

TRANSPORTATION SCIENCE**Car travel demand: spillovers and asymmetric price effects
in a spatial setting**

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Car travel demand: spillovers and asymmetric price effects in a spatial setting

Abstract

A novel analysis framework for the spatial aspects of car travel, measured by vehicle miles travelled (VMT), is introduced in this paper. The specification of a dynamic Spatial Durbin Model (SDM) enables the analysis of VMT spatial spillovers and diffusion between neighboring areas in the short and long-run. The framework is further developed to capture and introduce to a spatial setting potential asymmetry and hysteresis that can reflect reference dependence and habits. A panel dataset is compiled at sub-regional level, based on official car mileage recordings in England and Wales. In addition to the inelastic long-run responses of VMT to fuel price (-0.124) and income (0.116) changes, the results illustrate asymmetries and hysteresis in price elasticities with a significant spatial component. The impact magnitude on VMT from a number of factors, such as alternative fuel use, fuel deserts in rural areas, road network and car fleet characteristics, is also estimated. The results are consistent with the car use saturation hypothesis through the positive impact of motorization rate to VMT. The negative effect of public transport infrastructure on car travel is only significant in the spatial models. The paper demonstrates the applicability and importance of spatial econometrics in transport research.

1. Introduction

Private transport and especially car travel has been a major consumer of petroleum and its continuing prevalence raises questions about the sustainability of current mobility patterns (Ewing et al., 2013; Polydoropoulou et al., 2013; Schäfer and Victor, 2000). A key manifestation of travel demand is vehicle-miles travelled (VMT) by private cars. Despite the extensive literature analyzing VMT with respect to various determinants, there is a lack of explicitly accounting for the spatial aspect of car travel through spatial econometric approaches. Especially the spatial aspects of asymmetries and hysteresis are entirely absent from the literature. These two gaps constitute the focal point of this paper.

A review of the factors affecting VMT shows that income and fuel price effects feature prominently in the literature and are usually inelastic (Hymel et al., 2010; Goodwin et al., 2004). A number of other important aspects of VMT analysis have been discussed in the literature, including congestion (Grimal et al., 2013; Hymel et al., 2010), public transport coverage (Hymel et al., 2010; Sihvola et al., 2012), motorization rate (Schäfer and Victor, 2000), and asymmetries/hysteresis in price and income effects (Dargay, 2007; Dargay and Gately, 1997; Hess et al., 2008). Changing consumer preferences, and shifts in lifestyles are some of the additional explanations put forward for the potential car use levelling off (Grimal et al., 2013; Goodwin and Van Dender, 2013; Kamargianni et al., 2014).

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3 More specifically, congestion affects VMT negatively; particularly in high density urban
4 areas where car travel can be substituted by increasingly attractive public transport,
5 cycling, and/or walking (Grimal et al., 2013; Hymel et al., 2010; Kamargianni et al.,
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More specifically, congestion affects VMT negatively; particularly in high density urban areas where car travel can be substituted by increasingly attractive public transport, cycling, and/or walking (Grimal et al., 2013; Hymel et al., 2010; Kamargianni et al., 2016; Metz, 2010). Car motorization rate also affects VMT negatively, as additional cars in the household are driven less (Schäfer and Victor, 2000). This might not be the complete picture in developed countries, where the spatial variation of motorization rate can also be an indication of car dependency. Dargay (2007) suggests that rising incomes make it easier for households to own cars, and once acquired, cars are not readily disposed of even if the economic conditions worsen, pointing to car dependency.

The corollary issues of asymmetries and hysteresis, or rather the underlining behavioral causes, have been widely studied in behavioral economics and transport discrete choice modeling literature. Asymmetric responses are caused by consumers weighing losses more than equivalent sized gains, which is attributed to loss aversion and is a specific aspect of reference dependence and the endowment effects (Bao et al., 2014; Hess et al., 2008; Hardie et al., 1993; Tversky and Kahneman et al., 1991). Hysteresis is applicable to transport demand, when there is resistance to change that stems from the tendency of acquiring consumption habits more easily than to abandoning them (Costa and Gerard, 2015; Sharmeen and Timmermans, 2014; Gärling and Axhausen, 2003; Dargay and Gatel, 1997). Imperfect reversibility is defined as the failure of an effect to reverse itself, when its underlying cause is reversed (Dixit, 1989; Dargay and Gatel, 1997).

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Studies focusing on loss aversion, reference dependence and endowment effect typically employ disaggregate, cross-sectional data, often derived from stated preference experiments (Masiero and Rose, 2013; Hess et al., 2012; Louviere et al., 2008). There are only few studies using revealed preference data at different levels of aggregation to empirically examine these behavioral issues and their manifestations: asymmetries and hysteresis in this context (Dargay and Gatel, 1997; Dargay 2007; Wadud, 2014). For example, Goodwin (1998), Pendyala et al. (1995), and Dargay (2001) look at successive waves in pseudo-panel setting, relating car ownership changes to periods of income increases and reductions. Their findings present clear indications of asymmetry and hysteresis. The asymmetry and hysteresis concepts can provide causal links between an aggregate level of economic activity, as is the case here, and psychological responses and behavioral factors at the level of individual, such as loss aversion and habit formation.

Travel takes place in space (transport network) and traffic flows are not constrained within a certain area. VMT in a specific area are affected by the VMT and other demographic and transport network characteristics of neighboring areas. There is a gap in the literature regarding the incorporation of spatial and temporal effects in VMT modelling. Advancements in econometric techniques have made possible to capture and quantify such spatio-temporal effects, addressing econometric problems that would otherwise result in biased coefficients and imprecise variance estimation (Anselin, 2010; LeSage and Pace, 2009). Even though these techniques have been widely used in other fields (Arbia, 2011), there is only a very limited application of spatial econometrics in transport issues (Sung-Eun and Niemeier 2001; Parent and LeSage, 2010); mostly within

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3 an urban economic context (Dubé et al., 2014; Thanos et al., 2015), or employing spatial
4 or spatiotemporal Poisson models to examine transport safety issues (Castro et al., 2012).
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10 To the best of the authors' knowledge, only one study employed spatial econometric
11 methods to analyze VMT. Pirotte and Madre (2011) estimated spatial models employing
12 a panel dataset of the twenty-one French regions for 1973–1999. However, their model
13 specification allows only the derivation of short-run elasticities with respect to VMT, and
14 is in detail discussed in section 2.1.
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24 Against this background, the paper provides a flexible methodological framework that
25 captures the spatial and temporal aspects of car travel, by enabling the robust application
26 of spatial panel models to car travel demand. This framework is further developed to
27 capture asymmetries and hystereses in a spatial setting. The existence and type of spatial
28 interactions and the presence of asymmetries/hystereses are then tested on revealed
29 preference data. The data, compiled from a number of sources, is based on officially
30 recorded car mileage information at sub-regional level in England and Wales. Drawing
31 on the literature, the modelling approach includes information on fuel prices, income
32 levels, alternative fuel use, road network and car fleet characteristics, petrol stations,
33 motorization rate, and public transport infrastructure.
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50 We continue with Section 2, which introduces the methodological framework for spatial
51 models applied to VMT and its extension for capturing asymmetries and hysteresis.
52 Section 3 describes the data sources, the variable derivation and data characteristics.
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3 Section 4 presents and discusses the modelling results. The conclusions follow in Section
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10 **2. Methodology**

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15 This section addresses two methodological challenges for the estimation of a spatial
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17 model using panel data: first, the introduction of spatial econometrics to a sub-regional
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19 VMT model applied to panel data; second, the development of the spatial panel model to
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21 account for the behavioral aspects of reactions to fuel price changes that translate to
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23 asymmetries and hystereses.
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29 *2.1. Spatial panel models developed for VMT*

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32 Given that car travel varies across space and changes over time, the VMT per car, y , in a
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34 certain in area i ($1 \dots i \dots n$), at time t ($1 \dots \tau$) depends on the VMT effect (λ) from the
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36 previous period, and the impact (β) of K independent variables (x), such as fuel price,
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38 income, public transport infrastructure, road network and car fleet characteristics,
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40 motorization rate. This is the base model shown in Eq. 1, where μ is the heterogeneity
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42 component of either fixed or random effects and ε is an error term.
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$$49 y_{it} = \beta_0 + \lambda y_{it-1} + \sum_{k=1}^K x_{itk} \beta_k + \mu_i + \varepsilon_{it} \quad (1)$$

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53 The vast majority of the literature adopts a log-linear specification (e.g. Schäfer and
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55 Victor, 2000; Pirotte and Madre, 2011; Dargay and Gately, 1997) and the constant
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3 elasticity model specification simplifies the estimation process¹; hence, for brevity:
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5 $y \stackrel{\text{def}}{=} \ln(y)$ and $x \stackrel{\text{def}}{=} \ln(x)$. Equation 1 is estimated through least squares (LS) here and is
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7 based on the assumption of no spatial interrelationships between the different areas.
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12 Our hypothesis is that car travel in a specific area can be affected by the car travel, road
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14 network, and socioeconomic characteristics of other areas; therefore these interactions
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16 should be tested. Advances in spatial econometrics allow the estimation and testing of
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18 three different types of interactions between units/areas/observations² (LeSage and Pace,
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20 2009). These are: 1) the endogenous spatial interrelationships of the dependent variable at
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22 time t and/or endogenous spatiotemporal effects from the past at $t - 1$; 2) the exogenous
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24 spatial interaction in the explanatory variables; and 3) spatial interaction in the residuals
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26 (Elhorst, 2014).
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34 In the VMT context, the first type of interaction signifies that the VMT of neighboring
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36 areas are spatially interrelated, accounting for the significant proportion of trips usually
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38 shared between neighboring areas. This type of model is analogous to a temporal
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40 autoregressive specification, differing in that the effect is not unidirectional from past to
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42 present, but bi-directional between the neighboring areas. There can be also a bi-
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44 directional spatiotemporal effect from VMT of neighboring area j at $t-1$, affecting the
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46 VMT of area i in the subsequent time period t . The second type of interaction means that
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51 ¹ The Box–Cox specification or similar specifications that estimate rather than assume the
52 functional form are not readily implemented in the presence of spatial dependence (Kim et al.,
53 2003). Furthermore, Goodwin et al. (2004) found no strong consistent pattern of effect of
54 functional form.

55 ² The existence of any of these interactions would render the OLS estimation biased and/or
56 inefficient.
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attributes of an area, such as fuel prices, or road network characteristics, can affect the VMT of a neighboring area. The third type of interaction signifies that VMT is affected by unobserved spatial characteristics of neighboring areas, for example urban form, resulting into the model residuals containing spatial patterns instead of white noise.

Spatial weights a priori specify the spatial relations between observations or areas in the form of a matrix \mathbf{W} of dimensions $(n\tau \times n\tau)$, as the n cross-sections are stacked over τ times. The matrix contains the spatial link between observations i and j , w_{ij} , representing the strength of their spatial connection that is typically a function of distance shown in Equation 2.

$$w_{ij} = \begin{cases} f(d_{ij}) & \forall i \neq j \\ 0 & \forall i = j \end{cases} \quad i, j \in (1 \dots n) \quad (2)$$

Given data availability constraints, we specify the simplest and only form of spatial interaction we can be confident in at this stage. That is the contiguous weight matrix shown in Equation 3, where only areas that share a boundary (bnd) are taken to have a spatial relationship. Row normalization of \mathbf{W} is applied to make the corresponding coefficients readily interpretable.

$$w_{ij} = \begin{cases} 1 & \forall bnd(i) \cap bnd(j) \neq \emptyset \\ 0 & \forall bnd(i) \cap bnd(j) = \emptyset \end{cases} \quad (3)$$

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3 Equation 3 assumes that VMT and other characteristics from contiguous area j impact the
4 VMT of a specific area i and vice versa. This is reasonable for commuting and short
5 distance trips, given the data constraints outlined in section 3 and especially the lack of
6 information on long distance trips and their prevalence.
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15 Pirotte and Madre (2011) choose as their preferred specification a row normalized matrix
16 of inverse distances between regional capitals. This would denote strong and un-testable
17 assumptions about car travel interrelations between distant regions. However, a key
18 shortcoming of row normalizing an inverse distance matrix, as Elhorst (2014) stresses, is
19 that its economic interpretation in terms of distance decay is no longer valid. The main
20 consequence is that remote and central regions end up having similar impact, independent
21 of their relative location. Due to data constraints, Pirotte and Madre (2011) also calculate
22 VMT using information on fuel sales, changes in fuel efficiency, and share of fuel use by
23 light vehicles. The fuel sales are available at regional level whereas the other two pieces
24 of information are available only at a national level.
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41 Illustrating the different spatial models and their significance in this context, we start
42 from third type of spatial interaction assumption of unobserved processes, not uniformly
43 distributed in space, affecting the VMT and the residuals in Equation 1. The spatial error
44 model (SEM) in equations 4 and 5 captures this spatial structure. Equation 4 shows a
45 vector y_t of the dependent variable, in n areas ($1 \dots i \dots n$), depending on a matrix X_t of
46 explanatory variables including the constant of dimensions $[n \times (K + 1)]$.
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$$\mathbf{y}_t = \lambda \mathbf{y}_{t-1} + \mathbf{X}_t \boldsymbol{\beta} + \mathbf{u}_t, \quad (4)$$

$$\mathbf{u}_t = \rho \mathbf{W} \mathbf{u}_t + \boldsymbol{\varepsilon}_t \quad (5)$$

where $\boldsymbol{\beta} [(K + 1) \times 1]$ is the vector of parameters, \mathbf{u}_t and $\boldsymbol{\varepsilon}_t$ are vectors of disturbance terms. \mathbf{u}_t can also be expressed as in equation 6:

$$\mathbf{u}_t = \boldsymbol{\varepsilon}_t (\mathbf{I} - \rho \mathbf{W})^{-1} \quad (6)$$

where \mathbf{I} is the identity matrix, and ρ is the spatial autocorrelation coefficient. Substituting 6 into 4, solving for $\boldsymbol{\varepsilon}$ and rearranging we get Equation 7, which constrains the spatially lagged \mathbf{y} and the spatially lagged \mathbf{X} not to vary independently (Burrige, 1981). Another constraint is that spatiotemporally lagged \mathbf{y} don't vary independently to the spatial and temporal elements either.

$$\mathbf{y}_t = \lambda \mathbf{y}_{t-1} - \rho \lambda \mathbf{W} \mathbf{y}_{t-1} + \rho \mathbf{W} \mathbf{y}_t + \mathbf{X}_t \boldsymbol{\beta} + \mathbf{W} \mathbf{X}_t (-\rho \boldsymbol{\beta}) + \boldsymbol{\varepsilon}_t \quad (7)$$

To obtain a more flexible specification that allows to test a number of different constraints and restrictions that assume different model forms³, we substitute $-\rho \boldsymbol{\beta}$ with $\boldsymbol{\theta}$, and $-\rho \lambda$ with γ , allowing $\boldsymbol{\theta}$ and γ to vary independently of ρ , λ , and $\boldsymbol{\beta}$, as shown in Equation 8 below:

³ Model form is used interchangeably here to “data generating process” (DGP).

$$\mathbf{y}_t = \lambda \mathbf{y}_{t-1} + \gamma \mathbf{W} \mathbf{y}_{t-1} + \rho \mathbf{W} \mathbf{y}_t + \mathbf{X}_t \boldsymbol{\beta} + \mathbf{W} \mathbf{X}_t \boldsymbol{\theta} + \boldsymbol{\varepsilon}_t \quad (8)$$

Bearing in mind Gibbons and Overman (2012) admonition of mechanically applying spatial econometrics and selecting models solely based on goodness of fit, we provide a brief theoretical justification for the inclusion of different elements of equation 8 in the final model. The dynamic temporal autoregressive element of VMT ($\lambda \mathbf{y}_{t-1}$) is justifiable, especially since omitting a relevant time lag term can result in significant biases, while including an irrelevant time lag term causes little loss of efficiency in spatial models, as shown by Tao and Yu (2012). VMT of neighboring areas can be spatially interrelated ($\rho \mathbf{W} \mathbf{y}_t$), accounting for the significant proportion of trips usually shared between neighboring areas.

While the approach of Debarsy et al. (2012) of including $\gamma \mathbf{W} \mathbf{y}_{t-1}$ may be appropriate for examining cigarette consumption, we content that it might not be as appropriate for car travel demand. As mentioned above, car users do react to current VMT and resulting road conditions of neighboring areas ($\rho \mathbf{W} \mathbf{y}_t$). Car users are also affected by the VMT in previous periods ($\lambda \mathbf{y}_{t-1}$) in their own area, which is in turn influenced by the contemporaneous VMT of neighboring areas. However, $\gamma \mathbf{W} \mathbf{y}_{t-1}$ signifies that there is an additional and separate spatiotemporal effect from the past VMT in contiguous areas. Since we cannot hypothesize any valid underlining reason for such a spatiotemporal lag⁴,

⁴ If \mathbf{W} is time invariant, there may be an issue of double counting when we include $\gamma \mathbf{W} \mathbf{y}_{t-1}$, as \mathbf{y}_t is affected by \mathbf{y}_{t-1} and $\mathbf{W} \mathbf{y}_t$, and \mathbf{y}_{t-1} is in turn affected by $\mathbf{W} \mathbf{y}_{t-1}$. This is an issue that may require further research. There is spatial and temporal variation in our data, but no spatiotemporal variation. If \mathbf{W} was time variant, then $\gamma \mathbf{W} \mathbf{y}_{t-1}$ would be essential.

we see little economic justification for such an effect in this transport demand context. Nevertheless, we do proceed to test for $\gamma = 0$ in section 4.2.

The VMT interrelationship effect between area i and area j (1st type interaction) may well be different to the influence of the characteristics (X) of area j to the VMT of area i (2nd type interaction). This constraint ($WX_t(-\rho\beta)$) in equation 7 seems unrealistic in this context, as there is asymmetrical divergence in travel patterns, infrastructure, public transport availability, and land use characteristics between different areas. If $\theta = -\rho\beta$, we get a SEM (Equations 4-5 or 7). If $\theta = 0$, the resulting model is a spatial autoregressive (SAR) specification that can include temporal and spatiotemporal lags. Equation 9 provides the dynamic SAR specification (only 1st type interaction) without a spatiotemporal lag ($\gamma = 0$).

$$\mathbf{y}_t = \lambda\mathbf{y}_{t-1} + \rho\mathbf{W}\mathbf{y}_t + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t \quad (9)$$

If both $\theta + \rho\beta \neq 0$ and $\theta \neq 0$ then the dynamic Spatial Durbin Model (SDM) is employed, containing both the first and second types of spatial interactions in Equation 8. Section 4.2 provides the test results for all the constraints discussed here: $\theta = -\rho\beta$, $\theta = 0$, and $\gamma = 0$.

Even though certain independent variables, such as public transport networks, fuel price, motorization rate, and congestion are indeed expected to have significant spatial effects

on neighboring VMT, this may not be the case with all independent variables. This is taken into account in equations 10 and 11 that are estimated in section 4.2:

$$y_{it} = \beta_0 + \lambda y_{it-1} + \gamma \sum_{j=1}^n w_{ij} y_{jt-1} + \rho \sum_{j=1}^n w_{ij} y_{jt} + \sum_{k=1}^K x_{itk} \beta_k + \sum_{k=1}^{k-m} \sum_{j=1}^n w_{ij} x_{it(k-\theta)} \theta_{k-m} + \mu_i + \varepsilon_{it} \quad (10)$$

where m is the number of independent variables without any spatial effect. If $\gamma = 0$, then we get:

$$y_{it} = \beta_0 + \lambda y_{it-1} + \rho \sum_{j=1}^n w_{ij} y_{jt} + \sum_{k=1}^K x_{itk} \beta_k + \sum_{k=1}^{k-m} \sum_{j=1}^n w_{ij} x_{itk} \theta_{k-m} + \mu_i + \varepsilon_{it} \quad (11)$$

Two additional reasons reinforce the selection of SDM as the preferred specification in this context. First, it is less sensitive to omitted variable bias caused by un-captured spatial information⁵. Second, SDM minimizes non-identification⁶ issues that are prevalent in other spatial econometric models. Besides having little theoretical basis in the VMT context, a general spatial model (including all three types of spatial interactions) would

⁵ Lacombe and LeSage (2013) confirm that SDM specification works well, producing unbiased parameters, in all circumstances of correlation between omitted and included variables. Conversely, the SEM specification works well only in the extreme case of zero correlation between omitted and included variables. Furthermore, significant t-statistics for the indirect effects identify these omitted variable problems. The identification and accounting for omitted variable bias provides flexibility and contributes to the alleviation of the two key concerns in spatial econometrics: the a priori assumption that model form and \mathbf{W} are complete and correct maps of spatial interactions.

⁶ Gibbons and Overman (2012) indicate a potential identification problem of not recovering the unique unknown parameters from reduced model forms that contain a spatial autoregressive term. However, Bramoullé et al. (2009), examining the application of the SDM in the context of social network interactions, deliver a fundamental insight by providing the necessary and sufficient conditions for the identification of parameters β , ρ , θ . Identification is achieved provided that $\theta + \rho\beta \neq 0$, for all ρ such that $(\mathbf{I} - \rho\mathbf{W})^{-1}$ exists. Even though identification may fail for some particular structures of \mathbf{W} , these are not relevant to the VMT context of spatial interactions.

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3 forgo the SDM advantages, severely compromising identification and tractable estimation
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6 (Gibbons and Overman, 2012; Le Gallo, 2002; LeSage, 2014).
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10 We adopt the Quasi-Maximum Likelihood (QML) estimator by Yu et al. (2008) that can
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12 handle the dynamic fixed effects SDM in Equations 10 and 11 (see Table 3 for tests of
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14 fixed versus random effects). Elhorst (2010) found that the Yu et al. (2008) QML
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16 estimator outperforms the other estimators in terms of bias and root mean squared error
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18 when $\tau = 5$, which is the case for our data.
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24 Only in the case of SEM are the coefficients (β) directly interpretable as the impact of
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26 explanatory variable changes to VMT. LeSage and Pace (2009) demonstrate that the
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28 partial derivative, the only valid basis for testing hypotheses and interpreting the impact
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30 of variable changes (marginal effects and elasticities), is not equal to β in the case of
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32 SDM and SAR. This is due to the spatial autoregressive effect (1st type interaction) that
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34 creates a feedback loop for dependent variable changes passing through the dependent
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36 and explanatory variables of adjacent areas. Therefore, it is possible to distinguish
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38 between and estimate direct and indirect (spillover) spatial effects that are elasticities in
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40 our specification. The total short run elasticities are the combination of direct and indirect
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42 elasticities given for dynamic SDM in Equation 12 (Vega and Elhorst, 2015).
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$$\Psi_S \stackrel{\text{def}}{=} \begin{bmatrix} \frac{\partial E(y)}{\partial x_{1k}} & \dots & \frac{\partial E(y)}{\partial x_{nk}} \end{bmatrix} = (\mathbf{I} - \rho \mathbf{W})^{-1} \begin{bmatrix} \beta_k & w_{12}\theta_k & \dots & w_{1n}\theta_k \\ w_{21}\theta_k & \beta_k & \dots & w_{2n}\theta_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1}\theta_k & w_{n2}\theta_k & \dots & \beta_k \end{bmatrix} = (\mathbf{I} - \rho \mathbf{W})^{-1} [\mathbf{I}\beta_k + \mathbf{W}\theta_k] \quad (12)$$

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56 Equation 13 provides the equivalent long-run elasticity formula (Elhorst, 2014).
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$$\Psi_L \stackrel{\text{def}}{=} [(1 - \lambda)\mathbf{I} - \rho\mathbf{W}]^{-1}[\mathbf{I}\beta_k + \mathbf{W}\theta_k] \quad (13)$$

The diagonal elements of the matrix Ψ_S represent the direct effects and the off-diagonal elements, the indirect or spill-over effects (Vega and Elhorst, 2015). The direct effects denote the influence of an independent variable change in a particular area on that area's VMT, incorporating feedback effects of the adjacent areas and to the area in which the adjustment process was initiated. The indirect impact represents the effect of an independent variable change in a particular area on the VMT of all the contiguous areas. The explanation is equivalent for the long run elasticity matrix Ψ_L that also includes the temporal dynamic component $(I - \lambda)^{-1}$.

The total effects of SAR are different to SDM, as $\theta = 0$, and Ψ_S becomes $(\mathbf{I} - \rho\mathbf{W})^{-1}[\mathbf{I}\beta_k]$. Hence, the marked difference between SAR and SDM is that the ratio of the indirect and direct effects is the same for all independent variables in SAR. There is no theoretical justification for such a restriction and this is one of the reasons SDM is in principle preferred to SAR in this context.

2.2. *Decomposing the price, asymmetry and hysteresis in a spatial setting*

As discussed in section 1, asymmetric responses are potentially caused by loss aversion, reference dependence and the endowment effect, hysteresis reflects established habits and the ensuing inertia. The next step is to operationalize the process and introduce this specification to spatial panel models for the first time in the literature. This approach

provides a way to examine the link between behavioral aspects and their spatial dimension in this context.

The variable decomposition to capture asymmetries was first proposed by Wolffram (1971) and later improved to detect hysteresis effects (Dargay and Gately, 1997) that has subsequently become the standard in the transport and energy “asymmetry-hysteresis” literature (Wadud, 2014). However, the typical time-series formulae in the literature (e.g. Dargay and Gately, 1997; Wadud, 2014) is not precise enough to allow clear operationalization of the process. Hence, we provide a precise formulae for the panel format below. The decomposition is then further advanced to introduce asymmetries and hysteresis in the spatial dimension.

The variable x_{itg} [$g \in (1 \dots K)$], in this case the fuel price, is decomposed into three components given in Equations 14-16 (we drop subscript g for brevity).

$$x_{it}^m = x_{i1} + \begin{cases} \sum_{t=2}^{\tau} (\Delta x_{it}), & \forall \Delta x_{it} = (x_{it} - x_{it-1}) > 0 \\ 0, & \forall \Delta x_{it} \leq 0 \end{cases} \quad (14)$$

x_{it}^m refers to only positive cumulative increases added on the initial value of the variable at $t=1$. This captures the perceived general level of prices.

$$x_{it}^c = \sum_{t=1}^{\tau} (\Delta x_{it}), \forall \Delta x_{it} < 0 \quad (15)$$

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x_{it}^c refers to the cumulative series of only the reductions in the value of the variable, this is monotonically decreasing, and always negative. This captures consumer reactions to price decreases.

$$x_{it}^r = \begin{cases} 0 + \sum_{t=2}^t (\Delta x_{it}), \forall \Delta x_{it} \geq 0 \wedge \Delta x_{it} > (\Delta x_{it-h} < 0) \\ 0, & \forall \Delta x_{it} < 0 \end{cases} \quad (16)$$

Where h is a positive integer ($h \in \mathbb{N}^*$) and $t - h > 0$. x_{it}^r is a monotonically increasing cumulative recovery in the variable value preceded by a reduction, immediately or before $h - 1$ periods of no change. This component captures the consumer reaction to price recovery after decreases.

As the word decomposition denotes: $x_{it} = x_{it}^m + x_{it}^r + x_{it}^c$. Imperfect price reversibility holds when the parameters of x_{it}^m , x_{it}^r , x_{it}^c are unequal. Asymmetry holds when reactions to price reductions, x_{it}^c , and price recovery, x_{it}^r , are statistically different, indicating potential loss aversion and reference dependence. Hysteresis holds when the coefficients of x_{it}^m and x_{it}^r are different, denoting that responses to price increases depend on price history, and on whether the current price is above or below a previous maximum (Wadud, 2014).

This decomposition is extended to the spatial dimension by introducing the component(s) of the decomposed price into $WX\theta$. This provides the spatial aspects of the three price components: $w_{ij}x_{jt}^m\theta^m$, $w_{ij}x_{jt}^r\theta^r$, $w_{ij}x_{jt}^c\theta^c$.

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3 An example of a distinct spatial aspect of a price effect would be big rises in the overall
4 price levels, $x_{it}^m \beta^m$, having a direct negative impact to VMT, but also having a positive
5 indirect effect $w_{ij} x_{jt}^m \theta^m$ due to the extra mileage in search of petrol stations with lower
6 prices. A number of spatial aspects of potential imperfect reversibility can be tested
7 through statistically significant differences between $w_{ij} x_{jt}^m \theta^m$, $w_{ij} x_{jt}^r \theta^r$, $w_{ij} x_{jt}^c \theta^c$,
8 $x_{it}^m \beta^m$, $x_{it}^r \beta^r$, and $x_{it}^c \beta^c$.
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20 This section, in addition to theoretical justification for employing spatial econometrics in
21 a car travel demand context, also provides a robust model specification that has the
22 following advantages compared to “a-spatial” and/or standard spatial models: First, the
23 dynamic SDM is a flexible specification that allows the testing and removal of
24 restrictions producing SAR or SEM. Second, SDM minimizes potential biases and issues
25 of non-identification that are prevalent in spatial econometric models. Third, the dynamic
26 SDM is one of very few feasible spatial models (Elhorst, 2014) that can allow us to
27 account for the spatial aspects of behavioral effects, by analyzing asymmetry and
28 hysteresis in a spatial setting, in both the short and long-run.
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44 3. Data and Model Specification

45 3.1. Data

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48 As the literature suggests, information on socioeconomic, road network and car fleet
49 characteristics, fuel prices, and competition between modes of travel is needed to robustly
50 estimate car travel demand models. The diversity of the required information necessitates
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3 in this context the combination of data from a number of sources and the use of proxies in
4 cases of unavailable information. Compiled from a range of observed sub-regional data,
5 the dataset employed here includes third party recorded car mileage, instead of survey
6 self-reporting or of estimation from a number of spatially un-matching aggregate
7 information. The car mileage data are recorded during the annual test of vehicle
8 roadworthiness, MOT (DVSA, 2013), for 2005-2010. These are merged into a panel
9 dataset of 105 areas in England and Wales with spatially disaggregate data on petrol
10 prices and total fuel volume (Experian Catalist, 2014), disposable income (ONS, 2015),
11 public transport availability (DfT, 2014), road network (Ordnance Survey, 2014),
12 population and area census data (ONS, 2011).
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29 The MOT data includes the vehicle characteristics, engine size, make-model, age, fuel
30 and odometer readings from 2005-2013 (DVSA, 2013) of over 23 million tests per year
31 in England and Wales⁷. The analysis here focuses specifically to the vehicle category that
32 includes only cars and vans. Vehicles under other driving license categories, such as
33 taxis, ambulances, freight vehicles and motorbikes are not included, as their use is
34 determined by markedly different factors than private cars. One limitation of MOT is that
35 it is undertaken by cars after they complete 3 years of use. Hence, any “new car” effect
36 on mileage cannot be captured by this dataset. The MOT data include a vehicle identifier,
37 which can be used to calculate the miles travelled by each car between tests by the
38 respective odometer readings. However, there is a critical error in the continuity of the
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55 ⁷ Except the first year of data availability, 2005, when only 5.5 million tests were recorded. DfT
56 did not provide any clarification on the issue.
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3 vehicle identifier in 2011. The same vehicle can be identified in 2005-2010 and 2011-
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5 2013, but cannot be matched between the two periods⁸. Therefore, we use the data of the
6
7 longest time period, 2005-10.
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12 The only spatial identifier available in MOT data is the postcode area⁹ that translates to
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14 105 areas in England and Wales. These areas are comparable and just over the size of
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16 NUTS3¹⁰ areas for England and Wales. However, two areas (the WC and EC postcodes)
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18 in the center of London were dropped due to missing data in 2005, reducing the cross-
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20 sections to 103. Furthermore, WC and EC have at least an order of magnitude less land
21
22 area, respectively 357 and 413 hectares, than any other postcode area (e.g. the next
23
24 postcode area size is 5482 hectares) in the UK at the same level of spatial disaggregation.
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26 Given the uniqueness and peculiarity of the center of London with respect to car use,
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28 these areas are beyond the topic and data availability of this paper.
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36 As MOT tests may not take place exactly a year apart for each car, DfT (2013) guidelines
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38 were followed in weighting the observation according to the days elapsed between tests.
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40 Equation 17 shows the calculation of VMT per car/area/year, y_{it} from the MOT data.
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$$46 \quad y_{it} = \left(\sum_{c=1}^c \{ (O_{ct+1} - O_{ct}) \times [365 / (d_{ct+1} - d_{ct})] \} \right) / C_{it}, \forall (d_{ct+1} - d_{ct}) > 90 \quad (17)$$

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52 ⁸ This problem was reported to DfT and acknowledged on 02/05/2014, but to our knowledge there
53 has not been a correction to date.

54 ⁹ The first two digits of the full postcode.

55 ¹⁰ Nomenclature of Units for Territorial Statistics (NUTS) is a geocode standard for referencing
56 the subdivisions of countries for statistical purposes across the European Union.
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6 where O_{ct} is the odometer reading of car c at year t and d_{ct} is the date of MOT of car c in
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8 year t , and C_{it} is the number of cars in area i and year t . Prior to deriving VMT per
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10 car/area/year, we followed DfT (2013) recommendations to drop negative, extreme
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12 values of VMT over 100,000 miles per year and observations of cars that underwent two
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14 MOTs within 90 days¹¹. As a result, the VMT per car per area was calculated from
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16 16,127,410 observations of individual car VMTs in 2007, reaching 18,342,062
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18 observations in 2010.
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25 The second source of information is the Experian Catalist (2014) petrol station database,
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27 which is routinely used in UK government reports (Defra, 2012 and Office of Fair
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29 Trading, 2013). This is the only dataset in the UK that exhibits the required spatial
30
31 disaggregation and temporal coverage appropriate for this study, containing information
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33 on petrol/diesel prices, petrol stations, and fuel volume sold. Fuel cards provide price data
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35 whereas regular petrol stations surveys provide the remaining information. Experian
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37 Catalist (2014) states that all petrol stations are covered in the survey, but the price data
38
39 comes from 83% of fuel sites, which account for approximately 98% of UK fuel volume.
40
41 This data was used to derive the petrol prices, total mixed fuel volume, and petrol station
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43 number per area for each year between 2005 and 2010. It is also combined with MOT
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45 data to create an interaction variable between fuel volume consumed and the engine size
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47 per area/car/year.
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54 ¹¹ MOTs this close together signify car problems and a repeated test. However, there is no
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56 obvious non-random component to raise concerns about selection bias. If these were not dropped,
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58 Equation 17 would have assigned excessive weight to observations of very low or high mileage
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60 by extrapolating the one month mileage to a whole year, skewing the results.

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6 The disposable income data (ONS, 2015) is, to our knowledge, the only available
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8 spatially disaggregate household annual income estimate in the UK at the required level
9
10 of spatial disaggregation and time coverage. The disposable income data is actually at a
11
12 NUTS3 area level, thus ONS (2014) look up tables were employed to match the 111
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14 NUTS3 areas to the 105 postcode areas¹².
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20 The National Public Transport Access Nodes (NaPTAN) database (DfT, 2014) is a
21
22 nationwide system for uniquely identifying all the points of access to public transport in
23
24 the UK. Different versions of the data were employed, covering a period 2003-2014, to
25
26 capture the changes in public transport infrastructure over the study period. The
27
28 MasterMap Integrated Transport Network Layer (ITNL) (Ordnance Survey, 2013) was
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30 introduced to GIS software in conjunction with NaPTAN to pinpoint and derive the
31
32 number of public transport infrastructure and road network lane miles per postcode area.
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34 Unfortunately, no information on congestion was available at this level of spatial
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36 aggregation. Therefore, an interaction variable of total fuel consumed per lane mile is
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38 employed as a proxy for lower speed traffic.
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46 To include potential effects of alternative fuels on car travel demand, a proxy is created
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48 for using the alternative fuel (or its equivalent of standard fuel volume) consumption VA_{it}
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50 in area i and time t as shown in equation 18.
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54 ¹² As not all areas matched perfectly, the NUTS3 disposable income of 111 areas was expanded
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56 to the 181,408 Census outputs areas (COAs). The average income of output areas in postcode
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58 area i was computed as follows: $\overline{income}_i = \frac{\sum_{k=1}^z income_k}{z}$, where z is the number of COAs in area i .
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$$p_{it} = \frac{VA_{it}}{VA_{it}+VF_{it}} \Leftrightarrow VA_{it} = \frac{p_{it}}{(1-p_{it})} VF_{it} \quad (18)$$

where VF_{it} is the standard (petrol and diesel) fuel volume available in Experian Catalist (2014) data. p_{it} is the percentage of alternative fuel to total fuel use, which is not available. Therefore, it is approximated by the percentage of alternative fuel car mileage to the total car VMT from the MOT data. Recognizing the limitations, VA_{it} is the only proxy option for alternative fuel use, given the information availability.

The Census data for England and Wales (ONS, 2011) contain a wealth of information on land area, population, dwelling and socioeconomic characteristics. However, census provides data only for one year (2011) and as such it was used only for deriving area size and population characteristics, as it cannot be further employed in the fixed effects panel models, due to the strictly cross-sectional nature of the data. While we recognize that the Modifiable Areal Unit Problem (MAUP) may result to distortions from the choice of a specific spatial aggregation level (Briant et al., 2010), the lack of any other spatial information provides no such choice here. The resulting panel data captures the spatial and temporal aspects of car use, which are both essential for modelling, as seen in the literature and the methodology sections.

3.2. *Data characteristics*

This subsection presents an overview of key data characteristics, highlighting the variation over time and across areas, as illustrated in Figure 1. Income, car ownership and

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3 engine size show substantial spatial variation, while petrol prices seem bunched together
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5 across space, bearing in mind though that these prices are area annual means and mainly
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7 consist of taxes that don't vary across space and time. Regarding the temporal dimension,
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9 it is a quite evident that the petrol price variation consists of increases, reductions and
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11 recoveries, which seems to qualify the decomposition in section 2.2 even in such a short
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13 time-series. Unfortunately, the same is not true for income that exhibits small temporal
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15 variations and a slight increase across all areas over time.
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22 The VMTs per car/area from equation 17 are shown in Figure 2, where one can indeed
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24 see substantial spatial variation, reaching 3,500 miles per car per area. Contrary to
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26 income, car ownership, and engine size, we see a shallow negative trend in the VMT
27
28 across time. It would be interesting to gauge whether this negative trend is still significant
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30 after the other spatial and temporal factors that affect VMT have been accounted for.
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32 Table 1 provides the definition, the sources, and the descriptive statistics of the variables
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34 used in the models.
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50 **4. Model Specification and Estimation Results**

51 52 53 54 55 *4.1. Model specification and Base Model Results* 56 57 58 59 60

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3 The specification of the VMT models include price and income effects, availability of
4 other transport modes, motorization rate, low speed and congestion effects, petrol supply
5 infrastructure availability, “engine size and fuel consumption” effects. Table 2 provides
6 the expected effects of the variables included in the model, according to economic theory.
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15 TABLE 2 ABOUT HERE
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20 The results of the base fixed effects panel model (FE1) in equation 1 are presented in
21 Table 3. The overall fit is quite good for this type of model, explaining over 80% of the
22 variation in the data. Most coefficients are statistically significant and their signs are
23 indeed according economic theory expectations.
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32 Income and price effects are statistically significant and inelastic. Figure 1 illustrates the
33 trend of rising engine size; the “engine size & fuel consumption” captures the interaction
34 effect on VMT of car with larger engines and higher fuel consumption. This interaction
35 has a significant positive effect to VMT, as expected.
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43 Changes in the petrol supply infrastructure are an important factor that affects VMT.
44 Sparsely distributed petrol stations can affect the ease of access for refueling, resulting to
45 longer trips and higher VMT, as reflected in the negative coefficient of the base model.
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48 The problem of too few, very sparsely located petrol stations, reducing in number in rural
49 areas has been raised by the popular press (Collins, 2014) and is referred to as “Fuel
50 Deserts”. This variable might also partly capture the levels of urbanization that cannot
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3 otherwise be fully accounted for, as the use of strictly cross-sectional census data on
4 population density is impossible in a fixed effects panel model.
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10 Metro/underground and rail, are expected in principle to operate in competition to car
11 mileage. This may not necessarily be the case for buses using the same infrastructure as
12 cars. Increased bus use may not affect adversely VMT, as it can operate complementary
13 in some cases by different population groups. The importance of explicitly accounting for
14 the spatial interactions, when looking at public transport effects to VMT, is illustrated in
15 the next section, as no public transport coefficients are statistically significant in the base
16 model.
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29 AFU proxy controls for the subgroup of consumers, who may travel more due to
30 vehicles' increased energy efficiency or display a propensity of reduced car use, due to
31 smaller engine vehicles mainly used for urban trips. The AFU proxy coefficient is
32 negative, thus a high proportion of alternative fuel vehicle, in their vast majority hybrid,
33 does not result into a rebound effect due to increased energy efficiency, rather a
34 propensity of less car use. It is also stressed that this result may be affected by electric
35 vehicle use that has a limited range.
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48 Ceteris paribus, the fuel consumed per lane mile is expected to be higher in areas
49 suffering from congested roads, but it could also capture a road network, in which
50 vehicles are constrained to low speeds and higher fuel consumption (e.g. no motorways,
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3 too many traffic calming measures). These are reflected in the significant negative
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5 coefficient of this variable.
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10 The base FE1 model scope is primarily to ascertain data properties that allow the
11 estimation of spatial models in section 4.2. Hence, a number of statistical test results are
12 presented in Table 3. The Hausman tests point to a fixed effects model rather than
13 random, which precludes the use of census data that are strictly cross-sectional. The
14 Wooldridge test show that an autoregressive term should be included in the estimation.
15 The normality of the residual cannot be rejected, thus there should not be any issues with
16 the use of maximum likelihood (ML). All relevant tests reject the hypothesis of no spatial
17 dependence. The Lagrange multiplier (LM) tests (Anselin et al. 2008) reject a SAR type
18 of spatial interaction in favor of SEM (see test limitations in Table 3 footnote).
19 Conversely, Pirotte and Madre (2011) present the results of both SAR and SEM, with no
20 clear justification on the selection process between the two. The model selection process
21 will require further testing, as SEM is a constrained version of SDM.
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41 FE2 model is identical to the FE1 except for the inclusion of the decomposed price
42 elements in equations 14-16, instead of a single variable. These effects are indeed
43 statistically significant and improve the overall fit of the model, showing that there is
44 empirical support for asymmetries and hysteresis.
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51 52 53 4.2. *Dynamic Spatial Durbin Model Results* 54 55 56 57 58 59 60

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3 The estimation results of the dynamic SDM specification are also presented in Table 3. A
4 substantial improvement in the overall goodness of fit (reflected by AIC and BIC) is
5 observed for spatial models, compared to the respective base models, while the
6 coefficients remain relatively stable across specifications. The key estimation issue, of
7 dynamic spatial panel models satisfying the stability condition: $\lambda + \rho + \gamma < 1$ (Elhorst,
8 2014), is present here.
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19 The Wald test 1 in Table 3 rejects the restriction of SEM in favor of SDM (see test
20 restrictions in Table 3 footnote). The Wald test 2 shows that $\mathbf{WX0}^{13}$ is statistically
21 significant, thus rejecting the SAR in favor of SDM. We cannot reject the null hypothesis
22 that $\gamma = 0$ in SDM1, providing some empirical support to the contention of limited
23 economic significance for the spatiotemporal lag in this context. SDM1 overall fit to the
24 data is worse than SDM2, and given their similarity, SDM1 results are not discussed any
25 further.
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39 Interestingly, the negative trend in VMT is statistically significant across all models, after
40 having controlled for motorization rate. Both SDM2 and SDM3 exhibit highly significant
41 spatial autoregressive parameters (ρ) of 0.57 and 0.45 respectively, which are comparable
42 to the 0.47 of the Pirotte's and Madre's (2011) fixed effects SAR model. Furthermore, a
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50 ¹³ $\mathbf{WX0}$ captures the effect of changing an independent variable in a particular area on the
51 dependent variables of all the neighbouring areas. Hence, only variables that are expected to have
52 spatial effects on neighbouring VMT were included, such as the public transport infrastructure,
53 fuel price, motorisation rate, and the low speed proxy. The "Metro/underground interchange area"
54 is a dummy variable and as such was not included. Price cumulative reductions and recovery,
55 income, and petrol station number were dropped from $\mathbf{WX0}$, as their introduction did not produce
56 significant θ s, deteriorating the overall goodness of fit.
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3 number of independent variables with significant θ s demonstrate the substantial spatial
4 patterns affecting VMT that would otherwise go amiss and introduce bias to other types
5
6 of models. This is best illustrated by the coefficients of public transport that are not
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8 statistically significant in the base model, but gain significance in the spatial models.
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15 TABLE 3 ABOUT HERE
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20 SDM3 is identical to SDM2, except for the introduction of asymmetries and hysteresis in
21 equations 14-16. The better overall fit of SDM3, compared to FE2 and SDM2, suggests
22 that spatial specification with the decomposed price elements captures additional
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24 variation in the data.
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32 Wald tests 3 to 9 are employed to ascertain the statistical significance of price asymmetry
33 and/or hysteresis. In both FE2 and SDM 3, Wald test 3 rejects the difference between the
34 three price components coefficients being zero, showing that the price effect on VMT is
35 not completely reversible after a price shift. Wald test 4 shows that asymmetry between
36 price reductions and recovery is statistically significant in both models. The differences
37
38 between maximum price levels and price recovery are not significant in Wald test 6,
39 denoting no significant hysteresis. However, a “spatial” hysteresis becomes significant by
40 the introduction of the spatial component of maximum price levels, as shown in Wald test
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42 8. The price effect on VMT is also not reversible in a spatial setting after a price shift, as
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44 shown in Wald test 9. Wald tests 7-9 are only possible in SDM3, demonstrating that price
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3 reversibility, asymmetry, and hysteresis have indeed a significant impact, a big part of
4 which is overlooked if the spatial dimension is ignored.
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10 Section 2.1 illustrated that the β s in Table 3 would not be directly interpretable as
11 magnitudes of explanatory variable effects. Therefore, the partial derivative for each
12 independent variable is estimated from equations 12-13 to produce the direct, indirect,
13 and total short-run, and long-run elasticities in Table 4.
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22 TABLE 4 ABOUT HERE
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27 Starting the discussion from SDM2, the low speed proxy, alternative fuel use proxy and
28 number of petrol stations have significant indirect elasticities that contribute to their
29 increased magnitude compared to the base model. The direct short-term price elasticity of
30 -0.09 is close to the base model and to the elasticity of -0.094 in Pirotte and Madre
31 (2011). There is no significant indirect price elasticity in SDM2. The total short-term
32 price elasticity of -0.087 is also consistent with the non-spatial literature, for example, the
33 -0.026 elasticity in Hymel et al (2010), and the range of -0.06 to -0.33 in the review of
34 Goodwin et al. (2004).
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48 Income has a statistically significant indirect spatial effect in SDM2 that contributes to a
49 higher total income elasticity of 0.082 compared to 0.045 in the base model. This
50 inelastic income effect is a bit higher to studies reviewed by Goodwin et al. (2004)
51 showing a range of -0.02 to 0.005 short-term income elasticities. On the other hand,
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3 Pirotte and Madre (2011) find a direct short-term income elasticity of 0.42 and a total
4 short-term income elasticity 0.88. This is not unexpected given that the GDP indicator
5 they use instead of income would vary significantly over the long time series employed.
6
7 Moreover, Pirotte and Madre (2011) did not control for temporal autoregressive effects
8 that may bias results if present but not included (Tao and Yu, 2012).
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17 The positive direct elasticity of the motorization rate is significant across all models and
18 around 0.10, capturing car dependence rather than car use intensity. These findings are
19 consistent with car use saturation. Conversely, Pirotte and Madre (2011) find a
20 motorization rate elasticity of -0.43, which is understandable given the 1973–1999 study
21 period before any car use saturation conditions could have become observable. This could
22 also have contributed to their relatively high income elasticity.
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34 Another striking result is that public transport variables gain statistical significance in the
35 spatial models, confirming the important spatial element of these effects. The bus
36 network density has a statistically weak direct effect that is complementary to VMT.
37 Conversely, the proliferation of rail infrastructure has a significant direct negative effect,
38 and an indirect effect of much higher magnitude than the direct effect. This implies that
39 the effectiveness of rail to compete with car travel is highly dependent on the developed
40 infrastructure of neighboring areas and thus connectivity. This variable remains
41 significant and of similar magnitude across both models, whereas the existence of metro
42 stations only gains significance in SDM3. Other differences between the two models are
43 the “bus” variable dropping out of significance in SDM3, as do income, the “low speed”
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3 proxy and the “engine size & fuel consumption” interaction variable. It seems that the
4 price asymmetry and hysteresis and their spatial components in SDM3 capture a
5 significant part of the data variation.
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12 The spatial aspects of the decomposed price effect are also of particular interest. The first
13 noteworthy aspect is that the sum of the decomposed parts constitute “more” than the
14 “whole”, as the direct price elasticities sum up to -0.148 in SDM3 compared to -0.09
15 price elasticity in SDM2. This is not the case for the same comparison between the a-
16 spatial models FE1 and FE2. The indirect effects of both price reductions and recovery in
17 SDM3 are statistically significant, contrary to the indirect price effects in SDM2.
18 Surprisingly, the indirect maximum price level effect is positive, but not significant in
19 SDM3. This unexpected result may partly capture a slight increase in mileage when price
20 levels are higher, possibly due to an increased incentive to travel further for searching
21 cheaper petrol prices, which may drop this coefficient out of significance in the total
22 effects of SDM3. Therefore, the combination of the SDM specification with the price
23 decomposition approach provides unique insights on the spatial aspects of price
24 asymmetry and hysteresis.
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46 The magnitude of the temporal autoregressive effects remain relatively low, slightly
47 increasing in SDM3, hence the long-run elasticities in Table 4 are only a bit higher than
48 the short-run. The shortness of the time-series may potentially contribute to this. It would
49 be very interesting to see how temporal patterns interact with the spatial effects in long
50 time-series. The direct long-run price elasticity in SDM2 is -0.105 and SDM3 would
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3 provide a long-run elasticity of -0.18, if we were to sum up all the decomposed parts.
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5 Total long-run price elasticity increases in SDM2 to -0.124, but the price elasticities in
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7 SDM3 slightly reduce (-0.166) as maximum price level effect drops from significance.
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9 This is potentially due to the spatial issue of searching for cheap petrol discussed in the
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11 previous paragraph. Debarsy et al. (2012) also noted such issues in dynamic SDM on
12
13 cigarette consumption data, as positive indirect long-run price elasticities, attributed to
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15 bootlegging, ameliorated the negative direct long-run direct price effects, resulting to
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17 significantly lower long-run total price elasticities.
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24 The long-run price elasticities in both SDM2 (-0.124) and SDM3 (-0.166) are consistent
25
26 to the -0.131 long-run VMT elasticity with respect to per mile fuel cost in Hymel et al
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28 (2010). They are also within the -0.55 and -0.11 range reported by Goodwin et al.
29
30 (2004). The long-run income elasticity of 0.116 in SDM2 is also consistent but on the low
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32 side of the mean elasticity of 0.17 (range 0.00-0.4) reported in Goodwin et al. (2004).
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39 5. Conclusions

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43 Since car travel takes place across space and time, any comprehensive analysis of car use
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45 should take into account these two dimensions. The dynamic SDM specification
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47 introduced here, provides a robust and flexible methodological framework to capture the
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49 spatial and temporal aspects of car travel, exhibiting the following advantages compared
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51 to “a-spatial” and/or standard spatial models. First, the dynamic SDM allows testing for
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53 constraints that result in SEM or SAR forms. Second, this specification minimizes
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3 potential biases and issues of non-identification that are prevalent in spatial econometric
4 models. Third, the dynamic SDM is one of the very few feasible spatial models (Elhorst,
5
6 2014) that allow the novelty of examining the spatial components of asymmetry and
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8 hysteresis, in both the short-run and long-run.
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15 The applicability of this methodological framework is demonstrated in the context of sub-
16 regional car use demand for England and Wales. A unique dataset, based on the “official”
17 recordings of car mileage in combination with data from a range of public sources, is
18 analyzed. Despite the data limitations of short temporal coverage and restricted spatial
19 information, the dynamic SDM specification produces compelling results. In addition to
20 long-run price and income elasticities of -0.124 and 0.116 respectively that are broadly
21 consistent with the literature, the spatial aspects of petrol price are of particular interest.
22
23 The reaction to price changes indeed exhibits asymmetries that potentially indicate loss
24 aversion and deference dependence. Hysteresis that can reflect habits and inertia is
25 significant only when a spatial component is included. The spatial aspects of imperfect
26 price reversibility capture otherwise “unseen” sources of variation in the data, and the
27 sum of the price components are found to constitute more than the “whole”.
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46 Another striking result is that the effect of public transport infrastructure on car travel is
47 significant only in the spatial models, emphasizing the importance of including the spatial
48 dimension when analyzing such effects. The findings are also consistent with car use
49 saturation, as the positive effects of the motorization rate capture car dependence rather
50 than car use intensity. The proxy for low speed traffic that is partly affected by
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3 congestion has significant negative elasticities with respect to VMT in SMD2, becoming
4 slightly elastic in the long run. This underlines the potential significance of lower speeds
5 and congestion constraints in the long-run “evolution” of car use.
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12 One of the unique features of the analysis is to capture the “fuel desert” effects in rural
13 areas, brought about by the number of petrol stations affecting VMT due to refueling
14 access. VMT is reduced in areas with a high proportion of alternative fuel vehicle. It
15 seems that the subgroup of consumers, who own alternative fuel vehicles, also displays
16 the propensity of decreased car use, which is also true for cars with smaller engines and
17 lower fuel consumption, possibly used mainly for urban trips.
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29 The results provide novel insights to future policy initiatives toward influencing car travel
30 demand. These insights stem not only from the competing and complementary effects of
31 public transport, and the alternative fuel use impact, but also from evidence consistent
32 with car use saturation, supportive of the “fuel desert” hypothesis and the importance of
33 congestion constrains. Other novel aspects with policy implications are: the asymmetric
34 price elasticities; and the significance of the spatial dimension to hysteresis and imperfect
35 price reversibility.
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48 The methodological tools discussed in this paper can be applied to a number of transport
49 research contexts and levels of data aggregation, especially to fuel, car use, and
50 energy/transport demand models. Feeding into this framework, future innovations could
51 capture transport network effects in more advanced spatial matrix specifications. There
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3 are rapid developments regarding the spatial matrix construction in other fields, where
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5 weight matrices capture a range of complicated data linkage structures in social network
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7 settings (Bramoullé et al., 2009), or by space-time decay (Thanos et al., 2015; 2016), or
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9 by trans-dimensional simulated annealing algorithms for efficient matrix selection (Seya
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11 et al., 2013). These tools are ideal for condensing and analyzing large amounts of data,
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13 made possible by the recent advances in computational power. This underlines the future
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15 innovation potential of traffic-flows from transport models being incorporated into spatial
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17 weight matrices. This can also provide support to policy initiatives that explicitly address
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19 the dynamic, spatio-temporal, and behavioral issues in current transportation systems.
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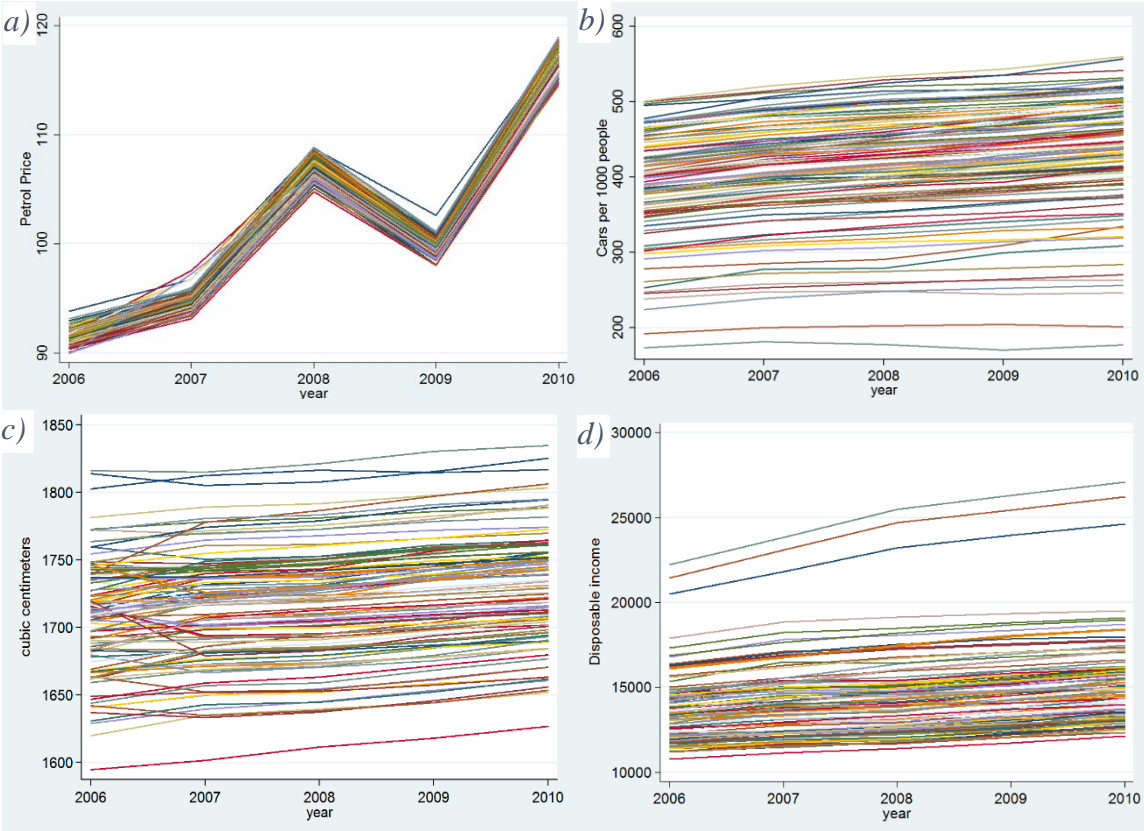


Figure 1: a) Petrol prices (pence), b) Cars per 1000 people, c) Disposable income per household (£), d) Average engine size (cubic centimeters) across areas

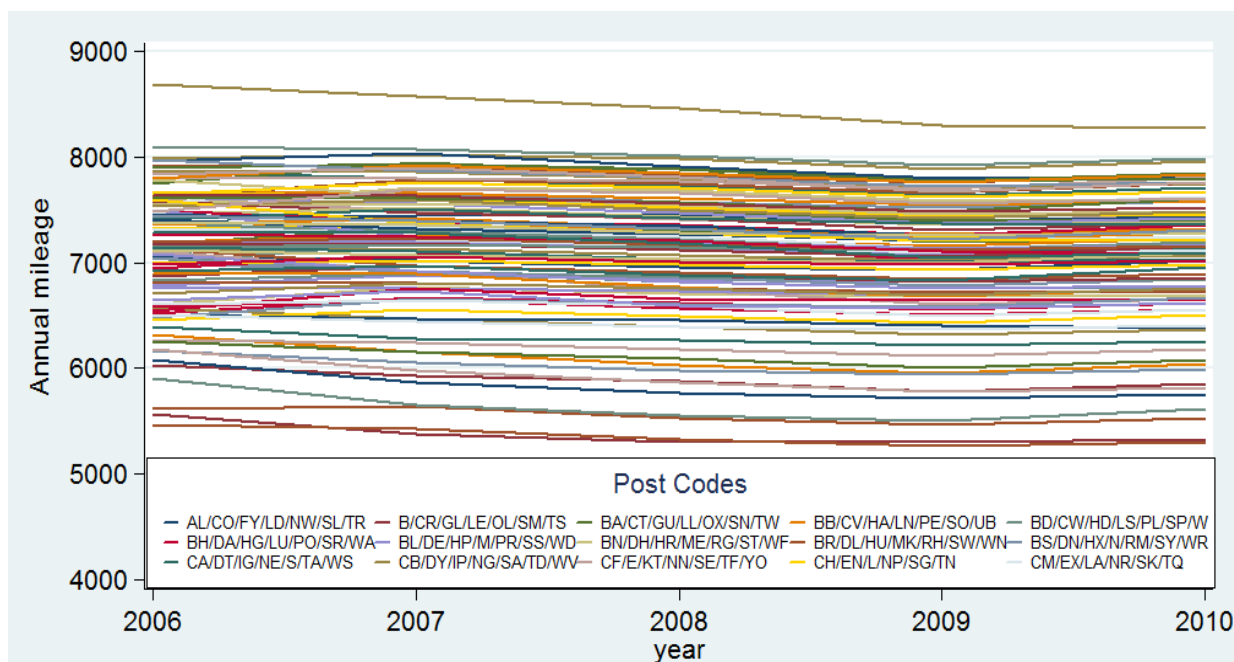


Figure 2: Annual VMT per car per region

Review Only

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Table 1: Descriptive statistics of the data

Variable	Variable Definition	Data Source(s)	Units	Mean	Std.Dev.	Min	Max
VMT	Vehicle Miles Travelled (VMT) per car per area	MOT	miles	7083	608	5264	8683
LN(VMT)		MOT	miles	8.86	0.09	8.57	9.06
Disposable Income	Disposable Income per household/area	ONS	£	14425	2479	10759	27091
LN(Income)		ONS	£	9.58	0.15	9.32	10.21
Petrol price	Petrol price per area	Experia Catalist	£	102.0	9.1	90.0	119.0
LN(Petrol price)		Experia Catalist	£	4.59	0.06	4.50	4.69
LN(Petrol price max)	Petrol price maximum, x_{it}^r , per area	Experia Catalist	£	4.58	0.08	4.45	4.69
LN(Petrol price recovery)	Petrol price recovery, x_{it}^r , per area	Experia Catalist	£	0.57	1.14	0.00	2.90
LN(Price cum. reductions)	Petrol price cumulative reductions, x_{it}^c , per area	Experia Catalist	£	-0.40	0.80	-2.10	0.00
LN(Petrol station number)	Petrol station number per area	Experia Catalist	count	4.03	0.57	1.39	5.30
Metro/underground	Metro/underground interchange area	NaPTAN	dummy	0.45	0.50	0.00	1.00
LN(Rail)	Rail stations per hectare per area	NaPTAN/Census	count	-10.24	0.58	-12.00	-8.25
LN(Bus)	Bus stops per hectare per area	NaPTAN/Census	count	-3.39	0.95	-6.34	-1.26
LN(Low speed proxy)	Fuel consumed per lane mile/area	NaPTAN/ITNL	liters/mile	15.94	0.19	14.96	16.35
LN(Motorization rate)	Number of cars per capita per area	MOT/Census	rate	-6.18	0.78	-7.89	-4.17
LN(Engine size & fuel consumption interaction)	Engine size×fuel volume per car/area	MOT/Experia	cc×liters	-0.86	0.27	-1.77	1.04
LN(AFU proxy)	Alternative fuel use (AFU) proxy per area	MOT/Experia	liters	6.13	0.53	4.01	8.20

Number of areas (n): 103 | Number of years (τ): 5 | Number of Observations(n×τ): 515

Table 2: Variable description, data sources, and expected effects

Variable name	Expected Effect (expected sign)
LN(VMT)	Dependent variable
LN(Income)	Income (+)
LN(Petrol price)	Price (-)
LN(Petrol price max)	Price reversibility (-)
LN(Petrol price recovery)	Price reversibility (-)
LN(Price cum. reductions)	Price reversibility (-)
LN(Petrol station number)	Refueling access, rurality (-)
Metro/underground	PT not in road network (-)
LN(Rail)	PT not in road network (-)
LN(Bus)	PT in road network (- or +)
LN(Low speed proxy)	Low speed proxy (-)
LN(Motorization rate)	Car dependency (+) or car use intensity (-)
LN(Engine size & fuel consumption)	Engine size and fuel consumption interaction (+)
LN(AFU proxy)	Population segment effect (- or +)

Table 3: Results-Spatial Diffusion and Asymmetries

	FE1: Base Model	FE2: Price asymmetries	SDM1: Spatial & Spatiotemporal lags	SDM2: Spatial diffusion	SDM3: Spatial diffusion & asymmetries
Dependent variable: LN(VMT)	Coef. (SE).	Coef. (SE).	Coef. (SE)	Coef. (SE).	Coef. (SE)
β: Independent Variable coefficients					
β ₁ :Trend	-0.020 (0.003)***	-0.0245 (0.0024)***	-0.0090 (0.0034)***	-0.0084 (0.0034)**	-0.0138 (0.0035)***
β ₂ :LN(Income)	0.045 (0.020)**	-0.0193 (0.0200)	0.0313 (0.0146)**	0.0343 (0.0137)**	0.0053 (0.0153)
β ₃ :LN(Petrol price)	-0.087 (0.005)***		-0.0882 (0.0417)**	-0.0885 (0.0417)**	
β ₄ :LN(Petrol price max)		-0.0209 (0.0098)**			-0.0831 (0.0419)**
β ₅ :LN(Petrol price recovery)		-0.0258 (0.0075)***			-0.0261 (0.0056)***
β ₆ :LN(Petrol price cum. reductions)		-0.0433 (0.0108)***			-0.0410 (0.0080)***
β ₇ :LN(Petrol station number)	-0.021 (0.009)**	-0.0074 (0.0084)	-0.0150 (0.0060)**	-0.0153 (0.0060)**	-0.0058 (0.0061)
β ₈ :Metro/underground	0.000 (0.001)	-0.0013 (0.0008)	-0.0009 (0.0006)	-0.0009 (0.0006)	-0.0014 (0.0006)**
β ₉ :LN(AFU proxy)	-0.002 (0.001)**	-0.0027 (0.0009)***	-0.0022 (0.0007)***	-0.0022 (0.0007)***	-0.0024 (0.0007)***
β ₁₀ :LN(Bus)	0.003 (0.002)	0.0014 (0.0018)	0.0030 (0.0014)**	0.0030 (0.0014)**	0.0032 (0.0014)**
β ₁₁ :LN(Engine size & fuel consumption)	0.557 (0.166)***	0.1388 (0.1587)	0.3054 (0.1165)***	0.3134 (0.1156)***	0.1558 (0.1193)
β ₁₂ :LN(Motorization rate)	0.121 (0.020)***	0.0810 (0.0190)***	0.0781 (0.0154)***	0.0791 (0.0153)***	0.0761 (0.0151)***
β ₁₃ : LN(Low speed proxy)	-0.579 (0.163)***	-0.1361 (0.1577)	-0.3128 (0.1168)***	-0.3205 (0.1159)***	-0.1589 (0.1196)
β ₁₄ : LN(Rail)	-0.007 (0.005)	-0.0056 (0.0044)	0.0009 (0.0036)	0.0008 (0.0036)	0.0008 (0.0035)
Fixed-effects mean	-4.198	5.0765	-4.275	-4.727	-0.0280
σ ² (ε)	0.349 (0.004)***	6.8E-02 (3.6E-03)***	8.3E-06 (5.2E-07)***	8.2E-06 (5.3E-07)***	8.1E-06 (5.1E-07)***
Temporal Autoregressive (λy_{t-1})					
λ: LN(VMT) at t-1	0.082 (0.027)***	0.1241 (0.0250)***	0.1279 (0.0204)***	0.1222 (0.0178)***	0.1423 (0.0182)***
Spatial Autoregressive (ρWy_i)					
ρ: LN(VMT)			0.5670 (0.0548)***	0.5725 (0.0548)***	0.4493 (0.0634)***
γ: LN(VMT) at t-1			-0.0252 (0.0412)		
Spatially lagged variables (WXθ)					
θ ₁ : LN(Petrol price)			0.0507 (0.0423)	0.0512 (0.0423)	
θ ₂ : LN(Petrol price max)					0.0770 (0.0431)*
θ ₃ : LN(Bus)			-0.0014 (0.0041)	-0.0012 (0.0041)	-0.0083 (0.0042)**
θ ₄ : LN(Low speed Proxy)			-0.0295 (0.0172)*	-0.0334 (0.0161)**	0.0019 (0.0169)
θ ₅ : LN(Motorization rate)			-0.0079 (0.0375)	-0.0150 (0.0365)	-0.0419 (0.0380)
θ ₆ : LN(Rail)			-0.0240 (0.0088)***	-0.0236 (0.0088)***	-0.0236 (0.0089)***

	FE1: Base Model	FE2: Price asymmetries	SDM1: Spatial & Spatiotemporal lags	SDM2: Spatial diffusion	SDM3: Spatial diffusion & asymmetries
AIC & BIC	-3493 & -3441	-3579 & -3518	-3591 & -3511	-3592 & -3516	-3626 & -3542
LL(model)	1759	1804	1815	1815	1834
R ² within	0.8132	0.8498			
Base Model Tests					
Hausman test, H0: Random effects [^]	321.40***	301.52***	[^] 86.34***	[^] 86.34***	[^] 90.67***
Wooldridge test (no autoregressive term) H0: No autocorrelation	88.405***				
Harris-Tzavalis unit-root test, H0: unit-root (Small-sample adjustment)	0.1752**				
Jarque-Bera LM Test, H0: Normality	3.5462				
Moran MI, H0: No Spatial Dependence	0.3838***				
Geary, H0: No Spatial Dependence	0.6011***				
Getis-Ords, H0: No Spatial Dependence	-2.3513***				
LM test, Spatial Error ^{^^}	70.53***				
Robust LM test, Spatial Error ^{^^}	70.58***				
LM test, Spatial Lag ^{^^}	0.0004				
Robust LM test, Spatial Lag ^{^^}	0.0524				
Wald Tests on SDM models					
Wald test 1, H0: $\theta + \rho\beta = 0$ ^{^^^}			21.98*** (34.38***)	21.95*** (38.94***)	16.21*** (30.35***)
Wald test 2, H0: $\theta = 0$			12.36**	13.17***	16.18***
Wald test 3, H0: $\beta_4 = \beta_5 = \beta_6$		22.87***			38.14***
Wald test 4, H0: $\beta_5 = \beta_6$		28.54***			36.02***
Wald test 5, H0: $\beta_4 = \beta_6$		0.17			1.88
Wald test 6, H0: $\beta_4 = \beta_5$		2.37			1.02
Wald test 7, H0: $\beta_4 = \beta_6 = \theta_2$					12.72***
Wald test 8, H0: $\beta_4 = \beta_5 = \theta_2$					18.85***
Wald test 9, H0: $\beta_4 = \beta_5 = \beta_6 = \theta_2$					46.45***

***significant at $p < 0.01$; ** = significant at $p < 0.05$; * = significant at $p < 0.10$. [^]Dynamic random-effects spatial models cannot be currently estimated, hence the test is conducted on the equivalent static spatial models. ^{^^}The respective LM tests for dynamic spatial panel models have not yet been derived, thus we employ the LM tests in Anselin et al. (2008) for static pooled spatial panel model. ^{^^^}The test in the brackets refers to the full **WX0** in equation 9 that includes all the independent variables and correctly rejects SEM in favor of SDM.

Table 4: Short-run and Long-run Elasticities from the preferred SDM Specifications

Direct Elasticities	SDM 2: Spatial diffusion		SDM 3: Spatial diffusion & price asymmetries	
	Short-run Elast. (SE [^])	Long-run Elast. (SE [^])	Short-run Elast. (SE [^])	Long-run Elast. (SE [^])
Income	0.041 (0.016)***	0.050 (0.019)***	0.006 (0.016)	0.008 (0.020)
Petrol price	-0.090 (0.035)***	-0.105 (0.041)***		
Petrol price max.			-0.073 (0.035)**	-0.086 (0.041)**
Petrol price recovery			-0.029 (0.006)***	-0.035 (0.008)***
Price cum. reductions			-0.046 (0.009)***	-0.056 (0.011)***
Petrol station number	-0.018 (0.007)***	-0.022 (0.008)***	-0.006 (0.007)	-0.008 (0.008)
Metro/underground ^{^^}	-0.001 (0.001)**	-0.001 (0.001)	-0.002 (0.001)**	-0.002 (0.001)**
AFU proxy	-0.003 (0.001)***	-0.003 (0.001)***	-0.003 (0.001)***	-0.003 (0.001)***
Bus	0.003 (0.002)*	0.004 (0.002)*	0.001 (0.002)	0.001 (0.002)
Engine size & fuel cons.	0.373 (0.128)***	0.447 (0.154)***	0.175 (0.135)	0.211 (0.163)
Motorization rate	0.089 (0.016)***	0.106 (0.020)***	0.074 (0.016)***	0.088 (0.020)***
Low speed proxy	-0.393 (0.128)***	-0.473 (0.154)***	-0.178 (0.134)	-0.214 (0.162)
Rail	-0.007 (0.004)*	-0.010 (0.005)**	-0.006 (0.004)*	-0.008 (0.004)*
Indirect Elasticities	Short run	Long Run	Short run	Long Run
Income	0.040 (0.017)**	0.066 (0.031)**	0.004 (0.010)	0.006 (0.017)
Petrol price	0.002 (0.036)	-0.018 (0.043)		
Petrol price max.			0.061 (0.038)	0.070 (0.046)
Petrol price recovery			-0.018 (0.006)***	-0.029 (0.010)***
Price cum. reductions			-0.028 (0.009)***	-0.046 (0.016)***
Petrol station number	-0.018 (0.008)**	-0.029 (0.014)**	-0.004 (0.005)	-0.007 (0.008)
Metro/underground ^{^^}	-0.001 (0.001)	-0.002 (0.002)	-0.001 (0.000)*	-0.002 (0.001)*
AFU proxy	-0.003 (0.001)**	-0.004 (0.002)*	-0.002 (0.001)**	-0.003 (0.001)**
Bus	0.000 (0.008)	0.001 (0.012)	-0.011 (0.006)*	-0.014 (0.009)
Engine size & fuel cons.	0.364 (0.155)**	0.605 (0.297)**	0.108 (0.091)	0.174 (0.153)
Motorization rate	0.057 (0.060)	0.100 (0.086)	-0.011 (0.054)	-0.004 (0.073)
Low speed proxy	-0.441 (0.161)***	-0.719 (0.317)**	-0.108 (0.093)	-0.175 (0.155)
Rail	-0.046 (0.016)***	-0.067 (0.024)***	-0.036 (0.013)***	-0.049 (0.019)***
Total Elasticities	Short run	Long Run	Short run	Long Run
Income	0.082 (0.032)***	0.116 (0.048)**	0.010 (0.0267)	0.014 (0.037)
Petrol price	-0.087 (0.010)***	-0.124 (0.017)***		
Petrol price max.			-0.012 (0.015)	-0.016 (0.021)
Petrol price recovery			-0.047 (0.011)***	-0.064 (0.016)***
Price cum. reductions			-0.075 (0.016)***	-0.102 (0.024)***
Petrol station number	-0.036 (0.014)**	-0.051 (0.021)**	-0.011 (0.011)	-0.014 (0.016)
Metro/underground ^{^^}	-0.002 (0.002)	-0.003 (0.002)	-0.003 (0.001)**	-0.004 (0.002)**
AFU proxy	-0.005 (0.002)***	-0.007 (0.003)**	-0.004 (0.001)***	-0.006 (0.002)***
Bus	0.004 (0.009)	0.005 (0.013)	-0.009 (0.007)	-0.013 (0.010)
Engine size & fuel cons.	0.737 (0.271)***	1.052 (0.426)**	0.283 (0.223)	0.385 (0.309)
Motorization rate	0.147 (0.068)**	0.207 (0.097)**	0.063 (0.061)	0.084 (0.083)
Low speed proxy	-0.834 (0.272)***	-1.192 (0.438)***	-0.286 (0.220)	-0.389 (0.307)
Rail	-0.054 (0.018)***	-0.076 (0.027)***	-0.042 (0.015)***	-0.057 (0.021)***

***significant at $p < 0.01$; ** = significant at $p < 0.05$; * = significant at $p < 0.10$.

[^] 2000 simulations for the Lesage and Pace (2009) MCMC procedure to computing the values and Std.Err. of Ψ_S and Ψ_L matrices in equations 12 and 13. ^{^^} The correction for the relative effect (% change) to VMT of a dummy variable is negligible in this case.