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Estimating the small area effects of austerity measures in the UK

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Abstract:

Governments across Europe are starting to implement a range of cost-cutting and income-generating programmes in order to re-balance their fiscal budgets following substantial investments in stabilising domestic financial institutions in 2008 and 2009. One method of doing this has been to increase tax rates such as the increase in VAT in the UK from 17.5% to 20% from January 1st 2011. In this paper we explore the different spatial impact of this VAT rise on household expenditure on public and private transport and communication technology from 2006 to 2016. We do this by combining three elements: an agent-based dynamic population microsimulation model that produces projected snapshots of the UK population in 2006, 2011 and 2016; an expenditure system model based on the familiar Quadratic Almost Ideal Demand System approach; and synthetic small area census tables produced by projecting historical UK census data. Taken together these elements provide a toolkit for assessing the potential spatial impact of rising taxes or prices (or both) and we use them to compare small area projections of household expenditure under two scenarios. The first is a 'no intervention' scenario where prices and income align to UK government inflation forecasts and the second is a one-off non-reversed 2.5% increase in VAT on goods and services rated at 17.5% on 1st January 2011. We present results for different areas (rural vs urban/deprived vs affluent) and for different income groups within them and discuss the potential implications for the telecommunications industry and for the usage of public and private transport.

Keywords/tags:small area, microsimulation, austerity, demand system

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1 INTRODUCTION

In response to recent economic and financial difficulties governments across Europe and beyond have implemented a range of cost-cutting and income-generating programmes in order to re-balance their fiscal budgets following substantial investments in stabilising domestic financial institutions in 2008 and 2009. One approach has been to increase tax rates such as the increase in Value Added Tax (VAT) in the United Kingdom (UK) from 17.5% to 20% from January 1st 2011.

Whilst analyses of changes to tax rates are relatively common and microsimulation of their effects is now relatively well known (Hancock, Sutherland et al. 1992; Mitton, Sutherland et al. 2000; Zaidi, Harding et al. 2009) we are not aware of substantial exploration of the small area effects of such changes despite indications of it's value in analyzing the potential small area effects of tax and benefit rate changes (Clarke 1996; Ballas and Clarke 2001; Chin, Harding et al. 2005; Tanton, Vidyattama et al. 2009). In addition as far as we are aware there has been no attempt to model, at the small area level, not just the impact of tax-rate changes on income or on expenditure on specific consumption items but the effect on a system of household expenditure into the future.

In this chapter we combine a number of research methods to explore the differential spatial impact of the UK VAT rise on household expenditure on public and private transport and communication technology from 2006 to 2016. We do this by combining three elements: an agent-based dynamic population microsimulation model that produces projected snapshots of the UK population in 2006, 2011 and 2016; an expenditure system model based on the familiar Quadratic Almost Ideal Demand System approach; and synthetic small area census tables produced by projecting historical UK census data.

Taken together these elements provide a toolkit for assessing the potential spatial impact of rising taxes or prices (or both) using a spatial microsimulation approach and we use them to compare small area projections of household expenditure under two scenarios. The first is a 'no intervention' scenario where prices and income align to UK government inflation forecasts and the second is a one-off non-reversed 2.5% increase in VAT on goods and services rated at 17.5% on 1st January 2011. We present results for different areas (rural vs urban/deprived vs affluent) and for different income groups within them and discuss their substantive and methodological implications.

2 PROJECTION AND ESTIMATION METHODS

Our approach to projecting small area estimates of household expenditure comprises three main strands. The first the projection of small area statistics for specific household attributes using historical census tables. The second is the projection of a household population sample together with their household attributes, income and expenditure patterns and the third is the development of a demand system model linking household expenditures to each other, to household attributes and to time. These are then combined using a spatial microsimulation approach to produce small area estimates of future household expenditures over time.

As we discuss below each of these strands presents a range of challenges but when in place they provide a set of tools for modelling the small area consequences of, for example, changes in prices, in area-level demographic change and, as here, changes in indirect consumption tax rates. A preliminary version of this approach was presented in previous work (Anderson, De Agostini et al. 2009) and in this chapter we discuss extensions to that work which bases the small area projections on Census data from 1971, 1981, 1991 and 2001 (rather than just 1981/1991 and 2001); which uses an agent-based dynamic population projection model (Lawson 2009) to produce synthetic households (rather than the autoregressive method) and which uses an improved system demand model to estimate future expenditures for the dynamically projected households.

2.1 Data

As in previous work we use the UK's Expenditure and Food Survey for 2001/2 to 2005/6 (EFS 2006) as our consumption survey data and the UK Census small area tables for 1971, 1981, 1991 and 2001. In addition we have conducted extensive analysis of the longitudinal British Household Panel Study (1991-2006) (BHPS 2010) as part of the development of transition probabilities for the dynamic agent-based population model.

2.2 Spatial projection

Our approach to the projection of small area statistics follows our earlier work (Anderson, De Agostini et al. 2009) in re-zoning UK census small areas (wards) to form consistent geographical zones over time (Norman, Rees et al. 2003; Gregory and Ell 2005). In the work discussed here we have instead aggregated data to the UK Office for National Statistics' Lower Layer Super Output Area (LSOA) level using Enumeration District (ED) data for the 1971/1981/1991 Censuses and Output Area (OA) level data for the 2001 Census.

Our rationale for moving to the LSOA level includes the availability of substantial local area data at the LSOA level, including updates of the English Indices of Multiple Deprivation and the commitment of the Office for National Statistics to the maintenance of these boundaries in future UK Censuses.

As before, postcodes were used as a proxy for population distribution and weights were calculated from the proportion of postcodes that the historic zone has within the total of the contemporary zone. These were used to re-weight the historical census data and allocate the weighted values to each fragment before the fragments were re-aggregated to Census 2001 LSOAs. Ideally we would use postcode counts for each contemporary census year but the available postcode files do not permit this prior to 1981. We therefore assumed that 1971 postcodes had the same geographical distribution as those from 1981. For 1981 and 1991 however we have been able to select only those postcodes that were 'live' at that time point.

Once the updated zones have been created through the production of a table allocating source EDs to target LSOAs it is a relatively straightforward matter to aggregate the historical census constraint counts by LSOA. However it must be remembered that not all of the constraints available for 2001 are also available in all previous years. From our analysis, those that are available are socio-economic/employment status of household representative person (HRP); the number of cars in the household; number of dependent children; the number of persons per household; number of rooms and type of tenure.

Following Ballas et al (2005), we use the Holt-Winters non-seasonal smoothing algorithm to smooth the LSOA level proportions of households in the observed constraint categories for 1971 to 2001 using Stata's 'tssmooth' command[1]. Following Ballas et al's approach, a gravitational model was then used to project constraint proportions and total household numbers forwards at LSOA level to 2011 and 2021 and then use household projections from the UK Government at Local Authority level[2] to normalise household numbers with respect to these official projections. We then convert the projected proportions to projected household counts using the normalised total household counts. As currently implemented the gravity model only contains three historical terms and so the projection for 2011 uses the smoothed observed data for 2001, 1991 and 1981 only whilst the 2021 projection uses the smoothed observed 1991, and 2001 data and the projected 2011 data. The method projects 1-n constraint proportions and then calculates the last constraint as the residual of the others so that they sum to 100%. Due to the processing requirements of this method the projections were limited to the 3,550 LSOAs in the East of England.

Following the projection stage the results were then 'corrected' by correcting any negative proportion to the most recent positive proportion and any zero value to a small non-zero number (0.000001) to prevent errors in any future spatial microsimulation process where

1 http://www.stata.com/help.cgi?tssmooth+hwinters

2 http://www.communities.gov.uk/publications/corporate/statistics/2031households0309

division by 0 would cause a failure. Finally proportions were re-scaled so that they summed to 1 (100%) for each constraint.

Following this correction step the projected constraint counts were then calculated using the projected total household counts that had been normalised to the most recent official Local Authority level estimates.

2.2.1 Census projection results

Figure 1 to Figure 6 show the overall results of this projection approach for the East of England for each of the census constraint variables. Overall the patterns appear relatively plausible given that they are contingent on historical trends. The growth in the number of households with 2+ cars is an excellent example of this (Figure 2) as is the reduction in those who are social/council renters (Figure 6). In these cases we might expect an earlier asymptote as the incidence of these kinds of households reaches a ceiling/floor due to socio-economic limits rather than following a historical curve. However considerably more complex dynamic projection modeling would be required to address this issue and it is outside the scope of this chapter.

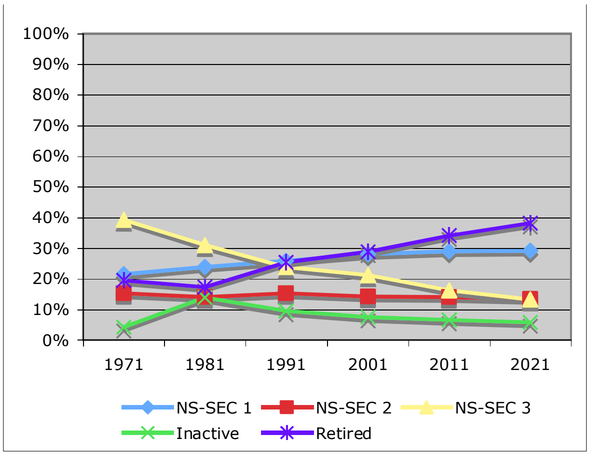


Figure 1: % households by HRP Employment status

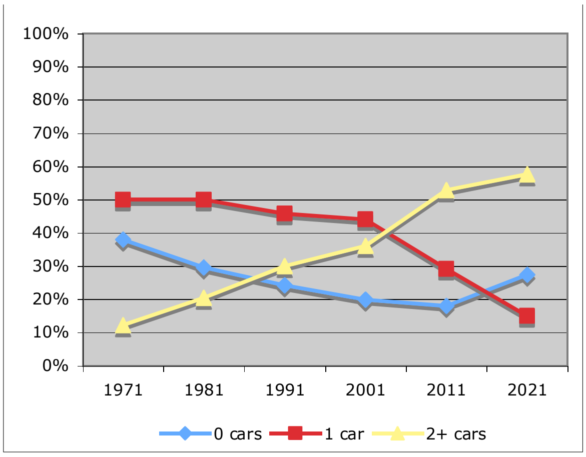


Figure 2: % households with 0,1 or 2+ cars

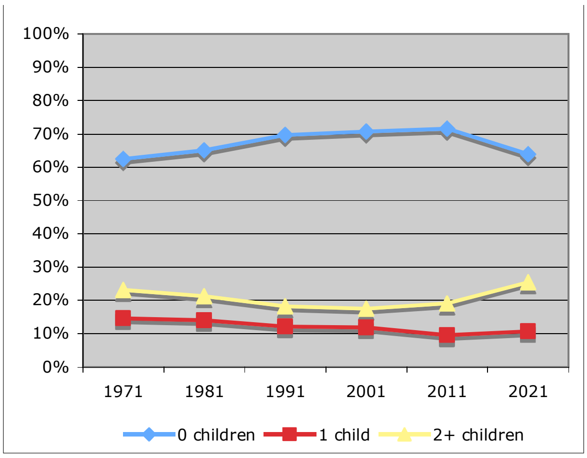


Figure 3: % households with 0,1 or 2+ children

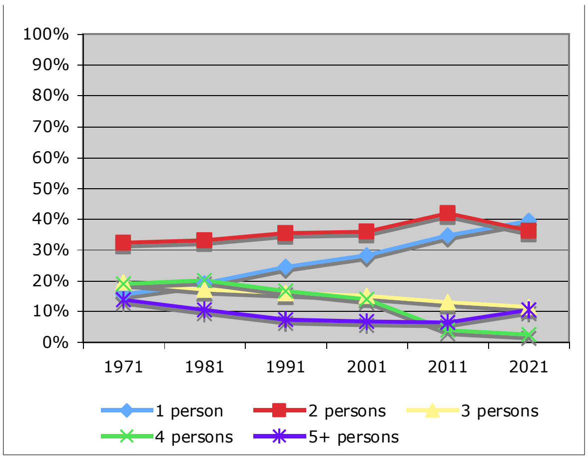


Figure 4: % households by number of persons

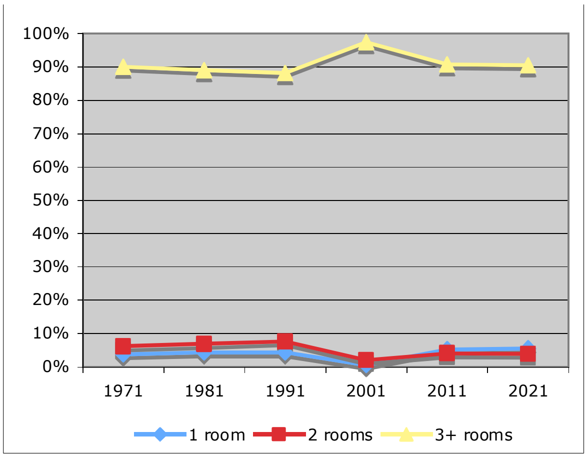


Figure 5: % households by number of rooms

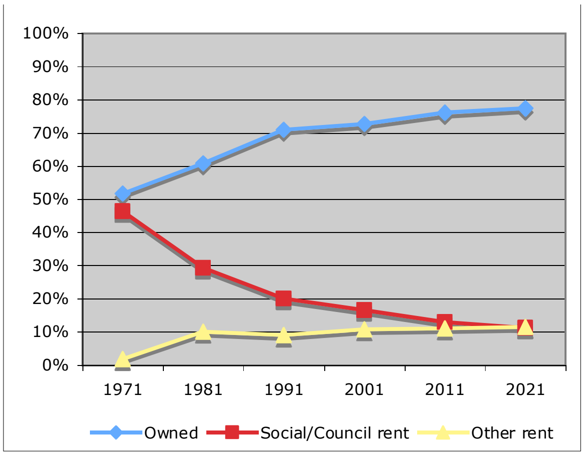


Figure 6: % households in different tenure types

2.3 Demographic projection

With the spatial projections in place, we now turn to the projection of a sample survey population as a basis for the microsimulation of the 2011 tax increase. As we have noted in contrast to our earlier work we have used an agent-based dynamic population projection model implemented in NetLogo to age a sample population (the Expenditure and Food Survey 2005/6 sample (n = 11,204 persons in 4,732 households)) through the application of a range of dynamic demographic projection modules (see Figure 7 and (Lawson 2009; Lawson 2011)).

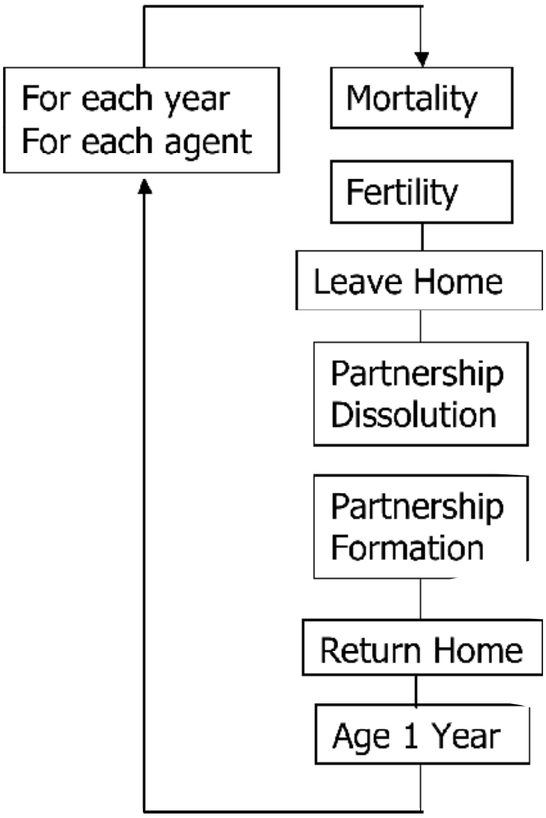


Figure 7: Agent-Based Population Projection Modules

Each line in Figure 7 corresponds to a transition between states. For example the partnership formation module selected a number of individuals from the population each year to either marry or cohabit whilst a mortality module selected which individuals were to be removed from the population. On top of this basic structure, modules were added to represent single people leaving and returning to the parental home. The modules are run sequentially each year and each transition between states takes place with a probability that depends on a number of factors (Zaidi and Rake 2001). For the most part the transition probabilities were calculated using the BHPS by constructing a set of logistic regression equations for each transition to be modeled whilst additional probabilities were taken from the SAGE Technical Notes (Scott 2003).

The detailed implementation of the model and its validation is discussed elsewhere (Lawson 2009; Lawson 2011) but in essence the validation suggested that the simulated projections parallel the actual data over the whole of the validation time period (1991 – 2006) giving some confidence that all other things being equal the model would project a population into the future contingent on the underlying transition probabilities not changing significantly over time.

However for the purposes of the work discussed here, once the modeling framework (transition probabilities and module processes) was in place, the BHPS survey sample was replaced by the EFS survey sample in order to then project the EFS sample 'forwards' in time to 2006, 2011 and 2016. In particular the agent-based model was used to project household income; number of persons in different age groups in each household; number of children in household; household composition (married/partnered couple, single parent, single person, other); employment status of the Household Response Person (NS-SEC 1, NS-SEC 2, NS-SEC 3, Inactive (including unemployed), Retired); the number of persons per household and the age of Household Response Person.

These variables form the basis for the demand system model used to estimate future household expenditures (see below) and also included most of the variables found in the projected small area Census data (see above).

2.3.1 Dynamic population projection results

As expected, the final (2021) "agent-based population" is slightly older compared to the EFS population 2000-2005 (Figure 8) and has a higher number of household response persons/household heads working in managerial (NS-SEC1) positions and fewer who are inactive (Figure 9). The number of households with pre-school and school children diminishes between 2006 and 2016 Figure 10). More than half of this population (51.24%) have no household members between 18-44 years of age, whilst the number of households with household members over 45 and 65 years old increases.

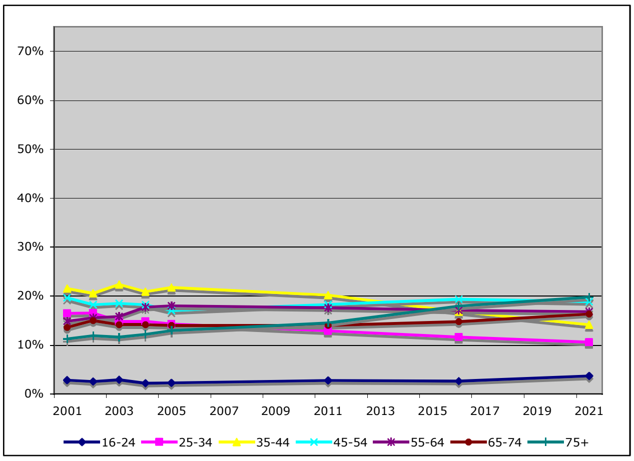


Figure 8: Observed (2001-2005) and projected age distribution of HRPs

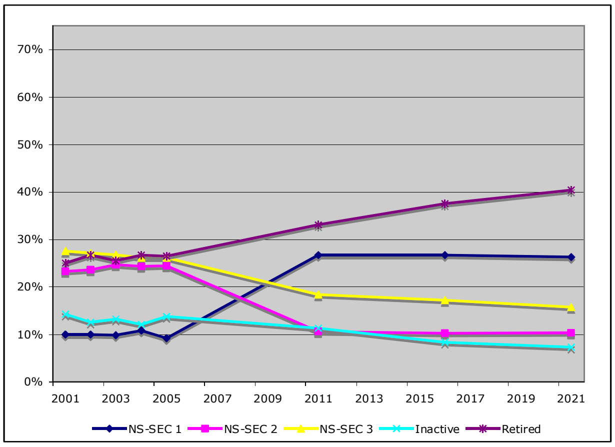


Figure 9: Observed (2001-2005) and projected employment status distribution of HRPs

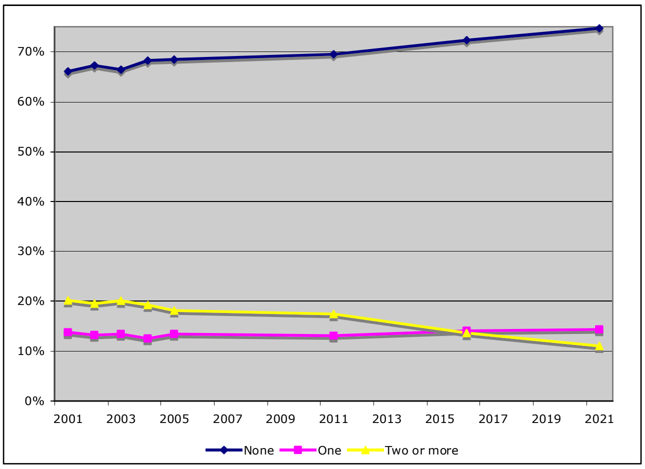


Figure 10: Observed (2001-2005) and projected distribution of children per household

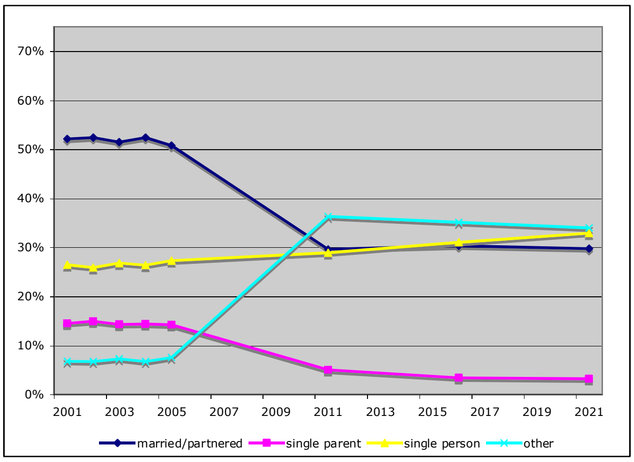


Figure 11: Observed (2001-2005) and projected household composition

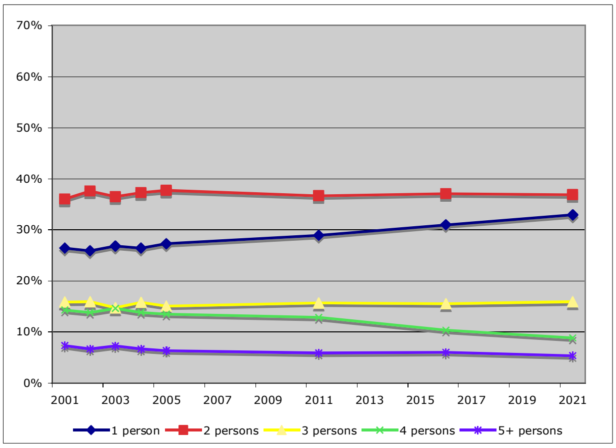


Figure 12: Observed (2001-2005) and projected number of persons per household

However the greatest difference between the EFS population 2001-2005 and the "agent-based population" is for household composition: while in 2000-2005 more than half of the sample is married or partnered, between 2006 and 2016, 36% of the sample live alone or in other household structures, and the proportion of lone parents decreases from 14% to 4% (Figure 11).

It is possible that these differences, especially the projected reduction in couple households may drive some of our subsequent results and so may need further investigation. For the purposes of this paper however we proceed to the expenditure projection using these data.

One absence from the dynamic population projection was housing tenure and as it was felt that its absence was likely to substantially reduce variation in the spatial microsimulation re-weighting procedure, household tenure was imputed for the projected EFS survey data using a multinomial regression model. This approach estimated a model to predict household tenure for the observed data based on income, number of children, number of persons, composition and employment status and then used the resulting coefficients to predict the probability that a projected household was of a given tenure type. This model was a reasonable fit to the data (Log likelihood = -23339.023, Pseudo R2 = 0.1481). Households were then selected into tenure type if their probability of being in that type was greater than the median predicted probability.

In addition the 'regional weighting' component of the spatial microsimulation approach required that each household to be allocated to a Government Office Region (see (Anderson 2012)) and so we households which still existed in 2006/11/21[3] were allocated to their original 2005/6 sample region. New households were then allocated to a region on the basis of a similar multinomial regression model using the same process as described for tenure. This model performed less well than the tenure model (Log likelihood = -74173.012, Pseudo R2 = 0.0136) and resulted in 185 of the 12,052 unallocated households still not being allocated to a region. These households were then removed from the subsequent datasets.

As Figure 13 and Figure 14 shows these imputations produced results which were largely in line with expectations although the proportion of households assigned to Northern Ireland shows a notable fall over time possibly reflecting the difficulty of modelling region. However given that this analysis focuses only on the East of England we leave the data as is.

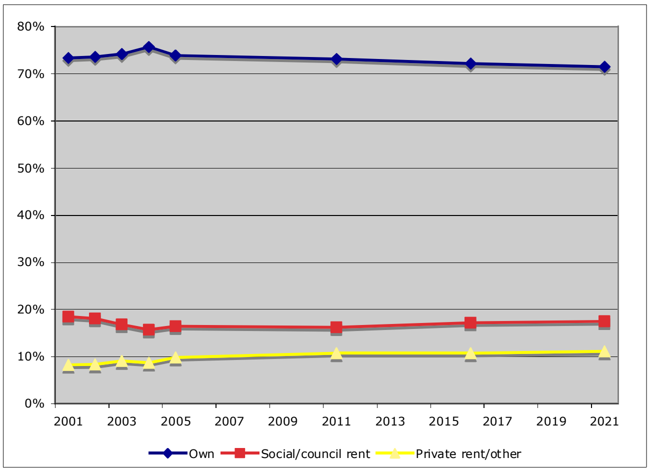


Figure 13: Imputed household tenure

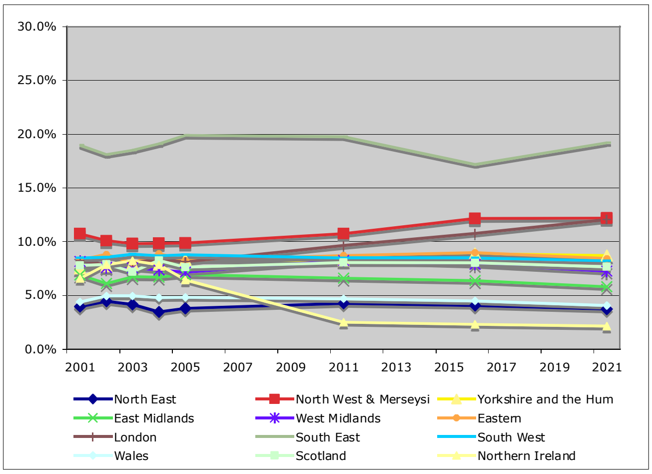


Figure 14: Imputed households by region

2.4 Demand system model

As in previous work (Anderson, De Agostini et al. 2009) an econometric system model was used for projecting consumers' behaviours into the future. More specifically, a Quadratic Almost Ideal Demand System model (Banks, Blundell et al. 1997) was estimated based on the assumption that consumers choose how much to purchase of each item in order to maximize their utility, given their budget constraints and their socio-demographic characteristics. In practice this model estimated a system of *n* share equations based on prices, household income and other household characteristics where n is the number of goods or services being considered. The estimated parameters allowed us to derive price and income elasticities, which indicate how UK households would change their demand following a one percent increase of market prices and/or household income.

In our previous work we used the QAIDS model to project expenditures into the future by up-rating economic variables and re-weighting the underlying population data on the basis of projected socio-demographic characteristics. In the work reported here however the projected socio-demographic information was replaced by the population projections from the agent-based dynamic simulation.

In summary we used the QAIDS model based on EFS data from 2001/02 to 2005/06 to estimate the share of spending in 2006, 2011 and 2016 using the projected household survey sample derived from the agent based dynamic microsimulation and derive household spending on six items (the base model). We then derive a measure of household response to prices and income variations (elasticity) and simulated a rise in the price of all modelled items by 2.08%[4]

[3] i.e. had not dissolved due to household transitions.

[4] Corresponding to a rise in the VAT rate of 2.5%

from January 2011 onwards (the scenario model).

From the original sample (EFS 2001/02-2005/06) two households were missing full information on the main variables such as spending or income; two households reported negative values on "other spending" which would have caused the shares of expenditure (our dependent variable) to be negative; eleven households reporting negative housing costs and 587 households spent and earned in total less than £25 per week in real terms or more than £2000 per week. All of these households were excluded reducing the sample by 1.9%. The final sample was therefore composed of 30,774 observations for the UK distributed roughly equally among the five years considered.

We chose to focus our attention on modelling a 'communication demand system' by including household expenditures on communications technologies (landline, mobile and internet), transport (car fuel and public transports) and as the residual, all other expenditures net of housing costs. Expenditures were converted to December 2007 prices using the Retail Price Index (RPI) provided by the ONS. Comparisons over time, therefore, refer to real-terms changes. Table 1 shows the mean weekly spending for each category[5] in each observed year.

Table 1: Observed weekly expenditures (£ GB) from EFS 2001-2005 (mean and (*standard error*), December 2007 prices)

	Landline	Mobile	Internet	Car fuel	Public Transport	Others	Total Expenditure without housing costs	Total Expenditure with housing costs
2001/02	7.48	5.60	1.65	18.04	4.42	350.78	387.96	463.27
	(6.19)	*(9.80)*	*(2.12)*	*(21.08)*	*(12.84)*	*(258.64)*	*(277.00)*	*(311.87)*
2002/03	7.24	5.78	1.80	17.93	4.07	352.91	389.72	464.27
	(5.38)	*(9.11)*	*(2.12)*	*(21.34)*	*(12.91)*	*(260.66)*	*(278.98)*	*(314.15)*
2003/04	7.08	6.70	1.97	17.59	4.01	353.61	390.95	466.98
	(5.57)	*(9.89)*	*(2.12)*	*(20.81)*	*(10.94)*	*(265.68)*	*(282.68)*	*(315.39)*
2004/05	6.76	6.73	2.09	18.23	4.26	350.91	388.99	473.07
	(5.31)	*(9.46)*	*(2.06)*	*(21.26)*	*(12.00)*	*(262.61)*	*(280.35)*	*(317.37)*
2005/06	6.38	6.93	2.04	19.11	4.29	341.61	380.36	464.44
	(5.11)	*(9.36)*	*(2.02)*	*(22.58)*	*(12.71)*	*(253.49)*	*(271.07)*	*(309.85)*

Although there may be many other factors affecting households' spending decision, for simplicity the demographic characteristics that were included in the agent-based population and which could therefore be used to calculate expenditure estimates for 2006, 2011 and 2016 were used as model co-variates. This demand system was estimated using STATA 10 (Poi 2002; Poi 2008) and full results are shown in Table 2. In addition we developed a separate regression model (not shown) which predicted total household expenditure as a function of household income and the same socio-demographic variables for use in estimating future expenditure in money-value terms.

For the socio-demographic variables that were included in our previous work (Anderson, De Agostini et al. 2009), the results are similar: the linear trend is significantly different from zero for all items considered and age and employment status of head of household/household response person are significant predictors of household spending.

[5] Household expenditure surveys are characterised by zero reported expenditures on many items for many households Bardazzi, R. and M. Barnabani (1998). "Modelling Zero Expenditures on Italian Household Consumption." Economic Notes(1): 55-96.. This is generally caused by those households who do not report spending on certain items within the timeframe of the survey (usually 1 or 2 weeks). These zeros can represent no spend on an item simply because of a household's preferences (the household does not buy that good), or the zero may represent a rare purchase that could not be observed within the period of the study. This has been corrected for mobile and internet spending using standard imputation approaches.

Among the new control variables, the presence of one or two children significantly affects household spending on landline telephone (positively) and public transport (negatively) compared to households without children. Similarly to age of head of household, the number of household members by age group is a good proxy for the average age of the household and is a significant predictor of household spending on "new" ICTs such as mobile and internet (younger households are more likely to spend on these items) as well as on the use of private and public transport.

Household composition was also a significant predictor for ICT and transport spending. For example, single parent households spend more than married/partnered households on mobiles and public transport and less on car fuel; similarly other households spend more on landline, mobiles and public transports and less on internet, car fuel and other expenditures compare to married/partnered households.

As noted the model now controls for a larger number of household characteristics and most of them add significant information to the projection of household spending. This can be seen by the relatively small size of the standard deviation values in Table 2 and so we suggest that this model is a better fit than the one tested in our earlier work.

Table 2: Estimated QAIDS model using EFS 2001/02-2005/06 (n. of observations 30,774)

		Landline		Mobile		Internet		Car Fuel		Public Transport		Other	
alpha[6]		0.029	*(0.87)*	0.029	*(6.00)*	0.010	*(0.87)*	0.124	*(5.01)*	0.038	*(1.61)*	0.770	*(11.85)*
gamma[7]	**landline**	-0.005	*-(0.90)*	0.000	*-(0.77)*	0.004	*(1.72)*	0.001	*(0.28)*	0.002	*(0.78)*	-0.002	*-(0.22)*
	mobile	(omitted)[8]										0.000	*(1.44)*
	internet	0.004	*(1.72)*	0.000	*(0.46)*	-0.002	*-(0.93)*	0.001	*(0.56)*	0.000	*-(0.32)*	-0.002	*-(0.60)*
	car fuel	0.001	*(0.28)*	0.000	*-(2.17)*	0.001	*(0.56)*	0.020	*(4.10)*	0.004	*(1.25)*	-0.026	*-(3.94)*
	Public transport	0.002	*(0.78)*	0.000	*-(1.83)*	0.000	*-(0.32)*	0.004	*(1.25)*	-0.001	*-(0.26)*	-0.005	*-(0.80)*
	others	-0.002	*-(0.22)*	0.000	*(1.44)*	-0.002	*-(0.60)*	-0.026	*-(3.94)*	-0.005	*-(0.80)*	0.035	*(2.00)*
beta[9]		-0.014	*-(25.70)*	-0.004	*-(5.49)*	-0.001	*-(4.76)*	-0.002	*-(2.02)*	-0.004	*-(5.24)*	0.024	*(15.77)*
lambda		0.005	*(43.38)*	-0.001	*-(5.07)*	-0.001	*-(19.63)*	-0.007	*-(28.78)*	-0.001	*-(4.06)*	0.004	*(12.61)*
rho[10]		-0.003	*-(4.78)*	-0.003	*-(3.88)*	-0.002	*-(12.33)*	-0.012	*-(9.35)*	-0.004	*-(4.46)*	0.023	*(13.73)*
Time (in years)		-0.001	*-(11.82)*	0.002	*(13.37)*	0.000	*(10.72)*	0.001	*(6.33)*	0.000	*(0.11)*	-0.002	*-(6.58)*
Age of HRP (16-24)	**25-34**	0.005	*(5.46)*	-0.015	*-(14.18)*	0.002	*(5.50)*	0.007	*(3.47)*	-0.005	*-(3.80)*	0.007	*(2.72)*
	35-44	0.005	*(5.78)*	-0.024	*-(22.42)*	0.002	*(6.43)*	0.007	*(3.56)*	-0.008	*-(6.47)*	0.019	*(7.19)*
	45-54	0.007	*(6.56)*	-0.032	*-(23.57)*	0.001	*(3.75)*	0.008	*(3.52)*	-0.009	*-(5.64)*	0.023	*(7.33)*
	55-64	0.007	*(5.87)*	-0.039	*-(27.78)*	0.000	*(0.05)*	0.008	*(3.24)*	-0.011	*-(6.67)*	0.035	*(10.46)*
	65-74	0.007	*(4.66)*	-0.043	*-(25.07)*	-0.001	*-(1.32)*	0.010	*(3.37)*	-0.011	*-(5.82)*	0.038	*(9.40)*
	75+	0.003	*(2.09)*	-0.047	*-(26.36)*	-0.001	*-(2.58)*	0.005	*(1.58)*	-0.012	*-(6.00)*	0.052	*(12.38)*

6 Alpha = constant term

7 Gamma: the effect of price on demand

8 Omitted in all but 'Other' as it is collinear with the price of landline (there is no way to distinguish between landline and mobile prices in the RPI provided by the ONS, thus the price for telecommunications in general was attributed to both landline and mobiles).

9 Beta and Lambda together represent the effect of income (proxied by total expenditure)

10 Rho = term to control for system endogeneity

Employment status of HRP (1 - Managerial and professional occupations)	**Intermediate occ.**	0.001	*(2.00)*	0.002	*(3.45)*	0.000	*-(2.45)*	0.002	*(2.03)*	-0.004	*-(6.32)*	-0.001	*-(0.35)*
	Routine and manual occ.	0.000	*-(0.67)*	0.006	*(10.03)*	-0.001	*-(6.94)*	0.002	*(2.12)*	-0.009	*-(12.23)*	0.002	*(1.06)*
	Inactive (Never worked, long term unemp)	0.002	*(2.30)*	0.005	*(6.55)*	0.000	*-(2.03)*	-0.007	*-(4.64)*	-0.007	*-(7.19)*	0.007	*(3.54)*
	Retired	0.001	*(1.51)*	0.000	*-(0.30)*	-0.003	*-(9.96)*	-0.012	*-(6.07)*	-0.009	*-(7.33)*	0.023	*(8.72)*
N. of children (none)	**One child**	0.002	*(2.09)*	-0.001	*-(1.18)*	0.000	*(1.04)*	-0.001	*-(0.58)*	-0.003	*-(2.96)*	0.004	*(1.50)*
	Two or more	0.002	*(1.37)*	-0.003	*-(1.70)*	0.000	*(0.26)*	0.000	*(0.02)*	-0.006	*-(2.67)*	0.007	*(1.47)*
N. of persons by age	**0-4**	0.000	*(0.30)*	-0.004	*-(5.24)*	-0.001	*-(4.54)*	-0.001	*-(0.90)*	-0.003	*-(2.80)*	0.009	*(4.62)*
	5-17	0.000	*(0.55)*	0.000	*(0.43)*	0.000	*-(1.42)*	-0.002	*-(1.39)*	0.001	*(1.51)*	0.000	*(0.09)*
	18-44	0.000	*(0.29)*	0.003	*(2.95)*	0.000	*-(0.93)*	0.004	*(2.41)*	0.004	*(4.07)*	-0.011	*-(4.97)*
	45-64	0.000	*-(0.15)*	0.004	*(3.98)*	0.000	*-(1.18)*	0.004	*(2.21)*	0.003	*(2.24)*	-0.010	*-(4.20)*
	65+	-0.001	*-(1.20)*	0.005	*(4.12)*	0.000	*-(1.07)*	0.003	*(1.43)*	0.002	*(1.54)*	-0.008	*-(3.00)*
N. of people in the household (single person)	**2**	-0.001	*-(0.52)*	-0.004	*-(1.43)*	0.000	*(0.49)*	0.003	*(0.53)*	-0.002	*-(0.64)*	0.004	*(0.64)*
	3	0.000	*(0.16)*	-0.002	*-(1.02)*	0.001	*(1.11)*	0.001	*(0.30)*	-0.001	*-(0.43)*	0.001	*(0.23)*
	4	-0.001	*-(0.71)*	-0.002	*-(1.73)*	0.000	*(0.39)*	0.000	*(0.09)*	-0.001	*-(0.83)*	0.004	*(1.26)*
	4+	(omitted)		(omitted)		(omitted)		(omitted)		(omitted)		(omitted)	
Composition (married/partnered)	**single parent**	0.000	*(0.66)*	0.004	*(6.76)*	0.000	*-(1.27)*	-0.005	*-(5.64)*	0.002	*(3.17)*	0.000	*-(0.28)*
	single person	-0.001	*-(0.40)*	0.005	*(1.19)*	0.001	*(0.89)*	-0.001	*-(0.09)*	0.003	*(0.58)*	-0.006	*-(0.67)*
	others	0.002	*(3.01)*	0.013	*(19.53)*	0.000	*-(2.49)*	-0.013	*-(10.66)*	0.013	*(16.27)*	-0.014	*-(8.87)*

Figures in italics are z values

With these results to hand we are now in a position to estimate the share of expenditure on the household consumption categories using both the observed sample data for 2001/2 to 2005/6 and the 2006/2011/2016 synthetic population sample produced by the agent-based approach. We do this by using the QAIDS model coefficients (Table 2) to calculate the expected share of total expenditure for each item for each projected household. This estimated budget share was then converted to a £ value using the estimated household expenditure values to provide the baseline projection of expenditures under a 'no price change' scenario but allowing for compositional change of the household population through the agent-based dynamic projection.

To calculate the estimated expenditures under the scenario condition of a 2.5% rise in VAT on 1st January 2011 price elasticities were calculated for each item using the QAIDS model results (see Table 3). In general own price elasticities (on the diagonal) are expected to be negative, indicating that an increase in the price of a good leads to a decrease in the demand for that good. Cross price elasticities can be negative, positive or zero, depending on whether the increase of the price of one good leads to a decrease in the quantity demand of another good (the goods are complements), to an increase in the quantity demand of another good (the goods are substitutes) or does not have an effect on the quantity demand of another good (the goods are unrelated).

Table 3: Mean own- and cross-price elasticity

		Variation of 1% in price					
		Landline	Mobile	Internet	Car Fuel	Pub. Tran.	Others
% Variation in quantity	Landline	**-1.20**	0.02	0.66	0.07	0.22	0.02
		(0.36)	*(0.12)*	*(7.18)*	*(0.55)*	*(2.82)*	*(0.01)*
	Mobile	0.00	**-1.00**	0.00	0.00	0.00	0.00
		(0.00)	*(0.02)*	*(0.03)*	*(0.00)*	*(0.04)*	*(0.00)*
	Internet Subscription	0.16	0.00	**-1.34**	0.01	-0.03	0.00
		(0.26)	*(0.00)*	*(3.90)*	*(0.04)*	*(0.40)*	*(0.00)*
	Car fuel	0.03	-0.01	0.09	**-0.57**	0.31	-0.04
		(0.07)	*(0.02)*	*(1.25)*	*(2.04)*	*(4.76)*	*(0.01)*
	Public Transport	0.11	0.00	-0.06	0.10	**-1.09**	0.00
		(0.18)	*(0.03)*	*(0.69)*	*(0.50)*	*(1.29)*	*(0.00)*
	Others	-0.10	-0.01	-0.35	-0.62	-0.41	**-0.98**
		(0.16)	*(0.16)*	*(3.86)*	*(3.12)*	*(5.92)*	*(0.00)*

Notes:
Figures in parentheses are standard deviations and indicate the degree of heterogeneity of response

Own-price elasticities are reported in bold on the main diagonal of Table 3. As we would expect these were all negative, indicating that an increase in the price of a good leads to a decrease in the demand for that good. Interestingly the own-price elasticity for car fuel was smaller than -1 (-0.57) showing that demand decreases more slowly than price increases – in other words people found it hard to reduce car fuel expenditure. We use these own-price elasticities to estimate the mean weekly expenditure on each of these items following a price rise of 2.08% corresponding to a VAT increase from 17.5% to 20%.

Cross price elasticities are the off-diagonal values and are of less critical importance here although they do help to explain some of the subsequent modeling results. For example the cross-price elasticity of mobile and landlines was positive suggesting that on average an increase of the price of one leads to an increase in the quantity demand of the other one (substitute), however the magnitude of this elasticity was very close to zero indicating that the relationship on average was quite weak.

Increasing the price of internet subscriptions was associated with a smaller increase in landline but there was some variation (large standard deviation). On the other hand increasing landline prices had a smaller (positive) effect on Internet but with much less variation.

Interestingly a price increase in car fuel leads to an increase in demand of ICTs (landline, mobile and internet). This may suggest that when private transport becomes more expensive, people use/spend more on telecommunication and public transport. This appears to be 'paid for' out of other expenditure suggesting that as (if) fuel prices rise substantially, revenue from consumer-based telecommunications will rise at the expense of other expenditures. The relatively small size of the variation suggests that this response was uniform across the sample.

Finally car fuel and public transport are also substitutes (positive cross price elasticity) although the rise in public transport's fares had a stronger effect on the use of car than the other way around – those who use cars are more likely to stick with them whilst those who used public transport were more likely to switch to cars when public transport prices rise. The difference in the level of heterogeneity of response is also relevant – car fuel demand responses to rises in the cost of public transport are much more varied (4.76) than the inverse (0.5).

2.4.1 Combined projection and expenditure estimation results

The results of combining these estimation and modeling processes suggest that on average (under both scenarios) household expenditures on 'other items' are projected to fall from 2006 levels (not shown). Landline expenditures are estimated to fall and the price increase in 2011 has little effect (Figure 15). Expenditure on mobiles on the other hand shows an overall increase from 2001 to 2011 but remains roughly constant from 2006 to 2011 but with a more noticeable price effect after 2011 (Figure 16). Internet access expenditure is projected to remain roughly constant (Figure 17) whilst car fuel expenditure is projected to fall by some 20% with, again, a slightly larger price increase effect as we might expect from the previous discussion of elasticity (Figure 18). In the case of both mobile and public transport expenditure (Figure 19) there is an anomalous steep rise from 2005 to 2006 that seems quite implausible. In the case of public transport spending this is the main cause of the apparent downward trend from 2006 and further work is needed to investigate these results.

Overall, raising general prices by 2.5% in January 2011 does not seem to strongly affect estimated household spending on the items modeled. In particular, given the inelastic[11] demand of some of the goods considered, a decrease in demand does not offset the price rise resulting in a more noticeable increase of expenditures on mobile and car fuel compared to the baseline forecast. However, it should be noted that a much more important impact of a recession would be to increase unemployment and reduce earnings which would reduce household income and make it much harder to maintain current consumption levels for those who become unemployed. To do this we would need to use the agent-based population projection model with time-varying employment risk rates to produce a new projected population. Such a model has been implemented (Lawson 2009) but the results are not used here.

11 Price elasticity close to zero.

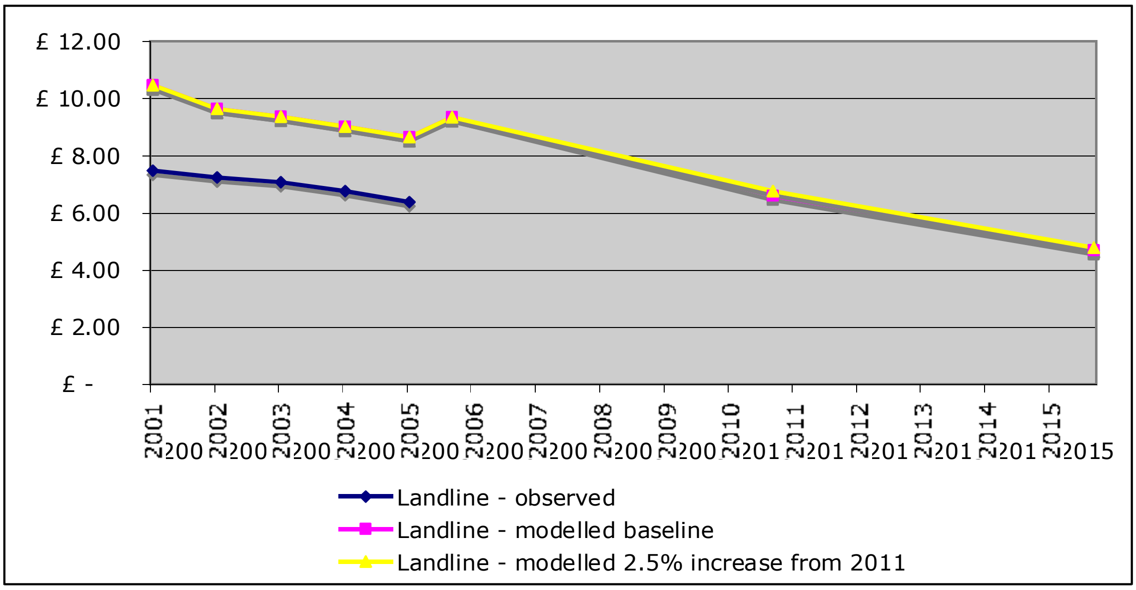

£ 12.00
£ 10.00
£ 8.00
£ 6.00
£ 4.00
£ 2.00
£ -
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015
Landline - observed
Landline - modelled baseline
Landline - modelled 2.5% increase from 2011

Figure 15: Observed, modelled and projected expenditure on telephony

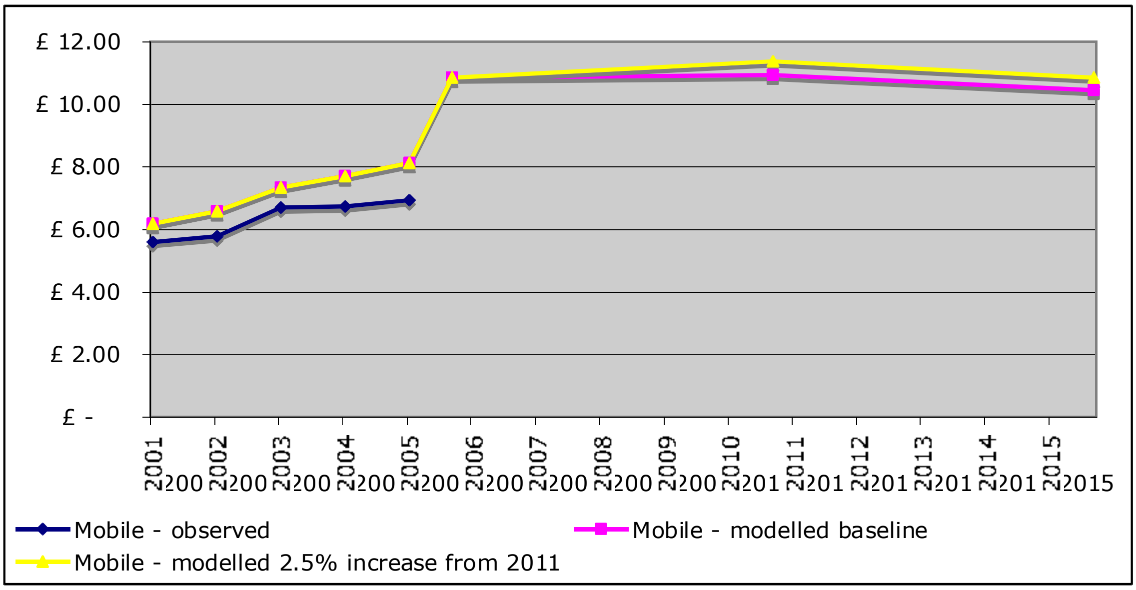


Figure 16: Observed, modelled and projected expenditure on mobile telephony

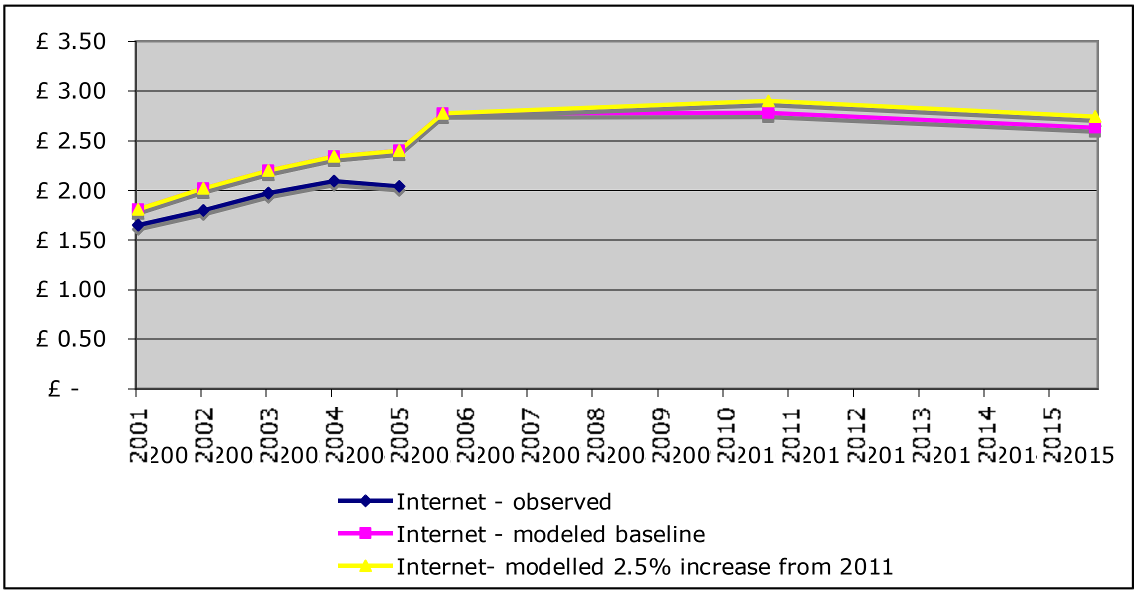


Figure 17: Observed, modelled and projected expenditure on internet access

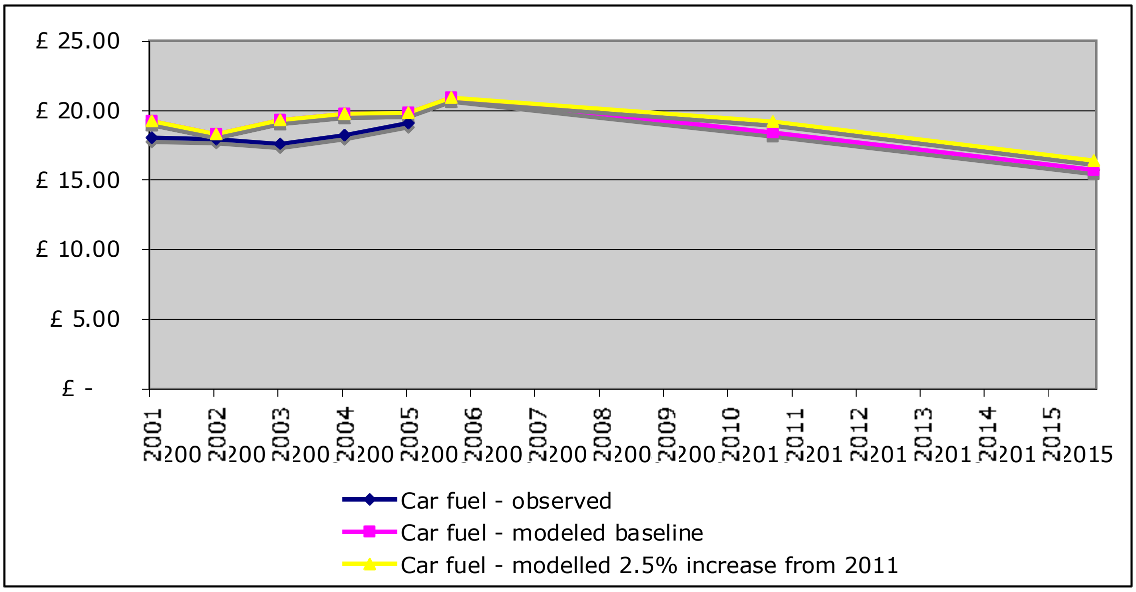


Figure 18: Observed, modelled and projected expenditure on car fuel

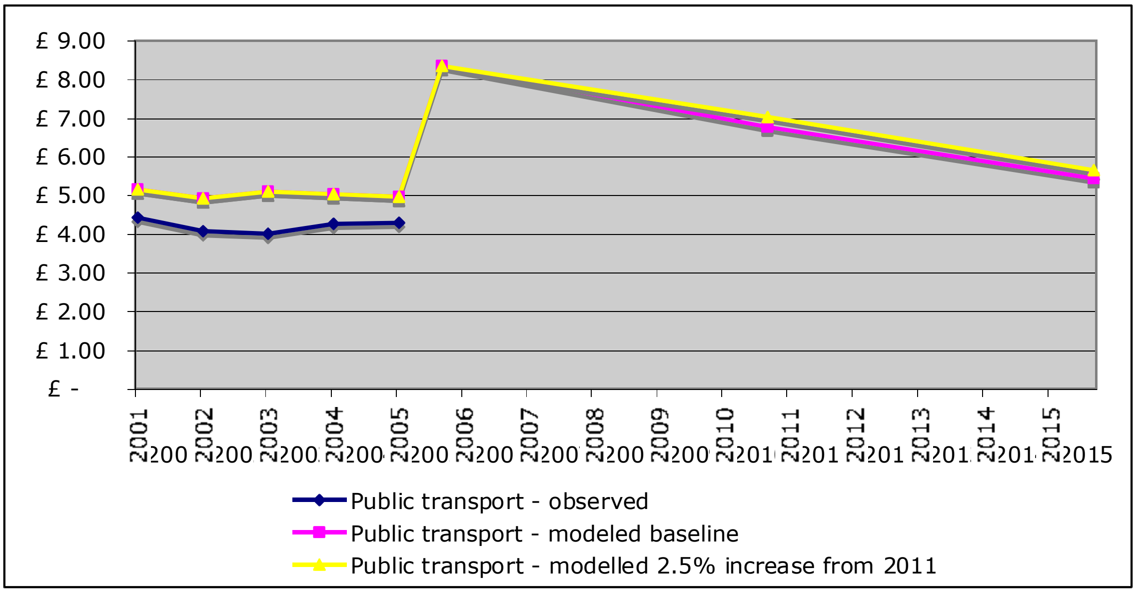


Figure 19: Observed, modelled and projected expenditure on public transport

2.5 Spatial microsimulation

With these results and data to hand it is now possible to combine the projected small area Census tables with the projected households to produce small are projections of future expenditures under the baseline and scenario conditions.

This was achieved using a spatial microsimulation method (Birkin and Clarke 1989; Ballas and Clarke 2001; Ballas, Clarke et al. 2005; Smith, Clarke et al. 2009) to iteratively re-weight the projected survey data to fit into each Census area on the basis of common constraints. As discussed elsewhere (Anderson 2012) the choice and ordering of the potential constraints was determined using a stepwise regression process. The results of the stepwise models suggest that the appropriate constraint orders are those shown in Table 4. Unsurprisingly given the limited constraints available there is very little variation between the models in terms of the ordering of the constraints and none are rejected.

Table 4: Constraints ordered by decreasing contribution to model

Model	R sq	Variables
Telephone	8.10%	Number of persons, Employment status, Tenure, Number of children
Mobile telephone	17.00%	Employment status, Number of persons, Number of children, Tenure
Internet access	25.40%	Employment status, Number of persons, Tenure, Number of children
Car fuel	23.20%	Employment status, Number of persons, Number of children, Tenure
Public transport	9.90%	Employment status, Number of persons, Number of children, Tenure

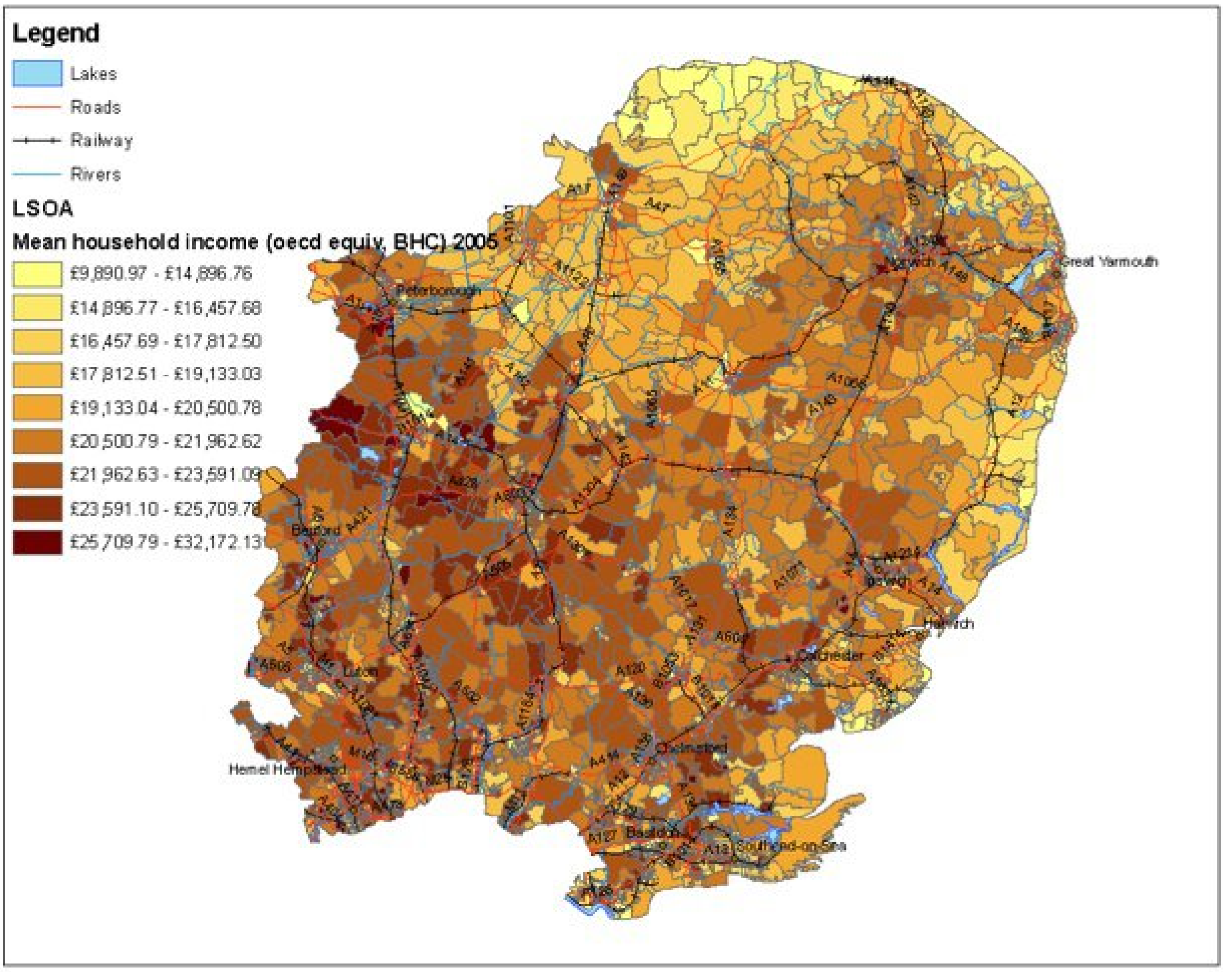
Having established the best constraints and the order in which to apply them in the spatial microsimulation process, the iterative proportional fitting spatial microsimulation method (Wong 1992; Simpson and Tranmer 2005; Anderson 2012) was used to generate 'snapshot' small area estimates of household expenditure on the five items in 2001-2002 and 2006 (as a baseline) and for both the baseline and +2.5% VAT scenario for 2011 and 2016 in the East of England. In this case with 3,550 LSOAs and only four constraint variables the estimation process for each expenditure variable took around two minutes.

2.5.1 Results

In this section we describe the results of this spatial microsimulation process and present them both as maps at the LSOA level for the East of England and also as charts. We make extensive use of the income deprivation sub-score of the most recent LSOA level Indices of Multiple Deprivation (McLennan, Barnes et al. 2010) in order to illustrate the relationships between expenditure change and levels of income deprivation. In most cases we have coded the income score into deciles for ease of analysis and we also make use of the DEFRA/ONS 2004 rural/urban classification scheme for LSOAs[12].

To provide a context for the LSOA level results, Figure 20 shows the estimated mean equivalised household income at the LSOA level for the East of England. The map shows the strong London and Cambridge effects as well as the effect of the inter-city rail line from Norwich to London and the poorer periphery of eastern Suffolk and north Norfolk. However as an equal area cartogram it de-emphasises the pockets of less wealthy areas in most urban areas in contrast to the visually more dominant rural areas.

[12] http://www.ons.gov.uk/about-statistics/geography/products/area-classifications/rural-urban-definition-and-la-classification/rural-urban-definition/index.html



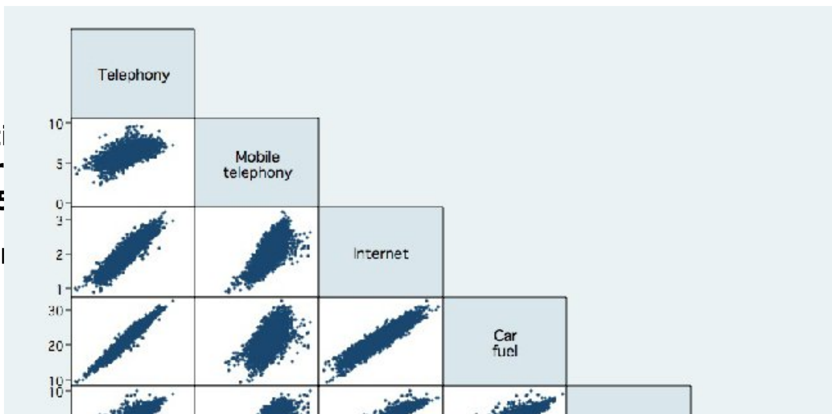
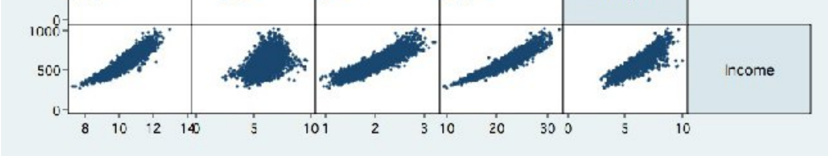


Figure 21: Esti... costs at the LSOA level for ... ily Resources Survey 2004-5 ... npared to the



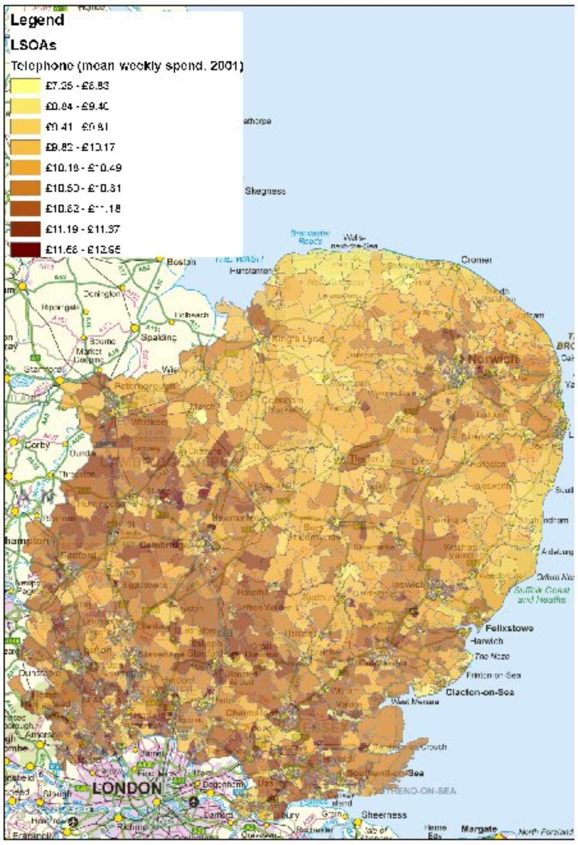
estimated 2001/2 LSOA level mean weekly household expenditures (EFS 2001-2, Census 2001).

In addition Figure 21 shows the relationship between mean estimated unequivalised income and the estimated mean weekly household expenditures for 2001 at LSOA level. As can be seen there are clearly strong relationships between the estimated income distribution and expenditure on all items with perhaps the exception of mobile telephony.

Finally we turn to the spatial results for landline telephony and car fuel and discuss these in turn with reference to the income deprivation of the areas and also their urban/rural classification. We focus on these two as they form an excellent example of a basic utility (in the case of telephony) and of a policy-relevant semi-commodity in the case of car fuel. In addition their projections did not exhibit the anomalous spike in 2006 and so the interpretation of changes over time are less uncertain. In these discussions we map, chart and refer to the 'Difference' statistic - the numerical difference between the baseline and 2.5% VAT scenario percentage change over 2006-2016 rather than a simple numerical difference in mean expenditure for any given year which may be instructive for a given year but gives no sense of change over time.

Landline Telephony

Figure 22 shows the distribution of estimated mean weekly telephone expenditure at LSOA level in 2001. The distribution correlates strongly with income (Figure 20). The map showing the numerical difference between the base line and 2.5% VAT scenario % change (Figure 23) suggests that the highest 'rises' by 2016 (i.e. the least fall from 2011 expenditures) relative to the baseline occur in relatively rural and peripheral areas. However this is misleading as the graph by rural/urban classification (Figure 24) shows. In fact the highest rises tend to be for urban areas while the IMD income score decile column and graph indicates they are also likely to be the poorest areas. Those areas where mean weekly expenditure increases least under the 2.5% scenario are urban or town and fringe and are much less deprived.



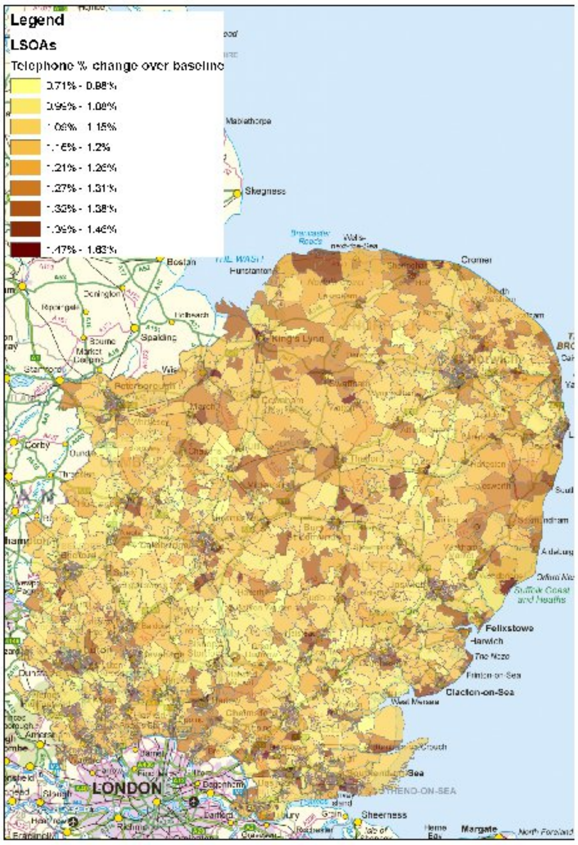


Figure 22: Estimated mean weekly telephony expenditure in 2001 at the LSOA level for the East of England (Spatial microsimulation, EFS 2001/2, Census 2001)

Figure 23: Difference between the baseline and 2.5% VAT scenario percentage change over 2006-2016 for the East of England (Spatial microsimulation, projected EFS, projected Census 2006-16)

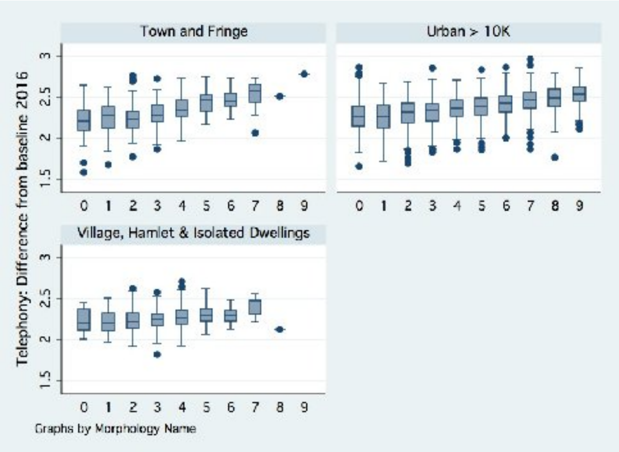


Figure 24: % difference between estimated mean weekly household expenditures on telephony for baseline and 2.5% VAT scenarios in 2016 (East of England, IMD 2011 income deprivation deciles, rural/urban categorisation)

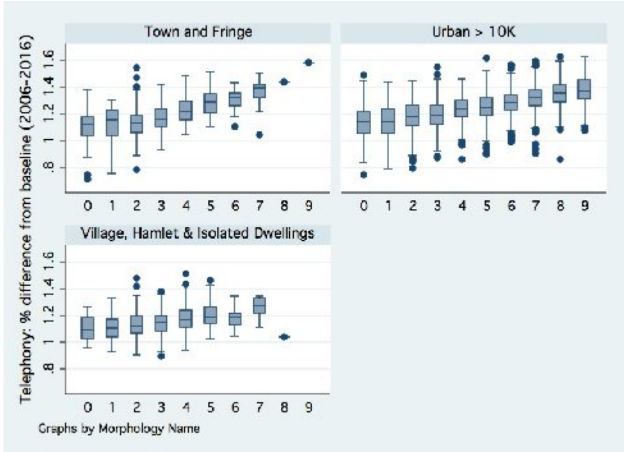


Figure 25: Difference between the telephony baseline and 2.5% VAT scenario percentage change over 2006-2016 by rural/urban classification and IMD 2010 income deprivation decile

Car fuel

Estimated expenditure on car fuel in 2001 also tended to correlate with estimated income distributions and whilst the spatial distribution of the effects of the 2.5% increase appear relatively evenly distributed the IMD income deprivation decile and rural/urban charts suggest that the biggest 'losers' will be tend to be some (but not exclusively) deprived urban areas perhaps reflecting the elasticity results reported above where we found that lower income households were less sensitive to car fuel price increases than were higher income households. Thus when car fuel prices rise, lower income households either choose or are forced to pay the higher prices whereas higher income households appear to substitute for other modes of transport or even for less travel perhaps through, for example, changes to commuting practices.

In this regard we might expect the biggest 'losers' to be households in rural areas where we would assume there to be poorer public transport infrastructure and therefore an inability to switch from car use. The fact that we do not see this effect suggests that these factors are not adequately captured by the microsimulation model and that this modelling approach performs less well where expenditures rely on an unevenly distributed infrastructure such as public transport which is not reflected in the socio-demographic distributions of the constraint variables used.

This was more explicitly tested by correlating the baseline estimated weekly expenditure on car fuel for 2011 with the 'Geographical Barriers[13]' sub-domain score of the IMD 2010. We found that there is a weak positive correlation between geographical barriers and baseline 2011 car fuel expenditure (r = 0.2626) and an even weaker (positive) relationship with expenditure on public transport (r = 0.1494). To some extent we would expect a weak positive effect for public transport given that for those in rural areas who (can) use it, the costs are likely to be higher but we would have expected a stronger correlation between car fuel

[13] Components: Road distance to a GP surgery; road distance to a food shop; road distance to a primary school; road distance to a Post Office. McLennan, D., H. Barnes, et al. (2010). The English Indices of Deprivation 2010. London, Department for Communities and Local Government.

expenditure and geographical barriers if the spatial microsimulation model adequately captured this aspect which it clearly does not.

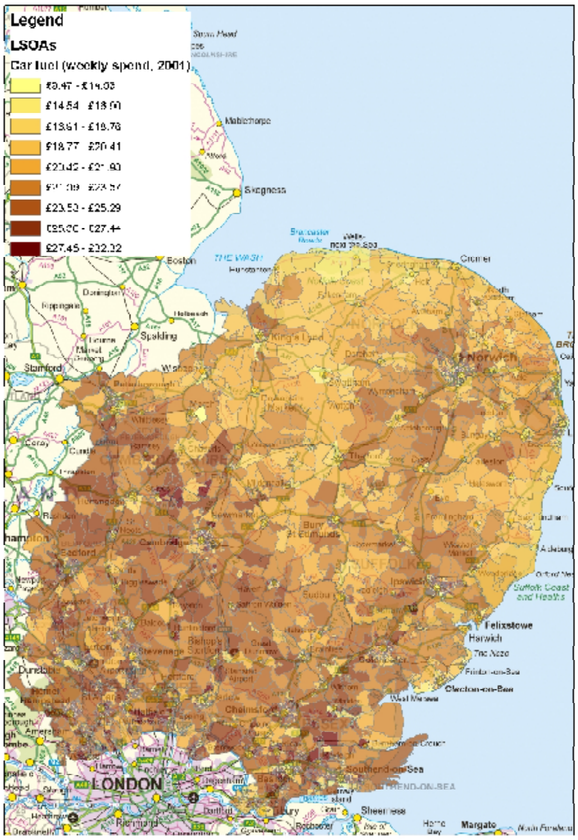


Figure 26: Estimated mean weekly car fuel expenditure in 2001 at the LSOA level for the East of England (Spatial microsimulation, EFS 2001/2, Census 2001)

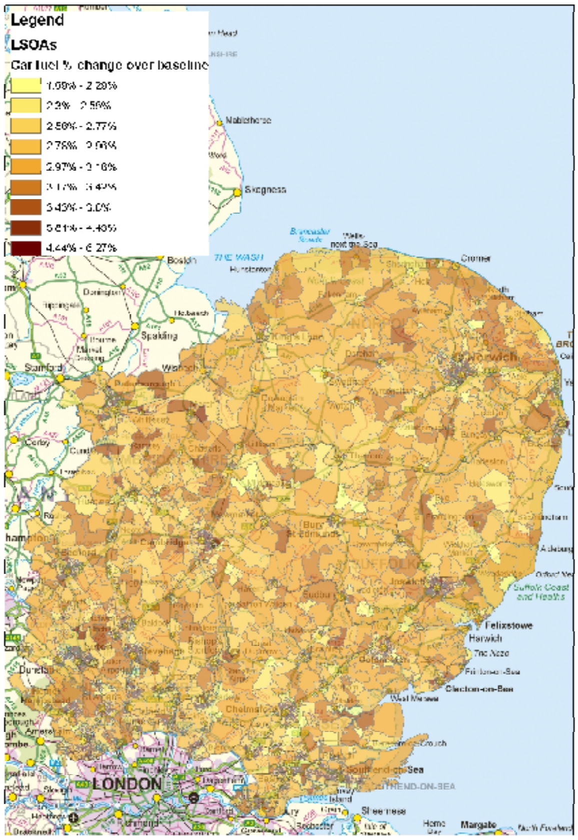


Figure 27: Difference between the car fuel baseline and 2.5% VAT scenario percentage change over 2006-2016 at the LSOA level for the East of England (Spatial microsimulation, projected EFS, projected Census 2006-16)

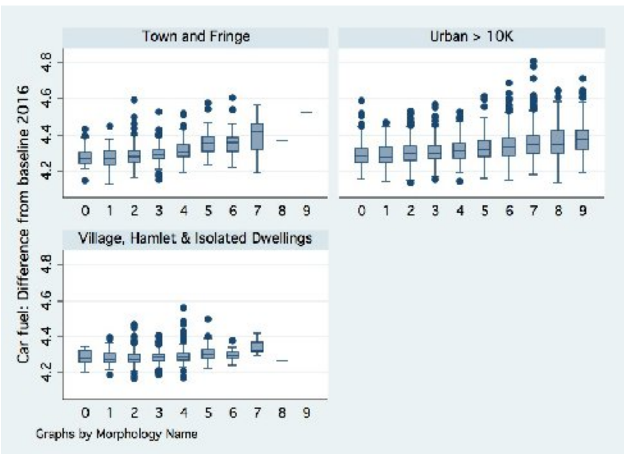


Figure 28: % difference between estimated mean weekly household expenditures on car fuel for baseline and 2.5% VAT scenarios in 2016 (East of England, IMD 2011 income deprivation deciles, rural/urban categorisation)

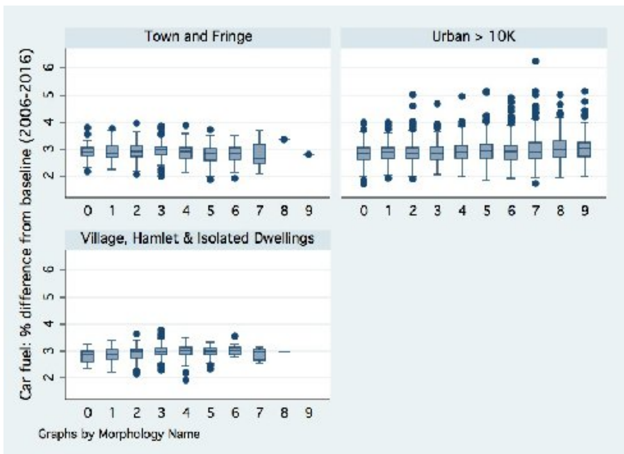


Figure 29: Difference between the car fuel baseline and 2.5% VAT scenario percentage change over 2006-2016 by rural/urban classification and IMD 2010 income deprivation decile

3 DISCUSSION

This chapter has brought together a number of modeling strands to produce small area estimates of household expenditures for the East of England to 2016 under baseline and 2.5% price increase scenarios using the approach set out Figure 30.

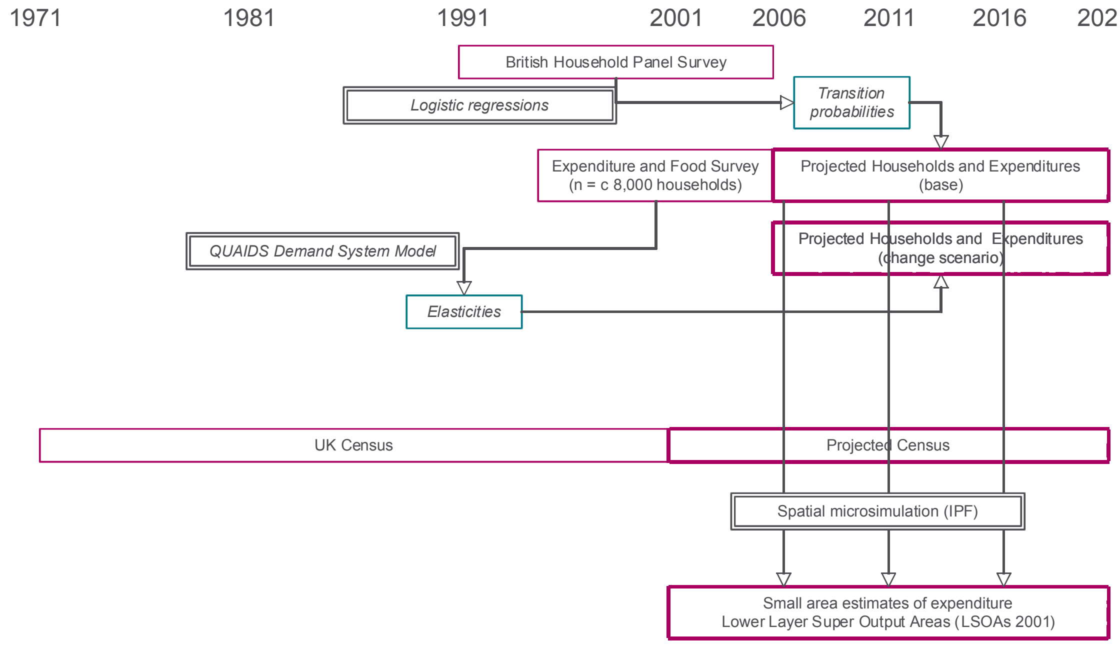


Figure 30: Summary of contributing models

Overall the method appears feasible in that each strand of the model produced generally plausible results with some exceptions that we have noted above and will discuss further below. The modelled responses to price rises for different kinds of households appeared to produce plausible spatial distributions and revealed effects in places that would have been expected given the demand system model results. With some amendments such as the estimation of area level totals rather than means the total reduction/increase in expenditure under the different scenarios could be calculated and compared with potential infrastructure investment costs in a similar manner to our previous example of broadband investment cost/benefit modelling (De Agostini and Anderson 2008). As an exercise in evaluating a socio-spatial policy relevant modelling approach it can therefore be seen as a success.

More specifically, as we have noted only a few of the own and cross price effects in the model turned out to be statistically significant. Whilst it could be argued that this may simply reflect non-response to price increases it is also possible that there is unmeasured variation (heterogeneity) caused by missing demographic and expenditure variables that could be included in the model and, if this were done, the price effects may become clearer.

Further, with only four constraint variables available of which one was imputed it is possible that the spatial microsimulation process is unable to sufficiently re-weight the households appropriately. This is more obviously the case where the constraints we have are relatively poor predictors of the expenditure variables (see Table 4). In this case the estimation process is unlikely to produce sufficient differentiation between areas due to missing constraint variables. Of course the number of constraints that can be projected using the methods described here are restricted to those available from the UK Census over time and which are also included in the dynamic population projection.

With respect to the anomalous expenditure rises for mobile telephony and public transport, as we noted above a weighting process was applied to the input to the dynamic population projection model in order to be able to claim 'representativeness' of any tables produced from the model. This was done by converting the fractional survey non-response weights into integer weights and duplicating households as appropriate. This 'expansion' method may have inadvertently increased apparent expenditure and household numbers in particular groups and produced peculiar spikes in the projected expenditure data.

The use of the QUAIDS model to estimate future expenditures relies on the use of coefficients (relationships) between variables that were true for the observed data period (2001/2 to 2005/6). We therefore make the assumption that these relationships, essentially the component 'value' of the goods and their relationship to socio-demographics as well as their elasticities remain constant over time. This is an unlikely situation since the values applied to different goods and services may vary over time.

The discussion of the results for car fuel and public transport expenditure illustrated the problem of trying to produce estimates of expenditure which is dependent on a highly uneven infrastructure distribution when that distribution is very unlikely to be captured by the distribution of the available constraint variables. The case in point here is public transport availability, which is unlikely to be predicted by particular distributions of the number of persons per household, household response person employment status, tenure or number children per household. A similar problem would arise should we attempt to estimate expenditure on gas or oil for heating. This could only be resolved if both the spatial data and the survey data include measures of proximity to or availability of the infrastructure in question. Even though such measures could be collected in a bespoke survey it would still remain problematic to identify suitable area level estimates from some other source. As an example the Index of Deprivation's geographical barriers sub-domain includes measures of road distance to a number of services but does not provide any indicator of availability of public transport and neither does one of the most comprehensive efforts to date to produce local area service availability estimates in rural areas (Huby, Cinderby et al. 2005) although there is now clear potential to extract such data from newly available public transport service websites and databases.

Finally, as will have become clear from the foregoing discussions there are multiple sources of potential error in these estimates. These include 'error' in the QUAIDS modelling process caused by unmeasured household characteristics, sampling bias and excluded variables; 'error' in the dynamic population modelling caused by assumptions about constancy of transition probabilities and fertility rates; 'error' in the census projection caused by the re-zoning process, the smoothing process and the projection approach. There is also potential error in the spatial microsimulation process caused by the reduced number of constraints available and the relatively low predictive power that these constraints have for some of the expenditure variables as well as the inability to adequately account for 'patchy' infrastructure.

Whilst there are recognised ways of modelling and characterising 'error' in econometric models such as QUAIDS (such as through t-values and confidence intervals), in dynamic projection models (such as through sensitivity tests) and in spatial microsimulation (through the SAE and other approaches (Smith, Clarke et al. 2009; Edwards, Clarke et al. 2011)) there is currently no accepted way to bring together these aspects of error in such a way as to express some form of 'robustnes' about the results for a given small area.

4 CONCLUSION

In conclusion whilst the work summarised in this chapter provides an exploration of the value of using a combination of methods to estimate small area household expenditure levels in to the future for the East of England it has also raised a range of potential issues that could and perhaps should be addressed in future research.

These might include the expansion of the demand system model to include additional related budget shares and/or socio-demographic variables although mindful of the additional estimation time/computing resources required. Attention should also be given to the extent to which 'patchy' infrastructures can be modelled by using 'constraints' based on characteristics of survey cases and geo-coded infrastructure data. An example might be the use of the UK

National Public Transport Access Nodes (NaPTAN[14]) database to provide spatial data on public transport availability together with time-diary survey data on travel via public transport.

As others have noted however (Birkin and Clarke 2011), perhaps most important of all is the need for the development of conceptual and methodological approaches to the characterisation of multiple sources and levels of error in small area microsimulation models drawing perhaps on recent developments in the analysis of multiple levels of survey error (Weisberg 2005).

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