EVIDENCE ON ASYMMETRIC GASOLINE PRICE RESPONSES FROM ERROR CORRECTION MODELS WITH GARCH ERRORS

by

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Abstract

This paper examines the possible asymmetric response of gasoline prices to crude oil price changes using an error correction model with GARCH errors. Recent papers have looked at this issue, including Borenstein, Cameron and Gilbert (1997), who find asymmetry in the response of retail gasoline prices to crude oil price changes, and Bachmeier and Griffin (2003), who find no evidence of asymmetry in both the response of wholesale and retail gasoline prices to crude oil price changes based on two-step Engle-Granger estimation procedure. These papers both estimate a form of error correction model, but neither accounts for autoregressive heteroskedasticity in estimation and testing for asymmetry and neither takes the response of crude oil price into consideration.

We find that time-varying volatility of gasoline price disturbances is an important feature of the data, and when we allow for asymmetric GARCH errors and investigate the system wide impulse response function, we find evidence of asymmetric adjustment to crude oil price changes in weekly retail gasoline prices.

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1. Introduction

Many observers claim that gasoline prices rise quickly but decline slowly. This issue of asymmetry in the response of gasoline prices to positive and negative shocks is one that has been investigated by previous researchers. Bacon (1991) looked at the U.K.'s gasoline market and described the asymmetric adjustment as a "rockets and feathers" phenomenon. Prices rise like a rocket and fall like a feather. In Bacon's work he found that the asymmetry was in the response of gasoline prices to crude oil price changes. He claimed that when crude oil prices increased, gasoline price responded very quickly, but when crude oil prices decreased, gasoline prices were much slower to respond.

Borenstein, Cameron and Gilbert (1997) (hereafter BCG) looked at the issue of asymmetry with an error correction model (or ECM). They estimated an ECM for weekly and semimonthly retail gasoline prices, with crude oil prices as an explanatory variable. They report strong evidence that gasoline prices respond asymmetrically to crude oil price changes, supporting the earlier findings by Bacon (1991).

Following up on BCG, Bachmeier and Griffin (2003) (hereafter BG) also use an ECM but with the two-step Engle-Granger estimation procedure instead of the less traditional approach used by BCG. BG investigates both daily spot (wholesale) gasoline prices and retail gasoline prices to see their response to crude oil price changes. BG report no evidence of asymmetry in the response of spot gasoline prices to crude oil price changes, and no evidence of asymmetry in the response of retail gasoline prices to crude oil price change if the two-step Engle-Granger estimation procedure is used for the ECM. BG claims BCG's asymmetry evidence may rest on their nonstandard estimation approach.

These papers provide differing conclusions regardng the retail gasoline price response to crude oil prices, based on different econometric model specifications and somewhat different data. We look again at the possible asymmetry of retail gasoline prices response, in order to consider a broader array of econometric models including system-wide impulse response functions and various specifications of heteroskedasticity. It is well known that assumptions of homoskedasticity, when inappropriate, can cause misleading inference, and we find that prior tests for asymmetry are strongly influenced by the treatment of possible heteroskedasticity.

Our paper investigates the system-wide retail gasoline price response instead of the univariate error correction model used in most previous research. The previous literature generally estimates a dynamic model for the retail gasoline price response and considers the impact of a crude oil price shock without allowing for crude oil prices to exhibit a dynamic response to the shock itself nor to changes in the retail price. This paper begins from the bivariate VAR model and estimates both the retail gasoline price impulse response function (IRF) and the crude oil price IRF in a system context. For expository purposes we call these system-wide IRFs to distinguish them from the IRF presented in BCG's paper.

Our approach is to estimate two broad classes of models that allow potential asymmetric responses. We focus on error correction models that are similar to those estimated by both BCG and BG. These models explicitly allow for differential dynamic responses to shocks. More specifically, the coefficients on explanatory variables including own-lags are allowed to vary depending on whether crude oil prices have increased or decreased. We will estimate versions of these models that follow the BCG and BG framework, and also versions that are more in accord with standard threshold model specifications, where there is a single threshold variable affecting all right hand side coefficients[1]. In all cases our estimation takes account of the presence of autoregressive conditional heteroskedasticity. In particular, we allow different asymmetric models for conditional volatility -- Exponential GARCH, GJR-GARCH, and logistic smooth transition GARCH -- to check whether the asymmetry conclusion is sensitive to the different choice of the conditional volatility model.

When considering these different models we focus on testing for asymmetric responses as indicated by different coefficients on positive and negative changes in crude oil prices. We attempt to characterize the nature of the asymmetry, including the speed of adjustment to a disturbance (rockets versus feathers), the size of adjustment to a disturbance, the permanence of shocks, and the impact of the initial state.

Overall, we find evidence of asymmetry in the weekly retail gasoline prices response on the crude oil prices in both classes of models. This asymmetry is both in the speed of adjustment to shocks and in the magnitude of adjustment. Rising crude oil prices tend to cause somewhat more rapid responses of gasoline prices than falling crude oil prices. Over comparable horizons, rising crude oil prices tends to cause a somewhat greater magnitude response of gasoline prices than falling

[1] Such threshold models are common in the literature. Bradley and Jansen (2000) is just one example.

crude oil prices. In all models we find it is important to account for ARCH errors.[2]

2. Model Specification

We investigate two sets of models. The first is an asymmetric error correction model that was popular in the previous literature. This model is often specified as a single-equation ECM, and for our purposes the key feature is that it is estimated assuming homoskedastic disturbances. We will compare results for this model with a second set of models that are asymmetric error correction models with a version of heteroskedastic disturbances.

2.1 Models with Homoskedastic Disturbances

Our starting point is the basic mark-up model. Obviously crude oil is a vital input into gasoline production, and crude oil prices are one of the most important cost factors affecting gasoline prices. In fact, the cost of crude oil accounts for roughly half of the retail gasoline price. Therefore it is natural to begin our analysis with the following mark-up model, and one that has been is widely used in previous research.

$$LPG_t = \alpha + \beta \cdot LPC_t \qquad (1)$$

[2] In addition to the debate over the empirical facts on asymmetry, there is a debate over theoretical explanations, and a number of explanations have been offered. Market concentration is a usual suspect. However, it is fair to say that a consensus is lacking. Peltzman (2000) and Brown and Yucel (2000) note that it is difficult to find a model based on market concentration that will explain asymmetric downstream price adjustment to an upstream price change, although Borenstein and Shepard (2002) point to tacit collusion and margins increasing when expected future demand increases. Johnson (2002) claims asymmetry is due to consumer search costs, and provides evidence supporting the search explanation over the oligopolistic behavior explanation from consumer gasoline and diesel markets. However, Radchenko (2005) shows that asymmetry declines with volatility, and argues that this supports oligopolistic coordination explanations over search-based explanations.

Here LPG is the log price of retail gasoline and LPC is the log price of crude oil. Both the log price of gasoline and the log price of crude oil appear to be I(1) processes, non-stationary in levels but stationary in differences. Gasoline prices and crude oil prices also appear to be cointegrated. When we test for cointegration between the log spot gasoline price and the log spot crude oil price, and separately, between the log retail gasoline price and the log spot crude oil price, we cannot reject cointegration.

Cointegration between LPG and LPC is consistent with using an ECM, the approach we take here and the approach used earlier by both BCG and BG. We use a two-step estimation strategy to estimate the ECM.[3]

Symmetric Error Correction Model

Our starting point is a standard, symmetric ECM. This model specifies that changes in the log price of gasoline is a function of lagged changes in the log price of gasoline, current and lagged changes in the log price of crude oil, and the lagged error correction term. This specification assumes that crude oil prices are weakly exogenous to gasoline prices.

$$\Delta LPG_t = \alpha + \sum_{i=0}^{m} \beta_i \Delta LPC_{t-i} + \sum_{j=1}^{n} \gamma_j \Delta LPG_{t-j} + \lambda(LPG_{t-1} - \varphi LPC_{t-1}) + \varepsilon_t \qquad (2)$$

We use this model as a point of departure, in order to compare to a model allowing asymmetry.

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[3] We report the cointegration test results in Appendix Tables A1.

Asymmetric Error Correction Model

An asymmetric ECM can be specified in a variety of ways, but the model frequently used by researchers in this area, including BCG and BG, specify different coefficients for positive and negative lagged changes in gasoline prices and for positive and negative current and lagged changes in crude oil prices. In what follows the superscript '+' refers to a positive change and the superscript '-' refers to a negative change. A common asymmetric ECM specification is:

$$\Delta LPG_t = \alpha + \sum_{i=0}^{m}(\beta_i^{+}\Delta LPC_{t-i}^{+} + \beta_i^{-}\Delta LPC_{t-i}^{-}) + \sum_{j=1}^{n}(\gamma_j^{+}\Delta LPG_{t-j}^{+} + \gamma_j^{-}\Delta LPG_{t-j}^{-}) + \lambda(LPG_{t-1} - \varphi LPC_{t-1}) + \varepsilon_t \quad (3)$$

Here $\Delta LPC^{+} = \Delta LPC$ if $\Delta LPC > 0$, and $\Delta LPC^{+} = 0$ if $\Delta LPC < 0$. Similarly, $\Delta LPC^{-} = \Delta LPC$ if $\Delta LPC < 0$, and $\Delta LPC^{-} = 0$ if $\Delta LPC > 0$. ΔLPG^{+} and ΔLPG^{-} are defined analogously.

As an alternative to equation (3), we can specify an asymmetric ECM within a standard threshold framework where the model switches between regimes depending on an indicator variable that switches value between zero and one depending on the relationship of the (single) threshold variable to a threshold value. In comparison, equation (3) has multiple threshold variables or states, depending on the sign of current and lagged values of ΔLPC and ΔLPG.

In our threshold asymmetric ECM, the threshold variable will be a lagged valued of LPG (or LPC), and the threshold level will be set at zero. We can write this threshold asymmetric ECM as:

$$\Delta LPG_t = \alpha + \sum_{i=0}^{m}(\beta_i^+ \Delta LPC_{t-i} \cdot I(Z_{t-d}) + \beta_i^- \Delta LPC_{t-i}) +$$
$$\sum_{j=1}^{n}(\gamma_j^+ \Delta LPG_{t-j} \cdot I(Z_{t-d}) + \gamma_j^- \Delta LPG_{t-j}) + \lambda(LPG_{t-1} - \varphi LPC_{t-1}) + \varepsilon_t \quad (4)$$

Here $I(Z_{t-d})$ is the indicator variable, with $I(Z_{t-d}) = 1$ if $Z_{t-d} > 0$ and $I(Z_{t-d}) = 0$ if $Z_{t-d} < 0$. The variable Z is the threshold variable, either $Z = \Delta LPG$ or $Z = \Delta LPC$. The subscript d is called the delay parameter, and for our purposes $d=0, 1,$ or 2.

2.2 Models with GARCH errors

This section describes our preferred specifications. It contains two points of departure from BCG and BG. First, in those papers the symmetry or asymmetry discussion is based on results from a univariate ECM or threshold model, which necessarily ignores system-wide dynamics and feedback between retail prices and crude oil prices. In constrast, we specify a bivariate vector ECM (VECM) and calculate IRFs for the system we estimate. Second, previous work assumes homoskedastic disturbances, but we will test for and model versions of GARCH.

A bivariate VECM Model

We consider a bivariate VECM model of the form,

$$\begin{pmatrix} \Delta LPG \\ \Delta LPC \end{pmatrix}_t = A(L)\begin{pmatrix} \Delta LPG \\ \Delta LPC \end{pmatrix}_{t-1} + BZ_{t-1} + \begin{pmatrix} \varepsilon_G \\ \varepsilon_C \end{pmatrix}_t \quad (5)$$

Here $A(L) = \begin{pmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{pmatrix}$, where L is the lag operator, Z is the error correction term, and $B = (b_1, b_2)'$ is a 2x1 vector. The variance covariance matrix of $\begin{pmatrix} \varepsilon_G \\ \varepsilon_C \end{pmatrix}_t$ is given by:

$$\mathrm{var}\begin{pmatrix} \varepsilon_G \\ \varepsilon_C \end{pmatrix}_t = \begin{pmatrix} \sigma_{GG,t} & \sigma_{GC,t} \\ \sigma_{GC,t} & \sigma_{CC,t} \end{pmatrix} \tag{6}$$

We will test for autoregressive conditional heteroskedasticity in the disturbances in (5). In results to be reported below, we find ARCH in the retail gasoline price innovations, but not in the crude oil price innovations. We also find evidence that crude oil prices are weakly exogenous, that the error correction term does not enter the crude oil price equation, so $b_2 = 0$.

These empirical findings suggest a particular Cholesky decomposition and a particular specification of the ARCH structure of our model innovations. In particular, we model the crude oil price residual ε_C as exogenous, so ε_C has a contemporaneous effect on ε_G but ε_G does not have a contemporaneous effect on ε_C. We can write this more explicitly as:

$$\varepsilon_{Gt} = \pi_1 \varepsilon_{Ct} + \eta_t, \tag{7}$$

where we suppose π_1 is constant and η_t is that part of the innovation in the gasoline price equation that is uniquely determined by the gasoline market. Equation (7) specifies the contemporaneous correlation between ε_C and ε_G in a way consistent with our Cholesky decomposition. Note that we can substitute equation (7) into the bivariate VECM model (5) to get,

$$\begin{pmatrix} \Delta LPG \\ \Delta LPC \end{pmatrix}_t = \begin{pmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{pmatrix} \begin{pmatrix} \Delta LPG \\ \Delta LPC \end{pmatrix}_{t-1} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix} Z_{t-1} + \begin{pmatrix} \pi_1 \varepsilon_{Ct} + \eta_t \\ \varepsilon_{Ct} \end{pmatrix} \tag{8}$$

From equation (8) we can derive our crude oil price equation as:

$$\Delta LPC_t = A_{21}(L) \cdot \Delta LPG_{t-1} + A_{22}(L) \cdot \Delta LPC_{t-1} + b_2 \cdot Z_{t-1} + \varepsilon_{Ct} \tag{9}$$

where we will eventually argue that $Var(\varepsilon_{Ct}) = \sigma_{cc}^2$, a constant.

We can also rewrite equation (9) to derive the crude oil price residual ε_C and substitute this into the gasoline price equation in the bivariate VECM model (8). Reorganizing, we obtain the following retail gasoline price equation:

$$\begin{aligned} \Delta LPG_t = & (A_{11}(L) - \pi_1 A_{21}(L)) \cdot \Delta LPG_{t-1} + \pi_1 \cdot \Delta LPC_t \\ & + (A_{12}(L) - \pi_1 A_{22}(L)) \cdot \Delta LPC_{t-1} + b_1 \cdot Z_{t-1} + \eta_t \end{aligned} \tag{10}$$

Here contemporaneous crude oil prices enter as an explanatory variable, and the error term η_t is that part of the innovation in the retail gasoline price that is uniquely determined in the gasoline market. We will assume that this is the term embodying the GARCH effects.

We estimate equation (10) with its implicit decomposition of the gasoline price disturbance or innovation term. This equation for gasoline prices is also the form used in much of the previous research, so it allows easy comparison of our results with the previous work.

In estimating GARCH models, we specify an equation for the conditional mean and an equation for the conditional variance. For the conditional mean we look at two versions, an asymmetric ECM and an asymmetric threshold ECM. These are essentially the models reported in equations (3) and (4) above, with the explicit assumption on the disturbance term.

Asymmetric ECM:

$$\Delta LPG_t = \alpha + \sum_{i=0}^{m}(\beta_i^+ \Delta LPC_{t-i}^+ + \beta_i^- \Delta LPC_{t-i}^-) + \sum_{j=1}^{n}(\gamma_j^+ \Delta LPG_{t-j}^+ + \gamma_j^- \Delta LPG_{t-j}^-)$$
$$+ \lambda^+ (LPG_{t-1} - \varphi LPC_{t-1}) + \lambda^- (LPG_{t-1} - \varphi LPC_{t-1}) + \eta_t \quad (11)$$

Asymmetric Threshold ECM:

$$\Delta LPG_t = \alpha + \sum_{i=0}^{m}(\beta_i^+ \Delta LPC_{t-i} \cdot I(Z_{t-d}) + \beta_i^- \Delta LPC_{t-i}) + \sum_{j=1}^{n}(\gamma_j^+ \Delta LPG_{t-j} \cdot I(Z_{t-d})$$
$$+ \gamma_j^- \Delta LPG_{t-j}) + \lambda^+ (LPG_{t-1} - \varphi LPC_{t-1}) + \lambda^- (LPG_{t-1} - \varphi LPC_{t-1}) + \eta_t \quad (12)$$

For each specification, we consider the impact of autoregressive conditional heteroskedasticity (ARCH) on our estimation results. The standard LM test for ARCH indicates strong evidence for ARCH in residuals from both our asymmetric ECM models. We provide estimates of our asymmetric ECMs specified with asymmetric generalized autoregressive conditional heteroskedasticity (GARCH) errors. This means, in terms of equation (10), that the gasoline price residual η_t follows a GARCH process.

We extend the above asymmetric ECMs to incorporate different asymmetric GARCH specifications. In particular, we consider models with Exponential GARCH errors, GJR-GARCH errors, and Logistic Smooth Transition GARCH errors.

Asymmetric ECMs with Exponential GARCH Errors

The EGARCH model was proposed by Nelson (1991), and can capture possible asymmetries in the response volatility response.[4] Thus we specify the conditional mean as in the asymmetric ECM in equation (11) above or in the asymmetric threshold ECM in equation (12) above. For either model we specify an EGARCH model of the conditional variance as:

$$\log(\sigma_t^2) = \omega + \sum_{j=1}^{q} \eta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^{p} \xi_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^{r} \phi_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \tag{13}$$

This specification allows asymmetry in the response of the conditional variance to shocks. For instance, large positive shocks will have a greater impact on the variance than negative shocks when Φ_K is positive.

Asymmetric ECMs with GJR - GARCH Errors

Another popular asymmetric conditional variance specification is introduced by Glosten, Jagannathan, and Runkle (1993), so called GJR- GARCH. The conditional variance equation will be

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \eta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \xi_i \varepsilon_{t-i}^2 + \sum_{k=1}^{r} \phi_k \varepsilon_{t-k}^2 \cdot f_k \tag{14}$$

Here f_k = 1 when $\varepsilon_{t-k} > 0$; f_k = 0 when $\varepsilon_{t-k} \le 0$.

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[4] We also considered EGARCH-in-mean specifications, allowing the asymmetric volatility to directly impact the response of gasoline prices, but we found little evidence that time-varying volatility impacts the conditional mean.

Asymmetric ECMs with LST - GARCH Errors

A final more generalized model also investigate the asymmetric response of conditional variance is Logistic Smooth Transition GARCH model (LST-GARCH) which has been introduced in Gonzalez and Rivera (1998) and Hagerud (1996). The conditional variance equation of LST-GARCH(p,q) has the following form.

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \eta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} (1 - F(\varepsilon_{t-i})) \cdot \xi_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} F(\varepsilon_{t-i}) \cdot \phi_i \varepsilon_{t-i}^2 \quad (15)$$

Here F(.) is logistic transition function,

$$F(\varepsilon_{t-i}) = \frac{1}{1+\exp(-\lambda \varepsilon_{t-i})}, \quad \lambda > 0 \quad (16)$$

If lambda is quite large, the LST-GARCH specification converges to the GJR-GARCH model. That is, the LST-GARCH is actually a more general form of GJR-GARCH model.[5]

3. Estimation Methods and Diagnostic Tests

We estimate the ECM models under homoskedasticity and also under various GARCH specifications. Estimation is by quasi-maximum likelihood. We assume the residual ε_t has a Student's t distribution, to better capture the excess kurtosis in the data. We use the Optmum procedure in GAUSS 6. When we estimate the asymmetric models, we take the GARCH estimation results as starting values. The different types of asymmetric GARCH models are estimated to provide evidence on how sensitive

[5] The Appendix has a graph of the logistic smooth transition function for different values of λ. It makes clear that the bigger is lambda, the faster the transition between regimes.

the results are to the specific model of heteroskedasticity.

A variety of diagnostic tests are used to check that the asymmetric GARCH-type models are correctly specified. First, we examine Lagrange multiplier (LM) tests for autoregressive conditional heteroskedasticity (ARCH) in the residuals (Engle 1982). Second, we calculate the Ljung and Box (1979) Q statistics for the level and the square of the residuals, to examine possible serial correlation in the residuals. Third, we examine the ability of the models to deal with potential biases and identify potential misspecification of the conditional variance. We calculated three tests proposed by Engle and Ng (1993) -- the Sign Bias Test, the Negative Size Bias Test and the Positive Size Bias Test. We also calculate the joint test.

For these tests we define the dummy variable S_{t-1}^{-} to be one when the residual ε_{t-1} is negative and equals zero otherwise. We define S_{t-1}^{+} to be one minus S_{t-1}^{-}. Finally, we define v_t^2 as the squared normalized residuals. The sign bias test, negative size bias test and positive bias test are based on the following regressions.

$$v_t^2 = a + b \cdot S_{t-1}^{-} + e_t \quad (17a)$$

$$v_t^2 = a + b \cdot S_{t-1}^{-}\varepsilon_{t-1} + e_t \quad (17b)$$

$$v_t^2 = a + b \cdot S_{t-1}^{+}\varepsilon_{t-1} + e_t \quad (17c)$$

The sign bias test is based on the significance of the slope coefficient on S_{t-1}^{-} in (17a). The negative size bias test is based on the significance of the slope coefficient on $S_{t-1}^{-}\varepsilon_{t-1}$ in (17b). The positive size bias test is based on the significance test of the slope coefficient on $S^{+}_{t-1}\varepsilon_{t-1}$ in (17c). Engle and Ng (1993) also propose a joint test based on regression

$$v_t^2 = a + b_1 \cdot S^{-}_{t-1} + b_2 \cdot S^{-}_{t-1}\varepsilon_{t-1} + b_3 \cdot S^{+}_{t-1}\varepsilon_{t-1} + e_t \qquad (18)$$

The t-ratios for b_1, b_2 and b_3 corresponds to the sign bias, negative size and positive size bias tests, respectively. The joint test is the LM test calculated as $T \cdot R^2$. If the variance model is correctly specified, all tests should be insignificant, which would indicate that the variables realized in the past but not included in the variance model have no power to predict the standardized residuals.

4. Data

Our retail price series is available from the U.S. Department of Energy website[6] from 1990. We use the U.S. regular conventional retail gasoline prices and the West Texas Intermediate crude oil price. There are some holes in the data series so that we begin our sample from January 1991. Our data covers the period from January 21, 1991 to February 13, 2006, a total 787 observations. This data set is similar to the weekly data set used by BG and BCG, but our series span a longer period. BCG and BG's weekly data sets cover the period from March 1986 to November 1992.

Figure 2 (a) provides a graph of the log retail gasoline price (LRP) and the log crude oil price (LCP), weekly, from January 1991 through the middle of February 2006. Retail gasoline prices, after holding fairly steady from 1990 through 1997, exhibited some downward trend in 1998,

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[6] http://www.eia.doe.gov/

followed by an upward trend to a new plateau of sorts by 2000, then increased volatility but an upward trend running through 2005. Crude oil prices show more apparent volatility, including a more pronounced decline during 1997 – 1998, a more dramatic upward movement in 1999, and a fairly steady upward trend from 2002 through 2005. For future reference, there seems to be a narrowing of the gap between these series after 2002.

Figure 2 (b) and (c) provides graphs of the log difference of gasoline prices (DLRP) and crude oil prices (DLCP). A noteworthy feature of both the gasoline price and the crude oil price date is the apparent increase in volatility. For the data on differences in gasoline prices, volatility seems to have increased after 1997. For the data on difference in crude oil prices, the volatility seems to have increased since 1996.

Table 1 summarizes some statistical features of the data. The standard deviation of crude oil prices, in levels and differences, is higher than the standard deviation of retail gasoline prices. The differenced data show exhibit fat tails, especially retail gasoline prices.

5. Estimation Results

We first examine the weekly data set for retail gasoline prices using the asymmetric ECM from the prior literature. A variety of diagnostic tests are conducted, to check for possible misspecification of the models. We then turn to our results for the asymmetric error correction models with GARCH errors. We then estimate various types of asymmetric GARCH error models. Finally, we present and analyze the impulse response functions of the ECM and threshold models.

Table 2 presents our coefficient estimates for the asymmetric ECM for weekly retail gasoline prices in column headed ECM. These are estimates for the homoskedastic model. Prior researchers have tested asymmetry with Wald tests of the hypothesis that the coefficients on the positive and negative price changes are equal. We report results of tests for asymmetry in Table 3. The column headed "ECM" reports tests for equality of coefficients on explanatory variables DLCP, DLCP(-1), DLRP(-1), and DLRP(-2). Note that equality of the coefficients on crude prices is not rejected, indicating no asymmetry in the adjustment of retail gasoline prices to crude oil price changes. Only the coefficients on DLRP(-1) are found to be statistically significantly different for positive and negative values of DLRP(-1).

However, we run a series of diagnostic tests on the ECM model. Results of the ARCH test are reported in Table 4. The first entry in Table 4, headed "Retail Gasoline Price Model: ECM" reports results of the ARCH test for our ECM model. Note that for lags one, two, or three, the test result is to strongly reject homoskedasticity.

Table 5 reports the Ljung-Box Q statistic for the residuals of the ECM model, both the levels and the squares of the residuals. We calculate the first 30 estimated residual autocorrelations. The test statistic Q(30) is 56.28 for the level of the residuals, and 100.80 for the squared residuals. The Chi-square critical value at the 5% significance level is 43.77. Thus for the traditional ECM we can strong evidence of serial correlation in both level and squared residuals.

These diagnostic tests suggest that the traditional ECM is misspecified, so we turn to models allowing heteroskedasticity. Estimation results are reported in Table 2 under the column headed

ECM-EGARCH. For the ECM-EGARCH model, we report estimates for both the mean equation and the variance equation. We specify that the conditional distribution of disturbances is a t-distribution and estimate the degrees of freedom as five. We do this because the residuals from the homoskedastic ECM show strong kurtosis, as can be seen in Figure 2.

For the ECM with EGARCH errors we cannot reject the null of no remaining ARCH, as can be seen in Table 4 under the heading "Retail Gasoline Price Model: ECM-EGARCH." The probability values are hugely greater than even ten percent for lags one, two, or three. Further, we report results of the Ljung-Box Q statistic in Table 5 under the headings "ECM-EGARCH." We again calculate the first 30 estimated residual autocorrelations, and the statistic Q(30) equals 31.29 for the level of the residuals and 9.16 for the squared residuals. The Chi square critical value for the 5% significance level is 43.77. Thus for our ECM specification with EGARCH errors we find no serial correlation in the levels or squares of the residuals.

We report asymmetry tests in Table 3. Recall that when we conduct this test for the ECM with homoskedastic errors we can't reject symmetry for the coefficients on crude oil price changes, a finding that is in accord with BG's conclusion. Note, however, that when we conduct this test for our ECM-EGARCH model we strongly reject the null of symmetry of the crude oil price coefficients. The probability value for this hypothesis test is 0.003. Thus we find that allowing EGARCH errors is key for our asymmetry result, and that BG's conclusion to the contrary is due to specifying homoskedastic errors.

We also calculate the sign and size bias tests for our ECM-EGARCH model, and report the results in Table 6. We cannot reject the hypothesis that the residuals from our ECM-EGARCH model have not sign bias, negative size bias, or positive size bias at even the ten percent significance level. To compare this model with others, we also estimated an ECM-ARCH model and an ECM-GARCH model. We do not report the model estimates here, but the diagnostic tests in Table 6 indicate that the ECM-ARCH model exhibits sign bias, and the ECM-GARCH model marginally rejects sign bias at the ten percent significance level. The probability value is 0.106, providing some motivation for estimating asymmetric GARCH-type models.

Table 7 reports estimation results for two other asymmetric GARCH type models – the GJR-GARCH and logistic smooth transition GARCH (LST-GARCH). We also include the EGARCH model results from Table 2 for ease of comparison. Notice that the estimates of the mean equation of these three models are quite close; the asymmetry conclusion is not sensitive to the different asymmetric conditional variance specifications. In terms of the two new models, the parameter lambda in the LST-GARCH model is quite large, indicating a fast transition between the two regimes. In this case the LST-GARCH model converges to the GJR-GARCH model. Finally, in the different models of the conditional variance the terms governing asymmetry are statistically significant, and all coefficients estimates indicate the asymmetry is such that positive shocks have bigger effects than negative shocks.

In order to better interpret their results, both BCG and BG provide a type of impulse response function. These trace out the response of gasoline prices to a temporary one-period shock to crude oil prices, where crude oil prices are treated as exogenous and future values of crude oil prices do not respond to the shock to crude oil prices. We present this impulse response function in Figure 3 for the homoskedastic ECM model and the ECM-EGARCH model. We graph the absolute value of the response to a negative and a positive shock to crude oil prices, in order to better see the possible asymmetric response to increases and decreases in crude oil prices. It is readily apparent that the homoskedastic ECM is quite symmetric, while asymmetry is stronger for the ECM/EGARCH model, at least in terms of the difference between the response to a positive and a negative shock to the price of crude. Thus the impact on gasoline prices of a positive shock to crude oil prices is greater in absolute value than the response of gasoline prices to a negative shock to crude oil prices. Moreover, the difference persists over time, and hints at a rockets and feathers hypothesis, since crude prices rise faster than they fall in response to a crude shock.

The impulse response function in Figure 3 illustrates the asymmetry in response to a crude oil shock. However, these are not standard impulse response functions in that they hold crude oil prices constant after the shock. We also present more standard impulse response functions that show the response of gasoline prices to crude oil prices shocks – and to gasoline price shocks – in a system context. These impulse response functions obviously require us to model crude oil prices as well as gasoline prices.

Table 8 shows the estimation results for the crude oil price equation. We found the error correction term was not significant when we estimate the crude oil price model, indicating that crude oil prices are weakly exogenous. We conducted diagnostic ARCH LM tests, and report these results in Table 4 under the heading "Crude Oil Price Model." Note that we cannot reject the null hypothesis of no autoregressive conditional heteroskedasticity in the crude oil price model. These empirical results support our assumption that the disturbance term in the crude oil price equation is homoskedastic.

Figure 4a presents impulse response functions for our ECM-EGARCH model. For nonlinear models the state of the world at the time of the shock is important. We picked April 15, 1991 as the day of the shock, a day near the beginning of our sample and not subject to extreme events.

The top panel in Figure 4a illustrates the response of gasoline prices to a shock to gasoline prices. There is little evidence of asymmetry. Both a positive and a negative three standard error shock generates just over a five percent magnitude change in gasoline price for the first period. The impact of a positive shock increases close to ten percent at the fifth period. The impact of negative shock increases to over ten percent at the fifth period. The 'rocket and feather' effect does not exist in the gasoline response to a shock to gasoline prices. This type of gasoline price – to - gasoline price impulse response function was not investigated in BG and BCG.

The bottom panel in Figure 4a illustrates the response of gasoline prices to a shock to crude oil prices. Here, unlike the impulse response function in Figure 3, crude oil prices are themselves allowed to respond to the shock. Most important for our purposes, the impact of a crude oil price shock on gasoline prices shows a strong persistence for all shocks both positive and negative. Indeed there is a tendency for the positive shock to have a bigger impact on gasoline prices. The positive three standard error shock generate gasoline price increases of 4.2 percent, but the negative three standard error shock generate gasoline price decreases of 2.3 percent until period 5. For the positive shock gasoline prices take 11 periods to increase 5 percent, while for the negative shock gasoline prices takes 22 periods to decrease 5 percent.

Figure 4b presents confidence intervals for the impulse response functions. These are empirical confidence intervals generated by Monte Carlo simulation with 1,000 draws. In order to facilitate presentation we illustrate these confidence intervals for a two standard error impulse to gasoline prices (the top panel) and crude oil prices (the bottom panel). Note that, in the top panel, the confidence intervals easily overlap between positive and negative shocks. However, in the bottom panel the confidence intervals do not overlap, at least at short horizons. At the fifth period the confidence band for a positive shock ranges roughly over the interval .023 ~ .034, whereas for a negative shock the confidence band ranges roughly over the interval -.009 ~ -.022.

We conclude from these impulse response functions that the system-wide impacts of an impulse to crude prices is asymmetric, with a tendency for gasoline prices to respond more (in magnitude) to positive shocks and a tendency for gasoline prices to exhibit more persistence in response to positive shocks.

We also estimate standard asymmetric threshold ECM models, with results reported in Table 9. We report six sets of results. We report results for three different choices of the threshold variable: DLCP, DLCP(-1), and DLRP(-1). For each choice of threshold variable, we report estimates of both a homoskedastic ECM model and an ECM-EGARCH model. There are several things to note in this table. First, the EGARCH models are preferred on statistical grounds to the homoskedastic models. The homoskedastic models all fail an ARCH test. The ECM-EGARCH models all have much higher likelihood values than their homoskedastic counterparts.[7] Second, the interaction terms involving the threshold variables are not always, nor even mostly, significant, though there is usually at least one significant interaction term in each equation, especially each EGARCH specification. Finally, the log likelihood values give us little reason to prefer one threshold variable over the other, although there is a slightly better fit when the threshold variable is the lag change in the gasoline price, DLRP(-1).

Figure 5a presents impulse response functions for the model with the threshold variable as the lag of the crude oil price changes[8], DLCP(-1). The top panel shows the response of wholesale gasoline prices to a shock in the gasoline price equation. There is little obvious asymmetry here. The bottom panel in Figure 5a illustrates the response of gasoline prices to a shock to crude oil prices. Here there is more evidence of asymmetry. Positive shocks have a larger impact, especially large positive shocks. The positive three-standard-error shock causes an increase in gasoline prices of 5.1% at period five, while the negative three-standard-error shock causes a decrease in gasoline prices of 3.1%. For the positive shock gasoline price takes 8 periods to increase 6%, while for the negative shock gasoline price takes 21 periods to decrease 6%. All crude shocks exhibit strong persistent effects on gasoline prices, with positive shocks exhibiting a somewhat greater magnitude of response than negative shocks. Thus the impulse response functions indicate a rockets and feathers type pattern in the response of gasoline prices to crude oil shocks similar to that documented by earlier researchers.

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7 ARCH test statistics are reported in Appendix Tables 4(1).

8 We present the model with threshold variable DLCP(-1) to facilitate a forecasting exercise we describe later in the text. That model also fits in-sample slightly better than the alternatives.

One caveat to interpretations of the impulse response functions in Figure 5a is the wide confidence bands we find and illustrate in Figure 5b. The estimated impulse response functions for the threshold models are less precise, and hence the confidence bands overlap at all horizons.

6. Prediction Tests and Forecasts

An alternative method used in BG's paper to choose between the symmetric and asymmetric model is based on an out-of-sample forecasting comparison. BG find that their symmetric model gives better forecasts than their asymmetric model. We conduct a small out-of-sample forecast comparison based on our symmetric ECM and our asymmetric ECM-EGARCH models. We choose two forecasting horizons, one week ahead and four weeks ahead. Three models are examined here -- the symmetric model, the asymmetric ECM-EGARCH, and the asymmetric threshold ECM-EGARCH errors.

We consider a variety of forecasting periods: 50 weeks, 100 weeks, 150 weeks, and 200 weeks. Results are reported in Table 10. We find for most cases that, no matter the forecasting horizon, the ECM-EGARCH model beats the symmetric model. For the one-step ahead forecast over 100 weeks, the sum of squared prediction errors of the symmetric model is 0.075, while for the ECM-EGARCH model it is 0.072. The threshold ECM-EGARCH model also beats the symmetric model at the shorter horizon, but not at the longer horizon. Comparing the two asymmetric models, the threshold ECM-EGARCH tends to beat the ECM-EGARCH at the one-week horizon, but not at the four-week horizon.

7. Further Discussion on Asymmetric Gasoline Price Response

In this paper, we estimate the system wide gasoline price and crude oil price response system and produce the impulse response function based on this system. More important, our analysis on system wide gasoline crude oil price response suggests a way to decompose the crude oil volatility and gasoline price volatility, and our empirical results support the idea that gasoline price volatility follows an EGARCH process. These empirical results and the characteristics of the data suggest that both crude oil price volatility and gasoline price volatility play an important role determining the asymmetric response of gasoline prices to crude oil prices.

Many theoretical papers have discussed reasons for the asymmetry of gasoline price response. Some popular explanations include oligopoly theory, search costs, inventory management, and the behavior of markup over the business cycle. BCG (1997) discuss several explanations for the apparent asymmetry. One is these is based on search theory, crude oil volatility, and a signal-extraction model. They argue that increased volatility of crude oil prices caused reduced consumer search in response to an increase in gasoline prices. This reduced search leads to a temporary increase in market power for retail gasoline dealers, and an asymmetry in the response of retail gasoline prices to an increase in crude prices.

Interestingly, Peltzman (2000) and Radchenko (2005) both report empirical evidence that the correlation between asymmetry and crude volatility is negative. This evidence is contrary to the argument outlined in BCG. We suggest a way to reconcile these discrepancies is to consider a signal extraction model that takes explicit account of both crude oil price volatility and retail gasoline price volatility. That is, crude oil price volatility may lead to retail price volatility, but retail prices may be volatile for reasons other than just crude oil price volatility. We present a simple signal extraction model in the appendix to illustrate our arguments, and show that our model suggests the following. First, the correlation between crude oil price volatility and asymmetry is indeed positive, as suggested by BCG. Second, the correlation between retail gasoline price volatility (other than that caused by crude oil price volatility) and asymmetry is negative. Because retail price volatility seems to have increased by more than crude oil price volatility in the second half of our sample, our model would suggest that asymmetry has declined for this reason. Our model might also reconcile Peltzman's empirical findings, because he looked at crude volatility and asymmetry, without controlling for retail price volatility.[9]

8. Summary and Conclusion

There is a debate in the literature concerning the existence and character of asymmetry in the response of gasoline prices to crude oil shocks. Borenstein, Cameron and Gilbert (1997) claim that retail gasoline prices respond asymmetrically to crude oil price changes, while Bachmeier and Griffin (2003) find no evidence of asymmetry in both retail and wholesale gasoline prices if the two-step Engle-Granger estimation procedure is used. We also get this result. That is, using the two-step Engle-Granger estimation procedure and assuming homoskedasticity, we can't reject the hypothesis of a symmetric response of gasoline prices to a crude oil price shock. However, we find that the homoskedastic ECM does not pass a battery of diagnostic tests.

[9] In the appendix we also graph the markup of retail gasoline prices over crude oil prices. Our signal extraction model predicts this would decrease with increased retail gasoline price volatility, and indeed this seems to be the case in the later part of our sample.

We estimate an ECM with EGARCH errors, as well as several other models allowing asymmetry in the conditional variance. This model does pass our diagnostic tests, and our analysis of impulse response functions indicates substantial asymmetry in both magnitude of response, speed of response, and persistence. Thus we conclude that asymmetry exists, and it requires estimation of an ECM with heteroskedastic errors in order to reliably detect this asymmetry. Our impulse response functions allow us to characterize this asymmetry, and for our models including the many-state model of BCG and a standard two-state threshold model, we find impulse response function patterns that are consistent with Bacon's rockets and feathers claim. That is, gasoline prices seem to rise more quickly in response to a positive crude oil price shock than they fall in response to an equivalent magnitude but negative crude oil price shock. Moreover, we find that gasoline prices respond in somewhat larger magnitude to a positive crude oil price shock, and the response to a positive shock is somewhat more persistent.

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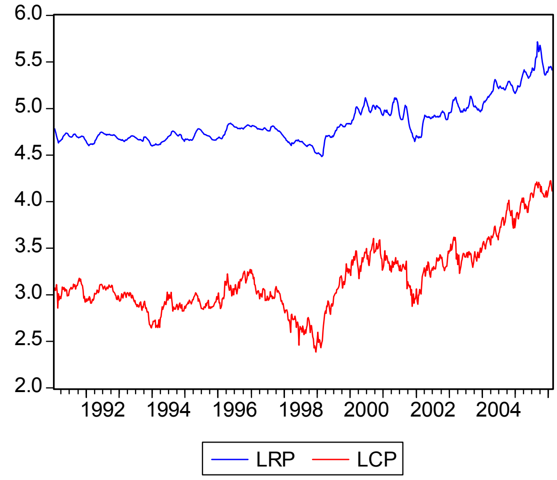
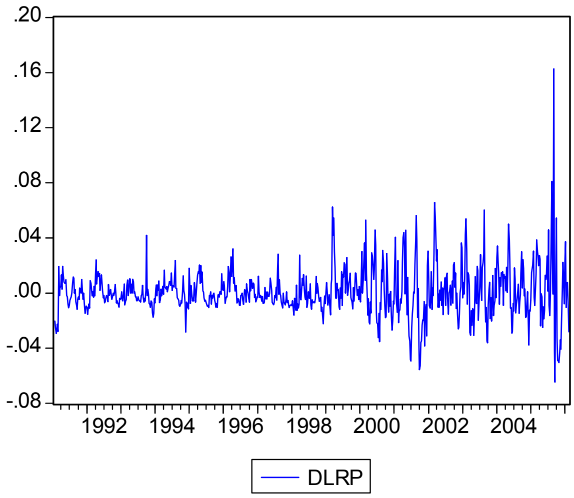
Figure 1: Retail Gasoline Price and Crude Oil Price (1/21/1991-2/13/2006)

Log retail price (LRP), log crude price (LCP), and differences in each (DLRP and DLCP)

(a)



(b)



(c)

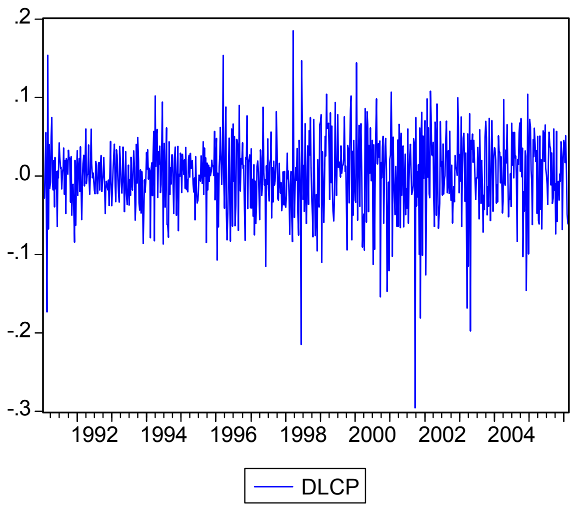


Figure 2: Residuals from the Traditional Homoskedastic ECM

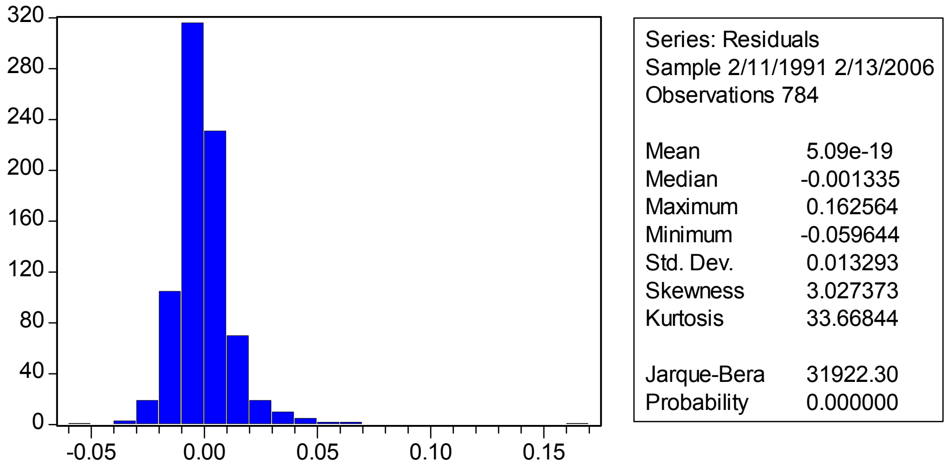


Figure 3: Impulse Response Function: BG and BCG Specifications

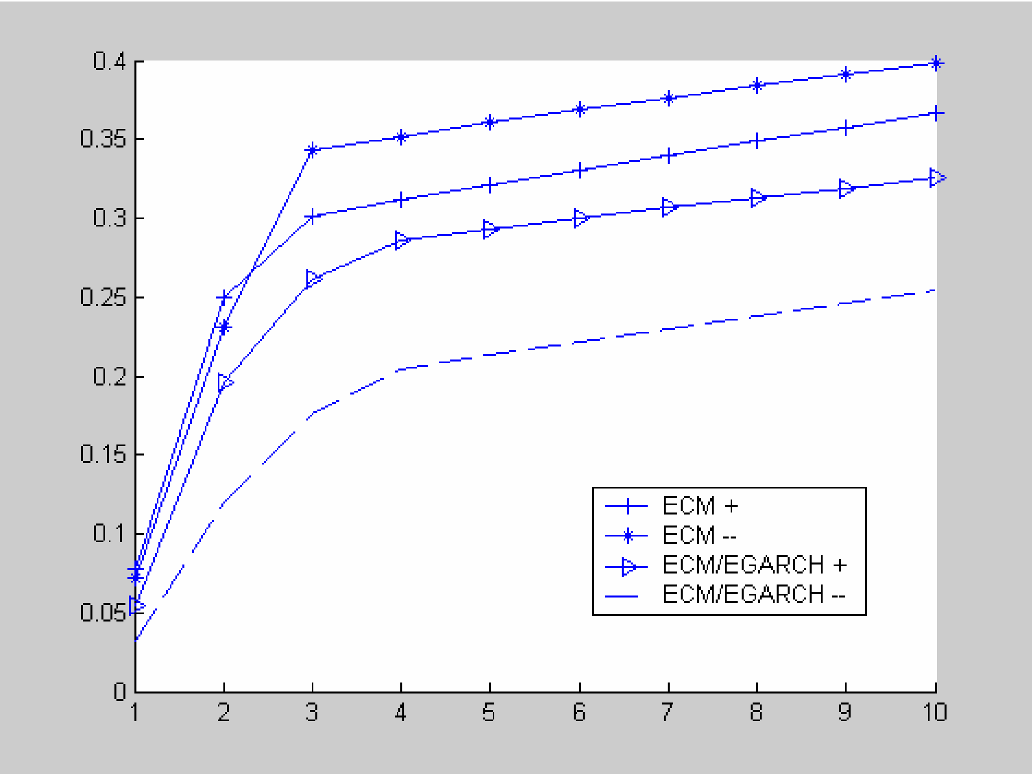
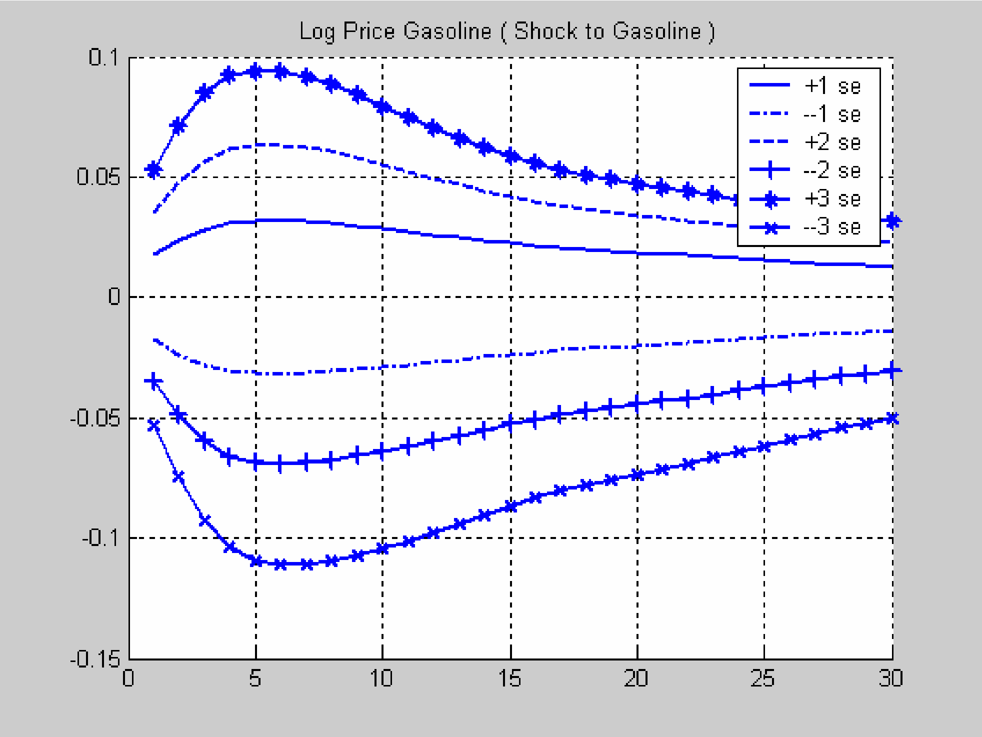


Figure 4a: Impulse Response Functions: System-Wide ECM-EGARCH



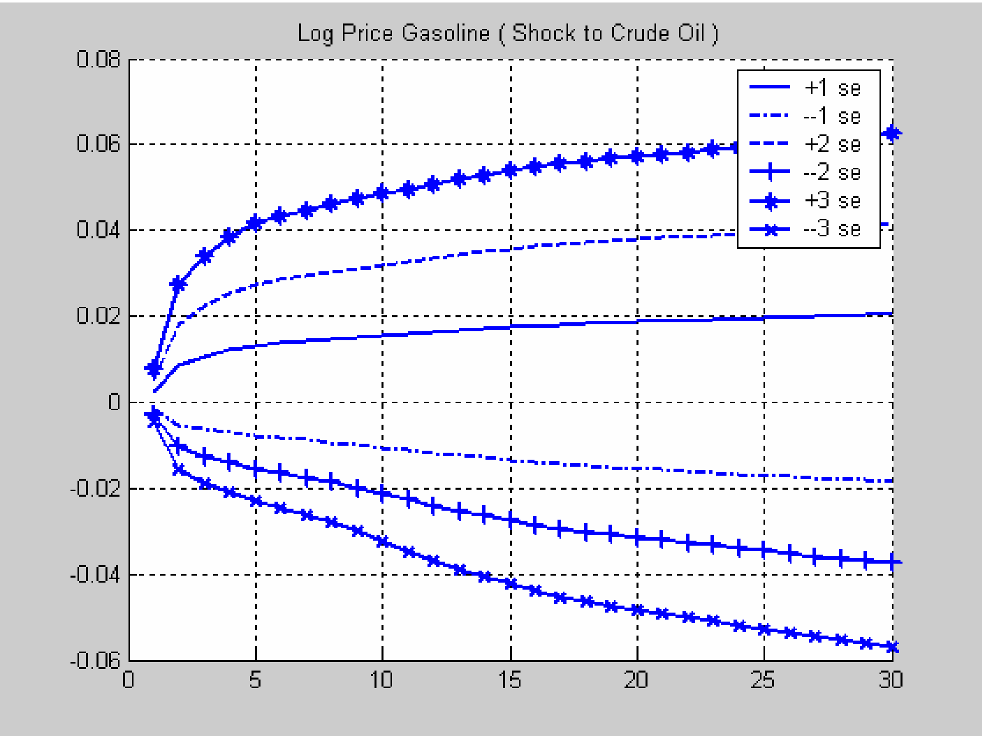
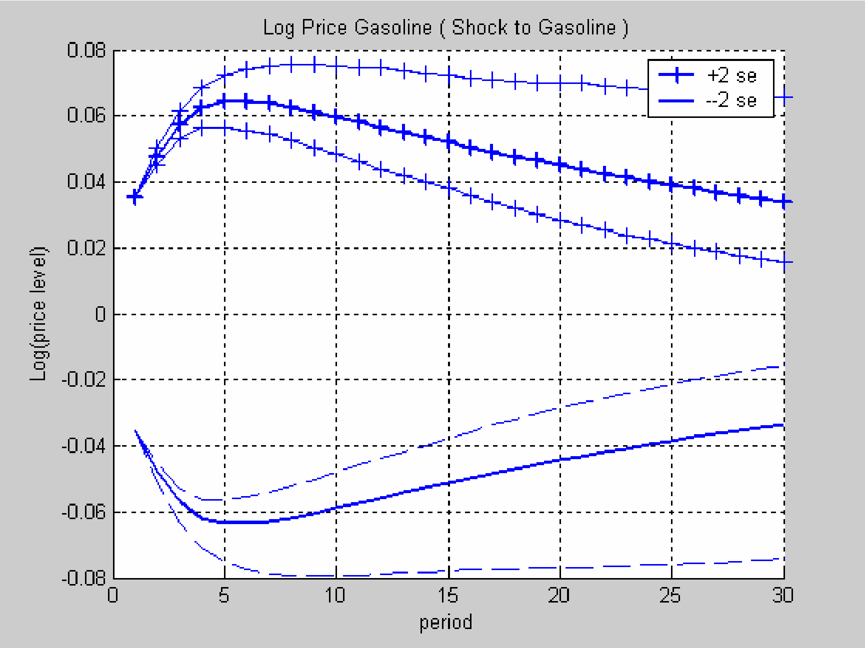


Figure 4b: Impulse Response Functions: System-Wide ECM-EGARCH

(90% Confidence Bands)



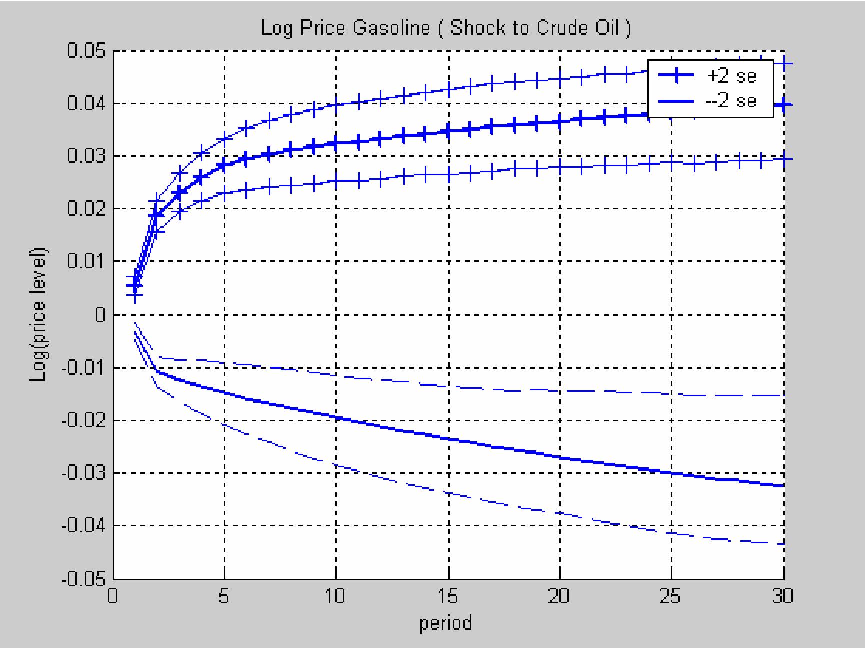
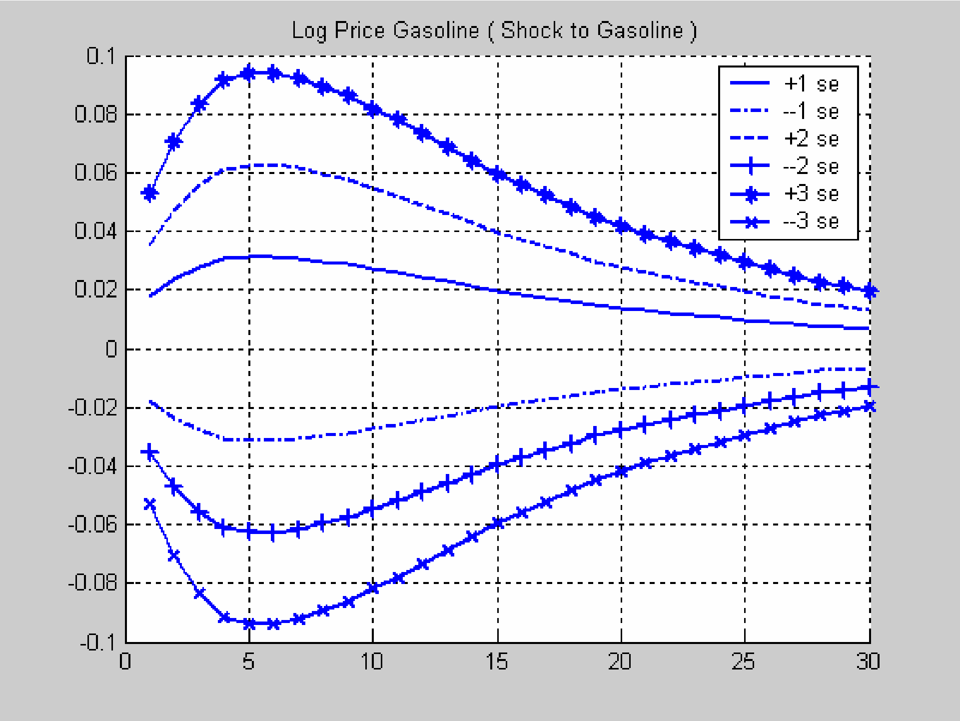


Figure 5a: Impulse Response Functions: System-wide Threshold ECM-EGARCH



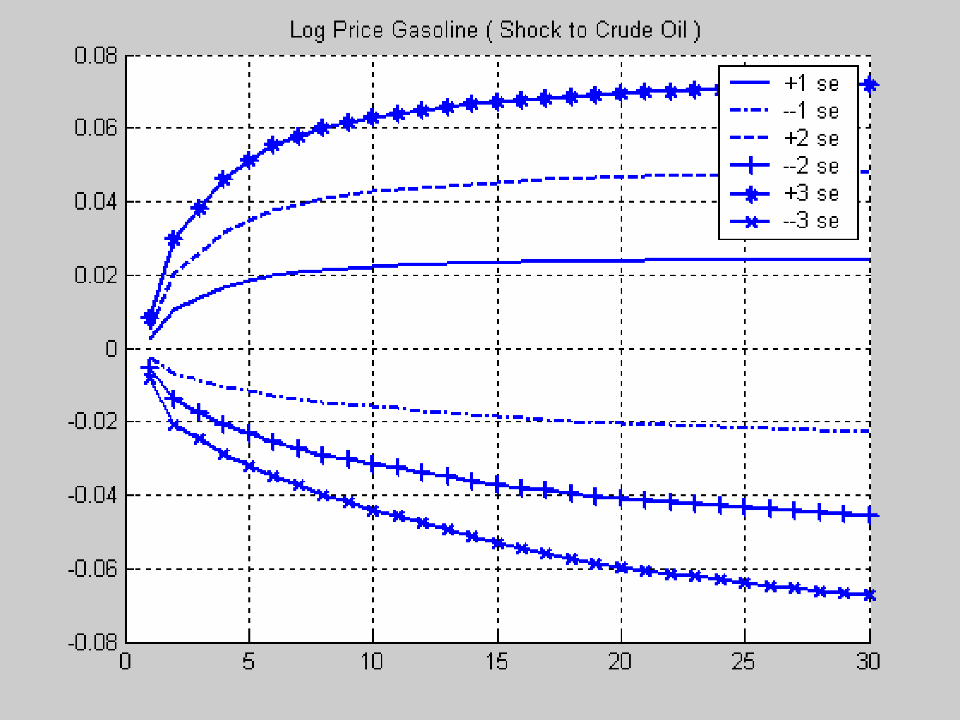
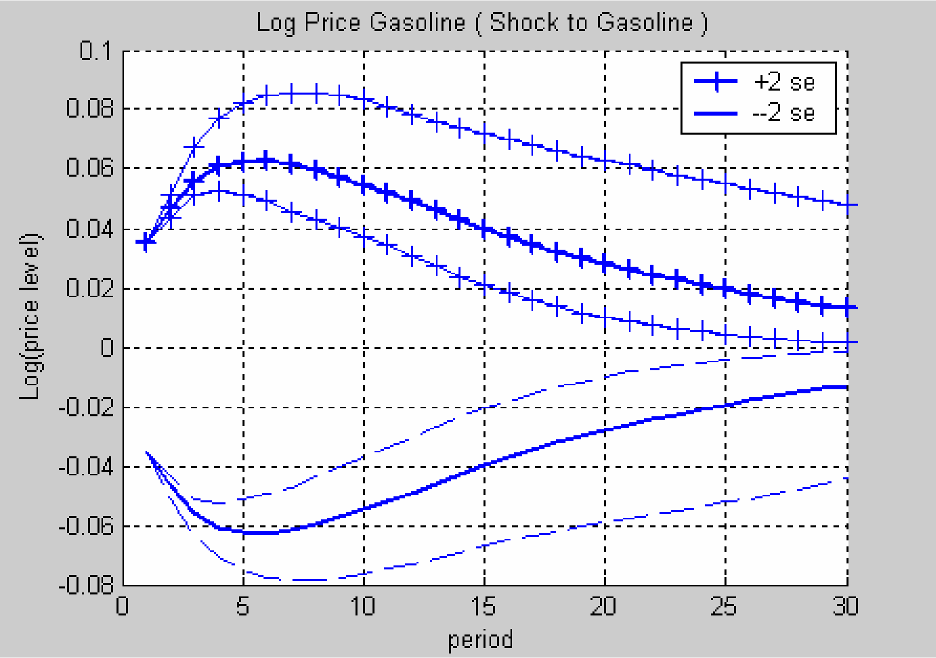


Figure 5b: Impulse Response Functions: System-wide Threshold ECM-EGARCH

(90% confidence bands)



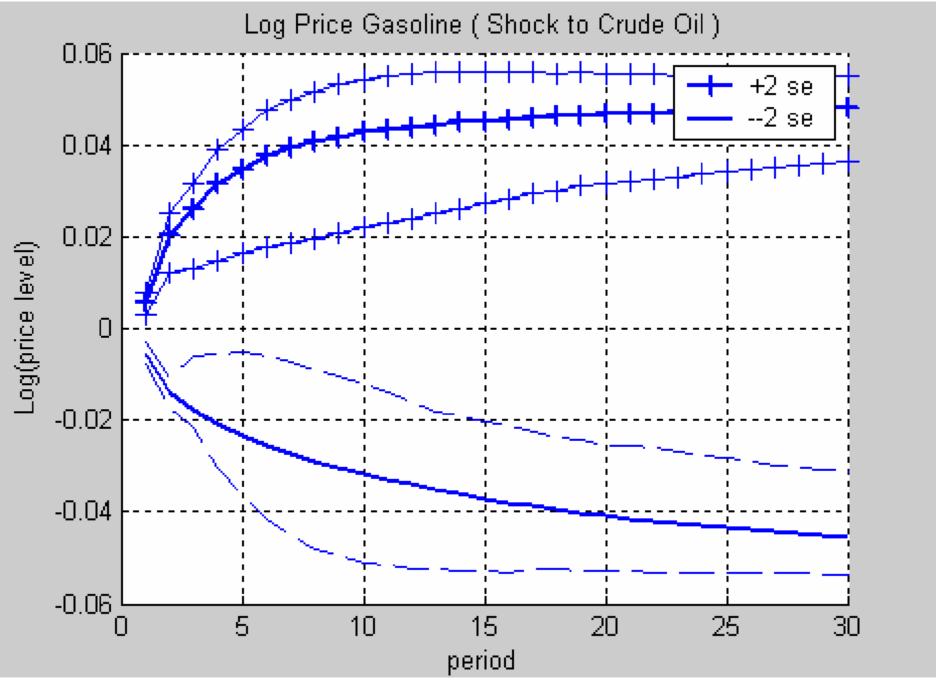


Table 1: Data Description, Retail Gasoline Price and Crude Oil Price

(Sample Period 1/21/1991 – 2/19/2006, weekly)

	LRP	LCP	DLRP	DLCP
Mean	4.853	3.177	0.001	0.001
Standard Deviation	0.233	0.377	0.018	0.049
Skewness	1.188	0.820	1.365	-0.638
Kurtosis	3.919	3.361	13.610	5.884
Observations	787	787	786	786

Note: LRP is log retail price of gasoline; LCP is log crude oil price; DLRPis difference in LRP; DLCP is difference in LCP.

Table 2: Models for Retail Gasoline Prices

	ECM		ECM-EGARCH	
	Coefficient	Std. Error	Coefficient	Std. Error
			Mean Equation	
C	0.003	0.001	-0.001	0.001
DLRP_P(-1)	0.234	0.044	0.355	0.043
DLRP_N(-1)	0.601	0.075	0.441	0.063
DLRP_P(-2)	0.069	0.044	0.124	0.044
DLRP_N(-2)	0.077	0.072	0.214	0.060
DLCP_P	0.076	0.020	0.055	0.011
DLCP_N	0.071	0.017	0.031	0.011
DLCP_P(-1)	0.140	0.020	0.111	0.011
DLCP_N(-1)	0.089	0.018	0.060	0.011
EC_P(-1)	-0.068	0.014	-0.032	0.011
EC_N(-1)	0.003	0.016	-0.015	0.008
			Variance Equation	
C			-0.585	0.145
$\lvert\varepsilon_{t-1}\rvert/(GARCH_{t-1})^{1/2}$			0.297	0.065
$(\varepsilon_{t-1})/(GARCH_{t-1})^{1/2}$			0.075	0.039
$Ln(GARCH_{t-1})$			0.961	0.013
T-DIST. DOF			5.039	0.767
R-squared	0.428		0.386	
S.E. of regression	0.013		0.014	
Log likelihood	2275.334		2531.968	

Table 3: Testing for Asymmetry
(Wald tests of equivalent coefficients on positive and negative changes in price variables)

Variables		ECM	ECM-EGARCH
DLCP	F-stat.	0.025	1.695
	p-value	0.875	0.193
DLCP(-1)	F-stat.	2.680	8.638
	p-value	0.102	0.003
DLRP(-1)	F-stat.	14.091	1.004
	p-value	0.000	0.317
DLRP(-2)	F-stat.	0.008	1.178
	p-value	0.931	0.278

Table 4: ARCH LM Tests

Retail Gasoline Price Model: ECM

Lag	1	3	5
F-statistics	19.519	21.955	15.683
Obs.*R-squared	19.092	61.030	71.745
p-value	0.000	0.000	0.000

Retail Gasoline Price Model: ECM-EGARCH

Lag	1	3	5
F-statistics	0.030	0.213	0.323
Obs.*R-squared	0.030	0.642	1.626
p-value	0.862	0.887	0.899

Crude Oil Price Model

Lag	1	3	5
F-statistics	3.262	1.046	1.250
Obs.*R-squared	3.257	3.143	6.249
p-value	0.071	0.371	0.284

Retail Gasoline Price Model: Threshold ECM

Lag	1	3	5
F-statistics	28.432	20.637	15.369
Obs.*R-squared	27.503	57.637	70.440
p-value	0.000	0.000	0.000

Retail Gasoline Price Model: Threshold ECM-EGARCH

Lag	1	3	5
F-statistics	0.160	0.207	0.368
Obs.*R-squared	0.160	0.623	1.349
p-value	0.690	0.892	0.930

Table 4: Ljung-Box Q Statistics

(Homoskedastic ECM versus ECM-EGARCH)

	Levels of the residuals				Squares of the residuals			
Lags	**ECM**		**ECM-EGARCH**		**ECM**		**ECM-EGARCH**	
	Q-Stat	**Prob**	**Q-Stat**	**Prob**	**Q-Stat**	**Prob**	**Q-Stat**	**Prob**
1	0.34	0.56	0.14	0.71	19.19	0.00	0.03	0.86
2	5.42	0.07	1.78	0.41	23.06	0.00	0.41	0.82
3	19.59	0.00	5.42	0.14	69.26	0.00	0.65	0.89
4	26.49	0.00	5.50	0.24	95.28	0.00	0.75	0.95
5	27.38	0.00	7.05	0.22	96.26	0.00	1.62	0.90
6	27.68	0.00	7.79	0.25	96.53	0.00	2.38	0.88
7	28.32	0.00	8.77	0.27	97.14	0.00	3.05	0.88
8	28.54	0.00	8.80	0.36	99.18	0.00	3.87	0.87
9	32.51	0.00	9.72	0.37	99.21	0.00	3.99	0.91
10	32.52	0.00	10.85	0.37	99.22	0.00	4.57	0.92
11	34.04	0.00	11.40	0.41	99.30	0.00	5.31	0.92
12	34.04	0.00	11.61	0.48	99.37	0.00	5.39	0.94
13	35.70	0.00	14.39	0.35	99.38	0.00	5.67	0.96
14	35.83	0.00	14.90	0.39	99.40	0.00	5.73	0.97
15	36.60	0.00	15.03	0.45	99.40	0.00	6.12	0.98
16	37.08	0.00	16.03	0.45	99.44	0.00	6.17	0.99
17	37.47	0.00	16.03	0.52	99.64	0.00	6.22	0.99
18	39.57	0.00	17.46	0.49	99.67	0.00	6.22	1.00
19	42.36	0.00	19.60	0.42	99.76	0.00	6.24	1.00
20	44.68	0.00	20.94	0.40	100.03	0.00	6.27	1.00
21	44.68	0.00	21.10	0.45	100.04	0.00	7.05	1.00
22	45.08	0.00	21.51	0.49	100.19	0.00	7.09	1.00
23	45.10	0.00	22.00	0.52	100.21	0.00	7.12	1.00
24	49.00	0.00	25.68	0.37	100.23	0.00	7.48	1.00
25	50.16	0.00	27.13	0.35	100.24	0.00	7.61	1.00
26	53.45	0.00	28.61	0.33	100.30	0.00	7.84	1.00
27	54.00	0.00	28.97	0.36	100.34	0.00	8.25	1.00
28	54.84	0.00	29.09	0.41	100.51	0.00	8.25	1.00
29	56.26	0.00	31.15	0.36	100.77	0.00	9.11	1.00
30	56.28	0.00	31.29	0.40	100.80	0.00	9.16	1.00

Table 6: Sign and Size Bias Tests

Models		Sign bias test	Negative size bias test	Positive size bias test	Joint test	
	coef.	-0.480	-15.544	-13.269	F stat.	1.504
ECM-ARCH	t stat.	-2.054	-1.117	-1.270	Chi square	4.512
	prob.	0.040	0.264	0.205	Prob.	0.212
	coef.	-0.386	-2.139	-5.435	F stat.	1.081
ECM-GARCH	t stat.	-1.617	-0.145	-0.517	Chi square	3.242
	prob.	0.106	0.885	0.605	Prob.	0.356
	coef.	-0.324	-9.208	-0.207	F stat.	0.558
ECM-EGARCH	t stat.	-1.176	-0.521	-0.017	Chi square	1.675
	prob.	0.240	0.603	0.986	Prob.	0.643

Table 7: Models for Retail Gasoline Price: Asymmetric GARCH Type Models

	ECM-EGARCH			ECM-GJR-GARCH			ECM-LST-GARCH	
	Coefficient	Std. Error		Coefficient	Std. Error		Coefficient	Std. Error
	Mean Equation			Mean Equation			Mean Equation	
C	-0.001	0.001		0.000	0.001		0.000	0.001
DLRP_P(-1)	0.355	0.043		0.337	0.055		0.337	0.055
DLRP_N(-1)	0.441	0.063		0.458	0.061		0.458	0.061
DLRP_P(-2)	0.124	0.044		0.133	0.052		0.133	0.052
DLRP_N(-2)	0.214	0.060		0.188	0.059		0.188	0.059
DLCP_P	0.055	0.011		0.053	0.013		0.053	0.013
DLCP_N	0.031	0.011		0.034	0.010		0.034	0.010
DLCP_P(-1)	0.111	0.011		0.100	0.013		0.100	0.013
DLCP_N(-1)	0.060	0.011		0.068	0.011		0.068	0.011
EC_P(-1)	-0.032	0.011		-0.033	0.009		-0.033	0.009
EC_N(-1)	-0.015	0.008		-0.013	0.009		-0.013	0.009
	Variance Equation			Variance Equation			Variance Equation	
c	-0.585	0.145	c	0.000	0.000	c	0.000	0.000
$\|\varepsilon_{t-1}\|/(GARCH_{t-1})^{1/2}$	0.297	0.065	ε_{t-1}^2	0.391	0.140	$(1-F)\varepsilon_{t-1}^2$	0.391	0.140
$(\varepsilon_{t-1})/(GARCH_{t-1})^{1/2}$	0.075	0.039	$GARCH_{t-1}$	0.402	0.050	$GARCH_{t-1}$	0.402	0.050
$Ln(GARCH_{t-1})$	0.961	0.013	$f^*\varepsilon_{t-1}^2$	0.578	0.229	$F\varepsilon_{t-1}^2$	0.578	0.227
						lambda	41320	375059
T-DIST. DOF	5.039	0.767		3.817	0.661		3.817	0.640
Log likelihood	2531.968			2502.041			2502.041	

Table 8: Model for Crude Oil Price

Dependent Variable:	DLCP	
Variable	Coefficient	Std.Error
C	0.002	0.002
DLRP(-1)	0.256	0.124
DLRP(-2)	0.217	0.123
DLRP(-3)	-0.304	0.112
DLCP(-1)	-0.137	0.037
DLCP(-2)	-0.141	0.039
R-squared	0.037	
S.E. of regression	0.048	
Log likelihood	1266.06	

Table 9: Model for Retail Gasoline Price: Threshold Models

Threshold Variable	DLCP				DLCP(-1)				DLRP(-1)			
	Threshold_ECM		Threshold_Egarch		Threshold_ECM		Threshold_Egarch		Threshold_ECM		Threshold_Egarch	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
			Mean Equation				Mean Equation				Mean Equation	
DLRP(-1)	0.170	0.044	0.363	0.045	0.308	0.044	0.348	0.049	0.631	0.065	0.475	0.057
DLRPG(-1)*Z	0.378	0.064	0.055	0.064	0.070	0.065	0.063	0.062	-0.408	0.090	-0.128	0.084
DLRPG(-2)	0.271	0.050	0.192	0.046	-0.004	0.040	0.136	0.044	0.070	0.041	0.170	0.044
DLRPG(-2)*Z	-0.314	0.064	-0.046	0.062	0.196	0.064	0.077	0.060	-0.016	0.063	-0.036	0.062
DLPC	0.072	0.017	0.031	0.011	0.064	0.015	0.029	0.010	0.042	0.014	0.031	0.008
DLPC*Z	0.009	0.030	0.029	0.018	0.015	0.020	0.027	0.012	0.068	0.020	0.031	0.012
DLPC(-1)	0.113	0.017	0.067	0.010	0.088	0.018	0.060	0.011	0.105	0.013	0.076	0.007
DLPC(-1)*Z	-0.015	0.022	0.023	0.013	0.042	0.032	0.049	0.018	0.017	0.022	0.021	0.013
EC(-1)	-0.038	0.011	-0.022	0.007	-0.072	0.011	-0.022	0.007	-0.027	0.011	-0.019	0.006
EC(-1)*Z	-0.009	0.016	-0.001	0.009	0.050	0.016	-0.006	0.009	-0.015	0.016	-0.003	0.009
c	0.000	0.001	-0.001	0.000	0.000	0.001	-0.001	0.000	0.003	0.001	0.000	0.000
			Variance Equation				Variance Equation				Variance Equation	
c			-0.754	0.177			-0.435	0.123			-0.814	0.182
$\lvert\varepsilon_{t-1}\rvert/(GARCH_{t-1})^{1/2}$			0.364	0.073			0.254	0.055			0.356	0.073
$(\varepsilon_{t-1})/(GARCH_{t-1})^{1/2}$			0.079	0.043			0.068	0.034			0.092	0.045
$Ln(GARCH_{t-1})$			0.948	0.016			0.973	0.011			0.941	0.017
df			5.243	0.817			4.770	0.717			4.928	0.766
R-squared	0.434		0.378		0.427		0.381		0.431		0.388	
S.E. of regression	0.013		0.014		0.013		0.014		0.013		0.014	
Log likelihood	2279.47		2529.76		2274.49		2533.10		2276.87		2531.33	

Table 10: Forecast Comparison

Symmetric ECM versus ECM-EGARCH and threshold ECM-EGARCH

		(1)	(2)	ratio	(3)	ratio
Horizon	Forecast Periods	Symmetric ECM	ECM-EGARCH	(2)/(1)	Threshold ECM- EGARCH	(3)/(1)
h=1	50	0.0656	0.0644	0.9819	0.0635	0.9687
	100	0.0747	0.0716	0.9587	0.0726	0.9719
	150	0.0864	0.0863	0.9985	0.0848	0.9810
	200	0.0958	0.0961	1.0031	0.0945	0.9859
h=4	50	0.0638	0.0622	0.9749	0.0645	1.0113
	100	0.0729	0.0718	0.9848	0.0739	1.0138
	150	0.0845	0.0840	0.9939	0.0866	1.0252
	200	0.0939	0.0939	0.9990	0.0965	1.0271

APPENDIX

Figure A1: Logistic Smooth Transition Function for Different Values of λ

Horizontal axis has values of ε; vertical axis values of F(λ,ε)

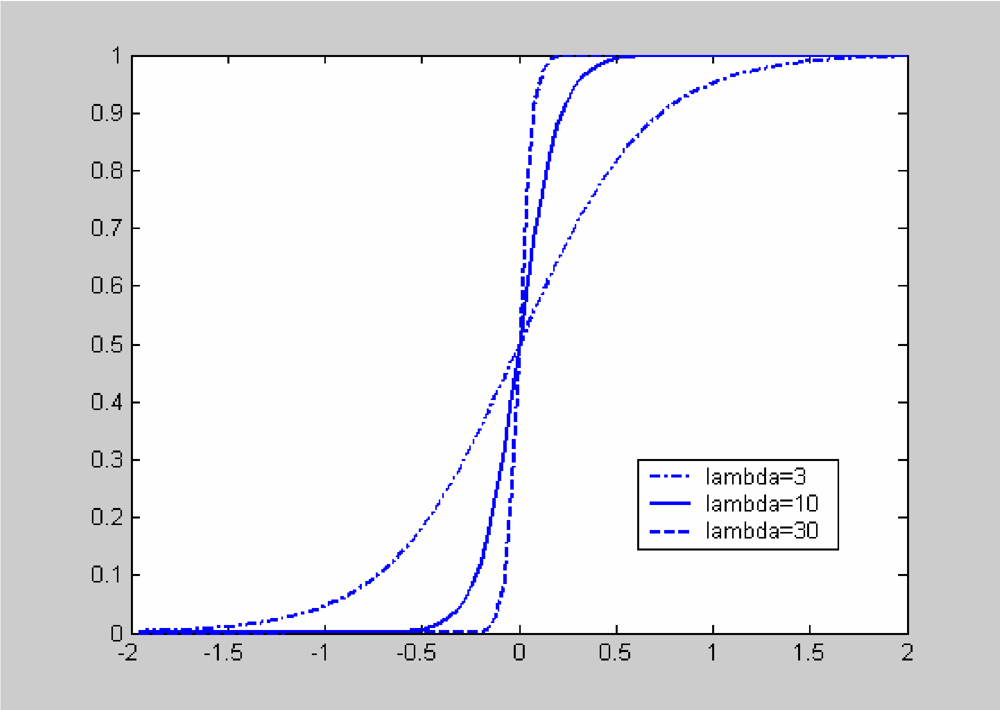


Figure A2: Mark-up between gasoline price and crude oil price

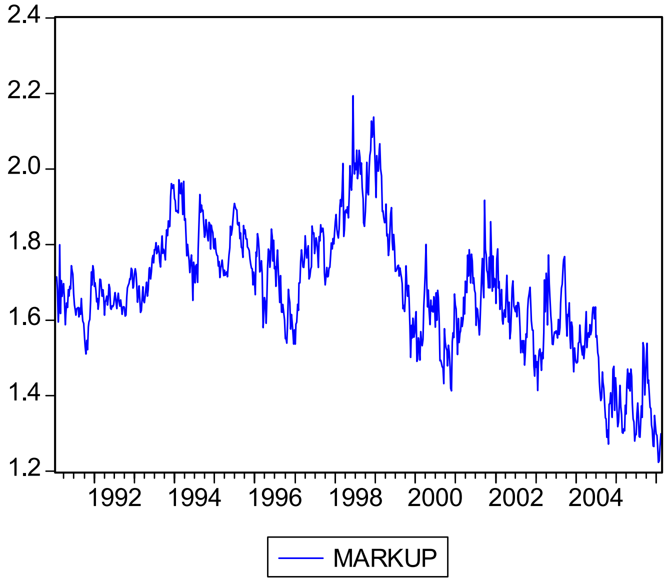


Table A1: Cointegration analysis on log of retail gasoline price and crude oil price

(Sample: weekly, 01/21/1991-02/13/2006)

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.062059	55.67441	25.87211	0.0000
At most 1	0.007101	5.573179	12.51798	0.5163

**MacKinnon-Haug-Michelis (1999) p-values

A signal-extraction model of consumer search in the retail gasoline market

Let p_c denote the crude oil price and $p_{g,i}$ the gasoline price of gas station *i*. Let $z_{g,i}$ be the specific factor related to gas station *i*. When a consumer shops at gas station *i*, the gasoline price of this station, $p_{g,i}$, is observable. Upon seeing this price, the consumer decides whether or not to search another gas station.

We model the price of gas at station *i* as consisting of a markup over the crude price and an idiosyncratic station – specific component:

$$p_{g,i} = \alpha p_c + z_{g,i}$$

where

$$p_c \sim N(\overline{p}_c, \sigma^2) \text{ and } z_{g,i} \sim N(0, \tau^2).$$

We assume that the crude price and the station-specific idiosyncratic shock are i.i.d. normal.

The consumer's search rule is as follows. When consumers observe that the gasoline price $p_{g,i}$ has changed, they attribute this price change either to a cost change -- a crude oil price shock -- or an idiosyncratic change at specific to gas station *i*, $z_{g,i}$. If a consumer thinks a gasoline price change is due to a crude oil shock, they consider this an aggregate shock that is the same for every gas station, so that the gasoline price would change proportionally to crude oil prices for every gas station. In such a case, consumers would not search in response to the observed change in gas prices. If, on the other hand, a consumer thinks a gasoline price change is due to the idiosyncratic shock specific to gas station i, $z_{g,i}$, he will choose to search the next gas station. In this case, the consumers decide whether they will keep searching or not, according to the expected relative change between gasoline price and crude oil price, $E(p_{g,i} - \alpha p_c)$.

In the above model, we have the following expressions for the variance of gasoline prices, and for the covariance between gasoline prices and crude oil prices:

$$\begin{aligned} \text{var}(p_{g,i}) &= E(p_{g,i} - E(p_{g,i}))^2 = E[\alpha p_c + z_{g,i} - \alpha \bar{p}_c]^2 \\ &= E\left[\alpha^2 (p_c - \bar{p}_c)^2 + z_{g,i}^2 + 2\alpha(p_c - \bar{p}_c) z_{g,i}\right] = \alpha^2 \sigma^2 + \tau^2 \end{aligned}$$

$$\begin{aligned} \text{cov}(p_{g,i}, p_c) &= E[(p_{g,i} - Ep_{g,i})(p_c - \bar{p}_c)] = E[(\alpha(p_c - \bar{p}_c) + z_{g,i})(p_c - \bar{p}_c)] \\ &= E[(\alpha(p_c - \bar{p}_c)^2] + E[z_{g,i}(p_c - \bar{p}_c)] = \alpha\sigma^2 \end{aligned}$$

In this case, the mean and variance of $p_{g,i}$ and p_c will be:

$$\begin{pmatrix} p_{g,i} \\ p_c \end{pmatrix} \sim N\left(\begin{pmatrix} \alpha \bar{p}_c \\ \bar{p}_c \end{pmatrix}, \begin{pmatrix} \alpha^2\sigma^2 + \tau^2 & \alpha\sigma^2 \\ \alpha\sigma^2 & \sigma^2 \end{pmatrix} \right)$$

For the consumers, the gasoline price $p_{g,i}$ is observable when they reach the gas station i, but the crude oil price is unobservable. When the consumers observe the change of gasoline price, they will form an expectation of how much the change comes from the crude oil price shock and how much from the idiosyncratic shock to a particular station. From a standard information extraction procedure, we have,

$$E(p_c \mid p_{g,i}) = \overline{p}_c + \frac{\operatorname{cov}(p_c, p_{g,i})}{\operatorname{var}(p_{g,i})}(p_{g,i} - Ep_{g,i}) = \overline{p}_c + \frac{\alpha\sigma^2}{\alpha^2\sigma^2 + \tau^2}(p_{g,i} - \alpha\overline{p}_c)$$

$$= \frac{\alpha\sigma^2}{\alpha^2\sigma^2 + \tau^2} p_{g,i} + (1 - \frac{\alpha^2\sigma^2}{\alpha^2\sigma^2 + \tau^2})\overline{p}_c$$

In this case, the expected markup will be,

$$E(p_{g,i} - \alpha p_c) = p_{g,i} - \alpha E(p_c \mid p_{g,i}) = p_{g,i} - \frac{\alpha^2\sigma^2}{\alpha^2\sigma^2 + \tau^2} p_{g,i} - \alpha(1 - \frac{\alpha^2\sigma^2}{\alpha^2\sigma^2 + \tau^2})\overline{p}_c$$

$$= (1-\phi)p_{g,i} - \alpha(1-\phi)\overline{p}_c = (1-\phi)(p_{g,i} - \alpha\overline{p}_c)$$

where $\phi = \frac{\alpha^2\sigma^2}{\alpha^2\sigma^2 + \tau^2}$.

Note the importance of the variance terms. When σ^2 increase, ϕ increases, so $1-\phi$ decreases. The markup will decrease, ceteris paribus. Then consumers will tend not to search. When τ^2 increases, ϕ decreases, and $1-\phi$ increases. The markup will increase, ceteris paribus. In this case consumers will tend to keep searching. Further, when search behavior increases, the degree of asymmetry in response to crude shocks will decrease.

From our empirical work, both gasoline price and crude oil price volatility increased in recent years, and the gasoline price volatility increased more than the crude oil price. This is consistent with the above signal extraction model.