Rockets and Feathers in the Oil and Gasoline Markets: In-Depth Analysis of Three Asymmetries

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Selected Paper prepared for presentation at the 2024 Agricultural & Applied Economics Association Annual Meeting, New Orleans, LA; July 28-30, 2024

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Abstract

This study extends the literature on asymmetric price transmission in energy–fuel markets to a three-regime smooth transition vector error correction model that allows price responses to have an asymmetric nonresponsive band. Combining coefficient- and impulse-based methods, we examine three types of rockets and feathers (RAF) effects: the nonresponsive band, the speed of error correction, and impulse responses. The results confirm the presence of a nonresponsive band for gasoline prices to respond to changes in oil prices. The asymmetric critical values indicate that the gasoline–oil spread must widen to a large margin before gasoline prices begin to adjust and pass the benefits on to fuel consumers. However, the spread only needs to fall minimally, and the price of gasoline will rise accordingly, transferring the increased input costs to consumers. We find evidence that supports asymmetric impulse responses but not error correction procedures. We further investigate gasoline price responses to oil price shocks during COVID-19 under extreme market conditions (i.e., top 5% and bottom 5% of oil price returns). The impulse analysis demonstrates asymmetric responses in both the top and bottom 5% cases, consistently favoring gasoline suppliers. Notably, in instances of sharp declines in oil prices, such as during the 2020 Russia–Saudi Arabia oil price war, gasoline suppliers largely refrain from passing on the cost reductions to fuel consumers. Conversely, when oil prices experience sharp increases, these suppliers promptly transfer the higher costs to consumers.

Keywords: COVID-19; smooth transition vector error correction model, GIRF, nonresponsive band; gasoline-oil; rockets and feathers

JEL code: C22, Q41

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1. Introduction

Asymmetric price transmission (APT) refers to instances where downstream prices respond differently to upstream price changes, depending on the direction and/or magnitude of these changes. In the gasoline-oil context, the rocket-and-feather (RAF) effect typically describes the phenomenon where gasoline prices rise faster when oil prices increase (like a rocket) than they fall when oil prices decrease (like feathers) (Bacon 1991; Moshiri 2020; Knotek II and Zaman 2021). This asymmetry can lead to significant consumer detriment, as fuel consumers do not fully benefit from oil price reductions, and it also highlights potential market inefficiencies that require policy attention, especially in addressing the market power of the gasoline industry and understanding varied consumer responses to price changes. Therefore, extensive research has been devoted to examining and understanding the RAF effect (e.g.,Atil, Lahiani and Nguyen 2014; Blair, Campbell and Mixon 2017; Bremmer and Kesselring 2016; Cook and Fosten 2019; da Silva et al. 2014; Kristoufek and Lunackova 2015; Lahiani et al. 2017; Rahman 2016; Shioji 2021; Venditti 2013).

Early research on RAF or APT primarily used regression methods to explore the relationship between changes in oil prices and adjustments in gasoline prices (see a review by Frey and Manera (2007)). The critical aspect of these studies was to assess whether the coefficients for positive (increases) and negative (decreases) adjustments in oil prices were statistically different. Later literature on APT documented the cointegration issue in price time series data, highlighting the likely existence of a stable long-run equilibrium between input and output prices. In response, recent APT studies typically start by estimating a long-run cointegrating relationship between the prices, thus providing a more precise depiction of the short-term price dynamics. They also added two error correction terms for positive and negative adjustments. The focus of the test also shifted to testing the equality of the error correction speeds (Perdiguero-García 2013).

Kilian and Vigfusson (2011a, 2011b) advocate for an impulse-response-based approach within a structural Vector Autoregression (VAR) framework. Based on the results of the impulse responses, researchers can visualize the magnitude and duration of responses to different shocks, in addition to testing the equality of the effects of positive and negative shocks. Referencing Kilian and Vigfusson, recent literature has adopted such an approach to study and test RAF (Knotek II and Zaman 2021; Qin, Zhou and Wu 2016; Rahman 2016; Venditti 2013).

In this study, we combine both coefficient-based and impulse-response-based methods, thereby offering a comprehensive analysis of price adjustment mechanisms in the fuel market. The impulse response method is effective for analyzing the immediate and evolving effects of unpredictable system shocks, while the coefficient-based method complements by evaluating deviations from long-term equilibrium. Both are valuable, as they reveal different information regarding price transmission and market interdependence.

In addition to impulse responses and adjustment speed, we consider incorporating a nonresponsive band in RAF analysis, using its upper and lower critical values to gain deeper insights. To test the asymmetric error correction coefficients, existing literature often uses zero as the critical point to manually divide the deviation term into two groups (positive and negative) (see Blair et al. 2017; Bremmer and Kesselring 2016; Cook and Fosten 2019; Venditti 2013, for examples). This approach ignores the fact that prices do not always respond, as, under certain conditions, the market (or market participants) *chooses* not to adjust. This price stickiness can also result from various factors, including pricing strategies, search costs, inventory management, and market power, as noted by Surathkal and Chung (2019) and Meyer and von Cramon-Taubadel

(2004). The critical values defining the nonresponsive band in APT analysis – the positive and negative points at which price adjustments begin – offer crucial insights. Intuitively, RAF suggests that the gasoline-oil margin needs to expand significantly before gasoline prices adjust downwards to benefit consumers. Conversely, a minimal reduction in this margin can prompt a swift increase in gasoline prices, quickly passing on higher input costs to consumers. Therefore, these two critical values, marking the thresholds for price adjustments, are expected to differ, reflecting the asymmetric nature of price responses in the fuel market.

The objective of this paper is to analyze three different asymmetries in gasoline-oil markets: the nonresponsive band, error correction speed, and impulse responses, using a smooth transition vector error correction model (STVECM) with generalized impulse response function (GIRF) analysis. We contribute to the literature in several ways. This is the first study to combine the two main methods (coefficient and impulse response approaches) to investigate three different types of APTs, providing multidimensional insights regarding rockets and feathers in fuel-energy markets. In addition, determining the existence of the nonresponsive band is more in line with actual market conditions. The nonresponsive zone has some applications in price transmission research in other subfields of economics, such as agricultural economics. For a discussion, see section 4.2 of the review article by Meyer and von Cramon-Taubadel (2004).

Secondly, our study examines the impact of the COVID-19 pandemic on oil and gasoline price reactions. Using data from January 2000 to May 2023 and employing GIRFs, we compare price responses to oil shocks before and after the pandemic's onset. When examining impulse responses, combined with the common practice of simulating the history and averaging (see Caggiano, Castelnuovo and Pellegrino 2017; Caporin, Fontini and Talebbeydokhti 2019; Le and Chang 2015, for examples), we also select some extreme market conditions (the top and bottom

5% price adjustments) to test for RAF effects. Our work investigates whether the drop in oil prices caused by reduced fuel demand and/or an oil price war during COVID-19 was quickly and predominantly passed on to consumers or whether extra time or spikes were required for fuel suppliers to make downward price adjustments. This aspect is important as it sheds light on how consumer welfare was affected during a global disruption.

Additionally, unlike previous literature using abrupt switching threshold models (Knotek II and Zaman 2021; Qin et al. 2016), we employ a smooth transition framework that allows continuous switching between regimes. We argue that reactions to upstream price adjustments take time, and market participants vary in the speed and magnitude of adjustments (Goodwin, Holt and Prestemon 2011). A gradual regime-switching model is more in line with reality and could also overcomes the bias issue of censored regressions criticized by Kilian and Vigfusson (2011a).

The remainder of the paper is organized into four sections. We introduce the econometric methods in Section 2, and then describe the data and empirical results in Sections 3 and 4. Concluding remarks and implications are presented in Section 5.

2. Methods

We investigate three types of rocket-and-feather effects in U.S. gasoline and oil markets: 1) the positive and negative critical values of the nonresponsive band, 2) the asymmetric error correction speed when gasoline–oil margins are stretching and shrinking, and 3) nonlinear price responses to different price shocks in crude oil markets. The first two asymmetric effects are investigated, estimating a three-regime STVECM, and nonlinear price responses are examined, simulating GIRFs based on the structural STVECM.

2.1. Smooth transition vector error correction model

The three regimes defined in our STVECM are the margin-tightening regime (regime 1), the nonresponsive regime (regime 2), and the margin-stretching regime (regime 3). Our three-regime STVECM can be specified as below:

$$\Delta \boldsymbol{y_t} = \left(\boldsymbol{\beta_{0,1}} + \boldsymbol{\beta_1} ECT_{t-1} + \sum_{i=1}^{p} B_{i,1} \Delta \boldsymbol{y_{t-i}}\right) + \left(\boldsymbol{\beta_{0,2}} + \boldsymbol{\beta_2} ECT_{t-1} + \sum_{i=1}^{p} B_{i,2} \Delta \boldsymbol{y_{t-i}}\right) \boldsymbol{G_1}(\boldsymbol{s_t}; \boldsymbol{\gamma_1}, \boldsymbol{c_1}) + \left(\boldsymbol{\beta_{0,3}} + \boldsymbol{\beta_3} ECT_{t-1} + \sum_{i=1}^{p} B_{i,3} \Delta \boldsymbol{y_{t-i}}\right) \boldsymbol{G_2}(\boldsymbol{s_t}; \boldsymbol{\gamma_2}, \boldsymbol{c_2}) + \boldsymbol{\varepsilon_t} \quad (1)$$

where $\boldsymbol{\Delta y_t} = \left[\Delta y_t^{gas}, \Delta y_t^{oil}\right]'$ is a 2×1 vector of gasoline and oil price returns and ECT_{t-1} reflects the gasoline-oil margin, specifically denoting the deviation from the long-run equilibrium in the previous period. The 2×1 vector β_j represent the speeds of adjustment. The subscripts $j = 1,2,3$ here represent three regimes. Transition functions $G_1(\cdot)$ and $G_2(\cdot)$ range from zero to one with transition parameters $(s_t;\, \gamma, c)$. The ε_t involves correlated error terms with a variance-covariance matrix Σ. This specification includes a middle regime that permits, but does not necessitate, nonresponsiveness.

For the transition function G(·), we use a logistic form as follows:

$$G(s_t; \gamma, c) = [1 + \exp\,(-\frac{\gamma(s_t - c)}{\widehat{\sigma_s}})]^{-1}$$

where s_t is the transition variable that governs the regime-switching behavior, γ represents the switching speed between regimes, and c is the critical value. The literature suggests two common forms of G(·): logistic and exponential functions. Intuitively, the logistic functional form allows for the investigation of rockets and feathers, and the exponential form imposes symmetry. For more details about the specification and selection of transition functions, refer to Goodwin et al. (2011) and Lütkepohl and Krätzig (2004).

To validate the choice of STVECM, we first perform a linearity test against the alternative hypothesis of smooth transition nonlinearity following Teräsvirta (1994). The tests are applied to both single equation using LM-type tests and the vector system using log-likelihood ratio tests, as suggested by Weise (1999) and Teräsvirta and Yang (2014). A recent application can be seen in Balcilar et al. (2021). We use a bootstrap approach suggested by Seo (2004) to draw the inference. We reject the linearity null if $p<0.05$ and move on to the estimation of the smooth transition model.

2.1.1. Identifying the nonresponsive band

To identify the asymmetric critical values of the nonresponsive regime, we impose restrictions to ensure that c_1 is negative and c_2 is positive, and the asymmetric price adjustments can be examined by comparing the absolute values of c_1 and c_2. To ensure adequate observations in estimating regime-dependent models, we follow the common practice (see an application in Qin et al. (2016)) and limit a (100*100) grid search for c_1 and c_2 within the range of 15 and 85 percentiles of the threshold variable.

2.1.2. Estimating error correction speed

After rejecting linearity and choosing the best transition variable and transition function, we estimate the STVECM using the nonlinear least squares (NLLS) technique. We construct a four-dimensional grid search for the transition parameters $(\gamma_1, \gamma_2, c_1, c_2)$ to initialize transition parameters in the NLLS estimation. The estimates that minimize the sum of squared estimate of errors are retained as the initial values (Dijk, Teräsvirta and Franses 2002).

In the nonresponsive regime, we anticipate that the speed of error correction, represented by $\beta_1 + \beta_2$, will be statistically insignificant. Conversely, in the other two regimes, the speeds of error correction, indicated by β_1 and $\beta_1 + \beta_2 + \beta_3$, are expected to be significant. To evaluate the statistical significance of these error correction speeds, we employ the delta method, a robust statistical approach suitable for this analysis.

2.2. Nonlinear price responses to oil shocks

Impulse response functions (IRFs) derived from regime-switching models are nonlinear depending on the shock sign, the shock size, and history. The computation requires simulation techniques. After estimating the smooth transition model, we further simulate IRFs to provide a complete profile of gasoline price responses to various oil shocks. Following Kilian and Vigfusson (2011a), we test whether the IRFs of positive and negative shocks are statistically different.

2.2.1. GIRF computation

We employ the GIRF proposed by Koop, Pesaran and Potter (1996), which can be formulated as:

$$GIRF_{\Delta\boldsymbol{y}}(h,\delta)=\frac{1}{T}\sum_{t=1}^{T}[E(\Delta\boldsymbol{y}_{\boldsymbol{t+h}}\mid\delta,\Omega_t)-E(\Delta\boldsymbol{y}_{\boldsymbol{t+h}}\mid\Omega_t)]$$

where h denotes the forecast horizon, δ denotes a prespecified shock hitting at time t with historical price information Ω_t, which is defined by a block of gasoline and oil price series up to time t. In our case, the results are given by 1,000 simulations based on the STVECM estimates.

We investigate the shock size of 1 and 3 S.D.s. It allows our assessment of whether the presence of asymmetry is affected by shock size, which coefficient-based checks are unable to answer. Since the GIRF is history-dependent, it is interesting to compare price responses in different historical periods within our data sample. A recent application of history-specific impulse responses is exemplified by Balcilar et al. (2021). We study the impact of COVID-19, using March 11, 2020 as the start, on the gasoline response to oil price shocks through history-specific GIRFs.

We also investigate GIRFs under extreme market conditions, using subsets of histories associated with top and bottom 5% oil price adjustments.

2.2.2. Test for asymmetry

After obtaining the GIRFs to positive and negative oil price shocks, we conduct the asymmetry test proposed by Kilian and Vigfusson (2011a), applications of which can be seen in Herrera, Lagalo and Wada (2011) and Rahman (2016). The null hypothesis of symmetry means the sums of responses to positive and negative shocks up to the horizon H are jointly equal to zero, which can be represented as follows:

$$GIRF_y(h,\delta) + GIRF_y(h,-\delta) = 0, h = 0,1,2,\ldots,H$$

The variance-covariance matrix of GIRFs is obtained from 10,000 bootstrap simulations. The test statistic follows an asymptotic χ^2_{H+1} distribution. We will reject the null hypothesis of symmetry if the p-value is smaller than 0.05. We apply the test to both 1- and 3-SD shocks in different market conditions.

3. Data and summary statistics

We use weekly price data from January 2000 to May 2023 with a sample size of 1221. For gasoline, we use the conventional gasoline spot price in New York Harbor in USD per gallon; and for crude oil, we use the West Texas Intermediate spot price in Cushing, Oklahoma in USD per gallon. Prices are deflated using the CPI (January 2020 = 100). The price data are retrieved from the U.S. Energy Information Administration (EIA) and the CPI are obtained from Federal Reserve Economic Data (FRED) database.

The price series are plotted in Fig. 1 (upper panel). Over the past 23 years, the two prices have been closely linked, with many small fluctuations and several extreme sharp declines, such as the oil price crisis in 2008 and the most recent oil price crash in 2020 due to the Russia–Saudi Arabia oil price war. In different time periods, we can observe the margins between the two vary substantially. The scatterplot in the lower panel shows an overall linear relationship between the two series.

Table 1 provides descriptive statistics for the two (log) price series. Table 1 also presents the results from three unit-root/stationarity tests: ADF (Dickey and Fuller 1981), DFGLS (Elliott, Rothenberg and Stock 1996), and KPSS (Kwiatkowski et al. 1992). All the tests suggest that the two (log) price series exhibit unit roots, and the two price returns are stationary. We conclude that the two prices are $I(1)$ series.

Next, we perform the Johansen cointegration test, and the results are shown in Table 2. The results confirm a linear cointegrating relationship, which is consistent with the scatterplot and existing literature. The estimated long-run price transmission elasticity is 0.92, which indicates that a 10% change in oil price is associated with a 9.2% change in gasoline price overall.

4. Results

4.1. Linearity test

We test the linearity of the error correction process using lagged deviation (from the long-run relationship) as the transition variable. Both the single-equation linearity test (F_0) and the multi-equation linearity test (LR_0), as described in the method section, reject the null hypothesis of linearity and support a smooth transition type of model specifications.

4.2. The STVECM estimation

We identify the two critical values for the nonresponsive band and estimate the STVECM with two lags and the transition variable deviations of lag 1, and the results are presented and discussed in the next two subsections.

4.2.1. Critical values of the nonresponsive band

The two identified critical values for the nonresponsive band are −0.054 and 0.109. Note that these are the mid-points of the two transition functions. The results confirm our hypothesis. A relatively small increase in oil prices (i.e., when the gasoline–oil spread drop to −5.4%) would immediately trigger corrective behaviors in the gasoline market. In contrast, oil prices would need to fall significantly (i.e., when the gasoline–oil spread reaches 10.9%) to cause a decline in gasoline prices. The result indicates that any deviations (spreads) from the long-term equilibrium in the range of [−5.4%, 10.9%] will not cause any adjustments in gasoline prices. Only when gasoline–oil margins increase by 10.9% or more, gasoline suppliers will pass on benefits to consumers; but a (small) drop in the gasoline–oil margin to −5.4% will cause an immediate increase in gasoline prices. This is a piece of evidence for RAF in the U.S. oil–gasoline markets.

4.2.2. Estimated coefficients/ Asymmetric error correction

The three regimes are defined below, based on the identified critical values. There are 32.4%, 52.6%, and 15.0% observations in regimes 1, 2, and 3, respectively, as defined below. Table 4 further presents the estimated coefficients from the STVECM. Fig. 2 presents scatterplots of the two fitted transition functions.

$$\text{Regime definition: } \begin{cases} Regime\ 1\ (margin\ \ tightening)\text{: } deviations\ <\ -5.4\% \\ Regime\ 2\ (nonresponding)\text{: } -5.4\% \leq deviations \leq 10.9\% \\ Regime\ 3\ (margin\ \ stretching)\text{: } deviations\ >\ 10.9\% \end{cases}$$

When deviations occur in the nonresponsive band (regime 2), the speed of adjustment is insignificant, affirming the market's tendency to not adjust. In regime 1, as $G1$ approaches 0, the speed of adjustment nears 0.064, indicating that around 6.4% of deviations are rectified in the subsequent week. In regime 3, the speed of adjustment rises to 0.088 (as $G2$ approaches 1), surpassing that of regime 1. However, regime 3 has a much longer transition period compared to regime 1. Many observations in this regime have a speed of adjustment that is smaller than 0.088. Thus, though the estimated speeds of adjustment suggest asymmetry, we cannot conclusively determine the presence of a RAF effect.

4.3. GIRFs and tests for asymmetric responses

4.3.1. The overall case

We first examine the overall responses of gasoline prices to oil price shocks. The GIRFs are calculated using entire histories (1,221 × 1,000 times of simulation), as discussed in Section 2.2.1. Fig. 3 (all-sample cases) presents the response of gasoline prices to positive and negative oil price shocks. We selected two different sizes, and the small size represents 1 S.D. (6.7%) of oil price returns and the large one represents 3 S.D.s. A 1-SD oil shock results in a contemporaneous impact of about 2.4% on the gasoline return due to the market correlations. Fig. 3 shows that the reaction of the gasoline price to a small oil price shock is symmetrical overall, and the impact of shocks (both positive and negative) shrinks to negligible in the second week, dying out in the fifth week.

Conversely, gasoline's response to large-scale oil shocks differs from that of small-scale shocks, exhibiting some asymmetric behaviors. The gasoline return reacted in the same direction to a large positive shock of oil, but its response to a large negative shock oscillated a bit. The positive oil shock led to a positive adjustment in gasoline prices, and the reaction was relatively large in the first two weeks, then weakened to zero after the third week. When gasoline prices faced a sharp drop in oil prices, corresponding price reduction adjustments occurred in the first two weeks. In the second week, the impact of the oil shock significantly weakened, reduced to 50% compared to that of a positive shock; gasoline prices continued the downward trend for the next two weeks, then the effect completely dissipated.

The results of the asymmetry test based on the impulse responses are presented in Table 5 (left side), confirming that when the oil price shock is small, there is no asymmetry in the gasoline impulse responses; however, when the oil price shock is large, gasoline's reaction has a statistically significant asymmetry. It is notable that though statistically significant, the difference (magnitude of asymmetry) of the gasoline price adjustments is not large.

4.3.2. COVID-19

Next, we continue to examine the GIRFs and asymmetry tests for the COVID-19 period. Overall, the GIRFs during COVID-19 (Fig. 3. the lower panel, COVID case) were very similar to those of the entire study period, with only a few minor differences. During the pandemic, the adjustment to the large positive oil shock differed slightly from general circumstances. Overall, the gasoline price reaction quickly disappeared after the second week, but a slight opposite adjustment arose in the third week. The asymmetric test results are also presented in Table 5 (right side). Similar to the previously discussed overall case, when the oil shock was small, no significant asymmetric adjustment in gasoline prices occurred; however, in the face of a large oil shock, the gasoline market appears to react differently.

4.3.3. GIRFs calculated based on the histories representing extreme increases in oil prices

The previous discussion is based on the simulation of all histories, reflecting the general/average market response. We next investigate the gasoline response in some special histories associated with the top and bottom 5% of oil price adjustments (representing extreme market upturns and downturns), comparing the differences in price responses before the pandemic and during COVID-19. Figs. 4 (the top 5% case) and 5 (the bottom 5% case) display the GIRF results.

For the top 5% case (large oil price increases), GIRFs prior to the pandemic (Fig. 4. upper panel) are very close to the overall case. In contrast, as shown in the lower panel of Fig. 4, the impulse responses to big oil shocks differed widely from the overall case during the pandemic.

For a positive 3-SD shock, the adjustment of gasoline price during COVID-19 was considerably larger than nonpandemic periods, especially in the first and fourth week. In addition, the asymmetric impacts of positive and negative oil shocks during the COVID-19 are more obvious, compared with the nonpandemic case. The adjustment pattern also substantially differed from the nonpandemic period. In the non-COVID-19 era, there was basically a one-way weakening adjustment path. During the COVID-19 period, the oscillation is obvious. The response to a large positive oil shock presented a quick, sharp rise followed by rapid recovery and overshoot. Finally, the responses during COVID-19 were more persistent, and did not diminish even after eight weeks.

4.3.4. GIRFs calculated based on the histories representing extreme decreases in oil prices

We next examine how gasoline prices respond to oil shocks during a period of substantial declines in oil prices (the bottom 5%). Similar to the top 5% case, the responses to oil price shocks in the case of nonpandemic (Fig. 5. upper panel) were similar to the general case as shown in Fig. 3 (upper panel), but COVID-19 (Fig. 5. upper panel) exhibited different patterns to the general case.

In the bottom 5% time during COVID-19, the response to large negative shocks became sharp and fast. The gasoline price responses only fell for the instantaneous week, and then remained positive during the first three weeks after the shock. The results imply that consumers do not benefit from the sharp drop in oil prices. This welfare loss lasted for about three weeks before the impact disappeared. Similar to the top 5% case, the magnitude of asymmetry became more evident, once again providing clear evidence of RAF effects in the case of the pandemic. Finally, the adjustment patterns differed substantially before and during COVID-19. Prior to the pandemic, the bottom 5% adjustment path presented a one-way fading path overall in which reactions to large oil shocks quickly disappear after about four weeks. During the pandemic, the overshoot and opposite-adjusting behaviors resulting from a large negative shock, are noticeable. Compared to those before COVID-19, the response was much less persistent.

5. Concluding remarks

We use a regime-switching error correction model with generalized impulse response analysis to investigate three types of rocket-and-feather effects in the U.S. gasoline–oil markets: the asymmetric nonresponsive band, asymmetric error correction speed, and asymmetric impulse responses to crude oil price shocks. The findings provide new evidence supporting the existence of RAF in the gasoline–oil price transmission and shock responses, with several significant implications. We summarize some key points in the following paragraphs.

5.1. Asymmetric nonresponsive band and error correction speed

The results confirm the existence of a nonresponsive band for gasoline prices to respond to changes in oil prices, and the two critical values of the band are asymmetric. The findings indicate that the gasoline–oil margin must expand by a relatively large level (10.9%) before gasoline prices adjust and pass along the benefits to consumers; however, for downturns, when the margin only falls by a small extent (5.4%), the price of gasoline will rise accordingly, quickly transferring the increase in input costs to consumers. Meanwhile, although we find that the error correction speed varies slightly across different regimes defined by the transition midpoint, the values during the transition are of varying magnitudes and not directly comparable. Therefore, we do not claim to have found evidence supporting the rocket-and-feather effect in the error correction procedure.

5.2. Asymmetric impulse responses

Regarding impulse responses, a small oil price shock (1-SD) does not cause gasoline prices to adjust like RAF, but a large shock (3-SD) does. Overall GIRF performance before and during COVID-19 is similar; however, the impulse responses representing top and bottom 5% of oil price increases and decreases dramatically differed before and during the pandemic. In particular, during extreme oil price surges, when faced with a large positive oil price shock, gasoline prices during COVID-19 had a significantly higher adjustment magnitude and persistence than those in the nonpandemic era. In contrast, during extreme oil price declines, when faced with a large negative oil price shock, the adjustment magnitude of gasoline prices during COVID-19 was significantly greater than the adjustment strength prior to the pandemic, often exhibiting overshoot.

During the pandemic, when oil prices fell sharply (for example, the 2020 Russia–Saudi Arabia oil price war), gasoline suppliers did not fully pass on the benefits of the cost reduction to fuel consumers; however, when oil prices rose substantially, gasoline suppliers quickly pass on the added cost to consumers. This asymmetry significantly harmed consumer welfare for adding to their financial pressures from the rising costs of fuel essentials. Policy interventions, such as temporary fuel subsidies for low-income families, could mitigate these challenges in the short term. Over the longer term, promoting alternative energy sources and enhancing regulations could decrease the gasoline industry's market power.

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Figures and Tables

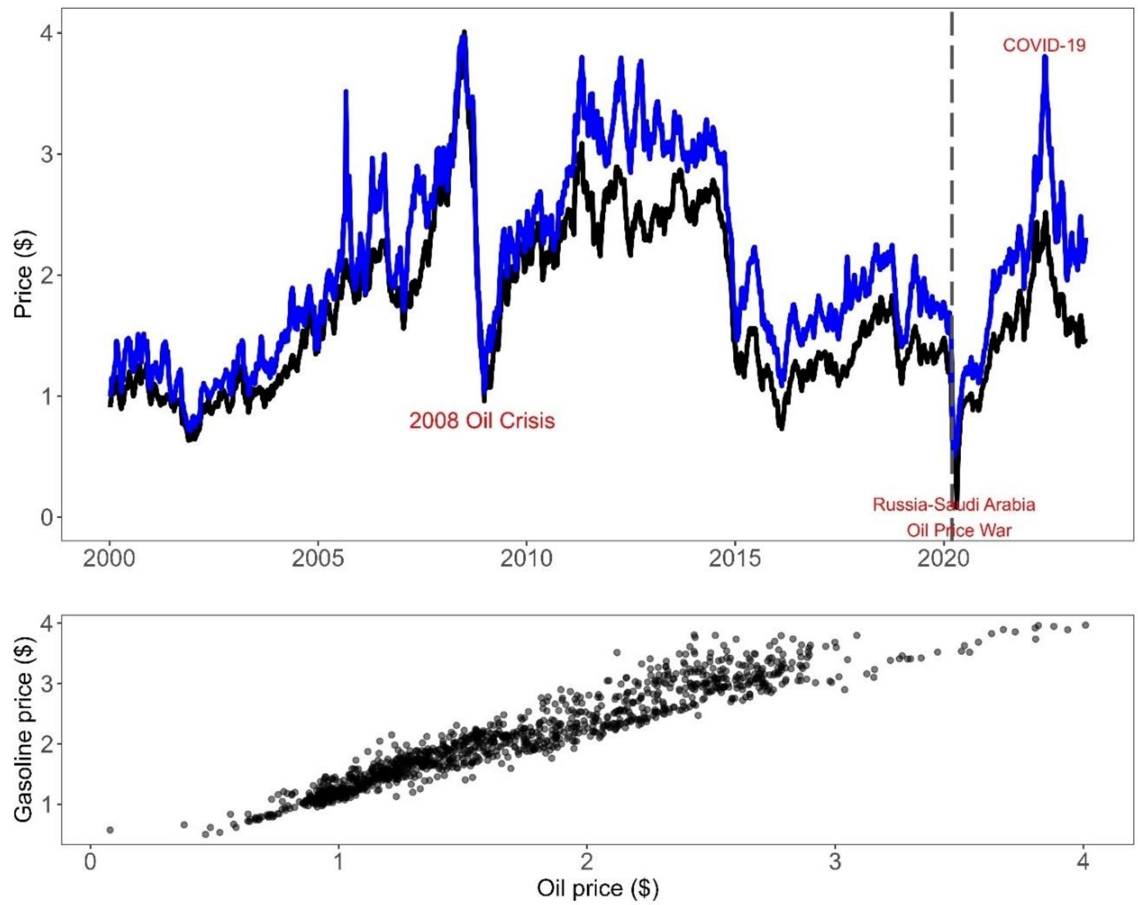

Fig. 1. Plots and a scatterplot for crude oil and gasoline prices (USD/gallon), 2000-2023

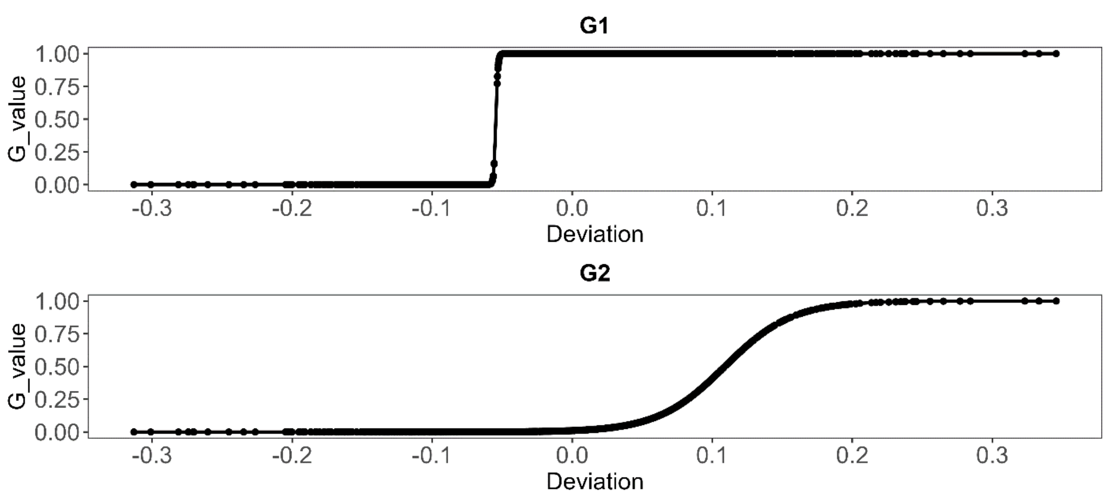

Fig. 2. Scatterplots for the fitted transition function and the transition variable

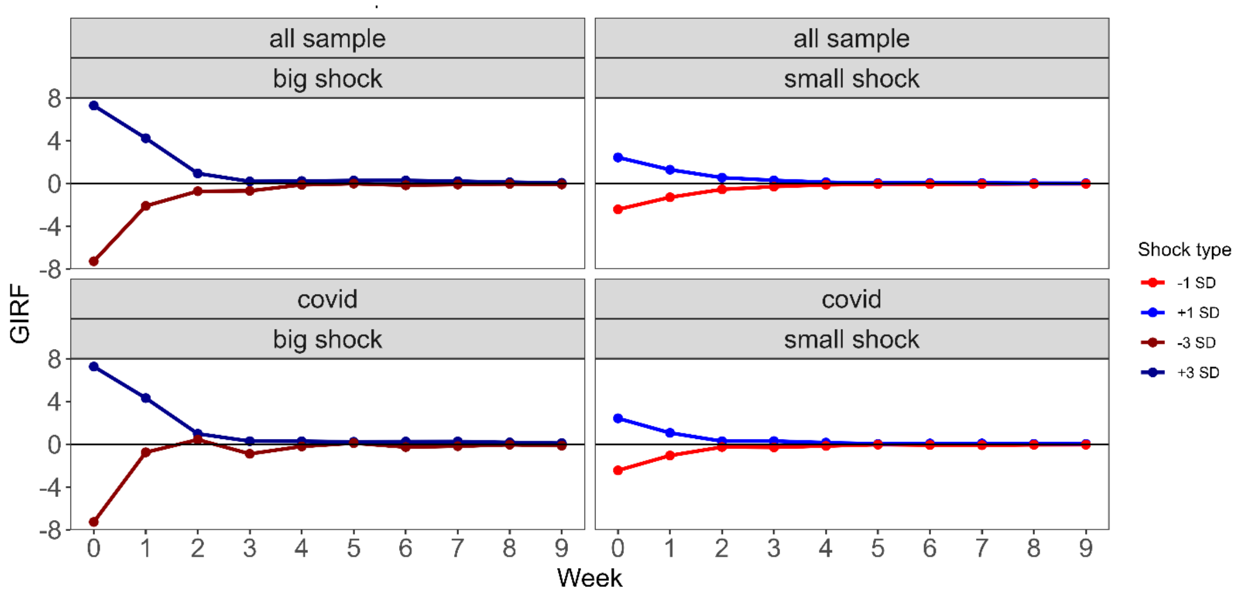

Fig. 3. GIRFs in the general case: all sample and during COVID-19

Note: The upper panel shows the GIRFs (in the unit of %) of the gasoline response to oil shocks over the entire sample period. The lower panel displays the GIRFs of gasoline response during COVID-19.

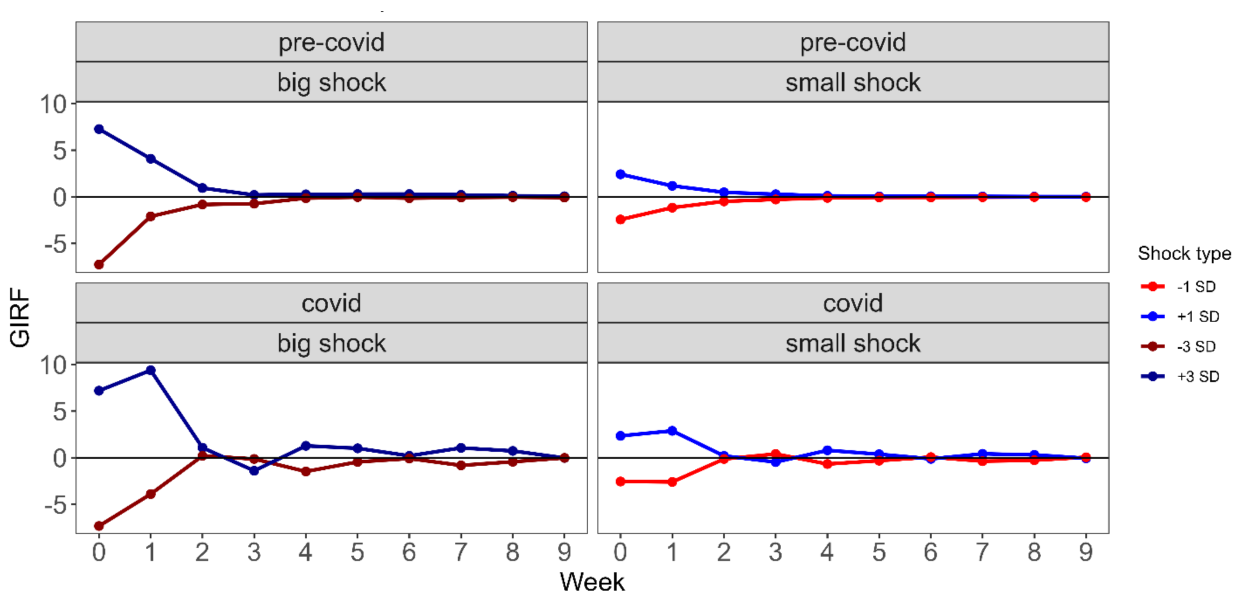

Fig. 4. GIRFs (%) before and during COVID-19 for the case of top 5% oil return

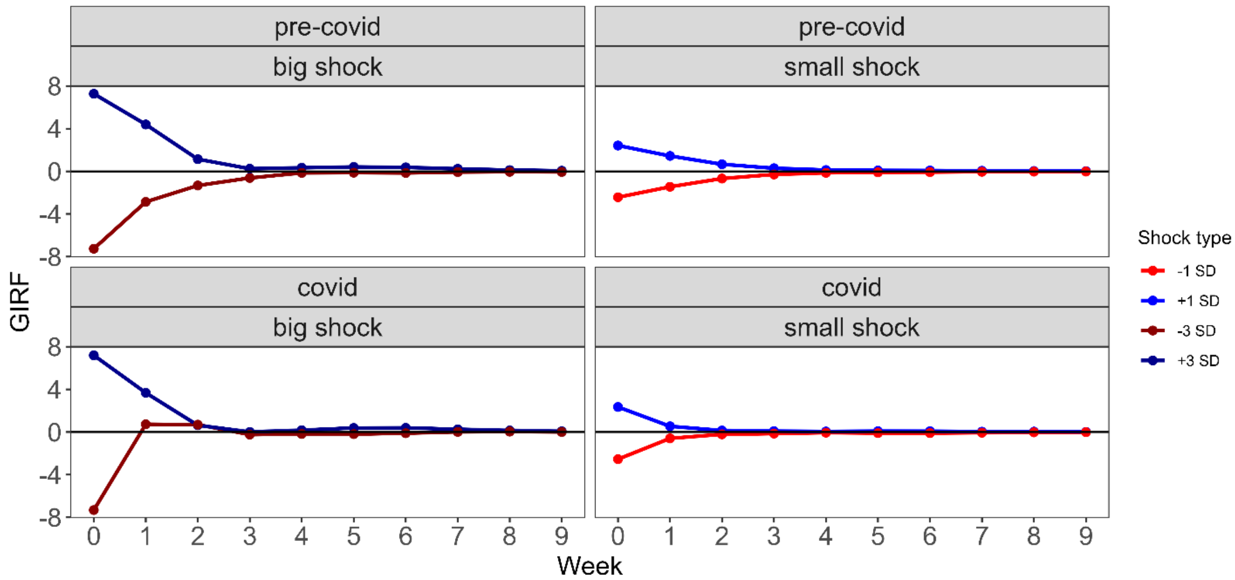

Fig. 5. GIRFs (%) before and during COVID-19 for the case of bottom 5% oil return

Table 1. Summary statistics and unit root tests

Panel a. summary statistics (observation=1130)

	log gasoline	log crude oil
Mean	0.66	0.46
Std. Dev.	0.38	0.40
Minimum	-0.69	-2.53
Maximum	1.38	1.39

Panel b. unit root tests

	price	return	price	return
ADF	-2.74 [15]	-8.41*** [22]	-2.66 [16]	-8.02*** [22]
DFGLS	-1.14 [9]	-5.47*** [8]	-1.66 [5]	-19.51*** [1]
KPSS	2.25*** [9]	0.04 [8]	2.92*** [5]	0.04 [1]

Note: ADF is the augmented Dickey-Fuller test (Dickey and Fuller 1981), DFGLS is the (Elliott et al. 1996) augmented Dickey-Fuller test using generalized least squares detrending, and KPSS is the (Kwiatkowski et al. 1992) stationarity test. For the ADF test, the lag length for log levels is determined by sequentially testing the significance for alternative lags and the last lag at 10% significance level is selected. For the DFGLS and KPSS tests, the lag length is selected using Akaike Information Criteria. The lag length that we use are reported in brackets. ***, **, and * denote significance levels of 1, 5, and 10%, respectively.

Table 2. Johansen cointegration test and the estimated L.R. relationship

	λ_{trace}	critical value (95%)
Johansen cointegration test	146.07	15.41
Cointegrating relationship	$p_t^{gas} = 0.24 + 0.92 p_t^{oil}$ (0.00) (0.01)	

Note: Standard errors are reported in the parentheses.

Table 3. Tests for linearity and S.T. function form selection

tests	gasoline equation	oil equation	muti-equations
Linearity test 0	0.000	0.000	0.000

Note: P-values are calculated based on 10,000 bootstraps.

Table 4. STVECM critical values and estimation results for gasoline

	G_1	G_2
Critical values c	-0.054	0.109
Transition speeds γ	148.413	4.482

Estimation results

Variable	G1=0, G2=0	G1=1, G2=0	G1=1, G2=1
ECT_{t-1}	-0.064***	-0.006	-0.088***
	(0.022)	(0.042)	(0.025)
Δy_{t-1}	0.209***	0.168***	0.006
	(0.074)	(0.059)	(0.074)
Δy_{t-2}	0.167**	-0.013	0.017
	(0.067)	(0.054)	(0.086)
Δx_{t-1}	0.085	0.180***	-0.113***
	(0.076)	(0.062)	(0.030)
Δx_{t-2}	-0.202***	0.143***	-0.231***
	(0.074)	(0.040)	(0.032)
Obs (mid-point)	32.4%	52.6%	15.0%

Note: Standard errors are reported in the parentheses. ***, **, and * denote significance levels of 1, 5, and 10%, respectively. Coefficients and standard errors for regimes 2 and 3 are calculated using the delta method.

Table 5. GIRF-based test for asymmetry

General Case					
full sample			*during COVID-19*		
Horizon	1-SD shocks	3-SD shocks	Horizon	1-SD shocks	3-SD shocks
H=0	0.981	0.981	H=0	0.982	0.998
H=1	1.000	**0.000**	H=1	0.997	**0.000**
H=2	1.000	**0.000**	H=2	1.000	**0.000**
H=3	1.000	**0.000**	H=3	1.000	**0.000**
H=4	1.000	**0.000**	H=4	1.000	**0.000**
H=5	1.000	**0.000**	H=5	1.000	**0.000**

Note: P-values are calculated based on 10,000 simulations of the STVECMs. The test statistic follows a χ^2_{H+1} distribution. The significant results are highlighted in bold.