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

Juliette Caucheteux* and Rebecca Mari†

27 February 2025

Preliminary version, please do not circulate.

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

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 agglomeration economies drive the patterns of business location. Agglomeration economies increase location-stickiness, with firms being less likely to move when flooded in regions that have higher employment, turnover or business density. But once the firm decides to relocate, conversely, they are more likely to move to regions with higher aggregate productivity. 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

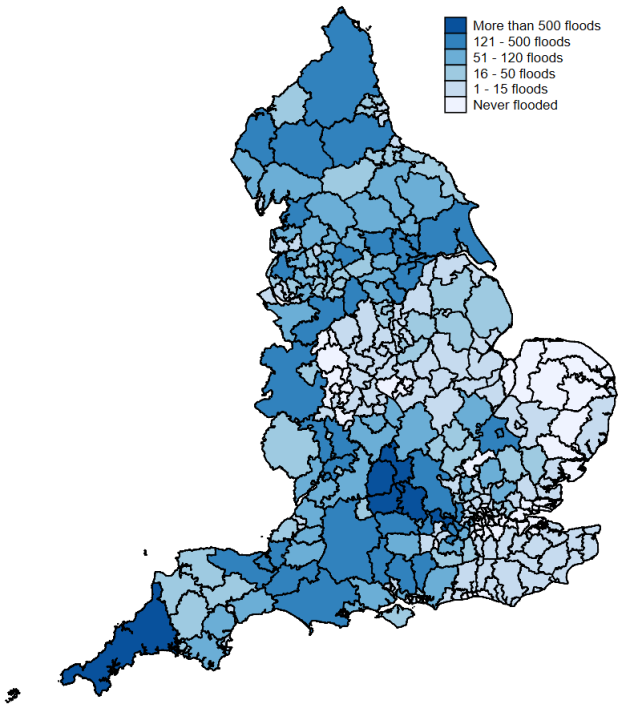
Keywords: *Floods, Firm performance, Relocation, Adaptation, Agglomeration Economies*

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 series of multivariate 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%. This probability 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.

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 analyse 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 firms are less likely to relocate after a flood when located in areas with agglomeration economies, defined as areas with high regional employment, turnover, or business density per square meter. But once the firm decides to relocate, conversely, they are more likely to move to regions with higher agglomeration economies. This result is robust across all definitions of agglomeration economies and multivariate specifications.

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.

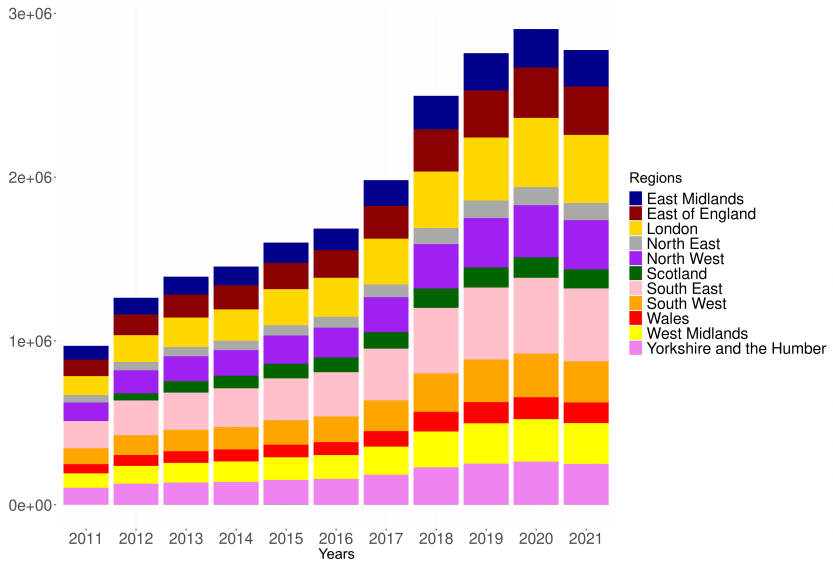
II.2 Stylised Facts on Firm Spatial Distribution

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 ITL2 regions. As of 2021, there were around 2.8 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.

FIGURE 2: Number of Premises per Region and Per Year

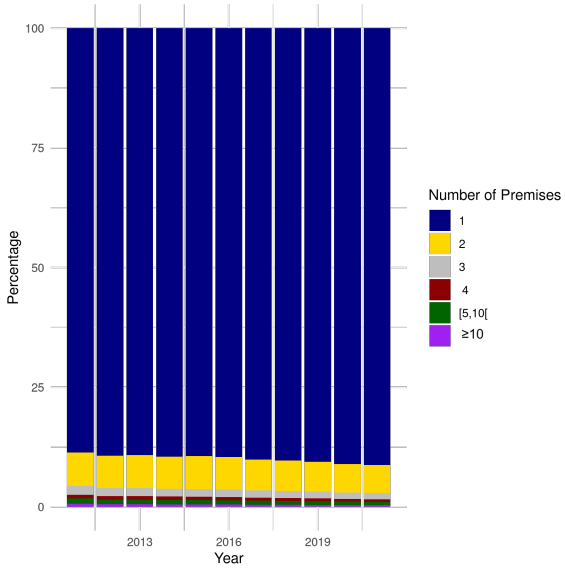


2. The majority of organisations operates from one business premise

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 [add ONS reference].

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



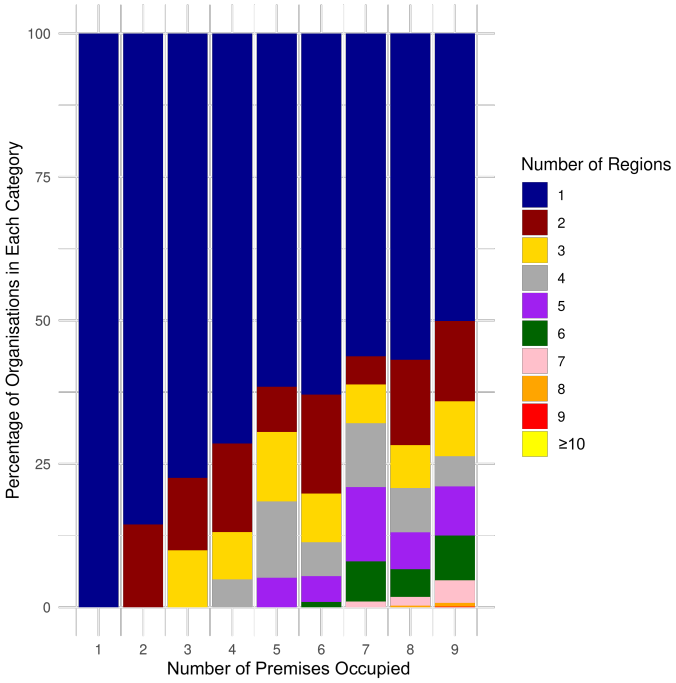
3. Organisations with multiple business premises predominantly operate from one region

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, 15% are present in two regions (i.e. the two business premises are located in two different regions), and 85% 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 regional concentration, with multi-establishment organisations still continuing to predominantly operate from one region only.

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

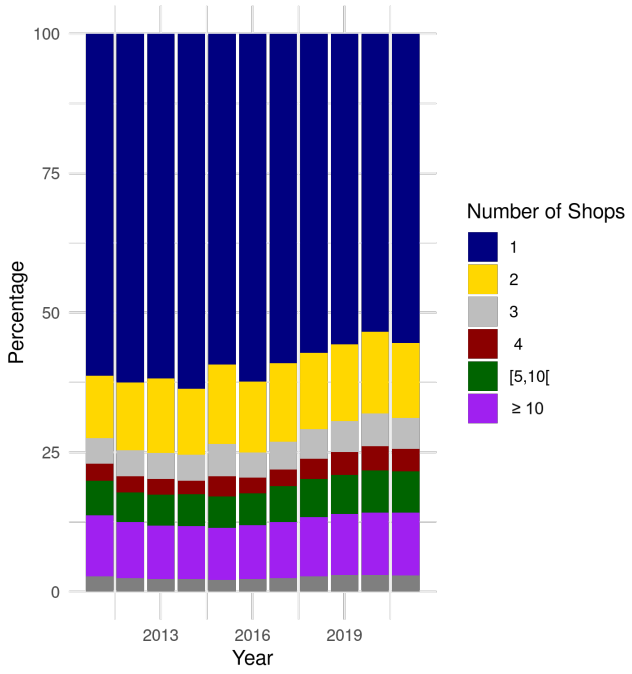
One striking fact is that, when investigating organisations that have experienced at least one flood event in their existence, their spatial organisational structure differs from that of the whole sample as shown by Figure 5. In contrast to Figure 3, the sample of firms having experienced a flooding event presents a larger share of multi-premise organisations. This fact can be traced back to

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



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

To understand the effect of floods on the probability to move out, we run the following regression:

$$\mathbb{P}(Move\ Out_{i,t}|Flood_{i,t} = 1) = \Phi(\beta Flood_{i,t} + \eta_i + \delta_t + \epsilon_{i,t}) \tag{1}$$

where $Move\ Out_{i,t}$ is a dummy for whether premise i witnessed a move out in year t, $Flood_{i,t}$ is a dummy for whether a flood happened. η_i and δ_t control for premise and year fixed effects

respectively. 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

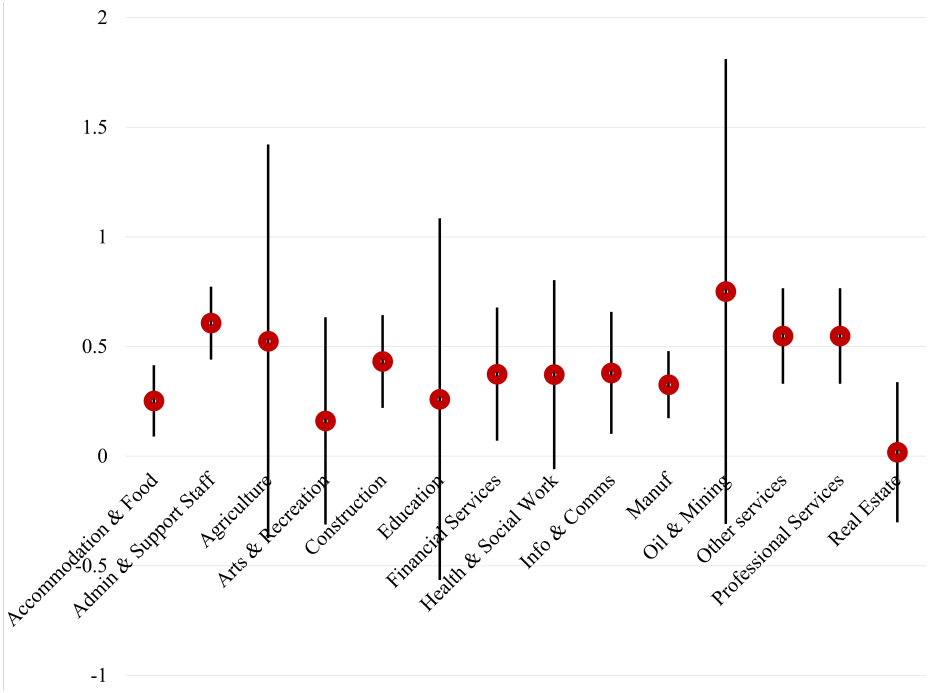
The results show that organisations are more likely to move out after a flood. To understand better the specific sectoral response, we also run regression equation (1) for each sector in our sample. Figure 6 plots the coefficient and its confidence interval for the probit specification. A statistically 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.

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:

$$\mathbb{P}(Move\ Out|Flood)_{i,j,t} = \Psi(\sum_{k=1}^{6} \alpha_k \mathbb{1}_{\text{Number of Floods}_{i,j,t}=k} + \eta_{i,j} + \delta_t + \epsilon_{i,t}) \tag{2}$$

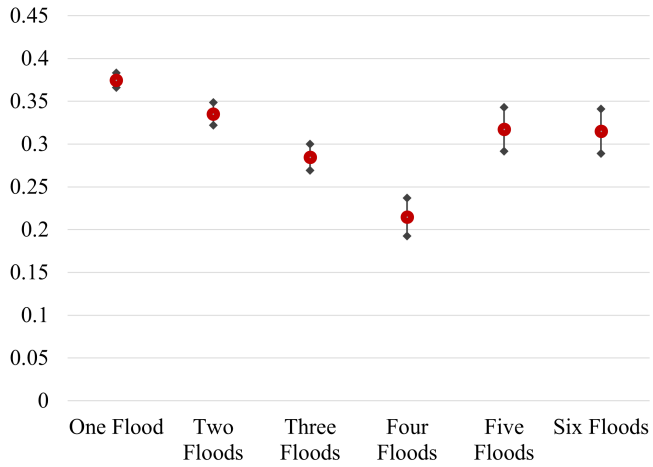
with Ψ taking the probit or logit functional form. Figure 7 presents the results for Ψ taken to be the normal distribution (probit). It displays a stark declining relationship between the probability of moving out and the number of floods, up until 4 floods.

Figure 6: 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.

Figure 7: 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.2 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:

$$\Delta Risk_{j,t} = \theta + \kappa Flood_{j,t-1} + \mu_j + \nu_t + \epsilon_{j,t} \tag{3}$$

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.3 Interaction with Agglomeration Economies

Sections III.1 and III.2 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 agglomeration economy at the regional level. For each region at the ITL2 level and each year, we compute the (i) total number of employees (ii) total turnover (iii) number of firms. All these variables are then divided by the area of the region in square meters.

For each region at the ITL2 level, indexed by r we then assign the z-score of the region in terms of each of these variables $q \in \{Employment, Turnover, Business\ Density\}$. We run the following regression:

$$\mathbb{P}(\text{Move Out}_{i,r,t}) = \Phi(\alpha + \beta Flood_{i,t} + \gamma ZScore_{q_{r,t}} + \delta Flood_{i,t} \times ZScore_{q_{r,t}} + \eta_i + \delta_t + \epsilon_{i,t}) \quad (4)$$

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, total turnover, 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 total employment 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.

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

	Dependent variable: Move Out Dummy
	Probit
Flood	0.323^{***}
	(0.038)
Z-Score$_{Employment}$	-0.032^{***}
	(0.001)
Flood $\times$ Z-Score$_{Employment}$	0.166
	(0.121)
Constant	-2.226^{***}
	(0.001)
Observations	16,869,702
Log Likelihood	$-1,167,091.000$
Akaike Inf. Crit.	2,334,190.000

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:

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

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 the number of employees while Tables 11 and 12 in Annex C present the results for the z-score of total turnover and business density respectively. 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. Together, these results imply that when making relocation decisions, agglomeration economies matter. Regions with high productivity attract more premises, while regions with low productivity or high floods deter them.

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. 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

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

	Dependent variable: Move In Dummy	
	Probit	
	(1)	(2)
Flood	-0.147^{***}	-0.113^{***}
	(0.018)	(0.028)
Z-Score$_{\text{Number of Employees}}$	0.029^{***}	0.029^{***}
	(0.0004)	(0.0004)
Flood $\times$ Z-Score$_{\text{Number of Employees}}$		0.141
		(0.088)
Constant	-1.348^{***}	-1.348^{***}
	(0.0004)	(0.0004)
Observations	16,869,701	16,869,701
Log Likelihood	−5,071,971.000	−5,071,969.000
Akaike Inf. Crit.	10,143,947.000	10,143,947.000
Note:	*p<0.1; **p<0.05; ***p<0.01	

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.

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, 50% of organisations that locate in more than one premise target one region, and the other half does 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. 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 showed that these play a role. In particular, firms flooded in regions that have a higher z-score in total number of employees, total turnover or firm density per square meter were less likely to move out of a premise.

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.

Bibliography

Balboni, C., Boehm, J. and Waseem, M. (2024), 'Firm adaptation and production networks: Structural evidence from extreme weather events in pakistan', *Working Paper* .

Crampton, B., Hu-Gilman, R. and Mari, R. (2025), 'Staying afloat: The impact of flooding on uk firms', *Working Paper* .

Ficarra, M. and Mari, R. (2024), *Weathering the Storm: Sectoral Economic and Inflationary Effects of Floods and the Role of Adaptation*.

Fried, S. (2021), 'Seawalls and stilts: A quantitative macro study of climate adaptation', *The Review of Economic Studies* **89**(6), 3303–3344.

Hallegatte, S. and Dumas, P. (2009), 'Can natural disasters have positive consequences? investigating the role of embodied technical change', *Ecological Economics* **68**(3), 777–786.

Keiller, A. N. and Van Reenen, J. (2024), *Disaster Management*.

Kendon, E. J., Fischer, E. M. and Short, C. J. (2023), 'Variability conceals emerging trend in 100yr projections of uk local hourly rainfall extremes', *Nature Communications* **14**(1).

Leiter, A. M., Oberhofer, H. and Raschky, P. A. (2009), 'Creative disasters? flooding effects on capital, labour and productivity within european firms', *Environmental and Resource Economics* **43**(3), 333–350.

A Response of Move Out Dummy to Agglomeration Economies

We present the results of regression 4 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 (5) 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	