Asymmetric price adjustment in the U.S. gasoline industry: Evidence from Bayesian threshold dynamic panel data models

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ABSTRACT This paper investigates the gasoline price adjustment to changes in the input cost price for a panel of 48 U.S. states using a monthly data set covering the period 1994-11. We build for the first time a non-linear threshold Panel Vector-Error-Correction Model (PVECM) and propose efficient Markov Chain Monte Carlo (MCMC) Bayesian techniques. Our findings indicate that states with high margin experience a slower adjustment and a more asymmetric response to input price cost shocks. Our results are robust to potential breaks in the threshold parameter, which is important as market conditions change over time and are very sensitive to production/consumption constraints. Lastly, we attribute fluctuations in the gasoline prices to input cost shocks arguing that the peak responses occurring one month after the shock are short-lived.

Key words: Asymmetric price adjustment; Gasoline industry; Non-linear threshold PVECM; Bayesian techniques;; 'Rockets and feathers' hypothesis

JEL classifications: C52, C11, L13

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I. INTRODUCTION

Consumers often tend to believe that oil companies adjust the retail gasoline prices more quickly to cost increases than to cost decreases, creating an asymmetric adjustment path towards the long-run equilibrium, known as the "*rockets and feathers*" hypothesis. This perceived asymmetry in retail price adjustment to changes in crude oil prices is commonly attributed to "gouging" engaged in by vertically integrated firms in an effort to increase retail profits, which in turn is made possible by their market power (Borenstein, et al, 1997, Deltas, 2008).

Within the last years there has been a plethora of studies on the existence of price asymmetry in the gasoline market with controversial results. Existing literature differs by country, sample period, data frequency and econometric methodology. The majority of these studies apply cointegration techniques and especially Engle-Granger methodology by utilizing an asymmetric error-correction model (ECM) in order to uncover the existence of price asymmetries. Since the empirical literature on this topic is quite broad, Table 1 summarizes the main empirical findings of the investigation of asymmetric adjustments in terms of methodologies, dataset and study periods used.

< Insert Table 1 about here >

Bumbass et al (2015) examine the long-run relationship between the spot oil price and retail and wholesale gasoline prices. They use a simple Threshold Autoregressive Model (TAR) in order to account for the existence of price asymmetry both in the long and the short run. They argue that both retail and wholesale gasoline prices respond symmetrically to an oil price shock in the long run, indicating little market power by gas stations and wholesalers. Moreover, Kristoufek and Lunackova (2015), reinvestigate the "*rockets and feathers*" hypothesis by employing error correction methodology (ECM). They find that the prices return to their equilibrium value much more slowly than would be typical for the ECM suggesting the validity of the "*Joseph effect*".

Polemis (2012) by using the error-correction model in the Greek gasoline market reports that retail gasoline prices respond asymmetrically to cost increases and decreases both in the long and the short-run. However, within the wholesale segment, there is a symmetric response of the spot prices of gasoline in adjusting a to the short-run responses of the exchange rate. Polemis and Fotis (2011) contains an application of Generalized Method of Moments (GMM) panel data Error Correction Model (ECM) to study the transmission between crude oil prices and retail gasoline prices in eleven European countries from 2000 to 2011.

Bermingham and O' Brien (2010) empirically test whether Irish and United Kingdom (UK) petrol and diesel markets are characterised by asymmetric pricing behaviour. The econometric assessment uses threshold autoregressive models and a dataset of monthly refined oil and retail prices covering the period 1997 to mid-2009. Their study concluded that for both the Irish and UK liquid fuel markets at national levels, there is no evidence to support the hypothesis that retail prices rise faster than they fall in response to changes in oil prices (price asymmetry).

Douglas (2010) finds little evidence of asymmetry in the transmission process from crude oil shocks to retail gasoline price in the United States. The author states that the minor evidence of asymmetry found is due to the presence of outliers in the data set. Clerides (2010) uses data from 2000 to 2010 for several European Union countries to investigate the response of retail gasoline and diesel prices to changes in the world oil price. The empirical findings indicate significant variation in the adjustment mechanism across countries. Fluctuations in the international price of oil are transported to local prices with some delay but evidence of asymmetric adjustment is fairly weak. Statistically significant evidence of asymmetric responses is only found in a small number of countries, while in some countries there is even (weak) evidence of asymmetry in the reverse direction: prices drop faster than they rise.

Faber (2009) explores 3600 gas stations in the Netherlands from 2006 to 2008 and concludes that gasoline price asymmetry is not a feature of the market as a whole. The author estimates that there are significant differences between gas stations: 38% of gas stations price asymmetrically and the remainder does not follow the same pattern. Deltas (2008) reports that U.S. states with high average retail-wholesale margins experienced a slower adjustment and a more asymmetric response in retail prices. Kuper and Poghosyan (2008) examine gasoline price asymmetry in the United States from 1986 to 2005. The authors divide the period under scrutiny into two sub periods. The analysis of period from 1986 to 1999 indicates that wholesale segment adjusts the production level of crude oil to control the long run oil prices. However, after 1999, the ability of wholesale producers to control the long-run price of oil has decreased since gasoline price symmetry holds only where the deviation from the long run exceeds 6%. Lastly, Galeotti et al. (2003) studied trends in Germany, France, UK, Italy and Spain from January 1985 to June 2000 and concluded that "*rockets and feathers*" appear to dominate the price adjustment mechanism of gasoline markets in many European countries.

Based on the above, three main empirical finings emerge. First, many previous empirical panel data asymmetric adjustment models have been constructed under the assumption of treating regression functions as identical across all observations in their sample and not allowing them to fall into a discrete number of classes. However, this premise is not credible since there are good theoretical reasons and there is strong empirical evidence suggesting that individual observations can be divided into classes based on the value of an unobserved variable (Hansen, 1999, Hansen, 2000, Caner and Hansen, 2004). We address these limitations by estimating a threshold parameter in a data driven approach that "endogenously" sorts the data into different regimes. The threshold variable that we use to sort observations into the different regimes is the level of profit margin as a proxy for market power (Deltas, 2008). The partitioning into a discrete number of classes (or bins) is economically meaningful since it allows the cross sections elements of the panel (states) to be sorted according to their level of competition in the gasoline market segments (wholesale and retail) placing them into competitive (low margin states) and non-competitive (high margin states) regimes. In this way, our analysis accounts for the existence of price asymmetry between different micro-economic levels (i.e. states) and links the level of market power with the price adjustment mechanism.

Secondly, many of the empirical studies focus on the investigation of gasoline price asymmetry expressed in a linear form (Yang and Ye, 2008, Tappata, 2009, Polemis, 2012, Lewis and Noel, 2011, Clerides, 2010, Faber, 2009, Honarvar, 2009, Hosken et al, 2008). It is noteworthy that nonlinear models have been quite recently used in order to address the price relationships in oil, gasoline and related markets (see for example Wlazlowski, et al 2012; Greenwood-Nimmo and Shin, 2013). However, estimation of the model dynamics will be intensely jeopardized when a nonlinear long run relationship is misspecified as linear (Blake et al, 1998, Shin et al, 2013, Greenwood-Nimmo and Shin, 2013).

Lastly, the majority of the existing studies (e.g. Polemis, 2012, Lewis and Noel, 2011, Clerides, 2010, Faber, 2009, Honarvar, 2009, Valadkhani, 2009, Balmaceda and Soruco, 2008, Bachmeir and Griffin, 2003, Bettendorf, et al, 2003, Galeotti, et al, 2003) have estimated Error Correction Models (ECMs) by employing the two-step cointegrating approach developed by Engle and Granger (1987). However, it is well documented in the literature that single step fully dynamic autoregressive distributed lag (ARDL) estimation is more efficient and yields improved performance compared to single equation ECMs (Banerjee et al., 1993, 1998; Pesaran and Shin, 1998; Pesaran et al., 2001, Greenwood-Nimmo and Shin, 2013). In order to account for this limitation, we use a Vector Error Correction Modelling (VECM) framework which is even more efficient and well suited to the joint analysis of short-run and long run asymmetric responses of gasoline prices to its input cost disturbances (Greenwood-Nimmo and Shin, 2013).

Our analysis implies that states with high profit margin experience a slower adjustment and a more asymmetric response compared to low profit ones. Moreover, the magnitude of the estimated short-run coefficients is in the most cases larger in the retail than in the wholesale level. However, the adjustment towards the equilibrium level is more gradual in the wholesale segment whereas both the wholesalers and retailers tend to react more to price increases than price decreases. In contrast to other studies (e.g Greenwood-Nimmo and Shin, 2013), we find significant evidence that the wholesale and retail price of gasoline before taxes and duties adjusts more rapidly in an upward than a downward direction.

The motivation of this paper is to contribute to the empirical literature on retail and wholesale gasoline price asymmetry nexus by, for the first time in the gasoline price asymmetry controversy, using a threshold PVECM and MCMC techniques in order to perform Bayesian inference. Using the relevant methodological framework, we have found strong evidence suggesting the validity of the "*rockets and feathers*" hypothesis. The oligopolistic structure of the local gasoline market triggers the price asymmetric adjustment path. This finding raises serious doubts about the existence of a rent seeking oligopolistic behavior by retailers. The difference in the existence of asymmetric pass-through suggests that empirical studies that ignore the role of a non linear model may miss an important element of the nature of price adjustment in the retail gasoline industry thus providing the wrong signal to government officials and policymakers. Lastly, estimating the degree of competition in the gasoline industry is crucial for regulatory and competition authorities. Regulators would like to know whether current regulation is conducive to competition. Likewise, competition authorities might gauge the current competitive situation in the gasoline industry and thus implement the appropriate policies to prevent anti-competitive behaviour by the market players (i.e. petrol stations, refineries, oil companies).

The rest of the paper is as follows. Section 2 describes the data and the structure of the gasoline market in the US. Section 3 introduces the empirical methodology. Section 4 presents the main hypotheses or conjectures that the empirical analysis tests. Section 5 discusses the econometric techniques, while Section 6 compares our findings to previous work. Finally Section 7 concludes the paper and provides some policy implications.

II. DATA DESCRIPTION AND ANALYSIS

Our empirical analysis is based on a panel dataset of 9888 monthly observations spanning the period from January 1994 to February 2011. We have to stress, however, that more recent data are not available since the retail and wholesale gasoline prices do not go beyond February 2011. The sample includes 48 US states except for Maine and Connecticut where no data was available. The use of monthly data takes away much price variation and higher frequency data would be more suitable for analyzing our research questions (Remer 2015) but our main data source (Energy Information Administration -EIA) publishes only monthly and annually time series.

Retail and wholesale (rack) motor gasoline prices before taxes and duties are obtained from the EIA of the U.S. Department of Energy. Spot prices of conventional gasoline (measured in dollars per gallon) traded in New York Harbor are taken also from the EIA. The reason for choosing New York Harbor instead of other hubs such as the U.S Gulf Coast is that the former constitutes the most significant logistic hub for refined gasoline both arriving by pipeline from the Gulf Coast and from abroad by tanker (Trench, 2001). Besides we have used other spot indicators such as The Gulf and the West Coast spot prices with similar empirical results. The cash price of bulk unleaded gasoline delivered to New York Harbor represents a good proxy for the input cost since it is estimated that on average, 96% of the wholesale price is represented by the cost of gasoline at the hub (Douglas and Herrera, 2010). Crude oil price measured in dollars per barrel accounts for the Cushing, OK WTI Spot Price FOB, also extracted from EIA. Lastly, as suggested by Deltas (2008), we calculate the difference between the retail and wholesale price known as the profit margin, in order to capture the presence of market power.

< Insert Table 2 about here >

Table 2 presents the descriptive statistics of our dataset. Over the sample period, retail prices averaged 1.4 dollars per gallon (not including taxes) while wholesale prices were approximately 16 cents lower (1.25). It is worth mentioning that retail and wholesale gasoline prices follow a similar pattern. Specifically, gasoline prices have been rising slightly over the examined period, with a drift of 0.10 cents per month. Regarding the short run price fluctuations, it is important to note that the standard deviation of retail prices is smaller than that of wholesale prices (0.144 and 0.146 respectively) suggesting the existence of a “dampening” effect in the gasoline market (Deltas, 2008).

Figure 1 depicts the relatively close co movement between the spot gasoline price and the level of wholesale and retail (pump) prices. Moreover, it is evident that gasoline prices were characterized by high volatility within the examined period. More specifically, the average retail gasoline prices (before taxes) in the US have shown an upward trend during the period from February 2002 until July 2008, reaching the highest level at 3.588 USD/gallon.

This trend is fully reversed within the next period (August 2008-March 2009) in which retail prices have dropped significantly by 55% approximately. It is noteworthy that the wholesale (rack) prices of gasoline follow a similar pattern with smaller fluctuations. Examining the distribution of the size of the adjustment, we see that they were quite small in the period from January 1994 to February 2005 whereas became more volatile from 2005 onwards. The price of spot gasoline has followed a similar pattern. More specifically, within the same period, the spot price of gasoline has fluctuated 205 times; 119(58%) adjustments were upward and 86 (42%) adjustments were downward.

<Insert Figure 1 about here>

III. ECONOMETRIC MODEL

Our model extends the study of Greenwood-Nimmo and Shin (2013) to a panel data framework. Specifically, the model is as follows. Suppose we have an asymmetric long-run relationship of the form:

$$y_{it} = \mu_i + \mathbf{x}_{it}^{+\prime}\boldsymbol{\alpha}^{+} + \mathbf{x}_{it}^{-\prime}\boldsymbol{\alpha}^{-} + u_{it},\ \forall i = 1,\dots,n, t = 1,\dots,T \tag{1}$$

where μ_i represents fixed effects, $\mathbf{x}_{it}$ is a $k\times 1$ vector of regressors, $\mathbf{x}_{it}^{+} = \sum_{j=1}^{t}\max\left(\Delta\mathbf{x}_{ij},0\right)$, $\mathbf{x}_{it}^{-} = \sum_{j=1}^{t}\min\left(\Delta\mathbf{x}_{ij},0\right)$ are partial sum processes representing positive and negative changes respectively. We have the following conditional Panel Vector-Error-Correction Model (PVECM):

$$\begin{aligned}\Delta y_{it} = \rho y_{i,t-1} + \boldsymbol{\delta}^{+\prime}\mathbf{x}_{i,t-1}^{+} + \boldsymbol{\delta}^{-\prime}\mathbf{x}_{i,t-1}^{-} + \sum_{j=1}^{p-1}\gamma_j \Delta y_{i,t-j} + \\ \sum_{j=0}^{q-1}\left(\boldsymbol{\pi}_j^{+\prime}\Delta\mathbf{x}_{i,t-j}^{+} + \boldsymbol{\pi}_j^{-\prime}\Delta\mathbf{x}_{i,t-j}^{-}\right) + e_{it}\end{aligned} \tag{2}$$

This is a minimal extension of the model in Greenwood-Nimmo and Shin (2013) and Shin, Yu, and Greenwood-Nimmo (2014). In the above asymmetric PVECM, changes in the input prices (crude oil and spot prices) are split into positive and negative changes, respectively. In other words, as suggested by Galeotti, et al (2003), short-run asymmetry is captured by similarly decomposing price changes into $\Delta x_t^{+} = x_t - x_{t-1} > 0$ and $\Delta x_t^{-} = x_t - x_{t-1} < 0$ for x=CR, SPG. Hence ΔCRP = ΔCR if ΔCR>0 and 0 otherwise. ΔSPGP = ΔSPG if ΔSPG>0 and 0 otherwise. The opposite holds for ΔCRN, and ΔSPGN. Finally ECMP and ECMN denote the one-period lagged deviation from the long-run equilibrium and account for asymmetry in the adjustment process. Similarly ECMP = ε_t>0 and 0 otherwise and ECMN = ε_t<0 and 0 otherwise.

The specification in Eq. 2 is the most general form, admitting both long-run and short-run asymmetries. The null hypotheses of long-run symmetry can be evaluated using a standard Wald test. Short-run symmetry restrictions can take either of the two following equations:

$$\boldsymbol{\pi}_j^{+} = \boldsymbol{\pi}_j^{-}, \forall j = 0,\ldots,q-1, \tag{3}$$

$$\sum_{j=0}^{q-1} \boldsymbol{\pi}_j^{+} = \sum_{j=0}^{q-1} \boldsymbol{\pi}_j^{-} \tag{4}$$

These expressions can be tested using standard Wald tests (Greenwood-Nimmo and Shin (2013). For a more general specification, we assume that: (i) long-run and short-run coefficients can be state-specific; (ii) there is an unknown threshold which defines the nonlinear relationship, and (iii) error terms can be cross-sectionally correlated. The extended model can be represented by the following short-run nonlinear ECM:

$$\begin{aligned}\Delta y_{it} = \rho_i y_{i,t-1} + \boldsymbol{\delta}_i^{+\prime}\mathbf{x}_{i,t-1}^{+}(\lambda) + \boldsymbol{\delta}_i^{-\prime}\mathbf{x}_{i,t-1}^{-}(\lambda) + \sum_{j=1}^{p-1}\gamma_{i,j}\Delta y_{i,t-j} + \\ \sum_{j=0}^{q-1}\left(\boldsymbol{\pi}_{i,j}^{+\prime}\Delta\mathbf{x}_{i,t-j}^{+}(\lambda) + \boldsymbol{\pi}_{i,j}^{-\prime}\Delta\mathbf{x}_{i,t-j}^{-}(\lambda)\right) + \varepsilon_{it},\end{aligned} \tag{5}$$

where:

$$\mathbf{x}_{it}^{+}(\lambda) = \begin{bmatrix} \sum_{j=1}^{t}\max\left(\Delta\mathbf{x}_{ij},0\right) \\ m_{it}\mathbb{I}\left(m_{it} \ge \lambda\right)\cdot\sum_{j=1}^{t}\max\left(\Delta\mathbf{x}_{ij},0\right) \end{bmatrix}, \quad \mathbf{x}_{it}^{-}(\lambda) = \begin{bmatrix} \sum_{j=1}^{t}\min\left(\Delta\mathbf{x}_{ij},0\right) \\ \sum_{j=1}^{t}\min\left(\Delta\mathbf{x}_{ij},0\right)\cdot m_{it}\mathbb{I}\left(m_{it} < \lambda\right) \end{bmatrix}, \tag{6}$$

are the modified partial sum processes, m_{it} represents the separating variable, the profit margin in our case, and λ is the threshold value. In the model of Greenwood-Nimmo and Shin (2013) the regressors are simply $\mathbf{x}_{it}^{+}(\lambda) = \sum_{j=1}^{t}\max\left(\Delta\mathbf{x}_{ij},0\right)$ and $\mathbf{x}_{it}^{-}(\lambda) = \sum_{j=1}^{t}\min\left(\Delta\mathbf{x}_{ij},0\right)$ so that partial sum processes have a known threshold of zero. In this study, the same regressors are included but, additionally, we investigate whether negative and positive price changes depend on exceeding a certain, unknown, profit margin λ. In other words, we enter the markup dummy variable if it exceeds an unknown λ representing the threshold value. As explained before, these procedures are based on non-standard asymptotic theory and specifically account for the estimation of an unknown threshold parameter in a data driven approach that "endogenously" sorts the data into different regimes, if such regimes exist.

Moreover, $\mathbb{E}\left(\varepsilon_{it}\varepsilon_{j\tau}\right) = \begin{cases}\sigma_{ij}, & t=\tau \\ 0, & \text{otherwise.}\end{cases}$

Suppose:

$$\boldsymbol{\beta}_i = \left[\rho_i, \boldsymbol{\delta}_i^{+\prime}, \boldsymbol{\delta}_i^{-\prime}, (\gamma_{i,j}, j=1,\ldots,p-1), (\boldsymbol{\pi}_{i,j}^{+}, \boldsymbol{\pi}_{i,j}^{-}, j=0,\ldots,q-1)\right]' \in \mathbb{R}^K,$$

for $i=1,\ldots,n$. For the coefficients $\boldsymbol{\beta}_i$ we assume:

$$\boldsymbol{\beta}_i \overset{\text{iid}}{\sim} \mathcal{N}_K\left(\overline{\boldsymbol{\beta}}, \boldsymbol{\Omega}\right), i=1,\ldots,n \ . \tag{7}$$

For the error terms we assume:

$$\boldsymbol{\varepsilon}_i = \left[\varepsilon_{i1},\ldots,\varepsilon_{iT}\right]' \overset{\text{iid}}{\sim} \mathcal{N}_T\left(\mathbf{0}, \boldsymbol{\Sigma}\right),$$

independently of all regressors and other stochastic elements of the model. Given the considerable amount of heterogeneity that we have allowed for, the assumption of a general covariance matrix, $\boldsymbol{\Sigma} = \left[\sigma_{ij}, i,j=1,\ldots,n\right]$ is, perhaps, excessive but we retain it for generality. The model can be written as a nonlinear VAR with regressors:

$$\begin{aligned} w_{it} = \textstyle\sum_{j=1}^{p-1}\gamma_{i,j}w_{i,t-j} + \rho_i y_{i,t-1} + \boldsymbol{\delta}_i^{+\prime}\mathbf{x}_{i,t-1}^{+}\left(\lambda\right) + \boldsymbol{\delta}_i^{-\prime}\mathbf{x}_{i,t-1}^{-}\left(\lambda\right) + \\ \textstyle\sum_{j=0}^{q-1}\left(\boldsymbol{\pi}_{i,j}^{+\prime}\Delta\mathbf{x}_{i,t-j}^{+}\left(\lambda\right) + \boldsymbol{\pi}_{i,j}^{-\prime}\Delta\mathbf{x}_{i,t-j}^{-}\left(\lambda\right)\right) + \varepsilon_{it}\end{aligned} \tag{8}$$

from which we obtain:

$$w_{it} = \textstyle\sum_{j=1}^{p-1}\gamma_{i,j}w_{i,t-j} + \mathbf{z}_{it}'\left(\lambda\right)\boldsymbol{\xi}_i + \varepsilon_{it} \equiv \mathbf{x}_{it}'\left(\lambda\right)\boldsymbol{\beta}_i + \varepsilon_{it}, \tag{9}$$

where $\boldsymbol{\xi}_i = \left[\boldsymbol{\delta}_i^{+\prime}, \boldsymbol{\delta}_i^{-\prime}, (\gamma_{i,j}, j=1,\ldots,p-1), (\boldsymbol{\pi}_{i,j}^{+}, \boldsymbol{\pi}_{i,j}^{-}, j=0,\ldots,q-1)\right]'$, viz. all elements of $\boldsymbol{\beta}_i$ except ρ_i.

In a Bayesian treatment of the problem, we have to address the following issues:

(i) The determination of lag orders p and q.

(ii) The determination of an informative prior for $\overline{\boldsymbol{\beta}}$ which, however, is not as high-dimensional as unrestricted coefficients would be in a general Bayesian VAR.

(iii) The determination of a prior for $\boldsymbol{\Sigma}$ and $\boldsymbol{\Omega}$.

(iv) The determination of a prior for the threshold parameter λ and a computational strategy to implement Markov Chain Monte Carlo (MCMC) for full Bayesian inference.

Problem (i) is relatively easy as we can implement model comparison via marginal likelihood and Bayes factors (see Appendix B and C). Regarding (ii) we can assume simply that $\overline{\boldsymbol{\beta}} = \mathbf{0}_K$ but (as part of problem (iii)) we have to choose a reasonable prior for $\boldsymbol{\Omega}$. Given the Cholesky decomposition $\boldsymbol{\Omega} = \mathbf{C}'\mathbf{C}$ and the unique elements c_{ij} of the lower triangular matrix $\mathbf{C}$ we assume:

$$c_{ij} \overset{\text{iid}}{\sim} \mathcal{N}\left(0,1\right),\ \forall j \leq i, i = 1,\ldots,n$$

For matrix $\boldsymbol{\Sigma}$ we assume a single-factor model based on the point that we made above. Specifically:

$$\boldsymbol{\varepsilon}_t = \boldsymbol{\varphi} f_t + \mathbf{v}_t, \tag{10}$$

where $\boldsymbol{\varepsilon}_t = \left[\varepsilon_{t1},\ldots,\varepsilon_{tn}\right]'$, the common factor:

$$f_t = a f_{t-1} + e_t,\ \ e_t \overset{\text{iid}}{\sim} \mathcal{N}\left(0,\ 1-a^2\right), \tag{11}$$

provided $|a|<1$. The formulation guarantees that (in the stationary case) the expected value of f_t is zero and its variance is equal to one.

Additionally, we assume: $\mathbf{v}_t \overset{\text{iid}}{\sim} \mathcal{N}_n\left(\mathbf{0}, \text{diag}\left[\omega_1^2,\ldots,\omega_n^2\right]\right)$ and $\boldsymbol{\varphi}$ is an $n \times 1$ vector of factor loadings. As our prior opinion is that cross-sectional correlations are similar, and to avoid the proliferation of parameters, we assume:

$$\varphi_1 = \ldots = \varphi_n = \varphi.$$

Moreover, we assume:

$$\mathbf{v}_t \overset{\text{iid}}{\sim} \mathcal{N}_n\left(\mathbf{0},\ \text{diag}\left[\sigma_1^2,\ldots,\sigma_n^2\right]\right). \tag{12}$$

We enforce parsimony by assuming:

$$\log\sigma_i^2 \mid \sigma_1^2 \sim \mathcal{N}\left(\log\sigma_1^2,\ \vartheta^2\right),\ \forall i = 2,\ldots,n,\ \ \log\sigma_1^2 \sim \mathcal{N}\left(\bar{a}_1, \bar{a}_2^2\right). \tag{13}$$

We set $\vartheta = 0.4$, $\bar{a}_1 = -3$, $\bar{a}_2 = 0.1$. The resulting prior for σ_1 averages 0.23 with a standard deviation of 0.034. The typical ratio $\sigma_i / \sigma_1, i \neq 1$ averages 1.06 and its 95% credible (Bayes) interval is from 0.69 to 1.70.

For λ we assume a flat prior:

$$p(\lambda) \propto \mathbb{I}\left(0 \leq \lambda \leq 1\right). \tag{14}$$

This can be used to assess the validity of posterior results as we do not impose restrictive assumptions on the behavior of the margin. For parameter a in (14) we assume:

$$p(a) \propto \mathbb{I}\left(-1 < a < 1\right). \tag{15}$$

For model selection (values of p and q) we rely on the computation and comparison of marginal likelihoods and Bayes' factors. The Bayes factors are computed using marginal likelihoods for threshold PVECM models (see Appendix C, D and E). We normalize the Bayes factor to 1 for $p = 2, q = 1$, the simplest possible model in our context. Suppose $\mathbb{Y}$ denotes the available data and $\theta \in \Theta \subseteq R^D$ is the vector of parameters. For any posterior distribution whose kernel[1] is:

$$p\left(\theta \mid \mathbb{Y}\right) \propto \mathcal{L}(\theta;\mathbb{Y})p(\theta), \tag{16}$$

where $\mathcal{L}(\theta;\mathbb{Y})$ is the likelihood function and $p(\theta)$ is the prior, the marginal likelihood can be expressed as:

$$\mathfrak{M}(\mathbb{Y}) = \int \mathcal{L}(\theta;\mathbb{Y})p(\theta)d\theta. \tag{17}$$

The posterior itself is:

$$p\left(\theta \mid \mathbb{Y}\right) \propto \frac{\mathcal{L}(\theta;\mathbb{Y})p(\theta)}{\int_{\Theta}\mathcal{L}(\theta;\mathbb{Y})p(\theta)d\theta} = \frac{\mathcal{L}(\theta;\mathbb{Y})p(\theta)}{\mathfrak{M}(\mathbb{Y})}. \tag{18}$$

Similarly, we can define the marginal likelihood:

$$\mathfrak{M}(\mathbb{Y}_{1:t}) = \int \mathcal{L}(\theta;\mathbb{Y}_{1:t})p(\theta)d\theta, \tag{19}$$

for data $\mathbb{Y}_{1:t}$ from period 1 up to t. Relative to a base model whose marginal likelihood is $\mathfrak{M}_0(\mathbb{Y})$ or $\mathfrak{M}_0(\mathbb{Y}_{1:t})$ we define the recursive Bayes factor as

$$BF_{1:t} = \frac{\mathfrak{M}\left(\mathbb{Y}_{1:t}\right)}{\mathfrak{M}_0\left(\mathbb{Y}_{1:t}\right)}. \tag{20}$$

For details of computation see Appendix A and C. Here, we use the entire-sample version of the Bayes factor (that is, we use $t = T$) and recursive Bayes factors will be used in the next section to compare with a model that does not allow for threshold effects. Based on the results of Table 3, we select a model with $p = 3$ and $q = 2$ which is strongly favored over the other alternatives.

<Insert Table 3 about here>

IV. FORMULATION OF RESEARCH HYPOTHESES

In this section we develop the main research hypotheses regarding the existence of an asymmetric price adjustment mechanism in the wholesale and retail market segment, which are then tested empirically in the subsequent section of the paper.

A widely used classification among studies that analyse the relationship between output and input gasoline prices is between short-run and long-run asymmetries. A short run analysis is suitable to compare the intensity of output price variations to positive or negative changes in input cost prices (i.e. crude oil price and spot gasoline price variations), while a long run analysis is needed if the empirical investigation focuses on the estimation and length of price fluctuations, as well as the speed of adjustment toward an equilibrium level (Frey and Manera, 2007). In this study, by using a PVECM, we will decompose the wholesale and retail price fluctuations to long-run and short-run relationships while investigating for possible asymmetries in the adjustment process. Instead of using a typical ECM procedure where all variables are expressed in first differences, except for the stationary residuals that represent the Error Correction Term (ECT), indicating the deviations from the long-run equilibrium (speed of adjustment), we use a PVECM that is a system of equations allowing for decomposing short-run and long run asymmetric responses of gasoline prices to its input cost disturbances in a more efficient way (see for example Greenwood-Nimmo and Shin, 2013).

As discussed above, one of the novelties of this paper is to split the sample allowing for different regimes determined by a threshold variable. This variable refers to the gross profit margin of the retailers, which is a good proxy for market power (Deltas, 2008) In that case states will be sorted according to their prevailing "attitudes" towards competition placing them into competitive (low margin states) and non-competitive (high margin states) ones. Hence we will try to investigate if there is a link between the level of market power (or competition) and the asymmetric adjustment mechanism. Lastly, one of the main research questions that we want to examine is the dynamic gasoline price adjustment mechanism to innovations (shocks) caused by fluctuations of the input cost prices (i.e crude oil price and spot gasoline price). In this way, we trace out the duration of an exogenous shock to be either permanent or transitory.

Based on the above, we formulate the following research hypotheses:

Hypothesis 1. *The effects of upstream price increases are larger than those of price decreases in the wholesale and retail segment (long-run asymmetry).*

Hypothesis 2. *The positive ECTs are larger than the negative ones in the wholesale and retail segment. Alternatively, the speed of adjustment toward long-run equilibrium is larger to positive than to negative fluctuations (long-run asymmetry).*

Hypothesis 3. *The positive short-run price effect is larger than its negative counterpart in the wholesale and retail segment (short-run asymmetry).*

Hypothesis 4. *States with high (low) profit margin experience a slower (faster) adjustment to input price cost shocks (dynamic price adjustment).*

Hypothesis 5. *The impact of an input price shock to the transmission mechanism of the wholesale and retail gasoline price is permanent or transitory.*

V. EMPIRICAL FINDINGS

1. Estimated coefficients.

Table 4 depicts the empirical findings. We present results for four threshold PVECM which capture the (asymmetric) transmission of spot gasoline and crude oil price changes to both the pre-tax wholesale and retail gasoline prices respectively. In the relevant table, Panel A depicts the gasoline price adjustment to fluctuations in the spot gasoline price, while Panel B, represents the estimated coefficients of the threshold PVECM when the input cost variable is the crude oil price.

Examining Panel A, it is evident that in both models (wholesale and retail) positive coefficients are larger, in absolute value, than their negative counterparts. This finding which is also evident in other empirical studies (Grosso and Manera 2007; Contin et al. 2006; Polemis, 2012) reflects the consumers' perception of the actual effects of oil price variations on gasoline price changes, meaning that the effects of upstream price increases are larger than those of price decreases. The coefficients ρ^+ and ρ^- indicate the asymmetric adjustment speed, which is a measure of long-run asymmetry (Polemis, 2012). In other words, the positive and negative error correction terms are associated with adjustment to the long-run equilibrium level of price from above and from below (Galeotti et al, 2003).

From the reported values, we argue that the speed of adjustment in Model 1 ranges from 42-57% per month. It is worth mentioning that, positive changes of the error correction term are larger, in absolute value, than their negative counterparts (0.571 and 0.421 respectively). This means that if the wholesale price of gasoline is 10% above its long-run equilibrium price, given the current spot price, the percentage change difference over a period of one month will be $0.10 \times (-0.571) = -0.0571$ or 5.7%. In other words, if we are off the long-run equilibrium, the wholesale (rack) gasoline price will reach equilibrium in a six month period approximately. the speed of adjustment in the retail market model follows a similar trend . Specifically, the positive change of the ECM to the long-run equilibrium is estimated to −0.638. This means that if the retail price of gasoline is 10% above its long-run equilibrium price, given the current spot price, 6.4% of the difference between the equilibrium price and the current price will be eliminated in the next month *ceteris paribus*.

Moreover, we find a positive (β^+) and negative (β^-) long-run coefficient equal to 0.92 and 0.87 respectively, indicating that wholesalers are driven by the fluctuations in the input price of gasoline in the long run. This result reveals a long-run rent-seeking oligopolistic behaviour by the oil companies, which in turns is consistent with an asymmetric gasoline price adjustment mechanism at least in the long run.

In addition, the empirical findings indicate that positive short-run price effect is larger than its negative counterpart (0.313 instead of 0.236). This means that wholesale gasoline prices in the US seem to react more to price increases than to price decreases. This finding can be traced in many European countries as well[2]. From the magnitude of the relevant estimates, we see that a 10% short-run increase in spot price of gasoline (input price) will increase the wholesale price of gasoline by about 3.1%.

< Insert Table 4 about here >

The discussion now turns to Model 2. Column 2, shows where the responsiveness of retail price is symmetric in decreases and increases of the spot price of gasoline. More specifically, an increase in the spot price of gasoline of one unit induces a contemporaneous retail price increase of about 0.44, whereas a fall in spot price of one unit, results in a contemporaneous price effect of 0.38. Taken together, this means that the price responded more rapidly to cost increases than to decreases. From the above analysis, it is evident that the short-run accumulated pass-through in the retail price of gasoline is asymmetric. This result reveals long-run rent-seeking oligopolistic pricing behaviour by the retailers giving strong evidence that asymmetric price adjustment can be attributed to the oligopolistic pricing behavior (Radchenko, 2005). Specifically, the increasingly short-run rate of response of retail price of gasoline to input cost (wholesale price), gives an indication that a market power effect stemming from the wholesalers to retailers prevails in the oil supply chain. This can be explained by the fact that, the US oil industry is dominated by large, multinational companies (BP, Exxon-Mobil, Texaco, Shell, etc). The oligopolistic structure of the oil market and the market power of oil companies (Verlinda, 2008), which has been reinforced by the low search intensity of final consumers (see among others Lewis, 2011, Deltas, 2008 and Johnson, 2002) have lead to asymmetric price adjustments in the oil market and high profit margins for the oil companies.

Lastly, if we try to compare the two-market segments (wholesale and retail), some striking features emerge. First, the magnitude of short-run coefficients is in the most cases larger in the retail than in the wholesale level. This means that, on the one hand, retailers do immediately transfer onto final prices (pump prices) all the adjustments in the spot gasoline prices. On the other hand, in the wholesale segment, oil companies tend to distribute changes over time. Second, the adjustment towards the equilibrium level is more gradual in the wholesale level revealing the differences between the two market segments. Furthermore, both the wholesalers and retailers tend to react more to price increases than price decreases. Lastly, the point estimates of the single threshold for the two models are also reported in the relevant table. More specifically, the estimates are very close ranging from 0.142 (Model 1) to 0.137 (Model 2). Thus the estimates indicate the existence of two regimes (low and high market power).

The existence of price asymmetry both in the wholesale and retail segment is also evident in Figure 2a. The latter provides finite-sample evidence about the parameters shown, $\rho+$, $\rho-$, δ and the threshold mark-up λ. The solid line is the posterior density of wholesale price, while the dashed line plots the distribution of retail gasoline price respectively. Most marginal posteriors deviate markedly from normal distribution. In other words, the gasoline price adjustment pattern to fluctuations in the spot price of gasoline in both market segments is far from symmetric.

<Insert Figure 2a about here>

Similarly, we find significant evidence of additively asymmetric dynamic adjustment to crude oil price fluctuations. It is evident from the following figure that marginal posteriors deviate significantly from the shape of normal distribution in both market segments. These results indicate that a crude oil price increase is passed through more forcefully than a price decrease supporting the "*rockets and feathers*" hypothesis.

<Insert Figure 2b about here>

Although the above analysis reveals that there are short run relationships between the variables of each gasoline price adjustment model (wholesale and retail), it does not reveal the direction of their causal relationship (Kilian and Park, 2009). An alternative way to obtain the information regarding the relationships among the variables of the two relevant models is through the estimation of the Posterior Generalized Impulse Response Functions (PGIRFs) along the lines of Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998). Our strategy is to compute the PGIRF for each MCMC draw and then average across draws (after convergence) to obtain a final measure, in order to account for parameter uncertainty.

The upper panel of Figure 3a shows the PGIRFs of the wholesale gasoline price to the transmission of shocks of the input cost variable (spot gasoline price). This figure shows the typical speed of response to a cost increase and a cost decrease and underscores the point that the responses of wholesale gasoline price may differ substantially, depending on the time period of the spot price increases. Specifically, it is evident that the effect of one standard deviation shock of the spot price of gasoline on wholesale price of gasoline is positive and significant for a limited amount of time (one month period after the shock). Subsequently, the graph shows that an increase in the spot price of gasoline,e all else equal, would cause a transitory downward trend within the next month which stabilizes thereafter. Lastly, the peak response of wholesale price to spot price innovations occurs one month after the initial shock and is estimated to be approximately 8%.

<Insert Figure 3a about here>

We now turn our attention to the examination of PGIRFs at the retail level segment (lower panel of Figure 3a). If we look carefully the relevant diagram, we observe that similar findings as. the response is also found to be positive and statistically significant one month after the shock. The cumulative effect reaches 10.0% in the first month, and then returns toward zero after the end of the second month. However, the increasing trend stops within the next month of the peak response. Subsequently, the PGIRF of the retail price to a 10% increase in the spot price of gasoline is stable across the rest of the simulated period (8 months). This representation provides a solid illustration of an asymmetric gasoline price response in the US retail market segment.

If we try to compare the PGIRFs between the two gasoline models, some important results emerge. First, the response of retail gasoline price to one standard deviation shock of the input price (spot price of gasoline) is more abrupt than the wholesale response since the relevant increase within a limited short run time span (one month) is estimated to 10% instead of 8% respectively. However, both series exhibit a decreasing trend after one month period stabilising thereafter. This finding reveals the absence of a sluggish adjustment price mechanism, which is often considered indicative of weak competition and significant market power (SMP) by the incumbents. Moreover, an oil shock in both models is short-lived. Specifically, the rate of response of wholesale (retail) price of gasoline to input price shocks, gives an indication that a market power effect stemming from the refiners to wholesalers (retailers) prevails in the wholesale gasoline price changes.

Finally, we turn our attention to the investigation of the response of downstream gasoline prices at the two stage level regime to upstream shocks in the spot gasoline price. Figure 3b illustrates that gasoline market specific demand shocks, such as shocks to input cost price, will generate a significantly negative relationship between wholesale/retail gasoline price adjustments and spot gasoline price. Regarding Model 1 (upper panel) a strong and negative rapid reaction of gasoline price to a 10% spot price decrease in the short-run. Similarly to Kilian and Park (2009), the peak response occurs one month after the shock and is estimated at 8%, revealing an incomplete pass-trough of wholesale gasoline price to the spot price decreases.

The response of retail gasoline price to a 10% spot price decrease is also found to be negative and statistically significant one month after the shock, reaching a peak at 5%. From the combined investigation of the two figures, it appears that the peak response of the PGIRFs to a cost price decrease is lower in absolute terms than its relevant increase. This finding provides a solid illustration of an asymmetric gasoline price response in the US retail market segment.

<Insert Figure 3b about here>

Since we use a random-coefficient model, it is possible to compute GIRFs for states with margin above and below the threshold (λ). In both cases the median PGIRF is used for the corresponding states and the posterior standard deviations of these functions of interest monitor. The results are presented in Figures 4a and 4b. These figures plot the responses for two states (high and low profit margin) in each market segment (wholesale and retail). Figures 4a and 4b depict the responses of the two states: one with a high profit margin of 14.2 cents and one with a margin of 13.7 cents per gallon. The red dotted lines represent the 95% Bayes probability intervals computed by MCMC.

<Insert Figure 4a about here>

By comparing the two relevant figures, some important findings emerge. First, high margin states have faster wholesale and retail price responses to spot gasoline price changes than states with low margins. Second, in a state that exceeds the threshold value (14.2 and 13.7 cent margin in both market segments), wholesale (retail) prices will reflect 9% (10%) of a change in the spot gasoline price fluctuations within the first month. If a state falls under the threshold parameter, the corresponding figures are estimated as 7% and 8%, respectively.

Lastly, similar to Deltas (2008), the degree of asymmetry varies systematically across states, especially in the first month after the shock, and is more pronounced in the high margin states. By the end of the second month, the gasoline price adjustment to increases and decreases of the input cost shocks does not appear to vary significantly, revealing that there is a symmetric response in the high and low margin states. However, a cost decrease produces mixed results in the low margin states for the direction of price responses in the two market segments after the first five months. More specifically, the wholesale gasoline price response to input cost decreases has surprisingly a positive but not statistically significant interaction effect. The reverse holds in the retail market segment. The above findings strengthen the notion that market power proxied by the level of gross profit margins appears to affect the extent to which it responds asymmetrically to cost increases and decreases.

<Insert Figure 4b about here>

2. Structural breaks

The previous estimates reveal strong evidence of asymmetric adjustment in the retail and wholesale gasoline prices. As a further sensitivity test, we account for the possibility of structural breaks in the threshold parameter λ (gross profit margin). Specifically, the possibility that the margin changed abruptly during the examined period cannot be excluded a priori since exogenous shocks such as the U.S invasion to Iraq (March –May 2003), and the two main Hurricanes (Katrina and Rita) that hit the U.S (August 2005 and September 2005 respectively) may have left a significant mark on the oil sector.

This analysis is also motivated by previous studies (Lewis, 2009, Sen et al, 2011), which suggest that retail price asymmetries became sharper in some U.S. states in the aftermath of Hurricane Katrina. , Retail prices in some states remained at high levels for a considerable time period after the Hurricane, despite a gradual decline in wholesale prices from post Katrina levels. The sharp increase in retail gasoline prices has resulted in public concerns of "*price gouging*" by vertically integrated refiners and initiated several antitrust government investigations[3]. As noted by Sen et al. (2011), a possible theoretical explanation for sharper retail asymmetries observed post-Katrina could be because the occurrence of the Hurricane resulted in a uniform cost shock on prices which served as focal points for tacit collusion, allowing oil companies to better coordinate, and sustain price-fixing agreements that hinder competition.

We allow for the possibility of an unknown number of breaks in the threshold parameter and use the Particle Filter suggested by He and Maheu, (2010) to compute the marginal likelihood and make inferences about the structural parameters of the model[4]. Apart from the two hurricane dummies e already in the model along with a break in the threshold parameter λ, we allow for a general break of the form:

$$y_t = \mathbf{D}_{t^*}'\boldsymbol{\gamma}^* + \mathbf{D}_{t_0}'\boldsymbol{\gamma} + \mathbf{x}_t'(\lambda_t)\boldsymbol{\beta} + u_t,\ t = 1,\ldots,T \qquad (21)$$

where $\mathbf{D}_t$ is the set of hurricane dummies at given dates t_0 , and $\mathbf{D}_{t^*}$ is a set of dummies at an unknown set of dates $t^* \not\subset t^0$. For the threshold we have:

$$\lambda_t = \mathbf{D}'_{t_\lambda}\boldsymbol{\gamma}_\lambda \tag{22}$$

where $t_\lambda \subset \{1,...,T\}$ without excluding the possibility that $t_\lambda \subseteq t_*, t_\lambda \subseteq t_0$. To search systematically for the possibility of breaks we use the stochastic search variable selection (SSVS) method developed by George et al, (2008) and Jochmann, et al, (2010). The SSVS involves a specific prior of the form:

$$\gamma \mid \delta \sim \mathrm{N}(0,\mathbf{D}) \tag{23}$$

where δ is a vector of unknown parameters and its elements can be $\delta_j \in \{0,1\}$. Also $\mathbf{D} = diag\left[d_1^2,...,d_G^2\right]$:

$$d_j^2 = \kappa_{0j}^2, if \delta_j = 0, \text{and } d_j^2 = \kappa_{1j}^2, if \ \delta_j = 1 \tag{24}$$

The prior implies a mixture of two normals:

$$\gamma_j \mid \ \delta_j \sim (1-\delta_j)N(0,\kappa_{0J}^2) + \delta_j N(0,\kappa_{1j}^2) \tag{25}$$

If κ_{0j} is "small" and κ_{1j} is "large", then, when $\delta_j = 0$ chances are that variable j will be excluded from the model while if $\delta_j = 1$ chances are that variable j will be included in the model.

The prior for the indicator parameter δ is:

$$P(\delta_j = 1) = q_j, P(\delta_j = 0) = 1 - q_j \tag{26}$$

and we set $q_j = \frac{1}{2}$. For κ_{0j} and κ_{1j}, George, Sun and Ni (2008) propose a semi-automatic procedure based on $\kappa_{0j}^2 = c_0 \hat{v}(\pi_j)$ and $\kappa_{1j}^2 = c_1 \hat{v}(\pi_j)$ for $c_0 = \frac{1}{10}$, $c_1 = 10$ and $\hat{u}(\gamma_j)$ is any preliminary estimate of the variance of γ_j. We set the preliminary estimate to the one obtained by nonlinear LS allowing for a simple constant threshold. For the threshold parameters, we set the preliminary estimate of the variance to 0.20. The results were reasonably robust to this choice.

Based on this model, we compute the Recursive Bayes factors for different number of Breaks (B). The results are shown in Figure 5. The break in the data is inconclusive for B=1 while for $B \geq 2$ the evidence against breaks is considerable. This evidence leaves little doubt that the threshold model captures the variation adequately and leaves no possibility for structural breaks in the parameters of the model.

<Insert Figure 5 about here>

3. *Robustness check*

ITthis subsection examines whether our conclusions are robust to alternative data and model specifications. The results are summarized in Table 3 (Panel B) and Figure 2b.

In the first stage we estimate a new threshold PVECM and perform MCMC Bayesian techniques using crude oil price changes as the input cost variable affecting the wholesale and retail gasoline price adjustment respectively. It is well documented in the literature that this marker captures real oil price shocks driven solely by supply-side disruptions in the crude oil market (Chang, and Hwang, 2015; Greenwood-Nimmo and Shin, 2013, Honarvar, 2009, Deltas, 2008). Our results are generally robust to this alternative measure of oil price shocks. Specifically, the estimated positive coefficients in the wholesale and retail segment of the gasoline market are larger, in absolute value, than their negative counterparts leaving no doubt for the existence of an asymmetric adjustment price path (see Table 2 -Panel B). It is worth emphasising that the absolute magnitude of the estimated coefficients in this case is in general terms larger than the previous model. This finding shows that the response of gasoline prices in the downstream market (wholesale and retail segment) to crude oil price fluctuations is instantaneous.

Figure 2b shows the marginal posterior densities for selected parameters accounting for the speed of adjustment (ρ^{+}, ρ^{-}), symmetry testing (δ) and lastly the threshold mark-up variable (λ) in the presence of crude oil price fluctuations. The posteriors are non-normal and, therefore, relying on asymptotic theory would be dangerous in this instance.

Another useful insight is obtained by comparing the proposed model with the model of Greenwood-Nimmo and Shin (2013) – employing the same prior- for the common coefficients. The models can be compared in terms of their marginal likelihoods or their ratio, the Bayes factor. The results are provided in Figure 6. All our empirical work uses 250,000 MCMC iterations the first 50,000 of which are discarded to mitigate the impact of startup effects. Convergence is assessed using Geweke's (1992) diagnostic and relative numerical efficiency as well as numerical standard errors are monitored.[5] It is evident that both models behave equally well before about 1999, when the model proposed here has a Bayes factor ranging from 20:1 to 40:1, until 2006 when it jumps to over 120 reaching a maximum of 160:1 near 2009. The Bayes factor remains well over 100 in the subsequent period.

<Insert Figure 6 about here>

VI. RESULT DISCUSSIONS

To contextualize these findings, we draw comparisons with Deltas (2008), a study which linearly evaluates the effects of market structure through interacting lagged wholesale and retail price changes with state specific margins. Deltas (2008) finds coefficient estimates of response differences for wholesale price changes to be positive, indicating a faster response to price increases than decreases, indicating retail price asymmetry. His results also reveal that both the speed of adjustment and the degree of asymmetry depend on the average retail-wholesale margin of a state. He claims that states with large average profit margins tend to have more asymmetric and slower adjustment than states with small margins. Our empirical findings are in alignment with the aforementioned study revealing an asymmetric response of gasoline price to crude oil and spot price fluctuations.

Deltas (2008) did not split the sample into high and low margin states by using a threshold analysis and allow for dynamic interactions of wholesale and retail gasoline price to input cost shocks (e.g. crude oil price). Instead following the specifications of Borenstein and Shepard, 1996, Borenstein et al, (1997) and lastly Lewis, (2003), he used a linear lag adjustment model with an error correction term in order to investigate wholesale and retail price asymmetries. As described above, a linear ECM suffers from estimation uncertainty or errors arising from the estimation of the long run cointegrating relationship (Greenwood-Nimmo and Shin, 2013). In this study this limitation is addressed by the estimation of a threshold PVECM and subsequent PGIRFs that to assess the timing and magnitude of the responses to one time demand or supply shocks in the spot gasoline market (Kilian and Park, 2009). Lastly, by using a threshold (sample splitting) PVECM, we treated all our variables as endogenous with the inclusion of an exogenous threshold variable in contrast to the above study which required that all right-hand-side variables are strictly exogenous.

Another study that discusses estimates from nonlinear ARDL (NARDL) models is the study of Greenwood-Nimmo and Shin (2013), the first attempt in the literature to perform a non-linear approximation for the investigation of "*rockets and feathers*" hypothesis effect in four fuel markets in the UK following changes in the price of crude oil. They find significant evidence that the retail price of unleaded petrol before taxes and duties adjusts symmetrically to fluctuations to crude oil. However, this outcome is fully reversed once one accounts for the taxation effect (excise and value-added tax), raising the possibility that firms can use the tax system to conceal rent-seeking behaviour.

The above study finds that the speed of adjustment (ρ) is estimated at 37% per month, indicating a sluggish adjustment towards the long-run equilibrium. This means that if the retail gasoline price is 10% above its long-run equilibrium price, given the current crude oil price, the percentage change difference over a period of 1 month will be 3.7%. In other words, if we are off the long-run equilibrium, the retail gasoline price will reach equilibrium in a four month period approximately. This finding is consistent with non-transitory periods of mispricing in the UK gasoline industry, revealing a weak competition among the market players (e.g. oil companies, retailers, hypermarkets, etc). Our study (see Table 2, column 4) claims that the speed of adjustment to the long-run equilibrium is larger in its impact ranging from 52-67% per month with larger positive changes of the error correction term (in absolute terms) than its negative counterpart. The difference between the magnitude of the speed of adjustment towards the long-run equilibrium reflects the dissimilar conditions that face the UK and the U.S. in their gasoline industry in terms of market structure (e.g. concentration level, level of vertical integration, barriers to entry, etc) and competitive behaviour among the marketers.

Regarding the dynamic responses of gasoline price to crude oil fluctuations simulated over a short-run time horizon, the study of Greenwood-Nimmo and Shin (2013) argues that there is a strong and rapid reaction to positive changes but a more gradual response to negative changes. They claim that positive crude oil shocks will generate a significantly positive effect in the retail price of gasoline. That effect (nearly 10%) starts on impact and reaches a peak in the first month after the shock. Similarly, we also find that the response of retail price to spot price fluctuations is positive and statistically significant one month after the shock, reaching a peak at 10% approximately. Contrary to our findings, the previous study estimates the peak response of retail gasoline price to a 10% negative crude oil price shock to 9% approximately. Similarly to our study, however, the peak response occurs one month after the shock and is short-lived. The positive discrepancy between the difference of positive and negative values to crude oil fluctuations is also evident in the aforementioned study providing a stark illustration of an asymmetric gasoline price response.

Similarly, Lewis and Noel, (2011) argue that in the U.S, it takes three weeks following a cost increase for retail prices to fully adjust to the long-run equilibrium level. The speed of adjustment to negative cost shocks is much slower since it takes nearly six weeks to approach full pass-through, suggesting an asymmetric gasoline price adjustment in the U.S cities. Specifically, a cost increase (decrease) is fully passed through to the retail price in almost five (seven) days, highlighting that these responses are short-lived.

From the exposition of related evidence from various strands of empirical literature, it is safe to conclude that the magnitude of our estimated coefficients is reasonable and comparable to prior studies revealing the relative importance of local market power in a coherent way.

VII. CONCLUDING REMARKS

In this paper, we revisit the "*rockets and feathers*" hypothesis in the US wholesale and retail gasoline market segments by proposing a panel approach which allows for asymmetry, threshold effects, and optimal lag selection based on Markov Chain Monte Carlo Bayesian techniques. In order to empirically test our research hypotheses, we develop a new empirical methodology based on nonlinear threshold PVECMs and propose MCMC techniques to perform Bayesian inference in order to account for the investigation of gasoline price asymmetry. In doing so, we develop new econometric techniques for multivariate non-linear threshold error correction models accounting for wholesale and retail gasoline price responses respectively.

The motivation of this paper is to contribute to the empirical literature on retail and wholesale gasoline price asymmetry nexus by using for the first time in the gasoline price asymmetry controversy, a threshold PVECM and MCMC techniques in order to perform Bayesian inference with the following novelties. First, we allow for random coefficients in the Bayesian PVECM. Second, we account for cross-sectional dependence. Third, instead of the standard Gibbs sampler, we use a Langevin diffusion sampler which can deal effectively with autocorrelation and the non-standard form of priors for the covariance matrices. Fourth, we propose new techniques in the conditional posterior sampling of the threshold parameter. Lastly, we account for model comparison with a standard model that does not allow thresholds by estimating recursive Bayes factors using the particle filtering methodology

We examine differences between downstream and upstream gasoline markets, as we evaluate possible asymmetries in retail price adjustment to wholesale price shocks as well as the relationship between wholesale prices and spot price of gasoline shocks. We also attempt to evaluate the possible impacts of retail market power on the transmission of wholesale prices, and its potential effect on asymmetries in retail price adjustment. This is important, as very few studies have attempted to assess the effects of state specific market structure.

In this respect, we focus on trends in retail and wholesale monthly gasoline prices in 48 U.S states over the period January 1994 to February 2011. Following Deltas (2008), we proxy the effects of market power through state specific gross profit margins. Our empirical findings suggest that there is a single threshold in all of the regression relationships, splitting the sample into two parts (high and low profit margin states). In addition, the econometric analysis support the notion that market power does result in behaviour that leads to higher retail prices, and potentially more profits. However, this is to be expected in oligopolistic markets and does not necessarily imply the existence of collusive behaviour. With respect to upstream markets, we do find evidence that wholesale prices respond asymmetrically to increases and decreases in spot gasoline price fluctuations. In order to sharpen the robustness of our results, we have addressed the impact of crude oil price changes on the wholesale and retail gasoline price adjustment. Our results are remarkably consistent and robust to this alternative measure of oil price shocks. In other words, our findings for the effects of oil price shocks do not conflict with the conventional view that an oil price increase has a larger output effect than an oil price decrease indicating an asymmetric price adjustment path downstream (wholesale and retail segment).

Our analysis implies that, states with high profit margin experience a slower adjustment and a more asymmetric response compared to low profit ones thus leading to the validity of Hypothesis 4. Moreover, the magnitude of the estimated short-run coefficients is in the most cases larger in the retail than in the wholesale level. However, the adjustment towards the equilibrium level is more gradual in the wholesale segment whereas both the wholesalers and retailers tend to react more to price increases than price decreases. In contrast to other studies (e.g Greenwood-Nimmo and Shin, 2013), we find significant evidence that the price of gasoline before taxes and duties in the wholesale and retail segment adjusts more rapidly in an upward than a downward direction of the input price shocks. This implies also the validity of Hypotheses 1, 2 and 3. Lastly, the sign of the difference between the positive and the negative values of wholesale and retail gasoline prices to input cost shocks gives further support of an asymmetric response in both market segments

Finally, our analysis claims that the traditional approach to studying asymmetric gasoline price adjustment must be rethought. An immediate implication of our analysis is that future researchers have to move beyond empirical models that treat regression functions as identical across all sample observations. Relaxing this counterfactual *ceteris paribus* assumption allows the individual observations to be divided into classes based on the value of an unobserved variable, which in our case is the level of local competition in the industry proxied by the gross profit margin. With this approach, panel cross section elements (states/cities, etc.) are sorted according to their level of competition in the gasoline market segments.

Notes

1. "Kernel" means that the normalizing constant is omitted. In most circumstances this is because it is not available in closed form.

2. For an extensive review of price asymmetry in the European Union see, among others, the study of Polemis and Fotis (2014).

3. See, for example, "FTC Releases Report on its Investigation of Gasoline Price Manipulation and Post-Katrina Gasoline Price Increases" for further details (https://www.ftc.gov/news-events/press- releases/2006/05/ftc-releases-report-its-investigation-gasoline-price-manipulation).

4. We implement this filter using 2^{16} particles. From 10 different runs the root mean square error of difference in posterior means was 10^{-5}. As a robustness check we recomputed using 2^{14} particles to obtain the same results to the number of digits reported here.

5. We use AR(10) processes fitted to the MCMC draws to compute the required long-run variance, the spectral density at zero.

6. This guarantees the existence of moments up to order four.

7. See also Poyiadjis et al. (2011).

8. The benefit of MALA over Random-Walk-Metropolis arises when the number of parameters n is large. This happens because the scaling parameter λ is $O(n^{-1/2})$ for Random-Walk-Metropolis but it is $O(n^{-1/6})$ for MALA, see Roberts et al. (1997) and Roberts and Rosenthal (1998).

Appendix A Computational strategy

We have a (large) Bayesian PVECM whose dimension is equal to n, the number of U.S. states. Without the random-coefficient specification, estimation of this VAR would present considerable challenges. For a given value of λ, MCMC analysis can be easily implemented using standard techniques involving the Gibbs sampler. Let us write the PVECM in the following form:

$$\mathbf{w}_t = \sum_{j=1}^{p-1} \boldsymbol{\Gamma}_j \mathbf{w}_{t-j} + \mathbf{Z}_t(\lambda)\boldsymbol{\xi} + \boldsymbol{\varepsilon}_t \triangleq \mathbf{X}_t(\lambda)\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t$$

The VAR can be written as

$$\mathbf{w}_i = \mathbf{X}_i(\lambda)\boldsymbol{\beta}_i + \boldsymbol{\varepsilon}_i,\ i = 1,\ldots,n$$

Making the substitution $\boldsymbol{\beta}_i = \overline{\boldsymbol{\beta}} + \boldsymbol{\eta}_i$, $\boldsymbol{\eta}_i \overset{\text{iid}}{\sim} \mathcal{N}_K(\mathbf{0}, \boldsymbol{\Omega})$ we obtain:

$$\mathbf{w}_i = \mathbf{X}_i(\lambda)\overline{\boldsymbol{\beta}} + \mathbf{e}_i$$

where $\mathbb{E}(\mathbf{e}_i) = \mathbf{0}_T$ and $\mathbb{E}(\mathbf{e}_i\mathbf{e}_j') = \delta_{ij}\mathbf{X}_i(\lambda)\boldsymbol{\Omega}\mathbf{X}_j(\lambda)' + \sigma_{ij}\mathbf{I}_T$, where δ_{ij} is Kronecker's *delta*.

Suppose $\mathbf{w} = \begin{bmatrix} \mathbf{w}_1 \\ \vdots \\ \mathbf{w}_n \end{bmatrix}$, $\mathbf{X}(\lambda) = \begin{pmatrix} \mathbf{X}_1(\lambda) & \cdots & \mathbf{0} \\ \vdots & \ddots & \vdots \\ \mathbf{0} & \cdots & \mathbf{X}_n(\lambda) \end{pmatrix}$ and $\mathbf{e} = \begin{bmatrix} \mathbf{e}_1 \\ \vdots \\ \mathbf{e}_n \end{bmatrix}$ so that the PVECM can be represented as:

$$\mathbf{w} = \mathbf{X}(\lambda)\overline{\boldsymbol{\beta}} + \mathbf{e}$$

and $\mathbb{E}(\mathbf{e}\mathbf{e}') = \mathbf{X}(\lambda)(\boldsymbol{\Omega} \otimes \mathbf{I}_n)\mathbf{X}(\lambda)' + \boldsymbol{\Sigma} \otimes \mathbf{I}_T \triangleq \mathbf{V}(\lambda)$. The likelihood function is

$$\mathcal{L}(\boldsymbol{\theta}; \mathbf{w}, \mathbf{X}) \propto |\mathbf{V}(\lambda)|^{-1/2} \exp\left\{-\tfrac{1}{2}(\mathbf{w} - \mathbf{X}(\lambda)\overline{\boldsymbol{\beta}})' \mathbf{V}(\lambda)^{-1} (\mathbf{w} - \mathbf{X}(\lambda)\overline{\boldsymbol{\beta}})\right\}$$

and the posterior can be obtained from Bayes' theorem:

$$\mathrm{p}\big(\boldsymbol{\theta} \mid \mathbb{Y}\big) \propto \mathcal{L}\big(\boldsymbol{\theta};\mathbf{w},\mathbf{X}\big)\mathrm{p}\big(\boldsymbol{\theta}\big)$$

where $\mathbb{Y} = \big[\mathbf{w},\mathbf{X}\big]$ denotes the data.

As we can see, the posterior is a complicated function of the threshold parameter, λ . The parameters $\boldsymbol{\theta}$ consists of $\bar{\boldsymbol{\beta}},\lambda,\boldsymbol{\Sigma},\boldsymbol{\Omega}$. It is useful to condition on the threshold parameter and define the conditional posterior:

$$\mathrm{p}\big(\boldsymbol{\theta}_{\lambda} \mid \mathbb{Y}\big) \triangleq \mathrm{p}\big(\boldsymbol{\theta} \mid \lambda,\mathbb{Y}\big) \propto \mathcal{L}\big(\boldsymbol{\theta}_{\lambda};\mathbb{Y}\big)\mathrm{p}\big(\boldsymbol{\theta} \mid \lambda\big)$$

where $\mathcal{L}\big(\boldsymbol{\theta}_{\lambda};\mathbb{Y}\big) = \mathcal{L}\big(\boldsymbol{\theta};\lambda,\mathbb{Y}\big)$ is the conditional likelihood and $\mathrm{p}\big(\boldsymbol{\theta} \mid \lambda\big)$ is the conditional prior. The dimensionality of the parameter vector, despite the fact that we have a Bayesian VAR is small as there are K elements in $\bar{\boldsymbol{\beta}}$, $\frac{K(K+1)}{2}$ different elements in $\boldsymbol{\Omega}$ and we have a single-factor model for the cross-sectional covariance matrix $\boldsymbol{\Sigma}$.

For given λ the posterior can be analyzed easily using the methods that we explain below. MCMC draws for λ are realized using a Metropolis-Hastings algorithm. Suppose we are currently at state s and the draw is $\lambda^{(s)}$. The new draw $\lambda^{(s+1)}$ is realized as follows. Suppose we have a candidate draw λ^{c} from a distribution with density $g(\lambda)$. Then, we set $\lambda^{(s+1)} = \lambda^{c}$ with probability

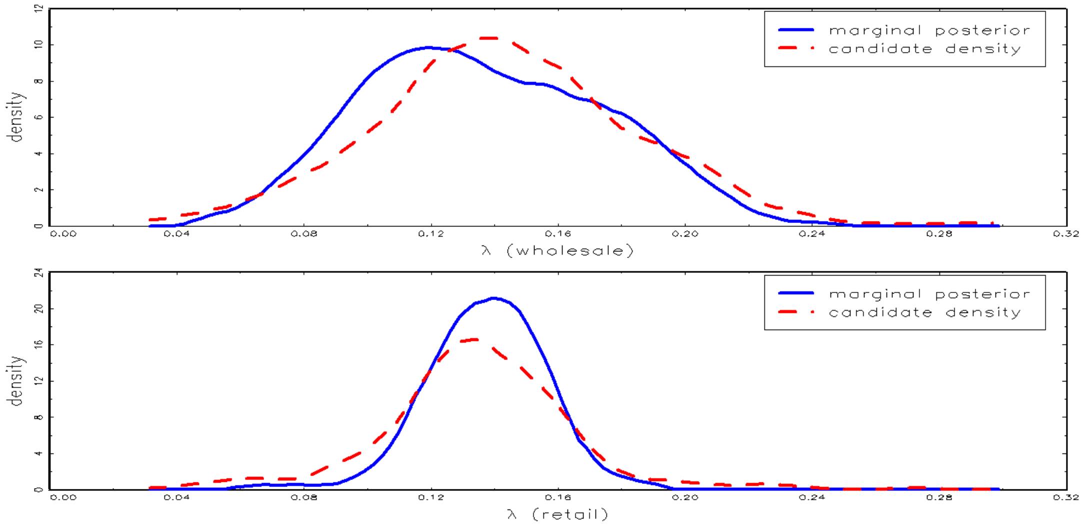
$$\min\left\{1,\ \frac{\mathrm{p}\big(\boldsymbol{\theta} \mid \lambda^{c},\mathbb{Y}\big)/\,\mathrm{g}(\lambda^{c})}{\mathrm{p}\big(\boldsymbol{\theta} \mid \lambda^{(s)},\mathbb{Y}\big)/\,\mathrm{g}(\lambda^{(s)})}\right\},$$

otherwise we set $\lambda^{(s+1)} = \lambda^{(s)}$. Our candidate generating density is crafted numerically as follows. Given a grid of values $\mathcal{G} = \big\{\bar{\lambda}_1,\ldots,\bar{\lambda}_G\big\}$ we compute the marginal likelihood of the model. Suppose these values are $\mathfrak{M}_g, g \in \mathcal{G}$. Our candidate generating density is based on a piecewise linear approximation to the obtained values of log marginal likelihoods. We do not need the normalizing constant in this expression. Marginal likelihoods are computed using the “candidate’s formula” (Chib, 1995):

$$\mathfrak{M}_g = \frac{\mathcal{L}\left(\hat{\boldsymbol{\theta}}_\lambda;\mathbb{Y}\right)p\left(\hat{\boldsymbol{\theta}}_\lambda \mid \lambda\right)}{\left(2\pi\right)^{-d_\theta/2} \mid \mathbf{C}_\lambda \mid^{-1/2}},\ \forall g \in \mathcal{G}$$

where $\hat{\boldsymbol{\theta}}_\lambda = S^{-1}\sum_{s=1}^{S}\boldsymbol{\theta}_\lambda^{(s)}$, $\mathbf{C}_\lambda = S^{-1}\sum_{s=1}^{S}\left(\boldsymbol{\theta}_\lambda^{(s)} - \hat{\boldsymbol{\theta}}_\lambda\right)\left(\boldsymbol{\theta}_\lambda^{(s)} - \hat{\boldsymbol{\theta}}_\lambda\right)'$, and $\left\{\boldsymbol{\theta}_\lambda^{(s)}, s = 1,\ldots,S\right\}$ represents the MCMC draws for the parameters for a given value of λ. The denominator is based on a normal approximation to the posterior $p\left(\boldsymbol{\theta}_\lambda \mid \mathbb{Y}\right)$ at the point $\boldsymbol{\theta}_\lambda = \hat{\boldsymbol{\theta}}_\lambda$. The candidate generating density has been found an excellent approximation to the marginal posterior distribution $p\left(\lambda \mid \mathbb{Y}\right)$. See Figure A1.

Figure A1. Marginal posterior and candidate generating densities



The candidate generating function is a spline approximation to $G = 20$ points equally spaced between the 10% and 90% percentiles of the empirical distribution of profit margins across all U.S. states and all time periods.

To implement this procedure we use $G = 20$ points equally spaced between the 10% and 90% percentiles of the empirical distribution of profit margins across all U.S. states and all time periods. In our application, this choice worked quite well.

We deviate from standard practice that uses the Gibbs sampler in the context of Bayesian VAR models. Part of the problem, is that the priors on the different element of $\mathbf{\Sigma}$ and $\mathbf{\Omega}$ are non-standard. Our procedure is based on the Langevin Diffusion MCMC methods proposed by Girolami and Calderhead (2011). As matrix $\mathbf{\Sigma}$ is not available in closed form we do have to update the common factor f_t via a separate MCMC step. The set of common factor values is jointly updated using, again, a Girolami and Calderhead (2011) MCMC update.

Appendix B Markov chain Monte Carlo

Following Girolami and Calderhead (2011) we utilize Metropolis-adjusted Langevin and Hamiltonian Monte Carlo sampling methods defined on the Riemann manifold, since we are sampling from target densities with high dimensions that exhibit strong degrees of correlation. Consider the Langevin diffusion:

$$d\boldsymbol{\theta}(t) = \tfrac{1}{2}\nabla \log p\left(\boldsymbol{\theta}(t);\mathbb{Y}\right)dt + d\mathbf{B}(t),$$

where $\mathbf{B}$ denotes the D-dimensional Brownian motion. The first-order Euler discretization provides the following candidate generation mechanism:

$$\boldsymbol{\theta}^{*} = \boldsymbol{\theta}^{o} + \tfrac{1}{2}\varepsilon^{2}\nabla \log p\left(\boldsymbol{\theta}^{o};\mathbb{Y}\right) + \varepsilon\mathbf{z},$$

where $\mathbf{z} \sim \mathcal{N}_D\left(\mathbf{0},\mathbf{I}\right)$, and $\varepsilon > 0$ is the integration step size. Since the discretization induces an unavoidable error in approximation of the posterior, a ***Metropolis step*** is used, where the proposal density is

$$q\left(\boldsymbol{\theta}^{*} \mid \boldsymbol{\theta}^{o}\right) = \mathcal{N}_D\left(\boldsymbol{\theta}^{o} + \tfrac{1}{2}\varepsilon^{2}\nabla \log p\left(\boldsymbol{\theta}^{o};\mathbb{Y}\right),\ \varepsilon^{2}\mathbf{I}\right),$$

with acceptance probability $a\left(\boldsymbol{\theta}^{o},\boldsymbol{\theta}^{*}\right) = \min\left\{1,\ \frac{p\left(\boldsymbol{\theta}^{*} \mid \mathbb{Y}\right)q\left(\boldsymbol{\theta}^{o} \mid \boldsymbol{\theta}^{*}\right)}{p\left(\boldsymbol{\theta}^{o} \mid \mathbb{Y}\right)q\left(\boldsymbol{\theta}^{*} \mid \boldsymbol{\theta}^{o}\right)}\right\}$. Here $\mathbb{Y}$ denotes the available data. The Brownian motion of the Riemann manifold is given by:

$$d\tilde{\mathbf{B}}_i(t) = \left|\mathbf{G}\left(\boldsymbol{\theta}(t)\right)\right|^{-1/2}\sum_{j=1}^{d}\frac{\partial}{\partial\boldsymbol{\theta}_j}\left[\mathbf{G}^{-1}\left(\boldsymbol{\theta}(t)\right)_{ij}\left|\mathbf{G}\left(\boldsymbol{\theta}(t)\right)\right|^{1/2}\right]dt + \left[\sqrt{\mathbf{G}^{-1}\left(\boldsymbol{\theta}(t)\right)}d\mathbf{B}(t)\right]_i,$$

for $i = 1,\ldots,D$.

The discrete form of the above stochastic differential equations is:

$$\boldsymbol{\theta}_i^* = \boldsymbol{\theta}_i^o + \tfrac{1}{2}\varepsilon^2\left[\mathbf{G}^{-1}\left(\boldsymbol{\theta}^o\right)\nabla \log p\left(\boldsymbol{\theta}^o;\mathbb{Y}\right)\right]_i - \varepsilon^2\sum_{j=1}^{d}\left[\mathbf{G}^{-1}\left(\boldsymbol{\theta}^o\right)\frac{\partial \mathbf{G}\left(\boldsymbol{\theta}^o\right)}{\partial \boldsymbol{\theta}_j}\mathbf{G}^{-1}\left(\boldsymbol{\theta}^o\right)\right]_{ij} +$$

$$\varepsilon^2\sum_{j=1}^{d}\mathbf{G}^{-1}\left(\boldsymbol{\theta}^o\right)_{ij} tr\left[\mathbf{G}^{-1}\left(\boldsymbol{\theta}^o\right)\frac{\partial \mathbf{G}\left(\boldsymbol{\theta}^o\right)}{\partial \boldsymbol{\theta}_j}\right] + \varepsilon\left[\sqrt{\mathbf{G}^{-1}\left(\boldsymbol{\theta}(t)\right)}\mathbf{z}\right]_i \triangleq$$

$$\boldsymbol{\mu}\left(\boldsymbol{\theta}^o,\varepsilon\right)_i + \varepsilon\left[\sqrt{\mathbf{G}^{-1}\left(\boldsymbol{\theta}(t)\right)}\mathbf{z}\right]_i .$$

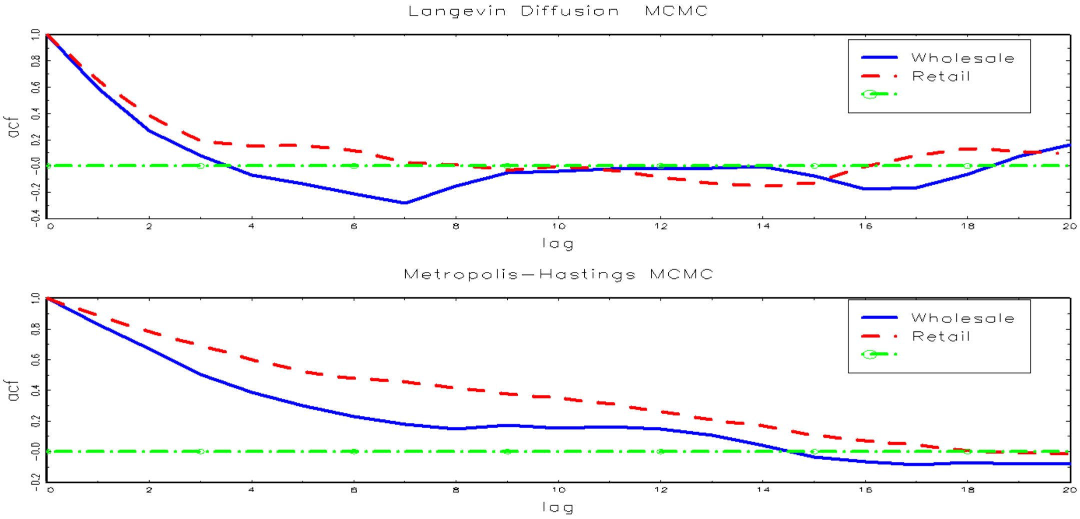
The *proposal density* is $\boldsymbol{\theta}^* \mid \boldsymbol{\theta}^o \sim \mathcal{N}_d\left(\boldsymbol{\mu}\left(\boldsymbol{\theta}^o,\varepsilon\right),\ \varepsilon^2\mathbf{G}^{-1}\left(\boldsymbol{\theta}^o\right)\right)$ and the acceptance probability has the standard *Metropolis form*:

$$a\left(\boldsymbol{\theta}^o,\boldsymbol{\theta}^*\right) = \min\left\{1,\ \frac{p\left(\boldsymbol{\theta}^* \mid \mathbb{Y}\right)q\left(\boldsymbol{\theta}^o \mid \boldsymbol{\theta}^*\right)}{p\left(\boldsymbol{\theta}^o \mid \mathbb{Y}\right)q\left(\boldsymbol{\theta}^* \mid \boldsymbol{\theta}^o\right)}\right\}.$$

The gradient and the Hessian are computed using analytic derivatives provided by computer algebra software. All computations are performed in Fortran 77 making extensive use of IMSL subroutines.

The numerical performance, in terms of autocorrelation functions, is presented in Figure A2. The Metropolis-Hastings procedure we use is a simple random walk whose candidate generating density is a multivariate Student-*t* distribution with 5 degrees of freedom[6] and covariance equal to a scaled version of the covariance obtained from the Langevin Diffusion MCMC. The scale parameter is adjusted so that approximately 25% of the draws are accepted. The performance of Langevin Diffusion MCMC turns out to be vastly superior relative to the random-walk Metropolis-Hastings procedure.

Figure A2. Autocorrelation functions



Appendix C Marginal likelihood and Bayes factors

For any posterior distribution whose kernel is $p\left(\theta \mid \mathbb{Y}\right) \propto \mathcal{L}(\theta; \mathbb{Y}) p(\theta)$ the marginal likelihood can be expressed as $\mathfrak{M}(\mathbb{Y}) = \int \mathcal{L}(\theta; \mathbb{Y}) p(\theta) d\theta$. Similarly, we can define the marginal likelihood $\mathfrak{M}(\mathbb{Y}_{1:t}) = \int \mathcal{L}(\theta; \mathbb{Y}_{1:t}) p(\theta) d\theta$ for data $\mathbb{Y}_{1:t}$ from period 1up to t. Relative to a base model whose marginal likelihood is $\mathfrak{M}_0(\mathbb{Y})$ or $\mathfrak{M}_0(\mathbb{Y}_{1:t})$ we define the recursive Bayes factor as:

$$BF_{1:t} = \frac{\mathfrak{M}\left(\mathbb{Y}_{1:t}\right)}{\mathfrak{M}_0\left(\mathbb{Y}_{1:t}\right)} .$$

The problem is, of course, how to compute the multivariate integrals involved in these calculations. From the expression:

$$\mathfrak{M}(\mathbb{Y}_{1:t}) = \int \mathcal{L}(\theta; \mathbb{Y}_{1:t}) p(\theta) d\theta ,$$

in reality, we have:

$$\mathfrak{M}(\mathbb{Y}_{1:t}) = \int \mathcal{L}(\theta, \mathcal{Z}_{1:t}; \mathbb{Y}_{1:t}) p(\theta) d\theta d\mathcal{Z}_{1:t} ,$$

where $\mathcal{Z}$ denotes the latent variables in the model –the common factor f_t in our case. To perform the computation we resort to particle filtering (PF) given $\theta = \bar{\theta}$, the posterior mean of the parameters. To conform with notation in the PF literature, we let $\mathcal{Z} := S$. In this work we use the PFMALA filter, see below.

Appendix D Particle filtering

The particle filter methodology can be applied to state space models of the general form:

$$y_T \sim p(y_t \mid x_t),\, s_t \sim p(s_t \mid s_{t-1})\,, \tag{A1}$$

where s_t is a state variable. For general introductions see Gordon et al. (1993), Doucet et al. (2000), Pitt and Shephard (1999), and Ristic et al. (2004).

Given the data $\mathbb{Y}_t$ the posterior distribution $p(s_t \mid \mathbb{Y}_t)$ can be approximated by a set of (auxiliary) particles $\left\{ s_t^{(i)}, i = 1,...,.N \right\}$ with probability weights $\left\{ w_t^{(i)}, i = 1,..., N \right\}$ where $\sum_{i=1}^{N} w_t^{(i)} = 1$. The predictive density can be approximated by:

$$p(s_{t+1} \mid Y_t) = \int p(s_{t+1} \mid s_t) p(s_t \mid \mathbb{Y}_t) ds_t \simeq \sum_{i=1}^{N} p(s_{t+1} \mid s_t^{(i)}) w_t^{(i)}\,, \tag{A2}$$

and the final approximation for the filtering density is

$$p(s_{t+1} \mid \mathbb{Y}_t) \propto p(y_{t+1} \mid s_{t+1}) p(s_{t+1} \mid \mathbb{Y}_t) \simeq p(y_{t+1} \mid s_{t+1}) \sum_{i=1}^{N} p(s_{t+1} \mid s_t^{(i)}) w_t^{(i)}\,. \tag{A3}$$

The basic mechanism of particle filtering rests on propagating $\left\{ s_t^{(i)}, w_t^{(i)}, i = 1,..., N \right\}$ to the next step, viz. $\left\{ s_{t+1}^{(i)}, w_{t+1}^{(i)}, i = 1,..., N \right\}$ but this often suffers from the weight degeneracy problem.

Appendix E Particle metropolis adjusted Langevin filter

Nemeth, Sherlock and Fearnhead (2014) provide a particle version of a Metropolis adjusted Langevin algorithm (MALA).[7] In Sequential Monte Carlo we are interested in approximating $p(s_t \mid \mathbb{Y}_{1:t}, \theta)$. Given that:

$$p(s_t \mid \mathbb{Y}_{1:t}, \theta) \propto g(y_t \mid x_t, \theta) \int f(s_t \mid s_{t-1}, \theta) p(s_{t-1} \mid y_{1:t-1}, \theta) ds_{t-1}\,, \tag{A4}$$

where $p(s_{t-1} \mid y_{1:t-1},\theta)$ is the posterior as of time $t-1$. If at time $t-1$ we have a set set of particles $\left\{s_{t-1}^i, i=1,...,N\right\}$ and weights $\left\{w_{t-1}^i, i=1,....N\right\}$ which form a discrete approximation for $p(s_{t-1} \mid y_{1:t-1},\theta)$ then we have the approximation:

$$\hat{p}(s_{t-1} \mid y_{1:t-1},\theta) \propto \sum_{i=1}^{N} w_{t-1}^i f(s_t \mid s_{t-1}^i,\theta) \,. \tag{A5}$$

See Doucet et al. (2000) and Cappe at al. (2007) for reviews. From (A3) Fernhead et al. (2008) make the important observation that the joint probability of sampling particle s_{t-1}^i and state s_t is:

$$\omega_t = \frac{w_{t-1}^i g(y_t \mid s_t,\theta) f(s \mid s_{t-1}^i,\theta)}{\xi_t^i q(s_t \mid s_{t-1}^i, y_t,\theta)}, \tag{A6}$$

where $q(s_t \mid s_{t-1}^i, y_t,\theta)$ is a density function amenable to simulation and:

$$\xi_t^i q(s_t \mid s_{t-1}^i, y_t,\theta) \simeq c g(y_t \mid s_t,\theta) f(s_t \mid s_{t-1}^i,\theta), \tag{A7}$$

and c is the normalizing constant in (A3). In the MALA algorithm of Roberts and Rosenthal (1998)[8] we form a proposal

$$\theta^c = \theta^{(s)} + \lambda z + \tfrac{\lambda^2}{2} \nabla \log p(\theta^{(s)} \mid \mathbb{Y}_{1:T}), \tag{A8}$$

where $z \sim N(0,I)$ which should result in larger jumps and better mixing properties, plus lower autocorrelations for a certain scale parameter λ. Acceptance probabilities are

$$a(\theta^c \mid \theta^{(s)}) = \min\left\{1,\ \frac{p(\mathbb{Y}_{1:T} \mid \theta^c) q(\theta^{(s)} \mid \theta^c)}{p(\mathbb{Y}_{1:T} \mid \theta^{(s)}) q(\theta^c \mid \theta^{(s)})}\right\}. \tag{A9}$$

Using particle filtering it is possible to create an approximation of the score vector using Fisher's identity:

$$\nabla \log p(\mathbb{Y}_{1:T} \mid \theta) = E\left[\nabla \log p(s_{1:T}, \mathbb{Y}_{1:T} \mid \theta) \mid \mathbb{Y}_{1:T},\theta\right], \tag{A10}$$

which corresponds to the expectation of

$$\nabla \log p(s_{1:T}, \mathbb{Y}_{1:T} \mid \theta) = \nabla \log p(| s_{1:T-1}, \mathbb{Y}_{1:T-1} \mid \theta) + \nabla \log g(y_T \mid s_T, \theta) + \nabla \log f(s_T \mid s|_{T-1}, \theta),$$

over the path $s_{1:T}$. The particle approximation to the score vector results from replacing $p(s_{1:T} \mid \mathbb{Y}_{1:T}, \theta)$ with a particle approximation, $\hat{p}(s_{1:T} \mid \mathbb{Y}_{1:T}, \theta)$. With particle i at time t-1 we can associate a value $\alpha_{t-1}^i = \nabla \log p(s_{1:t-1}^i, \mathbb{Y}_{1:t-1} \mid \theta)$ which can be updated recursively. As we sample κ_i in the PF (the index of particle at time $t-1$ that is propagated to produce the i th particle at time t) we have the update:

$$\alpha_t^i = a_{t-1}^{\kappa_i} + \nabla \log g(y_t \mid s_t^i, \theta) + \nabla \log f(s_t^i \mid s_{t-1}^i, \theta) . \tag{A11}$$

To avoid problems with increasing variance of the score estimate $\nabla \log p(\mathbb{Y}_{1:t} \mid \theta)$ we can use the approximation:

$$\alpha_{t-1}^i \sim \mathcal{N}(m_{t-1}^i, V_{t-1}) . \tag{A12}$$

The mean is obtained by shrinking α_{t-1}^i towards the mean of α_{t-1} as follows:

$$m_{t-1}^i = \psi \alpha_{t-1}^i + (1-\psi) \sum_{i=1}^{N} w_{t-1}^i \alpha_{t-1}^i , \tag{A13}$$

where $\psi \in (0,1)$ is a shrinkage parameter. Using Rao-Blackwellization one can avoid sampling α_t^i and instead use the following recursion for the means:

$$m_t^i = \psi m_{t-1}^{\kappa_i} + (1-\psi) \sum_{i=1}^{N} w_{t-1}^i m_{t-1}^i + \nabla \log g(y_t \mid s_t^i, \theta) + \nabla \log f(s_t^i \mid s_{t-1}^{\kappa_i}, \theta) \tag{A14}$$

which yields the final score estimate:

$$\nabla \log \hat{p}(\mathbb{Y}_{1:t} \mid \theta) = \sum_{i=1}^{N} w_t^i m_t^i . \tag{A15}$$

As a rule of thumb Nemeth, Sherlock and Fearnhead (2014) suggest taking $\psi = 0.95$. Furthermore, they show the important result that the algorithm should be tuned to the asymptotically optimal acceptance rate of 15.47% and the number of particles must be selected so that the variance of the estimated log-posterior is about 3. Additionally, if measures are not taken to control the error in the variance of the score vector there is no gain over a simple random walk proposal.

Of course, the marginal likelihood is:

$$p(\mathbb{Y}_{1:T} \mid \theta) = p(y_1 \mid \theta) \prod_{t=2}^{T} p(y_t \mid \mathbb{Y}_{1:t-1}, \theta), \tag{A16}$$

where:

$$p(y_t \mid \mathbb{Y}_{1:t-1}, \theta) = \int g(y_t \mid s_t) \int f(s_t \mid s_{t-1}, \theta) p(s_{t-1} \mid \mathbb{Y}_{1:T-1}, \theta) ds_{t-1} ds_t, \tag{A17}$$

provides, in explicit form, the predictive likelihood. Our implementation, for fixed θ, relies on 2^{16}=65,536 particles.

List of Tables and Figures

TABLE 1

Empirical studies on the existence of price asymmetry

Study	Country / product	Frequency / Period	Stage of transmission	Model	Findings
Kristoufek and Lunackova (2015)	Belgium, France, Germany, Italy, Netherlands, UK, USA / gasoline	Weekly / 1996-2014	Retail market	ECM	No evidence of price asymmetries
Bumbass et al (2015)	USA / gasoline	Monthly / 1976-2012	Retail market	TAR	Evidence in favor of long-run symmetric adjustment speeds to oil price shocks
Remer (2015)	New Jersey,Maryland, Virginia,Washington, Philadelphia, Washington DC / gasoline	Daily / July 2008-June 2009	Retail market	Panel ECM	Retail gasoline prices respond asymmetrically to cost increases and decreases.
Polemis and Fotis, (2015)	12 European countries / gasoline	Weekly / June 1996 August 2011	Retail market	Dynamic OLS	Existence of long-run price asymmetry in five European countries. Evidence of short-run price symmetry in all of the sample countries.
Polemis and Fotis, (2014)	12 European countries, USA / gasoline	Weekly / June 1996 August 2011	Wholesale & retail market	Dynamic OLS	Less competitive gasoline markets exhibit price asymmetry, while highly competitive gasoline markets follow a symmetric price adjustment path.
Polemis and Fotis, (2013)	11 Euro zone countries / gasoline	Weekly / 2000 February 2011	Wholesale & retail market	GMM panel data ECM	Evidence in favor of long-run symmetric adjustment speeds in the retail segment.
Greenwood-Nimmo and Shin (2013)	United Kingdom / unleaded gasoline, diesel, kerosene, gas oil	Monthly / 1999-2013	Retail market	Non Linear ADRL	Evidence of price asymmetry in diesel, kerosene and gasoil. Long-rum symmetry in pre-taxed unleaded gasoline
Polemis (2012)	Greece / gasoline	Monthly / 1988 mid 2006	Wholesale and retail market	ECM	Retail gasoline prices respond asymmetrically to cost increases and decreases.
Bermingham and O' Brien (2010)	United Kingdom and Ireland / gasoline and diesel	Monthly / 1997-mid 2009	Retail market	TAR	No evidence of price asymmetries

TABLE 1

Empirical studies on the existence of price asymmetry (continued)

Study	Country / product	Frequency / Period	Stage of transmission	Model	Findings
Clerides (2010)	Several European countries / gasoline and diesel	Weekly 2000-2010	Retail market	ECM	Mixed results for price asymmetry
Faber (2009)	Netherlands / gasoline	Daily / May 2006-July 2008	Wholesale / Retail market (3600 gas stations)	ECM	38% of stations respond asymmetrically. No evidence of asymmetry at the level of the oil companies.
Valadkhani (2009)	Australia / gasoline	Monthly / 1998-2009	Retail market	ECM	Evidence of price asymmetry in four out of seven Australian capital cities.
Kuper and Poghosyan (2008)	U.S. / gasoline	Weekly / 1986-2005	Retail market	ECM	Pre 1999: International oil price adjusts linearly to deviations from the long-term equilibrium. Post 1999: Evidence of price asymmetry.
Deltas (2008)	USA / gasoline	Monthly / 1988-2002	Retail market	ECM	Retail price asymmetry
Grasso and Manera (2007)	Italy, France, Spain, Germany, UK / gasoline	Monthly / 1985-2003	Retail market	ECM, Threshold ECM, M-TAR	ECM: Evidence of price asymmetry for all countries T – ECM: No evidence of price asymmetry M-TAR: Long – run price asymmetry
Radchenko and Tsurumi (2006)	US / gasoline	Monthly / 1976 - 1997	Retail Market	VAR	Evidence in favour of symmetric adjustment speeds in the retail segment.
Radchenko (2005)	U.S. / gasoline	Weekly / 1991, 1993(1994) - 2003	Wholesale and retail market	ECM, VAR and PAM	Evidence of price asymmetry
Kaufmann and Laskowski, (2005)	U.S. / gasoline and home heating oil	Monthly / 1986-2002	Wholesale and retail market	ECM	Mixed results for price asymmetry
Bachmeir and Griffin (2003)	U.S. / gasoline	Daily / 1985-1998	Wholesale market	ECM	Mixed results for price asymmetry
Galeotti, et al, (2003)	Germany, France, UK, Italy and Spain / gasoline	Monthly / 1985-2000	Wholesale and retail market	ECM	Mixed results for price asymmetry

Note: ECM (Error-Correction Model), M-TAR (Momentum Threshold Autoregressive Model), TAR (Threshold Autoregressive Model), ARDL (Autoregressive Distributed Lag Model), PAM (Partial Adjustment Model), GMM (Generalized Method of Moments), VAR (Vector Autoregression Model).

TABLE 2

Descriptive statistics

Variable	*Mean*	*Median*	*Maximum*	*Minimum*	*Standard deviation*	*Coefficient of variation*	*Skewness*	*Kurtosis*	*Observations*
Wholesale price	1.250	0.957	4.012	0.350	0.708	0.566	0.933	2.918	9,819
Retail price	1.414	1.124	4.197	0.474	0.716	0.507	0.938	2.944	9,871
Spot price	1.146	0.873	3.292	0.307	0.695	0.606	0.924	2.833	206
Crude oil price	41.781	29.635	133.88	11.35	27.08	0.648	1.113	3.588	206
Gross profit margin	0.157	0.147	1.902	-0.821	0.070	0.442	2.132	60.267	9,807
Δ (Wholesale price)	0.010	0.014	0.447	-1.096	0.146	14.394	-1.892	13.553	9,756
Δ (Retail price)	0.010	0.005	0.549	-1.146	0.144	14.461	-1.935	15.031	9,808
Average profit margin	0.158	0.153	0.265	0.110	0.034	0.212	0.972	4.093	48

Notes: Table reports summary statistics for the 48 US states in the sample over the period January 1994 to February 2011. All variables except for the price of crude oil (dollars per barrel) are in dollars per gallon. Δ denotes change over the previous month. The gross profit margin is computed as the difference between the retail and the wholesale price for conventional motor gasoline. The average profit margin is calculated as $\sum_t \left(retailprice_{i,t} - wholesaleprice_{i,t}\right)/T$ and is measured in dollars per gallon of unleaded gasoline.
Source: Energy Information Administration (EIA)

TABLE 3

Bayes factors for model selection

	$p = 2$	$p = 3$	$p = 4$	$p = 5$
$q = 1$	1.000	0.312	0.171	0.005
$q = 2$	0.216	51.11	1.556	0.054
$q = 3$	0.116	0.005	0.001	0.001
$q = 4$	0.0032	0.001	0.000	0.000

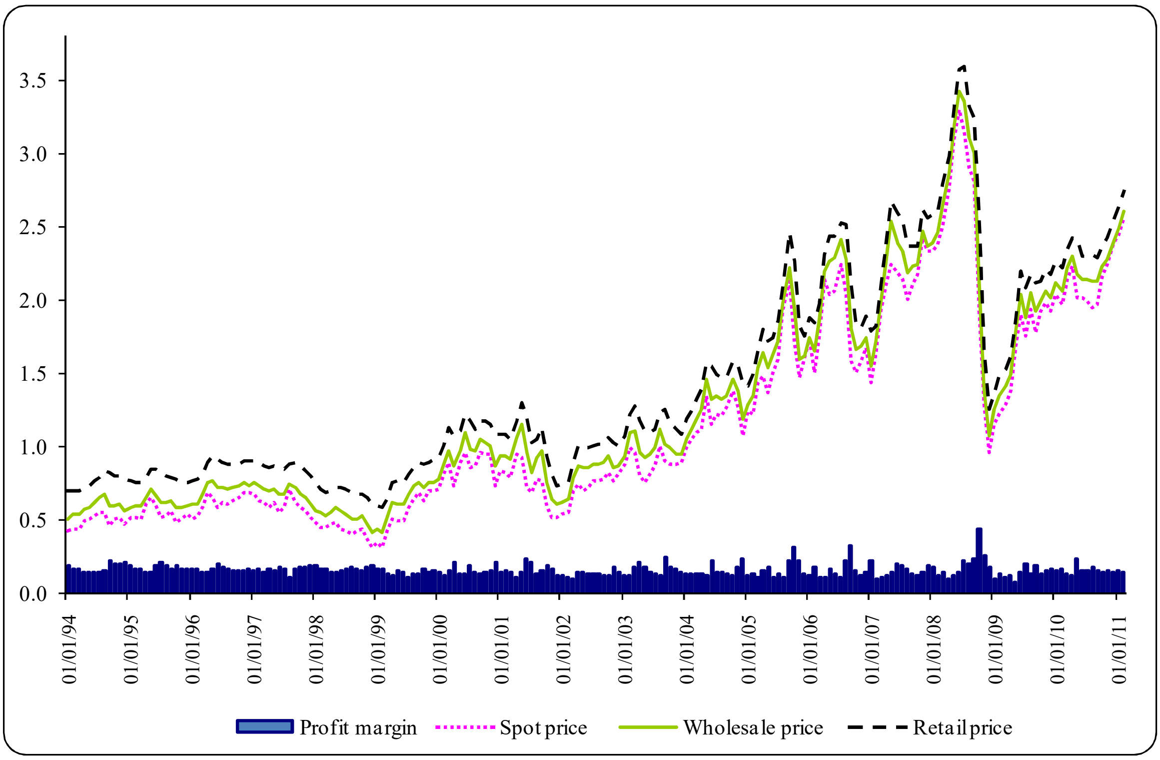
TABLE 4

Posterior means and standard deviations

Coefficients	Spot gasoline price Panel A		Crude oil price Panel B	
	Wholesale	*Retail*	*Wholesale*	*Retail*
ρ^-	-0.421 (0.085)	-0.515 (0.031)	-0.418 (0.027)	-0.522 (0.016)
ρ^+	-0.571 (0.036)	-0.638 (0.022)	-0.589 (0.022)	-0.677 (0.016)
β^+	0.920 (0.025)	0.917 (0.017)	0.913 (0.015)	0.919 (0.006)
β^-	0.872 (0.033)	0.910 (0.015)	0.875 (0.021)	0.914 (0.008)
π_0^+	0.313 (0.015)	0.441 (0.020)	0.302 (0.011)	0.461 (0.015)
π_0^-	0.263 (0.022)	0.381 (0.035)	0.212 (0.014)	0.392 (0.033)
$\sum_{j=1}^{q-1} \pi_j^+$	0.817 (0.007)	0.915 (0.018)	0.821 (0.005)	0.934 (0.008)
$\sum_{j=1}^{q-1} \pi_j^-$	0.770 (0.005)	0.887 (0.019)	0.781 (0.007)	0.892 (0.011)
λ	0.142 (0.033)	0.137 (0.021)	0.121 (0.021)	0.111 (0.013)
a	0.631 (0.077)	0.717 (0.022)	0.055 (0.044)	0.732 (0.015)

Notes: The entries in this table report posterior means and posterior standard deviations of the most important parameters of the model. Results are reported using both Spot and Crude oil price and Wholesale / Retail separately for the two time series.

Figure 1. Gasoline prices and profit margin (USD/gallon)



Source: EIA

Figure 2a. Marginal posterior densities (Spot price of gasoline)

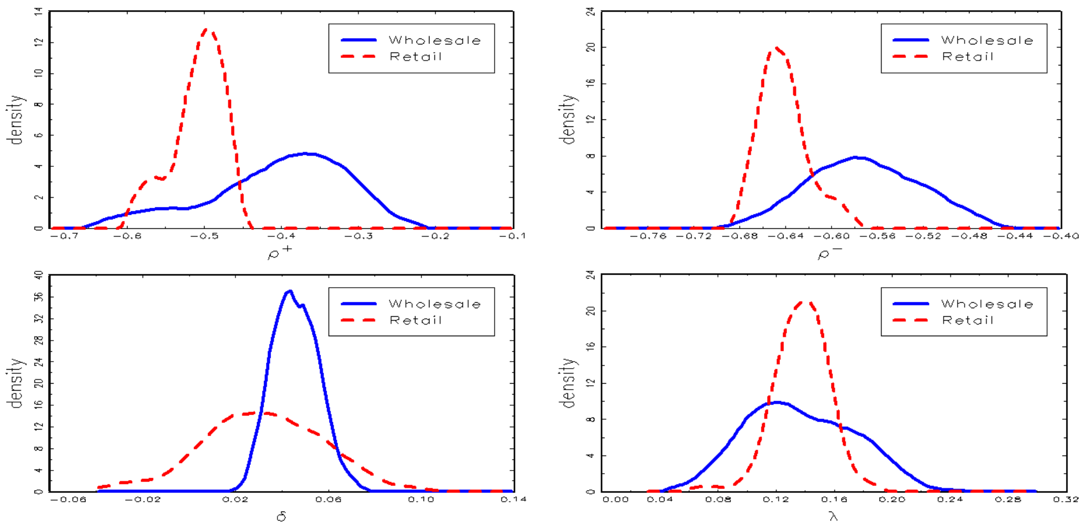


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Figure 2b. Marginal posterior densities (Crude oil price)

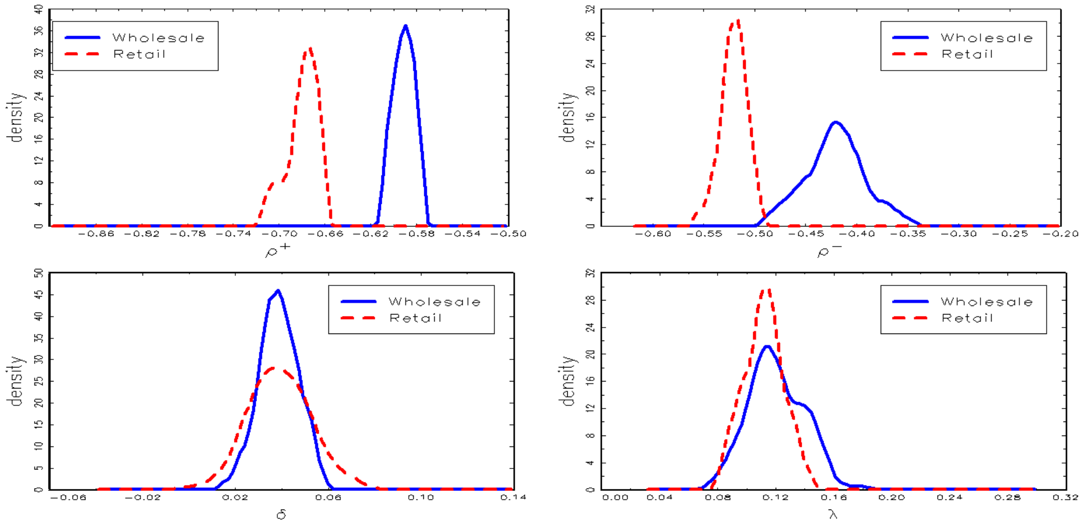
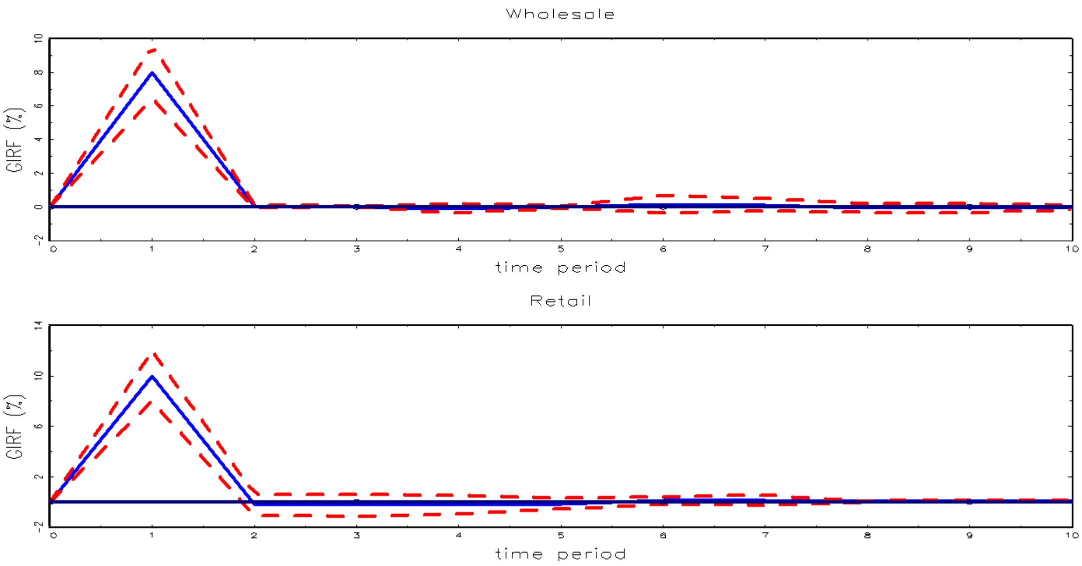
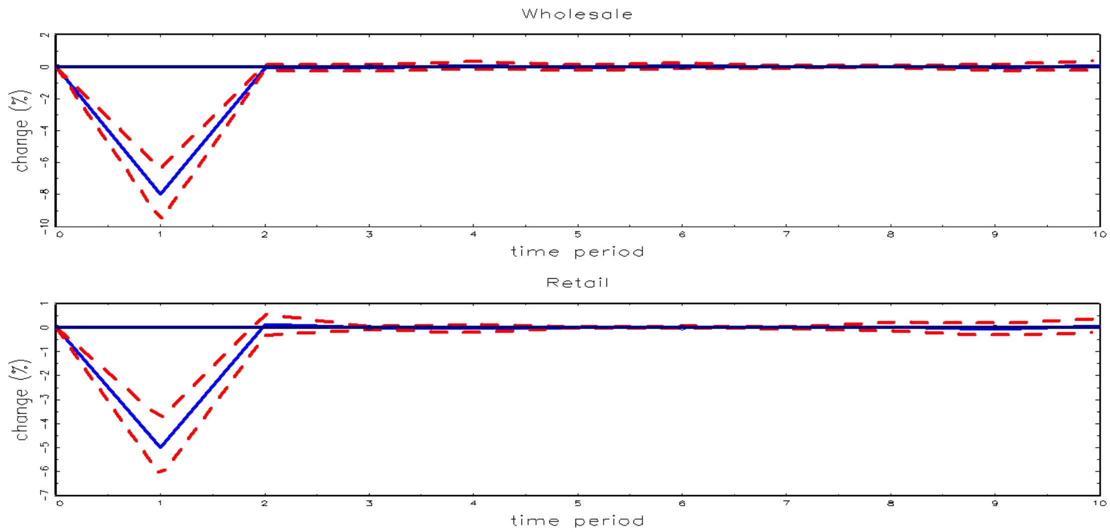


Figure 3a. Posterior generalized impulse response functions (Spot gasoline - 10% increase)



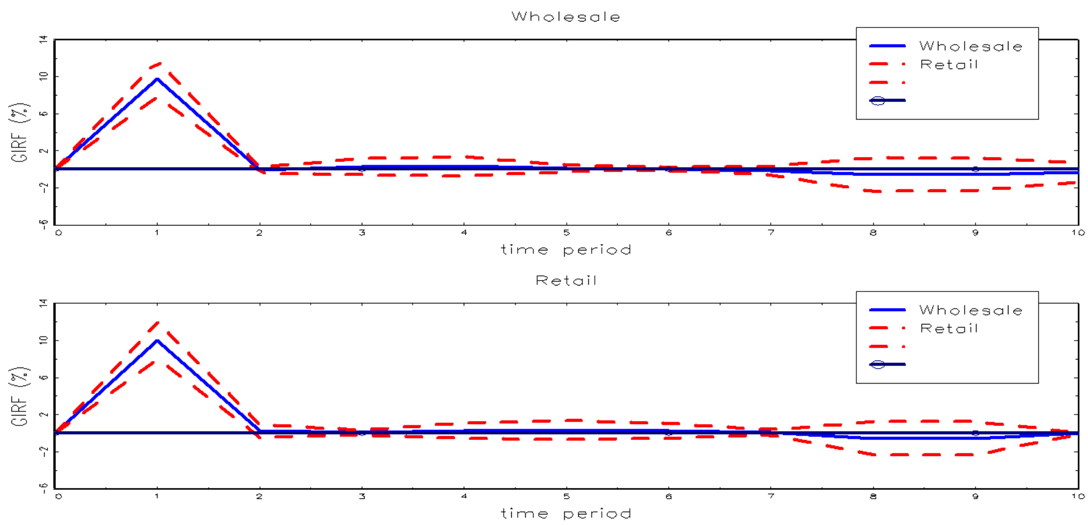
Notes: The figures present posterior mean estimates of impulse response functions corresponding to 10% increase in Spot price of gasoline. The vertical axis is in percentage units. 95% Bayes probability intervals (computed by MCMC) are shown in dotted lines.

Figure 3b. Posterior generalized impulse response functions (Spot gasoline - 10% decrease)



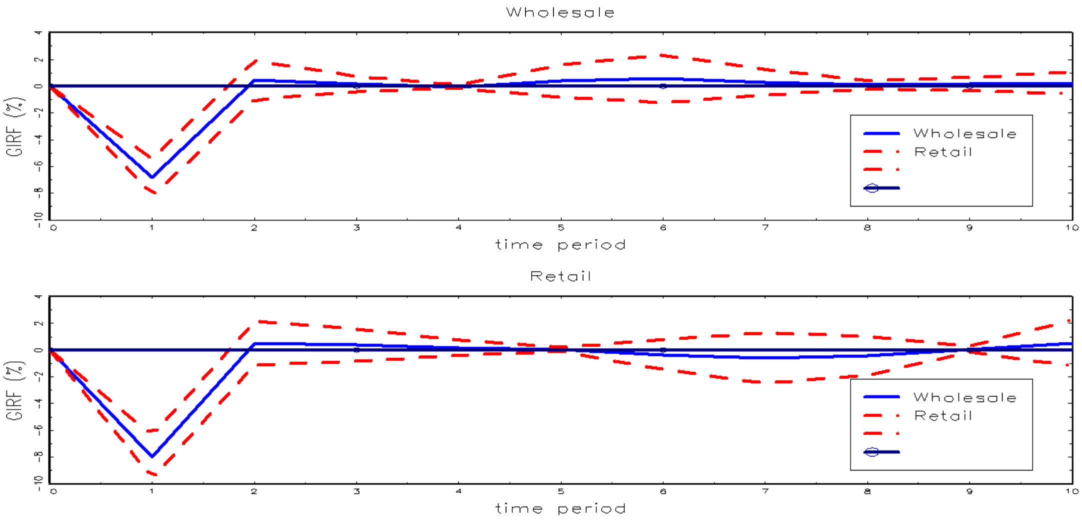
Notes: The figures present posterior mean estimates of impulse response functions corresponding to 10% decrease in Spot price of gasoline. The vertical axis is in percentage units. 95% Bayes probability intervals (computed by MCMC) are shown in dotted lines.

Figure 4a. Posterior generalized impulse response functions on high profit margin states (Spot gasoline - 10% increase)



Notes: The figures present posterior mean estimates of impulse response functions corresponding to 10% increase in Spot price of gasoline. The vertical axis is in percentage units. 95% Bayes probability intervals (computed by MCMC) are shown in dotted lines.

Figure 4b. Posterior generalized impulse response functions on low profit margin states (Spot gasoline - 10% decrease)



Notes: The figures present posterior mean estimates of impulse response functions corresponding to 10% decrease in Spot price of gasoline. The vertical axis is in percentage units. 95% Bayes probability intervals (computed by MCMC) are shown in dotted lines.

Figure 5. Bayes factors against structural breaks

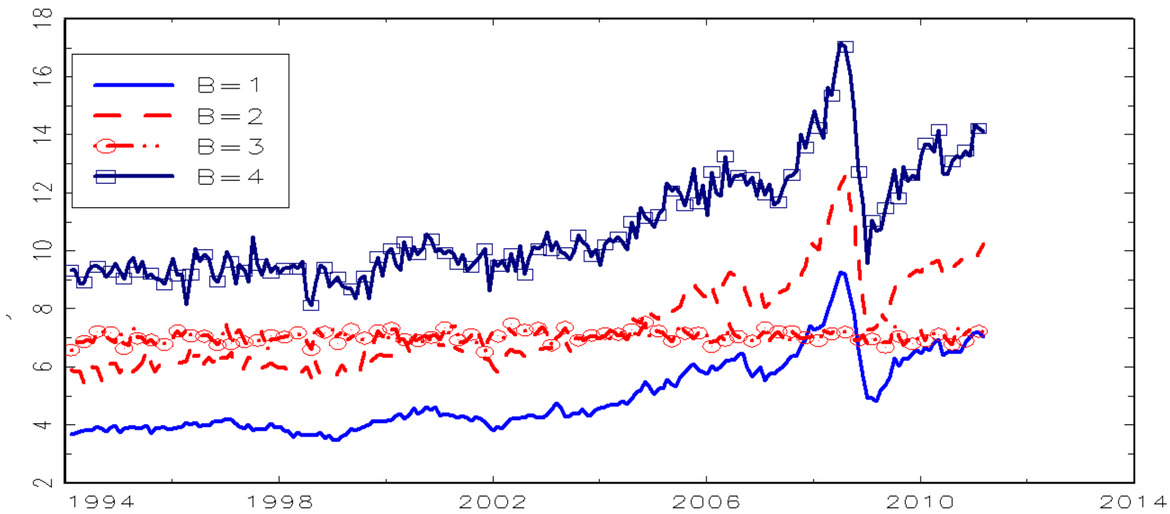
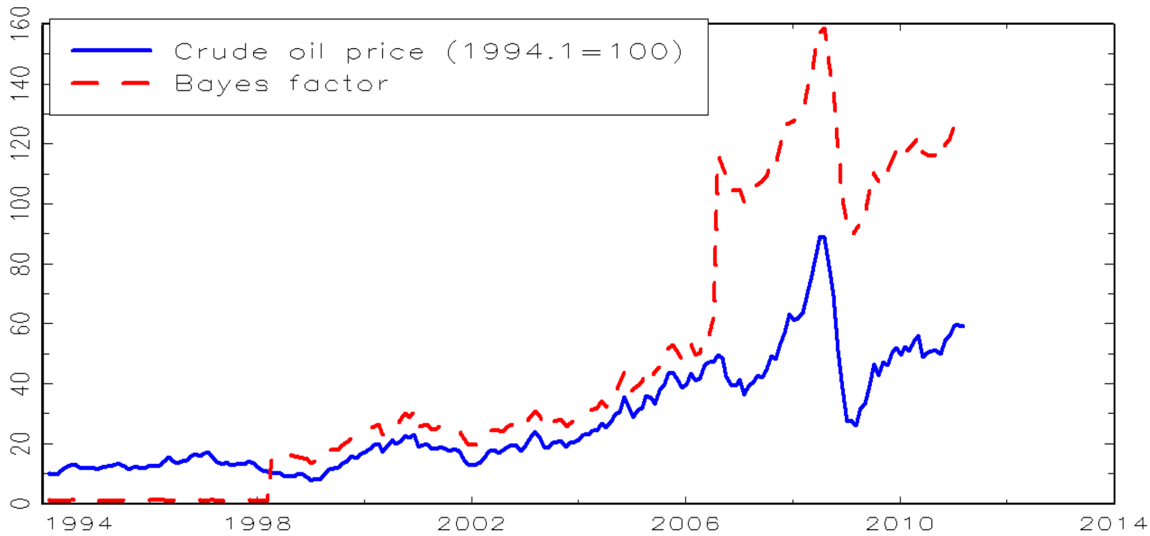


Figure 6. Recursive Bayes factors



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