Using dynamic spatial panel models to simulate housing affordability

Bernard Fingleton
University of Cambridge

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Introduction

- affordability is a major policy issue that has increasingly become a concern for UK Government as house prices have risen dramatically in recent years in relation to wages
- This is partly because of the importance of affordability for the recruitment and retention of key workers
- Political reasons, voter disaffection as housing costs continue to rise

What is affordability?

- The relevant variables are the price of houses and the level of incomes and the relation between the two.

What is affordability?

- affordability is defined here as an area's mean house price divided by the mean annual wage level available from employment in the area.

Year 2000 prices

	price	wage	ratio
• Cambridge	£194591	£18245	10.66
• Hackney	£185341	£27990	6.62
• Glasgow	£78090	£16640	4.69

- 'ten years ago house prices were 3.5 times people's annual salary' now 'house prices are 6 times annual salary', speech delivered by the Rt. Hon. John Prescott (The then Deputy Prime Minister) on 1st April 2005.

Effects of lack of affordability

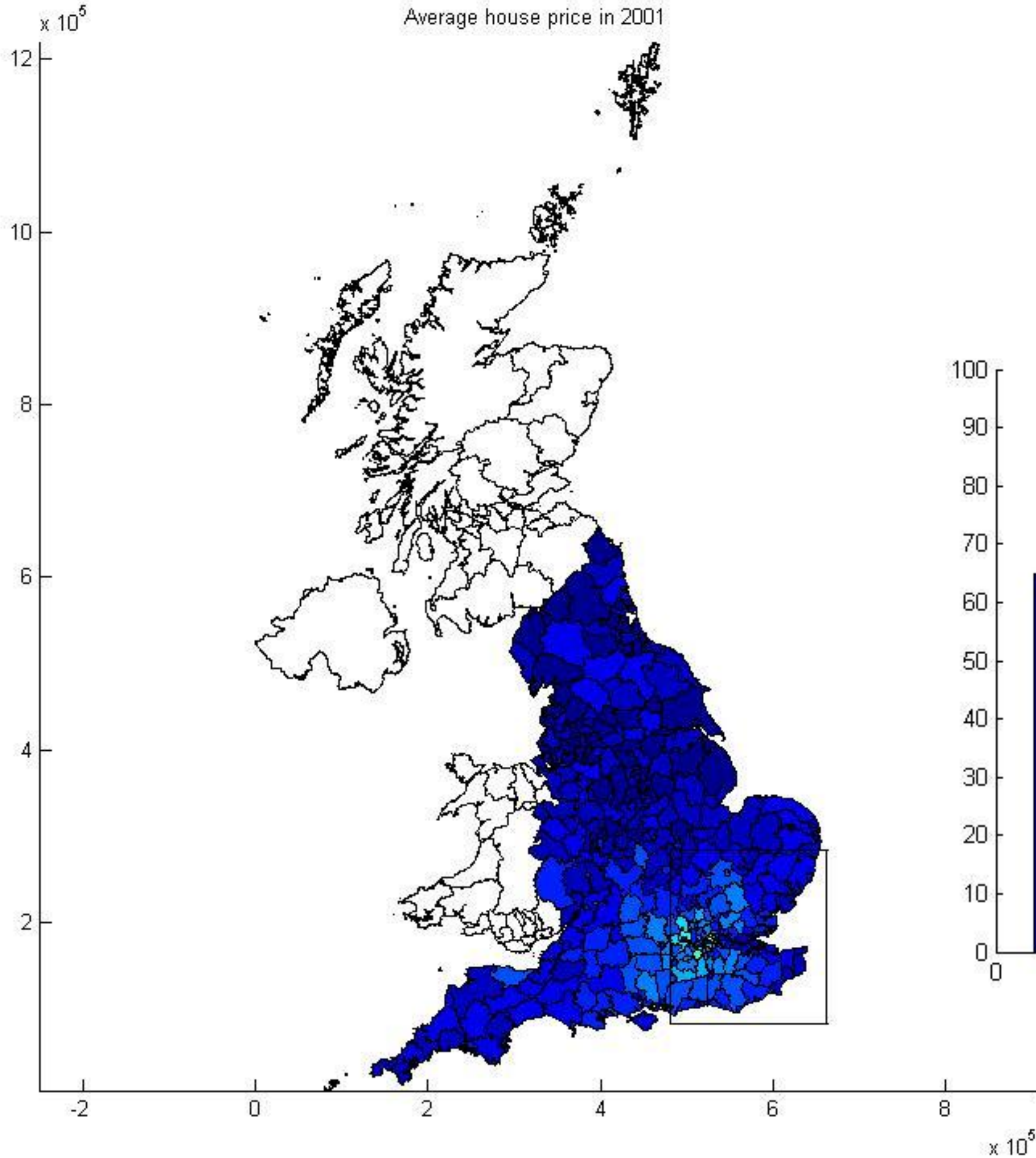
- what we mean by housing being affordable is when people who work in an area can also afford to live in the area
  - relatively few people who work in central London can afford to live there, so there housing is unaffordable
  - In the Provinces, both house prices and wages are lower, but housing is more affordable

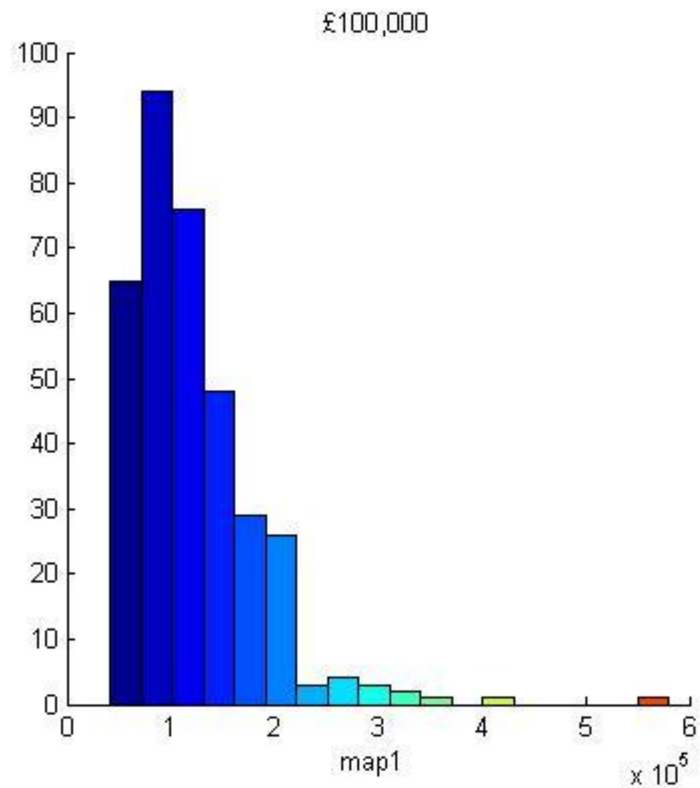
Effects of lack of affordability

- if people cannot afford to live and work in the same place, that generates <u>commuting</u>
  - Environmental impacts (eg pollution, impact of building new lines such as Crossrail, HS2)
  - Travel costs for commuters
  - An annual rail and London underground season ticket now costs between £3,600 and £6,000, depending on the length of the journey

Effects of lack of affordability

- Low affordability in the SE causes problems for labour mobility, people cannot afford to sell in the Provinces and move to the SE
  - labour shortages in the SE and an excess of labour in Provinces, leading to disparities in unemployment and labour market failure
  - Increasing wages in the SE to promote labour mobility can lead to wage inflation





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Districts_h_prices.m

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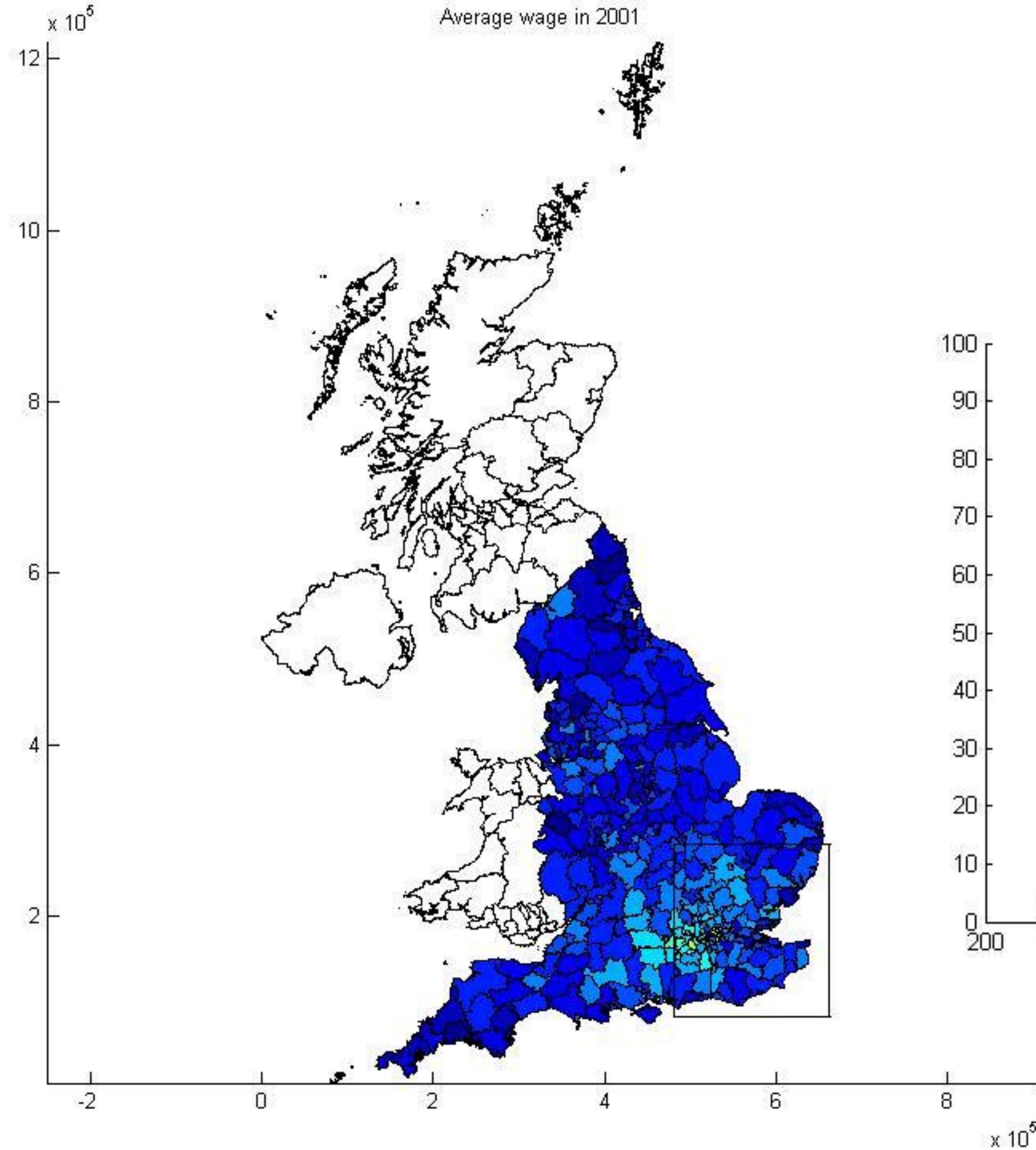

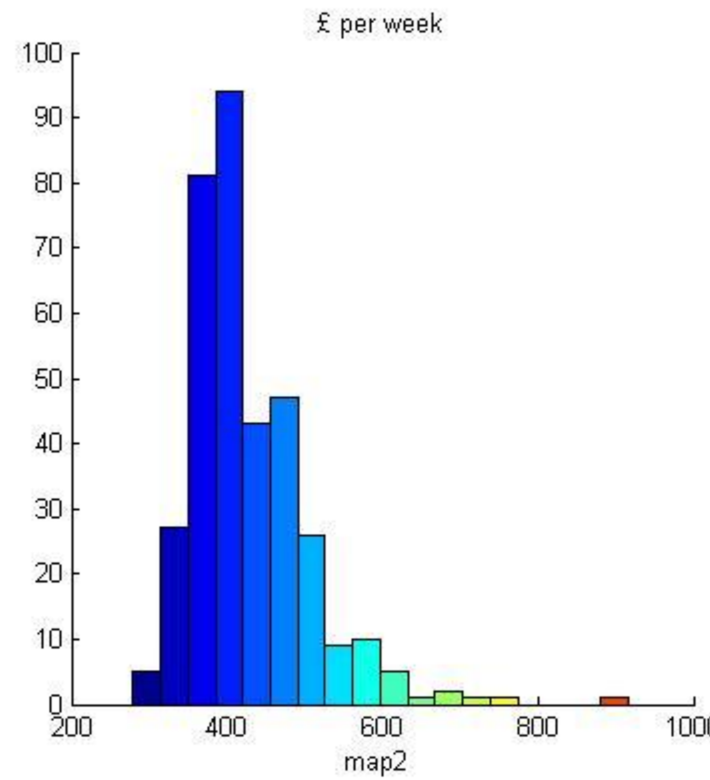

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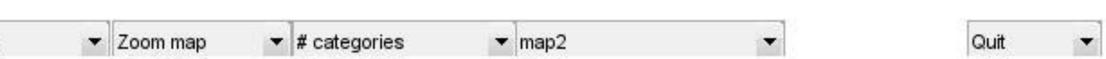
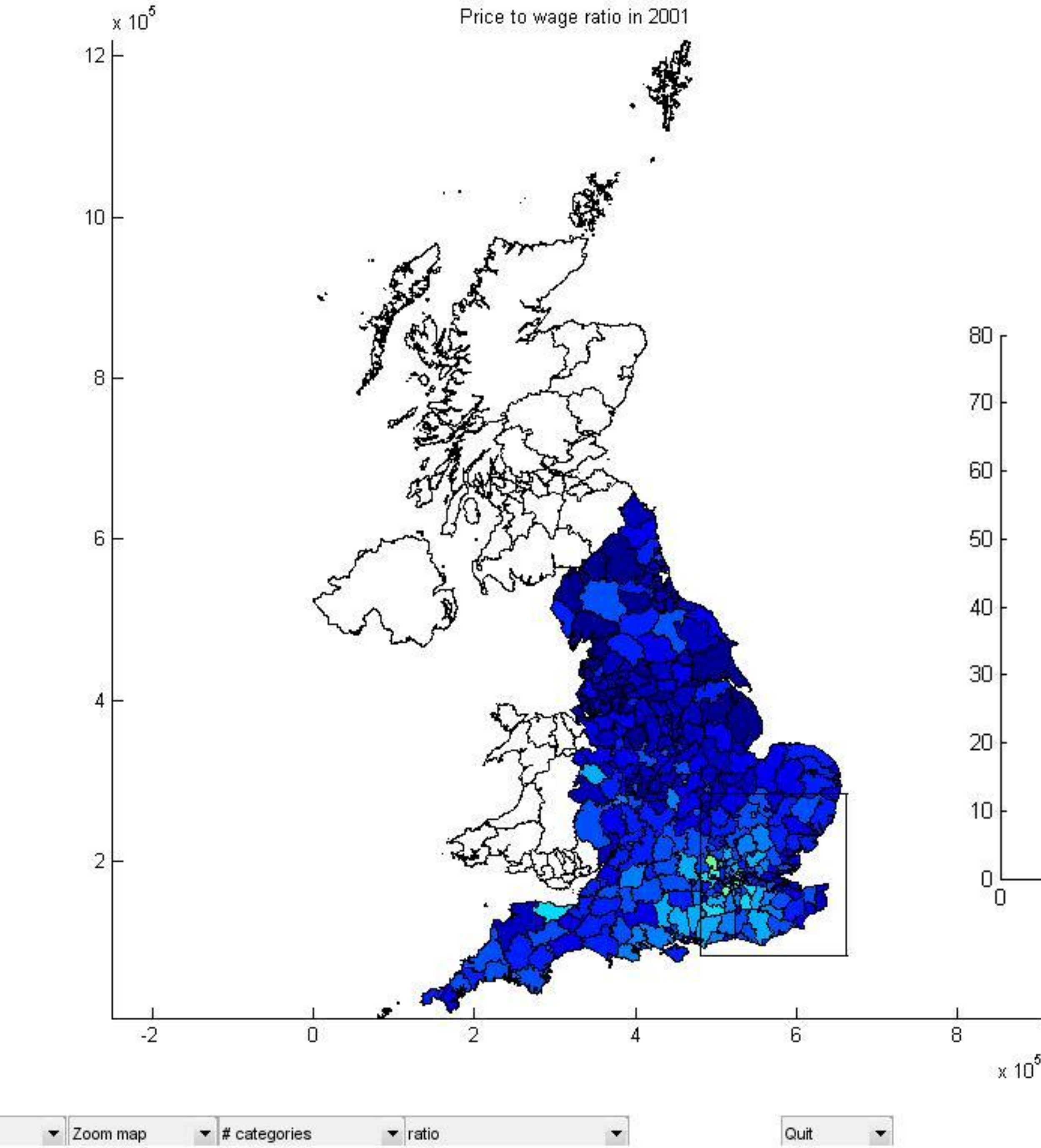
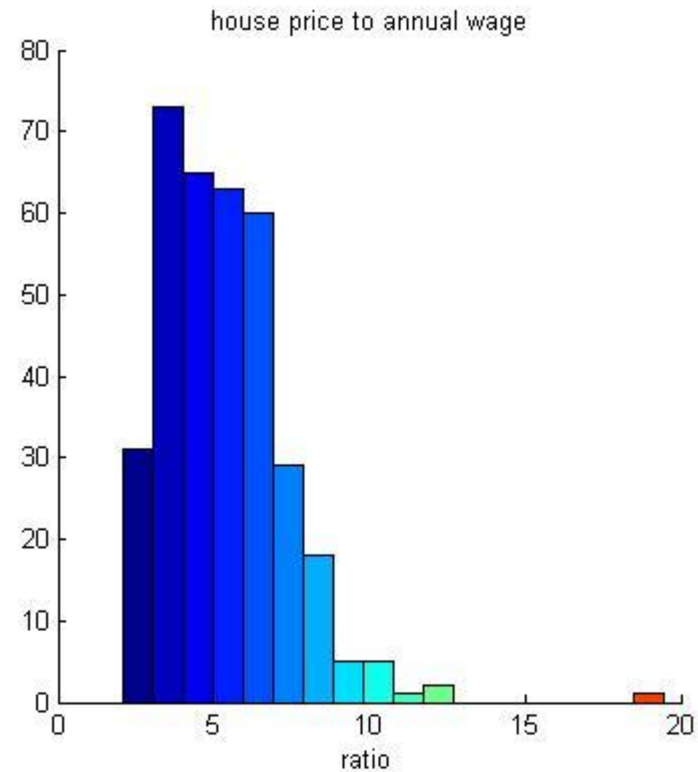
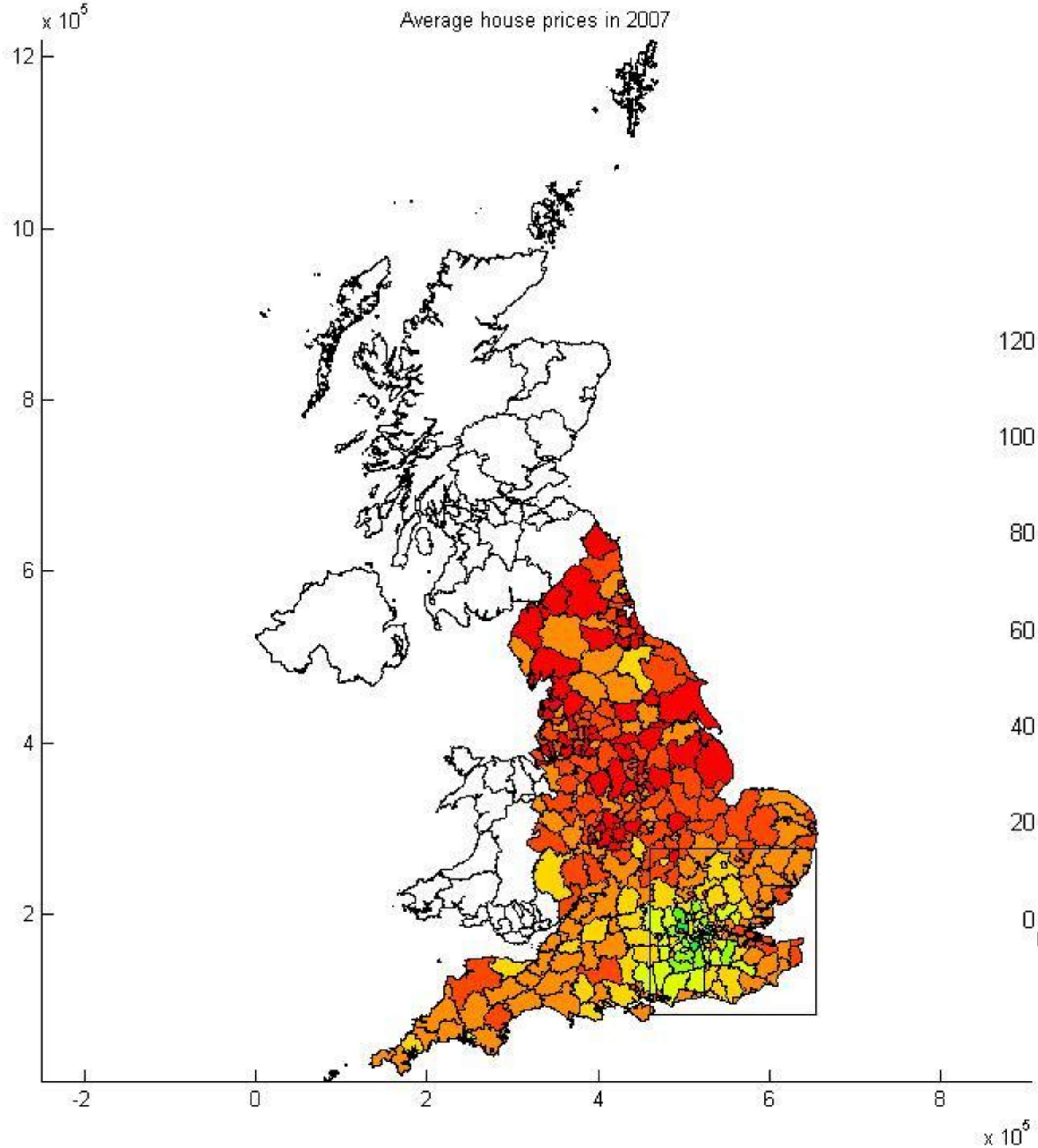
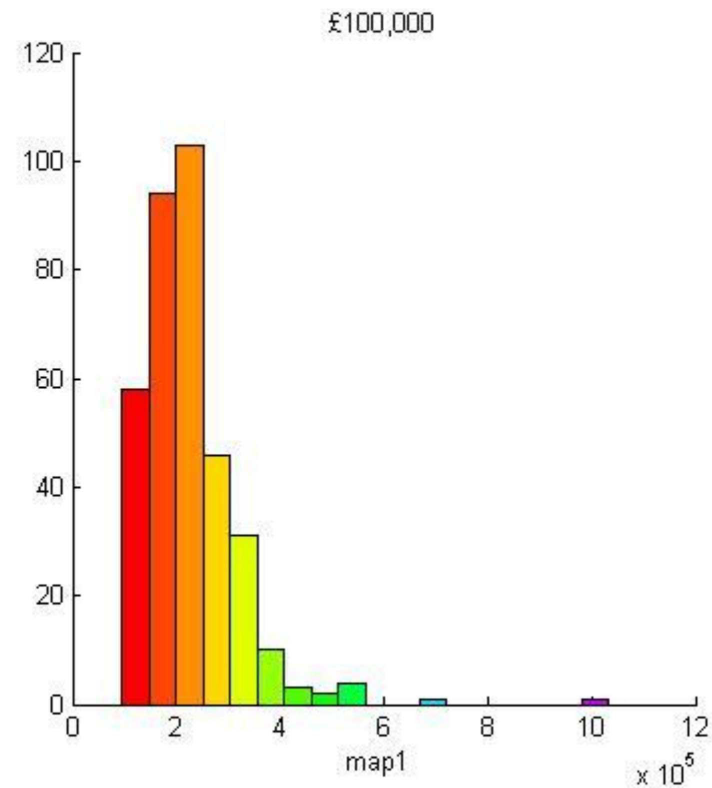






house_price_actual.m
Districts_h_prices.m





house_price_actual.m
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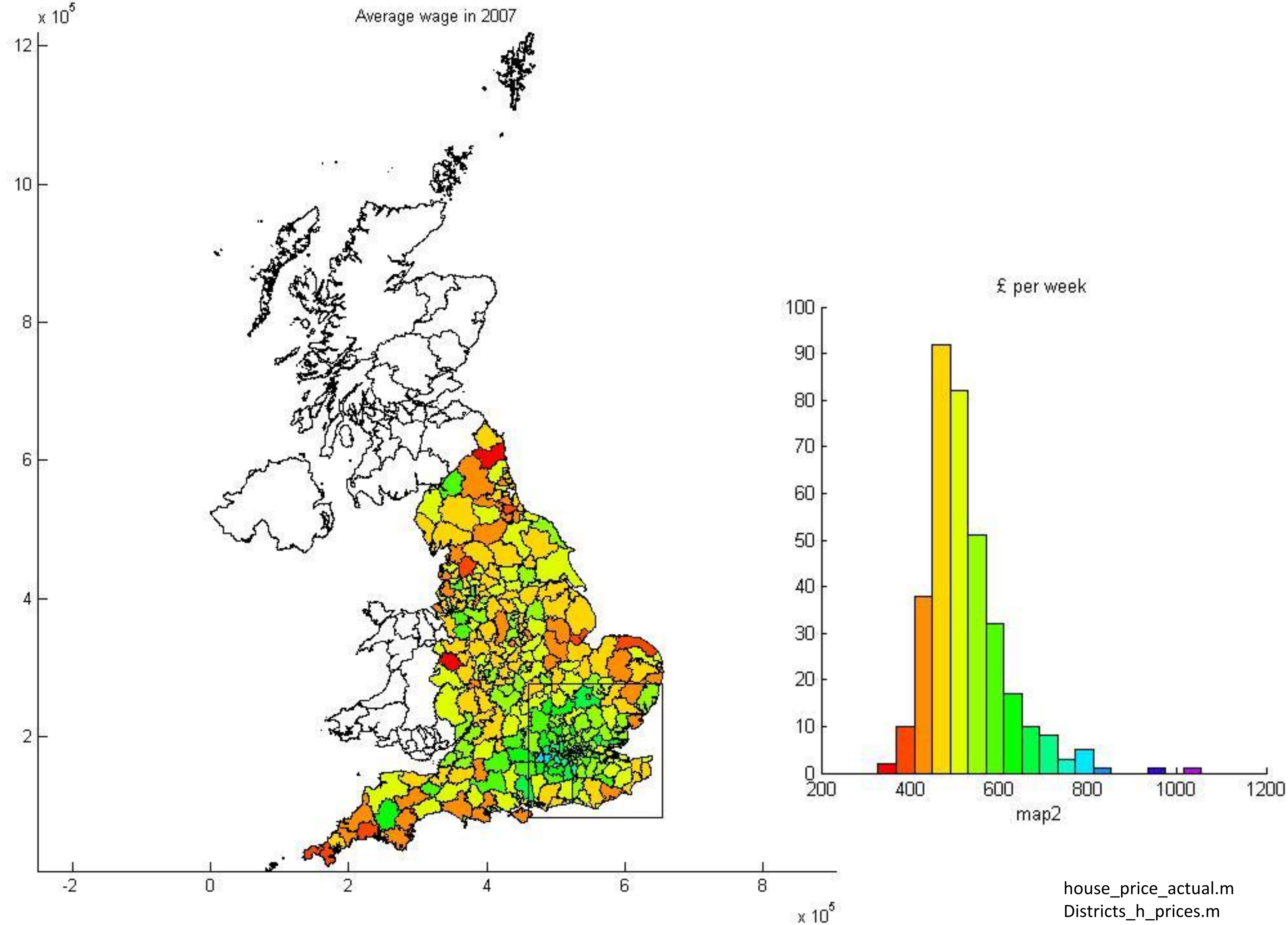

house_price_actual.m
Districts_h_prices.m

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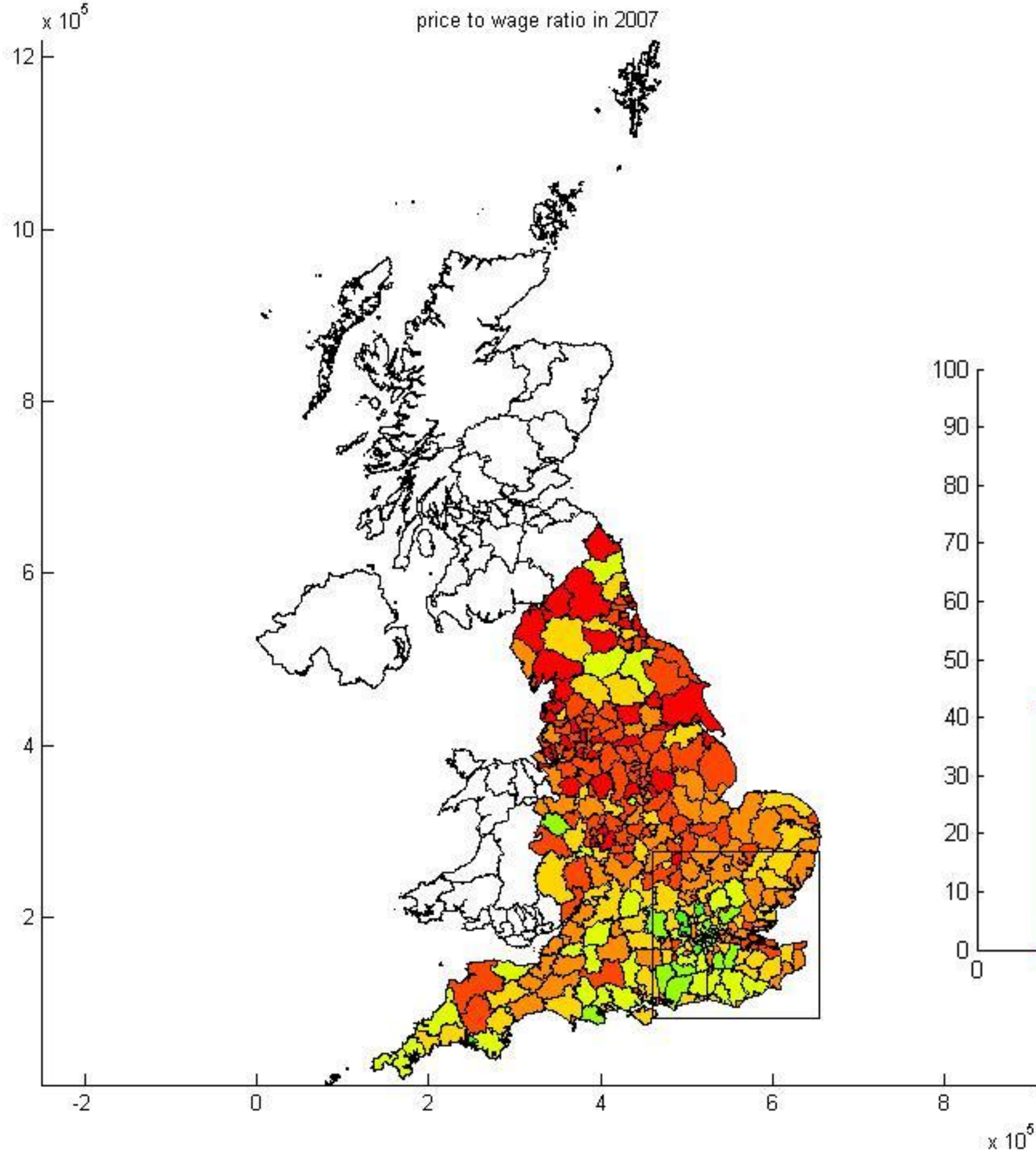

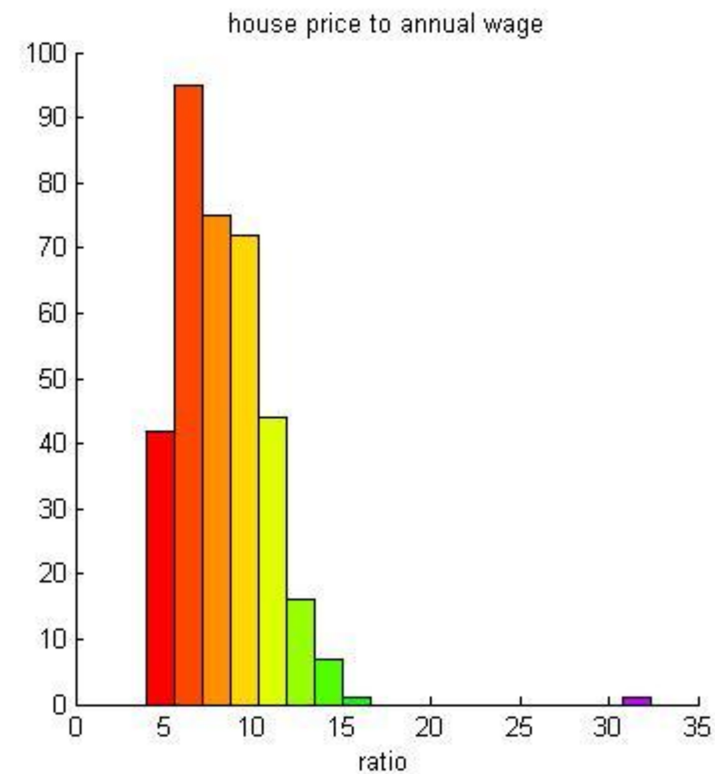

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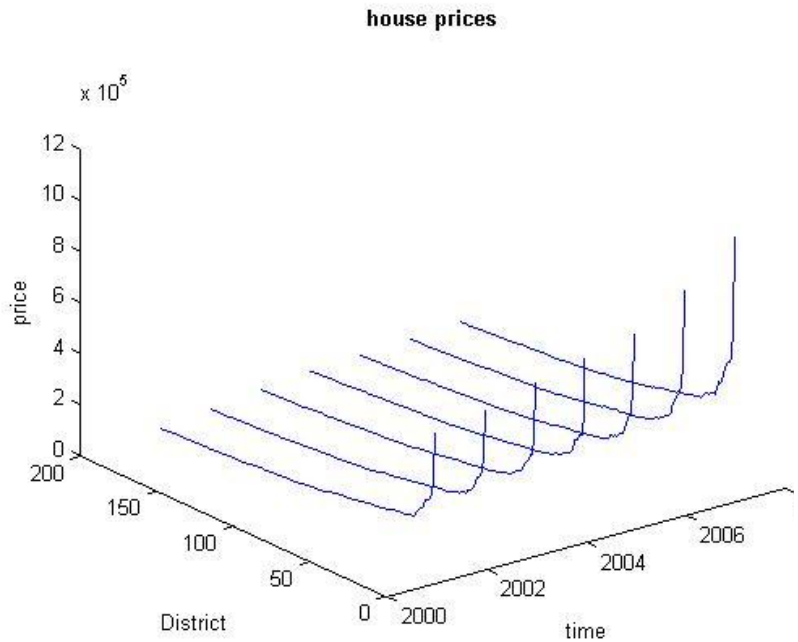
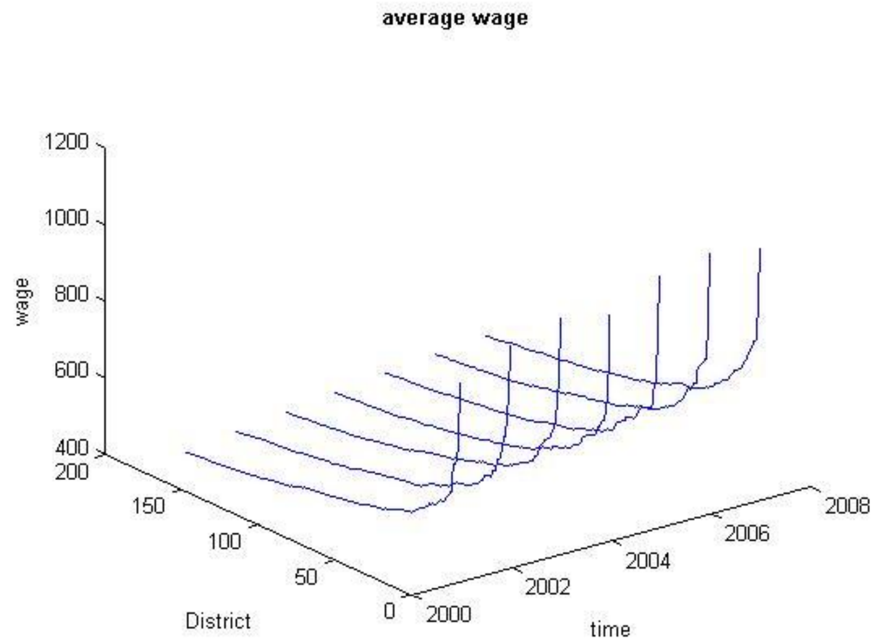
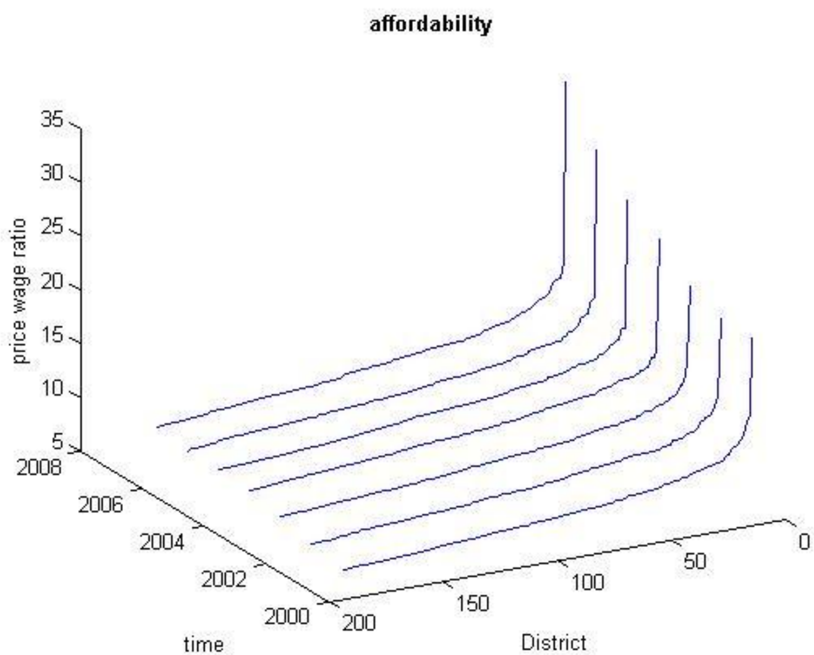
Districts_h_prices.m







house_price_actual.m

The solution to the low affordability problem?

- Government policy is to <u>increase the supply</u> of housing in order to improve affordability
- BUT this expansion in housing supply is also to be accompanied by an expansion in employment.
- The outcome is that there will also be an <u>increase in the demand</u> for housing
- There is a possibility that in some areas <u>affordability may worsen</u>, not improve

Aim

- To estimate a spatial panel model in which house prices depend on supply and demand
- Use the model to simulate the impact of hypothetical increase in number of dwellings (stock of housing) in specific areas of the South East of England
- Moderate the effect on prices of contemporaneous increases in demand due to increased stock
- Bottom line, does affordability improve with additional supply?

a spatial panel model of house prices

- Demand function (*q* demanded on lhs)
- Supply function (*q* supplied on lhs)
- Reduced form (*p* on lhs)

demand

- Housing demand depends on mean wage levels (w) and total employment levels (E), combining to give <u>total income level</u> (wE)
- Housing demand in district i depends on total income from jobs <u>within commuting distance</u> of i = I_i^c
- Use Census commuting flow data from i to job locations to weight total income in each district
  - We give less weight to jobs that are further away because the cost of travelling from i will be more, so fewer workers will actually commute from i

demand

- Other determinants of the quantity of housing demanded at *i*
- Price of housing at, and near to, *i*
- other unmeasured effects
  - demand coming from non-wage earners
    - such as the retired and students,
  - social quality of the neighbourhood
  - local taxes, etc..
  - Amenity etc.
  - Some Central London Boroughs consistently attract foreign investment
    - £187bn = the total value of housing stock in the boroughs of Westminster and Kensington & Chelsea, £11bn more than the value of the entire housing stock of Wales
- These unmeasured effects are represented by random disturbances

demand

$$q_{it} = f(I_{it}^{c}, p_{it}, p_{it-1}, Wp_{it}, \omega_{it})$$

$$q_{it} = a_1 I_{it}^{c} - a_2 p_{it} - a_3 p_{it-1} + a_4 Wp_{it} + \omega_{it}$$

- Quantity demanded positively related to

  income within commuting distance

- Quantity demanded is negatively related to

  the price of housing at t, t-1

- Quantity demanded positively related to

  Prices nearby

  Given that high prices drive down demand, it is assumed that high prices 'nearby' will cause displaced demand to spill over into *i*

- Quantity demanded affected by other unmeasured factors captured by the disturbance term

supply

$$q_{it} = f(p_{it}, p_{it-1}, S_{it}, Wp_{it}, \varsigma_{it})$$

$$q_{it} = b_1 p_{it} + b_2 p_{it-1} + b_3 S_{it} - b_4 Wp_{it} + \varsigma_{it}$$

- <u>Quantity supplied </u>at *i* is
increasing in price at t, t-1

Positively related to the <u>stock of dwellings</u>

•<u>Quantity supplied </u>at *i* is
Decreasing in average price nearby
high prices nearby will attract supply
away from *i*, hence the negative sign
for b_4 . This is referred to as a
<u>displaced supply effect</u>

•Affected by other <u>unmeasured factors</u>
captured by the disturbance term

Reduced form

reduced form is obtained by <u>normalizing</u> the supply function with respect to *p*

$$p_{it} = \frac{1}{b_1} q_{it} - \frac{b_2}{b_1} p_{it-1} - \frac{b_3}{b_1} S_{it} - \frac{b_4}{b_1} Wp_{it} + \frac{\varsigma_{it}}{b_1}$$

Then substituting for *q* using the demand function, thus

$$p_{it} = c_1 \left[a_1 I_{it}^{c} - a_2 p_{it} - a_3 p_{it-1} + a_4 Wp_{it} + \omega_{it} \right] - c_2 p_{it-1} - c_3 S_{it} - c_4 Wp_{it} + \xi_{it}$$

$$p_{it} = \gamma p_{it-1} + \rho_1 Wp_{it} + \beta_1 I_{it}^{c} + \beta_2 S_{it} + \varepsilon_{it}$$

Reduced form

$$p_{it} = \gamma p_{it-1} + \rho_1 W p_{it} + \beta_1 I_{it}^{c} + \beta_2 S_{it} + \varepsilon_{it}$$

Note that the average price nearby has a special coefficient ρ_1 symbolizing that it is the <u>net effect</u> of the displaced demand and displaced supply effects

Likewise we denote the coefficient on the temporal lag by γ

We treat time-invariant factors such as amenity as a component of the error term

data

- 353 Local Authority Districts
- Years 2001-2007
- Data on
  - average house prices in each District
  - Average wage by place of employment
  - Total number of employees
  - Number of dwellings in each District

data

$$p_{it} = \gamma p_{it-1} + \rho_1 W p_{it} + \beta_1 I_{it}^c + \beta_2 S_{it} + \varepsilon_{it}$$

$$I_{it}^c = \sum_{k=1}^{N} \tilde{C}_{ik} I_{kt} \qquad\qquad Wp_{it} = \sum_{k=1}^{N} w_{ik} p_{kt}$$

<u>Sample</u> of 353 by 353 Commuting matrix

2001 census - UK travel flows (local authority)

	Luton	Mid Bedfordshire	Bedford	South Bedfordshire	Bracknell Forest
Luton	54399	1071	865	6876	28
Mid Bedfordshire	3961	29925	5675	1662	30
Bedford	1888	4458	50165	599	17
South Bedfordshire	9446	987	716	27556	43
Bracknell Forest	12	0	8	6	30840

$\tilde{C} =$

0.6624	0.0130	0.0105	0.0837	0.0003
0.0623	0.4706	0.0892	0.0261	0.0005
0.0269	0.0634	0.7137	0.0085	0.0002
0.1654	0.0173	0.0125	0.4824	0.0008
0.0002	0.0000	0.0001	0.0001	0.5156

$W =$

0.0000	0.0386	0.0312	0.2480	0.0010
0.1176	0.0000	0.1686	0.0494	0.0009
0.0938	0.2215	0.0000	0.0298	0.0008
0.3195	0.0334	0.0242	0.0000	0.0015
0.0004	0.0000	0.0003	0.0002	0.0000

Full specification: random effects

$$p_{it} = \gamma p_{it-1} + \rho_1 \sum_{k=1}^{N} w_{ik} p_{kt} + \beta_1 I_{it}^{c} + \beta_2 S_{it} + \varepsilon_{it} \qquad i = 1,\ldots,N; t = 1,\ldots,T$$

$$\varepsilon_{it} = \rho_2 \sum_{k=1}^{N} m_{ik} \varepsilon_{kt} + u_{it}$$

$$u_{it} = \mu_i + \nu_{it}$$

$M = W$ an N x N matrix of known spatial weights

$\mu_i \sim iid(0, \sigma_{\mu}^2)$ the individual-specific time-invariant effect

$\nu_{it} \sim iid(0, \sigma_{\nu}^2)$ the remainder effect

$$\mathrm{cov}(\mu_i, \nu_{it}) = 0$$

Features dynamic specification with spatial lag and spatial <u>autoregressive</u> process for <u>disturbances</u>

Alternative estimators

- OLS
  - does not deal with the endogeneity of *Wy*
  - does not deal with the endogeneity of *y*(t-1)
  - ignores the individual effects μ
  - Ignores the SAR process for the disturbances
- Fixed effects (Within) estimator
  - wipes out the individual effects μ
  - does not deal with the endogeneity of *Wy*
  - does not deal with the endogeneity of *y*(t-1)
  - does not deal with the SAR process for the disturbance

Alternative estimators

- Maximum Likelihood
  - Elhorst (2005) combines cross-section dependence with autoregressive (temporal) dependence
  - Yu, de Jong and Lee (2008) Quasi Maximum Likelihood Estimator for spatial dynamic panel data with fixed effects
  - Neither accounts for endogeneity of regressors nor full panoply of spatial effects
- GMM
  - One way that does is GMM approach of Arellano and Bond (1991) and Blundell and Bond (1998) extended to the spatial case

BFP estimation

- Baltagi et. al. (2013) develop an estimator for this dynamic spatial panel model with autoregressive spatial disturbances
  - Baltagi BH, Fingleton B and A Pirotte (2013) ‘Estimating and Forecasting with a Spatial Dynamic Panel Model’ *Oxford Bulletin of Economics and Statistics* published online: 9 JAN 2013 | DOI: 10.1111/obes.12011
- Based on the work of Arellano and Bond (1991), and Mutl(2006), using a spatial generalized method of moments (GMM) estimator proposed by Kapoor, Kelejian and Prucha (2007).

BFP estimation - summary

- These moments provide the matrices of instruments leading to consistent IV/GMM estimates of $\gamma, \rho_1, \beta_1, \beta_2$
- the residuals provided by these estimates allow estimation of $\rho_2, \sigma_\nu^2, \sigma_\mu^2$
  - Based on GMM, KKP(2007)
- Following Arellano and Bond (1991) and Baltagi et al (2013), we obtain final estimates of $\gamma, \rho_1, \beta_1, \beta_2$
  - via a two-step spatial GMM estimator

Arellano and Bond (1991)

- The basic idea is
- take <u>first-differences</u> to remove unobserved time-invariant individual effects μ
- <u>instrument</u> the endogenous right-hand-side variables in the first-differenced equations using levels
  - Assume levels not correlated with differenced disturbances

Alternative estimators for BFP

- The basic Arellano and Bond (1991) GMM estimator
  - differences out the individual effects
  - handles the presence of the lagged dependent variable and spatial lag *Wy* by using appropriate orthogonality conditions
  - However, it ignores the SAR process for the disturbances
- Mutl (2006)
  - mixes the Arellano and Bond (1991) and Kapoor, Kelejian and Prucha (2007) approaches to estimate a dynamic model with spatially correlated disturbances
  - accounts for the lagged dependent variable and the SAR-RE process in the spirit of KKP (2007)
  - However, does not include the spatial lag *Wy*

BFP’s GMM-SL-SAR-RE estimator

- BFP propose a spatial GMM estimator in the spirit of Arellano and Bond (1991) and Mutl (2006) however
- Our model includes
- BOTH temporal and spatial lags on the endogenous variable
- together with SAR-RE disturbances
- Monte Carlo simulations show GMM-SL-SAR-RE superior to OLS, Within, Arellano&Bond, Mutl

BFP's GMM-SL-SAR-RE estimator

- Two important elements
- orthogonality conditions
  - Arellano and Bond (1991)
  - spatial
- KKP

Kapoor, M., Kelejian, H.H. and Prucha, I.R. (2007). 'Panel data models with spatially correlated error components', *Journal of Econometrics*, Vol. 140, pp. 97-130

BFP's GMM-SL-SAR-RE estimator

$$p_{it} = \gamma p_{it-1} + \rho_1 \sum_{k=1}^{N} w_{ik} p_{kt} + \beta_1 I_{it}^{c} + \beta_2 S_{it} + \varepsilon_{it} \qquad i = 1, \ldots, N; t = 1, \ldots, T$$

$$\varepsilon_{it} = \rho_2 \sum_{k=1}^{N} m_{ik} \varepsilon_{kt} + u_{it}$$

$$u_{it} = \mu_i + \nu_{it}$$

$M = W$ an N x N matrix of known spatial weights

$\mu_i \sim iid(0, \sigma_\mu^2)$ the individual-specific time-invariant effect

$\nu_{it} \sim iid(0, \sigma_\nu^2)$ the remainder effect

$\text{cov}(\mu_i, \nu_{it}) = 0$

$$u_{it} = \mu_i + \nu_{it}$$

we eliminate the individual effects μ which are correlated with the lagged dependent variable, by differencing the model yielding

$$\Delta p_{it} = \gamma \Delta p_{it-1} + \rho_1 \sum_{j=1}^{N} w_{ij} \Delta p_{jt} + \Delta x_{it} \beta + \Delta \nu_{it}$$

Use the lagged levels as instruments for the equations in first-differences

$$\Delta p_{it} = \gamma \Delta p_{it-1} + \rho_1 \sum_{j=1}^{N} w_{ij} \Delta p_{jt} + \Delta x_{it} \beta + \Delta \nu_{it}$$

Assume simple autoregressive model

$p_{it} = \gamma p_{it-1} + \mu_i + \nu_{it}$

$\Delta p_{it} = \gamma \Delta p_{it-1} + \Delta \nu_{it}$ corr$(\Delta p_{it-1}, \Delta \nu_{it}) \neq 0$ thus valid instruments for $\Delta p_{i,t-1}$, needed

$p_{it} - p_{it-1} = \gamma (p_{it-1} - p_{it-2}) + (\nu_{it} - \nu_{it-1})$

independence of lagged (t-2) levels and differenced error terms

$t = 2, p_{i2} - p_{i1} = \gamma (p_{i1} - p_{i0}) + (\nu_{i2} - \nu_{i1})$ *no* p_{i0}

$t = 3, p_{i3} - p_{i2} = \gamma (p_{i2} - p_{i1}) + (\nu_{i3} - \nu_{i2})$ $corr(p_{i2}, (\nu_{i3} - \nu_{i2})) \neq 0, corr(p_{i,1}, (\nu_{i3} - \nu_{i2})) = 0$

$t = 4, p_{i4} - p_{i3} = \gamma (p_{i3} - p_{i2}) + (\nu_{i4} - \nu_{i3})$ $corr(p_{i3}, (\nu_{i4} - \nu_{i3})) \neq 0, corr(p_{i,1}, (\nu_{i4} - \nu_{i3})) = 0$

$corr(p_{i,2}, (\nu_{i4} - \nu_{i3})) = 0$

$p_{it} - p_{it-1} = \gamma (p_{it-1} - p_{it-2}) + (\nu_{it} - \nu_{it-1})$ $corr(p_{i,t-2}, (\nu_{it} - \nu_{it-1})) = 0$

$corr(p_{i,t-3}, (\nu_{it} - \nu_{it-1})) = 0$

$corr(p_{i,t-4}, (\nu_{it} - \nu_{it-1})) = 0$

etc

there is an extra valid instrument for each extra period forward so that by period T, the set of valid instruments becomes

$(p_{i1}, p_{i2}, ..., p_{iT-2})$

$$E(p_{il}\Delta v_{it}) = 0 \quad \forall i, l = 1, 2, \ldots, T-2; t = 3, 4, \ldots, T$$

inst.	uncorrelated		
$p_{i,1}$	$\Delta v_{i,3}$	$\Delta v_{i,4}$	$\Delta v_{i,5}$
$p_{i,2}$		$\Delta v_{i,4}$	$\Delta v_{i,5}$
$p_{i,3}$			$\Delta v_{i,5}$

s

$$Z_i = \begin{bmatrix} p_{i1} & 0 & 0 & \ldots. & 0 & \ldots & 0 \\ 0 & p_{i1} & p_{i2} & \ldots & 0 & \ldots & 0 \\ . & . & . & \ldots & . & . & . \\ 0 & 0 & 0 & \ldots & p_{i1} & \ldots & p_{i,T-2} \end{bmatrix}$$

Δv_i is the $(T-2)$ vector $(\Delta v_{i3}, \Delta v_{i4}, \ldots, \Delta v_{iT})'$

$$E\left(Z_i' \Delta v_i\right) = 0$$

BFP's GMM-SL-SAR-RE estimator : moment conditions

1. <u>orthogonality conditions, Arellano and Bond (1991)</u>

$$E(p_{il}\Delta v_{it}) = 0 \quad \forall i, l = 1, 2, ..., T-2; t = 3, 4, ..., T$$

n.b. Lagged values of endogenous *y,x* variables dated t−2 and earlier can be used as instruments for the equations in first-differences

$$E(x_{k,im}\Delta v_{it}) = 0 \quad \forall i, k, \; m = 1, 2, \ldots, T; t = 3, 4, \ldots, T$$

assumes that the explanatory variables $x_{k,im}$ are strictly exogenous

rules out correlation between *x* and *v* at any dates

2. <u>Spatial orthogonality conditions</u>

use spatially dependent and explanatory variables as instruments

$$E(\sum_{i \neq j} w_{ij} p_{jl} \Delta v_{it}) = 0 \qquad l = 1, 2, ..., T-2; t = 3, 4, ..., T$$

$$E(\sum_{i \neq j} w_{ij} x_{k,jm} \Delta v_{it}) = 0 \quad \forall i, k, \quad m = 1, 2, ..., T; t = 3, 4, ..., T$$

the non-spatial instruments

$$Z = \begin{pmatrix} Z_3 & 0 & \cdots & 0 \\ 0 & Z_4 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & Z_T \end{pmatrix}$$

$$Z_t = \left(p_1, \ldots, p_{t-2}, x_1, \ldots, x_T \right)$$

the spatial instruments

$$Z^s = \begin{pmatrix} Z_3^s & 0 & \cdots & 0 \\ 0 & Z_4^s & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & Z_T^s \end{pmatrix}$$

$$Z_t^S = \left(p_1^S, \ldots, p_{t-2}^S, x_1^S, \ldots, x_T^S \right)$$

If we stack the matrices Z and Z^s, we obtain the valid instruments for the model

BFP DGP

BFP Data generating process

$$p_{it} = \gamma p_{it-1} + \rho_1 \sum_{k=1}^{N} w_{ik} p_{kt} + x_{it}\beta + \varepsilon_{it} \qquad i = 1,\ldots,N; t = 1,\ldots,T$$

$$\varepsilon_{it} = \rho_2 \sum_{k=1}^{N} m_{ik} \varepsilon_{kt} + u_{it}$$

$$u_{it} = \mu_i + \nu_{it}$$

$$\mu_i \sim iid(0, \sigma_\mu^2)$$

$$\nu_{it} \sim iid(0, \sigma_\nu^2)$$

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published online: 9 JAN 2013 DOI: 10.1111/obes.12011

KKP

The GM estimators of σ_1^2, σ_v^2 and ρ_2 are the solution of the sample moments

$$G\phi' - g = 0$$

$$G = \begin{bmatrix} \frac{2}{N(T-1)}\hat{e}'Q_0\hat{e}_{-1} & \frac{-1}{N(T-1)}\hat{e}'_{-1}Q_0\hat{e}_{-1} & 1 & 0 \\ \frac{2}{N(T-1)}\hat{e}'_{-2}Q_0\hat{e}_{-1} & \frac{-1}{N(T-1)}\hat{e}'_{-2}Q_0\hat{e}_{-2} & \frac{1}{N}t_1 & 0 \\ \frac{1}{N(T-1)}(\hat{e}'Q_0\hat{e}_{-2} + \hat{e}'_{-1}Q_0\hat{e}_{-1}) & \frac{-1}{N(T-1)}\hat{e}'_{-1}Q_0\hat{e}_{-2} & 0 & 0 \end{bmatrix}$$

$$g = \begin{bmatrix} \frac{1}{N(T-1)}\hat{e}'Q_0\hat{e} \\ \frac{1}{N(T-1)}\hat{e}'_{-1}Q_0\hat{e}_{-1} \\ \frac{1}{N(T-1)}\hat{e}'Q_0\hat{e}_{-1} \end{bmatrix}$$

$$\phi = \begin{bmatrix} \rho_2 & \rho_2^{\,2} & \sigma_\nu^2 & \sigma_1^2 \end{bmatrix}$$

$$G\begin{bmatrix} \rho_2 & \rho_2^{\,2} & \sigma_\nu^2 & \sigma_1^2 \end{bmatrix}' - g = \zeta(\rho_2 \quad \sigma_\nu^2 \quad \sigma_1^2)$$

solve by non – linear least squares

$$(\hat{\rho}_2, \hat{\sigma}_\nu^2, \hat{\sigma}_1^2) = \arg\min\{\zeta(\rho_2 \quad \sigma_\nu^2 \quad \sigma_1^2)'\zeta(\rho_2 \quad \sigma_\nu^2 \quad \sigma_1^2)\}$$

$$\sigma_\mu^2 = \frac{\sigma_1^2 - \sigma_\nu^2}{T}$$

BFP's GMM-SL-SAR-RE estimator

BFP modify the KKP approach as follows

1. First step, we use an IV/GMM estimator to get <u>consistent estimates</u> of γ ρ_1 and β

2. In the second GMM step, the resulting IV/GMM residuals are used to obtain consistent estimates of the autoregressive parameter ρ_2, σ_1^2, σ_v^2

$$\sigma_\mu^2 = \frac{\sigma_1^2 - \sigma_\nu^2}{T}$$

3. In the subsequent steps, given estimated ρ_2 we can obtain

$$\widehat{H}_N = \widehat{B}_N^{-1} = (I_N - \widehat{\rho}_2 W_N)^{-1}$$

following Arellano and Bond (1991)

$$V_N = \left[Z^{*\prime} \left(I_{T-2} \otimes \widehat{H}_N \right) (\Delta v)(\Delta v)' \left(I_{T-2} \otimes \widehat{H}_N' \right) Z^* \right]$$

$$(\gamma, \rho_1, \beta') \longrightarrow \hat{\delta}_2 = \left(\Delta\tilde{X}' Z^* \hat{V}_N Z^{*\prime} \Delta\tilde{X} \right)^{-1} \Delta\tilde{X}' Z^* \hat{V}_N Z^{*\prime} \Delta p$$

$$\Delta\tilde{X} = \left(\Delta p_{-1}, (I_{T-2} \otimes W_N) \Delta p, \Delta x \right)$$

$\Delta v \longleftarrow$ Differenced residuals

$Z^* \longleftarrow$ Matrix of instruments as defined by orthogonality conditions

Results : dynamic model with random effects and autoregressive errors

parameter	estimate	St. error	t ratio
γ	0.71295	0.01432	49.787
ρ_1	0.180534	0.0173965	10.3776
β_1	793.777	57.3665	13.8369
β_2	-2.625	0.173773	-15.1059
ρ_2	0.3905		
σ_ν^2	0.0010		
σ_μ^2	0.0001		

Parameter space conditions for stationarity, dynamic stability

$$|\gamma| < 1$$

$$e_{\min}^{-1} < \rho_1 < e_{\max}^{-1}$$

$$e_{\min}^{-1} < \rho_2 < e_{\max}^{-1}$$

$$|\gamma| < 1 - \rho_1 e_{\max}, \rho_1 > 0$$

$$|\gamma| < 1 - \rho_1 e_{\min}, \rho_1 < 0$$

house_prices_1.m

Results : static model with fixed effects

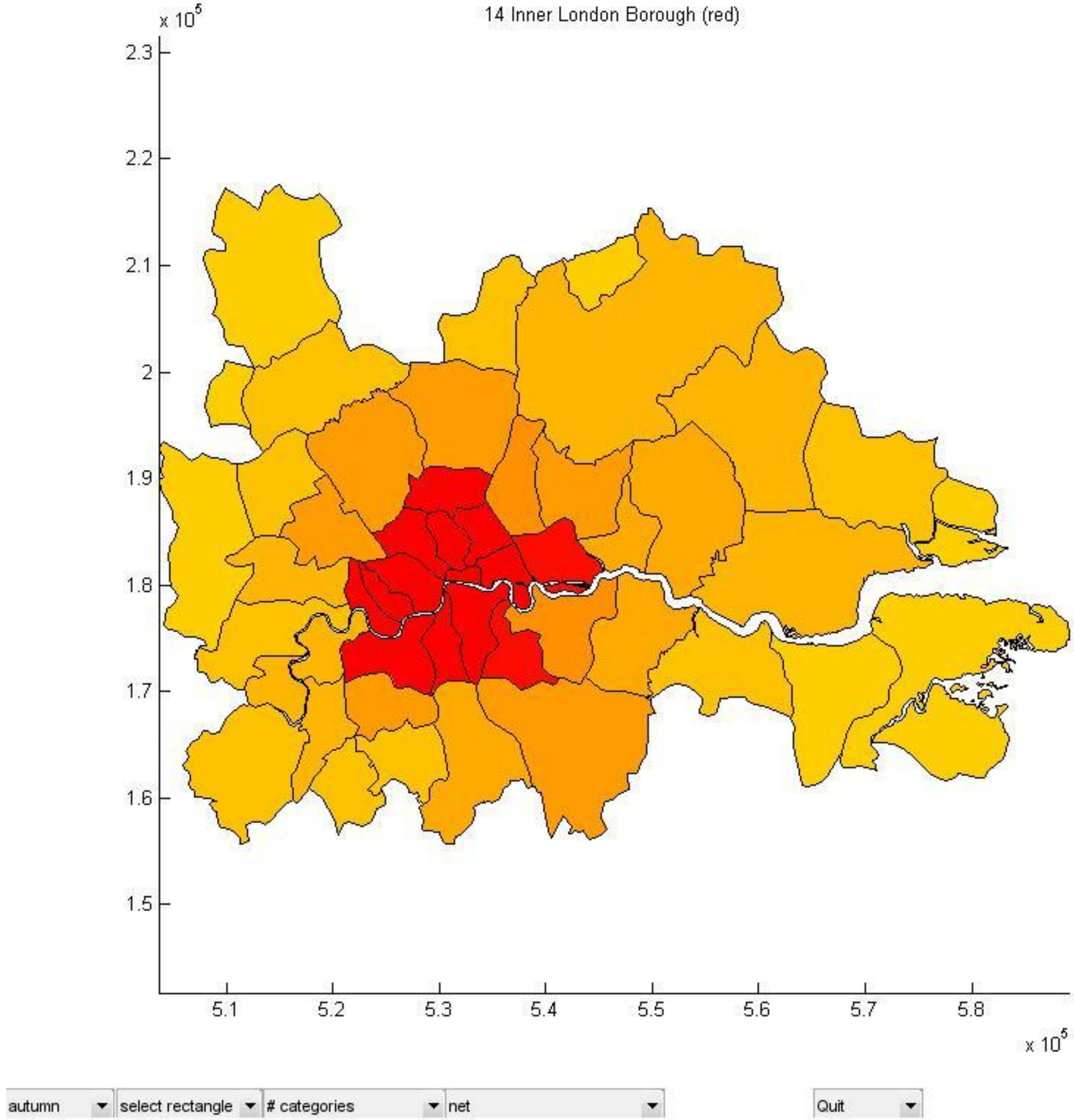
parameter	estimate	St. error	t ratio
γ	----------	----------	----------
ρ_1	0.580102	0.0228238	25.4166
β_1	703.174	89.9415	7.8181
β_2	-3.273	0.342966	-9.5439
ρ_2	----------		
σ_ν^2	----------		
σ_μ^2	----------		

n.b. includes both individual and year fixed effects

house_prices_1.m

simulation

- Inner London has an acute housing shortage
- Simulate the impact on prices of a 5% increase in no. of dwellings in Inner London
- This is spread equally over 14 London Boroughs
  - the housing stock in 10 boroughs of London worth more than the collective value of housing in Scotland, Wales and Northern Ireland
- Put the extra dwellings as non-zero elements of a vector *L*


14 Inner London Borough (red)
x 10^5
2.3
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
5.1
5.2
5.3
5.4
5.5
5.6
5.7
5.8
x 10^5
autumn
select rectangle
categories
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Quit

$$p_{it} = \gamma p_{it-1} + \rho_1 \sum_{k=1}^{N} w_{ik} p_{kt} + \beta_1 I_{it}^c + \beta_2 S_{it} + \varepsilon_{it}$$

$$B = I_N - \rho_1 W$$

$$p_t = B^{-1}(\gamma p_{t-1} + X_t \beta + \varepsilon_t)$$

$$A_t = \gamma^t (B^{-1})^t p_0$$

Debarsy et. al, 2012

$$p = A + \tilde{S}^{-1}(X\beta + \varepsilon)$$

$\tilde{S}$ is an NT x NT matrix

$$\tilde{S} = \begin{bmatrix} B & & & & & & \\ C & B & & & & & \\ 0 & C & . & & & & \\ . & . & . & . & & & \\ . & . & . & . & . & & \\ . & . & . & . & C & B & \\ 0 & . & . & . & . & C & B \end{bmatrix}$$

$$C = -\gamma I_N$$

$$p_b = A + \tilde{S}^{-1}(\beta_1 I^c + \beta_2 S + \varepsilon)$$

$$p_a = A + \tilde{S}^{-1}(\beta_1 I^c + \beta_2 (S + L) + \varepsilon)$$

$$p_{it} = \gamma p_{it-1} + \rho_1 \sum_{k=1}^{N} w_{ik} p_{kt} + \beta_1 I_{it}^c + \beta_2 S_{it} + \varepsilon_{it}$$

$$p_b = A + \tilde{S}^{-1}(\beta_1 I^c + \beta_2 S + \varepsilon)$$

$$p_a = A + \tilde{S}^{-1}(\beta_1 I^c + \beta_2 (S + L) + \varepsilon)$$

$$L = L(1...N, N+1...2N, 2N+1...3N, ..., N(T-1)+1.....NT)'$$

the first N cells correspond to the N regions at time 1,

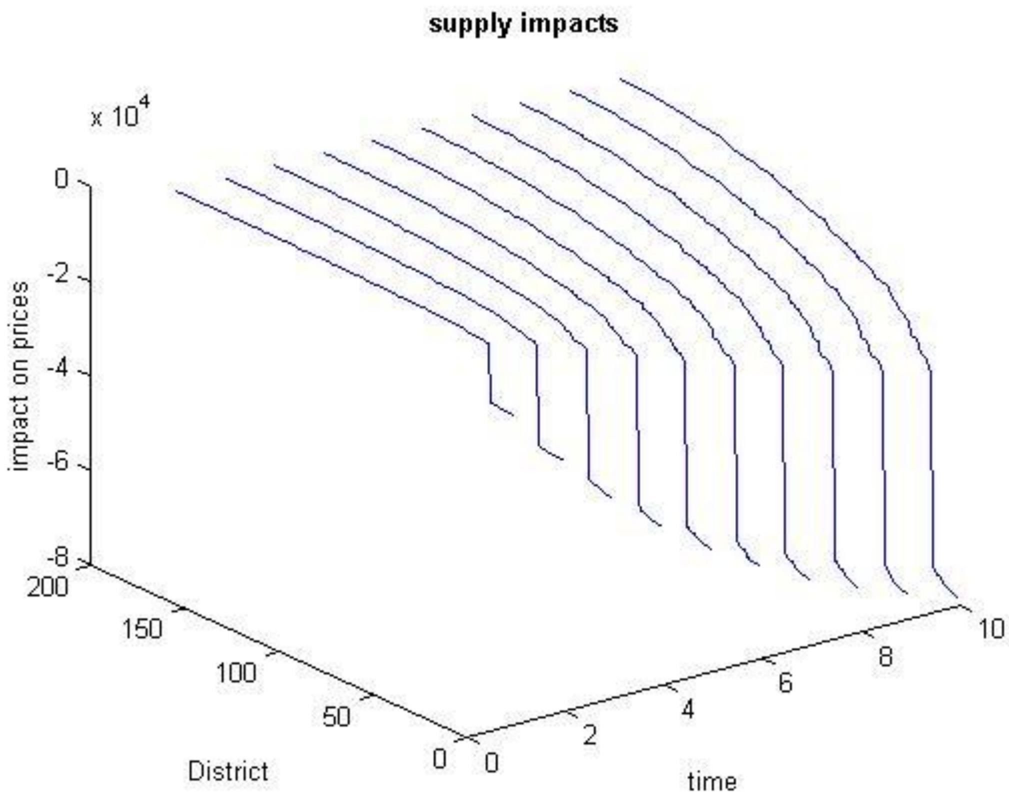
the second N cells are the same N regions but at time 2,

and so on up to representing the N'th region at time T.

the $(1 \le i \le NT)$'th cell, denoted as $L(i)$, takes a value of 0 or k_i', according to whether or not the particular region and time corresponding to cell i is subject to an increase equal to k_i'.

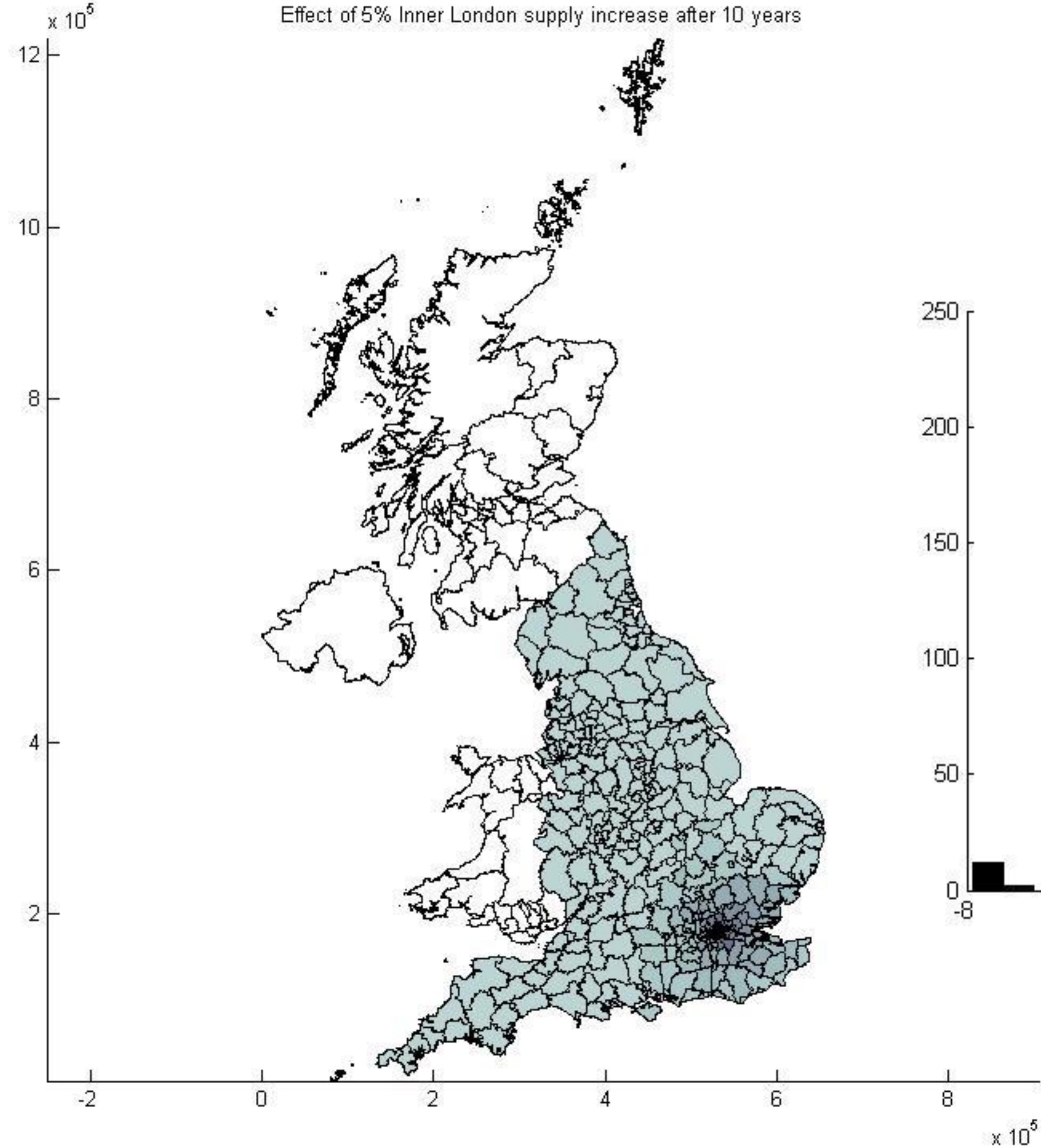
The impact of the k' in L is

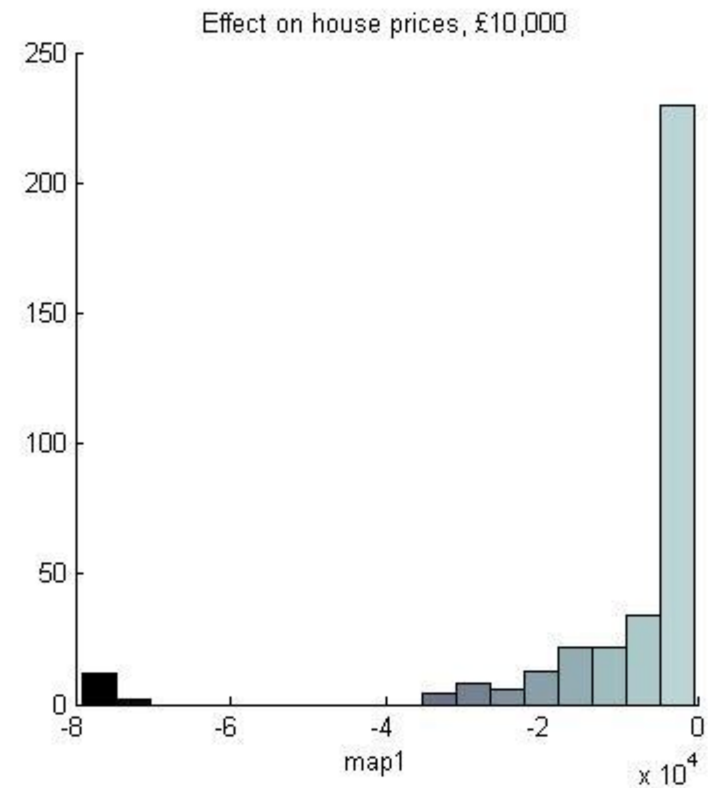
$$p_a - p_b = \frac{\Delta p}{\Delta S} = \tilde{S}^{-1} L \beta_2$$



Impact of 5% increase
In supply in Inner London
on house Prices over
10 years

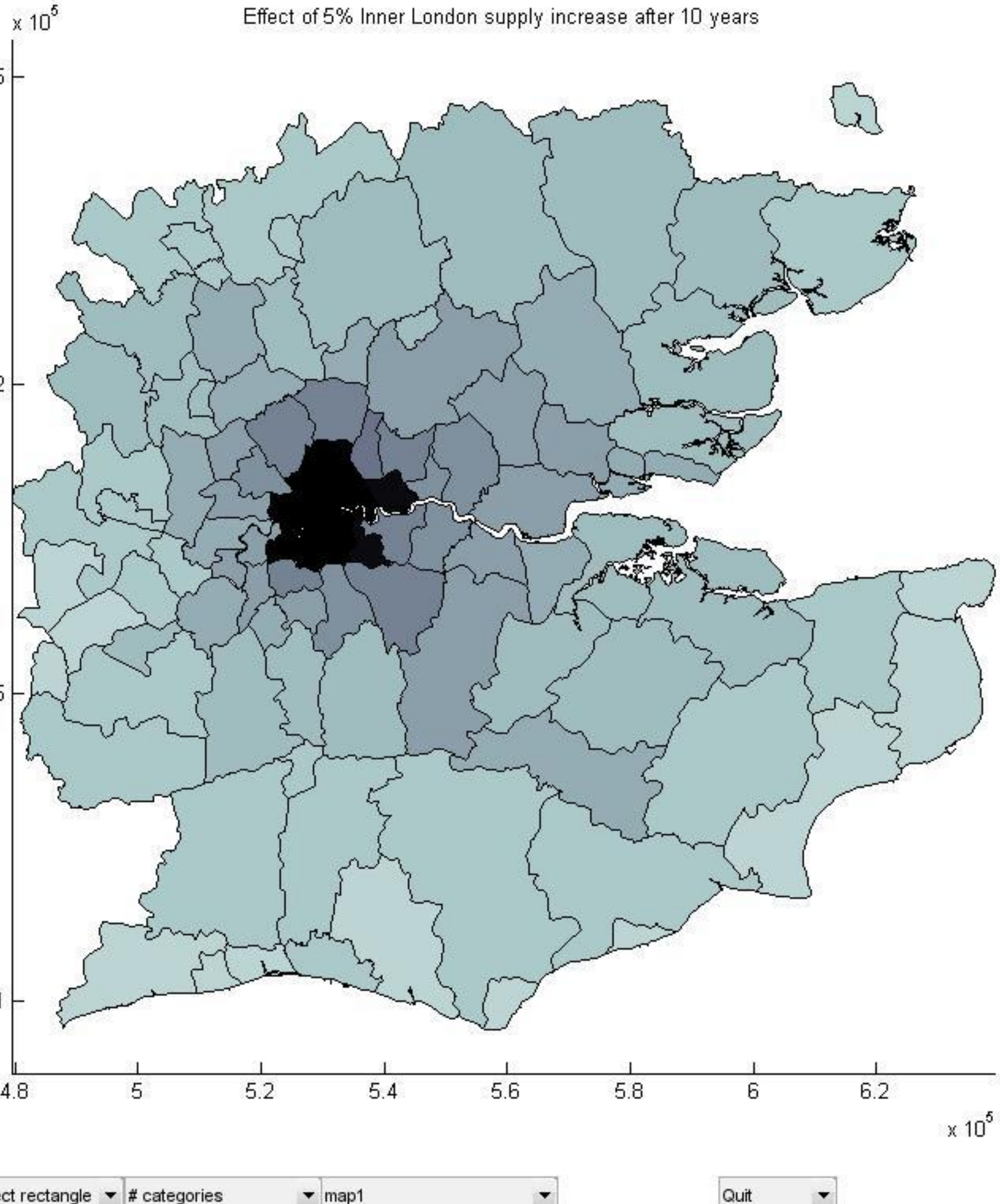
house_prices_1.m

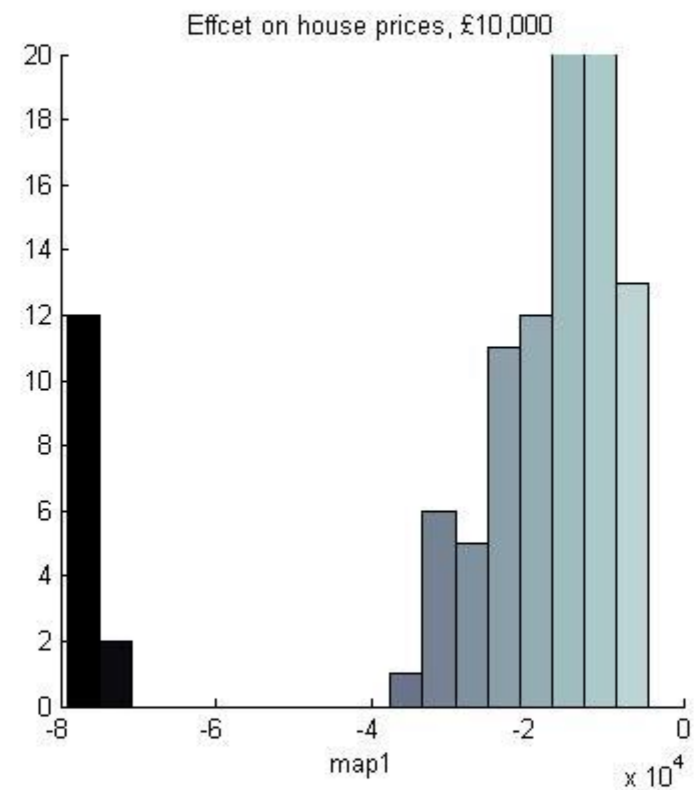




Districts_h_prices_SIM.m

ne ▾ | zoom out ▾ | # categories ▾ | map1 ▾ | Quit ▾



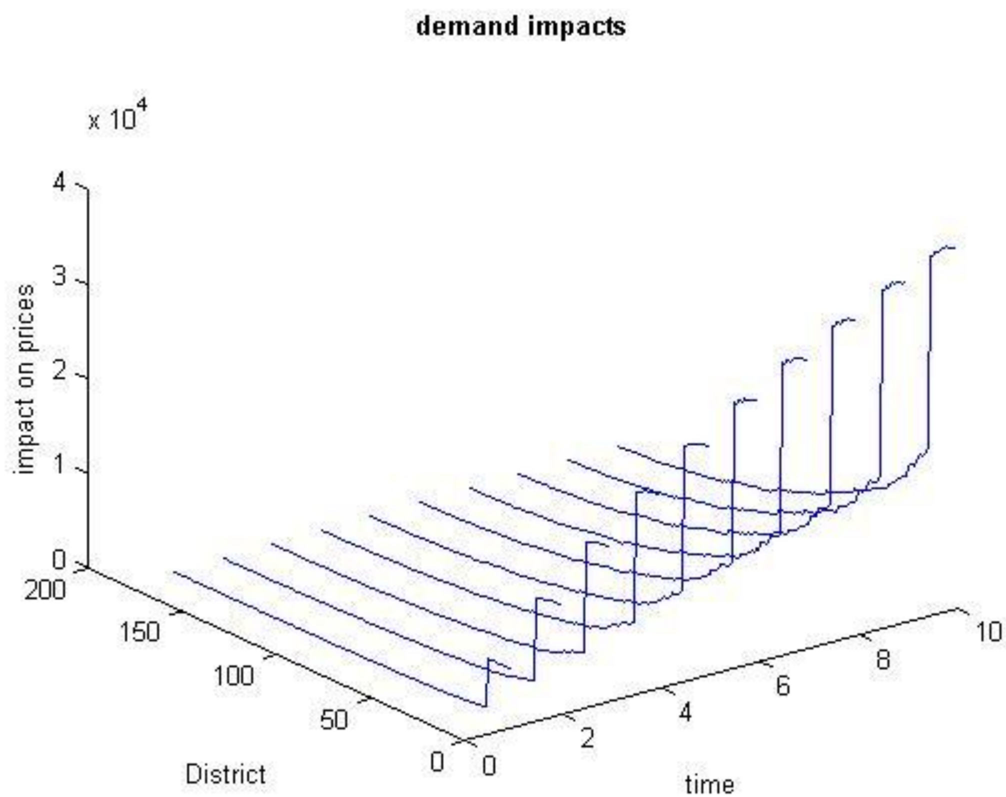


Districts_h_prices_SIM.m

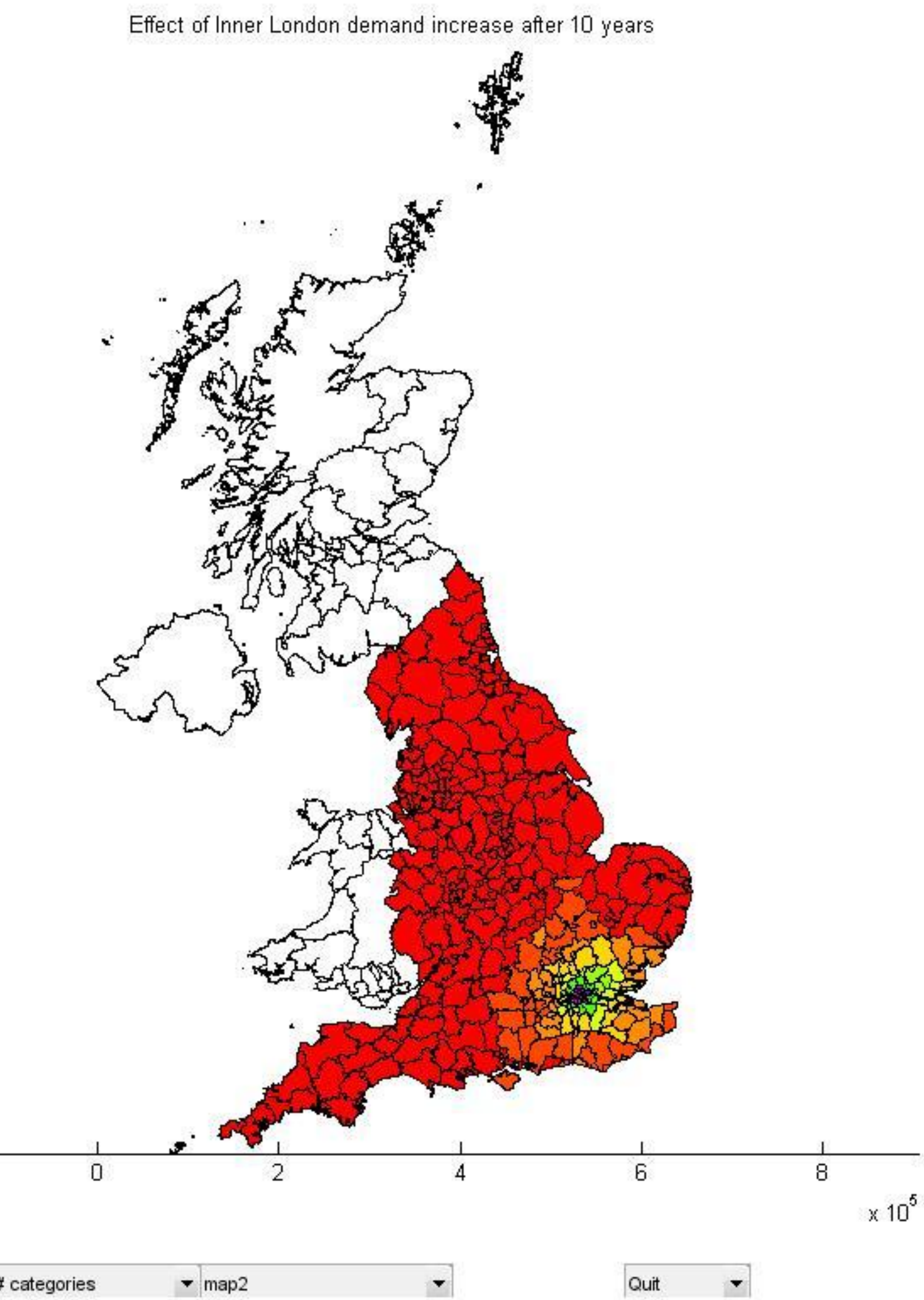
simulation

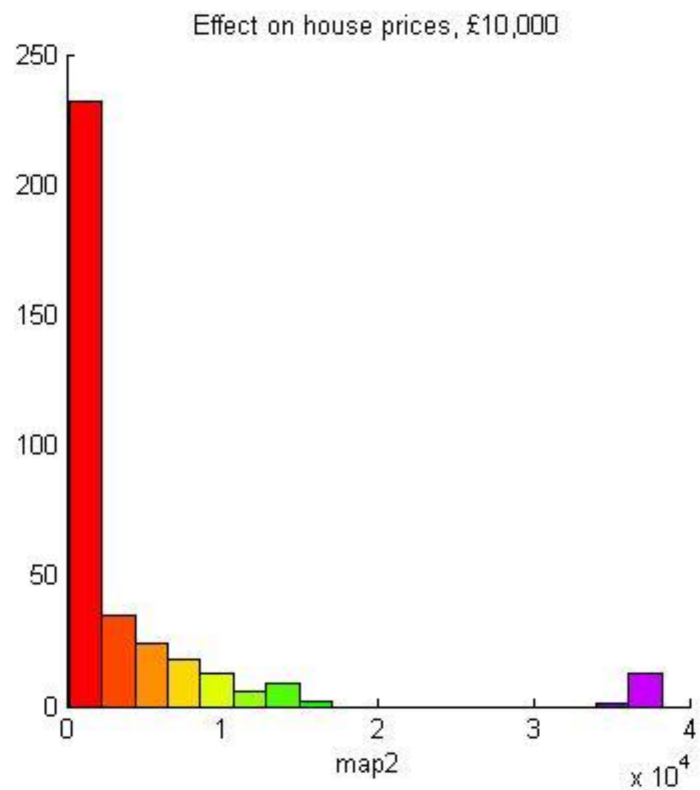
- A 5% increase in dwellings is assumed to produce an increase in workers in Inner London, hence an increase in demand
  – There were 1.844 employees per dwelling in Inner London in 2007
  – Multiply increase in employment by average wage gives increment in income hence demand
  – Average wage in Inner London in 2007 was £732.16
  – We allow this to grow at the rate of 2.5% p.a.

Impact of increase
In demand in Inner London
on house Prices over
10 years

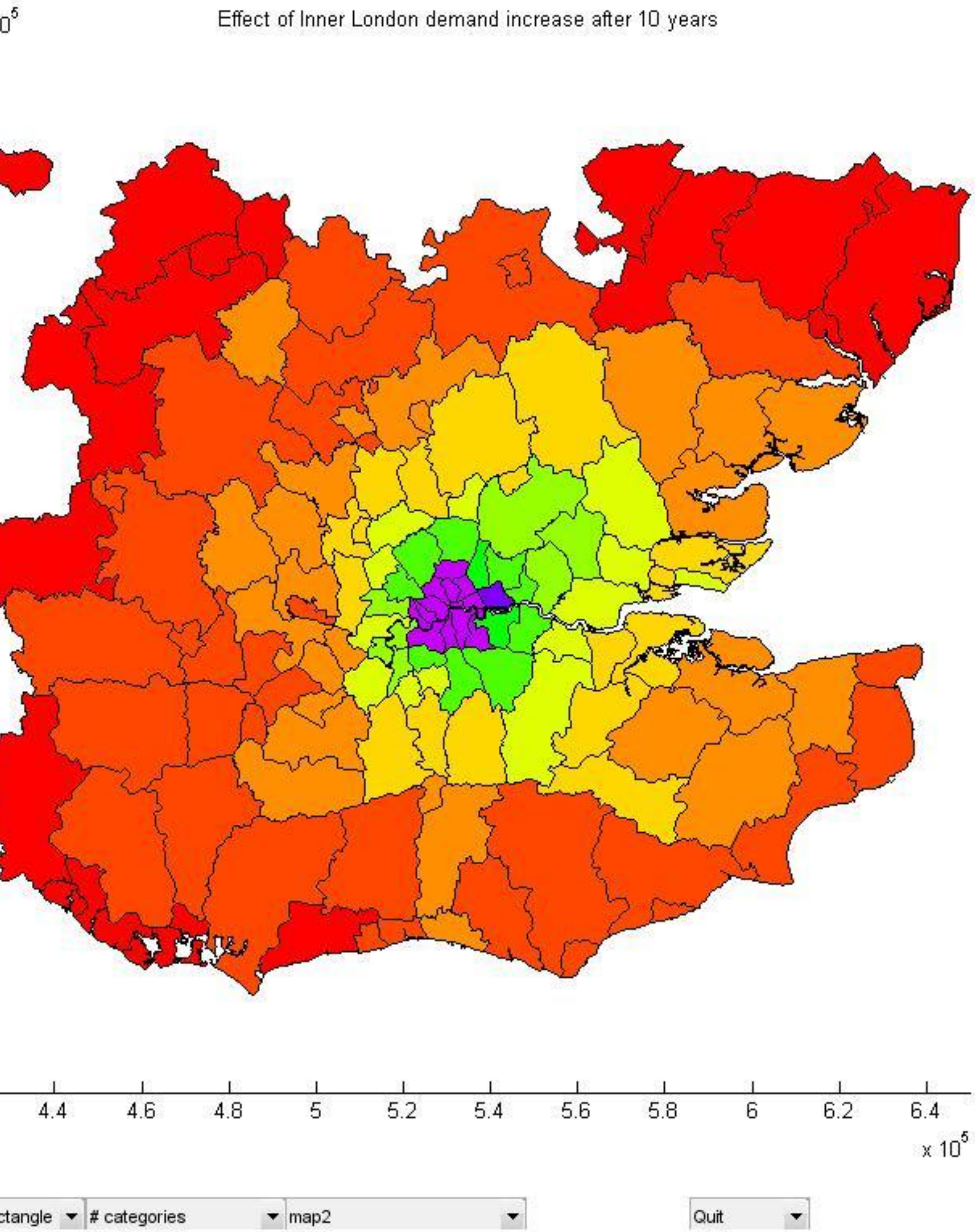


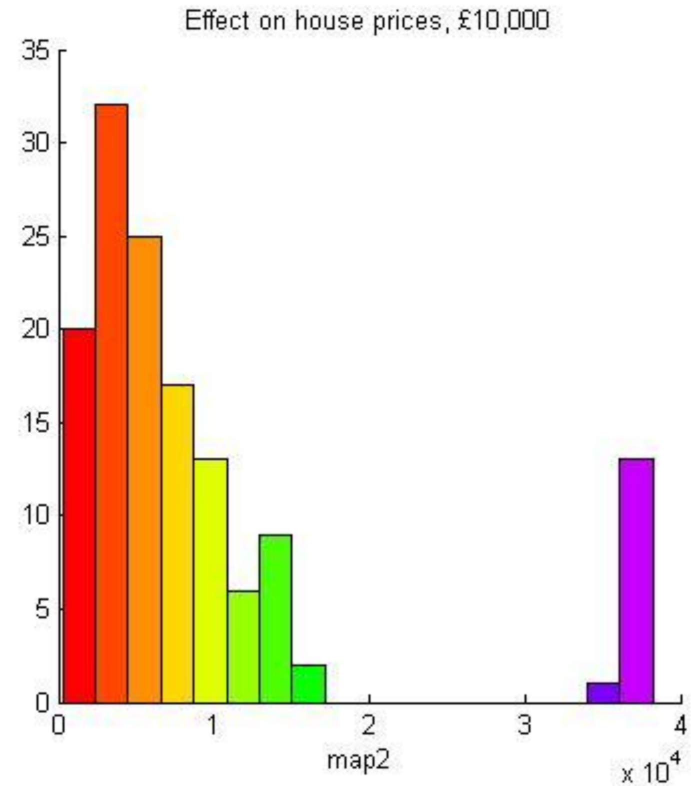
house_prices_1.m





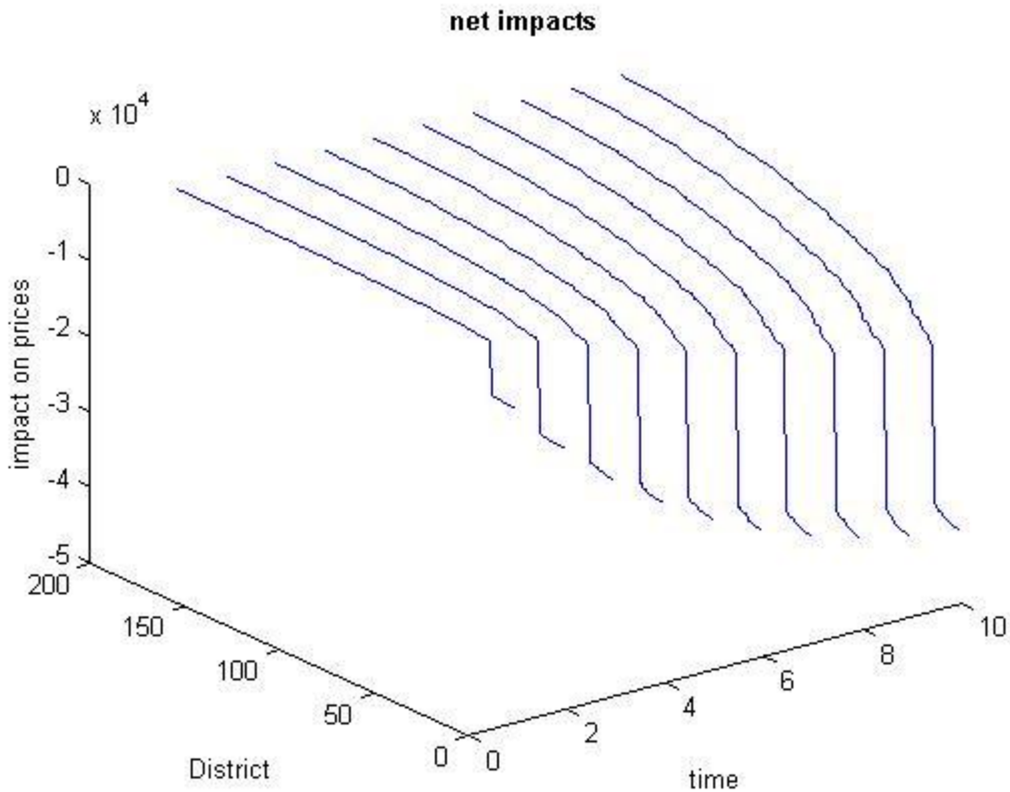
Districts_h_prices_SIM.m



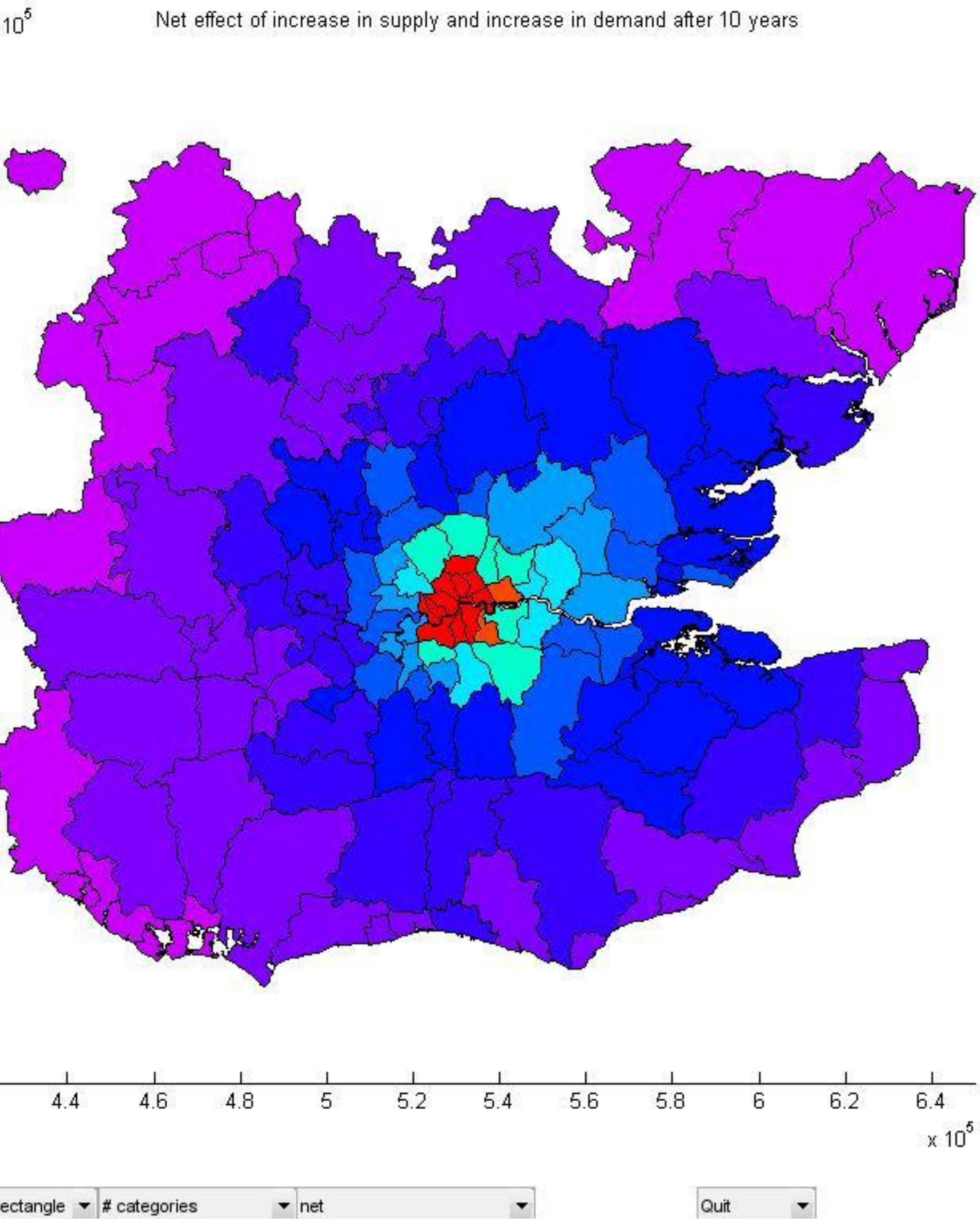


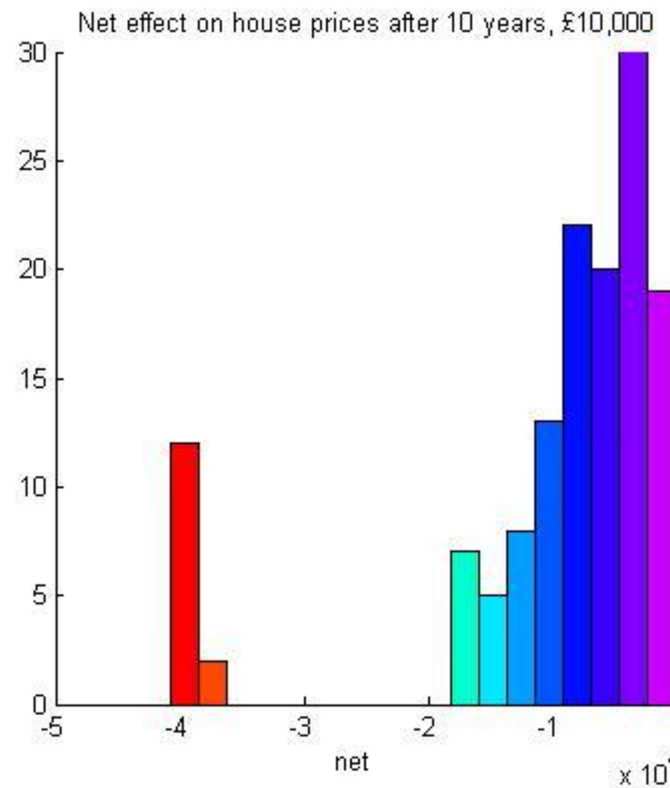
Districts_h_prices_SIM.m

Net effect of increase in supply plus
Increase in demand over 10 years



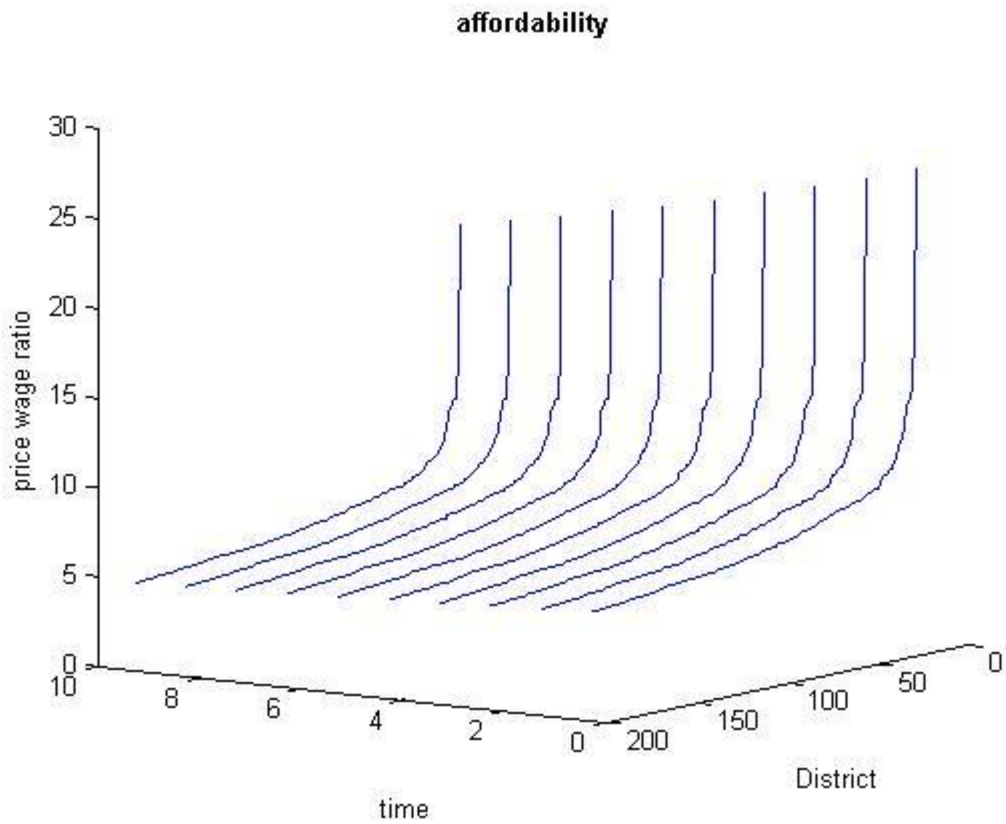
house_prices_1.m



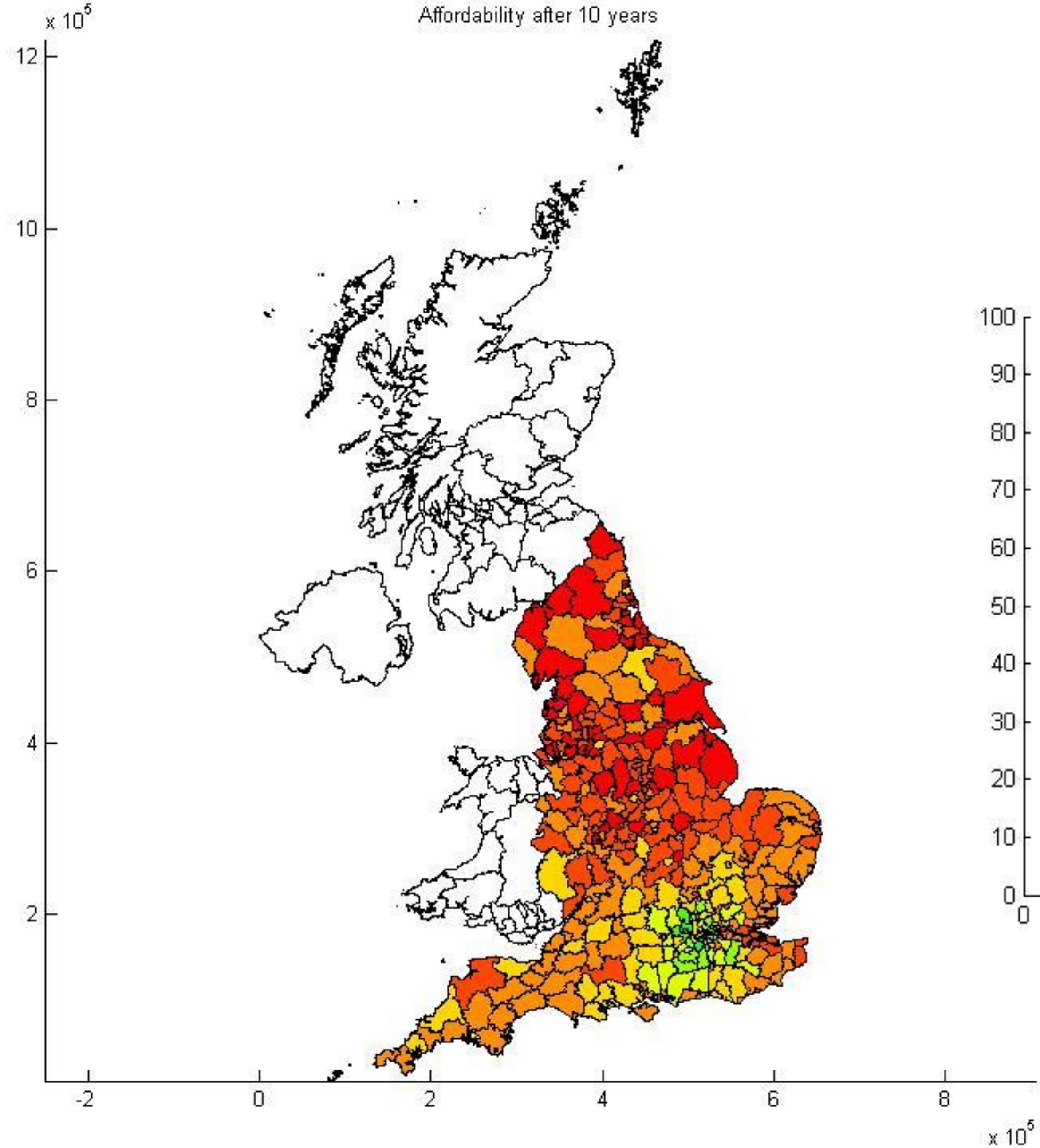


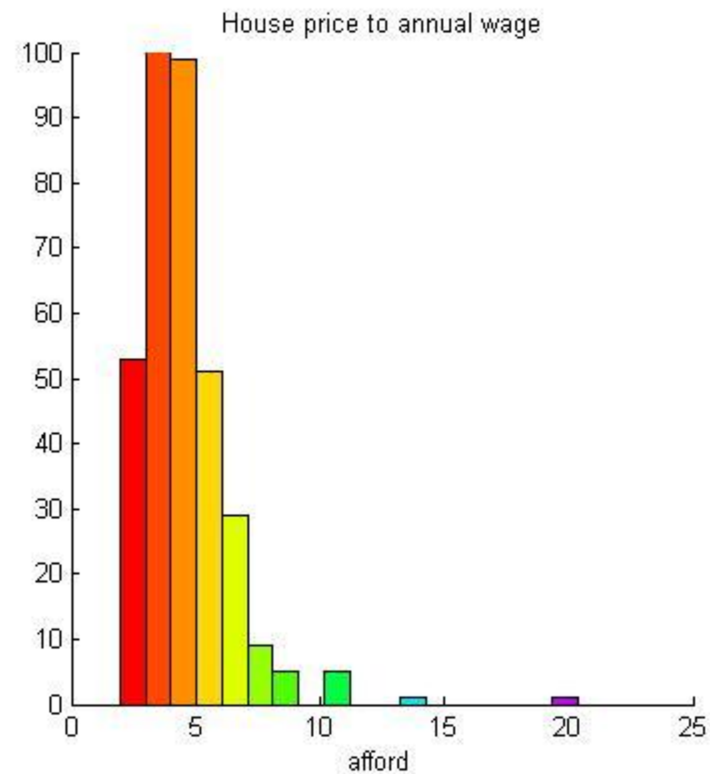
Districts_h_prices_SIM.m

affordability
Over 10 years



house_prices_1.m





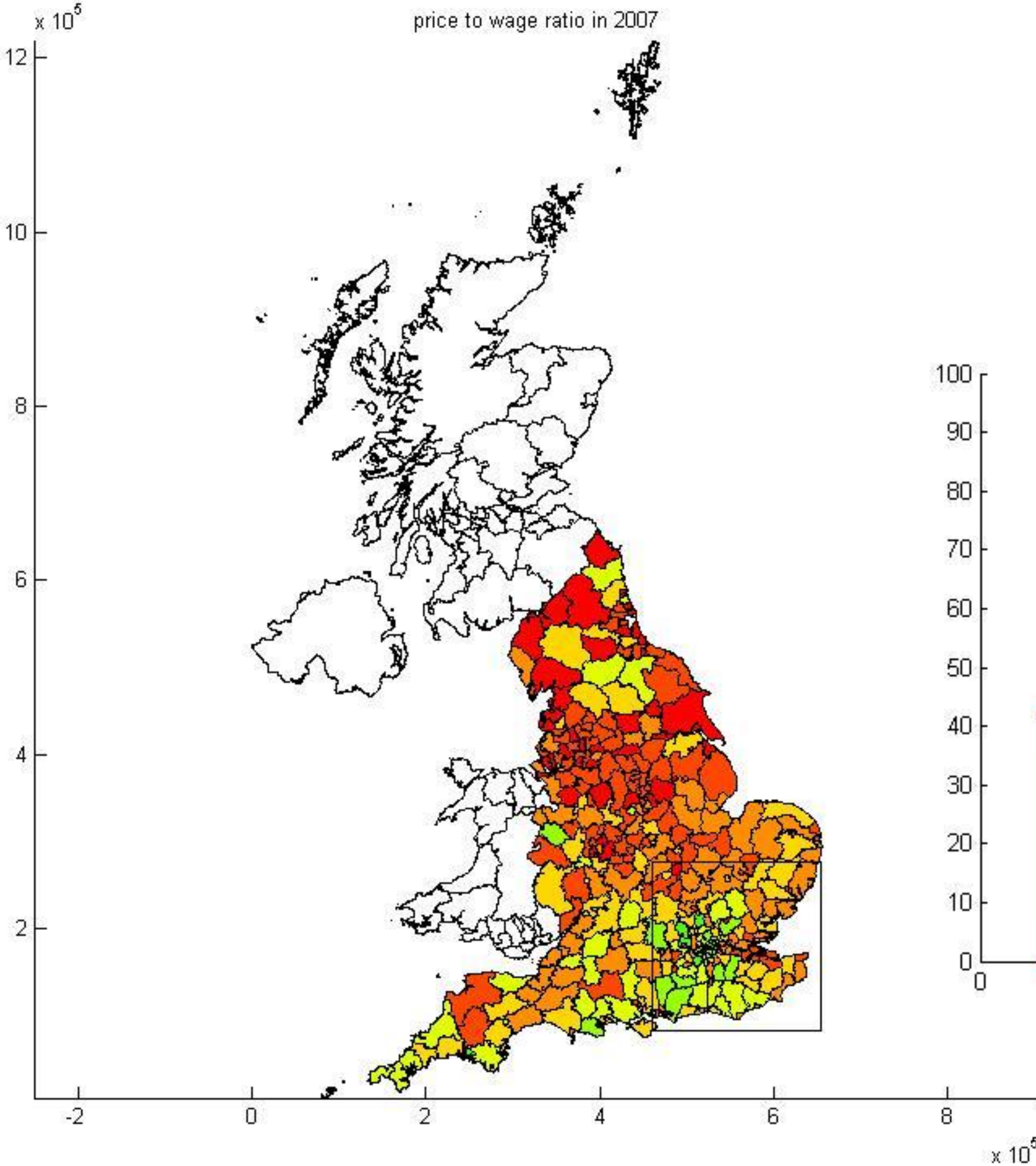
Districts_h_prices_SIM.m

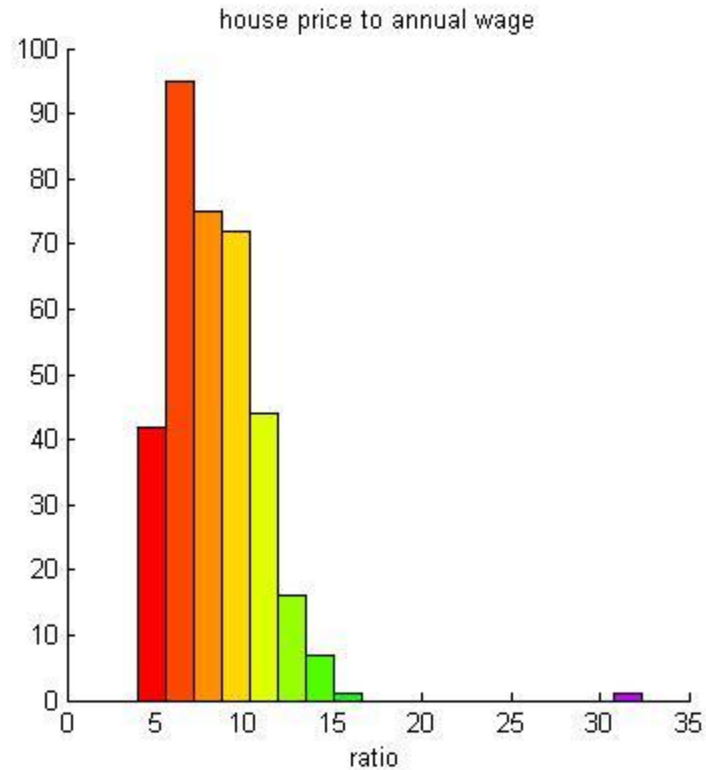
Zoom map

categories

afford

Quit





house_price_actual.m
Districts_h_prices.m

Zoom map | # categories | ratio | Quit

Caveats

- Demand depends largely on income, but more precisely the mortgage that the income can support, we are assuming this will remain the same in the future
  - But in reality interest rates can only go one way, upwards, thus reducing demand
- We are assuming commuting costs will remain as in the Census year 2001
  - But commuting costs have risen inexorably, up 18% in last 3 years
- In reality rising interest rates making Inner London less affordable and a slowing of transport cost increases could lead to additional commuting

Conclusions

- Increasing the supply of housing does not necessarily reduce the price
- We need to take account of the increase in demand also
- Our simulations indicate that affordability will be improved by increasing the supply, but not by as much as one might anticipate
- From a sustainability and environmental perspective, commuting from lower price locations to work in central London could be moderated, but will remain a significant feature of the city
- And commuting could increase if Inner London becomes more expensive due to rising interest rates and commuting costs stabilize

- Thank you!