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The Cost of Transportation : Spatial Analysis of US Fuel Prices

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Abstract

The geography of fuel prices has several implications, from a significant impact on accessibility patterns to issues of territorial equity and transportation governance. In this paper, we study its spatio-temporal patterns at a high resolution. We construct a dataset collecting daily oil prices for two months, on a significant proportion of US gaz facilities, using a specifically-designed large scale data crawling technology. The implementation of a web-application for interactive spatio-temporal data exploration guide further statistical investigations, namely that oil price exhibit patterns that are strongly non-stationary in space and time. The behavior of spatial autocorrelation suggests the use of specific spatial econometric methods to study the role of explanatory variables that are either geographical or temporal. We study the influence of socio-economic variables, by using complementary methods: Geographically Weighted Regression to take into account spatial non-stationarity, and Multi-level modeling to condition both at the state and county level. The former yields an optimal spatial range roughly corresponding to stationarity scale, and significant influence of variables such as population density or median income, but is less accurate around administrative borders. On the other hand, multi-level modeling reveals a strong state fixed effect, and also a non-negligible county effect. Through the combination of such methods, we unveil the superposition of a governance process with a local socio-economical spatial process. Results are furthermore consistent across the different dates. We discuss one important application that is the elaboration of locally parametrized car-regulation policies.

Keywords: Fuel Price, Data Crawling, Spatial Analysis, Geographically Weighted Regression, Multi-level Modeling

1. Introduction

What drives the price of fuel? Using a new database on oil price at a gas station level collected during two months, we explore its variability across time and space. Variation in the cost of fuel can have many causes, from the crude oil price to local tax policy and geographical features, all having heterogeneous effect in space and time. If the evolution of the average fuel price in time is an indicator that is carefully followed and analyzed by many financial institution,

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its variability across space remain a rather unexplored topic in the literature. Yet, such differences can reflect variation in more indirect socio-economic indicators such as territorial inequalities and geographical singularities or consumer preferences.

There exists to our knowledge no systematic mapping in space and time of retail fuel prices for a country. The main reason is probably that the availability of data have been a significant obstacle. It is also likely that the nature of the problem may also have influence, as it lies at the crossroad of several disciplines. While economists study price elasticity and measurement in different markets, transportation geography with method such as transportation prices in spatialized models, puts more emphasis on spatial distribution than on precise market mechanisms. Nevertheless, examples of somehow related works can be found. For example, Rietveld et al. (2001) studies the impact of cross-border differences in fuel price and the implications for gradual spatial taxation in Netherlands. At the country-level, Rietveld and van Woudenberg (2005) provides statistical models to explain fuel price variability across European countries. Macharis et al. (2010) models the impact of spatial fuel price variation on patterns of inter-modality, implying that the spatial heterogeneity of fuel prices has a strong impact on user behavior. With a similar view on the geography of transportation, Gregg et al. (2009) studies spatial distribution of gas emission at the US-state level. The geography of fuel prices also have important implications on effective costs, as shows Combes and Lafourcade (2005) by determining accurate transportation costs across urban areas for France. More closely related to our work, and using very similar daily open data for France, Gautier and Saout (2015) investigate dynamics of transmission from crude oil prices to fuel retail prices. However, they do not introduce an explicit spatial model of prices diffusion and do not study spatio-temporal dynamics.

In this paper we take the analysis one step further by proceeding to exploratory spatial analysis on US fuel prices.
to unveil possible spatial patterns and how they can link to socio-economic properties.

The rest of the paper is organized as follows: in the next section, we describe a generic procedure and the tool used for a systematic data collection. We also present our dataset. In section 3 we conduct statistical analysis in order to study the spatio-temporal variation of fuel price and test the potential correlation with some covariates. Finally, in section 4 we discuss our results and conclude.

2. Dataset

HOW MANY GAS STATION IN THE US? COMPARED TO OUR DATASET

2.1. Collecting large scale heterogeneous data

The availability of new type of data has induced consequent changes in various disciplines from social science (e.g. online social network analysis Tan et al. (2013)) to geography (e.g. new insights into urban mobility or perspectives on "smarter" cities Batty (2013)) and economics where the availability of exhaustive individual or firm level data is seen as a revolution. Study involving these new data are not always easy to situate or legitimate at the interface of implied disciplines, as shows the example of the difficult understanding between physics and urban sciences mentioned in Dupuy and Benguigui (2015).

Collection and use of new data has therefore become a crucial task in social-science.

The construction of such datasets is however far from straightforward, as their analyses because of the incomplete and noisy nature of data. Specific technical tools have to be implemented, often with a problem-specific tuning making them difficultly generic. We develop such a tool that fills the following constraints typical of large scale data collection: (i) reasonable level of flexibility and genericity; (ii) performance optimized, through parallel collection jobs; (iii) anonymity of collection jobs to avoid any possible bias in the behavior of the data source. The architecture, at a high level, has the following structure:

- An independent pool of tasks runs continuously socket proxies to pipe requests through `tor`.
- A manager monitors current collection tasks, split collection between subtasks and launches new ones when necessary.
- Subtasks can be any callable application taken as argument destination urls, they proceed to the crawling, parsing and storage of collected data.

The application is open and its module are reusable: source code is available on the repository of the project[1].

2.2. Dataset

Our dataset of fuel prices consists in crowdsourced information of retail fuel prices from various web sources. These information are aggregated with the above-described crawling tool. The dataset comprises around $41 \cdot 10^6$ unique observations, spanning in time from 2017-01-10 to 2017-03-19 and corresponds to 118,573 unique retail stations. For each of these stations, we associate a precise geographical location (city resolution). On average we have XX information by station.

Prices correspond to an unique purchase mode (credit card, other modes such as cash being less than 10% in test datasets, they were discarded in the final dataset) and four fuel types: Diesel (18% of observations), Regular (34%), Midgrade (24%) and Premium (24%). The best coverage of stations is for Regular fuel type (**C :** recompute proportion on full dataset), and we choose to work with this one in our exploratory analysis, keeping in mind that further developments with the dataset may include comparative analysis on fuel types.

C : Aggregate on which time span ? best is to check time to converge to a certain coverage of all stations (say 95%) → around one week seems ok (see stations count plot in repo)

C : French Open Data : https://www.prix-carburants.gouv.fr/rubrique/opendata/ → look to what extent our study could be transfered to France

The socio-economic data we use are basic population and job related variables (namely income, population, jobs, wage per job, jobs per capita), available from the US Census Bureau. We use the latest available, aggregated at the county level.

3. Results

3.1. Spatio-temporal Patterns of Prices

Before moving to a more systematic study of the variation of fuel price, we propose a first exploratory introduction to give insight about its spatio-temporal structure. This exercise is a crucial stage to guide further analyses, but also to understand their implications in a geographical context.

A lightweight web application for interactive exploration in space and time was implemented for that purpose, and is available at .

3.2. Spatial Autocorrelation

We now turn to the study of spatial autocorrelation of prices, which can be seen as an indicator of spatial heterogeneity. We use the Moran index (Tsai (2005)), with spatial weights of the form $\exp\left(-d_{ij}/d_0\right)$ with d_{ij} being the distance between spatial entities i and j, and d_0 a decay parameter giving the spatial range of interactions taken into account in the computation. We show in Fig. 2 its variations in time and as a function of decay parameter. The fluctuations in time of the daily Moran index for low and medium spatial range, confirms geographical particularities in the sense of locally changing correlation regimes. These are logically smoothed for long ranges, as price correlations drop down with distance. The behavior of spatial autocorrelation with decay distance is particularly interesting: we observe a first regime change around 10km (from constant to piecewise linear regime), and a second important one around 1000km, both consistent across weekly time windows. We postulate that these correspond to typical spatial scales of the involved processes: the low regime would be local specificities and the middle one the state level processes. This behavior confirms that prices are non-stationary in space, and that therefore appropriate statistical techniques must be used to study potential drivers. The two next subsections follow this idea and investigate potential explicative variables of local fuel prices, using two different techniques corresponding to two complementary paradigms: geographically weighted regression that puts the emphasis on neighborhood effects, and multi-level regression taking into account administrative boundaries.

[1] at `https://github.com/JusteRaimbault/EnergyPrice`

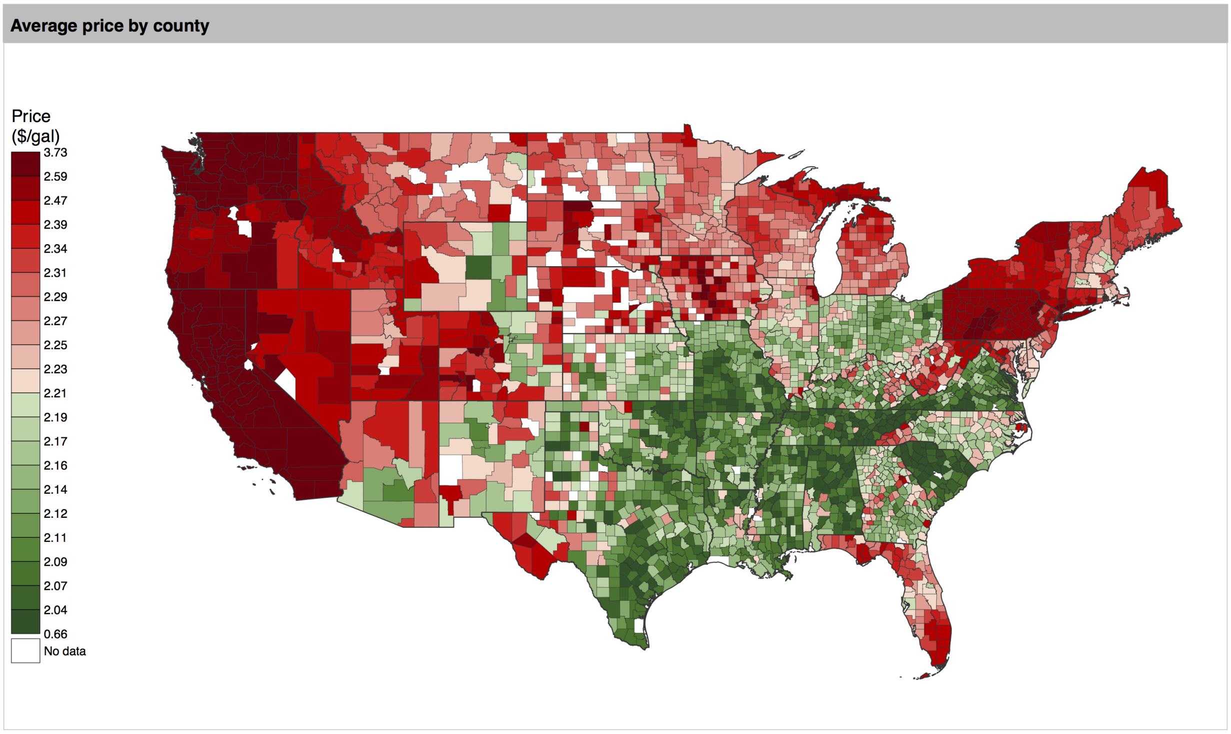

Fig. 1. Map of mean price for counties, regular fuel, averaged over the whole period.

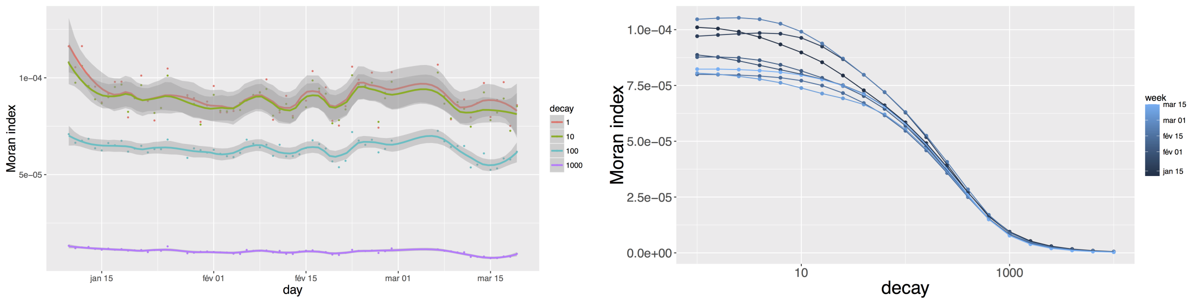

Fig. 2. **Behavior of Moran spatial-autocorrelation index.** (Left) Evolution in time of Moran index computed on daily time windows, for different decay parameter values. (Right) Moran index as a function of decay parameter, computed on weekly time windows.

3.3. Geographically Weighted Regression

The issue of spatial non-stationarity of geographical processes has always been a source of biased aggregated analyses or misinterpretations when applying general conclusions to local cases. To take it into account into statistical models, numerous techniques have been developed, among which the simple but very elegant Geographically Weighted Regression, that estimates non-stationary regressions by weighting observations in space similarly to kernel estimation methods. It was introduced in a seminal paper by Brunsdon et al. (1996) and has been consequently used and matured since. The significant advantage of this technique is that an optimal spatial range in the sense of model performance can be inferred, and that the corresponding model gives effect of variables varying in space, revealing thus local effects that can occur at different spatial scales or across boundaries. We proceed to multi-modeling to find the best model and associated kernel and spatial range. The workflow is the following: (i) we generate all possible linear models from the five potential variables (income, population, wage per job, jobs per capita, jobs); (ii) for each model and each

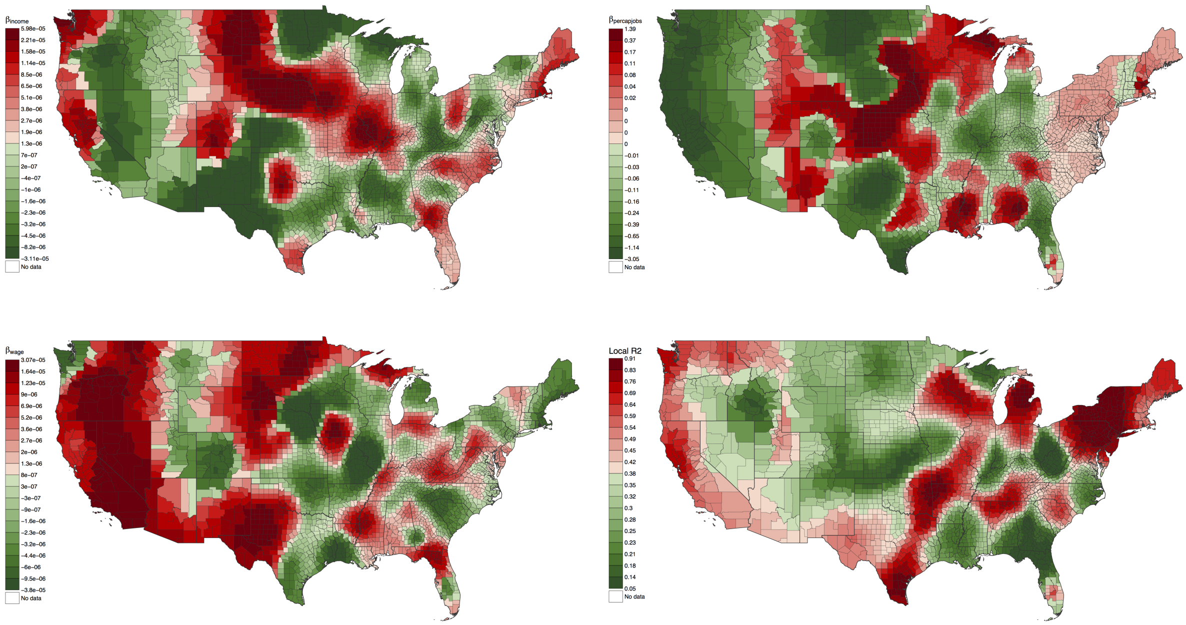

Fig. 3. **Results of GWR analyses.** For the best model in the sense of AICc, we map the spatial distribution of fitted coefficient, in order from left to right and top to bottom, β_{income}, $\beta_{percap jobs}$, β_{wage}

candidate kernel shape (exponential, gaussian, bisquare, step), we determine the optimal bandwidth in the sense of both cross-validation and corrected Akaike Information Criterion (AICc) which quantifies information included in the model, taking into account both model fit and number of parameters to avoid overfitting; (iii) models are fitted with this bandwidth. We choose the model with the best overall AICc, namely $price = \beta \cdot (income, wage, percap jobs)$ for a bandwidth of 22 neighbors and a gaussian kernel[2], with an AICc of 2900. The median AICc difference with all other models tested is 122. The global r-squared is 0.27, what is relatively good also compared to the best r-squared of 0.29 (obtained for the model with all variables, which clearly overfits with an AICc of 3010; furthermore, effective dimension is less than 5 as 90% of variance is explained by the three first principal components for the normalized variables). The coefficients and local r-squared for this model are shown in Fig. 3. The spatial distribution of residuals (not shown here) seems globally random, which confirms in a way the consistency of the approach: if a distinguishable geographical structure is found in residuals, it means that the geographical model or the variable taken into account fail to translate spatial structure.

3.4. Multi-level Regression

An other approach to take into account geographical heterogeneities without explicitly including spatial relations between objects is to proceed to regressions with random effects depending on geographical aggregations at different levels. The method of multi-level regression implements this idea, and has been shown to be particularly adapted for geographical research Jones (1991). We take here into account two administrative levels, the state and the county. Explorations of section 3.1 suggest a strong state-effect that GWR cannot capture around boundaries, what confirms the relevance and complementarity of using Multi-level Regression.

[2] note that the kernel

4. Discussion

4.1. On the complementarity on Spatial Analysis methods

C : bla bla on conclusions drawn with each method ; how they are complementary → also present it as a methodological contribution. some literature do both, e.g. Chen, D. R., & Truong, K. (2012). Using multilevel modeling and geographically weighted regression to identify spatial variations in the relationship between place-level disadvantages and obesity in Taiwan. Applied Geography, 32(2), 737-745. integrates both in a single approach.

4.2. Towards localized car-regulation policies

C : knowing local price dynamics and their drivers should help designing specific regulations/taxing policies ?

5. Conclusion

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