.0133	0.166
	(0.0736)	(0.0773)	(0.0861)	(0.399)
$T_{i,10}$	0.123	0.0904*	0.0697	-0.180
	(0.0737)	(0.0472)	(0.0555)	(0.204)
$T_{i,11}$	-0.0964	-0.0298	-0.0495	0.0388
	(0.102)	(0.108)	(0.109)	(0.409)
$T_{i,12}$	-0.0867	-0.0618	-0.0729	-0.179
	(0.0772)	(0.0876)	(0.0919)	(0.294)
Obs.	535	535	535	535
Area code FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes

Note: We perform our analysis at the quarterly frequency for the period 1995q1-2022q2. Each dummy ($T_{i,t+h}$) represents the interaction of a dummy identifying treated postcodes with a dummy controlling for the number of quarters after the flooding shock (h). We set max $h = 12$, equivalent to 3 years since the shock, This approach, combined with controls for the area code, proxying for the municipality, (η_i) and quarter (λ_t) fixed effects, aims to control for underlying macroeconomic conditions. The dependent variable is the natural logarithm of the median transaction price expressed in real 2019 GBP/square metre (regressions 1-3) and the natural logarithm of the number of transactions (regression 4) in postcode i at quarter t. The independent variables of interest are dummies ($T_{i,t+h}$), generated by the interaction of a dummy identifying treated postcodes with a dummy controlling for the number of quarters after the flooding shock (h), for up to 12 quarters after the shock. Each dummy All regressions include area code (i.e. the first part of the postcode, proxying for municipalities) and year fixed effects, and robust standard errors in parentheses.
* $p < 0.1$, **$p < 0.05$,*** $p < 0.01$, **** $p < 0.001$