Implications of Rising Flood Risk for Residential Real Estate Prices and the Location of Employment

A GMM Spatial Model with Agglomeration and Endogenous House Price Effects

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While there is a relatively small literature on the impact of flood events on employment at regional and national level, the effect of flood risk on employment density at the local level, and the link to housing prices are largely neglected. This paper attempts to fill these gaps and extend the literature in four ways. First, we argue that competition for land between firms and households will generate a potentially endogenous role for house prices, which we estimate using a GMM two-stage least squares spatial econometric model. Second, we model interaction effects between agglomeration and flood risk using a gravity-based measure of agglomeration. Third, our models utilise a high-resolution flood risk measure which incorporates both flood frequency and severity. Fourth, we use a high-resolution measure of employment to capture local effects of flood risk.

Keywords: house prices, employment, firm location, agglomeration, flood risk, climate change

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1. Introduction

Half of all fatalities across the world due to natural disasters are the result of flood events (Fay, Block, Carrington, & Ebinger, 2009, p.28) and there are major economic costs associated with lost output, damage to property, equipment and infrastructure (Ciscar *et al*. 2011, p.3; Stern, 2006). Moreover, flood events and their impacts are likely to rise significantly for many cities due to global warming (Stern, 2006) which will cause sea levels to rise (as a result of thermal expansion of the oceans and melting ice sheets) and cause precipitation to be more variable and have greater extremes. Given that cities have tended to emerge in close proximity to the coast or major rivers (McGranahan, Balk, & Anderson, 2007; Nicholls *et al*., 2007), these predictions raise serious concerns about the consequences of climate change for urban economies. Floods are already the most common natural disaster in Europe (European Environment Agency [EEA], 2004) with rapidly rising economic impacts (Barredo, 2007). Concerns about future trajectories are likely to continue due to the anticipated rise in severity and frequency of extreme weather events (Christensen & Christensen, 2003; Frei, Scholl, Fukutome, Schmidli, & Vidale, 2006). Ciscar *et al.*'s (2011, p.3) estimates, for example, of the economic consequences of climate change for Europe, show significant increases in economic and welfare loss, particularly for the UK due to the coastal/floodplain location of many of its cities. In addition to climate change effects, there are other major drivers that lead to flood impacts in urban areas arising from urban development and socio-economic trends (Djordjević *et al*. 2011).

Our interest in this paper is the impact of flood risk on urban employment, modelled at the small area level. Other things being equal, one would expect firms to aim to avoid flood hazards due to the disruption and damage that flood events cause to the physical capital stock, supply chains and infrastructure. However, firms have to weigh up such costs against the benefits of potentially lower land rents associated with high flood-risk areas, rents that are determined by the competition for land between firms and households. There may also be offsetting benefits of locating near other firms—"agglomeration economies" (see Fujita & Krugman 2004)—which are also drawn to low land prices and repelled by the pernicious consequences of floods.

Clearly, how firms respond to flood risk signals will be crucial to the economic impact of anticipated climate change. If firms are drawn to high flood risk areas because of lower land prices, then areas with increased flood risk will attract employment, and future flood events could affect many more firms. If, instead, firms tend, on balance, to be repelled by flood risk, then we might conclude that those areas predicted to have increases in flood risk will gradually lose employment over time, other things being equal. An important qualifying factor, however, is the extent to which agglomeration mitigates these effects. Such interactions, if valid, would imply heterogeneity across areas in the impact of the same increases in flood risk. Areas with strong agglomeration economies may be more robust to flood risk.

While there exists some literature on the impact of floods or other natural disasters, such as hurricanes and tornados, on employment at regional and national levels (e.g. Ewing, Kruse, & Thompson, 2003; Leiter, Oberhofer, & Raschky, 2009), little research has been conducted on the impact of flood *risk* on employment density at the local level, and the link to housing price is almost entirely neglected in this context. Addressing these omissions will become increasingly important as flood risk projections become more ominous.

Interdependencies between employment and residential land markets raise a number of methodological challenges for empirical estimation, however, not least the spatial dependency of employment-location, the endogeneity of agglomeration and house price effects, and the need for high-resolution spatial measures of employment, house prices and flood risk. This paper attempts to contribute to this surprisingly under-developed, yet critically important field, by making progress on each of these issues using GMM (Generalised Method of Moments) estimation of spatial two-stage least squares models of local employment density with endogenous house price and agglomeration effects, utilising a high resolution measure of flood risk that accounts for both expected severity and frequency of floods in Southeast London.

The remainder of the paper is structured as follows. Section 2 reviews existing evidence on the impact of flooding on employment and house prices. Section 3 briefly reviews the theoretical literature on firm location and land rent gradients, and draws insights from Lucas and Rossi-Hansberg (2002) and other models to articulate the hypotheses we seek to test in the empirical model. Section 4 summarises the econometric strategy marshaled to tackle the methodological challenges posed by the theory. In section 5, we describe the study area and data used in the study. Empirical results are presented in section 6. Section 7 concludes with a summary of findings.

2. Review of the empirical literature

The economics of firm location, and hence of employment location, has been a major theme in economics at least since Alfred Marshall (1890)[6]. The empirical literature has burgeoned in recent years (see review by Arauzo-Carod, Liviano-Solis, & Manjon-Antolin, 2010), with a growing number of studies that look at the impact of particular flood events on employment. There are, however, no studies that we are aware of that examine the effect on employment of flood risk. A further important limitation is the connection with the real estate sector. Many theoretical models

[6] See review by Arauzo-Carod *et al*. (2010), p.685.

include the competition for land as a core driver of industrial location (see section 3), but this has yet to enter the empirical literature on flood and employment location. Similarly, while agglomeration effects have been explored at length in urban economics and regional science, there do not appear to be any studies that examine the interaction between agglomeration and flood risks. There are also important issues of measurement, particularly in how, and at what scale, house price, flood risk and employment location variables are correlated. We explore these limitations of the literature in more detail below, first, in terms of the omission of endogenous house prices; second, the potential importance of agglomeration in mitigating flood risk; third, the measurement of flood risk; and fourth, the spatial scale of employment data.

Consider, first, the interdependency between house price and employment. As noted, we are not aware of any previous study of the employment impacts of floods that allows for endogenous house price effects. As such, there may be simultaneity bias in existing work in this field. As we discuss in the next section, this omission may arise from a rather belated treatment of the co-dependency of house prices and employment in the theoretical literature—for a long time theoretical models assumed either firm location was endogenous, or household location was endogenous, but not both. However, the new synthesis of employment location theory and urban economics is unequivocal about the co-dependency of these two variables, even if the empirical literature has been slow to catch on. The failure to model endogenous effects may also be due to the growing use of spatial econometric models. Spatial econometric papers generally have tended to neglect the issue of endogeneity, other than that arising from spatial lags of the dependent variable (notable exceptions include Anselin & Lozano-Gracia, 2008; Fingleton & Le Gallo, 2008; Kelejian & Prucha, 2004, 2007).

A second issue is the potentially important mitigating effects of agglomeration (proximity to other firms) on the impact of floods. Whilst agglomeration economies are often not considered in studies using methods of difference-in-difference or time series (e.g. Leiter *et al*., 2009), they are widely discussed in industrial location studies (see Arauzo-Carod *et al*., 2010 for a review). According to urban economic theory, industrial concentration offers positive externalities for firms to reduce costs and improve productivities, through three major mechanisms, namely labour market pooling, input sharing and knowledge spillovers (Duranton & Puga, 2004; Marshall, 1890). A thick and tight labour market assists firms to find suitable workers, and the concentration of firms enables them to share input suppliers, knowledge and ideas. The majority of empirical studies do find positive association between economic performance of firms and spatial concentration of economic activities (Arauzo-Carod *et al*., 2010), though the relative importance of the three mechanisms vary for different industries (Ellison, Glaeser, & Kerr, 2010; Glaeser & Kerr, 2009; Jofre-Monseny, Marin-Lopez, & Viladecans, 2011; Rosenthal & Strange, 2003).

The role and causation of agglomeration (economic concentration) in geographical space is the ‘defining issue of economic geography’ (Fujita & Krugman, 2004, p.140). Intrinsic to its complexity and importance is that agglomeration:

> ‘occurs at many geographical levels, having a variety of compositions. For example, one type of agglomeration arises when small shops and restaurants are clustered in a neighbourhood. Other types of agglomeration can be found in the formation of cities, all having different sizes, ranging from NewYork to Little Rock; in the emergence of a variety of industrial districts; or in the existence of strong regional disparities within the same country’ (Fujita & Krugman, 2004, p.140).

This raises an important question for empirical analysis: whether a single measure of agglomeration is sufficient to capture its multi-faceted effects, particularly the distinction between "local" effects—the benefits for firms of locating in the same neighbourhood, compared with the "global" externalities—the city-wide benefits of being located within the wider metropolitan area. Studies that do estimate agglomeration effects tend not to distinguish between global and local effects, and tend to assume—rather than estimate—the appropriate functional form of the distance-decay process associated with agglomeration (Fujita, Krugman, & Venables, 1999; Graham, 2007). Moreover, we are not aware of any study that allows for interaction effects between agglomeration and flood risk, yet there may be theoretical reasons (see next section) to expect the impact of flood risk to be weaker the stronger the agglomeration effect, and *vice versa*.

A third limitation of the literature is with respect to the measurement of flood risk effects on employment. While there are many studies of the effects of a particular flood event or other natural disaster (Baade, Barmann, & Matheson, 2007; Belasen & Polachek, 2008, 2009; Cuaresma, Hlouskova, & Obersterner, 2008; Ewing & Kruse 2002; Ewing *et al*., 2003, 2009; Leiter *et al*. 2009; Sarmiento, 2007), we are not aware of any empirical employment models that estimate the effect of flood *risk*. This is an important omission because the effect of a particular natural disaster may be regarded by the market as a one-off event and therefore has very particular or limited long-term term effects.

Indeed, some studies actually show a higher level of employment after a particular flood event. Ewing *et al*. (2003) reported that employment levels increased and regional labour markets became more stable following the 2000 tornado in Fort Worth. Using the 1999 tornado in Oklahoma as another natural experiment, Ewing *et al*. (2009) find negative effects on employment growth immediately after the tornado; but the drop was only temporary as the mean employment growth rate increased in the post-tornado period. Leiter *et al*. (2009) also find that employment growth is significantly higher in those European regions which were hit by the 2000 floods, and such positive effects prevail for companies with a high share of intangible assets which could not be destroyed by floods, such as patents and trademarks.

One explanation for the positive impact of floods on employment concerns rebuilding efforts financed by external sources, such as insurance claims and disaster relief funds. Another explanation is that older and less productive physical capital is updated and new technologies are adopted after the initial shock of a disaster (Ewing *et al*., 2009; Skidmore & Toya, 2002). Thus, natural disasters may be regarded as examples of Schumpeter's processes of 'creative destruction', providing opportunities to replace old and obsolete capital stock with new and more productive one (Okuyama, 2003).

However, the implications of persistent vulnerability to repeated flooding, may be rather different from effects of one-off events, particularly if that risk is set to rise substantially and persistently in particular locations, as would be the case in the event of global warming (Ciscar *et al*., 2011; McGranahan *et al.,* 2007; Nicholls *et al*., 2007; Stern, 2006). Moreover, endogenous house price effects may be an additional cause of rising employment in a particular area affected by floods if firms are less averse to floods and remediation than households. In summary, it is unclear what the existing employment literature tells us about the long-term effects of flood risk.

In terms of the impact of flood risk on house prices, most studies agree that flood risk negatively influences house prices. For example, MacDonald, Murdoch, and White (1987) find that floodplain location lowers house prices by 6% to 8%, using data of home sales prices in Monroe, Louisiana. Skantz and Strickland (1987) show that property values in a floodplain in Houston, Texas, are reduced by approximate 4%. Speyrer and Ragas (1991) reported that homes at high risk of flooding in New Orleans are valued 4.2% to 6.3% less than comparable flood-free homes. A recent study of Pope (2008) indicates that floodplain location results in house price discount of 3.8%-4.5% in North Carolina. Lower houses prices, controlling for type and size of dwelling, will imply lower land rents for firms and this will presumably have implications for firm location and employment density.

However, there are studies that have found a positive impact of flood risk on house prices, though this is likely to be due to unmeasured amenities associated with proximity to rivers, such as waterfront views and access to leisure amenities. If insurance premiums do not fully price risk (as is the case in the UK) then such effects can easily offset the negative consequences of flood risk if not appropriately controlled for in econometric estimation (Morgan, 2007). Also, there may be distortions from failing to account for endogenous employment effects (which existing house price research on flood risk does not take into account, though there is a growing hedonic literature more generally that incorporates employment effects, such as the polycentric model of Osland and Pryce 2012), and from the relatively crude measures of flood risk employed in most of these studies (the flood risk variable was typically either binary—indicating, for example, whether a dwelling is located on a flood plain—or with a simple categorisation of flood risk, with no indication of variation in potential flood severity; and usually these measures relate to fluvial or coastal flood risk, with the assumption of zero probability of pluvial flooding).[7] Ideally, then, we would like to have a measure of flood risk that (a) is of high spatial resolution; (b) includes both fluvial and pluvial risk; and (c) captures not just frequency of flooding, but severity as well.

[7] see Chen, Pryce and Mackay (2011) for a more detailed survey of the housing economics literature on flood risk and climate change.

The fourth limitation we seek to highlight in the empirical literature is the measurement of employment. Existing studies (e.g. Belasen & Polachek, 2008; Ewing *et al*., 2009; Sarmiento, 2007) utilise a regional or county level aggregation measure of employment. This is problematic because it conflates the impact on specific localities worst affected by flood events and flood risks with the wider economic impact which may well be positive, as indicated above. Indeed, this failure to disentangle the local and regional effects may partly explain the apparent contradiction in the literature between those studies (listed above) which find positive effects of flood events on employment, and those which reported negative impact of floods or other natural disasters. For example, Garber, Unger, White, and Wohlford (2006) reported that Hurricane Katrina resulted in a 9.6% decrease on total nonfarm employment in Louisiana from September 2004 to September 2005; the industries of leisure and hospitality, education and health services, trade, transportation and utility, were particularly negatively affected. Using data on flood events and employment in 1200 US municipalities during 1997 and 1999, Sarmiento (2007) finds that floods decrease local employment by an average of 3.4%. Belasen and Polachek (2009) employed data on hurricanes and employment in Florida between 1988 and 2005, and found that a high-intensity hurricane reduces employment by 4.76% while a low-intensity hurricane decreases employment by 1.47%).

3. Theoretical basis for linking real estate with employment location

Until the P&T (Papageorgiou & Thisse) synthesis in the mid-1980s, firm location theory and urban economics had developed largely independently: 'Whereas the former primarily seeks to determine supply characteristics given demand, the latter primarily seeks to determine demand characteristics given supply' (P&T, 1985, p.20-

21). The P&T model bridged the gap by permitting spatial interdependence between firms and households. Unfortunately, the P&T model assumed that firms did not occupy land and so the potentially important implications of competition for land between households and firms were overlooked.

Fujita's (1988) model of monopolistic competition showed how market processes can generate spatial agglomeration, and this approach was extended by Liu and Fujita (1991) to allow land-use density to vary over the urban space. An important implication of that model for the empirical estimation of employment is that floor space equilibrium conditions require that 'each unit of floor space must be occupied by either a household or firm which bids a higher floor rent at that location' (Liu & Fajita, 1991, p.88). In other words, spatial competition between firms and households for land is a crucial driver of urban economic geography, where the market is cleared through adjustments to the price of land. The implication is that constant quality house prices are likely to be endogenous to employment location. *Ceteris paribus*, firms will be attracted to sites with low land prices. If the marginal loss associated with flood risk is higher for households than firms, then firms will tend to locate in high flood-risk areas.

Various theoretical models have since been developed where competition for land between households and firms has a similarly critical role. Of particular note is the LRH (Lucas & Rossi-Hansberg, 2002) model which conceives of a circular city where firms and households can locate anywhere (i.e. there is no prior assumption about central business district or suburban location for firms). Equilibrium is determined through the countervailing forces of firms seeking to locate near other producers (agglomeration benefits) and the costs commuting for workers. Without agglomeration benefits, 'producers would disperse from cities to areas where land for production and residential use is cheaper' (LRH 2002, p.1445).

Given this theoretical backdrop, what might we expect the implications of variable flood risk across the urban system? There are four key components of the LRH and related models likely to be affected. First, the utility of (and hence demand for) housing may be reduced at flood-prone locations, other things being equal. This will result in lower land prices in those locations, *ceteris paribus*. If firms are resilient to flood risk, or less affected than households, we might expect an increase in employment in areas with high flood risk because of the lower land rents. Failure to control for land price effects of flood risk in empirical models is therefore likely to lead to biased estimation of the direct effect of flood risk on employment location.

Second, we might hypothesise that the long-run productivity of firms will be lower in high flood risk areas. Floods cause direct losses as a result of destruction of physical assets (Albala-Bertrand, 1993; Kahn, 2005) and labour shortage caused by human suffering (Leiter *et al*., 2009), as well as indirect losses due to disruption to companies up- and down-stream in the supply chain (Rose, 2004). Natural disasters can have deleterious long-term impacts on the local economy because disasters impede the accumulation of both physical and human capital stock (Skoufias, 2003). In the LRH model, a fall in productivity at particular location will result in a reduction of employment density. This in turn will increase commuting costs for households located in that area, which will then affect house prices, and have a feedback effect on firm location and employment density decisions.

Third, we might expect flood risk to have a more potent effect where agglomeration economies are weakest. Where network effects between firms are strong, there is greater collective potential to adapt to flood events, and these effects may be non-linear. For example, if there are only two suppliers of a particular input to firm A, even a geographically limited flood event might sever all supply links to A.

However, if there are 20 potential suppliers of that input, the probability of all lines of supply being affected by a particular weather event will be disproportionately lower.

Fourth, the pattern of flood risk might distort the geography of agglomeration benefits for a given set of firm locations. This is because flood risk may affect the interconnectedness between firms. For example, roads and railways which would otherwise be constructed as straight lines between two firms may have to take a circuitous route in a flood-prone topology. Similarly, there may be increased probability of disruptions to supply-chains and communications.

We shall now distil these implications into a series of testable hypotheses.

Hypotheses:

H1: *Ceteris paribus,* the effect of endogenous house prices on employment will be negative because of the competition for land.

H2: Because of expectations of the deleterious impact on productivity of flood events, employment density will be low where flood risk is high.

H3: There is likely to be a positive interaction effect between flood risk and agglomeration because agglomeration economies may help firms be resilient to localised disruptions to input supplies and transport links.

4. Econometric strategy

We employ spatial econometrics to capture spatial inter-dependence of employment. Our general specification of the employment equation is as follows:

$$\mathbf{E} = f(\mathbf{H}, \mathbf{X}, \mathbf{u}), \qquad (1)$$

where,

$$\mathbf{P}, \mathbf{WE}, \mathbf{G}, \mathbf{F^G} \in \mathbf{H} \qquad (1.1)$$

$$\mathbf{F}, \mathbf{Z} \in \mathbf{X} \qquad (1.2)$$

and where **E, H** and **X** refer to matrices of dependent variable (employment density), endogenous and exogenous independent variables, respectively; **u** is a potentially spatially dependent error term; **P, G, F**, and **Z** denote constant quality house prices (**P**), global (but distance weighted) agglomeration effects (**G**), flood risk (**F**), and other exogenous controls (**Z)**, respectively. **WE** is spatially lagged employment, formed as the matrix product of matrix **W** and vector **E**, which is included to capture localised agglomeration effects, and other factors (such as planning restrictions, topography, local effects) that affect the local pattern of employment location. Given *n* locations, **W** is an *n* by *n* contiguity spatial weight matrix with 1s and 0s indicating whether or not locations are contiguous (sharing boundaries). This is then subject to row standardisation, so that rows sum to 1. Standardisation implies that what is important is relative not absolute distance. The interaction effect between flood risk and agglomeration effects is given by $\mathbf{F^G}$, calculated through element by element multiplication of **F** and **G**. We treat **P**, **WE**, **G** and $\mathbf{F^G}$ as endogenous variables, and **F** and **Z** as exogenous.

Explanatory variables incorporated in **Z** include distances to transport nodes and CBD, population and property densities, and local deprivation. The choice of these variables follows the literature on firm location (Arauzo-Carod *et al*., 2010; Friedman, Gerlowski, & Silberman, 1992, Gottlieb, 1995; Moomaw, 1980;), which indicates that a firm locates where it maximizes profit, after weighing the benefits of a plant site, such as good access to transport and local public goods, proximity to amenities, and the cost components, including local wage rate, capital cost, tax rate, and costs of delivering inputs and outputs. As the variables of wage rate, capital cost and public finance (e.g. tax rates and government expenditure) are fairly uniform across our study area, they are not included in our model.

Because house prices and agglomeration variables are potentially endogenous, we face the challenge of how to account for this in a spatial econometric context. While the spatial lag is widely recognised as endogenous in spatial estimation, relatively few studies include other endogenous variables, as noted above. Given that "maximum likelihood of model with a spatial error process and endogenous variables … would be difficult, if not impossible, to implement" (Fingleton & Le Gallo 2008, p.320) we apply GMM estimation as advocated by Kelejian and Prucha (1998) and Fingleton and Le Gallo (2007, 2008).

Our estimation strategy is first to test the spatial independence of the residuals of an OLS[8] 2SLS[9] model without **WE** and spatially dependent error terms, to ascertain whether it is valid to assume zero spatial autocorrelation. Second, if there is evidence of spatial dependence, we shall estimate GMM Spatial 2SLS models with and without **WE**, to establish whether **WE** should be included ($\rho = 0$ *vs.* $\rho \neq 0$). We shall also experiment with different spatial models to check whether the error term **u** is best modelled as an autoregressive (AR) or moving average (MA) process (Fingleton & Le Gallo, 2008). The AR process assumes that a shock in one place is transmitted to all other places in the sample, while the MA process posits that a shock in one place only influences neighbouring locations as defined by the non-zero elements in the spatial weight matrix **W**. Finally, we shall compare the effect of the flood risk-agglomeration interaction term $\mathbf{F^G}$ using a continuous flood risk variable as well as a dummy variable of flood risk.

[8] Ordinary Least Squares
[9] Two Stage Least Squares

The above mentioned variables are explained in more detail below.

5. Study area and data

Our study focuses on five boroughs in Southeast London: Greenwich, Bromley, Bexley, Lewisham and Croydon. It is an area with a concentration of employment and properties, and where detailed flood risk data were developed as part of the EPSRC Community Resilience to Extreme Weather (CREW) project. The study area has a population of 1.35 million, most of whom live in densely populated urban area (Community Risk Register [CRR], 2008). Compared to London as a whole and other major cities in England, Southeast London is a relatively affluent area. According to the Office for National Statistics (2008), 59% of the working population are employed in managerial positions, the same as in all of London but 7% higher than that in England as a whole. The home ownership rate in the study area is 65%, 8% higher than that in London. In terms of land use, the percentages of domestic and non-domestic buildings (10%), water (3%), rail, road and path infrastructure (12%) within the study area are similar to other major cities in England.

Flood risk data

Due to climate change and rise in sea levels, Southeast London is at risk of both tidal and surface water flooding (pluvial flooding), as it is located near the Thames River (Thames Gateway London Partnership [TGLP], 2008). We use data on pluvial flood risk, because the Thames Barrier, a hard-engineered flood alleviation scheme, is reported to be adequate to protect London against a tidal flood with a one in 1000 year return period for the year 2030 (CRR, 2008). Pluvial flood risk data come from a 2D flood model built specifically for the 5-borough study area. The model was developed to produce flood depth and frequency estimates at a 10m x 10m grid resolution, using data on rainfall, terrain, soil types and land uses (Chen *et al*., 2009). A 100-year continuous series of the spatially distributed rainfall data produced by the STNSRP model (Burton *et al*., 2010) was applied as a projection of the future rainfall scenarios. This series was filtered down into a number of isolated events that were deemed intense enough to cause any flooding. The outputs for each event were processed to create a Hazard Number (*HN*) variable originally designed to give a measure of the frequency of floods above a certain level of severity, based on information of flood depths and extent. These were then further spatially aggregated to Lower Layer Super Output Area (LSOA) level according to the following formula:

$$HN = 2^{(a+b+c)} - (1-c),$$

where,

Parameter '*a*' is defined by maximum flood depth ($D_{\max}$) within a LSOA unit as follows:

a =0 for $D_{\max}$<=0.1m;

1 for $D_{\max}$>=0.6m;

Parameter '*a*' is linearly interpolated for $D_{\max}$ ranging from 0.1m to 0.6m.

Parameter '*b*' is defined by average flood depth (D_{avg}) of the LSOA unit:

b =0 for D_{avg}<=0.1m;

1 for D_{avg}>=0.6m;

Parameter '*b*' is linearly interpolated for D_{avg} ranging from 0.1m to 0.6m.

Parameter '*c*' is defined by the ratio of flooded area (F_{area_r}), where the flood depth is greater than 0.1m, to the area of the LSOA:

c =0 for F_{area_r}<=0.2;

1 for F_{area_r}>=0.5;

Parameter '*c*' is linearly interpolated for F_{area_r} ranging from 0.2 to 0.5.

Based on the definition, the *HN* of each LSOA is a value ranging from 0 to 8. A high *HN* represents an LSOA that is likely to be affected by high flood depths and a wider flood area. Floods with *HN* lower than one have negligible consequences. For the purpose of research presented in this paper, we define flood risk as the frequency of floods with *HN* greater than one in a time period of 100 years. About 70.6% of the LSOAs in Southeast London are subject to risk of floods with *HN* greater than one. The frequency of such floods in a hundred years' time ranges from 0 to 12. Figure 1(a) shows an illustrative high resolution map with maximum simulated flood depths for one isolated rainfall event. A low resolution map of flood risk for a selected number of streets in the study area is presented in Figure 1(b) to illustrate the adopted 100-year rainfall series. Figure 1(c) shows the borough boundaries in London and the location of the 5 boroughs for which the flood variables were computed.

Figure 1: Flood Risk

(a) Illustrative hi-resolution map-extract of maximum water depths for one flooding event

(b) Low resolution map-extract for the frequency of hazard numbers for the 100-year rainfall series

(c) Location of 5 Boroughs for which the flood variables were computed

Employment and house price data

We use employment density (number of employees per square kilometre) as the dependent variable thus controlling for area. Employment data come from the UK official labour market statistics database Nomis. In contrast to previous studies that model employment at a regional or national scale, we use a relatively disaggregated measure, i.e. at the LSOA level, to capture the local drivers of employment. The LSOAs have a minimum population of 1,000 and a mean population of 1,500. An advantage of LSOA over postal sectors is that LSOAs are fairly consistent in size and boundary length across England.

Housing price data are provided by the Nationwide building society. As the data are based at individual transaction level, we constructed a new variable of constant-quality house price, to control for property attributes. We achieve this by first estimating a house price surface for a typical property through hedonic models based on the transaction data, and then deriving prices for the typical property in different spatial locations. More details are provided in the results section and in the appendix.

Agglomeration variable

A simple gravity model (Hansen, 1959) suggests a measurement of agglomeration at a particular zone as an aggregation of numbers of jobs in other zones, discounted by the distance to each one. To improve flexibility, we define our agglomeration variable G_i as follows:

$$G_i = \sum_j (E_j^* e^{(bD_{ij})})$$

D_{ij} refers to the distance between LSOA i and j; E_j^* is the number of employees[10] at LSOA j; b is a scalar parameter, the value of which we determine empirically. *A priori* we assume b to be negative, with the contribution to agglomeration from more distant LSOAs to be relatively small, falling to practically zero at greater distances.

One complication in measuring agglomeration is determining the geographic scale over which economic activities are able to generate externalities. The existing literature on agglomeration economies emphasises proximity, yet it is unclear about the exact definition of proximity, or any distance threshold beyond which

[10] Not to be confused with dependent variable **E.**

agglomeration economies disappear (Mion, 2004). It is agreed, however, that the measurement of connection with economic activities elsewhere should not be limited by administrative boundaries. We generated a 30-kilometre buffer around the boundary of the Greater London Area, and assume that employment in this wider region is related to job opportunities in Southeast London, with its impact decreased by distance. Altogether there are 8,327 LSOAs in this wider region. We then generated a distance matrix between each LSOA within the study area and 8,327 LSOAs. After calculating the matrix of $\exp(bD_{ij})$, the diagonal elements were set to zero before multiplying the numbers of employees, to ensure that the number of employment in an LSOA itself is not included in the agglomeration variable. The parameter of '*b*' is estimated by a maximum likelihood grid search procedure using the employment model[11]. We experimented on values ranging from -5 to -0.1 with an interval of 0.002 (altogether 246 different values). The result shows that the most appropriate value for '*b*' is -2.82.

Other variables

From the Ordinance Survey we obtained data on distances between dwellings, Euclidean distances from postcode centroids to the nearest transport nodes (e.g. roads and railway stations) and amenities (e.g. woodlands and rivers). These distances were then aggregated to LSOA level by taking average of those within a LSOA. We also derive the easting and northing co-ordinates of underground stations in the study area and use a dummy variable to indicate LSOA with at least one underground station. A summary statistics of all variables is displayed in Table 1.

Table 1 Summary statistics of variables used in the study (N=841)

[11] The grid search procedure is based on an employment model without spatial lag and error terms.

6. Empirical results

Surface hedonic derivation of constant-quality house prices

In order to construct a variable of constant-quality house price for each LSOA, we estimate a surface of constant-quality house price for the study area, using Nationwide housing transaction data during 2006 and 2007. The following hedonic model is employed:

$$\mathrm{Ln}(P) = f(\mathbf{V_1}, x, y, x^2, y^2, xy, x^2y, xy^2, x^2y^2, x^3, y^3, x^3y, x^3y^2, x^3y^3, xy^3, x^2y^3, t, \mathbf{V}_2),$$

where Ln(P) is the natural log of house price, and t is the time period (month) in which the transaction takes place. The vector of attributes $\mathbf{V_1}$ includes the number of bathrooms, number of bedrooms, property type, new-property, floor size, central heating, age, age squared, freehold, single garage, double garage, parking space. x and y are location co-ordinates, referring to easting and northing, respectively. $\mathbf{V_2}$ is a vector interactions of x, y and t, and their interactions with local authority dummies, year 2007 dummy, and all attributes (see Fik *et al.* 2003 and Pryce 2011 for applications of this type of model to spatial variation in house prices). Detailed results of model coefficients are in the Appendix.

The model has a high R-square statistic of 0.8272. All attribute variables are significant and with expected signs. For example, more numbers of bedrooms and bathrooms, bigger floor size, new property, central heating and garage increase house prices; detached and semi-detached properties have higher prices than flats. This model is then used to estimate house prices of a typical property at locations with different x and y co-ordinates. A typical property in the study area, according to the Nationwide housing transaction data, is defined as a freehold flat with three bedrooms, one bathroom, a floor size of 90.26 square metres, 72.9 years old, with central heating, but no garage or parking space. Consistent with the measurement of access-to-transport variables at LSOA level, constant-quality house prices were first estimated at postcode centroids and then aggregated to the LSOA level by taking the average of those in a LSOA[12].

Employment models

An initial baseline OLS employment model was estimated to establish whether there was *prima facie* evidence of spatial dependence. Using the OLS residuals, the Moran I statistic was computed to be equal to 0.0655 (p = 0.0001549). A more reliable test is obtained by treating log house prices and agglomeration as endogenous, using the Moran's I statistic for two-stage least squares residuals (Anselin and Kelejian, 1997). This gives a test statistic equal to 0.376247 with p-value equal to 0.020788. Thus we reject the null hypothesis of zero spatial autocorrelation in the error term. We then estimated a variety of GMM/2SLS spatial models with AR (spatial autoregressive error) and MA (spatial moving average error) processes, with and without **WE**. There was very little difference between the AR and MA estimates and we therefore present only the results with AR error process, since the AR error process is the more typically adopted approach. The AR error process specification is $\mathbf{u} = \lambda\mathbf{Mu} + \mathbf{e}$ in which $\mathbf{u} \sim iid(0,\sigma^2\mathbf{I})$.

Our estimation method, which accommodates the spatial autoregressive error process together with several endogenous explanatory variables, is the feasible generalised spatial 2SLS procedure (FS2SLS) which is outlined by Fingleton and LeGallo (2007, 2008) and which is based upon Kelejian and Prucha (1998). The

[12] We used an alternative approach and constructed a house price variable by estimating constant-quality house prices in LSOA centroids. This variable is similar to the one used in the study and does not affect the results in the two-stage least squares models.

FS2SLS method involves three stages. First, two stage least squares residuals are obtained, ignoring the spatial error component. Next, GMM is used to estimate the parameters of the error process, applying a nonlinear optimisation procedure and moments conditions appropriate to an autoregressive process (see Fingleton, 2008 for the moments appropriate to a MA error process). Finally, in the third stage, the parameter estimate $\hat{\lambda}$ on the autoregressive error process is used to filter the spatial component from the data, using a Cochrane-Orcutt transformation, prior to consistent estimation again via two stage least squares. Note that, because for some models we have an endogenous spatial lag (**WE**) and an endogenous error process, we have the possibility of invoking two different **W** matrices. In our analysis, the error process involves the standardised contiguity matrix **M**. The endogenous spatial lag also is based on a standardised matrix, but in this case $W_{ij} = \exp(-0.2D_{ij})$ with $W_{ij} = 0$ if $\exp(-0.2D_{ij})$<0.05, where D_{ij} is the linear distance between locations *i* and *j* based on eastings and northings.

Table 2 displays the resulting FGS2SLS estimates. There are six models, the first three include the endogenous spatial lag (**WE**) in the specification, and the remaining three models exclude it but are otherwise identical. Model 1 and model 4 do not incorporate $\mathbf{F^G}$, an interaction variable of global agglomeration and flood risk; models 2 and 5 do include an interaction term based on a continuous flood risk variable, while models 3 and 6 specify the interaction using a dummy variable for flood risk. In these models, house prices (**P**), spatial lag of employment local agglomeration variable (**WE**), the global (but distance weighted) agglomeration variable (**G**) and its interaction with flood risk ($\mathbf{F^G}$) are treated as endogenous. Fitting these same specifications via standard two-stage least squares (that is omitting the AR error process), the Hausman tests indicate (see Table 2) that local agglomeration (**WE**) is not endogenous, but the other variables are endogenous using a 10% level of risk.

However, we retain global agglomeration in the set of endogenous variables because the interaction term is evidently endogenous, and since we treat flood risk as exogenous by definition, it appears that the source of this endogeneity will be global agglomeration. We therefore assume that the lack of identification of global agglomeration as endogenous is perhaps a statistical artefact rather than evidence that it is truly exogenous. The Hausman tests lead us to assume that these variables are indeed endogenous, and the 2SLS procedure is required for consistent estimation. We use distances to rivers and woodland and their spatial lags, and spatial lags of distances to transport nodes, as excluded instrument variables (IVs). The presence of more than one excluded instrument means that we have over-identification and can therefore test the validity of the instruments via the Sargan test. The results are mixed (see Table 2) although models 2 and 5 stand out as cases in which the Sargan statistics do not reject the null hypothesis, showing that the IVs are orthogonal to the disturbances. We therefore focus on the estimates produced by these models (2 and 5).

Table 2 Regression results

Both versions of the preferred model (2 and 5) include the global (but distance weighted) agglomeration effects (**G**) and flood risk interaction ($\mathbf{F^G}$) with flood risk in continuous (that is, non-dummy) form, and which differ by the presence or absence of the endogenous spatial lag **WE**. We see that in both these models, flood risk has a statistically significant negative effect on employment density. Lower density of employment in places with higher flood risk could be explained by damage and expected losses associated with floods. The global agglomeration variable is found to be statistically significantly and positive in model 2, suggesting that firms prefer to locate near each other to take advantage of business opportunities, though it is not statistically significant in model 5.

Since model 2 is capturing remnant marginally significant ($p < 0.01$) spatial autocorrelation via the endogenous lag, which may otherwise represent an omitted spatially autocorrelated variable from model 5, model 2 is our finally preferred specification. Under both models the interaction between agglomeration and flood risk is statistically significant, with the positive coefficient confirming our intuition that agglomeration economies mitigate the effect of flood risk on employment location.

Under both models the endogenous house price effect appears to be insignificant. This does not reflect weak instruments, as the majority of the p-values for correlation between the endogenous and exogenous variables are small enough to reject the null of no correlation, and the r-squared of the regression of the instruments on the endogenous variable log house price is equal to 0.803045. Our assumption is that high house prices will raise land values and deter the presence of firms hence employment, but the negative effect of house prices on employment may have been cancelled out by other factors captured in the house price variable. For example, house prices may capture positive location effects that would attract firms that are not otherwise adequately accounted for in the employment model, such as the location of skilled workers or transport links. Thus, while high house prices may indeed be deterring employment, at the same time, high house prices may be a reflection of a good supply of skilled workers and good transport links, thus offsetting the negative impact of land prices on employment density.

Table 2 also shows that better access to transport nodes, especially A roads, underground and railway stations, stimulate greater density of employment. This finding is consistent with previous studies demonstrating that access to transport is crucial for firms' location choice. For both models 2 and 5 the coefficient of distance to CBD is found to be insignificant, probably reflecting the fact that the agglomeration affects associated with proximity to CBD are adequately captured in the gravity measure, **G**. The effect of deprivation on employee density is also not significant. This perhaps reflects the fact that many business location decisions tend not to be governed by the social status of the location where production might take place, but are more related to the location of other businesses which potentially provide pecuniary and other externalities that could enhance profitability, and these locations may be quite widely scattered across the entire conurbation and beyond.

7. Conclusions

This paper has sought to address a number of limitations in the existing literature by: (i) accounting for the potentially endogenous role for house prices arising from competition for land between firms and households; (ii) including agglomeration-flood risk interaction effects using a gravity-based measure of agglomeration; (iii) developing a high-resolution flood risk measure which incorporates both flood frequency and severity; and (iv) utilising a high-resolution measure of employment to capture local effects of flood risk.

We have argued that, the extent to which firms respond to flood risk signals will have important implications for the economic effects of climate change in the UK and other countries where flood risks are anticipated to increase. If firms tend to be repelled by flood risk then we might conclude that those areas predicted to have increases in flood risk will gradually lose employment over time, other things being equal. A critical qualifying factor, however, is the extent to which agglomeration economies mitigate these effects.

Our results appear to confirm the existence of negative impacts on employment location as a result of flood risk, thus supporting the hypothesis that firms are deterred from locating close to areas with high flood risk and consequent damage and disruption to productive activity. Our results also confirm that there are mitigating effects from agglomeration. The effect of house prices on employment is found to be insignificant, however.

The interaction between agglomeration and flood risk has important implications for policy. It means that flood risk may have a more deleterious effect on employment in areas where agglomeration is weak. This means that policy makers cannot assume a uniform effect of future changes to flood risk as a result of climate change. Two areas could experience identical increases in flood risk but very different economic consequences because agglomeration economies are different. This complicates considerably the calculations for comparing the relative costs and benefits of flood defense interventions across different locations because it means that agglomeration economies will need to be taken into account when computing the economic benefits.

The ongoing progress in the domain of flood risk communication will only strengthen our conclusions. As firms and households become more aware both of flood frequency and severity through such efforts, and as insurers face greater pressures (due to the systemic implications of climate change) to fully price risk and to ration provision in the most vulnerable areas, the sensitivity of employment density to flood risk is likely to increase over time. Similar arguments can be made for the likely increases in sensitivity of house prices to flood risk (Pryce, Chen & Galster 2011).

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APPENDIX:

Constant Quality House Price Model

We include property attributes, x and y co-ordinates and their squared and cubed terms, month, and all possible interaction variables, to derive a geographical surface allowing us to estimate a Constant Quality House Price for each LSOA. Dummies for local authority and year are also incorporated to capture any step change effect in spatial and temporal dimensions. We adopt the general-to-specific estimation approach and used the significance level of 5 per cent to remove insignificant variables. The final regression model is displayed in Table A1 below.

Table A1 Constant Quality House Price Model

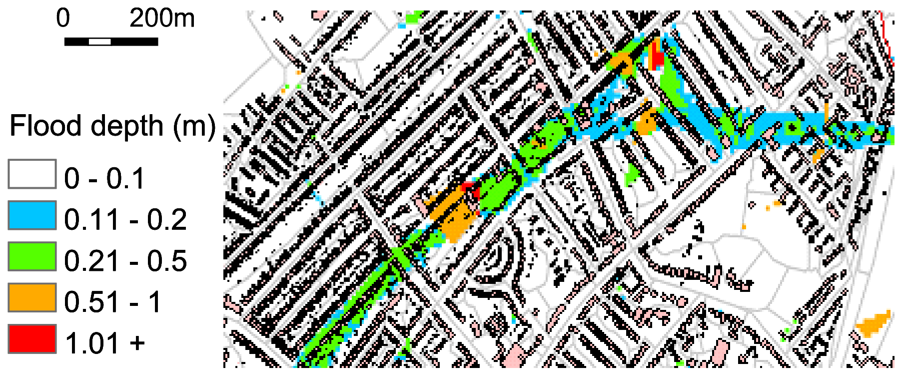
Independent variables	*Coefficients/Standard Errors*
x^2y	2.25e-13***
	(2.45e-14)
x^3y	-3.13e-19***
	(3.41e-20)
xy^3	1.08e-18***
	(1.19e-19)
x^2y^2	-1.67e-18***
	(1.84e-19)
x^3y^2	2.48e-24***
	(2.74e-25)
x^3y^3	-2.48e-30***
	(2.78e-31)
x(Dummy for Local Authority 2)	0.0038***
	(0.0004)
*txy*_bathroom	-3.05e-13***
	(8.62e-14)
*x*_lnfloorsz	-3.12e-06***
	(1.12e-06)
x^2(Dummy for Local Authority 2)	-3.09e-09***
	(3.52e-10)
y^2(Dummy for Local Authority 2)	3.82e-09***
	(5.97e-10)
x^2y^2(Dummy for Local Authority 2)	-1.29e-20***
	(2.04e-21)
x^2(Dummy for Local Authority 4)	-4.38e-11***
	(3.99e-12)
x^2(Dummy for Local Authority 5)	-2.45e-09***

	(1.77e-10)
y^2(Dummy for Local Authority 5)	-2.36e-08***
	(1.71e-09)
x^2y^2(Dummy for Local Authority 5)	8.20e-20***
	(5.91e-21)
y^2(bathroom)	-7.20e-12***
	(2.20e-12)
ty^2(bathroom)	1.08e-12***
	(2.75e-13)
t^2x^2(newproperty)	-8.22e-16**
	(3.26e-16)
Number of bathrooms	0.1759***
	(0.0636)
Number of bedrooms	0.0700***
	(0.0044)
Detached property	0.2250***
	(0.0095)
Semidetached property	0.0705***
	(0.0059)
New property	0.2260***
	(0.0252)
Ln(floor size)	2.1167***
	(0.6026)
Central heating	0.0651***
	(0.0120)
Age	0.0011***
	(0.0001)
Age^2	-1.25e-06***
	(2.14e-07)
Freehold	0.0826***
	(0.0065)
Single garage	0.0877***
	(0.0062)
Double garage	0.1319***
	(0.0139)
Parking space	0.0550***
	(0.0058)
Dummy for Year = 2007	0.0626***
	(0.0069)
Dummy for Local Authority 2 (Bromley)	-1126.5171***
	(114.9004)
Dummy for Local Authority 3 (Croydon)	-0.3822***
	(0.0342)
Dummy for Local Authority 4 (Greenwich)	12.9099***
	(1.1833)
Dummy for Local Authority 5 (Lewisham)	702.5505***
	(51.0427)
Constant	-910.4969***
	(99.3728)
N	4916

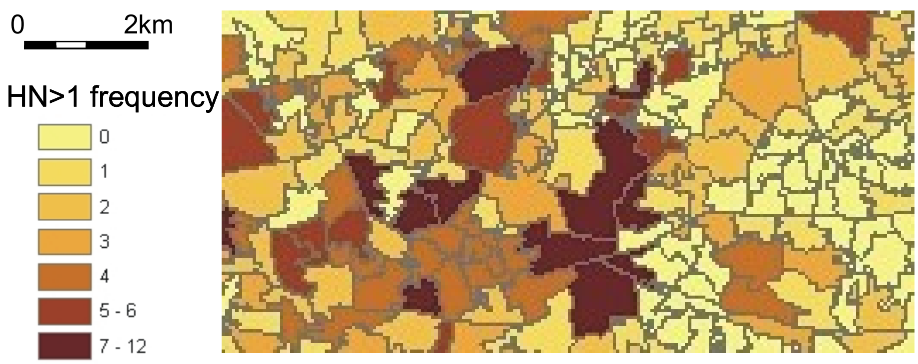
*Significant at 10%; ** significant at 5%; *** significant at 1%.
Omitted (i.e. reference category) dummy variables are: flats, no garage and Borough Bexley.

Figure 2: Flood Risk

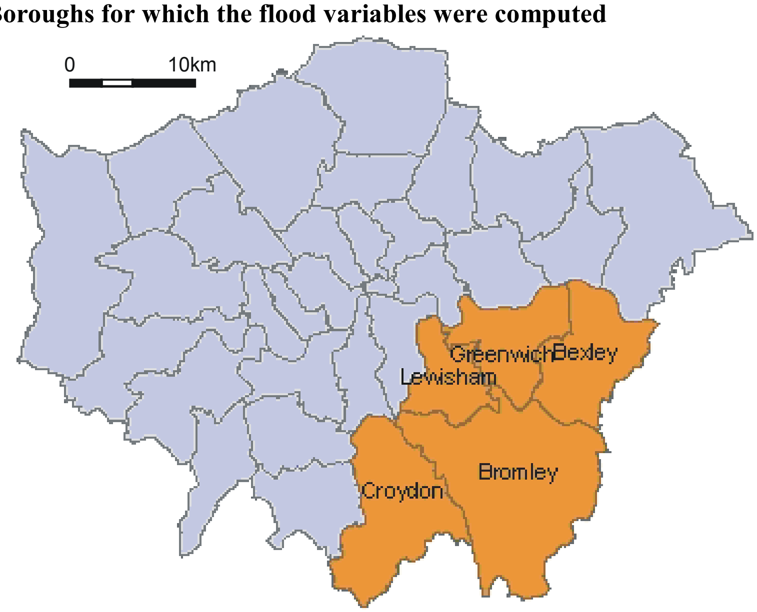
(a) Illustrative hi-resolution map-extract of maximum water depths for one flooding event



(b) Low resolution map-extract for the frequency of high hazard numbers for the 100-year rainfall series



(c) Location of 5 Boroughs for which the flood variables were computed



Note: (a), (b) and (c) each show different areas and are at different scales. Figure 1(a) depicts an illustrative map of flood depth of a particular event for a very small area, and the map image has been transformed to help preserve the anonymity of the streets shown. Figure 1(b) represents a considerably larger area and depicts the frequency of high *HN* values rather than a particular flood event. Figure 1(c) shows the borough boundaries in London and the location of the 5 Boroughs for which the flood variables were computed.

Tables:

Table 1 Summary statistics of variables used in the study (N=841)

Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
LN numbers of employees / km^2	6.5418	1.2007	2.3384	10.6392
LN constant-quality house price	12.4014	.1246	12.0726	12.9232
Income deprivation	.1672	.1062	.0129	.5593
Agglomeration	3655.4760	3863.8720	4.4234	29453.2300
Distance to A road	368.7027	326.4091	41.3145	2202.4600
Distance to B road	904.4049	663.6203	54.8547	3479.8020
Distance to motorway	10708.6000	3469.3260	1612.2030	16767.7900
Distance to rail station	947.8918	799.5115	98.5323	6581.5550
LSOA with subway station	.0939	.2919	0	1
Distance to CBD	15956.5400	4182.4410	6764.1040	26638.7300
Flood risk	1.8500	2.0593	0	12
Distance between dwellings	5.7369	3.7081	0	30.2541
Population density	5937.7260	3200.4270	147.1444	18950.5700
Distance to river	12577.9600	3816.4930	4168.8740	21304.2200
Distance to woodland	2743.6410	1826.0180	111.6141	7484.9000

Table 2 Employment Density Regression Results

Variables	*Model 1*	*Model 2*	*Model 3*
Local agglomoeration, **WE**	-0.884787	-0.727337	-0.729283
	(-2.174914)	(-1.853279)	(-1.899910)
Ln house price, **P**	0.130271	0.049483	-0.326599
	(0.168999)	(0.066239)	(-0.435694)
Global agglomeration, **G**	0.000172	0.000091	0.000140
	(4.346957)	(2.085505)	(3.665982)
Interaction of agglomeration and flood risk, $\mathbf{F}^{\mathbf{G}}$	-	0.000066	0.000177
		(3.422051)	(3.063213)
Distance to nearest A road	-0.000835	-0.000791	-0.000755
	(-6.257041)	(-5.911388)	(-5.696115)
Distance to nearest B road	-0.000094	-0.000062	-0.000079
	(-1.218508)	(-0.820446)	(-1.058432)
Distance to motorway	0.000005	0.000007	-0.000005
	(0.115300)	(0.150760)	(-0.123891)
Distance to railstation	-0.000168	-0.000160	-0.000144
	(-2.389765)	(-2.307564)	(-2.116905)
lsoa with station	0.386380	0.320464	0.374945
	(3.048185)	(2.374716)	(2.842419)
Distance to CBD	-0.000050	-0.000029	-0.000035
	(-0.901808)	(-0.535511)	(-0.655665)
Floodrisk, **F**	-0.045753	-0.235456	-0.131190
	(-2.350618)	(-4.013028)	(-3.869397)
Distance between dwellings	-0.016974	-0.017311	-0.018514
	(-1.268686)	(-1.253801)	(-1.356802)
Population density	-0.000035	-0.000035	-0.000034
	(-1.815453)	(-1.792244)	(-1.761623)
Income deprivation	0.450839	0.550885	0.335696
	(1.028177)	(1.231570)	(0.759639)
Lambda	0.205333	0.132866	0.121772
	(18.511811)	(10.664825)	(14.934978)
Constant	9.277453	9.967614	14.190487
	(1.042652)	(1.059728)	(1.497248)
N	841	841	841
Diagnostic p-values:			
Sargan	0.00154581	0.170382	0.0530044
Hausman WE	0.102357	0.102357	0.102357
Hausman ln_house_price	0.0234306	0.0234306	0.0234306
Hausman agglomeration	0.480984	0.480984	0.480984
Hausman interaction of agglomeration and flood risk	-	0.000462752	0.0658513

Table 2 Employment Density Regression Results (*continued*)

Variables	*Model 4*	*Model 5*	*Model 6*
Local agglomoeration, **WE**	-	-	-
Ln house price, **P**	0.342991	0.214588	-0.161078
	(0.467063)	(0.297213)	(-0.224971)
Global agglomeration, **G**	9.7999e-005	2.96391e-005	7.88601e-005
	(5.05937)	(1.09692)	(4.08043)
Interaction of agglomeration and flood risk, $\mathbf{F}^{\mathbf{G}}$	-	6.72633e-005	0.000177796
		(3.56503)	(3.20982)
Distance to nearest A road	-0.000838	-0.000794	-0.000753
	(-6.47103)	(-6.05668)	(-5.85642)
Distance to nearest B road	-5.796e-005	-3.1551e-005	-4.7202e-005
	(-0.798148)	(-0.434318)	(-0.672796)
Distance to motorway	8.17409e-006	9.16273e-006	-3.2566e-006
	(0.189065)	(0.216161)	(-0.0794287)
Distance to railstation	-0.000119	-0.000118	-0.000102
	(-1.84191)	(-1.84439)	(-1.63223)
lsoa with station	0.414194	0.339102	0.396132
	(3.32274)	(2.53731)	(3.04107)
Distance to CBD	-2.3703e-006	1.0383e-005	4.0529e-006
	(-0.0484833)	(0.215421)	(0.0872567)
Floodrisk, **F**	-0.0448333	-0.236989	-0.131014
	(-2.34787)	(-4.1468)	(-3.99301)
Distance between dwellings	-0.0227856	-0.0221116	-0.0233901
	(-1.7694)	(-1.65036)	(-1.77526)
Population density	-2.2319e-005	-2.5197e-005	-2.4206e-005
	(-1.24586)	(-1.34824)	(-1.31685)
Income deprivation	0.422762	0.524373	0.305319
	(0.987209)	(1.19117)	(0.706812)
Lambda	0.180611	0.114387	0.0916093
	(72.6992)	(20.1765)	(105.708)
Constant	2.12389	3.67337	7.99814
	(0.259222)	(0.422029)	(0.907697)
N	841	841	841
Diagnostic p-values:			
Sargan	0.000485505	0.0899364	0.0173073
Hausman WE	-	-	-
Hausman ln_house_price	0.0234306	0.0234306	0.0234306
Hausman agglomeration	0.480984	0.480984	0.480984
Hausman interaction of agglomeration and flood risk	-	0.000462752	0.0658513

Dependent variable is employment density (**E**)
t-statistics in parentheses.
In Models 2,5 interaction of agglomeration and flood risk = agglomeration * flood risk; flood risk is continuous.
In Models 3,6 interaction of agglomeration and flood risk = agglomeration * flood risk dummy variable; flood risk dummy variable is defined as one when the flood risk variable is greater than 1.