Juliette Caucheteux

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Reference : Professor Rick van der Ploeg

rick.vanderploeg@economics.ox.ac.uk

Application for the NBER PhD Student Workshop on Climate Finance

Please find attached in this PDF:

1) A cover letter indicating their name, complete contact information, university, description of their current and future research interests, expected completion date of their PhD program, and the name of at least one faculty adviser who could serve as a reference.

2) A curriculum vitae.

3) A research paper that is work-in-progress and for which feedback is sought. That is, the paper should not be published; it should be at the stage at which comments and feedback would be helpful.

Application for the NBER PhD Student Workshop on Climate Finance

Juliette Caucheteux
juliette.caucheteux@some.ox.ac.uk
PhD Candidate in Economics - University of Oxford
Reference: Professor Rick van der Ploeg
rick.vanderploeg@economics.ox.ac.uk

Dear Members of the Recruitment Committee,

As a current PhD student in Economics at the University of Oxford, I would like to submit my paper for consideration at the NBER PhD Student Workshop on Climate Finance.

My research focuses on Climate Change and Firms, and studies how firms spatial decisions are affected by natural disasters. I am in my fourth year of the PhD, and plan on going to the job market in September 2026. The paper I am submitting, jointly written with Rebecca Mari at the Bank of England, is entitled "Should I Stay or Should I Go? The Effects of Floods on Firms' Location Decisions". This paper starts from the observation that, although we know a lot about firms, little is known about their distribution across space and how this distribution is affected by floods and agglomeration economies. We thus leverage a unique dataset on the universe of all firms in the UK, comprised of not only headquarters but all types of businesses. We map this with historical floodmaps at 50m x 50m level and corporate information from Bureau Van Dijk, and analyse how firms' location decisions respond to experiencing flood events.

Using a difference-in-differences set up, first in a two-way fixed effects then in a staggered difference-in-differences following Callaway and Sant'Anna (2021) approach, we first find that firms operating from business premises affected by a flood are more likely to relocate elsewhere after being flooded. This effect decreases with the number of floods, a sign of location-stickiness arising from financial constraints or adaptation. We find significant sectoral effects. In particular, firms operating from sectors that are not reliant on the land and more mobile, namely services, technology, information and communications, are more likely to relocate following a flood. On the other hand, firms in less mobile sectors, such as agriculture, education, hospitals and mining, are less likely to relocate. Secondly, firms operating from premises which have been flooded internalise the risk of flooding when making subsequent location decisions and relocate to safer areas. Lastly, we find that while agglomeration economies drive the patterns of business location, with firms more likely to move out of low-productivity regions towards high-productivity region, they do not influence a firm's decision to relocate once a flood hits. Floods thus have irreparable damage on firms, whether they are in a high productivity area or not. Taken together, these results show that climate change affects the spatial equilibrium of firms, which is important to understand when designing policies.

The paper is currently at the ideal stage to receive feedback. We have been accepted at many prestigious conferences, in particular the CEPR European Summer Symposium in Climate Change and the Environment, the upcoming European Economic Association (EEA) and American Economic Association (AEA) annual meetings, as well as prestigious conferences in the US and Europe. I also finished a visiting at the London School of Economics and am about to embark on a visiting to UC Santa Barbara to take the paper forward. I am very ambitious for this project, and aim to submit it to top economic journals. To that end, I would greatly benefit from feedback from the workshop on how to frame the paper, how to present the results. I am particularly keen on adding a model to think about the interaction of firms' location decisions with insurance markets and non-bank financial institution stability. The conference is the ideal place to pursue this goal.

Should I be selected, I would be extremely proactive to seek feedback and make the most of this opportunity to improve the paper, ahead of the job market in September 2026.

Thank you very much for your consideration.

Yours faithfully,

Juliette Caucheteux

Juliette Caucheteux

PhD Candidate in Economics

Citizenships: French, British

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United Kingdom
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Education

DPhil in Economics - Oxford University *Sept 2021 - Present*

- Supervised by Professors Baldwin and Van der Ploeg
- Visiting Research Student - London School of Economics (Spring 2025), UC Santa Barbara (Autumn 2025)
- Research fields: Spatial Economics, Environmental Economics, Natural Disasters, Productivity
- Founder and co-convenor of the Environmental Economics Seminar (2021 - 2023)

Master of Public Administration - London School of Economics *Sept 2018 - July 2020*
(Distinction, top of the cohort)

- George W. Jones prize for best academic performance by an MPA student
- Excellence in Macroeconomics award in the MSc. Economics Macroeconomics course
- Courses in the Department of Economics: Microeconomics, Macroeconomics, Public Economics
- In the School of Public Policy: International Economics, Econometrics, Political Science, Development Economics
- Research project for the Bank of England Chief Economist: analysed the UK productivity gap using ORBIS historical

BSc. and MSc. in Mathematical Engineering - Ecole nationale des ponts et chaussées *Sept 2015 - Oct 2020*
(Top 5 French engineering school (*Grande Ecole*), member of Institut Polytechnique de Paris)

- Courses taken: Analytical calculus and algebra, Statistics, Continuum Mechanics, Game Theory, Computer Science, Environmental Economics, Econometrics, Economics of Transportation, Urban Economics, Development Economics

Professional experience

Bank of England - PhD Intern in the Inflation, Climate and Energy Team *Sept 2024 - Present*

- Conducting analysis in R, Python, QGIS on the effects of floods on UK firm relocation in the UK using flood maps, real estate (CoStar) and BVD data
- Drafting notes to the division and MPC committee on policy issues (energy crisis, cash squeezes and unemployment)

International Monetary Fund - PhD Intern in Western Hemisphere S3 *Jun 2024 - Sept 2024*

- Developed a methodology to assess the effect of droughts on agricultural output using satellite data in South America
- Expertise in satellite datasets: NOAA, SPEI, MapBioMas, manipulated in R, Python and QGIS

Oxford University - Research Assistant in the Climate Compatible Growth Programme *Jan 2022 - April 2023*

- Conducted a systematic literature review on climate mitigation policies in low income countries using Python

LSE STICERD - Pre-doctoral Research Assistant for Professors Landais, Reck and Spinnewijn *Aug 2020 - Aug 2021*

- Conducted the empirical analysis for the paper Retirement Consumption and Pension Design (AER)
- Leveraged a quasi-experiment and implemented an instrumental variable strategy to understand the behaviour of workers retiring in Sweden, their consumption patterns and health

European Central Bank - Research Assistant - DG International and European Relations *July 2019 - Sept 2019*

- Analysed the debt structure of fallen angels in the United States and their probability of default
- Conducted data gathering, cleaning and statistical analyses using Stata and Python using CRSP, Compustat, Capital IQ

French Embassy in Germany - Economic *attachée* the Macroeconomic and Finance division *Dec 2017 - Aug 2018*

- Analysed the main German Macroeconomic and Financial debates (minimum wages, financial stability, budget)
- Wrote policy memos to the French Ministry of Finance and French Ambassadress
- Monitored the German position on the Economic and Monetary Union, US tariffs, Greece rescue package

Crédit Agricole CIB - Junior Quantitative analyst in Securitisation - Global Market Division *June 2017 - Dec 2017*

- Realised feasibility studies on securitisation financing to support the development of off-grid solar energy in Africa
- Analysed portfolios and distributed energy solar companies' existing projects in Côte d'Ivoire, Ghana, Kenya
- Developed quantitative assessment of the proposed financing structures to evaluate projects viability and scaleability potential (weighted average live, tranching)

Teaching and other experience

Merton College - Deputy Principal for the Postmasters (Junior Dean for Discipline) *Sept 2024 - Present*

Oxford University - Graduate Teaching Assistant *Oct 2023 - July 2024*
Oct 2022 - July 2023

Somerville College - Stipendiary Lecturer in Economics and Organising Tutor *Oct 2022 - Dec 2022*

Publications

1) Climate Change Mitigation Policies for Developing Countries (with S. Fankhauser and S. Srivastav), Review of Environmental Economics and Policy

Abstract: Following the Paris Agreement, many low and middle-income countries (LMICs) have adopted climate change targets. They will need climate policies that are suited to their socio-economic and institutional contexts. Conventional policy prescriptions are geared toward high-income countries with entrenched high-carbon structures, universal energy access, deep financial markets, formal economies, privatized power markets, a capable public sector and relative macroeconomic stability. Not all these assumptions generalize to LMICs. We synthesize what is known about emissions reduction policies in LMICs. We find a strong emphasis on finance interventions and regulatory measures, including the need for power sector reform. Removing existing price distortions is emphasised over carbon pricing, which features mostly in middle-income countries, where energy access gaps and institutional capacity constraints are less severe. Skills policies are mostly about preparing a young population for a changing labor market, and less about re-skilling the existing work force.

Work in progress

1) *Should I Stay or Should I Go? The Effects of Floods on Firms' Location Decisions* (with R. Mari)
Presented at (* scheduled): Queen Mary University of London, London Business School, EAERE, CEPR (*), EEA (*), AEA-NARC (*)

Abstract: While the literature on firms is plentiful, little is known about their distribution across space and how the spatial equilibrium of firms changes in response to climate shocks. In this paper, we provide a unique account of the spatial distribution of corporate organisations in the UK, and analyse how firms' location choices are affected by floods and agglomeration economies. We combine various data sources to obtain a panel of business premises at the geocoordinates level overlayed with flood
maps and firm ownership structure. This allows us to first shed light on the spatial organisational structure of firms within the UK, a topic never studied before. We then investigate the effect of floods on firms' location and find three main results. Firstly, firms operating from business premises affected by a flood are more likely to relocate elsewhere after being flooded. This effect decreases with the number of floods, a sign of location-stickiness arising from financial constraints
or adaptation. Secondly, firms operating from premises which have been flooded internalise the risk of flooding when making subsequent location decisions and relocate to safer areas. Thirdly, we find that while agglomeration economies drive the patterns of business location, with firms more likely to move out of low-productivity regions towards high-productivity region, they do not influence a firm's decision to relocate once a flood hits. Floods thus have irreparable damage on
firms, whether they are in a high productivity area or not. Taken together, these results show that climate change affects the spatial equilibrium of firms, which is important to understand when designing policies.
Presented at (* scheduled): Bank of England, Oxford Graduate Workshop in Environmental Economics, Environment Agency, Bruegel, Queen Mary University London, London Business School, EAERE, CEPR, EEA(*), FAERE(*), ASSA-AEA (*), University of Illinois - Urbana Champaign (*)

2) *Weather-Related Extreme Events, Agricultural Output, and Insurance: Evidence from South America* (with S. Vtyurina and J. Nauerz), IMF Working Paper Series

3) *The Interactions Between Taxes and Nudges in Food Sustainability Choices: An Experimental Protocol*

4) *The Distributional Effects of Carbon Taxation With Credit Constraints*

Skills and interests

Languages

- French: Mother tongue
- English and German: Fluent
- Arabic and Persian: Intermediate (A2-B1)

Computer science skills

- Office Pack, VBA, MSAccess: Advanced
- Stata, Python, R, Git: Advanced
- QGIS, R Spatial, Satellite Data: Advanced
- C++, SQL: Good knowledge

Extra curiccular activities

- Treasurer and Music Representative of the Somerville College MCR
- Editor of the Public Sphere Journal, a student led journal of the School of Public Policy at the LSE
- Vice-President of Ponts Etudes Projets (2016), a student consultancy firm at the Ecole des Ponts
- Team captain, whip and treasurer of the English Debating Club while at the Ecole des Ponts
- Horse-riding: at a competition level ; Tennis: Regular practise for 6 years ; Piano: everyday practise for 10 years
- Volunteer at the Banque Alimentaire: collecting and distributing food for people in need every year for three years

Should I Stay or Should I Go? The Effects of Floods on Firms' Location Choices

Juliette Caucheteux* and Rebecca Mari†

7 August 2025

Preliminary version, please do not circulate.

*Bank of England and Department of Economics at University of Oxford & Somerville College
†Bank of England

We thank seminar participants at the Bank of England, Bruegel, CEPR, EAERE, Environment Agency, Queen Mary University London, London Business School and Oxford Graduate Workshop in Environmental Economics for valuable feedback and comments. Juliette Caucheteux gratefully acknowledges support from the Margaret Thatcher Scholarship Trust of Somerville College and of the Department of Economics, University of Oxford. Both authors acknowledge support from the HMT Economic Innovation Fund. The authors have no conflict of interest to disclose.

Abstract

While the literature on firms is plentiful, little is known about their distribution across space and how the spatial equilibrium of firms changes in response to climate shocks. In this paper, we provide a unique account of the spatial distribution of corporate organisations in the UK, and analyse how firms' location choices are affected by floods and agglomeration economies. We combine various data sources to obtain a panel of business premises at the geocoordinates level overlayed with flood maps and firm ownership structure. This allows us to first shed light on the spatial organisational structure of firms within the UK, a topic never studied before. We then investigate the effect of floods on firms' location and find three main results. Firstly, firms operating from business premises affected by a flood are more likely to relocate elsewhere after being flooded. This effect decreases with the number of floods, a sign of location-stickiness arising from financial constraints or adaptation. Secondly, firms operating from premises which have been flooded internalise the risk of flooding when making subsequent location decisions and relocate to safer areas. Thirdly, we find that while agglomeration economies drive the patterns of business location, with firms more likely to move out of low-productivity regions towards high-productivity region, they do not influence a firm's decision to relocate once a flood hits. Floods thus have irreparable damage on firms, whether they are in a high productivity area or not. Taken together, these results show that climate change affects the spatial equilibrium of firms, which is important to understand when designing policies.
JEL Classification Numbers: L25, O18, O52, Q54, R33, R11

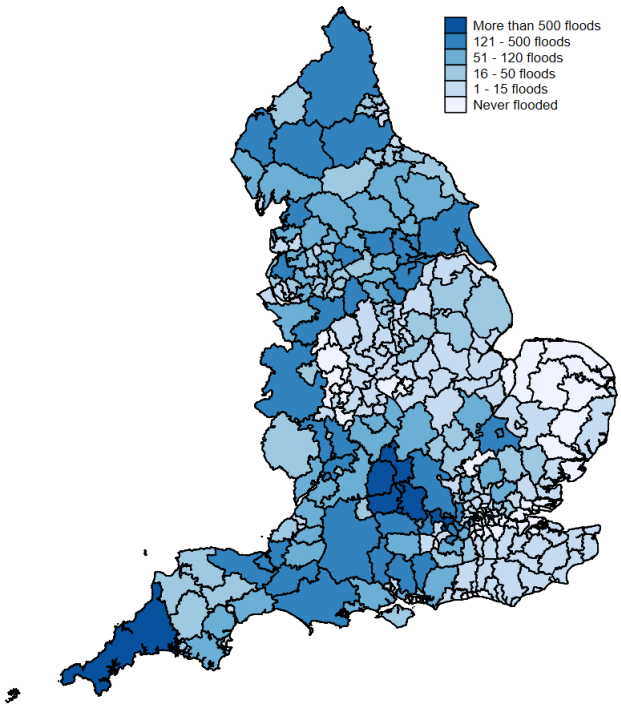
Keywords: *Floods, Firm performance, Relocation, Adaptation, Agglomeration Economies*

I Introduction

The rise in temperatures above 1.5°C relative to pre-industrial levels has dramatically increased the frequency and intensity of climate-related extreme events, be they floods, prolonged droughts, hurricanes or wildfires.

The United Kingdom has not been spared by this, and is meaningfully exposed to floods. Only in the year 2024, the UK has witnessed countless flood events, due to storms (Henk, Babet) or heavy rainfall (Devon), and floods are ubiquitous, as evidenced by Figure 1. With climate change, it is projected that the frequency of flooding events will increase. Under a high-emission scenario, Kendon et al. (2023) estimate that flash flood events provoked by heavy rainfall events will be four times more frequent in the UK by 2070.

Figure 1: Number of Flood Events Recorded Between 1998 and 2023



The cost of flooding is very large. Not only do floods destroy private homes, but they also impact business premises, making them inaccessible and destroying machinery, thus affecting firms' business performance. In more extreme cases, the human toll associated with them is also significant.

The literature on the effects of flooding at the firm-level mostly analyses its effects on firm performance or how this translates to changes in macroeconomic aggregates. Papers have investigated the effects of floods on firm turnover, employment and probability of business termination. However, the macroeconomic impacts in the long run are not clear. A strand of the literature estimates that floods have negative effects on firm, by destroying assets (see Fried (2021), Keiller and Van Reenen (2024)), lowering employment and increasing termination (see Crampton et al. (2025) in the UK). Looking at the effects of floods on economic output and prices in the UK, Ficarra and Mari (2024) find that sectoral output can decrease by up to 20% following a 1 standard deviation increase in the number of floods at local level. They find however large heterogeneity across sectors in the way they are affected by flooding, both in terms of impact on output and prices - with flooding acting as a demand side shock in some, a supply side shock in others, or a mix of both. On the opposite side, some papers find that the effects can be positive overall, as they allow firms to 'build back better' or increase their shock resilience (Hallegatte and Dumas (2009), Leiter et al. (2009)). More recently, papers have started to investigate the effects of floods on firm location choices and supply chain interactions. Balboni et al. (2024) use geo-coded data on firm location and supply chains and find that firms are more likely to relocate to less flood-prone areas and diversify their sourcing of inputs.

Although the effect of floods on firm performance has been studied extensively in the literature, little is actually known on the effect of floods on firm location choices in the UK. Given the spatial heterogeneous nature of the shock we are considering, this is an important channel to investigate. Indeed, floods are intrinsically local shocks that impact business operations at their core, forcing firms to internalise the risk of floods when making their location decisions. As climate shocks become more frequent and firms are force to reconsider their location choices, the spatial equilibrium and corporate landscape of the UK is likely to undergo a significant transformation, with consequences on demography, local unemployment and spatial inequality. Thus, understanding the spatial distribution of firms and how location choices respond to such shocks is important, in order to evaluate on one hand the cost of adaptation investments and on the other hand the spatial consequences of business relocation in absence of successful adaptation strategies. Needless to say a deeper understanding of both of these is essential to design adequate

policies supporting the structural change economies all over the world are facing from climate change.

Additionally, little is currently known about the spatial organisational structure of firms. This is mostly because the data on firm location is challenging to obtain. The micro-level datasets that do contain information on firm location mostly report the postcode of the headquarter, not of all the trading business premises. Understanding the spatial organisational structure of firms, independently from the effect of floods, is a topic worthy of attention in its own right, since this allows to understand spatial implications of business growth. Crampton et al. (2025) present an overview of the spatial distribution of business premises of firms across the UK, discussing patterns of agglomeration across sector and regions, but they don't consider the underlying spatial organisational structure at firm-level, which is instead the object of our documentation.

In this paper, we aim to shed light on the spatial organisational structure of firms in the UK and the interaction with floods and agglomeration economies. We build a unique dataset combining flood maps in the UK from the Department of Environment, Food and Rural Affairs (DEFRA) and Natural Resource Wales (NRW) with unique data on premises at the geocoordinate level from Ordnance Survey (OS) and Energy Performance Certificates (EPCs) as well as firm ownership structure from Companies House UK, sourced by Bureau Van Dijk between 2010 and 2021. Our contributions are threefold.

Firstly, we document the spatial organisational structure of firms in the UK, over time, across regions and across headquarters. This aspect is novel, since up until now firm-level datasets usually have information on headquarters only. We show that, in line with the observed business growth, the number of business premises has increased in the country over the last decade. Business premises are primarily located in three main regions, with London, South East and East of England accounting for more than 50% of premises in the UK. The new data on organisation location at the premise level allows us to uncover that, in the UK, the majority of corporate organisations operate from exactly one business premise, and that multi-establishment organisations account for less than 10% of our sample. This reflects somewhat the size distribution of firms, with small firms accounting for the largest share. This distribution is however not reflected in the sample of organisations that have been flooded between 2011 and 2021, whereby the majority of them

operates from more than one business premise. This is in line with the results from Crampton et al. (2025) who find that larger firms are more likely to get flooded as a result of sorting into flood-prone areas in a search for cheap-land where they can establish large business premises.

Secondly, we investigate the effects of floods on the likelihood of relocation, at the premise level. To do so, we build a panel at the business premise $\times$ year level that records each company located there, its balance sheet characteristics, as well as an indicator for whether a flooding event occurred or not. We are thus able to track if an organisation moved out of a business premise following a flood, defined by not observing this organisation trading at this premise address anymore, but the organisation being still active to rule out terminations. Running a difference-in-difference setup in linear probability model, logistic and probit regressions, we show that, following a flood, companies are more likely to move out of a trading address. In our probit regression, we find that having experienced a flood increases the likelihood of moving out by 10%. We show that this result is robust to accounting for staggered treatment effects and selection bias, by implementing a staggered difference-in-difference estimator à la Callaway and Sant'Anna (2021) and a propensity score matching based on firm characteristics. We also find that the probability to leave a premise declines with the number of floods experienced at that same address. We interpret this finding with two explanations. Either organisations are sticky due to financial constraints that make them unable to move, or there is adaptation in their operations/supply chains that makes them more resilient in the face of a shock. We also investigate the sectoral heterogeneity and uncover that organisations in sectors that rely more on the geographic characteristics of their premise to run their business are less mobile, such as education, oil and gas, agriculture are less likely to move following a flood. In contrast, organisations that are in services, information and communications or administration are more likely to move following a flood. Similarly, smaller firms are more likely to move out.

Additionally, we find that companies that choose to relocate after a flood internalise the risk of flooding. Our dataset records the exposure of each premise to flood risk, allowing us to construct an indicator of average flood risk exposure across business premises a firm newly moves-in. We find that, following a flood, the average risk of business premises the firm moves-in decreases by 7% on a scale from 1 to 4. This finding relates to the work of Balboni et al. (2024) who leverage

granular data on month-to-month firm-level transactions in Pakistan, and find that firms relocate after a flood to safer areas.

Thirdly, we analyse how the propensity to move interacts with agglomeration economies. Building on the literature on agglomeration economies, we investigate how firms weigh the trade-off between the aftermath cost of floods and the benefits from locating in areas with high employment, productivity or business density. We find that, while agglomeration economies determine the propensity to move in and out of a location, with more productive areas attracting more firms, local productivity does not matter once a flood hits an address. Indeed, floods still have an effect on the probability to move out of a place, no matter the productivity of the region, and local productivity does not seem to counteract this repulsive force. This means that floods have irreversible effects: once they take place, and outweigh the benefits of being in high productivity regions for some firms.

Taken together, our results indicate that, after a flood, firms are more likely to move out from a premise, that they internalise the effect of floods when making subsequent location decisions and that agglomeration economies play a role in how they respond to the shock.

To our knowledge, this is the first paper that attempts at analysing the spatial distribution of firms in the UK and how the spatial equilibrium is shifted in the face of climate shocks. As climate shocks heavily depend on the geography and their frequency will worsen in the future, there are several policy implications to take away from our results. As the intensification of physical risk from climate change is likely to be geographically concentrated, firms are likely to move away from those areas and towards less flood-prone but economically attractive regions. Our results indicate however that relocation is less likely to happen if the area where the firm originally operates is economically attractive. Firms seem to be willing to tolerate physical risk in the face of a positive business environment. That in itself is however subject to vulnerabilities from climate change as recurring floods can severely damage even a flourishing economy to start with (Ficarra and Mari (2024)), hence adaptation investments appear crucial to preserve thriving local economies exposed to physical risks from climate change.

The rest of the paper is structured as follows. Section II describes the various data sources, the process for the data construction as well as some descriptive statistics. Section III presents our

methodology and our results. Section IV outlines the policy implications. Section V concludes.

II Data and Stylised Facts

This section introduces the various data sources as well as the methodology adopted to build our final dataset, a panel at business premise × year level of corporate location information (2010-2021), and the definition of our main variables. We then provide stylised facts on the evolution of the spatial distribution of business premises across the UK.

II.1 Data Sources and Dataset Construction

In this paper we build on the dataset constructed by Crampton et al. (2025) integrating it with regional economic variables and structuring it at a more granular level. We summarise here the main data sources and refer the reader to Crampton et al. (2025) for a more detailed account on the data construction and underlying assumptions.

Historical flood maps: Following Crampton et al. (2025), we obtain floodmaps from the Recorded Flood Outlines provided by Department for Environment, Food and Rural Affairs (DEFRA) for England and Natural Resource Wales (NRW) for Wales. No similar records are available for Scotland, hence why we have been forced to exclude it from the analysis. The Recorded Flood Outlines are structured as a GIS layer recording individual flood extents at a 50m × 50m resolution from 1946 onwards, with attributes including the start date and source of flooding.

Flood risk maps: We obtain maps of flooding risk from rivers and sea from the same sources. These record the distribution of flood risk across England and Wales on a scale between 1 and 4 (with 1 meaning very low risk and 4 very high risk of flooding) and provide information on the existence of a flood defence the risk assessment is conditioned to.

Business premises address information: We obtain information on business premise location (at geocoordinate level), property classification and corporate organisation operating from each premise from Ordnance Survey's AddressBase Premium dataset for the years between 2010 and 2021. Each individual business premise is identified through a Unique Property Reference Number (UPRN).

We integrate additional information on the square footage of business premises from Energy Performance Certificates, which are matched at the year × UPRN level.

We overlay these three datasets. Each year, we define the variable "Flood" at UPRN × year level as a dummy equal to one if during that year a flood took place at the UPRN geocoordinate.

One limitation of the dataset is that it does not allow us to identify exactly which floor the business premise is located on. We believe that this doesn't pose a significant bias to our flood variable coding for two reasons. First, most business premises are located on the ground floor of buildings. Second, if they were instead located in upper floors, a ground flood flooded would still make the business premise inaccessible thus limiting the capability of the firm to operate from its premise. Data limitations also do not allow us to access information on the intensity of a flood (ie. flood height), thus constraining our ability to explore the intensive margin impact. Given that most firms rely on machinery and electrical equipment, capital which is affected as soon as water floods in, focusing on the extensive margin measure would still capture the main losses a company's decision to relocate after a flood.

Parent company data: We retrieve annual corporate balance sheet information at the corporate organisation level from business register records through Companies House in the UK via FAME Bureau van Dijk. This dataset records data at the organisation × year level on the number of employees, revenue turnover and total assets. It also provides the source of the sectoral classification attributed to the company. This information is integrated in the business premise level dataset matching by company name through the same algorithm strategy adopted in Crampton et al. (2025).

Final Dataset and Variable Definitions: Our final dataset is a panel dataset at the UPRN $times year level, between 2010 and 2021, with the key variables being the organisation operating from the UPRN-identified business premise, its balance sheet information, a dummy for flood occurrence, the flood risk score associated to the business location and aggregate regional economic variables. We create two additional key variables. A company-UPRN-year level dummy for whether a company moved out of a premise, defined as equal to one if (i) the parent company is still active on that year and (ii) this is the last year the parent company is observed operating from that

UPRN. Similarly, we define a company-UPRN-year level dummy for whether the company moved in a premise as equal to one if (i) the company is active on that year and (ii) this is the first year the parent company is observed operating from that UPRN. Defining the variables in this way allows us to exclude business terminations from the analysis.

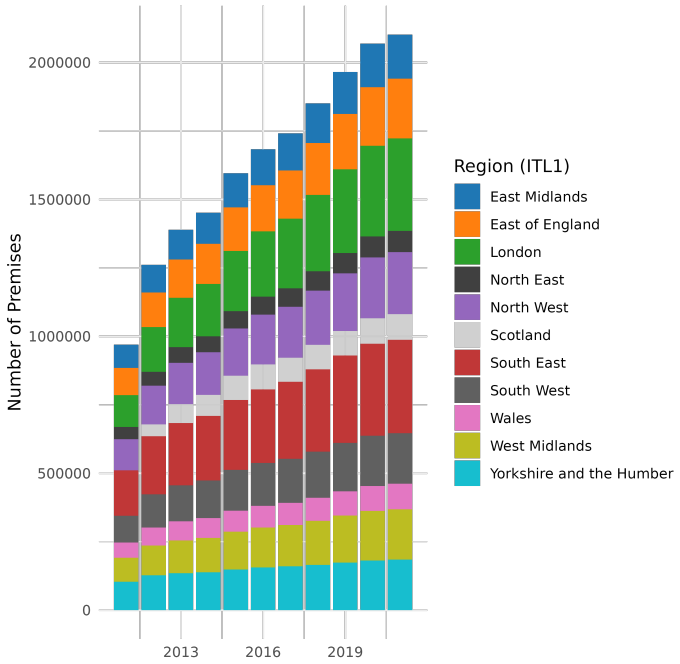
II.2 Stylised Facts on Firm Spatial Distribution

This newly structured dataset allows us to derive some stylised facts about the spatial distribution of firms in the UK.

1. There is a growing number of business premises

Figure 2 shows the number of business premises over time, and their distribution across ITL1 regions. As of 2021, there were around 2 million premises in the UK, and this trend has been growing over time. London is the region with the highest number of premises, followed by South England and East England. Such growth appears to have been homogeneous across regions, as the distribution of premises across regions appears to have remained broadly unchanged over time. This is in line with statistics published by the Office for National Statistics (ONS, 2024).

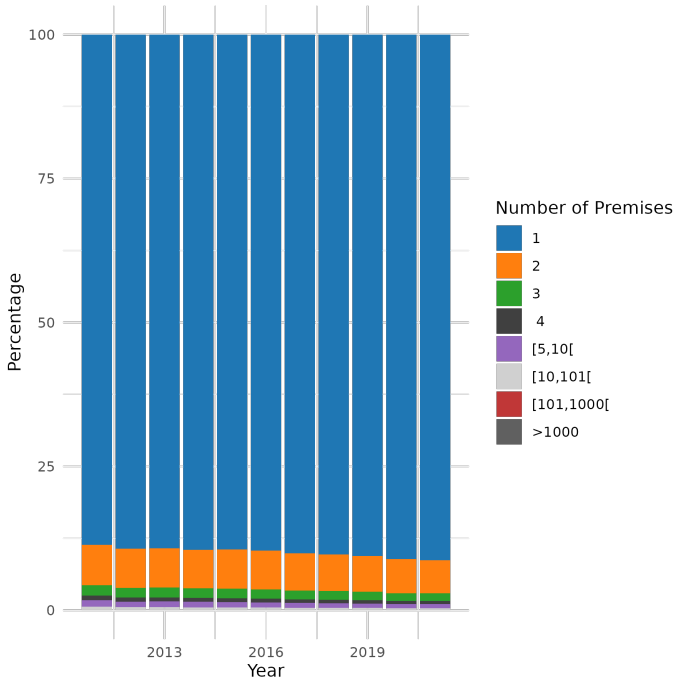
Figure 2: Number of Premises per Region and Per Year



2. The majority of organisations operates from one business premise

Figure 3 presents the share of organisations that operate from one, two or more business premises over time. The overwhelming majority of organisations (more than 80 percent) operates from only one business premise, with the trend being stable over time. This somewhat reflects the size distribution of firms in the UK, with small firms accounting for around 99% of the business population Department for Business and Trade (2024).

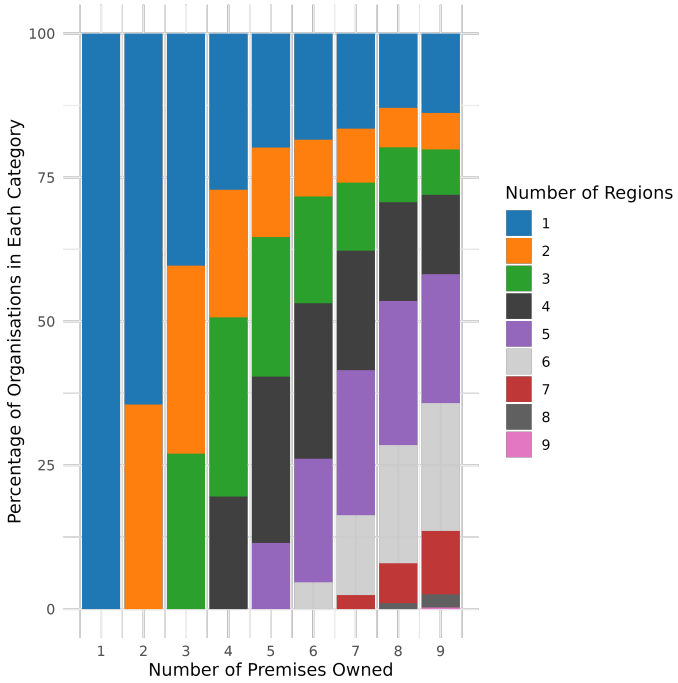
Figure 3: Share of Organisations by Number of Premises over Time



3. Organisations with multiple business premises do so to target multiple regions

To understand the regional distribution of organisations across business premise structure, we plot in Figure 4, the share of regional distribution by number of premises operating from. For instance, the second bar from the left shows that among organisations operating from two business premises, 30% are present in two regions (i.e. the two business premises are located in two different regions), and 70% are present in only one region (i.e. the two business premises are located within the same region). Of course the number of regions once can possibly operate from increases with the number of business premises of a given organisation. The figure however presents a marked trend, with multi-establishment organisations seeming to predominantly operate from more region as they locate in more than one premise.

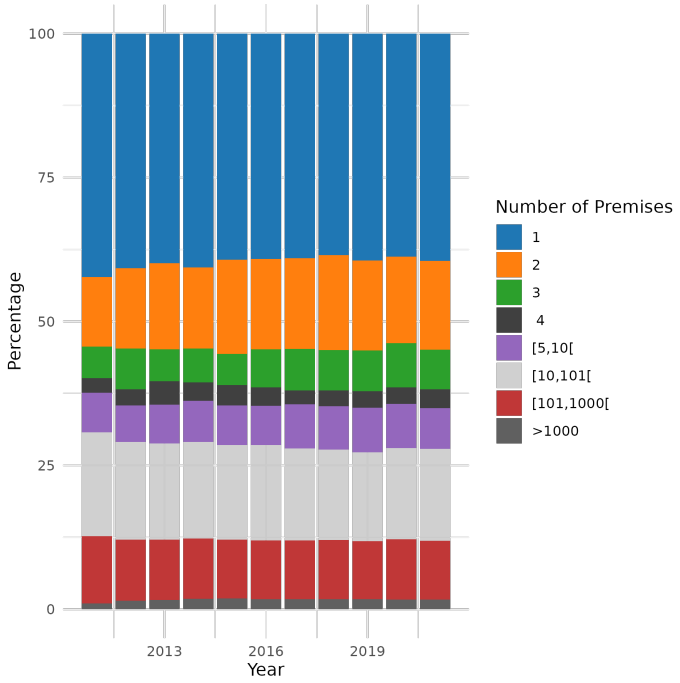
Figure 4: Regional Presence of Organisations by Number of Premises owned as of 2020



4. The sample of flooded business premises differs from the whole sample

One striking fact is that, when investigating organisations that have experienced at least one flood event in their existence, their spatial organisational structure differs from that of the whole sample as shown by Figure 5. In contrast to Figure 3, the sample of firms having experienced a flooding event presents a larger share of multi-premise organisations. This fact can be traced back to two mechanisms. Firstly, statistically, organisations that occupy more business premises are more likely to be flooded. In addition, as shown by Crampton et al. (2025), this is also driven by large firms seeking cheaper land for their necessarily large business premises, driving sorting to more floodprone areas. And large firms are more likely to operate from multiple premises.

Figure 5: Premise Structure Per Year for the Flooded Sample



III Methodology and Results

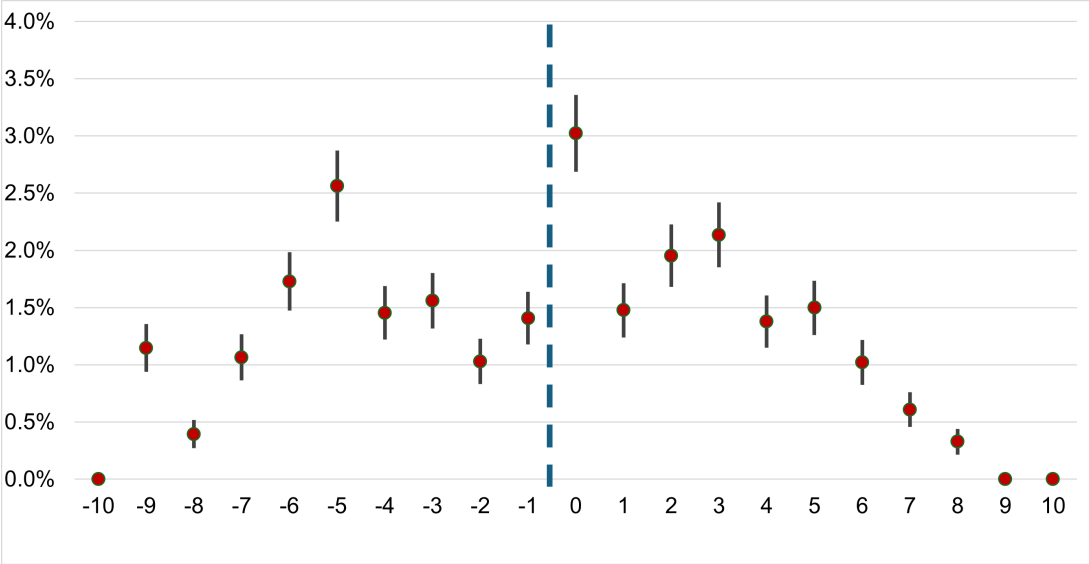
This section presents our methodology to address our three main research objectives. Firstly, we analyse the effects of floods on the probability to move out. We then turn to evaluating the effect of floods on how firms internalise the risk when making their subsequent location decision. Lastly, we investigate how agglomeration economies play a role, both on the likelihood to move out, and on the likelihood to move in.

III.1 Effects of floods on propensity to move out

Raw Means and Difference-in-Differences Results:

Before presenting our identification strategy, we first plot in Figure 6 the raw means of our variable of interest. For each time relative the flood event, we compute the average number of firms that move out along with the standard deviation. Figure 6 shows a jump in the probability to move out around the time of event relative to the years before.

FIGURE 6: Raw means of moving out relative to event time



To delve into the reasons behind this jump more thoroughly, and quantitatively estimate the effect of floods on the probability to move out, we run the following regression in a difference-in-differences approach:

$$\mathbb{P}(Move\ Out_{i,t}|Flood_{i,t} = 1) = \Phi(\beta Treat_i \times Post_t + \gamma Treat_i + \delta Post_t + \epsilon_{i,t}) \tag{1}$$

where $Move\ Out_{i,t}$ is a dummy for whether premise i witnessed a move out in year t, $Treat_i$ is a dummy for whether premise i suffered a flood $Post_t$ is a dummy equal to 1 after the flood year. Our functional form, $\Phi(.)$ will take the normal distribution (probit) or the log-normal distribution (logit). We also report the linear probability model coefficients. Under the identifying assumption that floods are exogenous relative to moving out, β gives us the causal effects of being subject to a flood on the probability to move out.

Table 1 presents the results for the probit, logit and linear probability model specification. The coefficients are positive and statistically significant, indicating that floods increase the probability of a firm leaving the premise. To obtain a magnitude of this effect, we also report the marginal effects in Table 2. With the probit and logit regressions, the results indicate that witnessing a flood increases the probability to move out by 0.097 and 0.093 respectively, that is 9.7 and 9.3 percent.

Table 1: Regression Results: Effect of Floods on Probability to Move Out

	Dependent variable: Move Out		
	OLS	Logit	Probit
	(1)	(2)	(3)
Flood	0.013***	0.723***	0.290***
	(0.001)	(0.060)	(0.025)
Constant	0.013***	−4.328***	−2.225***
	(0.00003)	(0.002)	(0.001)
Observations	16,877,929	16,877,929	16,877,929
R^2	0.00001		
Adjusted R^2	0.00001		
Log Likelihood		−1,173,274.000	−1,173,274.000
Akaike Inf. Crit.		2,346,552.000	2,346,552.000
Residual Std. Error	0.113		
F Statistic	153.798***		

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2: Marginal Effects

	Dependent variable: Move Out					
	AME	SE	z	p	Lower Bound	Upper Bound
Probit	0.097	0.0008	11.58	0	0.0968432	0.0971568
Logit	0.093	0.0008	12.13	0	0.0928432	0.0931568

Note: *p<0.1; **p<0.05; ***p<0.01

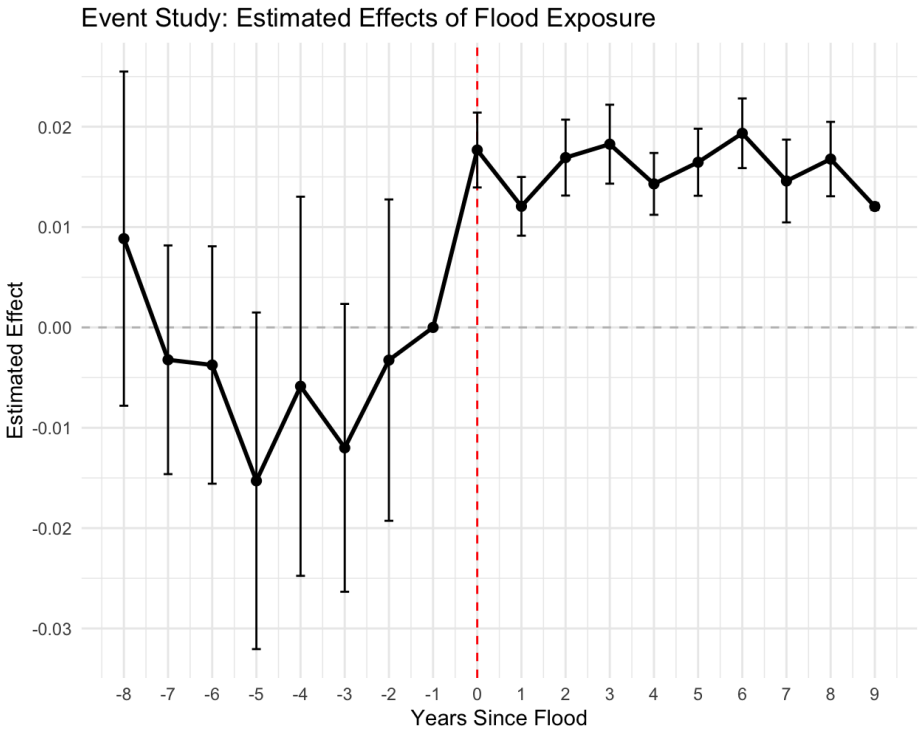
Robustness Checks

Although the two-way fixed effects (TWFE) approach provides a useful benchmark that allows us to compare results across the literature, recent advances in econometric theory have shown that this standard approach may yield biased estimates in settings with staggered treatment timing. In our context, the timing of flood exposure varies across premises, which means the TWFE estimator may use already-treated units as controls for units that receive treatment later. This can contaminate the estimated treatment effects, particularly if treatment effects are heterogeneous across groups or over time.

We therefore complement our main analysis with two robustness checks:

- **Staggered Treatment Adoption Estimator:** We implement the estimator developed by Callaway and Sant'Anna (2021), which is specifically designed to address the issues arising from staggered treatment adoption. We estimate group-time average treatment effects using the not-yet-treated as a control group. Figure 7 shows that our results remain robust when accounting for treatment timing heterogeneity. In particular, we continue to find that firms are more likely to relocate after a flood, with this effect persisting over time.

Figure 7: Staggered Treatment Adoption Estimator Callaway and Sant'Anna (2021)



- **Propensity Score Matching:** As a second robustness check, we address potential selection bias, namely that firms located in flood-prone areas may systematically differ from others. Using our rich dataset, we implement a propensity score matching (PSM) strategy to construct a valid counterfactual. Specifically, we estimate a logistic regression where the dependent variable is a binary indicator for flood exposure. The covariates include flood risk at the firm location, sector, regional productivity, turnover, and number of employees.

  Using the estimated propensity scores, we match each exposed firm to its three nearest neighbors among the non-exposed firms, requiring matches to fall within the same quartile of the firm size distribution. This ensures comparability between treated and control firms based on observable pre-flood characteristics.

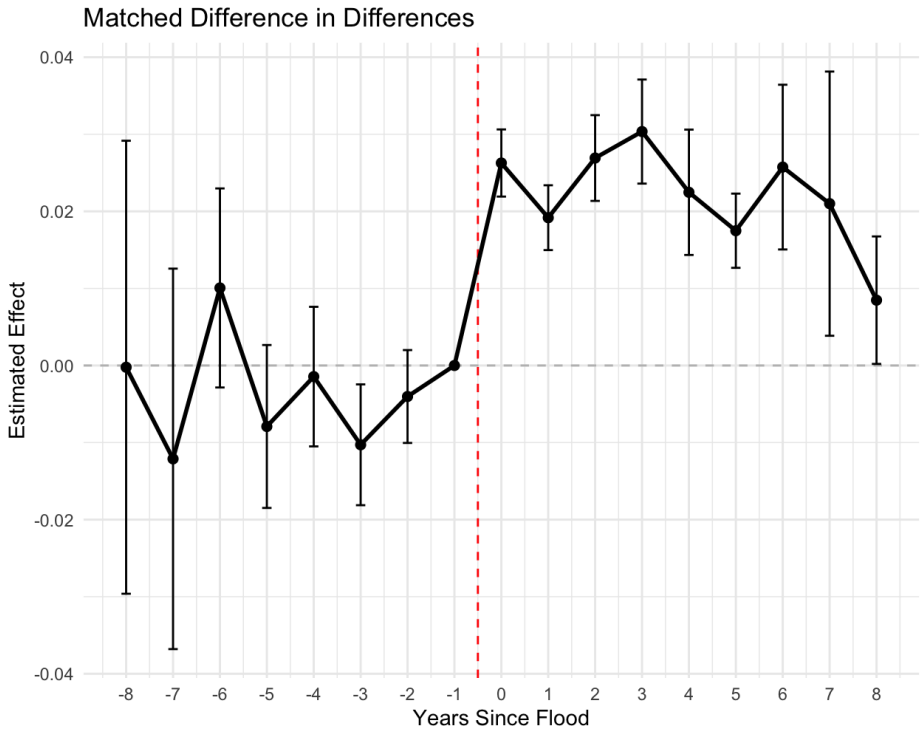
  We then estimate the following event study specification:

$$Y_{it} = \sum_{j=-10}^{10} \delta_j D_{i,j} + \alpha_{m(i),j} + \gamma_t + \varepsilon_{it} \tag{2}$$

  where Y_{it} is the outcome of interest for firm i in year t; $D_{i,j}$ is an indicator for event time j relative to the flood; $\alpha_{m(i),j}$ are match-by-time fixed effects; and γ_t are year fixed effects. The coefficients δ_j capture the differential outcomes between treated and matched firms in each event year. Standard errors are clustered at the match level.

  Figure 8 presents the results. Again, we find a robust increase in the likelihood of relocation following a flood event, with the effect persisting several years after exposure.

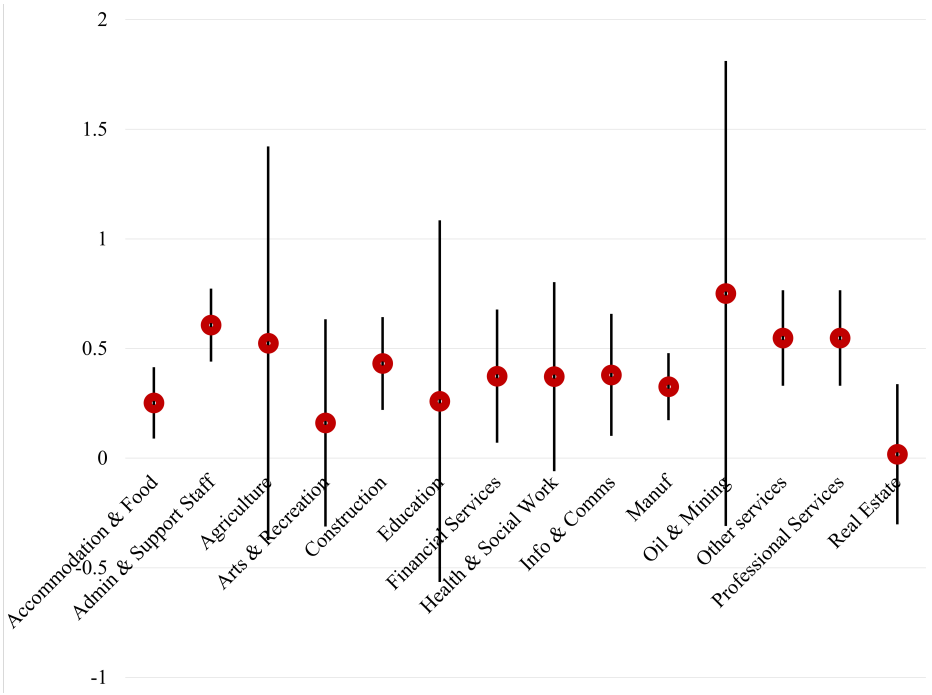
Figure 8: Event Study Estimates using Propensity Score Matching



III.2 Heterogeneity Analysis

The results show that organisations are more likely to move out after a flood. To understand better the specific sectoral response, we also run regression equation (1) for each sector in our sample. Figure 9 plots the coefficient and its confidence interval for the probit specification. A statistically significant coefficient indicates that organisations in this sector are more likely to move out after a flood. Specifically, organisations in sectors such as Agriculture (which include farms), Arts and Recreation, Education (which include schools), Oil and Mining are less likely to move out of a premise following a flood. This is likely to be explained by the fact that these sectors rely heavily on their land and specific location to conduct their business and might be unable to easily relocate. In contrast, organisations in service sectors, such as Administrative and Support Staff, Information and Communications, Professional and Other services are more likely to move out after a flood. This is likely explained by the fact that these sectors are more mobile, and rely less on the geographical location of their premise to operate.

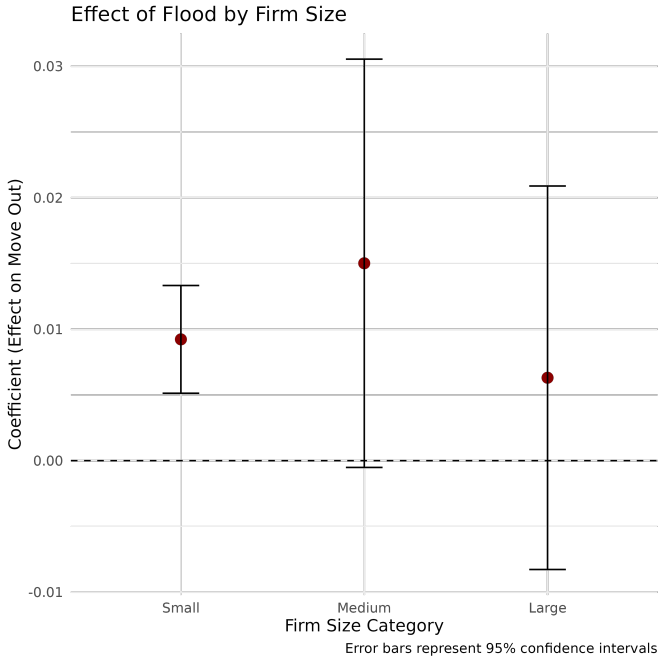
Figure 9: Probability to Move Out by Sector



Notes: To produce this figure, we ran regression equation (1) for each sector in our dataset in the probit specification. We plot the coefficient and its confidence interval for each sector. A statistically significant coefficient indicates a higher likelihood of moving out following a flood.

We also run regression equation (1) for each firm size to understand what type of firms move out. Specifically, we define three size bins based on the number of employees, following the ONS definition Office for National Statistics (n.d.). A firm is assigned to the small category if its number of employees is between 1 and 9 people included, a medium category if it is between 10 and 99, and large if above. Figure 10 presents the coefficients. It shows that smaller firms are more likely to move out when they are flooded relative to non-flooded firms. However, medium and large firms do not experience a significant change in the propensity to move out. This result can be interpreted by the fact that smaller firms are more flexible and might find the costs of relocating smaller.

Figure 10: Probability of Moving out By Firm Size

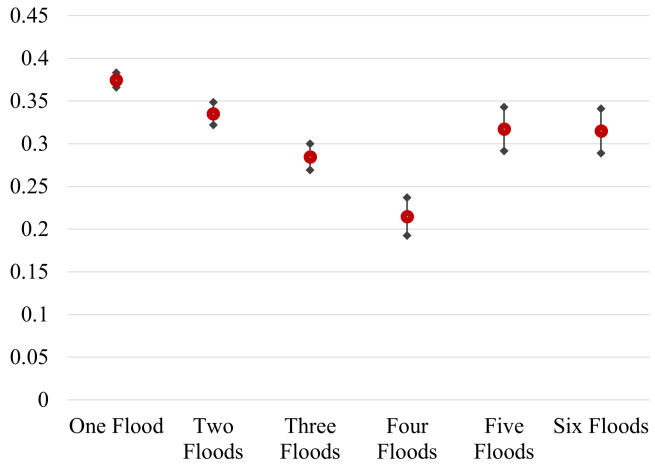


We then proceed to analysing the effect of cumulative floods on the likelihood to move. To that end, for each company j and each year t, we compute the number of floods the company has experienced from the beginning of the sample until that year. We then assign the number of floods the organisation is exposed to to each UPRN $\times$ organisation $\times$ year combination. We run the following regression:

$$\mathbb{P}(Move\ Out|Flood)_{i,j,t} = \Psi(\sum_{k=1}^{6} \alpha_k \mathbb{1}_{\text{Number of Floods}_{i,j,t}=k} + \eta_{i,j} + \delta_t + \epsilon_{i,t}) \tag{3}$$

with Ψ taking the probit or logit functional form. Figure 11 presents the results for Ψ taken to be the normal distribution (probit). It displays a stark declining relationship between the probability of moving out and the number of floods, up until 4 floods.

Figure 11: Probability of Moving out Following Several Floods



Two mechanisms could explain this result.

- **Firms could be sticky to move out due to financial constraints**. As shown by our literature review, floods become priced in the real estate price and decrease the value of a premise. Firms could realise these losses by selling, particularly if a loan is tied to the premise. This constraint could mean that firms have to stay in the premise. Further work could examine this channel, by leveraging commercial real estate data for instance.

- **Firms could adapt to the floods**. After several floods, premises could change their practices to adapt to the effects of floods, for instance by contracting insurance or by building operational resilience via supply chains changes.

III.3 Internalisation of the risk

As shown above, organisations are more likely to relocate after a flood. To shed light on their subsequent behaviour, we then turn to understanding the risk of subsequent move ins. We use the dummy for move ins and the flood risk scale variables described in section II and construct the variables *Average Risk Move In*$_{j,t}$ which is the average flood risk of the move ins that organisation j

conducted in year t, and *Average* $Risk_{j,t-1}$, which is the average flood risk of the premises owned by organisation j in year $t-1$. We then use Δ *Risk*$_{j,t}$ = *Average Risk Move In*$_{j,t}$ - *Average* $Risk_{j,t-1}$ as our dependent variable in the following regression:

$$\Delta Risk_{j,t} = \theta + \kappa Flood_{j,t-1} + \mu_j + \nu_t + \epsilon_{j,t} \tag{4}$$

Table 3 presents the coefficient of interest, κ for the regression with and without organisation and year fixed effects in columns (1) and (2) respectively. The coefficients are negative and statistically significant. Overall, this indicates that after a flood, subsequent move ins decided by an organisation have a lower risk. This means that organisations internalise the risk of flooding when making subsequent location decisions.

Table 3: Effect of Floods on Average Flood Exposure

	Dependent variable:	
	$\Delta Risk$	
	(1)	(2)
$Flood_{t-1}$	-0.068^{***}	-0.039^{***}
	(0.014)	(0.014)
Constant	0.007^{***}	
	(0.002)	
FE	NO	YES
Observations	129,046	129,046
R^2	0.0003	0.677
Adjusted R^2	0.0002	0.139
Residual Std. Error	0.599 (df = 129044)	0.556 (df = 48448)
F Statistic	32.681^{***} (df = 1; 129044)	
Note:	*p<0.1; **p<0.05; ***p<0.01	

III.4 Interaction with Agglomeration Economies

Sections III.1 and III.3 showed that organisations are more likely to move out of a premise after a flood, that this probability decreases with the number of floods witnessed at a premise and that they internalise the risk of flooding when deciding to move in another premise. As discussed in III.1, a potential channel explaining why organisations might be sticky in moving out could be due to agglomeration economies. Organisations derive benefits from locating close to each other, and might forego these benefits.

To analyse this aspect, we compute measures of local productivity at the regional level. For each region at the ITL3 (*i.e.* county) level and each year, we obtain the (i) labour productivity from the ONS, measured in gross value added per worker, and compute the (ii) number of firms from our data. All these variables are then divided by the area of the region in square meters.

For each region at the ITL3 level, indexed by r we then assign the z-score of the region in terms of each of these variables $q \in \{Productivity, Business\ Density\}$. We run the following regression:

$$\mathbb{P}(\text{Move Out}_{i,r,t}) = \Phi(\alpha + \beta Flood_{i,t} + \gamma ZScore_{q_{r,t}} + \delta Flood_{i,t} \times ZScore_{q_{r,t}} + \eta_i + \delta_t + \epsilon_{i,t}) \quad (5)$$

where i denotes the premise i in the region r in year t, the variable $Flood$ is defined as before, and $Zscore_q$ is the $Zscore$ of employment, business density of premise i in region r. As above, we adopt various functional forms, probit, logit and OLS. Table 4 reports the results for q being the Zscore of local productivity for our probit specification, while Annex A Tables 6 and 7 report the result for the total turnover and for the total number of firms respectively.

Overall the results paint the same picture. The coefficient for floods remains statistically significant and positive, meaning that organisations are more likely to move out following a flood. However, the coefficient in front of the Z-Score of each variable is negative, meaning that the proxies for stronger agglomeration economies effects make organisations less likely to move out afterwards. The magnitudes are to be noted: the effect of a flood seems much higher on the propensity to move out than the effect of productivity. Throughout all our specifications, the coefficient on the interaction term is zero. Taken together, these results indicate that floods have an effect on the propensity to move out of a place, no matter the productivity of the region. This means that

floods have irreversible effects, once they take place, and outweigh the benefits of being in high productivity regions for some firms.

Table 4: Response of move outs to floods and agglomeration economies

	Dependent variable:	
	Move Out	
	(1)	(2)
Flood	0.013^{***}	0.014^{***}
	(0.001)	(0.002)
$Z - Score_{ONS}$	-0.001^{***}	-0.001^{***}
	(0.00003)	(0.00003)
Flood $\times$ $Z - Score_{ONS}$		0.004
		(0.005)
Constant	0.013^{***}	0.013^{***}
	(0.00003)	(0.00003)
Observations	16,653,776	16,653,776
R^2	0.00004	0.00004
Adjusted R^2	0.00004	0.00004
Residual Std. Error	0.113 (df = 16653773)	0.113 (df = 16653772)
F Statistic	316.189^{***} (df = 2; 16653773)	210.996^{***} (df = 3; 16653772)
Note:		*p<0.1; **p<0.05; ***p<0 .01

Note: *p<0.1; **p<0.05; ***p<0.01

The results show that firms are less likely to move out when they benefit from high agglomeration economies. In return, how are move ins responding to this phenomenon? To analyse this, we run the following regression:

$$\mathbb{P}(\text{Move In}_{i,t}) = \Phi(\alpha + \beta Flood_{i,t} + \gamma ZScore_{q_{i,t}} + \delta Flood_{i,t} \times ZScore_{q_{i,t}} + X_{i,t} + \epsilon_{i,t}) \quad (6)$$

with Φ taking the probit, logit or linear probability functional form. The rationale behind this regression is that a region with a high Z-score has a higher than average productivity, and thus should witness more move ins. Conversely, a region with high floods should experience less move ins.

Table 5 presents the results for the probit specification and the z-score of our local productivity metric while Tables 11 in Annex C present the results for the z-score of business density. Across all our specifications and Z-score variables, the results present the same trend. The coefficient in front of the flood dummy is negative and statistically significant, meaning that floods in a premise i in year t decrease the likelihood of moving into this premise. The coefficient in front of the z-score is positive, meaning that areas with higher employment attract more firms. Similar to before, the interaction term is null.

Table 5: Response of Move Ins to Floods and Agglomeration Economies

	Dependent variable:	
	Move In	
	(1)	(2)
Flood	-0.019^{***}	-0.023^{***}
	(0.003)	(0.005)
$Z - Score_{ONS}$	0.004^{***}	0.004^{***}
	(0.0001)	(0.0001)
Flood $\times$ $Z - Score_{ONS}$		-0.009
		(0.013)
Constant	0.090^{***}	0.090^{***}
	(0.0001)	(0.0001)
Observations	16,653,776	16,653,776
R^2	0.0002	0.0002
Adjusted R^2	0.0002	0.0002
Residual Std. Error	0.285 (df = 16653773)	0.285 (df = 16653772)
F Statistic	$1{,}397.734^{***}$ (df = 2; 16653773)	931.984^{***} (df = 3; 16653772)
Note:		*p<0.1; **p<0.05; ***p<0.01

IV Policy Implications

To our knowledge, this is the first paper that attempts at analysing the spatial distribution of firms in the UK and how the spatial equilibrium is shifted in the face of climate shocks. As climate shocks heavily depend on the geography and their frequency will worsen in the future, there are several policy implications to take away from our results. Firstly, firms seem to locate in areas and realise the flood risk only when it materialises. As firms are flooded, they then internalise the flood risk in subsequent location decisions. This means that policies could investigate why firms are not internalising the flood risk ex-ante, and intervene on providing information. Secondly, the pattern of firms relocating following a flood is heterogenous, with more flexible firms choosing to relocate while firms in less mobile sectors (health, education, agriculture) are less likely to do so. This means that adaptation policies to help these sectors become more resilient to shocks are essential.

V Conclusion

This paper had two goals. The first one was to document the spatial distribution of organisations across the UK. Thanks to our unique dataset, comprised of business premises between 2011 and 2021 mapped with organisation characteristics and floodmaps, we were able to show that firms in the UK are majorly located in London, East England and West England, that the majority of organisations locate in one premise in the UK. In addition the majority of firms that locate in more than one premise do so to have a multi-regional presence. We also showed that the sample of organisations flooded is very different from the whole sample of organisations in the UK, in that flooded organisations are multi-premise in majority.

Given the ubiquity of floods and their intrinsically spatial nature, we then turned to analyse the effects of floods on firms and subsequent relocation decisions. We showed that, following a flood, organisations are more likely to move out of a premise. There is heterogeneity within sectors, since organisations that operate in sectors heavily tied to the land (education, oil and mining, agriculture) are not likely to move following a flood, when organisations in more mobile sectors (administration, information and communicationsn, professional services) are more likely

to move. Similarly, smaller firms are more likely to move. We also find that the probability of relocation decreases with the number of floods that an organisation experiences. Furthermore, flooded organisations internalise the risk of flooding when making subsequent location decisions and choose to relocate to safer areas. Tying this to the literature on agglomeration economies, we also found that floods have an irreversible damage on firms decision to move, regardless of whether they are in productive areas or not.

Taken together, these results mean that floods will dramatically reshape the corporate landscape in the UK, with implications for regional productivity and adaptation policies.

Although this paper uniquely studied the effect of floods on the firms spatial equilibrium, future work could understand the link between stickiness to move and financial constraints.

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A Response of Move Out Dummy to Agglomeration Economies

We present the results of regression 5 for the other two variables representing the agglomeration economies. Table 6 presents the results using the Zscore of total turnover, while Table 7 uses the Zscore of the total business density. Both regressions use the probit specification.

Table 6: Response of move ins to Floods and agglomeration economies

	Dependent variable:	
	Move Out	
	(1)	(2)
Flood	0.283^{***}	0.336^{***}
	(0.025)	(0.035)
$Zscore_{Turnover}$	-0.033^{***}	-0.033^{***}
	(0.001)	(0.001)
Flood$\times Zscore_{Turnover}$		0.235^{**}
		(0.112)
Constant	-2.226^{***}	-2.226^{***}
	(0.001)	(0.001)
Observations	16,869,702	16,869,702
Log Likelihood	−1,167,095.000	−1,167,092.000
Akaike Inf. Crit.	2,334,195.000	2,334,193.000
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 7: Response of move ins to Floods and agglomeration economies

	Dependent variable:	
	Move Out	
	(1)	(2)
Flood	0.282^{***}	0.351^{***}
	(0.025)	(0.035)
$Zscore_{Business\ Density}$	-0.034^{***}	-0.034^{***}
	(0.001)	(0.001)
Flood$\times Zscore_{Business\ Density}$		0.304^{***}
		(0.112)
Constant	-2.226^{***}	-2.226^{***}
	(0.001)	(0.001)
Observations	16,869,702	16,869,702
Log Likelihood	−1,167,032.000	−1,167,029.000
Akaike Inf. Crit.	2,334,070.000	2,334,065.000
Note:	*p<0.1; **p<0.05; ***p<0.01	

B Linear Probability Model

Table 8

	Dependent variable:	
	move_out	
	(1)	(2)
flood	0.013***	0.016***
	(0.001)	(0.002)
z_score_nb_emp	−0.001***	−0.001***
	(0.00003)	(0.00003)
flood:z_score_nb_emp		0.009*
		(0.006)
Constant	0.013***	0.013***
	(0.00003)	(0.00003)
Observations	16,869,702	16,869,702
R^2	0.0001	0.0001
Adjusted R^2	0.0001	0.0001
Residual Std. Error	0.113 (df = 16869699)	0.113 (df = 16869698)
F Statistic	759.646*** (df = 2; 16869699)	507.398*** (df = 3; 16869698)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 9

	Dependent variable:	
	move_out	
	(1)	(2)
flood	0.013***	0.018***
	(0.001)	(0.002)
z_score_nb_firms	−0.001***	−0.001***
	(0.00003)	(0.00003)
flood:z_score_nb_firms		0.019***
		(0.005)
Constant	0.013***	0.013***
	(0.00003)	(0.00003)
Observations	16,869,702	16,869,702
R^2	0.0001	0.0001
Adjusted R^2	0.0001	0.0001
Residual Std. Error	0.113 (df = 16869699)	0.113 (df = 16869698)
F Statistic	813.371*** (df = 2; 16869699)	546.409*** (df = 3; 16869698)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 10

	Dependent variable:	
	move_out	
	(1)	(2)
flood	0.013***	0.016***
	(0.001)	(0.002)
z_score_turnover	−0.001***	−0.001***
	(0.00003)	(0.00003)
flood:z_score_turnover		0.014***
		(0.005)
Constant	0.013***	0.013***
	(0.00003)	(0.00003)
Observations	16,869,702	16,869,702
R^2	0.0001	0.0001
Adjusted R^2	0.0001	0.0001
Residual Std. Error	0.113 (df = 16869699)	0.113 (df = 16869698)
F Statistic	757.488*** (df = 2; 16869699)	507.481*** (df = 3; 16869698)
Note:		*p<0.1; **p<0.05; ***p<0.01

C Response of Move In Dummy to Agglomeration Economies

This Annex presents the results of regression (6) for the two other definitions of agglomeration economies, namely $Zscore_{Turnover}$ and $Zscore_{Business\ Density}$, using the probit specification.

Table 11: Move In Dummy regressed on Flood and Z-Score Turnover (Probit)

	Dependent variable:	
	Move In	
	(1)	(2)
Flood	-0.147^{***}	-0.121^{***}
	(0.018)	(0.026)
$Zscore_{Turnover}$	0.029^{***}	0.029^{***}
	(0.0004)	(0.0004)
Flood$\times Zscore_{Turnover}$		0.117
		(0.084)
Constant	-1.349^{***}	-1.349^{***}
	(0.0004)	(0.0004)
Observations	16,869,701	16,869,701
Log Likelihood	−5,071,981.000	−5,071,980.000
Akaike Inf. Crit.	10,143,969.000	10,143,969.000
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 12: Move In Dummy regressed on Flood and Z-Score Business Density (Probit)

	Dependent variable:	
	Move In	
	(1)	(2)
Flood	-0.147^{***}	-0.113^{***}
	(0.018)	(0.027)
$Zscore_{Business\ Density}$	0.030^{***}	0.030^{***}
	(0.0004)	(0.0004)
Flood$\times Zscore_{Business\ Density}$		0.148^{*}
		(0.086)
Constant	-1.349^{***}	-1.349^{***}
	(0.0004)	(0.0004)
Observations	16,869,701	16,869,701
Log Likelihood	$-5,071,786.000$	$-5,071,784.000$
Akaike Inf. Crit.	10,143,577.000	10,143,576.000
Note:	*p<0.1; **p<0.05; ***p<0.01	

D Response of Risk of Move Ins to Floods and Agglomeration Economies

Table 13: Response of the Flood risk of move ins to agglomeration economies

	Dependent variable:	
	$\Delta Risk$	
	(1)	(2)
$Flood_{t-1}$	-0.066^{***}	-0.065^{***}
	(0.012)	(0.012)
$\Delta Zscore_{Turnover}$	-0.054^{***}	-0.054^{***}
	(0.003)	(0.003)
$Flood_{t-1} \times \Delta Zscore_{Turnover}$		-0.049
		(0.037)
Constant	0.006^{***}	0.006^{***}
	(0.002)	(0.002)
Observations	129,023	129,023
R^2	0.002	0.002
Adjusted R^2	0.002	0.002
Residual Std. Error	0.598 (df = 129020)	0.598 (df = 129019)
F Statistic	157.128^{***} (df = 2; 129020)	105.332^{***} (df = 3; 129019)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 14

	Dependent variable:	
	$\Delta Risk$	
	(1)	(2)
$Flood_{t-1}$	-0.066^{***}	-0.065^{***}
	(0.012)	(0.012)
$\Delta Zscore_{Business\ Density}$	-0.053^{***}	-0.052^{***}
	(0.003)	(0.003)
$Flood_{t-1} \times \Delta Zscore_{Business\ Density}$		-0.043
		(0.037)
Constant	0.006^{***}	0.006^{***}
	(0.002)	(0.002)
Observations	129,023	129,023
R^2	0.002	0.002
Adjusted R^2	0.002	0.002
Residual Std. Error	0.598 (df = 129020)	0.598 (df = 129019)
F Statistic	150.110^{***} (df = 2; 129020)	100.526^{***} (df = 3; 129019)
Note:	*p<0.1; **p<0.05; ***p<0.01	

E Split by Sector

Table 15: Accommodation and Food

	Dependent variable:		
	move_out		
	OLS	*logistic*	*probit*
	(1)	(2)	(3)
flood	0.022^{***}	0.563^{***}	0.252^{***}
	(0.007)	(0.179)	(0.083)
Constant	0.031^{***}	-3.435^{***}	-1.863^{***}
	(0.0002)	(0.007)	(0.003)
Observations	686,270	686,270	686,270
R^2	0.00001		
Adjusted R^2	0.00001		
Log Likelihood		−95,432.700	−95,432.700
Akaike Inf. Crit.		190,869.400	190,869.400
Residual Std. Error	0.174 (df = 686268)		
F Statistic	10.146^{***} (df = 1; 686268)		
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 16: Admin and Support Staff

	Dependent variable:		
	move_out		
	OLS	*logistic*	*probit*
	(1)	(2)	(3)
flood	0.055***	1.362***	0.607***
	(0.006)	(0.173)	(0.085)
Constant	0.020***	−3.872***	−2.046***
	(0.0001)	(0.007)	(0.003)
Observations	892,841	892,841	892,841
R^2	0.0001		
Adjusted R^2	0.0001		
Log Likelihood		−88,956.400	−88,956.400
Akaike Inf. Crit.		177,916.800	177,916.800
Residual Std. Error	0.141 (df = 892839)		
F Statistic	71.809*** (df = 1; 892839)		
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 17: Agriculture

	Dependent variable:		
	move_out		
	OLS	*logistic*	*probit*
	(1)	(2)	(3)
flood	0.030	1.272	0.524
	(0.022)	(1.022)	(0.458)
Constant	0.012***	−4.408***	−2.256***
	(0.0004)	(0.031)	(0.012)
Observations	85,498	85,498	85,498
R^2	0.00002		
Adjusted R^2	0.00001		
Log Likelihood		−5,574.732	−5,574.732
Akaike Inf. Crit.		11,153.460	11,153.460
Residual Std. Error	0.109 (df = 85496)		
F Statistic	1.770 (df = 1; 85496)		
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 18: Arts & Recreation

	Dependent variable:		
	move_out		
	OLS	*logistic*	*probit*
	(1)	(2)	(3)
flood	0.007	0.400	0.161
	(0.011)	(0.584)	(0.241)
Constant	0.016***	−4.145***	−2.155***
	(0.0002)	(0.015)	(0.006)
Observations	287,374	287,374	287,374
R^2	0.00000		
Adjusted R^2	−0.00000		
Log Likelihood		−23,090.840	−23,090.840
Akaike Inf. Crit.		46,185.680	46,185.680
Residual Std. Error	0.124 (df = 287372)		
F Statistic	0.475 (df = 1; 287372)		
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 19: Construction

	Dependent variable:		
	move_out		
	OLS	*logistic*	*probit*
	(1)	(2)	(3)
flood	0.026***	1.032***	0.432***
	(0.006)	(0.241)	(0.108)
Constant	0.015***	−4.167***	−2.163***
	(0.0001)	(0.008)	(0.003)
Observations	1,126,772	1,126,772	1,126,772
R^2	0.00002		
Adjusted R^2	0.00002		
Log Likelihood		−89,007.610	−89,007.610
Akaike Inf. Crit.		178,019.200	178,019.200
Residual Std. Error	0.123 (df = 1126770)		
F Statistic	20.033*** (df = 1; 1126770)		
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 20: Education

	Dependent variable:		
	move_out		
	OLS	*logistic*	*probit*
	(1)	(2)	(3)
flood	0.012	0.652	0.260
	(0.018)	(1.013)	(0.421)
Constant	0.013***	−4.341***	−2.230***
	(0.0003)	(0.024)	(0.009)
Observations	139,870	139,870	139,870
R^2	0.00000		
Adjusted R^2	−0.00000		
Log Likelihood		−9,619.126	−9,619.126
Akaike Inf. Crit.		19,242.250	19,242.250
Residual Std. Error	0.113 (df = 139868)		
F Statistic	0.429 (df = 1; 139868)		
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 21: Financial Services

	Dependent variable:		
	move_out		
	OLS	*logistic*	*probit*
	(1)	(2)	(3)
flood	0.034***	0.834**	0.374**
	(0.013)	(0.327)	(0.155)
Constant	0.028***	−3.562***	−1.917***
	(0.0003)	(0.011)	(0.005)
Observations	302,209	302,209	302,209
R^2	0.00002		
Adjusted R^2	0.00002		
Log Likelihood		−38,187.260	−38,187.260
Akaike Inf. Crit.		76,378.520	76,378.520
Residual Std. Error	0.164 (df = 302207)		
F Statistic	6.909*** (df = 1; 302207)		
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 22: Health & Social Work

	Dependent variable:		
	move_out		
	OLS	*logistic*	*probit*
	(1)	(2)	(3)
flood	0.019*	0.913*	0.372*
	(0.010)	(0.509)	(0.220)
Constant	0.013***	−4.306***	−2.217***
	(0.0002)	(0.013)	(0.005)
Observations	432,570	432,570	432,570
R^2	0.00001		
Adjusted R^2	0.00001		
Log Likelihood		−30,592.270	−30,592.270
Akaike Inf. Crit.		61,188.530	61,188.530
Residual Std. Error	0.115 (df = 432568)		
F Statistic	3.455* (df = 1; 432568)		
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 23: Info & Comms

	Dependent variable:		
	move_out		
	OLS	*logistic*	*probit*
	(1)	(2)	(3)
flood	0.016***	0.960***	0.380***
	(0.006)	(0.338)	(0.142)
Constant	0.010***	−4.546***	−2.308***
	(0.0001)	(0.010)	(0.004)
Observations	937,020	937,020	937,020
R^2	0.00001		
Adjusted R^2	0.00001		
Log Likelihood		−54,618.610	−54,618.610
Akaike Inf. Crit.		109,241.200	109,241.200
Residual Std. Error	0.102 (df = 937018)		
F Statistic	8.696*** (df = 1; 937018)		
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 24: Manufacturing

	Dependent variable:		
	move_out		
	OLS	*logistic*	*probit*
	(1)	(2)	(3)
flood	0.026***	0.745***	0.326***
	(0.006)	(0.169)	(0.078)
Constant	0.025***	−3.679***	−1.967***
	(0.0002)	(0.007)	(0.003)
Observations	871,496	871,496	871,496
R^2	0.00002		
Adjusted R^2	0.00002		
Log Likelihood		−100,718.200	−100,718.200
Akaike Inf. Crit.		201,440.300	201,440.300
Residual Std. Error	0.155 (df = 871494)		
F Statistic	20.383*** (df = 1; 871494)		
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 25: Oil & Mining

	Dependent variable:		
	move_out		
	OLS	*logistic*	*probit*
	(1)	(2)	(3)
flood	0.079*	1.643	0.751
	(0.045)	(1.055)	(0.541)
Constant	0.021***	−3.840***	−2.033***
	(0.001)	(0.043)	(0.017)
Observations	26,429	26,429	26,429
R^2	0.0001		
Adjusted R^2	0.0001		
Log Likelihood		−2,700.114	−2,700.114
Akaike Inf. Crit.		5,404.228	5,404.228
Residual Std. Error	0.144 (df = 26427)		
F Statistic	3.021* (df = 1; 26427)		
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 26: Other services

	Dependent variable:		
	move_out		
	OLS	*logistic*	*probit*
	(1)	(2)	(3)
flood	0.045***	1.246***	0.548***
	(0.008)	(0.231)	(0.111)
Constant	0.020***	−3.913***	−2.062***
	(0.0002)	(0.008)	(0.003)
Observations	761,325	761,325	761,325
R^2	0.00004		
Adjusted R^2	0.00004		
Log Likelihood		−73,476.330	−73,476.330
Akaike Inf. Crit.		146,956.700	146,956.700
Residual Std. Error	0.139 (df = 761323)		
F Statistic	32.921*** (df = 1; 761323)		
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 27: Professional services

	Dependent variable:		
	move_out		
	OLS	*logistic*	*probit*
	(1)	(2)	(3)
flood	0.045***	1.246***	0.548***
	(0.008)	(0.231)	(0.111)
Constant	0.020***	−3.913***	−2.062***
	(0.0002)	(0.008)	(0.003)
Observations	761,325	761,325	761,325
R^2	0.00004		
Adjusted R^2	0.00004		
Log Likelihood		−73,476.330	−73,476.330
Akaike Inf. Crit.		146,956.700	146,956.700
Residual Std. Error	0.139 (df = 761323)		
F Statistic	32.921*** (df = 1; 761323)		
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 28: Real Estate

	Dependent variable:		
	move_out		
	OLS	*logistic*	*probit*
	(1)	(2)	(3)
flood	0.001	0.045	0.018
	(0.007)	(0.412)	(0.163)
Constant	0.016***	−4.123***	−2.146***
	(0.0001)	(0.009)	(0.004)
Observations	752,281	752,281	752,281
R^2	0.00000		
Adjusted R^2	−0.00000		
Log Likelihood		−61,520.990	−61,520.990
Akaike Inf. Crit.		123,046.000	123,046.000
Residual Std. Error	0.125 (df = 752279)		
F Statistic	0.012 (df = 1; 752279)		
Note:		*p<0.1; **p<0.05; ***p<0.01	