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

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This Paper

What is the spatial distribution of firms in the UK and how is it shaped by floods?

Why?

- Frequency of extreme events has increased, with the UK particularly suffering from floods (Henk, Babet).
- Floods destroy capital and render business premises inaccessible, making it impossible to conduct operations.

What?

- We leverage a unique dataset of UK firms' business premise addresses at the premise $\times$ year level, overlayed with yearly flood maps and data on company ownership structure and characteristics.
- We document the spatial distribution of corporate organisations across the UK.
- We investigate the effect of floods on firms' location choices & examine the interaction with local productivity.
- *In progress:* We look at the interaction with commercial real estate prices.

Preliminary Results and Contribution

1. Following a flood, firms are 10 % more likely to relocate.
   - There is heterogeneity across sectors, firm size, productivity.
2. Companies that relocate after a flood internalise the risk of flooding.
3. Local productivity affects firms' location choices but doesn't seem to affect firms' location choice in response to a flooding event.
4. *Preliminary:* Floods have a significant effect on sale price declines, not necessarily on rental price.

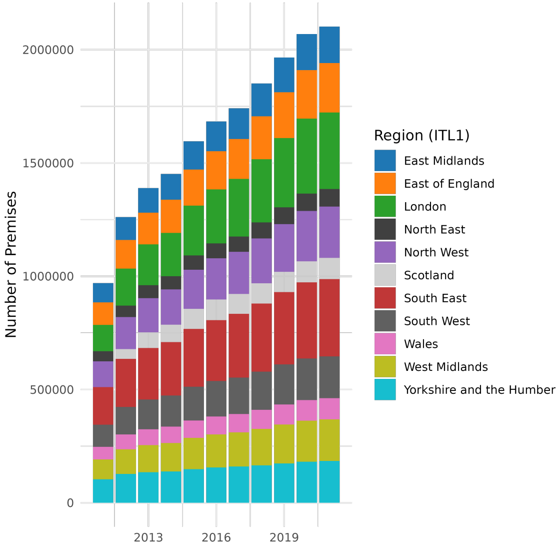
Contribution:

- Few papers have attempted to look at the effects of flooding on firm relocation (Balboni et al. Forthcoming). $\rightarrow$ we provide the first evidence for the UK.
- We further contribute by investigating one of the channels affecting the chance of relocation: developments in commercial real estate prices.

Dataset

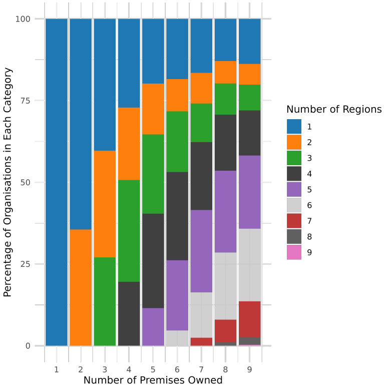
- Floodmaps from the Environment Agency (EA) and Natural Resource Wales.
  GIS Layer at 50m × 50m resolution from 1946 onwards.
- UK business premises' address information (geo-coordinates) and corporate organisation identifier from Ordnance Survey AddressBase Premium.
- Extent of each business premise from Energy Performance Certificates
  Area in square feet at the UPRN (premise ID) level.
- Corporate balance sheet information at the organisation level from Companies House in the UK (BVD).
- Final dataset: panel at the premise × year level recording information on business premise characteristic (area, organisation that operates from the business premise and its characteristics), flood information for the years 2011 - 2021.

Stylised Fact 1 - Growing number of business premises over time



Stylised Fact 2 - Organisations with multiple business premises operate from multiple regions

Figure: Number of regions organisations are present in, split by number of premises as of 2020



- Example: among organisations with two premises 70% are operating in one region, 30% in two.

Stylised Fact 3 - The flooded sample of organisations differs from the whole sample

Figure: Flooded Sample

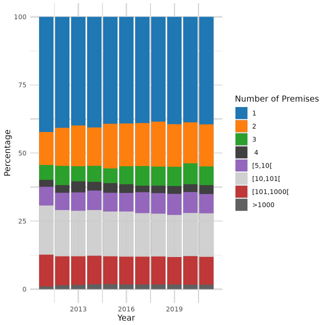
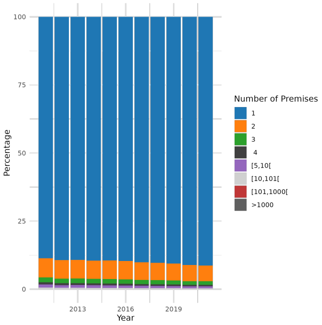


Figure: Whole Sample

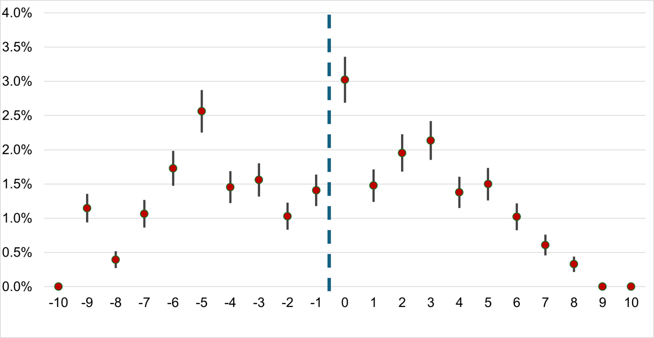


- Partly because having more business premises increases the likelihood of being flooded (by statistical definition).
- Partly as result of larger organisation searching for cheaper land and sorting in more flood-prone areas (Crampton et al. 2025).

Raw Means - Interaction between move out and flooding

- For the flooded sample, we plot the percentage of firms that are moving out, with respect to the time of the flood.
- Excess mass at exactly the time of flood.

Figure: Raw Means: Probability to Move Out as a Function of Time to Flood ($t = 0$)



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Identification Strategy - Do organisations move following a flood?

- We want to understand what is the effect of floods on the probability of moving out. Difference-in-differences setting.

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

  - $Treat_i$ is a dummy for whether the premise i has been exposed to a flood.
  - $Post_t$ is a dummy for after the year of the flood.
  - $Move\ Out_{i,t}$ is a dummy for whether the company moved out of the premise i.

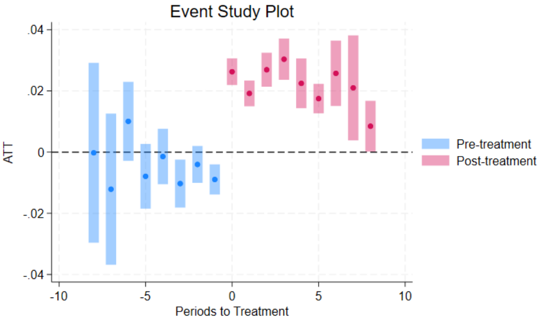
- Specifically, *Move Out* is equal to 1 if this is the last year an organisation is observed at this premise, but the organisation is still in business.

- Callaway and Sant'Anna + Propensity score matching estimator

- Identification assumption: floods are exogenous with respect to move out.

Baseline results

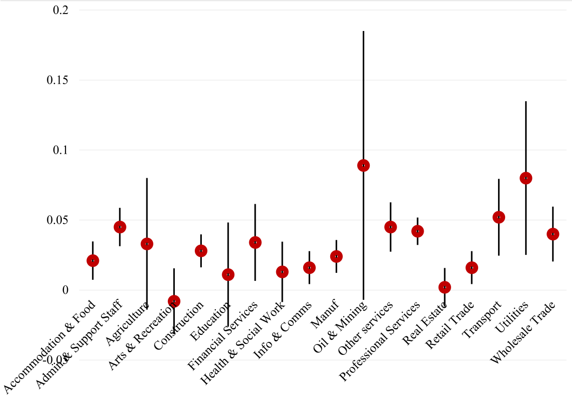
- Callaway and Sant'Anna (2021) estimator to account for staggered treatment.
- Results using the not-yet-treated as a control group.
- Floods increase the probability of moving out by around 10%.



Marginal Effects

Decomposition by sector

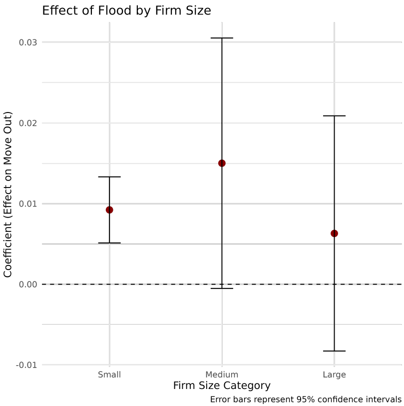
Figure: Effect of flood dummy on probability to move by sector



- Agriculture, Education, Oil and Mining not statistically significant.
- Services, Administration, Info and Communications more likely to move.

Decomposition by size

Figure: Effect of flood dummy on probability to move by size

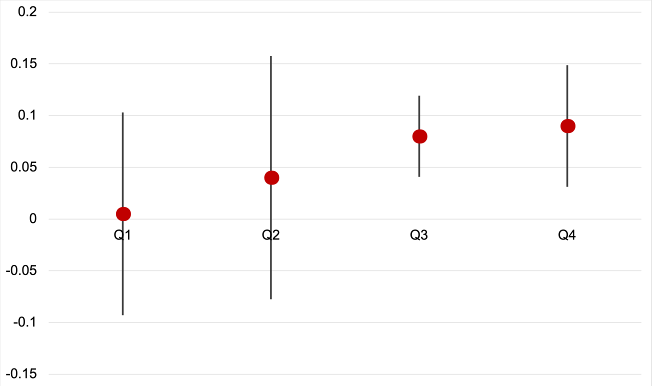


- Results driven by small firms.
- Similar trend for turnover.

Decomposition by productivity

- Compute the labour productivity of the parent company.
- Assigns each premise to a productivity quartile.
- More productive firms are more likely to move.

Figure: Effect of flood dummy on probability to move by productivity quartile



Effects on Average Risk

- We observe flood risk exposure for each business premise (identified by UPRN).

- Define the following variables:
  - $Average\ Risk_{j,t}$: average risk across all UPRNs organisation j operates from in year t.
  - $Average\ Risk\ Move\ In_{j,t}$: average risk across the new UPRNs organisation j moves into in year t
  - $\Delta\ Risk_{j,t} = Average\ Risk\ Move\ In_{j,t}$ - $Average\ Risk_{j,t-1}$
  - $Flood_{j,t}$: total number of floods the organisation has been exposed to that year (sum across the UPRNs the organisation has been operating from)

- Run the following regression

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

Effects on Average Risk - Results

Table: 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:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

Do Local Characteristics Matter?

- How does the probability to move out depend on local productivity?
- At the regional level (ITL3) $\times$ year level, use ONS measures of labour productivity and compute the number of firms per square meter.
- Compute the z-score of each region for each of these variables, i.e. the deviation from the average number of business premises, rescaled by the standard deviation. A higher z-score would mean that a region is more productive.
- Run the following regression:

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

- Coefficients of interest: β, γ, δ
- Control for year and premise fixed effects

Agglomeration Effects On Move Outs

	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

Other definitions

Agglomeration Effects On Move Ins

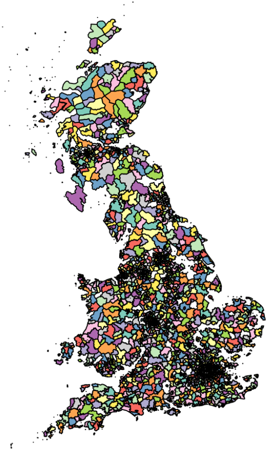
	Dependent variable:	
	Move In	
	(1)	(2)
Flood	-0.019^{***}	-0.023^{***}
	(0.003)	(0.005)
Z-Score$_{ONS}$	0.004^{***}	0.004^{***}
	(0.0001)	(0.0001)
Flood $\times$ Z-Score$_{ONS}$		-0.009
		(0.013)
Constant	0.090^{***}	0.090^{***}
	(0.0001)	(0.0001)
Observations	16,653,776	16,653,776
R^2	0.0002	0.0002
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

Other definitions

Investigating the link with commercial real estate prices - *(Preliminary)*

- *Do companies stay because prices collapse?*
- CoStar: Rent, sale prices per square feet for commercial real estate between 2005 and now.
- Instrument floods by the percentage of each postcode district that has been flooded each year.
- For now: hedonic regression with postcode and year fixed effects.

Postcode districts



Commercial Real Estate: Results *(Preliminary)*

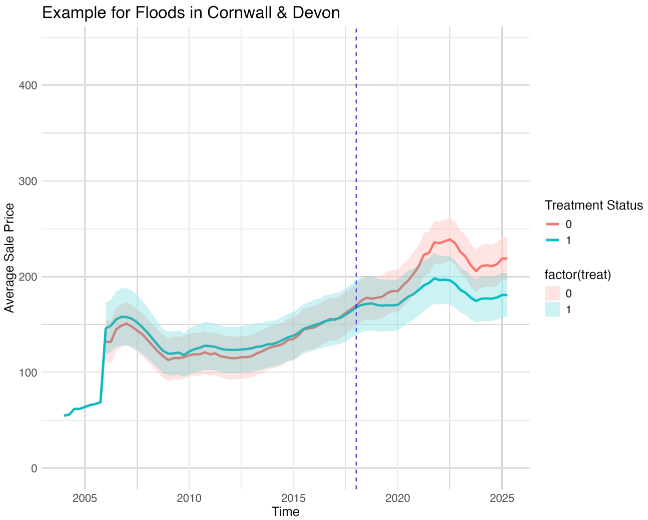
$$ln(Price)_{p,t} = \beta_{p,t} Share\ Flooded_{p,t} + \rho_p + \eta_t + \epsilon_{p,t}$$

- Where p is the postcode district, t is the year.
- Price is the price per square feet recorded across all transactions that took place per year in that postcode district.

	Dependent variable:			
	ln(Sale Price)		ln(Rent Price)	
	(1)	(2)	(3)	(4)
Share Flooded	-0.0486^{***}	-0.052^{**}	-0.029	0.056
	(0.010)	(0.021)	(0.084)	(0.038)
Constant	4.870^{***}		2.405^{***}	
	(0.002)		(0.002)	
Observations	119,800	119,800	119,800	119,800
Year FE	NO	YES	NO	YES
Postcode FE	NO	YES	NO	YES
R^2	0.0002	0.964	0.0001	0.811
Adjusted R^2	0.0002	0.963	0.0001	0.808
Residual Std. Error	0.663 (df = 119798)	0.128 (df = 117933)	0.640 (df = 117145)	0.280 (df = 115405)
F Statistic	22.673^{***} (df = 1; 119798)		11.949^{***} (df = 1; 117145)	

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Example for floods in Devon & Cornwall



Conclusion and Policy Implications

- Following a flood, premises are more 10% more likely to move out.
- Strong sectoral effects driven by firms in more mobile sectors.
- Flooded companies internalise the flooding risk when making subsequent location decisions.
- Local productivity significantly drives firms' location choices.
- But local productivity doesn't manage to retain firms in response to flooding.
- Floods seem to negatively impact commercial real estate sale price, not necessarily rent.

What does this mean for policy?

- Floods will shape the corporate landscape in the UK and potentially elsewhere.
- Some immobile sectors and large firms will not move: adaptation policies are essential.
- Firms internalise the risk of flooding when they have been flooded: how to convey information effectively?
- General equilibrium effects: impacts on regional productivity, inequality, employment.

Next steps?

- Propensity Score Matching to deal with unobservable firm characteristics.
- Refine the analysis on CRE prices.
- How do CRE prices affect firms' decisions?
- Model on regional productivity.
- Think about insurance? Keen to have your thoughts.
  Data on premia / insurance penetration at the sub-regional level?

Thank you! ☺

Comments and suggestions welcome:
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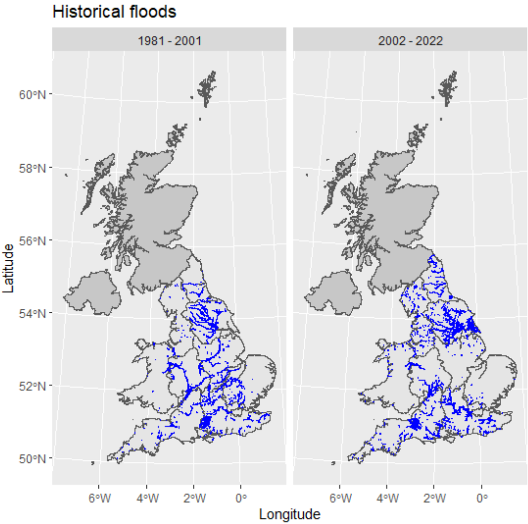
Prevalence of Floods



Back to Context

Regression Results

	Dependent variable: Move Out		
	OLS	Logit	Probit
	(1)	(2)	(3)
$Treat_i \times Post_t$	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: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Marginal Effects

Marginal Effects, Probit Move Out

Table: Marginal Effects

	Dependent variable: Move Out					
	AME	SE	z	p	Lower Bound	Upper Bound
Probit	0.097	0.008	11.58	0	0.0812	0.1143
Logit	0.093	0.008	12.13	0	0.0928	0.0931

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

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Move Out Interaction with Agglomeration Effects

	Dependent variable:	
	Move Out	
	(1)	(2)
Flood	0.013***	0.015***
	(0.001)	(0.002)
Z-Score$_{Density}$	$-$0.001***	$-$0.001***
	(0.00003)	(0.00003)
Flood $\times$Z-Score$_{Density}$		0.006*
		(0.003)
Constant	0.013***	0.013***
	(0.00003)	(0.00003)
Observations	16,653,776	16,653,776
R^2	0.0001	0.0001
Adjusted R^2	0.0001	0.0001
Residual Std. Error	0.113 (df = 16653773)	0.113 (df = 16653772)
F Statistic	547.760*** (df = 2; 16653773)	366.251*** (df = 3; 16653772)
Note:		*p<0.1; **p<0.05; ***p<0.01

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Agglomeration Effects On Move Ins - Density

	Dependent variable:	
	Move In	
	(1)	(2)
Flood	-0.019^{***}	-0.018^{***}
	(0.003)	(0.004)
Z-Score$_{Business\ Density}$	0.004^{***}	0.004^{***}
	(0.0001)	(0.0001)
Flood × Z-Score$_{Business\ Density}$		0.004
		(0.009)
Constant	0.089^{***}	0.089^{***}
	(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	$1{,}857.695^{***}$ (df = 2; 16653773)	$1{,}238.554^{***}$ (df = 3; 16653772)
Note:		*p<0.1; **p<0.05; ***p<0.01

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

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