

The Cost of Transportation : Spatial Analysis of US Fuel Prices

J. Raimbault^{1,2}, A. Bergeaud³
juste.raimbault@polytechnique.edu

¹UMR CNRS 8504 Géographie-cités

²UMR-T IFSTTAR 9403 LVMT

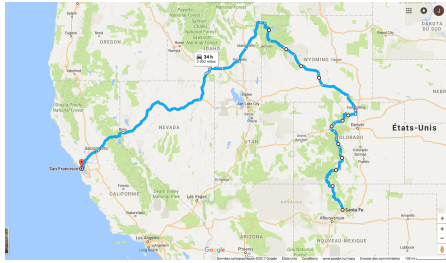
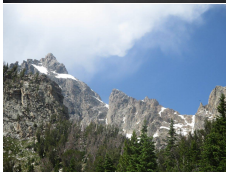
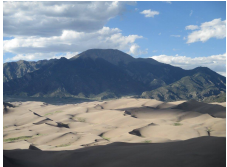
³Paris School of Economics

EWGT 2017 - Budapest

Session 10B: Transport Economics and Financing

September 6th, 2017

Road Trippin' : Californication



Geography and Fuel prices

→ In the US you fuel your (necessary big) car everywhere and everyday, and directly feel the strong variability of prices !

Spatio-temporal variability of Fuel Price captures geographical properties of a particular energy market, of the transportation system, of interactions between transportation and territories.

Diverse approaches mostly by economists :

- [Rietveld et al., 2001] cross-border variability
- [Gregg et al., 2009] influence on carbon emissions
- [Combes and Lafourcade, 2005] effective transportation costs
- [Gautier and Saout, 2015] from crude oil price to retail price

Exploratory Spatial analysis

Research Objective : *Construction and Exploratory analysis of a large and detailed dataset of US fuel retail price, focusing on spatio-temporal variability*

- Focus on geographical patterns and structures
- Complementarity of spatial analysis methods
- Interdisciplinary point of view on a fundamentally heterogenous system

Dataset Construction

Crowdsourced Big Data as a new way to unveil structure of complex socio-technical systems

→ Construction of a large scale dataset covering most of US fuel stations on two month

Requirements : Flexibility, performance and anonymity

Architecture : Pool of proxy tasks to pipe requests through tor; manager monitors and launches collection tasks; subtasks crawl and parse target webpages.

Dataset available upon request, “grey area” of semi-open data.

Dataset Summary

- $41 \cdot 10^6$ unique observations, between January and March 2017
→ 5,204,398 gas station - day observations for main purchase mode and regular fuel, used in the analysis, aggregated at the county level
- Socio-economic data from US Census Bureau

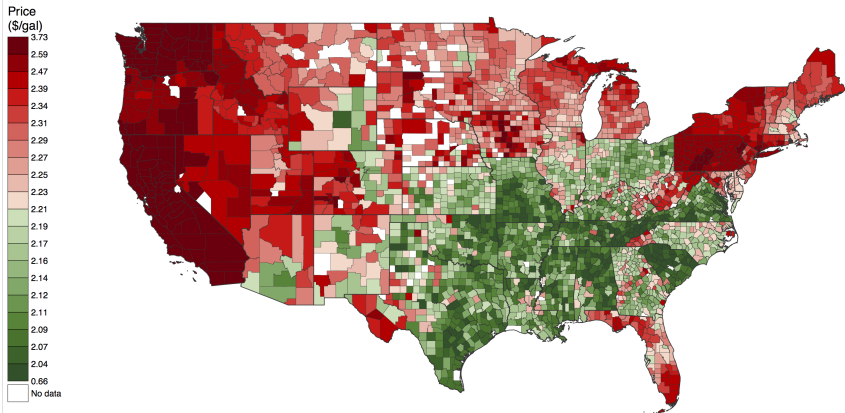
Table: Descriptive statistics on Fuel Price (\$ per gallon)

Mean	Std. Dev.	p10	p25	p50	p75	p90
2.28	0.27	2.02	2.09	2.21	2.39	2.65

Data Exploration

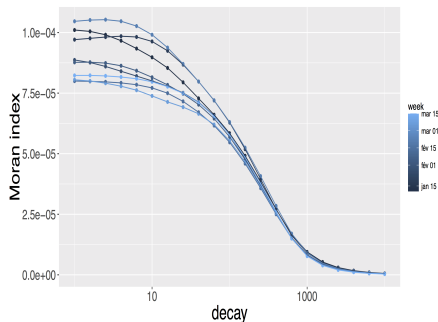
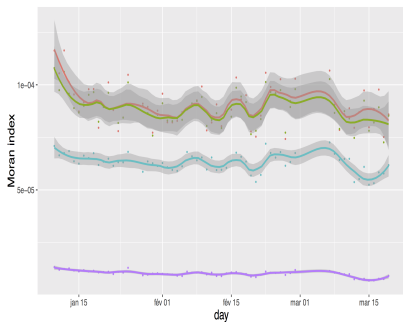
Interactive web-application for spatio-temporal exploration

Average price by county



Spatio-temporal correlations

Variability in space and time of Moran spatial auto-correlation index unveils strong non-stationnarity



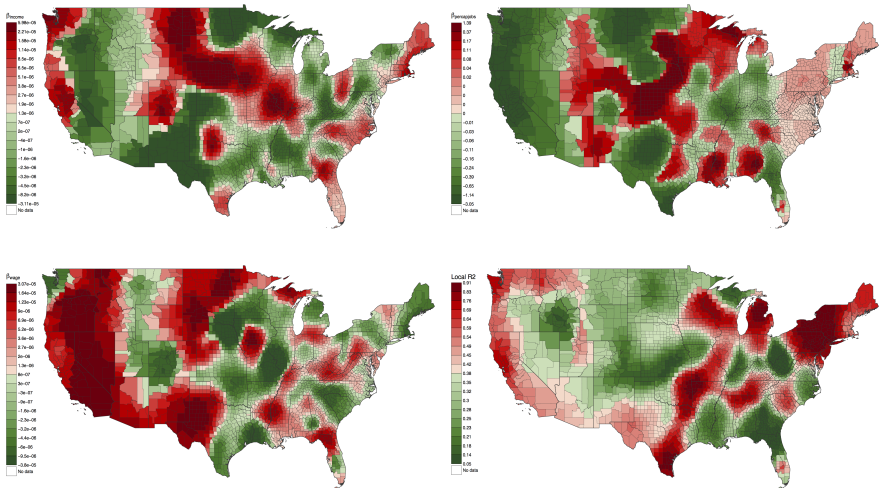
Geographically Weighted Regression

- Geographically Weighted Regression (GWR) [Brunsdon et al., 1996] to tackle spatial non-stationarity : capturing a variable influence in space of explicative variables for prices
- Multi-modeling using corrected AIC for model selection : find the best model and the best bandwidth controlling for overfitting

Best model : $price = \beta \cdot (income, wage, percapjobs)$ with an optimal bandwidth around 75km (22 neighbors with adaptive bandwidth), interpreted as spatial stationarity scale of price processes in relation to economic agents.

Geographically Weighted Regression : Results

Fitted coefficients and R^2 for the best model



Multi-level Regression

Fixed effect regression at the level of the state : multi-level modeling to capture spatial effect of administrative boundaries

$$\log(x_i) = \beta_0 + X_i\beta_1 + \beta_{s(i)} + \varepsilon_i, \quad (1)$$

- Clustering of standard error at the state level motivated by the strong spatial autocorrelation: capture county-level variation controlling for State fixed effect
- Regressing the log of price on a state fixed-effect explains 74% of the variance
- influence of taxes: regressing the log of oil price on the level of state tax gives a R-squared of 0.33%

Multi-level Regression : results

	(1)	(2)	(3)	(4)	(5)
Density		0.016*** (0.002)	0.016*** (0.001)	0.016*** (0.001)	0.015*** (0.001)
Population (log)		-0.007*** (0.001)	-0.040*** (0.011)	-0.041*** (0.011)	-0.039*** (0.010)
Total Income (log)			0.031*** (0.010)	0.031*** (0.010)	0.027*** (0.009)
Unemployment			0.001 (0.001)	0.000 (0.001)	0.000 (0.001)
Poverty			-0.028** (0.011)	-0.030*** (0.011)	-0.029** (0.011)
Percentage Black				0.000*** (0.000)	-0.000 (0.000)
Vote GOP					-0.072*** (0.015)
R-squared	0.743	0.767	0.774	0.776	0.781
N	3,066	3,011	3,011	3,011	3,011

Multi-level Regression : summary

- Strong influence of state-level tax
- Dense urban counties have higher fuel price, but price decreases with population
- Fuel price increases with total income, decreases with poverty
- It decreases with the extent to which a county has voted for a Republican candidate: suggests a circular link
- Overall, local socio-economic features have explanatory power when removing State fixed effect

Implications

Methodological

→ Complementarity of Spatial analysis and econometrics methods : towards integrated approaches to territorial systems

Practical

→ Possible design of territory-targeted car-regulation policies, allowing both sustainability and territorial equity




Possible Developments

- Microscopic data analysis (requires precise geocoding)
- Longer time series (collection in progress) and time-series modeling
- Parametrization of a large-scale ABM of the spatialized fuel market : investigation of adaptive policies effects at the local and global level
- Scales and ontologies to study relations between network and territories

Conclusion

- A novel insight into spatio-temporal dynamics of fuel price and their determinants thanks to big data harvesting
 - Complementary approaches and conclusions through GWR and multi-level modeling
 - Fundamental role of spatio-temporal non-stationarity and existence of typical stationarity scales
-
- All code available at <https://github.com/JusteRaimbault/EnergyPrice>
 - Raw dataset available upon request
 - Paper preprint available at <http://arxiv.org/abs/1706.07467>

References I

-  Brunsdon, C., Fotheringham, A. S., and Charlton, M. E. (1996). Geographically weighted regression: a method for exploring spatial nonstationarity. *Geographical analysis*, 28(4):281–298.
-  Combes, P.-P. and Lafourcade, M. (2005). Transport costs: measures, determinants, and regional policy implications for france. *Journal of Economic Geography*, 5(3):319–349.
-  Gautier, E. and Saout, R. L. (2015). The dynamics of gasoline prices: Evidence from daily french micro data. *Journal of Money, Credit and Banking*, 47(6):1063–1089.

References II



Gregg, J. S., Losey, L. M., Andres, R. J., Blasing, T., and Marland, G. (2009).

The temporal and spatial distribution of carbon dioxide emissions from fossil-fuel use in north america.

Journal of Applied Meteorology and Climatology, 48(12):2528–2542.



Rietveld, P., Bruinsma, F., and Van Vuuren, D. (2001).

Spatial graduation of fuel taxes; consequences for cross-border and domestic fuelling.

Transportation Research Part A: Policy and Practice, 35(5):433–457.

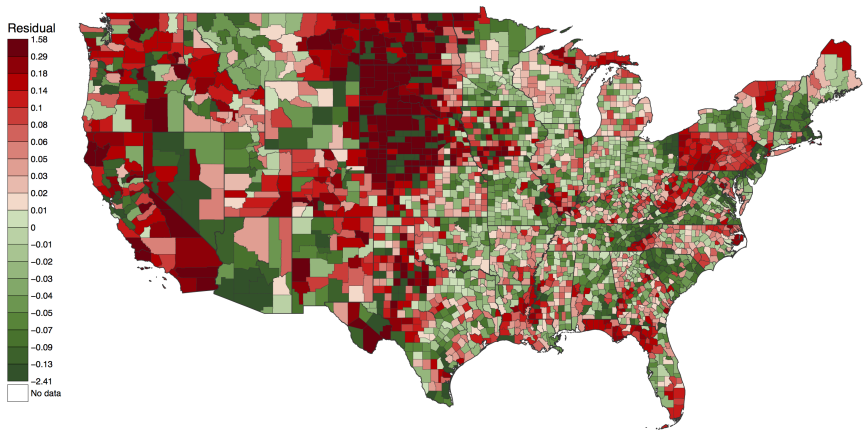
Spatial Heterogeneity

Spatial Autocorrelation as an index of spatial variability, for link i

$$\rho_i = \frac{1}{K} \cdot \sum_{i \neq j} w_{ij} \cdot (c_i - \bar{c})(c_j - \bar{c}) \quad (2)$$

with spatial weights $w_{ij} = \exp\left(\frac{-d_{ij}}{d_0}\right)$

GWR Residuals



High dimensional fixed effects

With $x_{i,s,c,t}$ the fuel price in day t , in gas station i , in state s and in county c , we start by running high dimensional fixed effect regressions

$$x_{i,s,c,t} = \beta_s + \varepsilon_{i,s,c,t} \quad (3)$$

$$x_{i,s,c,t} = \beta_c + \varepsilon_{i,s,c,t} \quad (4)$$

$$x_{i,s,c,t} = \beta_i + \varepsilon_{i,s,c,t} \quad (5)$$

$$(6)$$

Where $\varepsilon_{i,s,c,t}$ contains an idiosyncratic error and a day fixed effect.

→ It confirms that most of the variance can be explained by a state fixed effect and that integrating more accurate levels has only small effect on the fit of our model as measured by the R-squared.