Chapter Code: 3

Estimating the small area effects of austerity measures in the UK

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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 (Zaidi et al., 2009, Mitton et al., 2000, Hancock et al., 1992) 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 et al., 2005, Tanton 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.

Projection and Estimation Methods

Our approach to projecting small area estimates of household expenditure comprises three main strands. The first is 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 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.

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.

Spatial projection

Our approach to the projection of small area statistics follows our earlier work (Anderson et al., 2009) in re-zoning UK census small areas (wards) to form consistent geographical zones over time (Gregory and Ell, 2005, Norman et al., 2003). In this work we have switched 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.

As discussed in more detail elsewhere (Anderson et al., 2013), a postcode-based aerial interpolation approach was used to re-weight the historical census data and allocate the weighted values to fragments of historical zones before the fragments (and available historical data) were re-aggregated to Census 2001 LSOAs. A review of the census data suggested variables available to be 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 then used the Holt-Winters non-seasonal smoothing algorithm to smooth the LSOA level proportions of households in the observed census variable categories for 1971 to 2001 and a gravitational model to project constraint proportions and total household numbers forwards at LSOA level to 2011 and 2021. Household projections from the UK Government at Local Authority level[1] were used to normalise household numbers and the projected proportions were converted to projected household counts using these normalised total household counts. The method projected 1-n constraint proportions and then calculated the last constraint as the residual. Any negative proportions were changed to the most recent positive proportion and any zero value to a small non-zero number to prevent errors in any future spatial microsimulation process where 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. Due to the processing requirements of this method the projections were limited to the 3,550 LSOAs in the East of England.

Overall the projected trends appeared relatively plausible given that they are contingent on historical trends (see also (Anderson et al., 2013)). In some cases, such as the proportion of households with 2+ cars () or the reduction in the proportion of those who are social/council renters () an earlier asymptote might have been expected as socio-economic limits are reached. However considerably more complex dynamic projection modeling would be required to address this issue and it is outside the scope of this chapter.

[1] http://www.communities.gov.uk/publications/corporate/statistics/2031households0309

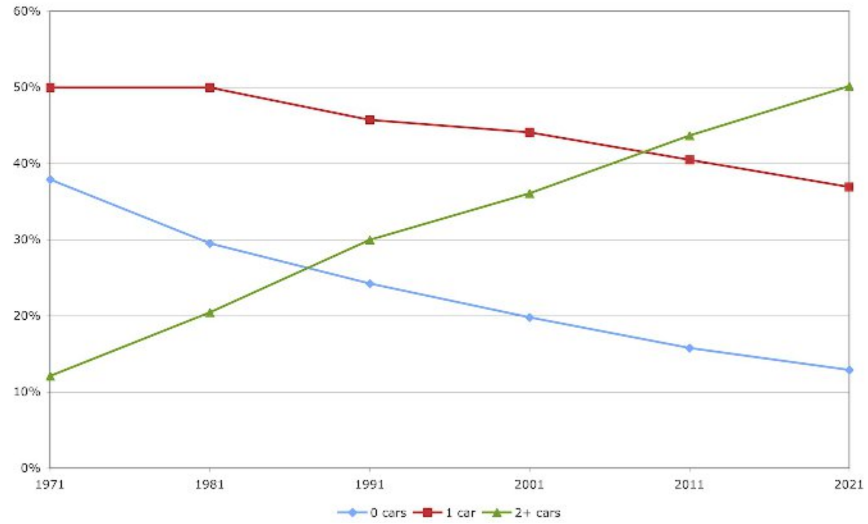

Figure 1: % households with 0,1 or 2+ cars

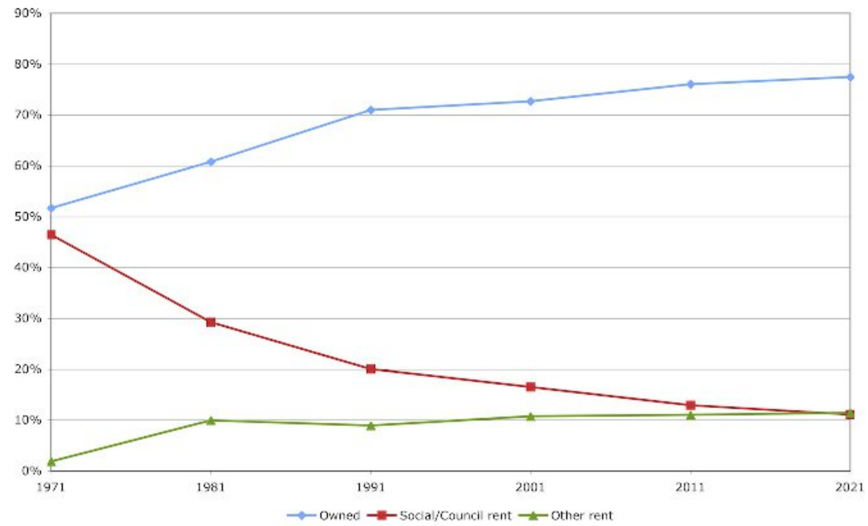

Figure 2: % households in different tenure types

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 using an agent-based dynamic population projection model. This model aged a sample population (EFS 2005/6, n = 11,204 persons in 4,732 households) through the application of a range of dynamic demographic projection modules (Lawson, 2009, Lawson, 2011). These modules included a partnership formation module which 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. Additional modules were added to represent single people leaving and returning to the parental home and were run sequentially for each simulated year. Each transition between states is controlled by transition probabilities estimated mainly from BHPS-derived logistic regression models although additional probabilities were taken from the SAGE Technical Notes (Scott, 2003).

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. 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).

One absence from the dynamic population projection was housing tenure which was imputed for the projected EFS survey data using a multinomial regression model based on income, number of children, number of persons, composition and employment status. The resulting coefficients were then used to predict the probability that a projected household was of a given tenure type and households were selected into tenure type if their probability of being in that type was greater than the median predicted probability (see also (Anderson et al., 2013)).

Demand system model

As in previous work (Anderson et al., 2009) a Quadratic Almost Ideal Demand System model (Banks et al., 1997) model was used to project consumers' behaviours into the future by estimating a system of *n* share equations using the EFS data from 2001/02 to 2005/06 based on prices, household income and other household characteristics where n is the number of goods or services being considered.

The model focused on 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.

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. The demand system was estimated using STATA 10 (Poi, 2008, Poi, 2002) and full results are shown in Table 1. 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.

Table 1: Estimated QAIDS model using EFS 2001/02-2005/06 (n. of observations 30,774)

		Landline		**Mobile**		**Internet**		**Car Fuel**		**Public Transport**		**Other**	
alpha[2]		0.029	*(0.87)*	0.029	*(6.00)*	0.010	*(0.87)*	0.124	*(5.01)*	0.038	*(1.61)*	0.770	*(11.85)*
	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)[4]										0.000	*(1.44)*
gamma[3]	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[5]		-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[6]		-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)*
	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)*
Age of HRP (16-24)	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)*
	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)*
Employment status of HRP (1 - Managerial and professional occupations)	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,	0.002	*(2.30)*	0.005	*(6.55)*	0.000	*-(2.03)*	-0.007	*-(4.64)*	-0.007	*-(7.19)*	0.007	*(3.54)*

[2] Alpha = constant term
[3] Gamma: the effect of price on demand
[4] 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).
[5] Beta and Lambda together represent the effect of income (proxied by total expenditure)
[6] Rho = term to control for system endogeneity

	long term unemp)												
	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 1) to calculate the expected share of total expenditure for each item for each projected household in each year. 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 2).

Table 2: Mean own- and cross-price elasticity

% Variation in quantity	Variation of 1% in price: Landline	Mobile	Internet	Car Fuel	Pub. Tran.	Others
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 2 and 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. Own-price elasticity for car fuel was smaller than -1 (-0.57) showing that demand decreases more slowly than price increases – people found it hard to reduce car fuel expenditure.

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 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).

The own-price elasticities are then used 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%. The full results area discussed elsewhere (Anderson et al., 2013) but in summary they suggest that on average, raising general prices by 2.5% in January 2011 does not strongly affect estimated household spending on the items modeled. In particular, given the inelastic[7] 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

[7]Price elasticity close to zero.

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.

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 area projections of future expenditures under the baseline and scenario conditions.

This was achieved using a spatial microsimulation method (Birkin and Clarke, 1989, Smith et al., 2009, Ballas et al., 2005, Ballas and Clarke, 2001) to iteratively re-weight the projected survey data to fit into each Census area on the basis of common constraints. The choice and ordering of the potential constraints was determined using a stepwise regression process (Anderson, 2012). 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 3).

Table 3: 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

An iterative proportional fitting spatial microsimulation method (Anderson, 2012, Simpson and Tranmer, 2005, Wong, 1992) was then used to generate 'snapshot' small area estimates of household expenditure on the five items in 2001-2002 and 2006 and for both the baseline and +2.5% VAT scenario for 2011 and 2016 in the East of England.

Results

In this section we describe the results of this spatial microsimulation process and whilst the full set of results are discussed elsewhere (Anderson et al., 2013), we concentrate here on the car fuel results as an explicative exemplar of a policy-relevant semi-commodity. In these discussions we 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.

We present the results as maps at the LSOA level for the East of England and also as charts making use of the income deprivation sub-score of the most recent LSOA level Indices of Multiple Deprivation (McLennan et al., 2010) 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[8].

The estimated expenditures on car fuel suggest that 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 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.

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

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'[9] sub-domain score of the IMD 2010. This showed 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). This is to some extent expected 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 expenditure and geographical barriers if the spatial microsimulation model adequately captured this aspect.

[9] 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., BARNES, H., NOBLE, M., DAVIES, J., GARRATT, E. & DIBBEN, C. (2010) The English Indices of Deprivation 2010. London, Department for Communities and Local Government.

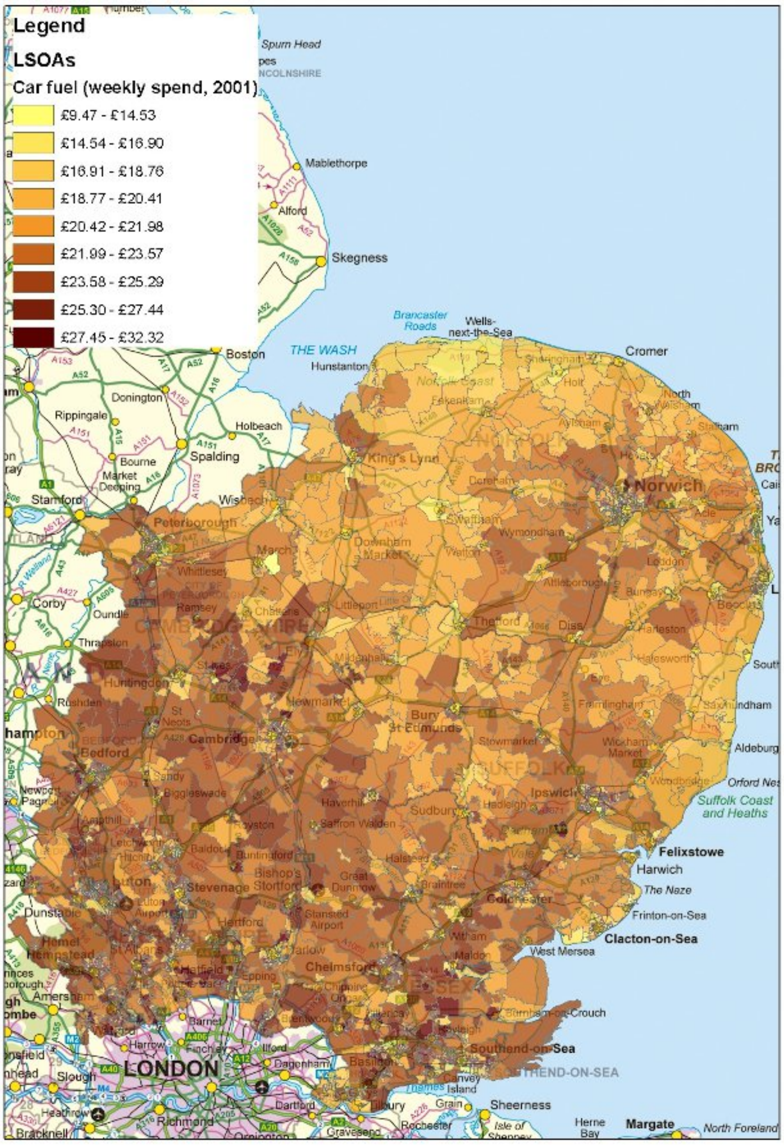

Figure 3: Estimated mean weekly car fuel expenditure in 2001 at the LSOA level for the East of England (Spatial microsimulation, EFS 2001/2, Census 2001)

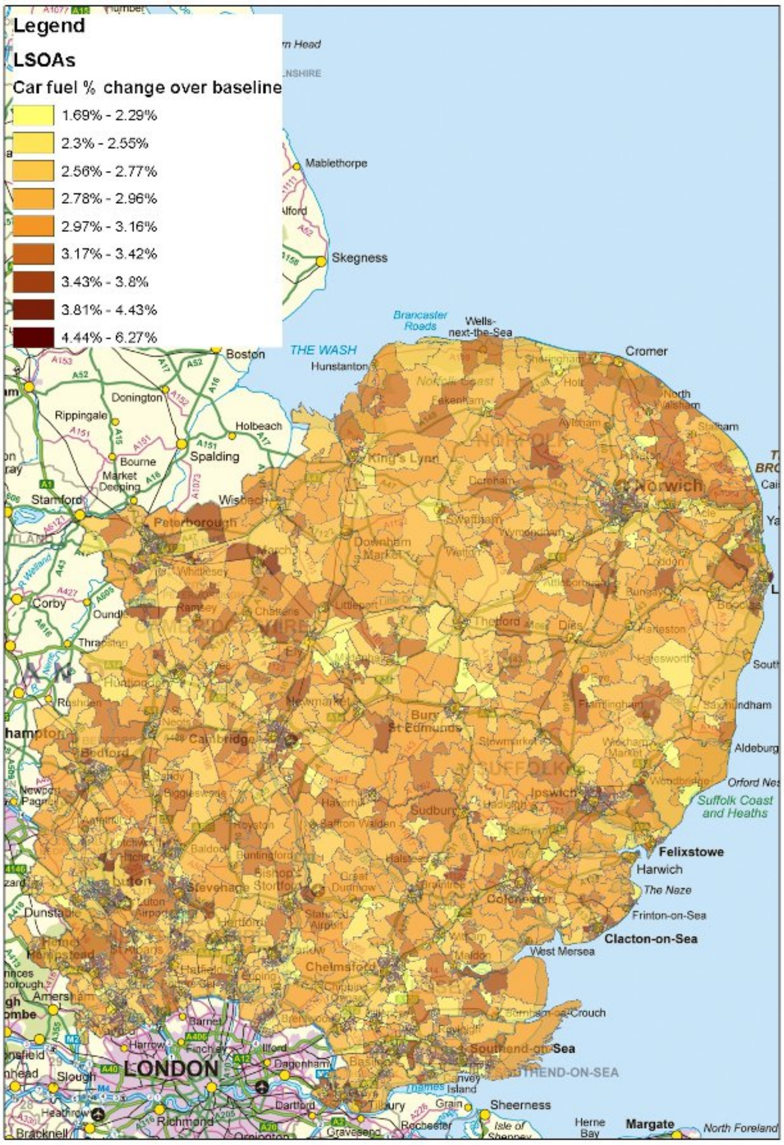

Figure 4: Difference between the car fuel baseline and 2.5% VAT scenario percentage change over 2006-2016 at the LSOA level for the East of England (Spatial microsimulation, projected EFS, projected Census 2006-16)

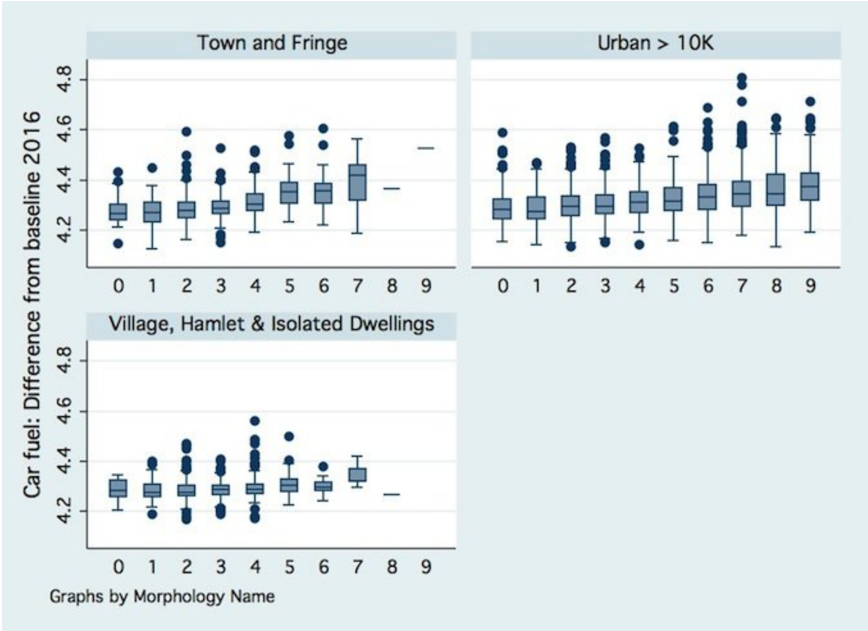

Figure 5: % difference between estimated mean weekly household expenditures on car fuel for baseline and 2.5% VAT scenarios in 2016 (East of England, IMD 2011 income deprivation deciles, rural/urban categorisation)

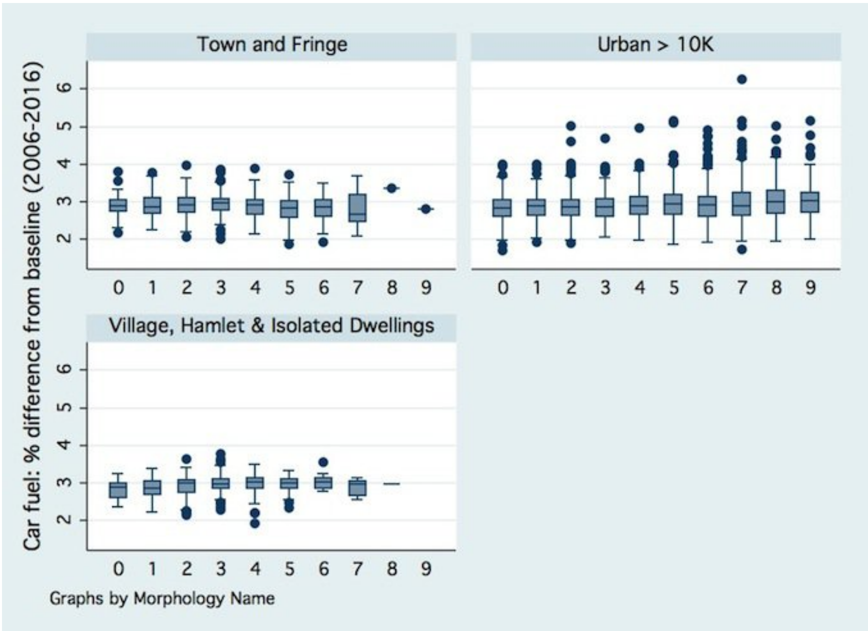

Figure 6: Difference between the car fuel baseline and 2.5% VAT scenario percentage change over 2006-2016 by rural/urban classification and IMD 2010 income deprivation decile

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 .

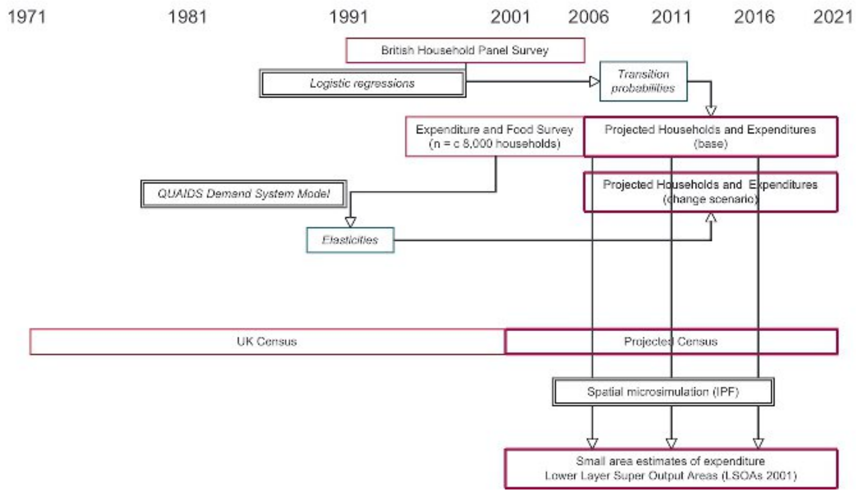

Figure 7: Summary of contributing models

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. 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 3). 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.

Of course 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.

In addition the discussion of the results for car fuel illustrate the difficulty of estimating expenditure which is linked to 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 and yet has a role to play in substituting for private transport (c.f. Table 2).

Finally, as will have become clear from the foregoing discussions there are multiple layers 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 et al., 2009, Edwards 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.

Conclusion

Overall 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 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.

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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