Fuel taxes and consumer behaviour: 
a Markov-switching approach

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Abstract: Fuel taxes can be employed to correct externalities associated with 
automobile use and raise government revenue. The general understanding of 
the efficacy of existing taxes is largely based on empirical analyses of 
consumer responses to fuel price changes. In this paper, we directly examine 
how fuel taxes, as distinct from tax-exclusive fuel prices, affect fuel demand. 
To do so, we use a Markov-switching approach on monthly observations of 
French fuel prices from 1983 to 2013. Our analysis reveals that consumers 
respond significantly faster to increases in fuels taxes than to increases in tax-
exclusive fuel prices. This result raises questions about our understanding of 
the efficacy of existing fuel taxes and of the optimal tax to achieve the various 
goals for which they are implemented.

Keywords: energy; fuel; fiscal policies; consumer behaviour.

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1 Introduction

Fuel taxes are an important policy tools to address externalities such as local air 
pollution, carbon dioxide emissions, traffic congestion and traffic accidents. In addition
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to addressing externalities, fuel taxes can reduce fuel consumption and may mitigate concerns regarding the sensitivity of the economy to oil price volatility thereby restoring trade balances and diminishing foreign policy constraints. Finally, fuel taxes are a common source of government revenue as the price-elasticity of fuel is supposedly low.

Fuel taxes constitute a large proportion of after-tax fuel prices but little research examines their impact on consumer behaviour. Articles on the optimal gasoline tax (see Parry and Small, 2005; Lin and Prince, 2009) compute the optimal fuel tax based partly on empirical estimates of the elasticity of gasoline consumption to gasoline prices. While dozens of studies estimate price elasticities of fuel consumption, such estimates are not appropriate for evaluating the effects of taxes on demand. Fuel consumption is likely differentially affected depending on whether consumers face a change in the average fuel price or tax. An underlying assumption of previous policy analyses on the effectiveness of higher fuel taxes and the optimal level to ensure durable consumption is that consumers react to tax changes similarly to fuel price changes. Nevertheless, rational consumers should be more sensitive to price changes that are perceived as more persistent than others (Scott, 2012). Indeed, consumers can adjust their consumption either to changing market conditions or to what they interpret as permanent price increases. These changes in consumption are worthwhile only if they yield a benefit over several periods, agents might ignore changes in the tax-inclusive price because they have limited time or attention (Chetty et al., 2009). In fuel markets, changes in taxes can be perceived as more persistent than others because they are driven by political reasons, while changes in the tax-exclusive price are perceived as driven by market forces in the short-run.

In this paper, we attempt to disentangle consumer responses to fuel taxes and tax-exclusive prices. Our analysis focuses on short-term responses to fuel taxes and tax-exclusive fuel prices. We use a monthly dataset of aggregated national values of fuel prices, taxes and consumption in France from 1983 to 2013. This dataset allows us to describe the entire temporal path of the response of fuel consumption to changes in fuel prices. The monthly measures reveal variations in price and consumption that may be obscured in annual data.

Our contribution is twofold. First, we identify regime changes in the volatility of consumer responses to fuel taxes and tax-exclusive prices. As most economic and financial variables exhibit a nonlinear behaviour over time and may interact with each other in a nonlinear manner, we use a nonlinear approach based on a Markov-switching model to model the fuel demand. This approach allows us to identify two different regimes of volatility: the early 1980s are characterised by a high volatility while the remaining period mostly explicitates low volatility. Such a methodology is used in a series of paper on the volatility of oil price and margins in France using similar datasets (Boroumand et al., 2016; Boroumand et al., 2014). As our empirical model decomposes tax-exclusive prices and taxes to assess the impact of each component on consumption, we then compare the relative impact of the two components of the fuel price on demand. We find that consumers tend to over-react to changes in taxes. There are at least two explanations for this result. First, fuel taxes are subject to substantial media coverage and are often argued to be the principal driver of increasing fuel prices. As a result, changes
in tax-exclusive prices may be less salient than equal-sized changes in taxes. Second, changes in fuel taxes are likely considered more persistent than changes in oil prices, which occur more frequently. According to our results, higher fuel taxes would thus be justified to address externalities such as air pollution and climate change.

Our paper is linked to a growing literature on tax salience. In a tax system with a high level of salience, consumers (who are also taxpayers when they consume) are aware of the level of taxes when they make economic decisions. On the contrary, when salience is low, consumers do not integrate in their decisions the full costs of taxes, even if they can have a perception of them. As Finkelstein (2009) points out in her seminal paper, tax salience is a long-term concern for economists as tax misperception is often correlated with the growth in government (Mills, 1848; Buchanan and Wagner, 1977). Finkelstein (2009) studies the link between the use of electronic tolls passes, usually taking the form of plastic boxes fixed on the windshield of the car, and the rate of the toll. She finds that drivers are less price sensitive when they switch to electronic payment. The argument is that drivers are less aware of the toll that they are paying and that consequently, the government raises the rate of the toll. Experiments in the lab or on the field show that consumers are more sensitive to prices when they are quoted with taxes. Feldman and Ruffle (2012) provide subjects in the lab with an endowment and observe that their spending are 30% higher when prices are quoted without taxes compare to the situation in which prices are quoted with taxes. Chetty et al. (2009) use a similar setting in real grocery stores in the US and find that demand decreases by 7.6% when prices are quoted with taxes. Recent articles on fuel consumption by Davis and Kilian (2011), Scott (2012) and Linn et al. (2014) explore the impact of gasoline taxes on consumption. Davis and Kilian (2011) employ a dynamic approach to compare the impact on demand of a change in tax-inclusive price and fuel taxes. They show that consumers react more extensively to tax changes (the 12-month tax elasticity is −0.13) than to price changes (the 12-month price elasticity is −0.12). Scott (2012) and Linn et al. (2014) use a price decomposition in a static model and find that consumers are more sensitive to the tax-driven price component than to the market-driven price component. They both interpret their results as the potential perception that tax changes are more permanent than market-driven price changes.

The paper is organised as follows. Section 2 presents background information on gasoline prices and taxes in France. We then present our empirical model and the results in Section 3. A brief conclusion follows.

2 Aggregate data analysis

Our empirical analysis exploits changes in tax-exclusive prices and taxes to investigate the effects of taxes on fuel consumption. In this paper, we focus on diesel which accounts for 80% of fuel sales in France to study the efficacy of fuel taxes. The dataset consists of monthly observations.
Figure 1 describes the evolution of tax-inclusive and tax-exclusive fuel prices over the period 1990-2013 based on data from the French Department of Energy and Environment. Fuel prices and taxes were deflated using the French consumer price index. The period considered runs from January 1983 to August 2013 because a continuous time series of fuel prices and taxes in France is not available prior to 1983. As one can observe, the relationship between price and tax changes is linear. Prices fluctuate between 0.5 and 1.5 euros per litre. Figure 2 depicts the share of taxes in retail prices. Taxes can be decomposed in two components: the value-added tax, which compromises 20% of the price during the period, and the domestic tax on energy and gasoline products, which is a per-unit excise duty. At the median, taxes comprise approximately 63% of the after-tax price. This varies substantially over time; the proportion evolves from a low of 45 to 50% to a high of over 75%. Tax-exclusive prices are primarily explained by crude oil prices and how firms operating in the market adjust their margins when costs evolve. We are specifically interested in identifying shifts in consumption driven by tax and tax-exclusive price changes.

The consumption data come from the Pegase dataset constructed by the French Environment Ministry and are depicted in Figure 3. Consumption is generally increasing, but there is some seasonality at the monthly-level. The increase in diesel consumption is correlated with a decline in premium gasoline consumption due to increased taxes on the latter. A substantial share of consumption can be explained by changes in GDP and vacation periods.
3 Model and results

3.1 A Markov switching model

To deepen the previous analysis based on linear cases, we use a Markov-switching (MS) methodology. MS models have been widely used in economics and finance since the seminal work of Hamilton (1989). Shortly afterwards, Cai (1994) and Hamilton and Susmel (1994) used this kind of methodology to capture highly volatile financial
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Generally, in MS models, econometricians distinguish two or more regimes that are the outcome of a Markov chain whose realisations are unobserved. MS modelling is a major tool with which to better interpret Forex conditions by inferring the latent state of the market and the economy.

Let \( T > 0 \) be a fixed maturity time and denote by \( (X_t)_{t \leq T} \) a homogenous continuous time Markov chain on finite state space \( S := \{1, 2, \ldots, N\} \). It can be viewed as an observable exogenous quantity and as an economic factor. We assume that the time-invariant matrix \( Q \) denotes the infinitesimal generator \( (q_{ij})_{i,j=1,...,m} \) of \( X \), where \( q_{ij} \) is an infinitesimal intensity of \( X \). This generator is defined as \( q_{ij} \geq 0 \), for all \( i \neq j \in S \) and \( q_{ii} = -\sum_{j \neq i} q_{ij} < 0 \) for all \( i \in S \).

To model gasoline consumption, we consider the following commonly used specification (see e.g. Hughes et al., 2008). National gasoline consumption in month \( t \) in logs \( \text{Demand}_t \) is postulated to depend on the one-month lagged volume-weighted average inflation-adjusted tax-exclusive price of gasoline in logs \( \text{Price}_{t-1} \), the one-month lagged level of taxes in logs \( \text{Tax}_{t-1} \) and the one-month lagged demand \( \text{Demand}_{t-1} \). As demand, the price and the tax are highly persistent and trending, the following markov switching model with log differences is estimated:

\[
\text{Demand}_t = \alpha_0 + \alpha_1 \text{Demand}_{t-1} + \alpha_2 \text{Price}_{t-1} + \alpha_3 \text{Tax}_{t-1} + \alpha_4 \text{Demand}_{t-1} + \epsilon_t,
\]

Moreover, \( \epsilon_t \sim N(0, \sigma^2) \). for all \( i = 0, 1, \ldots, 3 \), the \( \alpha_{i,t} \) are parameters whose values depend on the state of the Markov chain \( X \) at time \( t \in [0, T] \). In fact, we have \( \alpha_{i,t} := \langle \alpha, X_t \rangle \), where \( \langle \cdot \rangle \) denotes the standard scalar product in \( \mathbb{R}^N \), \( \alpha := (\alpha_1, \alpha_2, \ldots, \alpha_N) \in \mathbb{R}^N \) and \( X_t = e_j \) with \( e_j \) a vector of the canonical basis of \( \mathbb{R}^N \) (i.e. \( e_j := (0, \ldots, 0, 1, 0, \ldots, 0) \)).

We tested a large panel selection of possible Markov-switching models following our model specification (1). We give in the following section the results from the best model obtained.

### 3.2 The impact of gasoline taxes on consumption

Indeed, to discriminate among all possible models, firstly, the model with the best fit is the one yielding the highest log likelihood value. The higher the value, the better the fit of the data. However, we have to weight these values with a good indicator of the regime-switching classification. An ideal model is one that classifies regimes sharply and has smoothed probabilities that are either close to zero or one. In order to measure the quality of regime classification, we propose two measures:

1. The regime classification measure (RCM) introduced by Ang and Bekaert (2002).

With \( K \geq 0 \) the number of regimes, the RCM statistics is given by:

\[
\text{RCM}(K) = 100 \left( 1 - \frac{K}{K-1} \frac{1}{T} \sum_{k=1}^{K} \sum_{z_k} P(Z_k = i | \mathcal{F}_t^{X}; \hat{\Theta}) - \frac{1}{K} \right)^2, \tag{2}
\]
where the quantity $P\left(Z_t = i \mid \mathcal{F}_t^T, \hat{\Theta}\right)$ is the smoothed probability and

$$\hat{\Theta} = \left\{ \beta_1, \beta_2, \ldots, \beta_k, \beta_{k+1}, \ldots, \beta_N, q, \sigma_\epsilon^2 \right\}$$

is the vector parameter estimation result (see Goutte and Zou, 2013; Goutte, 2014 for more details). The constant serves to normalise the statistic to be between 0 and 100. Good regime classification is associated with low RCM statistical value: a value of 0 means perfect regime classification, and a value of 100 implies that no information about regimes is revealed.

(2) The smoothed probability indicator introduced by Goutte and Zou (2013). For all $i, j \in S$ and $k = \{M - 1, M - 2, \ldots, 1\}$,

$$P\left(X_t = i \mid \mathcal{F}_t^T, \Theta^{(k)}\right) = \frac{\sum_{j \in S} \left[ P\left(X_t = i \mid \mathcal{F}_t^T, \Theta^{(k)}\right) P\left(X_{t-1} = j \mid \mathcal{F}_t^T, \Theta^{(k)}\right) \Pi_t^{(k)} \right]}{P\left(X_t = j \mid \mathcal{F}_t^T, \Theta^{(k)}\right)}$$

(3)

A good classification for data can also be seen when the smoothed probability is less than 0.1 or greater than 0.9. This then means that the data at time $t \in [0, T]$ are, with a probability exceeding 90%, in one of the regimes with the 10% error.

Consequently, even if a model has the highest log likelihood value, its RCM needs to be close to zero. After testing a panel of possible Markov switching parameters we obtained the following model which give the better results:

**Model**

$$\text{Demand}_t = \alpha_0 + \alpha_1 \text{Price}_t + \alpha_2 \text{Tax}_t + \alpha_3 \text{Demand}_{t-1} + \epsilon_t, X_t.$$  \hfill (4)

**Table 1**  
Estimated model switching Markov variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>State 1</th>
<th>State 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_0$</td>
<td>0.0048*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0040)</td>
<td></td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>0.0872</td>
<td>-0.1256</td>
</tr>
<tr>
<td></td>
<td>(0.208)</td>
<td>(0.5342)</td>
</tr>
<tr>
<td>$\alpha_2$</td>
<td></td>
<td>-0.1269*</td>
</tr>
<tr>
<td></td>
<td>(0.0201)</td>
<td></td>
</tr>
<tr>
<td>$\alpha_3$</td>
<td>-0.4476***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0487)</td>
<td></td>
</tr>
<tr>
<td>$\sigma^2$</td>
<td>0.004766***</td>
<td>0.012543***</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
<td>(0.0033)</td>
</tr>
<tr>
<td>Transition probabilities</td>
<td>0.9947</td>
<td>0.9521</td>
</tr>
</tbody>
</table>

Note: Robust standard errors in parentheses with *** $p<0.01$, ** $p<0.05$, * $p<0.1$. 
Table 1 reports the results of the best estimated specification of the model switching Markov variables. State 1 reports the results for the low-volatility regime (period 1), and state 2 shows the results for the high-volatility regime (period 2). At the bottom of the table, the transition probability $q_{ij}$ is reported. The transition probability is close to 1, so there is little opportunity for a switch from one regime to another. As we use a log-log model, our $\alpha_1$ and $\alpha_2$ coefficients can be interpreted as elasticities. If consumers tend to over-react to changes in the level of taxes rather than in the level of price, we would expect $\alpha_1$ to take values comprised between $\alpha_2$ and 0 which is the case in State 2. In State 1, $\alpha_1$ is positive but not significant. $\alpha_2$ has a significant negative coefficient of $-0.1269$.

In the following, we evaluate the RCM statistics and the smoothed probability indicators for all models. The results are stated in Table 2.

Table 2: RCM statistics and percentage given by the smoothed probability indicator for 10%

<table>
<thead>
<tr>
<th>Model</th>
<th>RCM</th>
<th>Perc10%</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>14.70</td>
<td>83.04%</td>
</tr>
</tbody>
</table>

Let us now discriminate among models A and B. Firstly, the model with the best fit is the one yielding the highest log likelihood value. The higher the value the better the fit of the data. However, we have to weight these values with those given by the (RCM) reported in Table 2, which measures the good classification of the data. Even if a model has a log likelihood value, its RCM needs to be close to zero.

Figure 4: First graph shows our data. The second shows the conditional standard deviation of model A. The third shows the smoothed probabilities obtained with Model A.
Our model 4 obtains a RCM of 14.70 and a Smoothed probability indicator of 83.04%, which are the best compared to all possible tested models. Moreover, Table 2 clearly documents that the regime classification measure (RCM) is close to zero and the smoothed probability indicator is always higher than 80%. This result indicates that the two regime states obtained via the Markov-switching estimation procedure classify the data very effectively. As a consequence, the Markov-switching methodology is an appropriate method for evaluating the dynamics of the margin demands.

3.3 Discussion

There are two potential factors explaining why consumers might over-react to changes in taxes. First, tax makes up a large proportion of the tax-inclusive price and a significant share of households spending. This situation is opposite to Chetty et al. (2009) who propose a simple bounded rationality model in which agents face a small cognitive cost of computing tax-inclusive prices. Small cognitive costs can lead agents to ignore a large range of taxes because the utility gain from computing the tax-inclusive price is often quite small. In their model, when taxes make up a small proportion of the tax-inclusive price, since agents are near an optimum to begin with, the gain from re-optimising relative to the true tax rate is second-order: individuals with limited time or attention choose not to compute tax-inclusive prices for small goods. Even though individual welfare is not taken into account in the individual optimisation of individuals, the same taxes can have large impacts on social welfare and tax revenue. When there are no externalities on the market, increasing taxes can raise a significant amount of revenue and could create significant deadweight losses. In markets like fuel, where there are negative externalities due to consumption and when tax is not neutral as in competitive markets (i.e. its incidence can be on consumers or producers). Our results are consistent the mechanism described in Finkelstein (2009). A decline in tax salience reduces the proportion of individuals who directly observe tax changes, then it is associated with an increase in tax rates, since individuals are less responsive to any given tax increase. By the same token, the share of individuals who observe the magnitude of the tax change declines. Whether individuals tend to over-estimate or to under-estimate the magnitude of tax changes remains an open question. Our empirical results show that consumers tend to over-estimate tax changes as the change in demand following the change in tax is higher than when the tax-exclusive price increases.

Second, consumers might perceive a change in the tax-free price as less persistent as it results from a change in market conditions. On the contrary, tax changes are perceived as long-lasting and more permanent. Indeed, fuel tax changes are often pointed out as the main driver of retail price changes in public debates. This likely contributes to the salience of fuel tax changes. This result is similar to those reported in Linn et al. (2014) who found a larger impact of gasoline taxes on gasoline consumption. One might argue that demand might depend on the level of income or the global amount of paid taxes. However, the necessity to use fuel to move from a point to another, and the use of a lagged value of demand, allow us to control for a part of these unobserved factors; the best predictor of demand today being demand yesterday. Such a lagged variable also helps to control for seasonality.
4 Conclusion

In this paper, we analysed historical data from France to assess the effect of increased fuel taxes on fuel consumption. We use a Markov-Switching approach to carefully study the effects of historical variations in fuel tax rates over time. Our results imply that consumer over-react to changes in fuel taxes. Fuel taxes are thus an effective means to decrease fuel consumption and thereby reduce carbon emissions. We argue that consumers do not respond to changes in fuel taxes in the same way that they respond to a similar change in tax-exclusive gasoline prices. The reason for this differentiated reaction is that tax-exclusive prices are more salient and perceived as more long-lasting than equal-sized changes in taxes. This assumption is examined by separately estimating consumer responses to gasoline taxes and tax-exclusive gasoline prices. Our evidence indicates that fuel taxes might be an efficient tool to achieve the various goals these taxes have been assigned by successive governments.

To a certain extent, fuel taxes can be considered as Pigouvian taxes. In the standard case, such a tax is effective because it increases prices to reflect marginal damages. Adding marginal damages to private marginal costs yields social marginal costs, thereby leading to the socially optimal level of production. This solution is predicated on the notion that, in the absence of the tax, prices would be equal to private marginal costs. Although we do not discuss the margins of the industry in this article, our data provide evidence of substantial mark-ups in the retail gasoline markets. Pre-existing distortions are important to consider when evaluating fuel taxes and other policies that would increase the marginal prices of energy products. As prices are above the social marginal cost of fuel, our results show that imposing a tax would shift consumption in the wrong direction, further potentially reducing consumption below the efficient level.

While our analysis makes full use of the available data, there are at least two disadvantages to our approach. First, we exploit time series data but do not observe cross-sectional changes in consumption when taxes vary. Second, our analysis does not account for the introduction of more efficient vehicles, which may change consumers’ price sensitivity. Further work is needed to disentangle the effects of these two factors.

References


**Note**