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Car Traffic, Habit Persistence, Cross-Sectional Dependence, and Spatial Heterogeneity: New Insights using French Departmental Data

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Abstract

This paper adopts a dynamic general nesting spatial panel data model with common factors to explore the effect of population density, real household income per capita, car fleet per capita, and real price of gasoline on departmental traffic per light vehicle in France over the period 1990-2009. Spatial heterogeneity is modeled by a translog function in the first three explanatory variables, which are dominated by variation in the cross-sectional domain, while the real price of gasoline, which is dominated by variation in the time domain, is treated as an observable common factor. Additional unobservable common factors are controlled for by principal components with heterogeneous coefficients, building on previous work of Shi and Lee (2017), thereby, generalizing the dynamic spatial panel data model with spatial and time period fixed applied in recent studies. It is found that the spatial lag in the dependent variable becomes insignificant due to these extensions. This paper explains the wider implications of this finding for spatial econometric modeling of cross-sectional dependence. In addition, the elasticities of the first three explanatory variables are shown to vary across space and time and to follow a plausible structure. Among other, an important result is that the long run income elasticity of car traffic diminished from 1.0 in 1990 to 0.4 in 2003, and then remained almost constant until the end of our sample period in 2009, i.e., during the peak-car traffic period.

Keywords: Car traffic, panel data, cross-sectional dependence, common factors.

JEL Classification: C23, R40, R41.

1 Introduction

The social impacts of car traffic is and remains a topical issue. It is responsible for a large part of energy consumption, for congestion, for pollution, and for its contribution to global warming. At the same time, car traffic contributes to a great sense of individual freedom. Understanding the determinants of car use, measured either by distance traveled per car, total vehicle kilometers on the road network, or gasoline demand, has

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been subject of research for many decades. We come back to these different studies in the next section.

Over the period 1990-2003, car traffic in France increased by 30.7 per cent, at an average annual growth rate of 1.9 per cent, while it remained almost constant over the period 2003-2011. Since then it started to increase again, driven by an increase in the number of vehicles, and by the oil price fall in 2014.

Nevertheless, due to multi-car ownership and an upward trending and volatile fuel price, the use of each vehicle has diminished. Overall, the average annual mileage has declined by 8 per cent between 1999 (just before the fuel price peak in 2000) and 2011, despite the growing share of diesel cars which have a higher average annual mileage than gasoline cars. Generally, the evolution of car traffic proceeds from the existence of multi-car ownership, urban sprawl, household income, and the volatile fuel price. Examining the impact of these variables on car traffic at a disaggregated level offers an interesting challenge from different policy perspectives, among which environmental concerns (global warming and climate change), urban design, and the dependence of the population on gasoline.

Using data pertaining to 93 French administrative departments (NUTS3 level) observed over the period 1990-2009, this paper merges three modeling approaches that have been considered in the literature before, some of which only recently, but not in combination and not within transport economics. The first and oldest modeling approach is habit persistence. The evolution of car traffic tends to be strongly correlated in time: car traffic today depends strongly on that in the past. This is also one of the reasons why long term fuel price elasticities exceed their short term counterparts and it may take so long before policy measures are effective. Panel data rather than cross-sectional data are required to be able to control for habit persistence.

The second modeling approach is heterogeneity across space and time. Since Anselin's (1988) influential textbook on spatial econometrics, spatial heterogeneity has attracted a lot of studies. One way to account for spatial heterogeneity is to estimate one equation for each single unit in the sample. However, this requires that the time dimension of the panel is large, which in most empirical studies is not the case. Geographically weighted regression, quantile regression, and parametric, semi or nonparametric methods are alternative methods to deal with parameter heterogeneity across space. The disadvantage of these methods, however, is that they do not provide any non-statistical explanation why the coefficients are different or change over time. The method explored in this study is a translog function, which includes the basic explanatory variables and their cross-products. These cross-products have the effect that the elasticities of the explanatory variables will vary across departments and over time, thereby, providing an economic explanation for the observed heterogeneity not only across space but also over time. The results confirm that a "one-size fits all" policy might not work, since the differences are indeed substantial.

The third, more recent, and most innovative modeling approach this study accounts for is cross-sectional dependence. According to Elhorst, Gross and Tereanu (2018), building on previous work of Bailey, Holly and Pesaran (2016a) and Bailey, Kapetanios and Pesaran (2016b), it can range from totally being absent, to weak, strong, and

finally to global cross-sectional dependence. Weak cross-sectional dependence is one between local dominant units of observations represented by a limited number of links, i.e., the number of links is fixed or declining with the economic, political or geographical distance separating them. This type of cross-sectional dependence occurs if car traffic in one unit is co-determined by that of others in a linear regression equation through the dependent variable, the independent variables, and/or the error term. Due to the geographical dimension of the units of observation in this study, this may also be labeled as spatial dependence. Note this approach requires the specification of a spatial weight matrix, denoted by the symbol W , describing the spatial arrangement of the units in the sample. If the cross-sectional dependence is weak, this matrix tends to be sparse (i.e., many zero and a limited number of non-zero elements). When the cross-sectional dependence is strong, the number of links increase and fall less with distance, i.e., the interactions among the units and the number of non-zero elements in the W matrix become larger, as a result of which the sparsity of this matrix decreases or its density increases. If the cross-sectional dependence is global, an extreme form of strong cross-sectional dependence arises where all units move up and down together over time, though not necessarily to the same extent. Global cross-sectional dependence occurs if car traffic in all units is affected by external factors, such as business cycle effects, aggregate shocks (e.g. oil price shocks), or changes in legislation or government policy. This form of cross-sectional dependence does not require the specification of a spatial weight matrix W , but the use of common factors, such as time-fixed effects, cross-sectional averages or principal components. We come back to this shortly. Ignoring cross-sectional dependence, when present, both weak, strong or global, can have serious consequences in terms of bias and spurious inference, see Anselin (1988), Phillips and Sul (2003), Andrews (2005), and Pesaran (2015a). The approach proposed in this study will test for and model all of them.

To test for the existence of spatial dependence (weak or strong cross-sectional dependence), we start from a general nesting spatial (GNS) model. This is a linear spatial econometric model with a full set of three types of spatial lags: lags in the dependent variable, the explanatory variables, and the error term. Remarkably, this model is almost never used in empirical research. In their overview of spatial econometric models, LeSage and Pace (2009) consider all possible extensions of the linear regression model with one or two types of spatial lags, except the model with three types of spatial lags. Although the model is mentioned on page 53, it is the only extension in their book that is not numbered. However, the year 2017 marks a change in spatial econometricians' way of thinking about this model. Burridge, Elhorst and Zigova (2017) test the feasibility, empirical implications and relevance of this model when working with group interaction matrices, while the textbook of Kelejian and Piras (2017) discusses the specification and estimation of this model by generalized method of moments. This is an important step forward since the spatial autoregressive (SAR) model with a spatial lag of the dependent variable only, denoted by WY , where Y is a vector of the dependent variable observed in different units, is still the most popular one in most empirical studies dealing with spatial dependence, even though it has been severely criticized. This critique is summarized in the next paragraph and in this study operationalized

by one simple testable hypothesis.

Pinkse and Slade (2010, p. 106) criticize the SAR model for the notion that the entire spatial dependence structure is reduced to one single unknown coefficient. Corrado and Fingleton (2012) show that the coefficient estimate of WY may be significant due to omitted WX variables or nonlinearities in the X variables that are erroneously specified as being linear. If WY is part of the model but not any spatial Durbin terms (i.e., spatial lags of the explanatory variables, denoted by WX), Halleck-Vega and Elhorst (2015) demonstrate that the marginal effect of a change in one of the explanatory variables on the dependent variable in the unit itself and that in the other units, is the same for every explanatory variable, which is unlikely from an empirical point of view. Another problem is that the marginal effect of a change in one of the explanatory variables in one unit might cause spillover effects on other units, even if these units are not considered to be neighbors of each other, which is difficult to justify if cross-border effects are mainly local (Halleck-Vega and Elhorst, 2015). Finally, a special theme issue of the Journal of Regional Science (Volume 52, Issue 2, 2012) criticizes spatial econometric researchers for the fact that the inclusion of WY is still used as a quick fix for nearly any model misspecification issue related to space. This also holds for the dependent variable in this study. When running Moran's I test on our car traffic variable, the corresponding null hypothesis that this variable is not spatially autocorrelated needs to be rejected. When subsequently estimating a SAR model, i.e., a linear regression model extended to include WY , we can easily find empirical evidence in favor of a significant coefficient of this variable for several potential specifications of W . However, there is no convincing economic-theoretical argument that can explain why car traffic in one French department is likely to depend on car traffic in other departments. In contrast to many previous empirical studies, we therefore posit a different testable hypothesis. Although our data turns out to be cross-sectionally dependent and this phenomena should, no doubt, be part of the model to avoid biased estimates, we presume that this cannot be explained by a spatial lag in the dependent variable of the model. Importantly, whereas some studies exclude WY in advance, among which LeSage and Pace (2009, Ch.6) and Korniotis (2010), we include this variable to show that its coefficient is close to zero and insignificant on the data.

The inclusion of time fixed effects is a widely accepted method in the panel data literature to control for global cross-sectional dependence, but a limitation of this method is that their impact is assumed to be the same across every unit in the sample, which is not likely to be the case in many applied settings, and also not for our data as we will also show in our empirical application. By contrast, common factors, which can be modeled by cross-section averages of the variables in the model, as in Halleck-Vega and Elhorst (2015), or by principal components, as in Shi and Lee (2017, 2018), are allowed to have a different impact on each single unit. This paper employs the principal component approach applied to a dynamic general nesting spatial panel data model of Shi and Lee (2017), as it is still relatively unexplored methodology in the applied literature. Another disadvantage of time fixed effects is that the coefficients of spatial-invariant variables or variables that only vary a little in the cross-sectional domain, notably the gasoline price, cannot be accurately estimated, while it is one of

the most important variables from a policy viewpoint. When time-period effects are replaced by common factors, this problem no longer occurs, as we will show in this paper. As an alternative and a robustness check, we also reformulate and estimate the model in spatial first-differences (Yu, De Jong and Lee, 2012; Elhorst, Zandberg, De Haan, 2013).

To test for the existence of common factors, whether global cross-sectional dependence has effectively been factored out after controlling for common factors, and whether spatial dependence (weak or strong) has been modeled adequately, we apply the cross-sectional dependence (CD) tests developed by Frees (1995) and Pesaran (2015b).

This article is organized as follows: in Section 2, we review the literature concerning car traffic. In Section 3 we describe the econometric specification, and in Section 4 the data and its main sources. In Section 4 we report and discuss the main empirical findings, and in Section 5 we draw the main conclusions.

2 Related Literature

Understanding the determinants of car traffic and gasoline demand has been of interest to economists during the past four decades, mainly since the first oil crisis in 1973. In the literature, several measures have been used, among which vehicle kilometers (miles) traveled on the road network (by private cars), the total volume of gasoline delivered, the total number of vehicles owned, either in total or averaged per capita, and the vehicle stock. Since 1973, a vast literature has emerged on this topic, among which Baltagi and Griffin (1983, 1997), Dahl (1986), Dahl and Sterner (1991a, 1991b), Johansson and Schipper (1997), Graham and Glaister (2002), Baltagi, Bresson, Griffin and Pirotte (2003), Basso and Oum (2007), Pirotte and Madre (2011) and Thanos, Kamargianni and Schäfer (2018). The main body of this literature has sought to identify and estimate the determinants of gasoline demand or car traffic. Since the Arab oil embargo in 1973-74 and the Iranian crisis in 1978-79, numerous studies focused on the estimation of price and income elasticities using aggregated data, so as to better understand the impact of taxation or pricing policies on nationwide gasoline demand. The issue of energy security was also a major concern.

Within this literature a wide variety of specifications has been considered and estimated, using several static and dynamic forms and estimation methods, covering different data types (cross-sections, time-series or panel data sets) and different time periods. For example, Dahl and Sterner (1991a, 1991b) break the studies down into ten different model types, while according to Leung, Burke, Cui and Perl (2019), publications on fuel price changes and their impact on transport can be divided in eight clusters. A wide range of price, stock of cars and income elasticities have been estimated. Over the period 1992-2004, Goodwin, Dargay and Hanly (2004) found 69 new studies published in academic journals, government reports, and consultancy reports. These publications contain 175 various (static 89, dynamic 86) equations and 491 elasticities. These 175 equations are estimated on different data sets (i.e. 83 obtained

using time series data, 77 using panel data, and 15 using cross-sectional data) covering different time periods between 1929 and 1991. The results are related mainly to fuel consumption (101) and traffic levels (34). According to Goodwin et al. (2004), the elasticities provided by studies on panel data sets vary significantly in magnitude. The elasticities of car traffic per vehicle generated by static approaches vary from -0.41 to -0.13 for fuel price, and from 0.05 to 1.44 for income. Similarly, those generated by dynamic approaches vary from -0.14 to -0.06 in the short term and -0.55 to -0.11 in the long term for fuel price, and from -0.02 to 0.005 in the short term and 0.01 to 0.41 in the long term for income. These ranges are broadly similar to those included in earlier reviews. Recently, Brons, Nijkamp, Pels and Rietveld (2008) employed a meta-analysis to analyze price and income elasticities and to explain the variation by systematic interstudy differences. Also the work of Epsey (1997, 1998) underlines the importance of modeling assumptions and data characteristics (i.e. level of aggregation).

One disadvantage of time-series data is that it is often only available at a highly aggregate level. Stapleton, Sorrell and Schwanen (2017) find that changes in income, the fuel cost of driving and the level of urbanization largely explain travel trends in Great Britain. Reductions in car travel are explained by a combination of rising fuel cost, increased urbanization, as well as the 2008 financial crisis. This high level of aggregation, however, does not always help to understand individual behavior, especially since many studies show that the response among individuals and households is heterogeneous, among which Kayser (2000), Nicol (2003), West and Williams (2004), Dargay (2007), and Wadud, Graham and Noland (2007). Following Moulton (1986, 1987), failure to control for unobservable heterogeneity can have serious consequences in terms of consistency and efficiency of the parameter estimates. According to Hsiao (2003), the opportunity to control for unobserved heterogeneity is one of the reasons to switch to panel data. Bastian and Börjesson (2015) find that, by writing the price and income elasticities as a function of public transport supply, population density, share of foreign-born inhabitants, and the average income level, and by controlling for municipality fixed effects (though surprisingly not for time fixed effects¹) these elasticities appear not to be homogenous across space and time. Nevertheless, GDP per capita and fuel price still explain most of the aggregate trends in car distances driven per adult in Sweden (80% over the years 2002 to 2012) in that the estimated elasticities can reasonably well reproduce the trend in car distances driven per adult back to 1980.

There is also a growing literature examining the relationship between travel behavior and built environments. For reviews, see Hansen (1997), Ewing and Cervero (2001), Handy (2005), Cao, Mokhtarian and Handy (2008). Among this recent literature, there are also a few articles focusing on the relationship between energy consumption/travel behavior and urban spatial form. However, they are based mainly on cross-sectional data (Newman and Kenworthy, 1989; Cervero and Kockelman, 1997; Mindali, Raveh and Salomon, 2004; Bento, Cropper, Mobabrak and Vinha, 2005; Small and Van Dender, 2007; Brownstone and Golob, 2009; Karathodorou, Graham and Noland, 2010). One exception is Su (2010), who analyzes travel demand of 85 U.S. urban areas over

¹In addition, the dependent variable is car traffic (vehicle-kilometers-traveled) per adult, rather than per car as in this study.

the period 1982-2003, using a dynamic autoregressive model estimated by SYS-GMM. His main results underline that road density and urban spatial size have statistically significant positive effects, whereas urban population density and urban congestion have statistically significant negative effects on vehicle-miles-traveled per capita. At the same time, he refers to four previous studies that find that population density plays an ignorable role in affecting people's travel behavior and pattern.

The question of the relationship between travel behavior and urban spatial form is raised because of the interaction between continuous urban sprawl and increasing dependence on car travel especially during the last thirty years. Moreover, climate change and environmental issues have become major concerns. A better understanding of the main determinants of car traffic is therefore a necessary prerequisite to developing effective policy tools to solve environmental concerns (global warming and climate change) and to curb the dependence of the French population on gasoline.

Finally, Pirotte and Madre (2011) find that by estimating a static spatial panel data model using regional panel data over the period 1973-1999, traffic per light vehicle exhibits significant spatial dependence; traffic inside a region may also be caused by transit and exchange traffic generated by the inhabitants of neighboring regions. Thanos et al. (2018) adopt a dynamic spatial Durbin model explaining vehicle miles-traveled using data of England and Wales over the period 2005-2010. They find a spatial autoregressive coefficient for WY ranging from 0.45 to 0.57, but a major objection to this study concerns the omission of the most simple form of common factors, i.e., time-specific effects. Lee and Yu (2010) show that ignoring these effects, when relevant, induces an overestimation of the spatial autoregressive coefficient.

3 The Econometric Specification

The model that is taken as point of departure in this study is a dynamic general spatial panel translog model with common factors. This model is used to explain car traffic across 93 departments in France over the period 1990-2009. It reads as

$$\begin{aligned}
y_{it} = & \tau y_{it-1} + \delta \sum_{j=1}^N w_{ij} y_{jt} + \eta \sum_{j=1}^N w_{ij} y_{jt-1} + \sum_{k=1}^K \beta_k x_{ikt} + \\
& 0.5 \sum_{k=1}^K \sum_{l=1}^K \beta_{kl} x_{ikt} x_{ilt} + \sum_{k=1}^K \theta_k \sum_{j=1}^N w_{ij} x_{jkt} + \\
& \sum_p^P \rho_p z_{ipt} + \sum_{r=1}^R \Gamma_{ir} f_{rt} + \nu_{it}
\end{aligned} \tag{1}$$

where y_{it} denotes the dependent variable of department i ($= 1, \dots, N$) at time t ($= 1, \dots, T$), which for this study is the natural logarithm of car traffic. The variables y_{it-1} and $\sum_{j=1}^N w_{ij} y_{jt}$ represent, respectively, the temporal and spatial lag, and $\sum_{j=1}^N w_{ij} y_{jt-1}$ the spatiotemporal lag of y_{it} , while τ , δ , and η are the corresponding

response parameters of these variables, better known as, respectively, the serial, spatial, and spatiotemporal autoregressive coefficients. w_{ij} represents the element of an $N \times N$ non-negative matrix W of known constants describing the spatial arrangement of the departments in the sample. The specification of this matrix will be further discussed in the empirical application. The notation x_{ikt} with coefficient β_k reflects the k^{th} explanatory variable of y_{it} . These variables cover the natural logs of income per capita, of the number of cars per capita, and of population density. Just as x_{ikt} , z_{ipt} stands for an explanatory variable, in this study the price of gasoline, with coefficient ρ_p . The difference between these two types of variables is that the variation of the first set of variables is dominated by variation in the cross-sectional domain, and the second set by variation in the time domain. Another difference is that for the first set of variables we also control for their cross-products in each department, such that a translog specification results, as well as their spatial lags. Due to lack of variation in the cross-sectional domain, this is not possible for the second (set of) variable(s). Since we have three single explanatory variables, the number of cross-products amounts to six. The term $\sum_{j=1}^N w_{ij}x_{jkt}$ reflects the exogenous spatial lag of the k^{th} explanatory variable x_{ikt} with coefficient θ_k .

The variables premultiplied by elements w_{ij} of the spatial weight matrix are meant to cover potential spatial dependence (weak or strong cross-sectional dependence) among the observations. The common factors, meant to cover potential global cross-sectional dependence, can be subdivided into observable and non-observable factors. The price of gasoline is an observable factor. The hypothesis is that if the price of gasoline in France increases (resp. decreases), car traffic will diminish (resp. increase) in all of its departments. In addition, it may increase or decrease due to R non-observable common factors. Γ_{ir} is the i^{th} column of Γ_r , which is a vector of length N representing the factor loadings of common factor r . f_t is of order $R \times T$ such that its transpose consists of R columns of length T .

It should be stressed that the variables covering spatial dependence and the observable common factor(s) are assumed to have common (or homogenous) response parameters, while the non-observable common factors are assumed to have unit-specific (or heterogenous) coefficients. The proposed model encompasses many models of empirical interest, among which the popular dynamic spatial panel data model with additive spatial and time period fixed effects. Shi and Lee (2017) demonstrate that this model is obtained by imposing the restrictions $R = 2$, $\Gamma_1 = (\mu_1 \dots \mu_N)$, $\Gamma_2 = (1 \dots 1)$, and $f_t = (1 \ \xi_t)'$, where μ_i and ξ_t ($i = 1, \dots, N; t = 1, \dots, T$) are standing for, respectively, spatial and time period fixed effects.

Finally, the error term ν_{it} is assumed to follow a local spatial autoregressive process, $\nu_{it} = \lambda \sum_{j=1}^N w_{ij}\nu_{jt} + \epsilon_{it}$, where ϵ_{it} reflects an i.i.d. disturbance term with zero mean and finite variance σ^2 . The parameters of the model specified in Equation (1), together with this spatially autocorrelated error term, can be estimated by the quasi maximum likelihood (QML) estimator developed by Shi and Lee (2017) and does not require any specification of the distribution function of the disturbance term. The coefficients estimates are bias-corrected for the Nickell bias and the impact of this bias on the other coefficients in the equation. For this purpose, a Matlab routine called “SFactors” can

be used, which the first author made available at his web site <https://www.w-shi.net>.

Interpretation of the coefficients in Equation (1) is difficult, because they do not represent the marginal effects of the explanatory variables. Following Elhorst (2014, Ch. 4), the $N \times N$ matrix of marginal effects of the expected value of the dependent variable with respect to the k th explanatory variable x_{ikt} in the long term reads as

$$\begin{pmatrix} \frac{\partial E(y_{1t})}{\partial x_{1kt}} & \cdots & \frac{\partial E(y_{1t})}{\partial x_{Nkt}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(y_{Nt})}{\partial x_{1kt}} & \cdots & \frac{\partial E(y_{Nt})}{\partial x_{Nkt}} \end{pmatrix} = ((1 - \tau)I_N - (\delta + \eta)W)^{-1} \quad (2)$$

$$\times \begin{pmatrix} \beta_k + \sum_{l=1}^K \beta_{kl}x_{1lt} & \theta_k w_{12} & \cdots & \theta_k w_{1N} \\ \theta_k w_{21} & \beta_k + \sum_{l=1}^K \beta_{kl}x_{2lt} & \cdots & \theta_k w_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_k w_{N1} & \theta_k w_{N2} & \cdots & \beta_k + \sum_{l=1}^K \beta_{kl}x_{Nlt} \end{pmatrix}$$

Every diagonal element of this $N \times N$ matrix, obtained by the product of two $N \times N$ matrices on the right-hand side of this equation, represents the direct effect of a change in one of the explanatory variables on the dependent variable of a particular unit ($i = 1, \dots, N$). Importantly, since the diagonal elements of the second matrix on the right-hand side due to the inclusion of x_{ilt} will vary across both space and time, so will these direct effects. Similarly, every column sum of off-diagonal elements represents the spillover effect of a change in one of the explanatory variables on the dependent variable in all units other than the unit instigating this change. These spillover effects will vary across space (not across time) because the structure of the column elements of the spatial weight matrix W describing the spatial arrangement of the units in the sample is different from one unit to another. Note that Equation (2) is used to compute the long-term direct and spillover effects. Their short-term counterparts can be obtained by setting $\tau = \eta = 0$, while the significance levels of these short and long-term direct and spillover effects will be bootstrapped (see Elhorst, 2014, Section 2.7.2 for details). Further note that the coefficients of the cross-products will be assumed to be symmetric ($\beta_{kl} = \beta_{lk}$), and that the direct and spillover effects of the p th explanatory variable z_{ikt} can be obtained by setting $\theta_k = \beta_{kl} = 0$ and replacing β_k by ρ_p . Since the determination of the direct and spillover effects was not part of Shi's original Matlab routine, we extended his routine with code determining them, as well as with code determining the R -squared and the log-likelihood function value of the model. This extended routine will be made available at the web site <https://www.spatial-panels.com> or will be supplied on request.

Applications of the dynamic spatial panel data model from the very beginning that also report direct and spillover effects, but do not account for common factors, are of Debary, Ertur and LeSage (2012) and Elhorst (2014). The first studies incorporating common factors are of Bailey et al. (2016a), Halleck-Vega and Elhorst (2016), and Ertur and Musolesi (2017), but these studies do not consider direct and spillover effects, since they either do not include independent variables (first two studies) or only include spatial lags in the error term specification (last study). The first study applying a

dynamic spatial panel data model, that reports direct and spillover effects and controls for common factors in the form of cross-sectional averages of the dependent variable and explanatory variables, inspired by the work of Bailey et al. (2016a), is of Ciccarelli and Elhorst (2018). In view of this short overview, this study is therefore among the first to consider the sensitivity of the coefficients of the spatial lags, and related to that, the direct and spillover effects of the explanatory variables for the inclusion of common factors in the form of principal components. Another study is of Shi and Lee (2018), but in contrast to our study they do not consider heterogeneity of the direct and spillover effects across space and time due to the inclusion of cross-products of the explanatory variables.

4 Data Description

Our data set consists of a pooled sample of 93 administrative departments (NUTS3 level) over the period 1990 to 2009 (20 years).² Some departments are predominantly rural in the Western (Charente, Vienne, Deux-Sevres) and central hilly part of France (Allier, Cantal, Haute Loire, Puy-de-Dome, Correze, Creuse, Haute Vienne), while others are very urbanised, among which Ile-de-France (Paris, Seine-et-Marne, Yvelines, Essonne, Hauts-de-Seine, Seine-Saint-Denis, Val-de-Marne, Val-d'Oise) and the Northern part of France (Nord, Pas-de-Calais).

The data set is drawn from several sources. The dependent variable is restricted to traffic (mileage) per light vehicle (TRA/CAR , i.e. $CAR < 3.5$ tons), which implies that trucks and buses are excluded). Car traffic in department i at time t is obtained from

- fuel sales, $FUEL_{lit}$, $l = g$ for gasoline, and d for diesel, published for each department i at time t by the Professional Committee of Petrols;
- taking into account changes in fuel efficiency (that is, miles per gallon separately for diesel and gasoline, MS_{lt}) and of the share of these fuels used by light vehicles (LV_{lt}), using

$$TRA_{it} = FUEL_{git} \times MS_{gt} \times LV_{gt} + FUEL_{dit} \times MS_{dt} \times LV_{dt}, \quad (3)$$

since data of the variables MS_{lt} and LV_{lt} are available only at the national level.

The explanatory variables are defined as follows. The price of gasoline (P_{MG}) is an average of the prices for diesel fuel and for gasoline, weighted by the quantities sold to each category of light vehicle in the department for a given year. It takes into account the growing part of diesel vehicles for which fuel tends to be cheaper. Despite the fact that this price is no longer determined by the government after 1985, it hardly differs per department. Household income (Y) is published by the National Institute of Statistics

²The island Corse and the four overseas departments are not included, while Haute Saône and Territoire de Belfort are merged.

and Economic Studies (INSEE). The consumer price index (P_{CPI}), used to correct for inflation, is also published by INSEE (index base 100 = 2009). The stock of cars (CAR) is computed from the annual tax on car ownership (“*la vignette*”, which has been canceled in 2001); it was published for each department by the Ministry of Economy and Treasury. After this period, we use the number of registration cards (“*cartes grises*” for light vehicles less than 15 years old). Overall, we obtain an appropriate evaluation of the stock of light vehicles. The departmental population (POP) is published by INSEE. The population density ($DENS$) is computed using the departmental population and its area in km² published by INSEE. The consistency of all these time-series available at the departmental level (stock of light vehicles, fuel sales for diesel fuel and gasoline) is obtained by calibrating the departmental totals on the national figures given each year by the Commission of National Transport Accounts (CCTN).

The first panel of Table 1 reports the extent of data variation in the cross-sectional and in the time domain for the key variables measured in levels: car traffic, stock of cars, population, household income, price of gasoline and density. This table shows that the variation of these variables predominantly arises in the cross-sectional domain, i.e., among departments, with the exception of the price of gasoline. In the proposed econometric model, we use variables composed of these key variables expressed in logarithms. Their extent of variation is reported in the second panel of Table 1. Variation in the gasoline price again predominantly occurs in the time domain (over 97%). Variation in income per capita in the time domain (about two-thirds) also exceeds its counterpart in the cross-sectional domain (about one-third). By contrast, for all other variables, including the dependent variable, variation in the cross-sectional domain dominates.

<< Table 1 about here, see at the end of this TeX file >>

Figure 1 illustrates the huge heterogeneity of car traffic across departments over the period 1990-2009. Mean mileage per vehicle traveled on the road network (in km) amounts to 13,163. The department of Paris has the lowest value of 7,820, while the department of Aude, with a small population and an important transit to Spain, is characterized by the highest value of 20,982. Figure 1 also shows that there are clusters of departments where car traffic is low or high, suggesting the existence of local spatial dependence. Using a normalized binary contiguity matrix, Moran’s I test statistic takes an average value over time of 0.133 with p-value of 0.069, which implies that the null hypothesis of no spatial dependence must be rejected at the 5% significance level when adopting this spatial weight matrix. Many studies consider such an outcome as evidence that spatial dependence needs to be accounted for in a regression framework. The argument could be that, while car traffic inside a department is explained mainly by the number of vehicles registered (read: population) and disposable income, a proportion of this traffic is generated by vehicles registered elsewhere, presumably in neighboring departments³:

³The share of foreign vehicles car traffic is quite low and remains almost constant over the period 1990-2009 (i.e. between 4 and 5 per cent). For this reason, car traffic induced by non-residents may be said to be limited.

<< Figure 1 about here, see in the other Word-file >>

- the departments in Bourgogne (Yonne, Cote-d'Or, two-thirds along the way between Paris and Lyon, the two largest metropolitan areas in France);
- the departments in Rhone valley (Rhone, Drome, Vaucluse, Bouches-du-Rhone with Marseille, the third largest urban area in France, then Var and Alpes-Maritimes) connecting to Italy despite of the Alpes;
- the departments of Languedoc-Roussillon (Gar, Herault, Aude, Pyrenees-Orientales), connecting to Spain;
- and the departments of Centre (Eure-et-Loire, Loiret, Loir-et-Cher, Indre-et-Loire), those of Poitou Charentes (Vienne, Charente, Charente-Maritime) in the South-West direction from Paris, including the departments of Aquitaine (Gironde, Landes, Pyrenees-Atlantiques), which are also connected to Spain.

Alternatively, it might be that the determinants of car traffic show similar heterogeneous patterns and clusters of similar values such that the residuals of a regression in which car traffic is explained as a functional form of these determinants are free of any spatial dependence. Figures 2, 3 and 4 show the quantile distributions of respectively income per capita, car fleet per capita and population density.⁴ These figures show that the spatial heterogeneous patterns and clusters of either high or low values do not overlap or coincide, but are different from one variable to another. Therefore, it is difficult to say, based on this exploratory data analysis, whether spatial dependence is really relevant. The results of confirmatory data analysis, based on Equation (1), in the next section will provide a better answer.

<< Figures 2, 3 and 4 about here, see in the other Word-file >>

5 Results

Spatial weight matrices W , part of Equation (1), can take many forms. The most popular are: (1) p -order binary contiguity matrices (if $p = 1$ only first-order neighbors are included, if $p = 2$ first and second order neighbors are considered, and so on); and (2) Inverse distance matrices (with or without a cut-off point). Since it is difficult to state in advance which spatial weight matrix is most likely, we investigate the degree of cross-sectional dependence using the CD-tests developed by Frees (1995) and Pesaran (2015b). The first examines whether this degree is zero (null hypothesis) or positive (alternative hypothesis), and the second whether this degree is weak (null hypothesis) or

⁴The gasoline price is left aside here due to lack of variation in the cross-sectional domain.

strong (alternative hypothesis), both independent from any pre-specified specification of W . The distinction weak or strong is taken from Chudik, Pesaran and Tosetti (2011). Since we work with geographical units, we can also express this distinction in terms of the degree of distance decay. Elhorst et al. (2018) demonstrate that the transition from weak to strong for a parameterized inverse distance matrix in which each off-diagonal element of W takes the form $1/d^\phi$, where d denotes the geographical distance between two units and ϕ is a parameter to be determined, occurs at a value of $\phi = 1$.

Starting from car traffic patterns of the 93 departments over the period 1990-2009 ($N = 93$, $T = 20$), Frees' CD-test amounts to 116.30 and Pesaran's CD-test to 13.36, both with an average pairwise correlation coefficient of 0.05. Both outcomes are greater than their critical values of respectively 30.14 and 1.96 and therefore statistically significant.⁵ Especially the second outcome indicates that the degree of cross-sectional dependence among the departments is stronger ($\phi < 1$) than the type of spatial dependence spatial econometric studies generally account for, i.e., the spatial weight matrices specified in the previous paragraph which imply a value of $\phi \geq 1$. In this respect, the outcome of Moran's I in the previous section that the null hypothesis of no spatial dependence needs to be rejected based on a binary contiguity matrix does not seem to be so informative. This implies that the identification of the right spatial econometric model in combination with the right specification of the spatial weight matrix is more complex than one might think in advance.

Table 3 reports the results of five models that have been considered in this paper. The first column reports the results of a dynamic spatial autoregressive (SAR) model with fixed effects in space and time using the binary contiguity matrix. Characteristics of this spatial weight matrix are recorded in Table 2. This model together with this matrix represents the default approach since it has been applied in many previous empirical studies. It is obtained from Equation (1) by imposing the parameter restrictions $\beta_{kj} = \theta_k = \lambda = 0$, as well as the common factor restrictions $R = 2$, $\Gamma_1 = (\mu_1 \dots \mu_N)$, $\Gamma_2 = (1 \dots 1)$, and $f_t = (1 \ \xi_t)'$, as a result of which the two common factors boil down to fixed effects in space and time. The second column reports the results of a dynamic spatial Durbin model with cross-products between the explanatory variables, and fixed effects in space and time, again using the binary contiguity matrix. This model is used to find out whether the extension with spatial Durbin terms and cross-products helps to improve the fit of the model. This model is obtained from Equation (1) by imposing the parameter restriction $\lambda = 0$, as well as the same common factor restrictions to get the first model. The third column shows the results of the same model as employed in the second column, but then reformulated in spatial first-differences. The rationale behind this model is discussed shortly. The fourth and the fifth column report the results of the proposed model, i.e., a dynamic general spatial nesting model with cross-products between the explanatory variables and common factors, respectively using the binary contiguity matrix and an inverse distance matrix of which the cut-off point at which interaction with other departments no longer occurs is explored. Step by step we will show why the last model outperforms the four previous ones.

⁵Frees' CD-test follows a chi-square distribution with $T - 1$ degrees of freedom, and Pesaran's CD statistic a standard normal distribution.

<< Tables 2 and 3 about here, see at the end of this TeX file >>

To determine the importance of controlling for habit persistence, we consider the coefficient estimate and its significance level of the temporal lag of y_{it} . We find that $\tau = 0.8348$ with t-value 57.96 in the default model (first column), $\tau = 0.8134$ with t-value 55.31 in the preferred model (last column), and similar or lower but still strongly significant values for models 2-4. This finding indicates that major changes in the behavior of people with respect to car traffic due to a policy change will occur only in the long term. The half-life of a change in one of the explanatory variables in the proposed model amounts to 3.34 years (the term τ^κ falls to 50% if $\kappa = -3.34$; while 10% remains only after 11.15 years).

The coefficient δ of the spatial lag of y_{it} turns out to be close to zero and statistically insignificant in all five models. By contrast, the coefficient η of the spatiotemporal lag of y_{it} appears to be positive and significant in the (first) default model: $\eta = 0.1550$ with t-value 2.77. One might conclude that this is in line with the outcome of Moran's I test statistic and the argument of cross-border car traffic among departments set out at the end of the previous section. A similar result has been found by Pirotte and Madre (2011) for the coefficient δ of the spatial lag of y_{it} using a static spatial panel data model, and by Thanos et al. (2018) using a dynamic spatial panel data model. However, there are four reasons why this model and the results it produced need to be rejected. First, the sum of the serial, spatial, and spatiotemporal autoregressive coefficients, $\tau + \delta + \eta$, amounts to 1.0181, while the restriction $\tau + \delta + \eta < 1$ is required for the model to be stationary. Second, the probability that the empirical regularity $\eta = -\tau * \delta$ is satisfied equals 0.00. Parent and LeSage (2011, 2012) show that imposing this parameter constraint might avoid overidentification problems, while Elhorst (2010) shows that under this constraint the impact of a change in one of the explanatory variables gradually diminishes over both space and time, i.e., these two effects can be separated from each other mathematically. The impact of a change in one of the explanatory variables over space falls by the factor δW for every higher-order neighbor, and over time by the factor τ for every next time period. Although this regularity does not have to be met, empirical evidence in favor of this constraint has been found in many studies. Thanos et al. (2018), studying the same topic as in this paper, find a negative but insignificant value for η of -0.0252, as a result of which the constraint $\eta = \tau * \delta$ ($-0.0252 \approx -0.1279 * 0.5670$) holds. In the short empirical application on housing prices accompanying the work of Shi and Lee (2017, Table 4), the authors find a positive and this time significant value for η of 0.05405, while the constraint $\eta = \tau * \delta$ ($0.05405 \approx -[(-0.05527) * 0.68981]$) holds as well. The fact that this empirical regularity does not hold for the default model, η and δ even do not have opposite signs, is a second indication that this model is misspecified.

Third, there is no reasonable economic-theoretical argument that can explain why car traffic in one French department (NUTS3) is likely to depend on that in other departments due to global spillovers. No doubt, local spillovers might occur due to cross-border car traffic among departments, but global spillovers implied by a significant

non-zero value of δ or η are unlikely (see the explanation below Equation 2). It would mean that a change in income per capita, cars per capita, or population density in one part of France, say, the most northern department of France, will eventually affect car traffic in the southern part of France, say, Cote d’Azur. This is not very likely. Corrado and Fingleton (2012) established an explanation (see Section 1) why the coefficient estimate of WY might become significant: it could pick up the effects of omitted spatial lags of the explanatory variables (SLX) or nonlinearities in the X variables if they are erroneously specified as being linear. Due to the empirical regularity $\eta = -\tau*\delta$ and the fact that τ appeared to be large and highly significant, the same applies to WY lagged one period in time. For this reason, the second column of Table 3 shows what happens when cross-products and SLX variables are added to the model. To determine their importance, we count how many of them are significant. Of the six cross-products in model 2, three turn out to be significant at the 5-percent level. In the preferred model (last column) to be discussed later, this number even increases up to five, while their significance levels in this specification also exceed the 1-percent critical value. Of the three spatial lags of the explanatory variables in model 2, one turns out to be significant at the 10-percent level, and one in the preferred model at the regular 5-percent level. In addition, the likelihood ratio test comparing (minus two times) the log-likelihood function value of the default model (model 1) with that of the extended model (model 2) amounts to $-2 * (3222.82 - 3291.27) = 136.90$. Since the LR-test follows a chi-squared distribution with 9 degrees of freedom (due to the extension with six cross-products and three spatial lags) and this outcome exceeds the 5-percent critical value of 16.92, the hypothesis whether the coefficients of the cross-products and spatial lags are jointly insignificant and may be set to zero therefore needs to be strongly rejected. This is an important finding since this extension also supports Corrado and Fingleton’s claim: the coefficient η of the spatiotemporal lag drops down from a significant value of 0.1550 in model 1 to an insignificant value of 0.0623 in model 2. Further note that the probability that the nonstationarity condition $\tau + \delta + \eta \geq 1$ holds drops down to 0.00 and the probability that the empirical regularity $\eta = -\tau*\delta$ holds increases to 0.06. However, there is one crucial problem that remains: the gasoline price elasticity amounts to -2.01 in the default model (the fourth problem regarding this model) and to -2.52 in the extended model, which is not in line with the available empirical evidence of this elasticity, summarized by Goodwin et al. (2004) (see section 2). The explanation for this finding is the near perfect multicollinearity between the time fixed effects and the gasoline price, caused by the fact that the latter varies only a little across space (see Table 1). Since the gasoline price elasticity is the main focus of this type of research, many empirical studies decide not to control for time fixed effects, perhaps to get rid of this multicollinearity problem, among which Bastian and Börjesson (2015) and Thanos et al. (2018). However, if one or more variables are omitted from the model, when relevant, the coefficient estimates of the remaining variables may become biased and inconsistent (Greene, 2008, pp. 133-134). This also holds for time fixed effects. Instead of removing them to get rid of the multicollinearity problem, we therefore adopt two alternative approaches. The first reformulates the dynamic spatial panel data model with spatial and time fixed effects into spatial first-

differences. The ins and outs and methodology of this approach are set out in Yu et al. (2012) and Elhorst et al. (2013). We apply this approach as a kind of robustness check of the second approach, as well as at request of one the reviewers. This second approach is the proposed model which generalizes the time fixed effects by giving up the common factors restrictions $\Gamma_1 = (\mu_1 \dots \mu_N)$, $\Gamma_2 = (1 \dots 1)$, and $f_t = (1 \ \xi_t)'$, i.e., by allowing the time fixed effects to have a different impact on each single department.

The third and the fourth column of Table 3 show that taking spatial first-differences and controlling for common factors are an effective tool to tackle the multicollinearity problem: the short-term gasoline price elasticity drops down in both cases to a more realistic value in the range of -0.07 to -0.06. In addition, the stationarity condition is again satisfied, while the empirical regularity only holds for the model in spatial first-differences. However, in terms of the log-likelihood function value, R-squared, and estimate of σ^2 , the common factor approach turns out to perform much better. Although the results of models 3 and 4 are statistically not the same, they point in the same direction, i.e., all the misspecification problems we observed for models 1 and 2 disappear along the same lines, except for the empirical regularity in model 4. We come back to this last issue shortly. To further determine the importance of the inclusion of common factors, we compare the log-likelihood function value of the last model, the proposed model, with that of model 2 in which the common factors are replaced by spatial and time period fixed effects and with that of model 3, representing the reformulation of model 2 in spatial first-differences. The corresponding LR-test amounts to respectively $-2 * (3291.3 - 3562.3) = 542.0$ and to $-2 * (3190.5 * (1767/1748) - 3562.3) = 674.24$. Both statistics follow a chi-squared distribution with respectively $N + T = 112$ and $N = 93$ degrees of freedom.⁶ Both outcomes exceed the 5-percent critical value of approximately 67.22 and make clear that the basic idea in many studies that business cycle effects can be captured by time dummies with homogenous coefficients need to be rejected in favor of time dummies (read: common factors) with heterogeneous coefficients.

The coefficient λ measuring the degree of spatial autocorrelation left in the error time amounts to -0.0177 and is insignificant. The CD-statistic applied to the residuals of this model is -0.304, which is within the interval $[-1.96, +1.96]$, indicating that the two common factors taken up in the model effectively factor out the global cross-sectional dependence, which was found when applying the CD-test on the raw data. Note however that this also holds for all the other models that have been considered. A potential objection to Pesaran's CD-test is that it loses power when controlling for common factors such as time fixed effects (Sarafidis and Wansbeek, 2012; Millo, 2017). For this reason, we also tested for any remaining cross-sectional dependence in the

⁶In model 4 for $R = 2$, Γ is of dimension $(N, 2)$ and f of $(T, 2)$. The corresponding dynamic panel data model contains N spatial fixed effects, $T - 1$ time fixed effects (one less to avoid perfect multicollinearity with the spatial fixed effects), and no spatial error correlation. This implies that the number of additional parameters in the proposed model is $(N + T - 1) + 1$. The model in spatial first-differences is based on $(N - 1) * T$ observations, the factor 1767/1748 is used to correct for this difference, and does not contain time fixed effects and spatial error correlation. This implies that the number of additional parameters is $(N - 1) + 1$.

residuals of the model using the CD-test developed by Frees (1995). The result are similar; all forms of cross-sectional dependence have effectively been accounted for.

The empirical evidence in favor of our hypothesis that δ , or alternatively η due to the empirical regularity $\eta = -\tau*\delta$, are close to zero and insignificant might also be driven by a wrong specification of the spatial weight matrix, i.e., the binary contiguity matrix. For this reason it has been tested which spatial weight matrix gives the best performance. We considered again the binary contiguity matrix, as well as the inverse distance matrix for different cut-off points first between 50 and 1000 kilometers with a stepsize of 50 kilometers and then between a smaller interval with a stepsize of 10 kilometers. The best performance in terms of R-squared and log-likelihood function value was obtained at a cut-off point of 150 kilometers. This outcome can be explained by the fact that the majority of people are willing to travel back and forth this distance on one day for business purposes or to visit family, while beyond this distance one might need an overnight stay.⁷ The last column of Table 2 provides information on the connectivity characteristics of this matrix. Although this matrix is denser than the binary contiguity matrix, the percentage of non-zero elements increases from 5.41 to 6.80, and the average number of links from 5.03 to 6.32, it is nonetheless still sparse. Another important difference is that the matrix has not been row-normalized but normalized by its largest characteristics root, so as to avoid that the mutual proportions of the elements get lost and, as a result, the matrix would lose its economic interpretation of distance decay (Kelejian and Prucha, 2010). The results when adopting this spatial weight matrix are reported in the last column of Table 3. Compared to model 4 based on the binary contiguity matrix, the log-likelihood function value further increases from 3562.3 to 3571.3, while in contrast to model 4 the empirical regularity is satisfied again. In addition, the price elasticity decreases to -0.0461 in the short term and to -0.2472 in the long term. Both outcomes are significant and in line with the existing empirical evidence.

So far we focused on the marginal effect of the gasoline price, a variable dominated by variation in the time domain. We now turn to the marginal effects of the other three explanatory variables, income per capita, cars per capita and population density, variables dominated by variation in the cross-sectional domain. Since all variables are in log-form, their marginal effects can also be interpreted as elasticities. We repeat that these elasticities are determined by using Equation (2), depend on the own value and on the value of the other explanatory variables in the model, and for this reason vary across both space and time. In addition, there is a gap between the short term and long term elasticities. The first only considers the effect of changes in the explanatory variables on the dependent variable in the same time period. The second considers the effect of changes up to the point that the dependent variables in different departments converge to a new steady state ($y^* = y_t = y_{t-1}$). It was found before that this convergence process takes more than 11.15 years to get close (less than 10%) to this steady state. This implies that the elasticities vary across $N = 93$ departments and $T = 20$ years, and increase in magnitude the longer the time horizon being considered, which

⁷There are no doubt people who are willing to travel more than twice the distance of 150 kilometer on one day, but statistically this is only a minority.

ranges from 1 to approximately 12 years. Since it is impossible, due to lack of space, to show all $(93 * 20 * 12)$ elasticities, we condensed them to the following form. Table 4 shows how the short-term and long-term elasticities of the three variables evolve over time, using cross-sectional averages of the variables over all departments for each time period. Tables 5, 6 and 7 show how the short-term and long-term elasticities vary across space, using time-averages of the variables over the whole time span of the sample for each single department. Since both the spatial autoregressive coefficient δ and the spatiotemporal coefficient η are insignificant and close to zero, these coefficients have been ignored in these calculations.⁸.

<< Tables 4, 5, 6 and 7 about here, see in the other Word-file >>

Table 4 shows that the short term income elasticity has fallen from a statistically significant value of 0.1931 in 1990 to a statistically significant value of 0.0726 in 2003. During the peak-car travel period afterward, the period of stagnation of global car traffic growth which started in 2003, this elasticity remained almost constant. The same applies to its long-term counterpart, which is a factor 5.36 higher. Evidence in favor of a small decline in income elasticities has also been found by Van Dender and Clever (2013) for five strongly developed countries (France, the UK, Germany, the US, and Japan).

The income elasticity is positive and also appears to be significant in most departments (Table 5), though negative and significant in Paris and in its three surrounding departments.⁹ A similar pattern is found for population density (¹⁰ 7). Population density has a positive and significant effect in most departments, except for Paris where density has a negative and strongly significant effect of -0.2865 (t-value -3.01) on car traffic in the short term. The same applies to its surrounding departments, among which Yvelines, Essone, Hauts-de-Seine, Seine-Saint-Denis, Val-de-Marne, and Val-d'Oise, where this negative effect is also significant either at the 5 or at the 10-percent level. Population density, whose elasticity is also slowly falling over time, from 0.0592 in 1990 to 0.0362 in the short-term (0.3174 to 0.1942 in the long-term, see Table 4), is also the only variable that has a significant spatial lag (t-value -2.09, see Table 3), causing an average negative spatial spillover effects to other department of approximately -0.14×0.28 , where the first number denotes the coefficient estimate of this spatial lag and the second number is the average column sum of the spatial weight matrix. Note this column sum ranges from 0.05 to 1.49, depending on the relative location of each department. It is the variation in this local spillover effect that partly

⁸Note that the sum $\delta + \eta = -0.0110 + 0.0066 = -0.0044$, part of Equation (2), is even closer to zero, as a result of which the first $N \times N$ matrix on the right-hand side of this equation is almost identical to the identity matrix and so hardly has any effect on the elasticities, i.e., global spillovers do not occur. Only the second $N \times N$ matrix on the right-hand side, representing local spillovers, affect the elasticities

⁹This result might partly be due to the omission of variables representing the competitive effect of public transport in the Paris region. Due to lack of data on public transport at the department level, we are unfortunately not able to investigate this proposition.

¹⁰Table

explains the observed cluster of departments in which population density starts to have a decelerating effect on car traffic and, related to that, car use is not experienced as a necessary good anymore, since the income elasticity is smaller than 0 rather than between 0 and 1. These findings can be explained by the greater availability of compact public transport networks within cities, and the fact that the average trip length in cities tends to be shorter, as a result of which the share of people who are able to walk or cycle will also be larger. These different positive and negative elasticities across space and positive but declining elasticities of population density over time further explain why some studies have found a negative relationship between car traffic and the level of urbanization, while others did not. A good example is Su (2010), who found a statistically significant negative effect but also cited several studies that found that its role is limited and might be ignored.

Car ownership has a negative effect on vehicle-kilometer-traveled, both in Table 4 and Table 6, but its elasticity does not vary significantly over time. On average, households having more than one car will drive more than households having one car, but the number of kilometers per car will be lower. The elasticity fluctuates around -0.3 in the short term and between -1.7 and -1.3 in the long-term. Especially the last few years its magnitude increased. The elasticity of car ownership ranges from values smaller in magnitude than -0.1 in the urbanized departments Hauts-de-Seine and Seine-Saint-Denis located in Ile-de-France (Paris) to values greater in magnitude than -0.4 in Ardennes, Marne, Haute-Marne, Cote-d'Or and Meuse, a cluster of mainly rural departments located north-east of Ile-de-France. It shows that when car ownership falls due to urbanization, the use of the car(s) that are left becomes less sensitive for higher levels of urbanization. People might keep using their car, but only for longer trips outside peak hours.

6 Conclusion

In this paper we develop a model simultaneously accounting for (1) serial dynamics to control for habit persistence, (2) cross-sectional dependence, subdivided into local spatial dependence and common factors, to explore whether the dependent variable is co-determined by independent variables observed in neighboring units and/or whether the dependent variable in all units move up and down due to observable or non-observable external factors, and (3) heterogeneity across space and time employing a translog specification. This model can be paraphrased as a dynamic general spatial translog model with common factors that generalizes the dynamic spatial panel data model with fixed effects in space and time frequently applied in recent empirical research. As an application, we investigate vehicle-kilometers-traveled as a function of income per capita, number of cars per capita, population density and the gasoline price for 93 departments in France over the period 1990-2009.

When estimating the frequently applied dynamic spatial autoregressive (SAR) model with fixed effects in space and time using a binary contiguity matrix, the default approach in the existing empirical spatial econometric literature, it is found that traffic

behavior slowly adjusts itself to changes in the explanatory variables not only due to habit persistence, expressed by the temporal lagged value of car traffic in the own department, but also due to the spatiotemporal lagged value of car traffic in neighboring departments. However, this would imply the existence of global spillovers, i.e., a change in income per capita, cars per capita, or population density in one part of France eventually will affect car traffic in another part of France. This is unlikely both from an empirical and an economic-theoretical viewpoint. We show that the reason for obtaining this result is underspecification. The default model ignores heterogeneity in space and time, both with regard to the explanatory variables and to the time fixed effects. When extending the model with cross-products among the explanatory variables showing sufficient variation in the cross-sectional model and when allowing the time fixed effects to have a different impact on each single unit, employing the recent approach developed by Shi and Lee (2017), it turns out that the main reason why cross-sectional dependence occurs is because car traffic in all departments go up and down over time due to the volatile gasoline price (with an elasticity which amounts to -0.0461 in the short term and -0.2472 in the long term), and due to non-observable common factors. Only population density appears to cause significant local spillover effects.

Another important result is that the long run income elasticity of car traffic diminished from 1.0 in 1990 to 0.4 in 2003, and then remained almost constant until the end of our sample period in 2009 (i.e. during the peak-car traffic period). A main advantage of the model is also its ability to estimate the impact of variables showing low variability in the cross-sectional dimension (e.g. fuel price), though only by a common coefficient or elasticity for the whole period. A limitation of our results is lack of data on public transport; due to its competitive effect on car traffic especially in the central part of Paris, the income elasticity of this region might have been underestimated.

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Table 1. Data variation

Variable	<i>Between</i> depart.	<i>Within</i> depart.	<i>Between</i> time	<i>Within</i> time
<i>TRA</i>	96.41	3.59	1.01	98.99
<i>CAR</i>	95.96	4.04	2.35	97.65
<i>POP</i>	99.61	0.39	0.17	99.83
<i>Y</i>	94.46	5.54	3.25	96.75
P_{MG}/P_{CPI}	1.89	98.11	97.79	2.21
<i>DENS</i>	99.96	0.04	0.01	99.99
$\ln(TRA/CAR)$	75.52	24.48	0.75	99.25
$\ln(Y/POP)$	36.92	63.08	60.38	39.62
$\ln(CAR/POP)$	69.25	30.75	24.87	75.13
$\ln(P_{MG}/P_{CPI})$	2.09	97.91	97.50	2.50
$\ln(DENS)$	99.86	0.14	0.11	99.89

Table 2. Connectivity characteristics of two spatial weight matrices

	Binary contiguity matrix	Inverse distance cut-off=150
Dimension	93	93
% of non-zero elements	5.41	6.80
Number of non-zero links	468	588
Maximum number of links	10	15
Average number of links	5.03	6.32
Average link*	0.17	0.05

* Sum of non-zero elements divided by number of non-zero links

Table 3. Parameters estimates of Equation (1)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
$y_{it-1}(\tau)$	0.8348 (57.96)	0.7476 (48.63)	0.8029 (50.80)	0.8126 (54.75)	0.8134 (55.31)
$\sum_{j=1}^N w_{ij}y_{jt}(\delta)$	0.0283 (0.59)	0.0093 (0.20)	0.0129 (0.25)	0.0052 (-0.07)	-0.0110 (-0.09)
$\sum_{j=1}^N w_{ij}y_{jt-1}(\eta)$	0.1550 (2.77)	0.0612 (1.13)	-0.0363 (-0.062)	0.0094 (0.06)	0.0066 (0.54)
Income per capita, $\ln(Y/POP)$	-0.0001 (-0.00)	7.4210 (3.63)	4.3453 (1.94)	-0.2185 (-1.82)	-0.1926 (-1.90)
Cars per capita, $\ln(CAR/POP)$	-0.1841 (-4.55)	1.1261 (0.59)	1.9193 (0.95)	6.0186 (4.54)	5.7934 (4.49)
Gasoline price, $\ln(P_{MG}/P_{CPI})$	-2.0111 (-2.01)	-2.5235 (-11.87)	-0.0653 (-1.75)	-0.0675 (-2.55)	-0.0461 (-2.22)
Population density, $\ln(DENS)$	-0.0006 (-0.01)	0.9174 (2.97)	0.4626 (1.40)	1.5458 (5.80)	1.5015 (6.04)
$0.5 * \ln(Y/POP)^2$		-0.7446 (-3.49)	-0.4252 (-1.83)	0.0595 (2.70)	0.0548 (2.99)
$\ln(Y/POP) * \ln(CAR/POP)$		-0.1589 (-0.82)	-0.1940 (-0.93)	-0.6423 (-4.74)	-0.6232 (-4.73)
$0.5 * \ln(CAR/POP)^2$		0.7079 (2.27)	0.8149 (2.43)	0.9834 (3.74)	1.0027 (3.82)
$\ln(Y/POP) * \ln(DENS)$		-0.0365 (-0.98)	-0.0364 (-0.90)	-0.1370 (-5.45)	-0.1331 (-5.65)
$\ln(CAR/POP) * \ln(DENS)$		0.1030 (2.35)	0.0373 (0.79)	0.1322 (3.60)	0.1415 (3.89)
$0.5 * \ln(DENS)^2$		-0.1228 (-1.89)	-0.0210 (-0.30)	-0.0020 (-0.17)	-0.0053 (-0.40)
$W * \ln(Y/POP)$		-0.0544 (-0.84)	0.0157 (0.19)	0.0204 (0.65)	0.0720 (1.48)
$W * \ln(CAR/POP)$		0.1692 (1.84)	0.1821 (1.81)	0.0099 (0.16)	0.1208 (1.08)
$W * \ln(DENS)$		-0.1793 (-1.25)	-0.1978 (-1.32)	-0.0281 (-0.87)	-0.1363 (-2.09)
$\sum_{j=1}^N w_{ij}\nu_{jt-1}(\lambda)$				-0.0177 (-0.1)	-0.3535 (-1.84)
σ^2	0.0031	0.0029	0.0032	0.0021	0.0020
# observations	1767	1767	1748	1767	1767
R-squared	0.6732	0.7002	0.6677	0.9467	0.9474
Log-Likelihood	3222.82	3291.27	3190.52	3562.30	3571.30
CD test residuals (Pesaran)	-0.399	-0.393	-0.800	-0.304	1.423
CD test residuals (Frees)	16.45 (0.56)	15.43 (0.63)	16.00 (0.59)	17.01 (0.52)	21.30 (0.33)
$\tau + \delta + \eta - 1$	0.0181 (0.61)	-0.1819 (0.00)	-0.2205 (0.00)	-0.1831 (0.00)	-0.1319 (0.00)
Probability $\eta = -\tau * \delta$	0.00	0.06	0.45	0.04	0.17

Notes: t-values in parentheses for parameter estimates and p-values for test statistics; since $-\log(\sigma^2) > 0$ if $\sigma^2 < 1$, all log-likelihood function values are positive.