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Are Gasoline Demand Elasticities Different across Cities?

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Abstract: In this paper, we examine the heterogeneity in gasoline demand price and income elasticities across 40 cities in the province of Quebec Canada using quarterly data over the 2004 to 2009 period. We reject the hypothesis of identical elasticities across markets. However, the range of values for the price elasticity, between -0.65 and -0.14, is relatively narrow and confirms that the demand for gasoline is price inelastic. We find evidence that the average price and income elasticity is somewhat larger in markets with public transportation. Furthermore, these markets experience a strong declining trend in gasoline use per capita.

1. Introduction

This paper investigates how gasoline demand varies across markets. In particular, we compare the responsiveness of gasoline demand to price and income in two types of markets namely large urban cities with a good public transportation system and small to median cities that rely almost exclusively on private vehicles. First, we show, theoretically, that the demand for gasoline in a city with a public transportation system is not necessarily more price elastic than the demand in a city without the presence of this substitute. Second, we carry out an empirical analysis using quarterly data on gasoline sales in 40 municipalities and metropolitan areas in the province of Quebec (Canada) over the 2004-2009 period. For the two market groups, we estimate a demand function that depends upon the price of gasoline, the level of disposable income, seasonal effects and a random market specific effect. Furthermore, we allow some coefficients to be random in order to account for within group heterogeneity. Our empirical results show that the price and income elasticities are statistically different across markets but with a range of values that is relatively limited. We also find that the average price elasticity in cities with public transit is larger than in cities without (0.22 versus 0.12). However, the most striking result is the sharp negative trend in per capita gasoline demand in large urban cities with public transit. Indeed, in these markets, we obtain an average annual reduction of 2% (all else being equal) which provides additional evidence that the use of cars in large cities may be stagnating or even declining (Goodwin and Van Dender, 2013).

There is an important body of literature on gasoline demand but the number of studies testing for variations in gasoline elasticities across markets is rather smaller. Some of the existing studies compare elasticities values across countries (Dahl, 1982; Baltagi and Griffin, 1983; 1997; Brons

et al 2008) finding few systemic variations. Some recent studies compare the elasticity across time periods and find evidence that the price elasticity of gasoline in the US has declined over time (Small and Van Dender, 2007; Hughes et al. 2008). This decline would be caused by urban sprawl and improved standard of living which would have increased automobile dependency.

Another strand of the literature uses micro level data to study heterogeneity in gasoline demand elasticities across households. These analyses either directly estimate household gasoline demand (Wadud et al. 2009, Wadud et al. 2010) or they study one of its main determinants namely vehicle miles traveled (Gillingham, 2013, Wang and Chen, 2014). Overall, these studies confirm the existence of heterogeneity across households but provide, so far, little consensus on its pattern. For example, while some studies find that price elasticity decreases with the level of household income (West and Williams, 2004, Wadud et al. 2009, Wadud et al. 2010) others find the opposite (Kayser, 2000, Gillinghma, 2013). A U-shaped relationship is derived by West (2004) and an inverted U-shape by Wand and Chen (2014). Some researchers find that the price elasticity is more important in urban settings (Wadud et al. 2009, Wadud et al., 2010) but others find the opposite (Gillingham, 2013). The evidence on income elasticity also varies greatly across studies. For the US, Wadud et al. (2009) finds lower price elasticity in rural regions (-0.17) than in urban areas (-0.3).

Compared to a country (or state) level analysis, using city level data offer more opportunities to analyze demand in differentiated environments. Household level data allows a very precise analysis of demand heterogeneity but these data are not always available. Moreover, they are often either cross sections or short panels thereby making the identification of the price effect somewhat more difficult. Obviously, using city level data has its own shortcomings especially the risk that gasoline sales in a city (particularly in small ones) do not necessarily reflect gasoline

demand of its residents adequately. Indeed, residents may buy gasoline elsewhere and non-residents may inflate city sales.

To our knowledge, our study is amongst the first studies to use gasoline data at city level. Recently however, Levin, Lewis and Wolak (2013) have used daily expenditure data and prices to analyse the demand for gasoline in 243 U.S. metropolitan areas from 2006 to 2009. While, the main focus of their analysis is on the impact of using high frequency data, they do however also report some results on variations in price elasticities across cities. They find that almost all cities have gasoline price elasticities ranging from -0.35 to -0.45. They also find that more densely populated cities, those with more low income households or a higher share of commuters using subways or rails have somewhat more elastic demand. Besides using data from a different country, our study is different as it compares cities of very different size ranging from large metropolitan areas to small cities with a few thousands residents.

In section 2, we present a very simple theoretical model to illustrate the potential impact of public transportation on gasoline demand at the city level. In section 3, we describe the data and the criteria used to classify cities. The empirical specification and results are presented in section 4. We conclude in section 5.

2. The impact of public transportation on gasoline demand

A distinguishing feature of many large cities is the supply of public transportation, a substitute to private vehicles. It may be tempting to anticipate that markets with public transportation should necessarily exhibit greater price elasticity of gasoline demand. In fact, the very simple model below illustrates that this initial intuition may not necessarily be adequate.

Suppose individual i has the following Cobb-Douglas utility function

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$$U_i = \alpha \ln(x_i) + (1 - \alpha)\ln(m_{ai} + m_{bi}) \quad (1)$$

with x_i a composite good, m_{ai} the distance travelled by cars and m_{bi} the distance travelled by public transit (e.g. bus or light rail). For the sake of simplicity, cars and public transit are assumed to be perfect substitutes. Thus, the mode choice only depends upon the comparison of the generalized travel costs. For the automobile, the cost per unit of distance is given by:

$$P_a = \tau\, p_f + c + \left(\frac{w_i}{\vartheta_a}\right) \quad (2)$$

The first term is the fuel cost per unit of distance with τ the fuel consumption rate per unit of distance and p_f the price of gasoline. c comprises the other monetary costs such as insurance and vehicle depreciation. The third term is the cost of travel time which depends upon the value of time evaluated by the individual hourly wage w_i and the average speed of car travel ϑ_a. Similarly, the public transit generalized cost is

$$P_b = b + \left(\frac{w_i}{\vartheta_b}\right) \quad (3)$$

with b the monetary costs of using public transit. To make the analysis interesting, we assume that $b < \tau\, p_f + c$ and $\vartheta_a > \vartheta_b$ so that depending upon w_i some individuals find it cost efficient to travel by transit and others by car. Specifically, individuals with

$$w_i > w^* = \frac{(\tau\, p_f + c - b)\vartheta_a\vartheta_b}{\vartheta_a - \vartheta_b} \quad (4)$$

travel by car ($m_{ai} > 0$ and $m_{bi} = 0$). For those individuals, the distance travelled m_{ai} is given by maximizing (1) under the budget constraint

$$w_i Z = x_i + P_a m_{ai} \quad (5)$$

with Z the exogenous number of hours worked per day. Individual i's gasoline demand is

$$d_i = \tau m_{ai} = \tau \frac{(1-\alpha)w_i Z}{\tau p_f + c + (\frac{w_i}{\vartheta_a})}. \quad (6)$$

Her gasoline price elasticity is

$$\varepsilon_{d_i, p_f} = \frac{\tau p_f}{\tau p_f + c + \frac{w_i}{\vartheta_a}} \quad (7)$$

which is decreasing in w_i.[1] Her income elasticity

$$\varepsilon_{d_i, w_i} = \frac{\tau p_f + c}{(\tau p_f + c + \frac{w_i}{\vartheta_a})} \quad (8)$$

is also decreasing in w_i.

Assuming a continuum of individuals with an income density distribution $f(w)$ over the support $[w_l, w_h]$ with $w_l < w^*$ and $w_h > w^*$, the aggregate gasoline demand in a market with public transit (referred with superscript T for Transit) is given by

$$D^T = \int_{w^*(p_f)}^{w_h} d_i(p_f, w) f(w) dw \quad (9)$$

It can easily be shown using Leibniz integral rule that the aggregate demand price elasticity is

$$\varepsilon_{D^T, p_f} = \frac{1}{D^T} \int_{w^*(p_f)}^{w_h} d_i(p_f, w) \, \varepsilon_{d_i, p_f} f(w) dw + \frac{d_i(p_f, w^*(p_f))}{D^T} w^*(p_f) \, f\left(w^*(p_f)\right) \varepsilon_{w^*(p_f), p_f}$$

$$(10)$$

The first term is a weighted average of the individual demand elasticity of those travelling by cars. The weight is given by the individual share in the aggregate demand. The elasticity is

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[1] In this section and for simplicity, we define all the price elasticities in absolute value.

however higher as some car users transfer to public transit following the price increase. This shift is measured by the second term in (10) with $\varepsilon_{w^*(p_f),p_f}$ measuring the elasticity of $w^*(p_f)$ with respect to p_f.

In a city with no public transit system (referred by superscript *NT* for No Transit), the only available mode is the automobile so that the aggregate demand is given by:

$$D^{NT} = \int_{w_l}^{w_h} d_i(p_f, w) f(w) dw \qquad (11)$$

and the elasticity is:

$$\varepsilon_{D^{NT}, p_f} = \frac{1}{D^{NT}} \int_{w_l}^{w_h} d_i(p_f, w) \, \varepsilon_{d_i, p_f} f(w) dw \qquad (12)$$

Comparing (10) and (12), it can be easily shown that the first term in (10) is smaller than (12) if the price elasticity is declining with the level of income.[2] The intuition is clear: transit subtracts from the gasoline demand low-income individuals that have higher ε_{d_i, p_f}. So it is very well possible that, if the second term in (10) is small, we have $\varepsilon_{D^T, p_f} < \varepsilon_{D^{NT}, p_f}$ i.e. the price elasticity is smaller in the city with public transit.

As an example, suppose that there are only two groups of individuals: group 1 has N_1 individuals with hourly wage w_l and group 2, N_2 individuals with wage w_h. In this case, in a city without public transit, the gasoline demand price elasticity is a weighted average of the two groups elasticity $\varepsilon_{D^{NT}, p_f} = (\frac{N_1 d_1}{N_1 d_1 + N_2 d_2}) \varepsilon_{d_1, p_f} + (\frac{N_2 d_2}{N_1 d_1 + N_2 d_2}) \varepsilon_{d_2, p_f}$. With public transit, only group 2 individuals have a positive demand for gasoline so that the demand elasticity is $\varepsilon_{D^T, p_f} = \varepsilon_{d_2, p_f}$.

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[2] This is the case despite the fact that D^{NT} is higher than D^T (see Appendix 1 for the proof).

It follows in this case that, we end up with a gasoline demand which is more price elastic in the market without the substitute, i.e. $\varepsilon_{D^{NT},p_f} > \varepsilon_{D^T,p_f}$.

Obviously, the opposite may also occur. In fact, three aspects are required for observing lower price elasticity in markets with public transit: i) transit is chosen by low income individuals (i.e. it is an inferior good), ii) these individuals have higher elasticities and iii) modal shift is low following a gasoline price increase. While public transportation is often used as an example of an inferior good, the empirical evidence is mixed. Holmgren (2007) reviews 22 studies and reports income elasticities of transit demand ranging from -0.82 to 1.18 with a mean at 0.17. A review of the literature by Paulley et al. (2006) provides more conclusive evidence with transit being an inferior good when the impact of income on car ownership is properly taken into account. They report income elasticities ranging from -0.5 to -1.

As already mentioned in the introduction, the empirical evidence concerning point ii) are mixed. In fact, some empirical studies (Kayser, 2000, Gillingham, 2013) find that low income households have lower price and income elasticities. One explanation is that these households have very little latitude to reduce gasoline consumption as they already only use their cars for bare necessities. It is easy to modify our model to include a minimum level of travel m_s.[3] In such a setting, low income households may end up having a demand for gasoline that is perfectly inelastic. Also, higher income households have more options to adjust to higher prices. They can reduce discretionary travels or switch to air travel for long distance trips. Moreover, high income households often have several cars thereby allowing reductions in gasoline consumption by increasing the use of the most efficient vehicles.

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[3] $U_i = \alpha \ln(x_i) + (1 - \alpha)\ln(m_{ai} + m_{bi} - m_s)$

Concerning the modal transfer due to a change in gasoline price, the empirical evidence on the related concept of transit demand elasticity with respect to gasoline price indicates some mode shifting. For example, Lane (2011) obtained a long term elasticity of 0.4 for bus and 0.8 for rail using data for 33 metropolitan areas in the US. Even if these elasticties are high, the impact on gasoline demand may still be quite low when the initial market share of transit is low.

In conclusion, it is ambiguous based on economic theory whether cities with transit should exhibit higher or lower price and income elasticities. We therefore turn next to an empirical investigation of this question.

3. The data

Data on quantities of gasoline sold by market are provided by *The Kent Group,* a private company that collects data through on-site visits at about 7000 gasoline stations in more than 300 markets in Canada. Our sample includes quarterly volume from 2004 to 2009 in 40 markets located in the province of Quebec (Canada).[4] Most markets correspond to either a municipality or a metropolitan area. There is however one exception; the largest metropolitan area in the province, Montreal, is divided into 4 markets.[5] The average quarterly price of gasoline (regular only) is obtained through the *Régie de l'Énergie*, a public regulating organization. The price data are however only available by administrative regions, a territorial division that is usually larger than the city limits. We expect however that the correlation between the regional and market prices is high. Moreover, the price variability across markets is marginal relative to the temporal

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[4] All the grades of gasoline (regular, premium, premium plus) are aggregated. Diesel is not included but diesel light duty vehicles represent less than 1% of the vehicle fleet in Quebec. The data initially included 43 markets but we have aggregated three markets with other existing markets in the Montreal area.

[5] Montreal Centre, East, West, South and North.

price changes. The socio-demographic market characteristics including city population and per capita personal income are provided by *Institut de la Statistique du Québec* and *Statistics Canada*. Unfortunately, these variables are only available on an annual basis thereby reducing their variability.

Table 1 provides some descriptive statistics with markets being classified in two groups based on the importance of public transportation. Specifically, we regroup all the markets where at least 10% of workers commute by public transit based on the 2006 census data. This group includes seven markets which are all located in the province's three largest metropolitan areas. We refer to this group as *HTransit* for high transit markets. The remaining 33 markets include municipalities with population ranging from 3,000 to 400,000. In this group, the share of workers commuting by transit ranges from 0 to 6.4%. We refer to this group as *LTransit* for low transit markets. Figure 1 illustrates the changes in the average gasoline sale per capita in both market groups over the 2004-2009 period.

We observe that the *HTransit* group is characterized by gasoline sales per capita that are 30% lower and a smaller number of vehicles per capita.   All the markets in the transit group have experienced a statistically significant negative trend in per capita gasoline sales over the 2004 and 2009 period.[6] For the *LTransit* group, 16 markets experience a positive trend, 10 a negative one and the remaining 7 markets no significant trend. The average income in the *Htransit* group is 14% higher and the average population density is close to six times larger than in the *LTransit* group.[7] There is little difference in the average gasoline price across the two groups. In the

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[6] For each market, we regress the log of per capita sales on a trend.

[7] Some markets in the transit group have an average population density that is relatively low. Still, these markets have a highly dense urban core that sustains a public transit system.

LTransit group, we observe a very wide range in gasoline per capita. Some markets have very large sales per capita because of substantial external demands. This is the case for markets located along highways and cities with touristic attractions. Finally, Figure 2 illustrates the changes in the average gasoline real price over the 2004 to 2009 period. We observe a steady increase from 2004 to 2008 followed by a severe drop following the financial crisis.

Table 1. Descriptive statistics by market groups (mean and [min./max.])

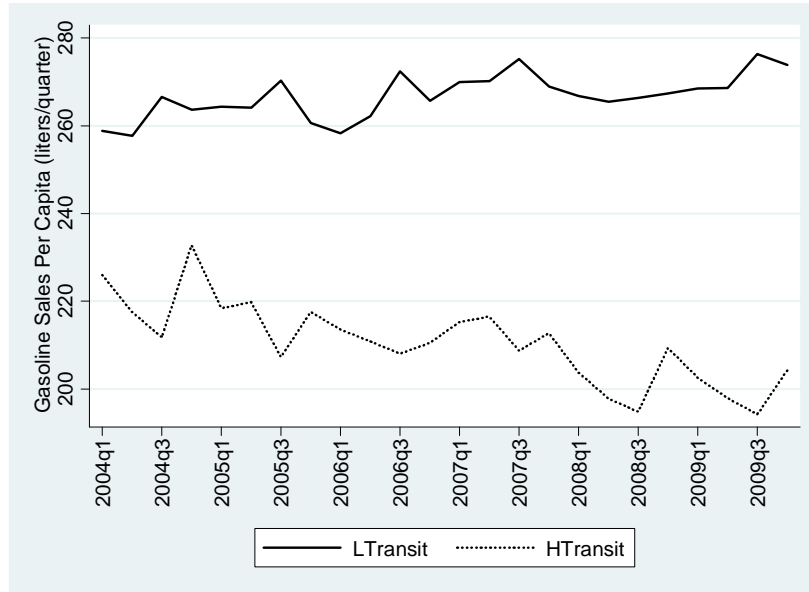|	*HTransit*	*LTransit*
Gasoline sale per capita (litres)	221	319
	[142/296]	[114/1722]
Average annual variation in gasoline sale per capita (%)	-2.2	1.12
	[-3.9/-0.52]	[-2.4/6.9]
Real gasoline price	93	93
(cents per litres - $ of 2002)	[71/126]	[75/125]
Real per capita personal annual income (2002 $)	23,129	20,231
	[19,587/28,111]	[15,917/25,331]
Population (in 1000)	595	49
	[240/1 307]	[3/377]
Population density	1,370	235
	[198/4,483]	[7/847]
Share of worker commuting with transit in 2006 (%)	18.8	1.5
	[11.2/37.6]	[0/6.3]
Number of vehicle per capita	0.52	0.58
	[0.36/0.6]	[0.39/0.92]
Number of markets	7	33

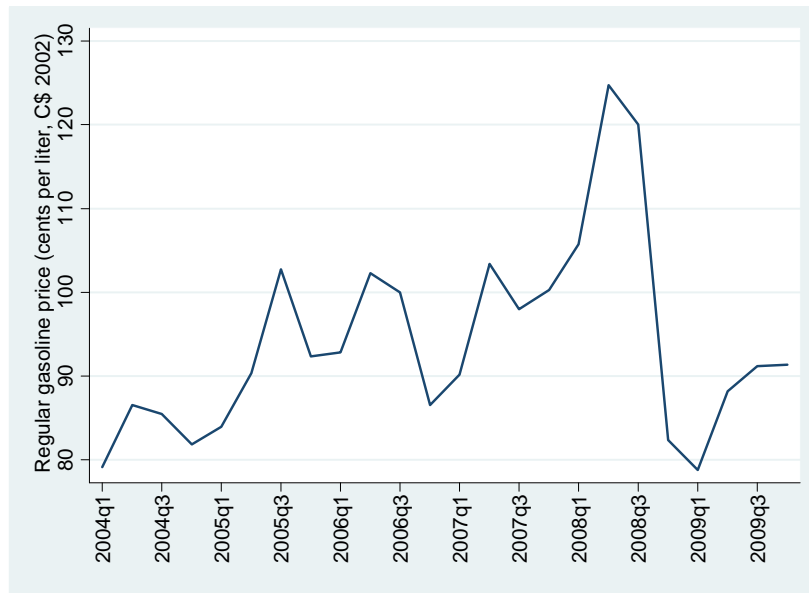Figure 1. Average Per Capita Gasoline Consumption for HTransit and LTransit markets (liters per quarter)

Figure 2. Real regular gasoline price in the Montreal market

4. The empirical analysis and results

We start the empirical analysis by comparing a restricted model that imposes the same slope parameters for all markets with an unrestricted model that allows all coefficients to be market specific. Specifically, the unrestricted model has the following structure:[8]

$$Ln(G_{m,t}) = \alpha_m + \beta_m Ln(Price_{m,t}) + \gamma_m Ln(Inc_{m,t}) + \theta_m Trend + \tau_m Crisis + \sum_{i=1}^{i=3} \mu_{im} Q_{im} + \varepsilon_{m,t}$$

(13)

where $G_{m,t}$ is the quantity of gasoline per capita sold in market m at time t, $Price_{m,t}$ is the average gasoline price and $Inc_{m,t}$ the average per capita personal income. We control for the time trend and also add a dummy to control for the possible impact of the 2008 financial crisis (*Crisis* is set to one starting in 2008Q3). Indeed, as illustrated in Figure 1, the price of gasoline dropped by 35% in 2008Q3. While the province of Quebec was initially spared from the economic downturn in the U.S. (*i.e. Inc* continued to grow), it cannot be excluded that the economic uncertainty led households and business to become more prudent and modify their gasoline consumption. Q_{im} are three dummy variables to control for quarterly changes in $G_{m,t}$. The parameters α_m, β_m, γ_m μ_{im}, τ_m are allowed to vary by markets. $\varepsilon_{m,t}$ is the error term.

The restricted model imposes that all the parameters are identical across markets (e.g. $\beta_1 = \beta_2 = .. = \beta_m$). The intercepts are however allowed to vary by markets to control for difference in the average level of gasoline consumption. We compared a fixed effects (α_m are fixed parameters to be estimated) and a random effect model (α_m are random draws from a Normal distribution).

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[8] This is equivalent to having one regression per market.

Both the restricted and unrestricted specifications are static models. In fact, our time series dimension is too short (5 years) to properly estimate a dynamic model. Static models are traditionally viewed as measuring medium term effects with elasticities estimates that are comprised between the short- and long-term effects measured with dynamic models.[9]

Table 2 reports the results for the restricted fixed and random effects models. The results obtained are very close. In fact, a Hausman test confirms that the random effects specification should be preferred. The price elasticity is low and the income elasticity is is not statistically significant. Note however that the income coefficient becomes significant and remains around 0.3 when the trend variable is excluded (these two variables are highly correlated). The model only explains 14% of the within market variability.

We do not report here the unrestricted estimates as the number of coefficients is very large. Instead, Table 3 reports some descriptive statistics and Figure 2 shows the kernel density of the estimated price and income elasticities values. 35 out of the 40 markets provide negative price elasticities and 9 are statistically significant at 10%. For the 5 markets that have positive price elasticity none is statistically significant. Overall however, the gasoline demand appears to be price inelastic in all markets. The range of statistically significant price elasticity is between -0.14 and -0.65. The income elasticities values are more instable. They are positive and statistically significant for 7 markets and negative and statistically significant for 3 markets.

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[9] Note however that in a cointegration framework, the static specification is used to measure the long term relationships. In our setting with a short panel short, it is however unlikely that our elasticities capture all the long term demand adjustment processes such as, for example, the fleet replacement.

Table 2. Restricted fixed and random effects model

	Fixed effects	Random Effects
$Ln(Price\ )$	-0.133	-0.135
	(0.049)***	(0.05)***
$Ln(Inc\ )$	0.281	0.244
	(0.131)	(0.129)
Trend	-0.0003	0.0005
	(0.0012)	(0.001)
Crisis	-0.007	-0.008
	(0.012)	(0.017)
Q1	-0.016	-0.16
	(0.007)**	(0.007)***
Q2	-0.003	-0.002
	(0.008)	(0.008)
Q3	0.06	0.06
	(0.007)***	(0.007)***
Q4	Reference	Reference
Constant	3.40	3.77
	(1.33)**	(1.31)***
R-sq within	0.14	0.14
N	953	953

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

In parenthesis, robust standard deviation

A Chow test for the equality of slope coefficients across markets clearly rejects the hypothesis of homogeneity.[10] The unrestricted model provides however economically implausible results for some markets. This may be caused by unobservable market-specific idiosyncrasy and the limited number of time period which make the estimation imprecise. This is the same type of trade-off between accounting for heterogeneity and sample size experienced by Baltagi and Griffin (1997)

[10] $F(273,634)=9.92$.

in estimating gasoline demand in OECD countries. As a compromise, we proceed with the estimation of a model that account for some heterogeneity while still imposing some structure.

Table 3. Summary statistics for the elasticities estimated by the unrestricted model

	Price-elasticity	Income-elasticity
Average	-0.15	0.21
Minimum	-0.65	-5.12
Maximum	0.21	3.41
Number of economically implausible values*	0	3
Standard deviation	0.17	0.42

* For the price elasticity a positive and statistically significant value is considered economically implausible. For the income elasticity, the value should be negative and statistically significant.
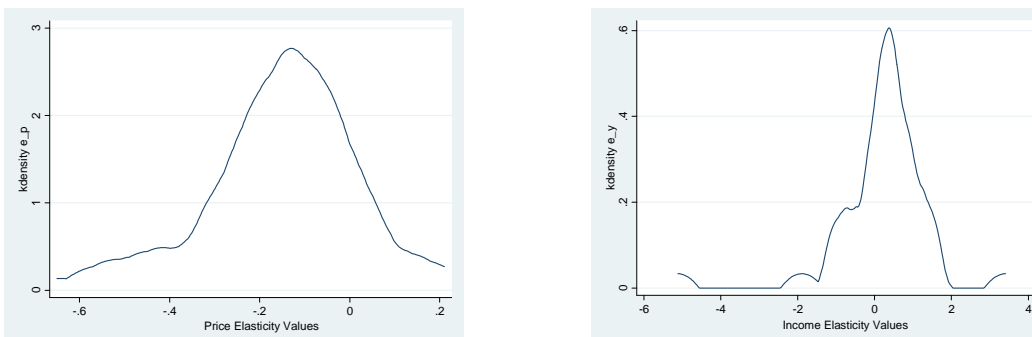

Figure 2. Kernel density based on parameters estimated in the unrestricted model

Specifically, we estimate separate models for the two market groups identified above namely *HTransit* and *LTransit* as the preliminary evidence discussed in section 3 clearly point to differences between these two groups. Furthermore, to better account for heterogeneity, we also allow for some parameters to be random. Specifically, we estimate for both market group *gr=HTransit, LTransit* the following model:

$$lnG_{m,t} = \alpha_0 + (\beta_{gr} + \vartheta_m)lnPrice_{m,t} + (\gamma_{gr} + \varepsilon_m)lnInc_{m,t} + (\rho_{gr} + \omega_m)Trend + \tau_{gr}Crisis +$$

$$\mu_{1gr}Q1 + \mu_{2gr}Q2 + (\mu_{3gr} + \varphi_m)Q3 + (\alpha_m + \varepsilon_{m,t}) \quad \text{with } m \in gr \qquad (13)$$

With this specification, the average price elasticity in the *HTransit* group is given by $\beta_{HTransit}$.

However, it is allowed to vary across markets through the random term ϑ_m, which is assumed to

be i.i.d. normal with zero mean and variance σ_ϑ^2.[11] Once these parameters are estimated, it is

possible to compute the best linear unbiased predictions of the random effects and thereby derive

market specific impacts (Bates and Pinheiro, 1998).[12] Note that we have the same structure for

the other parameters except for those associated with *Q1, Q2* and *Crisis* which are assumed fixed

parameters.[13] α_m is the market specific random effect.

The results are presented in Table 4. The average price elasticity is about twice as large as in

markets with significant transit at -0.22 versus -0.12. This is in line with the results obtained by

Levine, Lewis and Wolak (2013). In *HTransit* markets, we do not find any significant

heterogeneity in this parameter ($\sigma(Price) = \sigma_\vartheta$ not statistically significant) while in *LTransit*,

the price elasticity varies between -0.27 and -0.05 across markets. The average income elasticity

in *HTransit* is around 0.7 and does not exhibit significant heterogeneity. In *LTransit*, we do not

find any significant effect of *Inc*. This seems once again linked to the correlation between the

trend and the variable *Inc*. Average per capita gasoline consumption has been declining at an

average rate of 0.5% per quarter in *HTransit* markets all else being equal. The range of decline

across these markets is between 0.2% and 1%. In *LTransit* markets, the average trend is positive

at 0.4% per quarter with significant heterogeneity across markets (between -0.4% and +1.7%).

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[11] This parameter is obviously also group specific.

[12] A market specific impact is obtained as the sum of the average effect plus the prediction for the random term.

[13] When all the coefficients are assumed random, the model becomes too complex to be estimated.

The financial crisis is associated with a significant decline of about 5.4% in *HTransit* markets while the impact is not statistically significant in *LTransit*. Moreover, we find that if this variable is excluded, the average price elasticity in *HTransit* is biased downward at -0.09. We observe very different seasonal patterns. High transit markets sales per capita decline by an average of 4% during the summer months. At the same period, sales per capita are increasing by 8.5% *LTransit*. There is also significant seasonal heterogeneity across markets within groups (the overall range is between -7% and +32%). These results are therefore consistent with a demand transfer across regions due to tourism and other summer specific activities.

Several alternative specifications were tested in order to assess the robustness of the results. First, the price elasticity increases at -0.3 if we use a criterion of 15% instead of 10% for defining *HTransit*. Inversely, it is reduced to -0.16 with a 6% cut-off point. For the *Ltransit* market, the results are very similar if we eliminate markets with a high level of external demand. The price elasticity results are also very similar if the estimation is carried over only for the data before the financial crisis (2004 to 2008Q2). We have to mention however that the income elasticity estimate and trend are much more unstable and become not statistically or economically meaningful for several specifications. This instability is likely due to the lack of variability in this variable (recall it varies only annually), the short time period of our data and the difficulty to disentangle the impact of these two variables.

Table 4. Results of the random coefficient models

	HTransit	LTransit
$Ln(Price\ )$	-0.223	-0.125
	(0.062)***	(0.032)***
$Ln(Inc\ )$	0.697	-0.099
	(0.287)**	(0.169)
Trend	-0.005	0.004
	(0.001)***	(0.002)**
CRISIS	-0.054	-0.003
	(0.021)**	(0.013)
Q1	-0.032	-0.008
	(0.004)***	(0.008)
Q2	-0.019	-0.004
	(0.006)***	(0.006)
Q3	-0.043	0.085
	(0.012)***	(0.016)***
Constant	-0.497	7.126
	(3.096)	(1.650)***
$\sigma(Price)$	0.008	0.061
	(0.105)	(0.019)***
$\sigma(Inc)$	0.000	0.012
	(0.000)	(0.070)
$\sigma(trend)$	0.002	0.050
	(0.0009)***	(0.000)***
$\sigma(Q3)$	0.023	0.091
	(0.011)***	(0.013)***
$\sigma(Cons)$	0.131	0.365
	(0.108)**	(0.249)***
$\sigma(Res)$	0.033	0.045
	(0.007)***	(0.004)***
N	168	785

(Robust Std. Err. Adjusted for market clusters)

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

5. Conclusions

In this paper, we examine how price and income responsiveness of gasoline demand vary across cities in the province of Quebec (Canada). We are especially interested in the impact of public transit. Theoretically, we illustrate that observed price and income elasticity could be either higher or lower in cities with public transportation, a substitute for private car. Our empirical results indicate that the price elasticity is about doubled at -0.2 in markets with significant transit supply compared to market without. The income elasticity is around 0.7 in high transit markets while it does not appear to be statistically significant in low transit markets. These latter results should however be considered with caution as data limitations probably affect the estimation of the effect of income. The other distinguishing feature of high transit markets is the negative trend with an average annual decline in gasoline consumption close to 2% in large urban markets. The investments in public transportation, the ageing of the population, the improvements in fuel economy, congestion issues, the reduction in automobile dependency in young people but also the 2008 crisis could be some the driving factors behind this trend. The evidence we have provided here can be added to the limited but growing evidence of a peak in car use in developed countries (see Goodwin and Van Dender, 2013).

The main shortcomings of our analysis are the following. Our panel is short making the estimation of a dynamic model perilous and making it difficult to identify the income effect. Furthermore, we certainly do not measure the complete long term impacts of price and income variations. Finally, some of our results could be contaminated by the impact of the financial meltdown of 2008 even though we have tried to control for this event.

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Appendix

We prove that the first term of equation (10) is smaller than (12) i.e.:

$$\frac{1}{D^T} \int_{w^*(p_f)}^{w_h} d_i(p_f, w) \, \varepsilon_{d_i, p_f} f(w) dw < \frac{1}{D^{NT}} \int_{w_l}^{w_h} d_i(p_f, w) \, \varepsilon_{d_i, p_f} f(w) dw$$

or equivalently

$$D^{NT} \int_{w^*(p_f)}^{w_h} d_i(p_f, w) \, \varepsilon_{d_i, p_f} f(w) dw < D^T \int_{w_l}^{w_h} d_i(p_f, w) \, \varepsilon_{d_i, p_f} f(w) dw \quad (A1)$$

with

$$D^T = \int_{w^*(p_f)}^{w_h} d_i(p_f, w) f(w) dw \text{ and } D^{NT} = \int_{w_l}^{w_h} d_i(p_f, w) f(w) dw$$

where the superscript *T and NT* refers to the market with transit and without transit respectively.

First note that

$$D^{NT} = \int_{w_l}^{w^*(p_f)} d_i(p_f, w) f(w) dw + \int_{w^*(p_f)}^{w_h} d_i(p_f, w) f(w) dw$$

$$= \int_{w_l}^{w^*(p_f)} d_i(p_f, w) f(w) dw + D^T \quad (A2)$$

Given (A2), (A1) can be written as:

$$\left(\int_{w_l}^{w*(p_f)} d_i(p_f, w) f(w) dw + D^T \right) \int_{w*(p_f)}^{w_h} d_i(p_f, w) \, \varepsilon_{d_i, p_f} f(w) dw$$

$$< D^T \left(\int_{w_l}^{w*(p_f)} d_i(p_f, w) \, \varepsilon_{d_i, p_f} f(w) dw + \int_{w*(p_f)}^{w_h} d_i(p_f, w) \, \varepsilon_{d_i, p_f} f(w) dw \right)$$

After elimination of the common term and rearranging the expression, we obtain:

$$\frac{\int_{w*(p_f)}^{w_h} d_i(p_f, w) \, \varepsilon_{d_i, p_f} f(w) dw}{D^T} < \frac{\int_{w_l}^{w*(p_f)} d_i(p_f, w) \, \varepsilon_{d_i, p_f} f(w) dw}{\int_{w_l}^{w*(p_f)} d_i(p_f, w) f(w) dw}$$

which is true if ε_{d_i, p_f} is declining with w. Indeed, the term to the left of the inequality is a weighted average of the elasticities of individuals that stay in the gasoline market even though they have access to public transit (i.e. individuals with w>w*). The term to the right of the inequality is also a weighted average of elasticities but for individuals that switch to public transit when it is available (i.e. those with income w<w*).