Weathering the Storm: Sectoral Economic and Inflationary Effects of Floods and the Role of Adaptation

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Abstract

This paper investigates the impact of floods on economic output and prices at the industry 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 bp) following a 1 sd flood shock. This evidence explains well the delayed response of 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. Using local authority expenditure on flood defences and a proxy for adaptation capital, we further find that investments in adaptation strongly reduce the likelihood of flooding, but they are less effective at mitigating economic damages once a flood hits, and only in some sectors. Our analysis highlights the importance of disentangling the economic impact of climate change at the sectoral level and the importance of adaptation.

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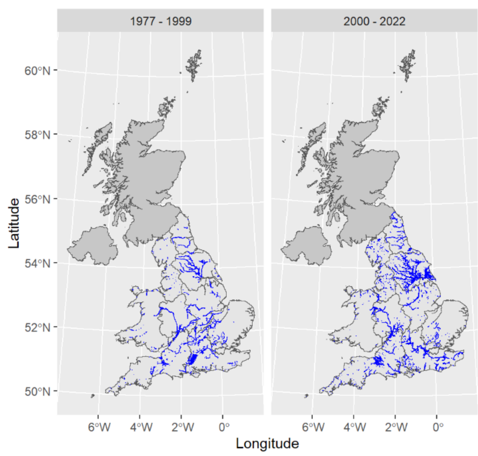
1 Introduction

Frequency and intensity of heavy precipitation events have increased over the last decades, especially in North America, Europe and Asia, causing more frequent and severe flooding (IPCC, 2021). Moreover, hydrological models project a larger fraction of land areas to be affected by an increase in floods. The European Commission has estimated that floods are the most costly natural disaster in Europe, having caused more than €170 billions in damages since 1980[1]. In the UK, the focus of this paper, flooding has intensified significantly over the last 50 years (Figure 1), and there is evidence of more frequent and more extreme flooding and faster and more extreme coastal erosion (Environment Agency, 2022). The 2018 UK climate change projections suggest that that there could up to 35% more precipitation in winters by 2070, which will lead to even more river flooding. Rainfall intensity will increase, which will lead to more surface water flooding.

The July-December 2023 semester was the wettest on record since 1890[2], putting pressure on the government's handling of floods[3]. Today, the UK 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). But England's exposure to flooding is far from new. A map of all floods recorded since the XVIIIth century (Figure 2) shows that roughly a third of the country has been flooded before. Flooding represents a significant expenditure item on the UK government's budget. It is estimated that around £1.4bn are spent each year on damages from flooding (HMGovernment, 2023). Considerable amounts of money are also disbursed towards flood and coastal risk erosion management: in 2021 expenditure reached more than £1 billion, twice as much as in 2006[4]. In this paper we study how floods impact output and prices at the aggregate and sectoral level.

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.

Floods directly impact properties and business activities through the damages they can cause to their business premises, inventory and machines (Crampton et al., 2024). These warrant repair costs, loss of inventory and, at times, temporary suspension of business activities. Whether and how these direct impacts translate into macroeconomic effects is less obvious. Through the damages to physical and human capital, flood events can cause increased uncertainty and relocation of economic and human activity (Panwar and Sen, 2020), thus harming

[1] European Commission, see https://environment.ec.europa.eu/topics/water/floods_en.
[2] 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.
[3] Financial Times, Janury 7th, 2024 see https://www.ft.com/content/78573e49-ee72-4140-807a-bc79a11aea8a.
[4] See here.

local economic growth both in the short- and medium-run if, for instance, relocation becomes permanent or reconstruction is not adequately supported (Fried, 2022). At the same time, destruction of physical assets as a result of the disaster could lead to a "build back better" scenario (Hallegatte and Dumas, 2009), in which rapid turnover of capital and earlier adoption of new technologies yield positive outcomes on potential and observed growth. Theoretically, floods can have simultaneous effects on demand and supply (Cevik and Jalles, 2023), with different consequences e.g. on prices.

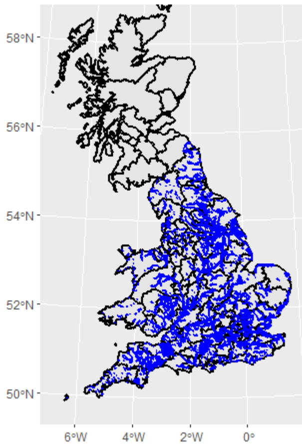
Despite the growing concern over increasingly severe and frequent flooding, available evidence on the economic impact of floods is scarce and inconclusive[5] and it is lacking along three dimensions. First, most studies pool together hundreds of countries from different climate zones and with different economic systems (see for example Kabundi et al., 2022; Cevik and Jalles, 2023). This makes it hard to draw significant conclusions for any particular country or group of similar countries. The only two exceptions focus on emerging economies (Panwar and Sen, 2020; Crofils et al., 2023). Flooding, however, is a problem also in advanced countries, where climate is more mild and the economic system and the infrastructures are more developed. Against this backdrop, in this paper we focus on local authorities in England, an advanced economy with a growing flooding issue.

Second, floods are often poorly measured. Because of the lack of comprehensive and easy to manipulate data on recorded flood events, most studies resort to proxies such as fatalities, the number of people affected or economic damages (e.g., Parker, 2018; Heinen et al., 2019). In most cases floods do not cause death, and the number of affected people is not necessarily indicative of how severe a flood is but rather of where it happened. Using these proxies overestimates the true impact of floods. Another approach is to use dummies for whether an area was hit at least once by a flood in a given time span (see Barbaglia et al., 2023). This too leads to a misestimation of the true impact of flooding, as one single flood has the same weight as 100. Departing from the existing literature, in this paper we make use of a detailed dataset with all verified records of flooding in England. This allows us to take into account small and large floods alike, thus providing more credible estimates.

Lastly, and perhaps most importantly, existing evidence so far always analyses the impact of floods at the aggregate level. While we do not dismiss the importance of understanding how GDP and inflation react to flooding, we believe that a more disaggregated, sectoral approach is more appropriate. Studying the response of different industries to the same shock not only allows us to better understand the underlying drivers of aggregate results, but it also reveals significant heterogeneities. The impact varies by sector and it is not trivial to determine *a priori*. To the best of our knowledge, we are the first to study the impact of floods at such a disaggregated level.

[5] Parker (2018); Panwar and Sen (2020); Crofils et al. (2023); Kabundi et al. (2022) for example, all find contradicting results.

Figure 2: Historical Map of Flood Events



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

Against this backdrop, this paper studies the impact of floods on output and prices at the aggregate and industry level in local authorities in England. Several factors make an answer to this question empirically challenging. First, the probability of flooding is not entirely random at this level of geographical granularity and the risk of flooding is heterogeneously distributed across regions. The presence of coasts and watercourses increases the probability of flooding for a specific region (Environment Agency, 2009). But these "structural endowments" also affect the historical economic growth trajectory observed at regional level (Andrew et al., 2000). For instance, the presence of coasts or large and deep rivers has historically been associated with more trading opportunities. Simply looking at the impact of floods on regional economic outcomes could therefore be biased by the fact that regions more exposed to flooding respond differently because of structural economic differences. While structural characteristics can be accounted for through fixed effects, there is increasing evidence of economic activity (e.g., intensive farming) altering river flows and worsening flooding.[6]

Investments in adaptation capital pose further endogeneity concerns. On the one hand, an increase in adaptation capital acts as a confounding factor. As it reduces the frequency of flood events, adaptation can increase output through a simple multiplying effect and by reducing the economic damages caused by floods (Fried, 2022). On the other, richer areas or areas with more dynamic economic activity might have more policy space or political will to build up adaptation capital, that in turn can reduce flooding. The most popular approach adopted in the climate literature rests on the identification of plausibly exogenous climate anomalies in the form of deviations from long-term means (e.g., Kabundi et al., 2022; Crofils et al., 2023) or unanticipated climate events (e.g., 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. A simple OLS regression of economic outcomes on floods, on the other hand, is likely to suffer from significant downward bias and, at most, allow us to grasp a lower bound effect on output and prices. This offers a limited insight, especially in light of an increase in vulnerabilities from climate change.

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. Rain is the main trigger of floods (Environment Agency, 2009; IPCC, 2021). If, for example, heavy rainfall overwhelms an area's local drainage capacity or an already waterlogged catchment, it can lead to groundwater and river flooding. Generally, changes in extreme precipitation are the main proxy for inferring changes in fluvial and urban flood patterns assuming there is no additional structural change (i.e. flood mitigation measures, see IPCC, 2021). What causes flooding events is thus an unusually large and unsustainable amount of rain, which can occur in the form of either or both heavy,

[6] See here.

short-lived rainstorms and prolonged precipitation. Therefore, 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 (Röckert and Kraehnert, 2022), farmers' changes in behaviour (Di Falco et al., 2019), and land ownership (Bezabih et al., 2021; Murken et al., 2024) appear to be also relevant only for developing countries.

We find that following a one standard deviation shock in the number of floods (which corresponds to around 17 floods), aggregate GDP drops by more than 1 percent after two years and is still 2 percent lower than its initial level after five years. Prices fluctuate significantly, 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 main finding is 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 more to see an impact. Importantly, output in accommodation services and civil engineering increases on impact. In all sectors, the variation in economic activity is 3 to 6 times higher than what we observe at the aggregate level. Similarly, sectoral 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.

We further investigate the drivers of our results by studying the impact of floods on investments and on the real estate market. 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. In line with the presence of a wealth effect, floods significantly affect the number of real estate market transactions and their value. This is consistent with the demand-side like behaviour of floods we observe in wholesale and retail trade, but it is harder to reconcile with the more ambiguous response of output and prices in other sectors. To shed further light on the on the nature of flood shocks, we investigate how they propagate 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 determine whether floods are a pure supply or demand shock, this exercise shows they are not an isolated shock and highlight the importance of focusing at the industry level.

Another important contribution of this paper is our assessment of adaptation policy. While it does not tackle the issue of flooding at its core, namely climate change, adaptation capital is the most readily available tool to local authorities and central governments to limit the damages of floods. To this day, however, there is still no evidence as to the effectiveness of adaptation.[7]. We show that investing in adaptation does mitigate the impact of flooding. This happens primarily because flood defences reduce the likelihood of floods, meaning they are effective at the extensive margin. On the other hand, we find some 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.

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

[7] Two notable exceptions are Fried (2022) and Canova and Pappa (2022). However, the former introduces adaptation capital in a heterogeneous agent model to show it can reduce the economic impact of floods, but does not test this assumption empirically. The latter focuses 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.

inflation is *a priori* ambiguous and depends on the predominance of demand- or supply-side effects. Heinen et al. (2019), for example, 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. In the absence of reliable flooding records, they proxy flooding with a weighted measure of the three-day moving sum of daily rainfall. They find a large inflationary effect of hurricanes, while the increase in inflation from floods is smaller and rarely significant. This approach has two limitations. First, while heavy precipitation is the main trigger of floods, whether rainfall accumulation causes a watercourse to overflow depends on various other region- and time-specific factors. The authors' estimates are capturing the impact of high, prolonged precipitation rather than floods, which could explain the low reaction of inflation. Secondly, and unlike other economic shocks, floods are more localized. A high potential flood destruction index, on the other hand, can be driven by widespread precipitation on the whole country which does not induce any flooding events at the local level.

An important dimension is that of geographical and sector 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. Interestingly, they are only relevant for headline inflation, while food, housing and energy inflation are not affected. Parker (2018) computes an intensity index based on the fatalities caused and the number of people affected by each natural disaster. This approach lies on the implicit assumption that floods affect prices solely through their impact on people. However, flooding can occur in scarcely populated but economically relevant areas, such as agricultural lands and industrial hubs. In other words, using casualties and affected population as measures of floods' intensity assumes a predomnantly demand-driven impact, thus underestimating the potential supply-side channels. In this paper, we provide a more precise measure of flood events and find that floods can affect prices in advanced economies as well. Moreover, we expand Parker (2018)'s analysis by focusing 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. Similarly to this paper, they proxy flooding with a moving-average precipitation z-score. As already discussed, weather anomalies have the advantage of identifying floods more precisely, but shift the focus purely on out of the ordinary weather events. Moreover, taking the deviation from the moving average implies an almost immediate adaptation to floods by agents, while it usually takes years to build up sufficient human and physical adaptation capital. 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. 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. Like in other studies, 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 sector 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 instead focus on adaptation policy. Finally, 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.

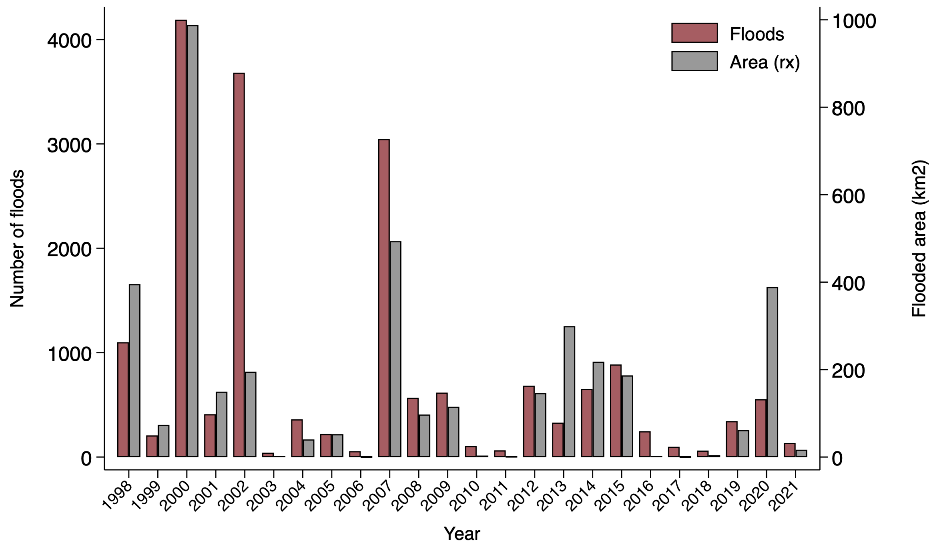
2.1 Flood Events

We retrieve flood events for England from the UK Environment Agency's (EA) Recorded Flood Outlines database. This dataset is a GIS layer, with 50×50m 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, when predecessor bodies to the EA started collecting detailed information about flooding incidents, 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 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 than for floods themselves. 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 thus risks underestimating their economic impact. Hence, we depart from the existing literature and focus instead on the number of floods in local authority i in year t.

We perform our analysis at the regional level. There are 309 local authorities in England (ITL3 regions, 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 to almost 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 3 below. Not surprisingly, 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).

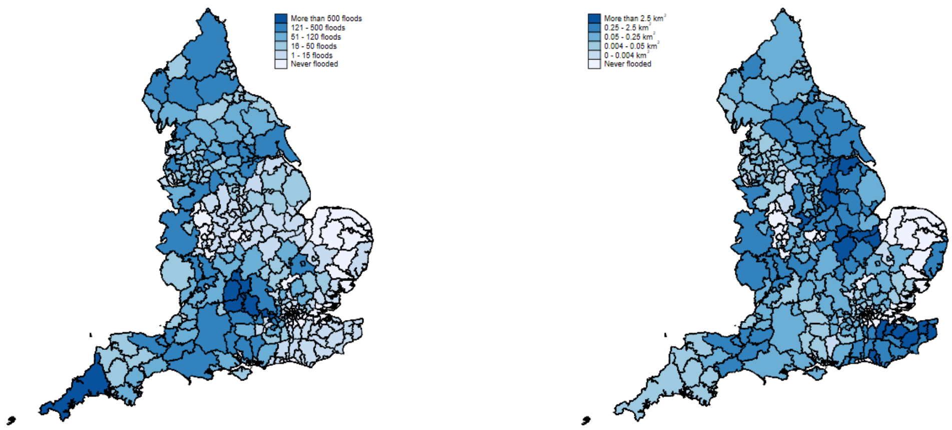
Figure 3: England's annual number of floods and total flooded area



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 4 we show the spatial distribution of floods across England's local authorities (see Appendix Figure 16 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 Appendix Figure 17).

Figure 4: Overall number of floods and average flood extent by local authority



(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, including sea areas, 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 from weather stations. Rainfall records from weather stations are generally more precise, but only include observations around the weather stations, thus 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.

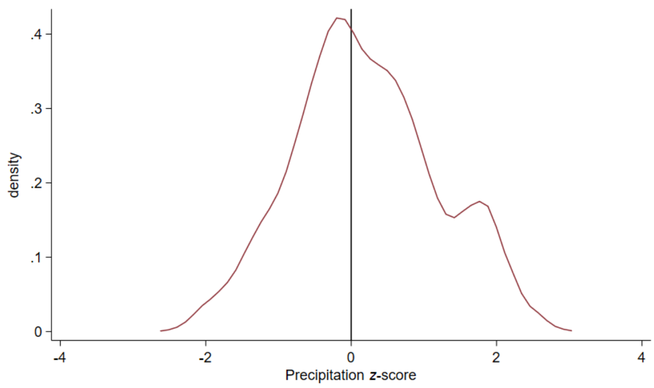
Rain is the main trigger of floods (Environment Agency, 2009; IPCC, 2021). If, for example, heavy rainfall overwhelms an area's local drainage capacity or an already waterlogged catchment, it can lead to groundwater and river flooding. Therefore, to instrument floods we are interested in unusually large 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:

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

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, for instance through better drainage systems or maintenance or flood defences. If area fixed effects can't absorb this feature (e.g., it does not hold throughout the whole sample), 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 5 shows that the z-score is skewed to the right, which suggests that heavy rainfall events are more severe than low precipitation events.

Figure 5: Precipitation z-score



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

2.3 Other Geospatial Data

For illustration purposes, we use data on flood defences and watercourse.

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.

2.4 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 industry 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[8]. Inflation data is not directly available at the ITL3 level. For both aggregate and industry 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:

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

Industry-level GDP and inflation are available for 3 macro-sectors (production, construction, and services) and 18 industries. The ONS further decomposes these industries into 43 different sub-groups of activities. We provide a breakdown in the Appendix. In our analysis, we focus on the 10 sectors that, either directly or indirectly, are 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. Importantly, for industry-level data the ONS aggregates some local authorities that would not be relevant individually into larger economic areas. Hence, the final sample when studying GDP and inflation by industry is composed of 133 regions.

Investments. To dig deeper into the potential mechanisms described in Section 4, we use a proxy for annual investments from the ONS. The dataset presents experimental regional gross fixed capital formation estimates

[8] 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.

for the years 1997 to 2020, both at the aggregate and industry level. Industries 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. We verify whether floods are akin to a wealth effect by looking at how they impact house prices. The HM Land Registry Price Paid Data tracks property sales in England at daily frequency from 1995 to 2024. However, prices are in absolute terms 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.

Other data. 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.[9] 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).

We study the role of production networks in propagating flood shocks using UK industry by industry 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.

[9]This data alone is not enough to solve the endogeneity issues discussed in Section 3. 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, and perhaps most importantly, 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.

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
Housing transactions	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. Flooded area is expressed in squared kilometres, total precipitation in millimetres. z-scores are computed as defined in equation (1). GDP, investments and adaptation expenditure from the ONS are expressed in constant 2019 million pounds. Inflation is expressed as the percentage change in the GVA deflators. We report the total number of property transactions from the HM Land Registry Data for the years 1995 - 2023. Price/square metre expressed in 2019 prices.

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 cumulated dynamic response of GDP and inflation to floods at the regional level. We use industry-level GDP and inflation to explore heterogeneity across sectors.

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

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

where $f_{i,t}$ is the number of floods in local authority i in year t. In our robustness check, we weight the number of floods by the 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 cumulated impact of floods on annual GDP/inflation in h years. $X_{i,t}$ controls for population size, as more populated areas might be economically more performing, 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 industry-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 reduces the frequency of flood events, adaptation capital can increase output through a simple multiplying effect and by reducing the economic damages caused by floods (Fried, 2022). Moreover, richer areas or areas with more dynamic economic activity might 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 be able to capture them and there is room for an omitted variable bias and reverse causality. For this reason, 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:

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

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

3.2 Rainfall as an Instrument for Floods

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 assuming there is no additional change in the surface condition (IPCC, 2021), multiple studies use rainfall as a proxy for floods. 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. Appendix Table 3 reports first-stage regressions results, where we regressthe 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 developed 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, e.g. livestock death (Röckert and Kraehnert, 2022), farmers' behaviours (Di Falco et al., 2019), land ownership (Bezabih et al., 2021; 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 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 18 - 19 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. In other words, 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 (e.g., 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 Main Results

This section presents the main empirical results. First, we 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 an industry-level analysis reveals significant heterogeneities and explains well the aggregate results.

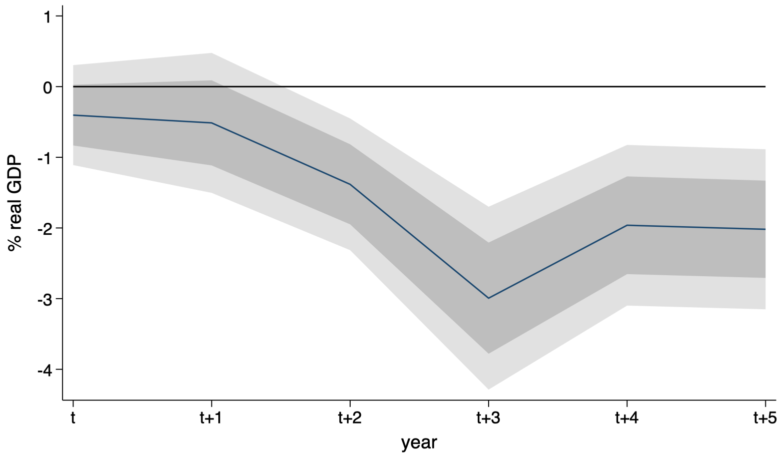
4.1 Aggregate Analysis

We begin with the analysis on aggregate economic activity. Figure 6 and 7 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 6). In terms of size, the economic impacts 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 (e.g., 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[10]. Compared to other studies (and to our LP-OLS estimates) finding a dampening effect of flooding (e.g., Kahn et al., 2021), our results are strongly significant. We believe this might be due to the more precise measurement and identification of flood events.

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

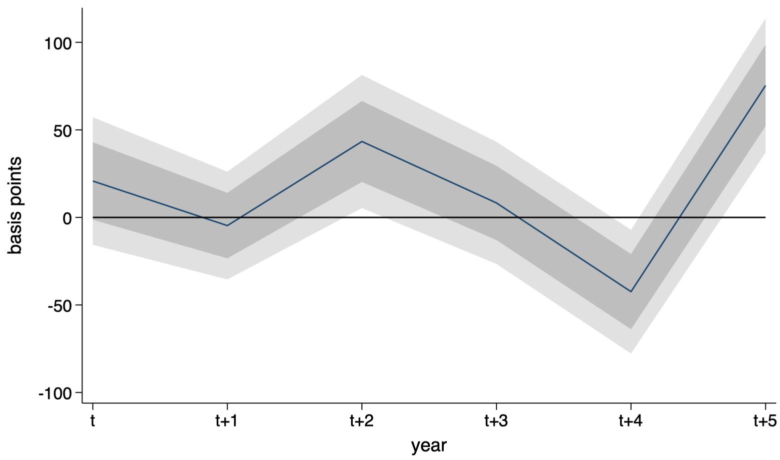
Figure 6: GDP Response to Floods



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 7). 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 still around 75 basis points higher than their steady state. 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 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 7: 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 (Fried, 2022) and by damaging properties and business activities (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 (see for example Bilal and Känzig, 2024). Because flooding is a rather local 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 eventsd. Instead, the focus should be at the sector level as not all sectors are affected in the same way. For example, Panwar and Sen (2020) argue that agriculture can benefit from increased flooding through higher land productivity. As our aggregates results combine the different reactions of individual sectors, we now turn our attention to the industry-level.

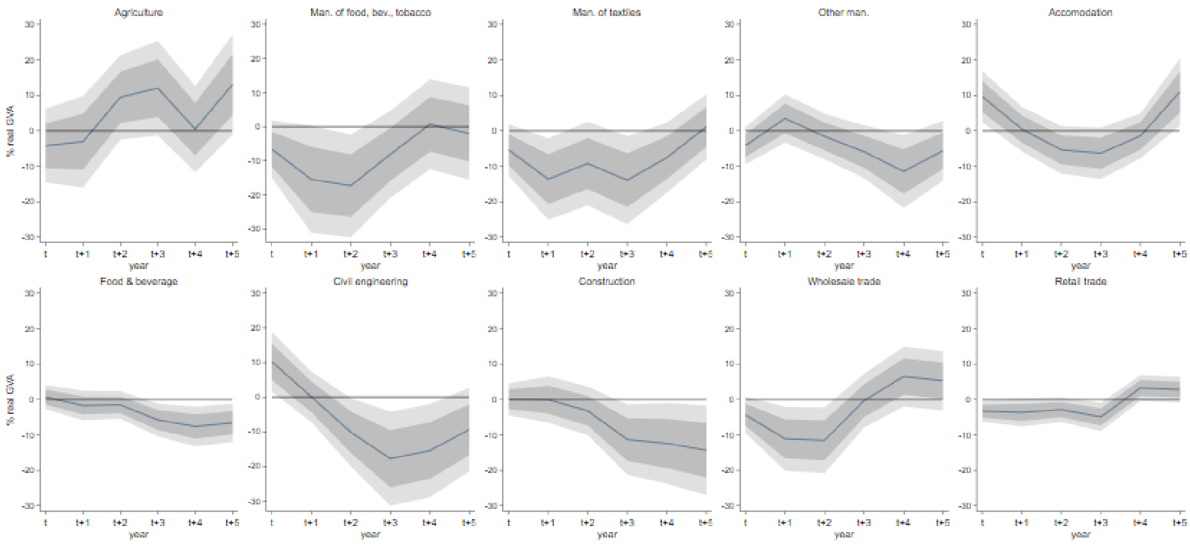
4.2 Exploring Industry Heterogeneity

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 8 plots the IRFs of real GVA for agriculture, forestry and fishing; manufacture of food, beverages and tobacco; manufacture of textiles, wearing apparel and leather; other manufacturing, repairs and installation; accommodation services; food and beverage services; civil engineering; construction of buildings; wholesale trade; and retail trade. We plot the corresponding IRFs for inflation in Figure 9. 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 22-23) 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 industries 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 goes back to its initial level 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 outputs negatively and permanently (-6% and -10% to -12% respectively), but the impact takes three years to emerge. Interestingly, 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 displacements following the shock, which damages or destroys private properties forcing people to find temporary solutions. The positive impact on civil engineering's GVA is driven by reconstruction and repair efforts. The civil engineering sectors 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 (Panwar and Sen, 2020; Crofils et al., 2023), floods do not significantly affect GVA in the agricultural sector.

Taking together industry-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 8: GVA Response to Floods

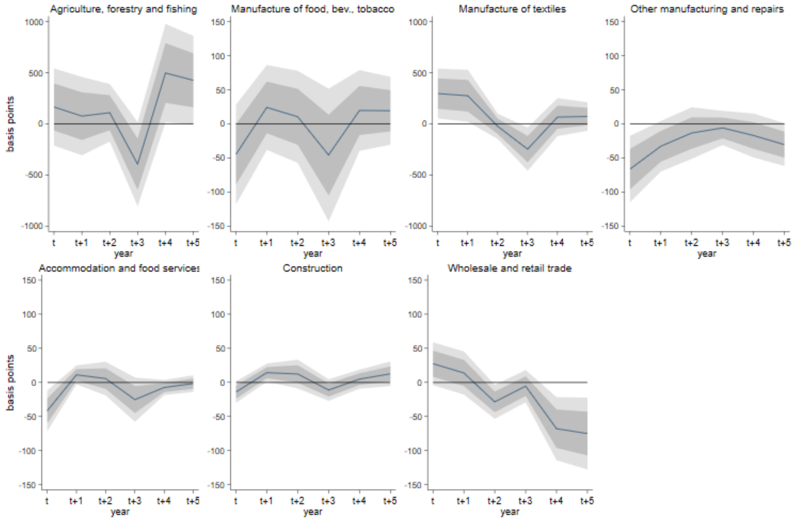


Note: Dynamic impulse response functions of GVA to a one standard deviation increase in the number of floods. Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population size and one lag of GVA. Standard errors are clustered at the ITL3 level. Shaded 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. For example, the flood shock does 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 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 in the accommodation and food services sector along with an increase in GVA in accommodation. When output decreases in the food services sector, however, prices have already gone back to their steady state.

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 are still 75bp lower than their initial level five years after the shock. In the manufacturing of textiles, wearing apparel and leather sector the increase in GVA is preceded by a 300bp rise in inflation, suggesting a supply-side mechanism is at play.

Figure 9: Inflation Response to Floods



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 industries. Sectors 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 the economy 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 (e.g., Kabundi et al., 2022; Bilal and Känzig, 2024; Eickmeier et al., 2024). We argue that focusing on industries solves this puzzle.

Our sectoral estimates reveal that one cannot simply label floods as a supply- or demand-side type of shock. 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 most likely 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.

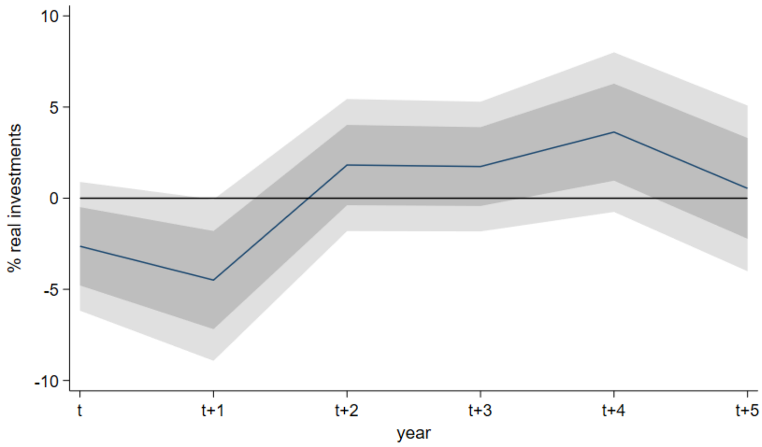
5 What Lies Behind the Industry Results?

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 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. In the medium- and long-run, however, investments can rebound pushed by a rapid turnover of capital and an increase in climate adaptation investments.

We estimate the response of investments using the empirical specification introduced in equation (3) and (4), where $y_{i,t+h}$ is now the log of (industry) investments in 2019 prices. We plot our estimates for aggregate and sector-level investments in Figure 10 and Figure 11, respectively. At the aggregate level, we find a borderline significant (p-value = 0.095) and temporary reduction in investments of 4.5% the year following a one standard deviation shock in the number of floods. This 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 11 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. This suggests that, albeit critical, investments alone cannot explain the dampening impact of floods on economic activity.

Figure 10: Aggregate Investments Response to Floods



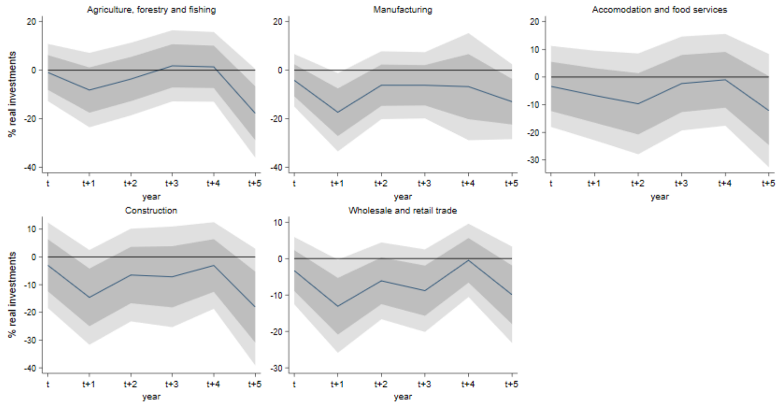
Note: Dynamic impulse response functions of investments to a one standard deviation increase in the number of floods. All specifications include ITL3 and year fixed effects. Controls include population size and one lag of investments. Standard errors are clustered at the ITL3 level. Shaded areas denote 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).[11] This does not allow us to draw straightforward comparisons between sector-level investments and GVA.

Our estimates show that investments contract only in manufacturing. This explains at least partially the decline in GVA that we find in the various subcategories of manufacturing, suggesting that firms, either voluntarily or because they are credit constrained, choose to 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 industries, 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.

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

Figure 11: Investments Response to Floods by Industry



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

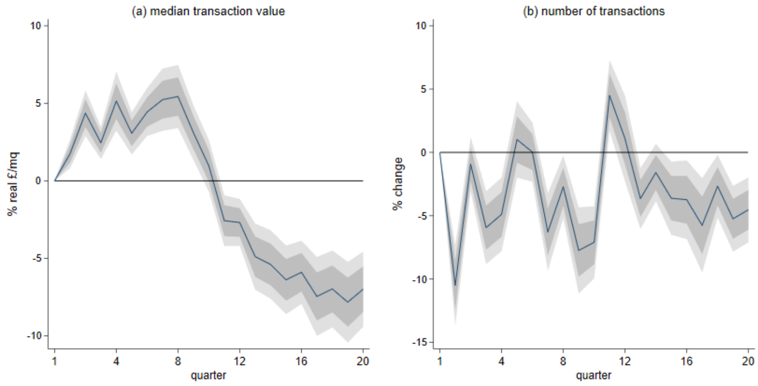
We now focus on real estate market transactions. Floods can cause temporary or permanent damages to private properties, causing a loss in the wealth of households which would be consistent with a demand-side type of shock. If households have to incur unexpected expenses to repair or protect their properties or 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. 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, 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 £/square metre and the natural logarithm of the number of transactions in local authority i and quarter t. $\hat{f}_{i,t}$ is the fitted value of the number of floods from the first stage. We plot our estimates in Figure 12.

Figure 12: 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 quarter immediately after the shock, and remains above its initial level for around 10 quarters, with a peak of slightly more than 5%. Transaction prices start to decline entering the third year, and are still decreasing and around 7.5% lower than their initial level 5 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 transactions fluctuate significantly, but stabilise at 5% below their initial level up until 5 years later.

The intuition is as follows. Floods cause damages to private properties, thus reducing supply in the real estate market in the short run (i.e., the number of transactions declines). At the same time, despite their high level of geographical granularity, ITL3 regions are vast areas that often encompass multiple towns. Therefore, floods will only affect a portion of the stock of housing. This is likely enough to generate a wealth effect at the local authority level, as the number of people affected by the flood event is large. However, in the short run households unaffected by floods will still be active in the real estate market, but with a reduced supply. As a consequence, prices increase in the first two years akin to a supply-side shock. As time goes by, more channels start to emerge. In particular, increased perceived flood risk can lead to relocation (Siders, 2019; Seebauer and Winkler, 2020) and economic uncertainty (Panwar and Sen, 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 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[12], 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 sector-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

[12] Figure 23 further proves that floods cause an inflationary surge in the real estate sector, followed by persistent deflation.

hand, for some industries (e.g., 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 (in our case following a flood event) 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, on the other hand, 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 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 (Foerster et al., 2011; Gabaix, 2011) and empirically (Barrot and Sauvagnat, 2016; Acemoglu et al., 2016; Carvalho et al., 2021). In a setting somewhat similar to ours, for example, 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.[13] 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})[14]:

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

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. 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:

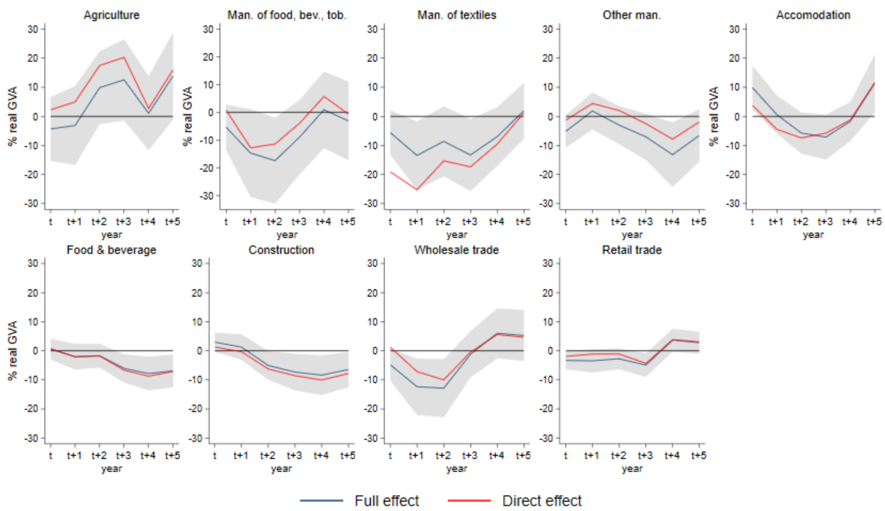
$$y^k_{i,t+h} = \alpha_i + \beta^D_{k,h} \hat{f}_{i,t} + \sum_{\tau=0}^{T} \psi^\tau_{k,J,N} \sum_{j=1}^{J} u_{kj} \sum_{r \in N} y^j_{r,t-\tau} + \sum_{\tau=0}^{T} \phi^\tau_{k,J,N} \sum_{j=1}^{J} d_{kj} \sum_{r \in N} y^j_{r,t} + \gamma X_{i,t} + \lambda_t + \varepsilon^D_{i,t+h}. \tag{8}$$

[13]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.

[14]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.

We multiply the upstream and downstream weights u_{kj} and d_{kj} introduced in equation (6) by 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 most likely 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 cumulated *direct* effect of the flood shock. It follows that $(\beta^{F}_{k,h} - \beta^{D}_{k,h})$ gives a lower bound of the cumulated *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 13. In what follows, we limit our analysis to sectoral GVA.

Figure 13: Full and Direct Response to Floods by Industry



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 cumulated 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. This means that 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 0.

In the Appendix (Figure 25) 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 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 is relevant, for example, with respect to the adaptation debate we introduce in the next Section. 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 industry rather of 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 this, 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.

This is not merely an academic exercise, but also a policy relevant experiment as governments are increasingly pressured to take action.[15] During the most 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.[16] 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.[17]

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*.

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

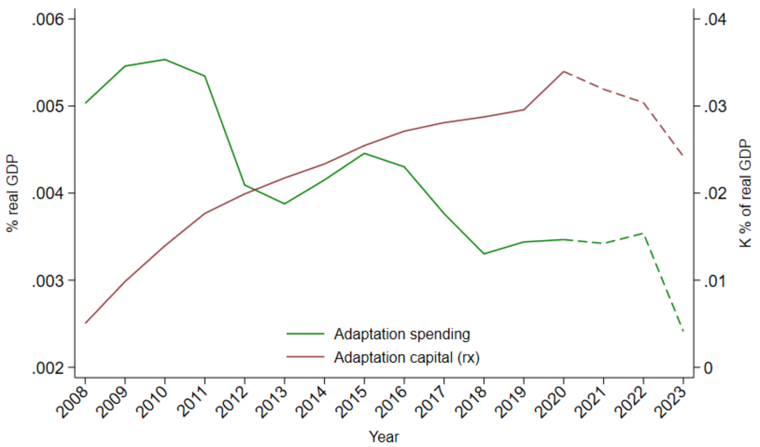
[15] See here.
[16] See here.
[17] See here and here.

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. This is crucial, 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 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 ($\delta = 0.067$).[18] We plot the time series for both adaptation expenditure and adaptation capital in Figure 14. Adaptation expenditure by local authorities has been steadily declining, but the opposite is true for the central government as a big part of expenditure in the UK is sustained by the Environment Agency.

Figure 14: 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:

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

where $def_{i,t}$ is in turn adaptation expenditure ($exp_{i,t}^{adapt.}$) and our proxy for adaptation capital ($k_{i,t}^{adapt.}$) 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 $\overline{f}_i > \overline{f}$).

[18] 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, for the sake of this analysis we abstain from any assumptions as to the depreciation of adaptation capital following a flood.

Hence, γ measures how an increase in adaptation expenditure or capital affects flooding in a non-flood prone local authority, and ϕ tells us how this relationship changes when a local authority is flood prone.[19] 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 regression 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 two caveats. First, the delayed effect of adaptation is in line with the idea that expenditure itself does not necessarily reduce flooding. What matters is adaptation capital, and capital takes time to build up. Secondly, a 1 percentage point increase in adaptation expenditure is far off what we observe in the data. The median expenditure is 0.002% of GDP, meaning that the median flood prone local authority will reduce the number of floods by 0.15 units.[20]

The third and fourth row summarise the effect of adaptation capital. We find that 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. Unsurprisingly, unlike for adaptation expenditure, the impact of capital does not take years to materialize. In particular, a 1 percentage point increase in the stock 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 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.[21] Nevertheless, 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.

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

[20]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 $\frac{1}{0.002}$.

[21]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.

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 causing significant damages. Therefore, 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), where instead of determining the state through a transition function F(.) we follow Ramey and Zubairy (2018) and use a regime-switching dummy:

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

where

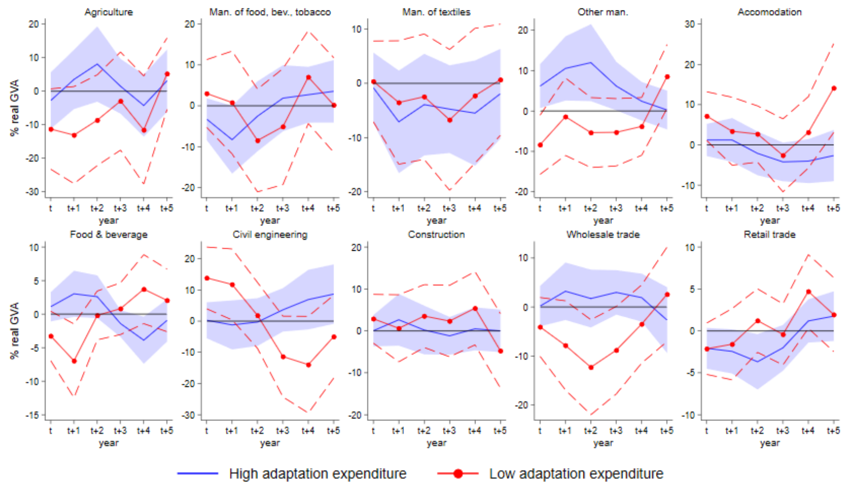
$$I_{i,t-1} = \begin{cases} 1 & \text{if } exp_{i,t-1} > \overline{exp} \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

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. In other words, β_H^h is the cumulative impact of floods on sectoral GVA in a high adaptation expenditure state, while β_L^h is the cumulative 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 15. 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, 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. This happens 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 some 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 has important consequences for the policy debate, and indicates that adaptation is an effective way to protect the economy.

Figure 15: State Dependent Response of GVA to Floods by Industry



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 and one lag of GVA. Standard errors are clustered at the ITL3 level. Shaded areas denote 90% confidence bands.

7 Conclusions

Flooding has intensified significantly in the last decades, and its frequency and severity is expected to get worse. We study the economic and inflationary effects of floods in England, where already today flooding represents a significant expenditure item on the UK government's budget both in terms of damages and in flood risk management. Departing from the existing literature, we employ a precise measurement of flood events and a rigorous econometric specification that instruments for floods using precipitation z-scores. Our most important result is the heterogeneity of the economic response to floods at the sector level, which helps explain seemingly puzzling aggregate results.

Drawing on highly granular regional economic data and weather observations, we find that the delayed decrease in aggregate GDP and the positive and negative fluctuations in aggregate prices are explained by sectors reacting heterogeneously in terms of size, timing and sign. Our estimates show that investments cannot explain all of the variation in sector level output. Transactions in the real estate market, on the other hand, are consistent with a wealth effect that would explain the demand-side behaviour of floods in wholesale and retail trade.

We further check the role of production networks, and find that input-output linkages propagate flood shocks both upstream and downstream. While this result does not help us identify the true nature of flood shocks, it highlights the deep connections between sectors and the importance of working at a more disaggregated level.

Lastly, we investigate the effectiveness of adaptation policy. Our estimates show that expenditure in adaptation and building up of adaptation capital can strongly reduce the likelihood of flooding. Once a flood happens, however, flood defences are only partly able to limit economic damages. These results stress the importance for local authorities and central governments of increasing investments in adaptation policy.

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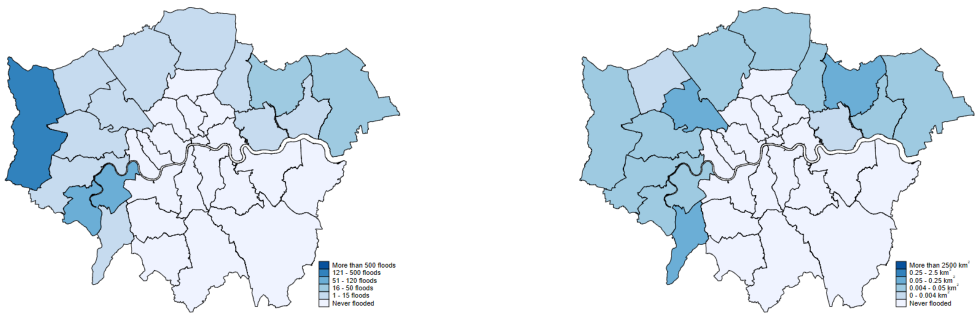
A Appendix

Data

Aggregating grid data. 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.

Tables and Figures

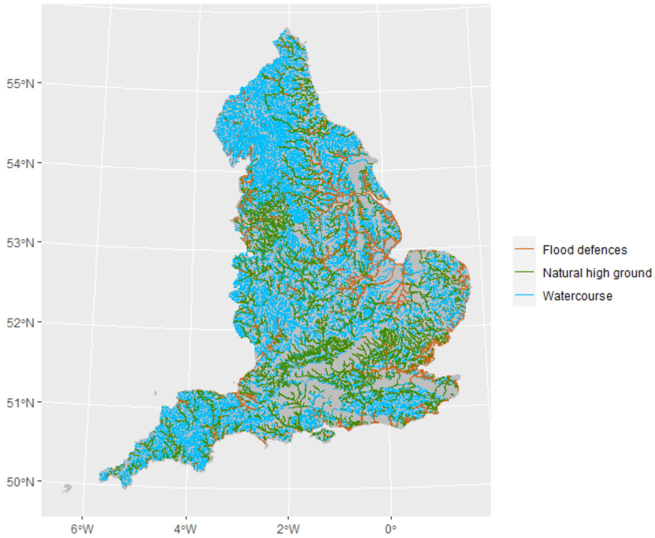
Figure 16: Overall number of floods and average flood extent by local authority (London)



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

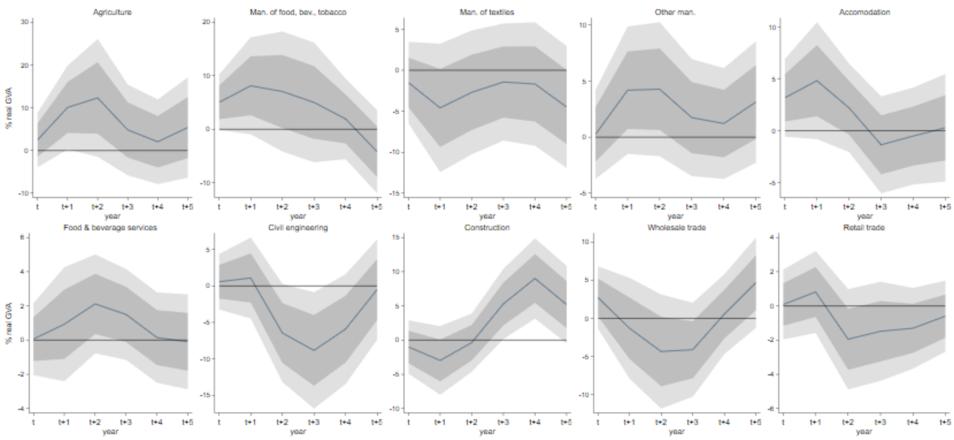
Source: EA Recorded Flood Outlines and authors' calculations.
Note: We treat each flood event as a single flood, and assign it to every ITL3 area hit and compute the flooded area accordingly. Average flood extent is computed as each ITL3 area's total area flooded over the panel divided by the total number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

Figure 17: Map of watercourse and flood defences



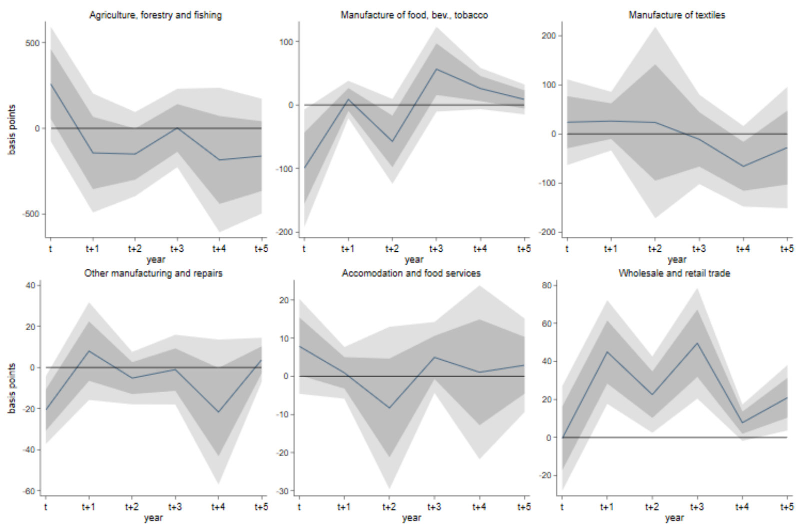
Source: OS Open Rivers, AIMS Spatial Flood Defences, and authors' calculations.
Note: We map watercourse and flood defences by matching the nodes and links in the data with shapefiles for England.

Figure 18: Confirming the Exclusion Restriction - GVA and Neighbouring Floods



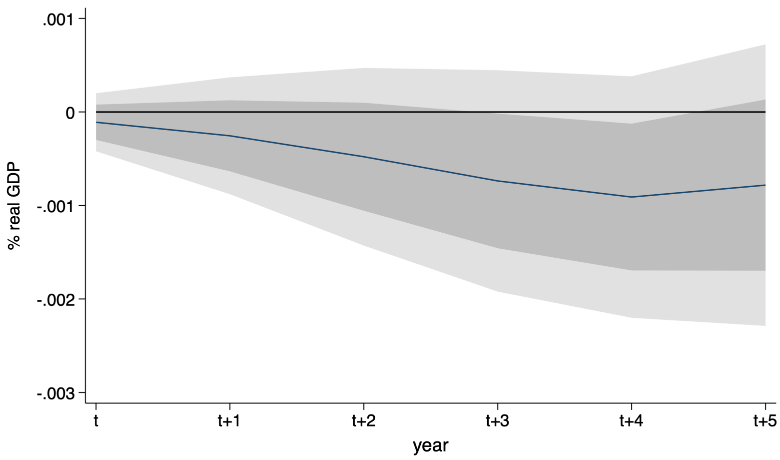
Note: Dynamic impulse response functions of GVA in region i to a one standard deviation increase in the number of floods in all of i's neighbouring regions. Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population size, $P^{z}_{i,t}$ and one lag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

Figure 19: Confirming the Exclusion Restriction - Inflation and Neighbouring Floods



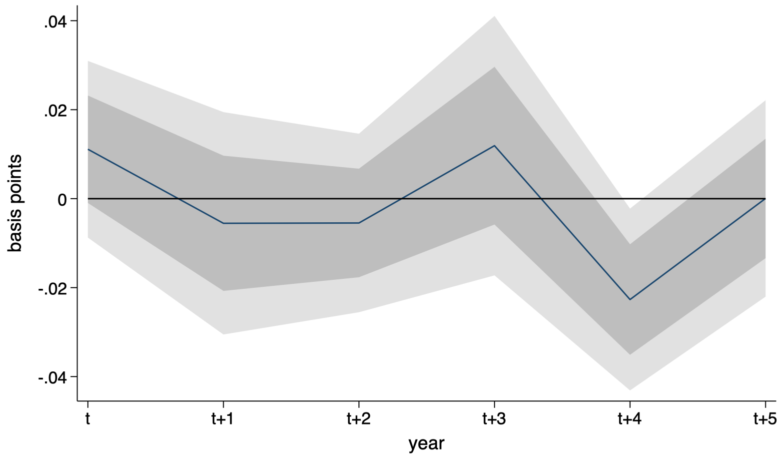
Note: Dynamic impulse response functions of inflation in region i to a one standard deviation increase in the number of floods in all of i's neighbouring regions. Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population size, $P^z_{i,t}$ and one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

Figure 20: GDP Response to Floods - LP OLS



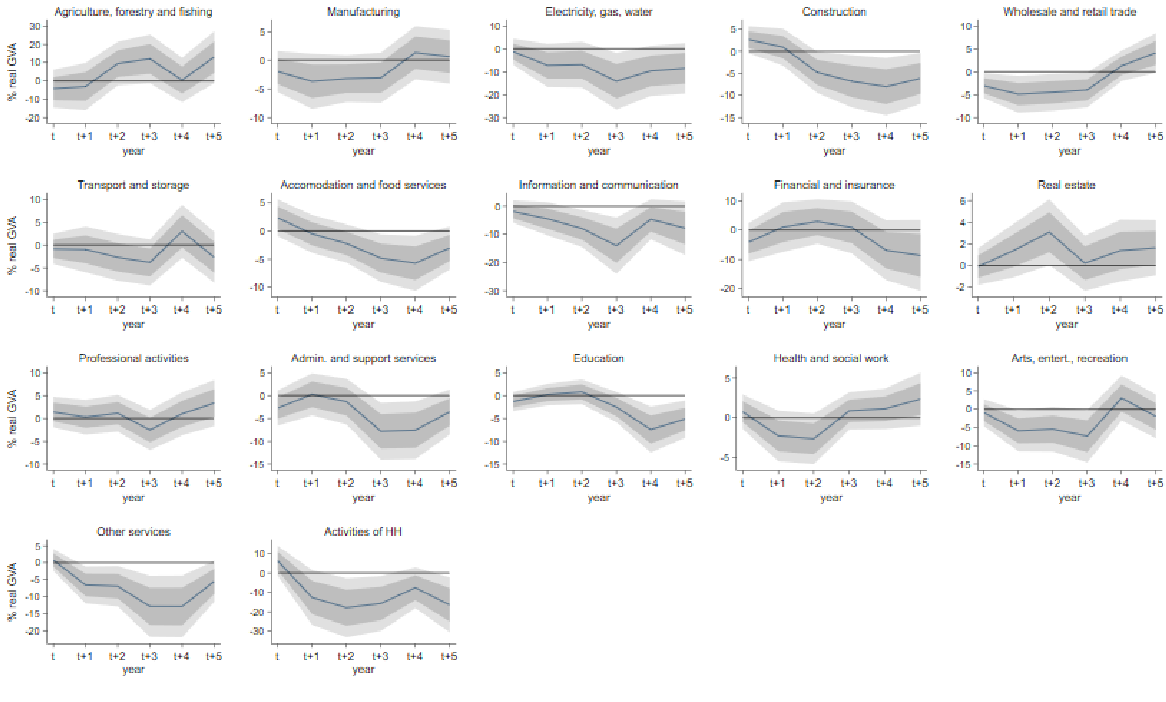
Note: Dynamic impulse response functions of GDP to a one standard deviation increase in the number of floods . All specifications include ITL3 and year fixed effects. Controls include population size and one lag of GDP. Standard errors are clustered at the ITL3 level. Shaded areas denote 68% and 90%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

Figure 21: Inflation Response to Floods - LP OLS



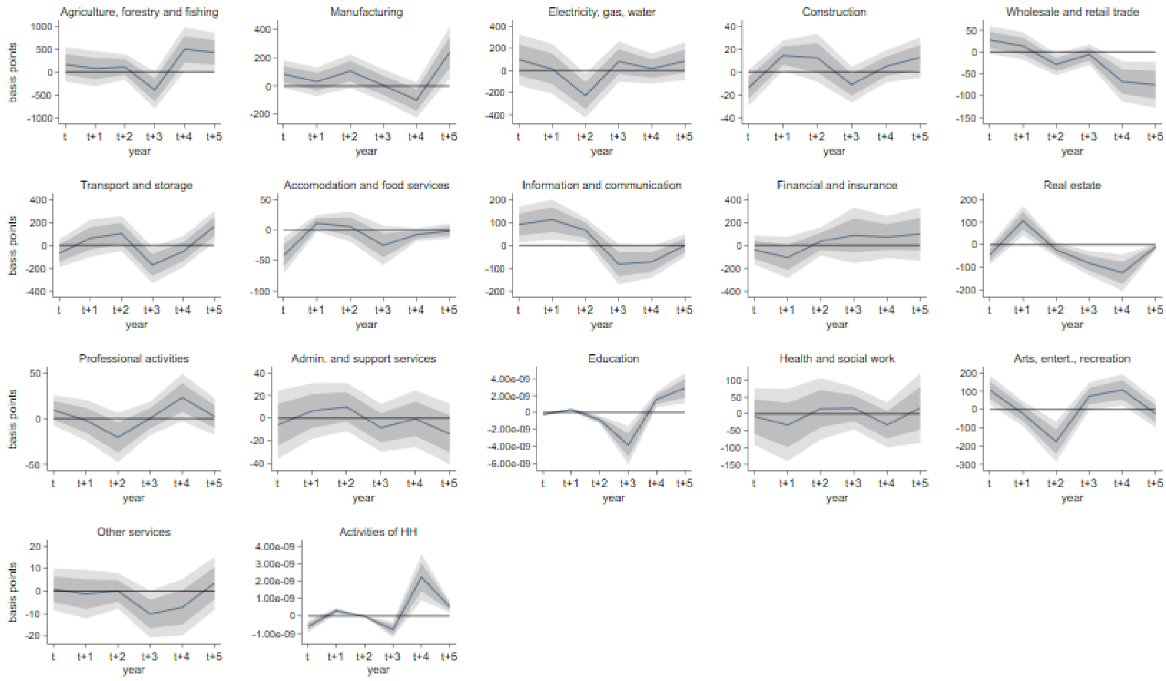
Note: Dynamic impulse response functions of inflation to a one standard deviation increase in the number of floods. All specifications include ITL3 and year fixed effects. Controls include population size and one lag of inflation. Standard errors are clustered at the ITL3 level. Shaded areas denote 68%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

Figure 22: GVA Response to Number of Floods by Industry (Main Industries)



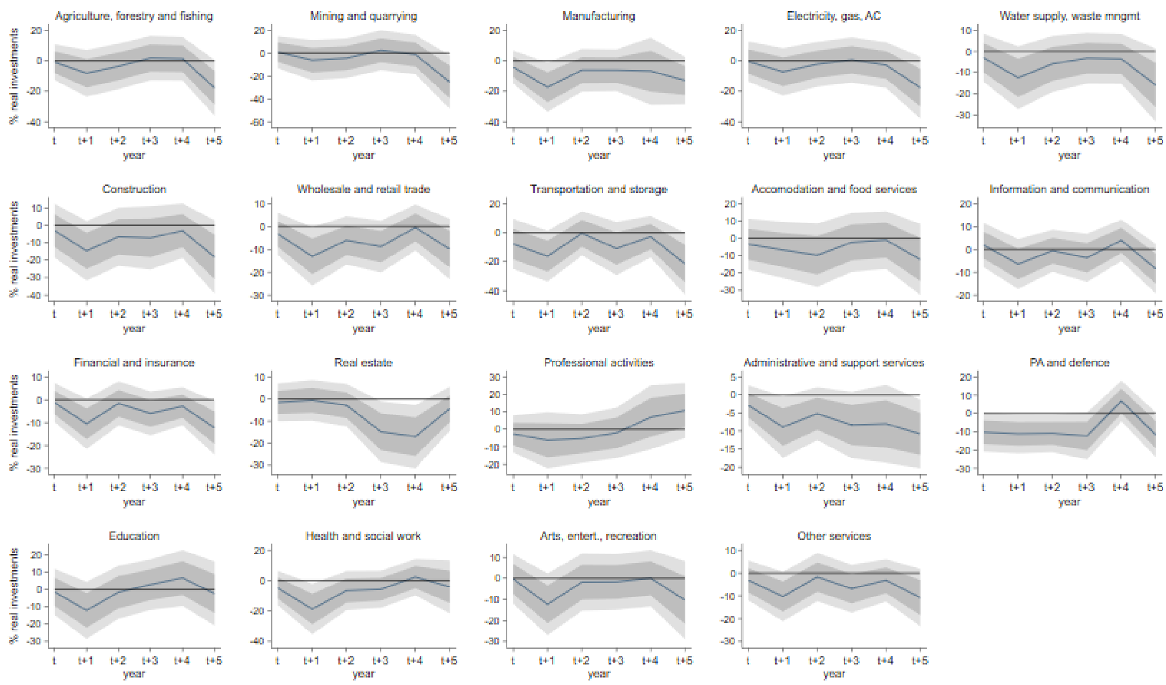
Note: Dynamic impulse response functions of GDP to a one standard deviation increase in the number of floods. Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population size and one lag of GDP. Standard errors are clustered at the ITL3 level. Shaded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

Figure 23: Inflation Response to Number of Floods by Industry (Main Industries)



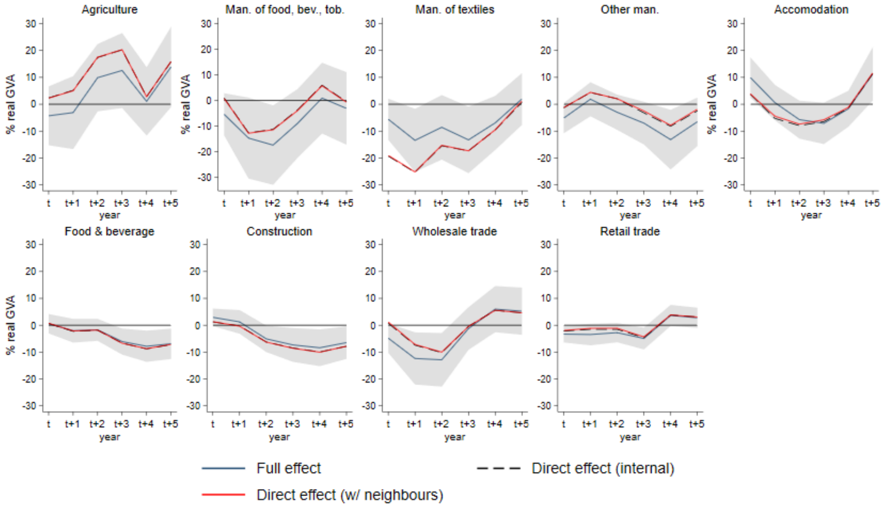
Note: Dynamic impulse response functions of inflation to a one standard deviation increase in the number of floods. Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population size and one lag of inflation. Standard errors are clustered at the ITL3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

Figure 24: Investments Response to Number of Floods by Industry (Main Industries)



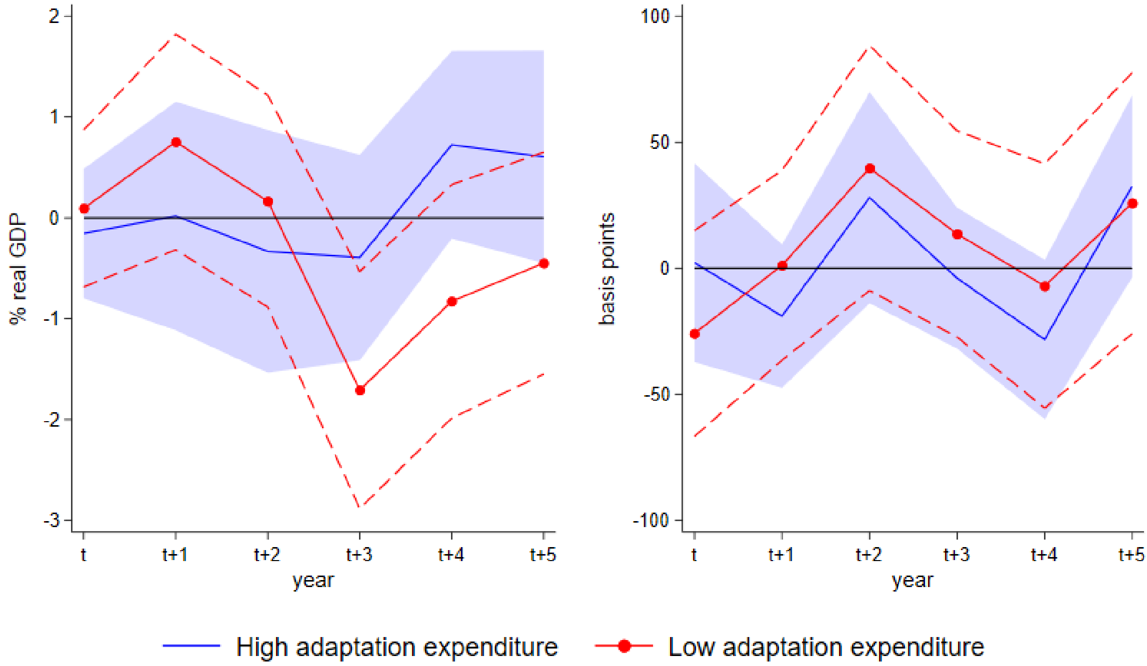
Note: Dynamic impulse response functions of investments to a one standard deviation increase in the number of floods. Estimates are based on LP-IV. All specifications include ITL3 and year fixed effects. Controls include population size and one lag of investments. Standard errors are clustered at the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

Figure 25: Full and Direct Response to Floods by Industry - An Extension



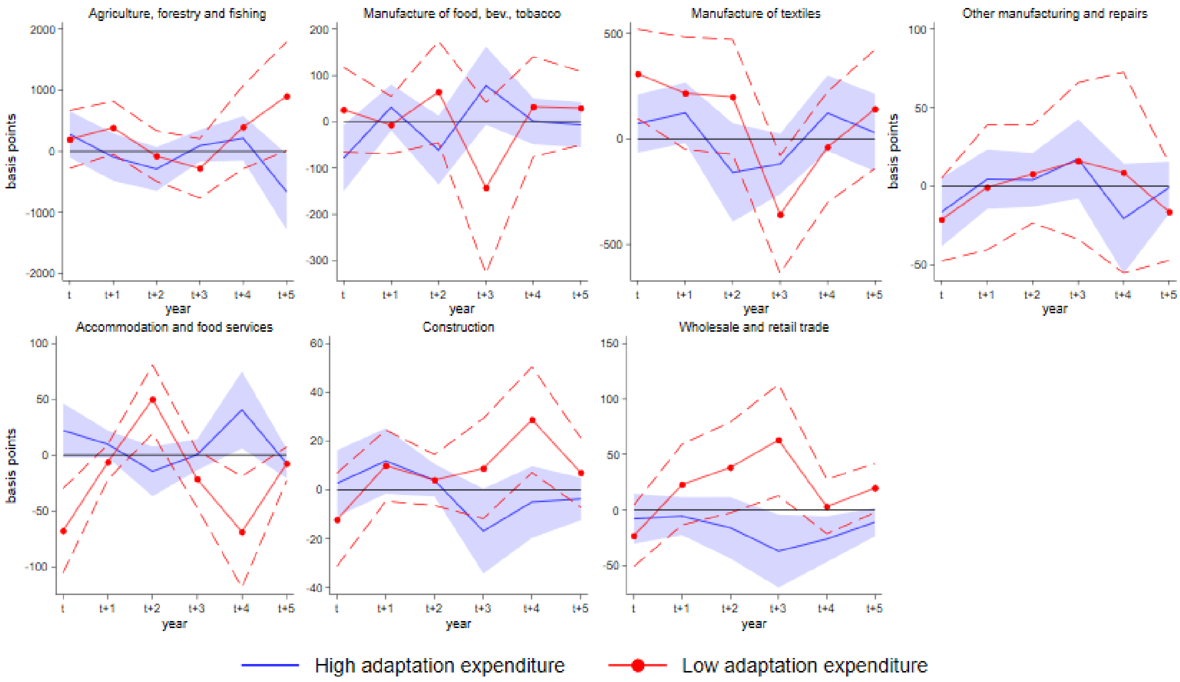
Note: Dynamic impulse response functions of GVA to a one standard deviation increase in the number of floods: full (blue line, $\beta^F_{k,h}$) and direct ($\beta^D_{k,h}$) effects. We compare the direct effect including both i and its neighbours' GVA (red solid line), and i's only (dashed black line). The difference between the full and the direct effects gives a lower bound of the cumulated 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 26: 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 27: State Dependent Response of Inflation to Floods by Industry



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 3: 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 4: Breakdown of industries

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

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

Table 5: Breakdown of industries

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

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